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AN INVESTIGATION OF THE ROLE OF BODY-WORN INERTIAL SENSING IN THE ANALYSIS OF ELITE SWIMMING PERFORMANCE

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Abstract

Swimming is a technically demanding sport that requires ongoing quantitative assessment in order to monitor technical progression and improvements in performance. Traditional methods of monitoring a swimmer's technique rely on the use of video-based systems. However, the primary motivation for this thesis is that these systems have several limitations when applied in aquatic environments. Such limitations are hindering the extent to which quantitative analytical practices are used by elite swimming coaches. As a consequence, alternative solutions are required and the advancement in the miniaturisation of microelectromechanical systems (MEMS) has led to a recent increase is the interest in applying such technology in swimming.

This thesis describes a set of studies focused on investigating the application of existing MEMS technology for the analysis of elite swimming performance. MEMS sensors such as accelerometers and gyroscopes have been shown to be capable of registering some basic parameters relevant to the analysis of swimming, such as lap time and stroke count, but further research and development are necessary in order to improve the functionality of these devices and to increase the applicability of this approach in elite settings.

This thesis also describes the development of a novel swimming analysis system, based on the use of MEMS inertial sensor technology. A user-centred design approach was followed to fully investigate current practices and to understand the challenges of incorporating this technology in applied training environments. A key contribution of this work is the development of a number of novel feature detection algorithms for the analysis of swimming turns. These studies demonstrate the feasibility of incorporating MEMS technology in an elite swimming environment to inform and enhance the coaching process.

Chapter 1 – Introduction

1.1 Technical analysis of swimming performance

Elite swimming is a highly competitive sport, with world class athletes constantly challenging themselves against their rivals and tiny margins deciding the outcome of races. Consequently, elite swimmers and coaches continually strive for methods and strategies to optimise their performance. A fundamental aspect of this preparation involves regular, quantifiable, data measurement to assess skill acquisition and technical development for the different components of swimming races, namely starts, turns and free-swimming. With the continued advancement of technology in sports, athletes and coaches have ever increasing access to information of their performances.

Swimming is characterized by a sequence of coordinated actions of the trunk and limbs, in a repeated, synchronous pattern. Arm action during each of the four competitive swimming strokes comprises specific phases. A commonly used description of these phases defines the stroke as various sweeps of the arms, which are specific to each stroke (Figure 1.1). For example, the downsweep; insweep; and upsweep movements are completed during frontcrawl swimming [1]. Important kinematic variables such as velocity and acceleration fluctuate greatly throughout each phase [1]. Variations between different swimmers are also typical. Techniques for accurately acquiring these valuable data can therefore be used as part of a quantitative biomechanical analysis process and to inform the coaching process.

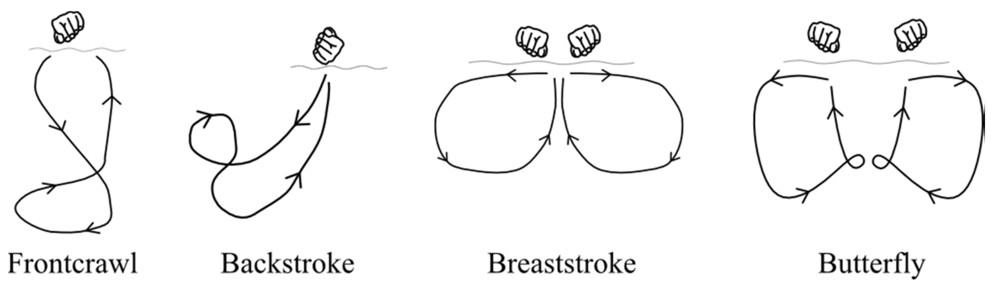

Figure 1.1 Typical hand movement patterns for each of the four competitive swimming strokes. Representation of typical arm actions during swimming, viewed from the front, highlighting the characteristic patterns of movement and sweeps of the arms during each of the four competitive strokes. Adapted from Maglischo [1].

Predominant methods for quantitative biomechanical analysis of swimming performance are video-based [2]. Images from cameras positioned above or below the water surface allow for the entire swimming stroke to be captured in training and competition. Video capture in aquatic environments has inherent disadvantages however, such as limited capture volumes, parallax error, hidden or obscured body segments and water turbulence, all of which affect the accuracy of data [3, 4]. Moreover, the video editing; digitization and data analysis process for video analysis is labour intensive and time consuming, thus reducing the practicality of the technique for routine use [5]. Furthermore, video analysis also often requires expensive and specialised equipment, which is a limiting factor in many coaching environments. Consequently, it is argued that current performance analysis methodologies may not adequately meet the needs of competitive swimming coaches who require rapid feedback to maximise performance gains. Therefore, a requirement exists for alternative solutions to obtain these essential quantitative data that can overcome the limitations with current technologies.

In 1979, Holmer outlined a novel technique for measuring linear acceleration in swimming using an accelerometer attached to a swimmer with a nylon cord and pulley system [6]. Spectral analysis of recorded data highlighted specific frequencies corresponding to both the arm and leg actions of swimmers. The author postulated that this technique could potentially lead to a new method of recording acceleration and velocity during swimming. Later work demonstrated the feasibility of this approach using prototype microelectromechanical systems (MEMS) [7-9] and recent years has seen an expansion in research interest in this area [10, 11]. The potential benefits of this approach include providing swimming coaches with an accessible, low cost solution for rapidly obtaining data to support the biomechanical analysis of swimming technique. This may enable more efficient, effective and quantitative coaching by reducing the demands on a coaches time and equipment requirements. This has led some to suggest that this technology may offer significant advantages over traditional video-based coaching approaches [12]. However, this research area is in its infancy, particularly the translation of research findings into coaching practice, and anecdotal evidence suggests that MEMS technology is currently not in common usage in coaching settings. Additional research work in this area is therefore warranted to fully realise how this technology may be applied in elite swimming. Two research objectives have been established and frame this body of work. Firstly, to comprehensively investigate the application of existing inertial sensing techniques for the analysis of swimming. Additionally, to propose, design and test a novel inertial sensor system, specifically for the quantitative analysis of turns in elite swimming.

1.2 Outline of the thesis

The work outlined in this thesis investigates the use of MEMS-based inertial sensor technology for the analysis of competitive swimming. This thesis comprises of ten chapters. The structure of the thesis is as follows:

Chapter 1 – Introduction: introduces the problems associated with current practices for biomechanical evaluation of swimming in elite athletes and provides an overview of the whole thesis.

Chapter 2 – Analysis of swimming performance: Perceptions and practices of US-based swimming coaches: describes the results of a survey conducted with competitive swimming coaches working in the United States of America. The primary aim of this study was to gain an understanding of the methods and procedures employed by coaches when conducting a technical examination of swimming performance. A secondary aim of this study was to examine the extent of the use of MEMS technologies amongst high level swimming coaches and to gain insight into coaches' awareness of the potential of this technology to provide a solution for quantitative biomechanical analysis. This chapter has been published in the *Journal of Sports Sciences* (2016;34:997-1005).

Chapter 3 – Review of the relevant literature (Part 1: video-based analysis of swimming): provides a comprehensive review of traditional video-based methods of analysing elite swimming performance. The current processes involved in capturing swimmers' movements using video and the rationale for these processes are discussed. A discussion of the limitations associated with video-based methods is presented, focusing on how these issues may impact on coaching effectiveness. This chapter has been published in the *Sport and Exercise Medicine Open Journal* (2015;1:133-150).

Chapter 4 – Review of the relevant literature (Part 2: inertial sensor-based analysis of swimming): investigates the current state of the art of MEMS-based inertial sensor technology for the analysis of swimming. with a particular emphasis on providing an evaluation of the accuracy of different feature detection algorithms described in the literature for the analysis of starts, turns and free-swimming. A detailed review of the technical considerations relevant to the application of MEMS-based systems in aquatic environments follows. This chapter has been published in *Sensors* (2015;16:1-18).

Chapter 5 – Evaluation of commercially available swimming activity monitors: describes a study designed to investigate the accuracy of two commercially available swimming devices that incorporate MEMS technology. The primary aim of this study was to test the hypothesis that these devices provide an accurate and reliable means of measuring key indices of swimming performance. A secondary aim of this study was to evaluate the suitability of these devices for use in elite swimming environments. This chapter has been published in *PLoS ONE* (2017;12:1-17).

Chapter 6 – Application of a User Centred Design approach in the development of an inertial Sensor-based System for the analysis of swimming turns: describes how the application of a User Centred Design (UCD) methodology was used for the conceptual development of a novel system for analysing swimming performance – specifically for the analysis of swimming turns. A Use Case was developed and tested that outlined how the intended end users (sports scientists, coaches and athletes) would interact with the system during various stages of its operation. By following this UCD methodology, it was intended to maximise the usability of the proposed system and thus increase the likelihood of the adoption of the proposed new technology into existing practices of analysing swimming performance in applied settings, thus providing justification for future hardware and software development. This chapter has been presented at the *2016 International Society for Performance Analysis in Sport (ISPAS) Conference*.

Chapter 7 – Swimming sensor prototype development: describes the development of a prototype hardware system that can be used for the acquisition of human movement data during swimming activities. A detailed description of the hardware programming code and prototype testing procedures is presented. The design of the prototype hardware system is intended to meet the user requirements identified in Chapter 6, including factors such as the enclosure size, sensor positioning on the swimmers body and minimizing any interference with respect to the ability of the swimmer to perform their normal swimming activities.

Chapter 8 – A method for the analysis of swimming turns using a head-worn inertial sensor: provides a comprehensive description of the development of novel feature detection algorithms for analysing swimming turns. Tri-axial acceleration and angular velocity signals that are recorded from a head mounted inertial sensor prototype device were investigated, using post-processing methods, to identify key signal features that are relevant to different turning styles performed during each of the four competitive swimming strokes. The primary aim of this study was to examine whether the signal outputs display characteristics which are consistent between different swimmers and to test the hypothesis that these signals could be used to automatically extract key features of interest for the purpose of analysing a swimmer's performance.

Chapter 9 – Evaluation of the Feasibility of Applying MEMS Inertial Sensor Technology for the Analysis of Swimming Turns: provides an evaluation of the suitability of the developed prototype system and associated algorithms for analysing swimming turns. A particular emphasises is placed on assessing the accuracy of these algorithms in an applied aquatic training environment. The principal hypothesis being tested in this study was that inertial sensor-based technologies could be used to accurately detect and measure important quantitative biomechanical parameters related to the performance of turns in swimming, such as turn time, wall contact time and rotation time. The implications are that this information could be used to inform the coaching process and beneficially impact on methods to improve swimming technique and performance.

Chapter 10 – Discussion and Conclusion: the final chapter of this thesis discusses the primary observations and conclusions of this PhD programme of research and presents potential avenues for future research.

The main contributions to the research domain that are described in this body of work include:

- A comprehensive and rigorous evaluation of existing technology for use in the examination of swimming performance, including current practices, current methodologies and emerging technologies.
- The incorporation and methodological description of a user centered design focus into the development of sports technology.
- The development of a novel system of analysis, demonstrating a potential role for inertial sensor technology in an elite swimming environment, including the description and evaluation of a wide range of new feature detection algorithms.

1.3 References

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Chapter 2 – Survey of Elite Swimming Coaches

Published as:

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A starting point for this research project is to attempt to understand current practices of swimming coaches working in competitive environments. Anecdotal evidence and the researcher's prior experience suggest that despite the availability of a wide range and ever expanding variety of equipment that is available for the analysis of swimming performance, coaches may not be incorporating these tools into their coaching practices. These suggestions have not been substantiated however. Moreover, the reasons for these suggestions are highly speculative and have not been explored in a research capacity. Therefore, it was decided to undertake a large scale coaching survey at the outset of this research project to try to elicit answers to some of these questions. The findings of this study are presented in this chapter.

2.1 Introduction

The preparation of elite swimmers for competition is characterised by detailed annual training plans designed to improve all aspects of performance. Central to these preparations are processes of regular testing and measurement as a method to assess and monitor progression. The swimming coach plays the vital role in the training process, with responsibility for instigating a positive change in a swimmer's performance. This is achieved by implementing a structured, periodised programme of training and competition that simultaneously addresses physical, mental, tactical and technical components [1, 2]. Consequently, control over the nature of sports science service provision typically lies with the coach.

Ultimately, an extensive range of resources must be considered to decide the appropriate method of analysis for any given training environment. A comprehensive review of the area summarised that performance analysis of competition using video is the most complete method available, providing a method of analysing the outcome of a performance that incorporates all the factors necessary for that performance [3]. Performance analysis can be defined as the provision of objective feedback to athletes and coaches through the use of different means, typically involving video analysis and statistical information. The analysis can then be used to (i) make a permanent record of performance; (ii) monitor progress; (iii) track changes in performance related variables; and (iv) identify strengths and weaknesses of both the athlete and opposition. However, many other analysis options exist. These include force platforms, tethered devices and recently developed inertial-sensor-based technologies for biomechanical assessment; physiological tools such as heart rate and lactate monitors; as well as an assortment of systems and methods for assessing other areas including psychology, nutrition and strength and conditioning. What is unclear is the extent to which coaches incorporate these various tools when analysing their swimmers' progression.

Competitive swimming is a highly researched area and technological developments have aided advances in the understanding of the biomechanical principles that underpin these elements and govern propulsion through the water [4-6]. Deterministic models have been developed through biomechanical research to highlight the interplay between various temporal, kinematic and kinetic principles during swimming performance [7-10]. These models serve to identify the key parameters that practitioners could monitor to assess improvements when conducting performance analysis.

Commonly, coaches conduct the analysis themselves, through observation and qualitative assessment using the naked eye and video playback [11, 12]. Qualitative biomechanical assessment is based on the coach's own knowledge and experience. A key advantage is that it is both low cost and easy to implement with large numbers of athletes. The value of qualitative analysis of technique should not be ignored. Researchers have argued that biomechanical laws and principles can be counterintuitive [13], causing confusion when explaining & interpreting the meaningful information that results from quantitative analysis. However, a subjective methodology also relies heavily on the coach's expertise and requires them to know what they should be looking for.

A coach may utilise the services of a sports scientist or biomechanist who will use specialist equipment and semi-quantitative analysis approaches to assess specific aspects of performance [14]. Semi-quantitative analysis is useful in conditions where direct measurement is not feasible and can be defined as gathering approximate, rather than exact, data measurements. For example, using video analysis software to estimate the distance travelled during the underwater glide phase following a turn or to approximate a joint angle or segment position using lines overlaid on video footage. However, time delay in data processing can often limit the effectiveness and use of such approaches in applied settings [15].

Finally, a coach may access a biomechanical service delivery that uses quantitative methods through a nationally coordinated programme [16, 17]. Quantitative approaches allow for the greatest level of detail and access to sophisticated equipment and therefore are often reserved for only elite level athletes. In practice, this type of delivery would not be coordinated by a club coach and focus would be on an individual swimmer's needs rather than that of a group. However, research work conducted using similar methods can produce findings that can be generalised for wider impact potential.

The coach is the link between research and practice and therefore it is important to understand their views and investigate practices carried out in elite swimming. However, despite their critical role in the process, the opinions of swim coaches have rarely been reported in the extant literature. Stewart and Hopkins [18] surveyed 24 swim coaches and 185 swimmers to investigate the relationship between training prescription and performance outcome. The focus of that paper was on the periodisation of training, measuring training intensity, duration and volume. Surveys of swimmers themselves have explored the incidence of injury [19]; training practices [20]; coaching climate and behaviours [21] or nutritional considerations [22, 23]. However these studies have collectively failed to address methods of monitoring performance progression through measurement and testing.

To the authors' knowledge, no published research paper has yet aimed to quantify the practices of top-level swimming coaches regarding the performance analyses that they conduct. It is unclear to what extent various tools are used and for what purposes. Understanding the motivations of coaches and how environmental constraints impact on their decisions is important. Previous surveys of other sports coaches have reported poor knowledge transfer between research and applied settings [24, 25], therefore coaches may not analyse swimmers' techniques based on the key findings emerging from research studies, potentially limiting coaching effectiveness.

Therefore, the aim of this paper was to survey a large sample of elite swim coaches regarding their practices and to gain insight into their perceptions regarding the performance analysis tools that they use. Particular attention was given to biomechanical analysis of swimming performance and exploration of the use of various systems, specifically video-based methods of analysis and emerging sensor-based technologies.

2.2 Methods

A self-administered online questionnaire was distributed to all swim coaches affiliated with the ASCA. The survey was reviewed by the Chairman of the NUI Galway Research Ethics Committee and the conditions of the Helsinki Declaration were satisfied. The United States can be regarded as the top swimming nation internationally and consistently tops the rankings at major competitions. For example, USA won 30 medals at the 2012 Olympic Games (31% of the total medals available), including 50% of gold medals. Therefore, the opinions and practices of coaches working in the United States are important and may provide insight into the preparations of elite athletes for competition. In total 635 coaches responded to the survey. However, in order to gain insight into the practices of more senior level coaches with experience working in an elite or competitive setting, a filtering process was carried out and the final analysis was limited to responses from coaches with a minimum of ASCA Level 3 swim coaching qualification (N = 298). This level of coaching qualification was deemed appropriate as coaches will be more likely to be coaching older, more senior/elite level swimmers with national and international level experience.

Categories of questioning included (i) coaching experience; (ii) importance of various areas of sport science service provision; (iii) types of analysis conducted and equipment used for these analyses and (iv) advantages and disadvantages of various video and inertial-sensor-based systems. Opportunities for coaches to express their views in their own words were also included to gain a better insight into their perceptions and to allow them to expand on the responses provided. Questions were intended to be general in nature regarding all available systems and tools for analysis in swimming, to avoid bias regarding the specific aims of the survey. Coaches were asked to consider their experiences over the preceding six years, in order to gain awareness of their current practices, taking into account the latest technological developments.

The majority of the data presented in the results are descriptive in nature. Statistical analyses were carried out using Minitab (version 16.0, Minitab Inc., State College, PA, USA). The Chi-Square test was used to test for association between coaching experience and level of success and to compare the proportions of qualitative and quantitative video-analysis practices used by coaches [26]. In order to investigate if differences existed between coaches rankings of different service areas, a one-way ANOVA and Kruskal Wallis test was conducted on the mean and median scores respectively. A significance level of 0.05 was used for all analyses.

2.3 Results

2.3.1 Characteristics of participants

Table 2.1 provides descriptive information for the final group of survey respondents (N = 298, 245 male, 53 female). More than half of respondents have over 20 years swim coaching experience and almost one third of respondents have coached an athlete ranked inside the top 100 in the world in the previous six years. There is evidence of a significant association between coaching experience and ranking, where the more senior coaches tend to produce better ranked swimmers. Over 40% of coaches with 20+ years' experience have coached swimmer(s) in the top 100 of the world rankings.

Table 2.1. Descriptive information for survey respondents, detailing years of coaching experience and highest world ranking of athletes coached.

Coaching Experience	*N* =	Top 25	Top 26-50	Top 51-100	Top 101-250	>Top 250
0-4 years	8	0	0	0	0	8
5-9 years	34	3	2	1	5	23
10-14 years	46	4	2	7	4	29
15-19 years	39	2	3	6	7	21
20+ years	171	37	16	19	23	76
Total	**298**	**46**	**23**	**33**	**39**	**157**

2.3.2 Sports science and medicine service provision

Coaches were asked to rank, in order of importance, several areas of sport science service provision typically included as part of the annual training plan of elite swimming programmes (1 = most important; 10 = least important). The ranking was based on perceived impact of the service area on swimming performance. Figure 2.1 summarises these results. Biomechanics was ranked most important in order of priority for coaches. There was a significant difference in mean (ANOVA) and median (Kruskal Wallis) rankings across the service areas where biomechanics tends to be ranked higher, on average, compared to the other service areas. Interestingly, medical related areas such as sports medicine, physical therapy and physiotherapy were ranked lowest in order of perceived importance and potential for performance impact, but these rankings do not represent the views of any one coaching group (i.e. more successful or more experienced coaches).

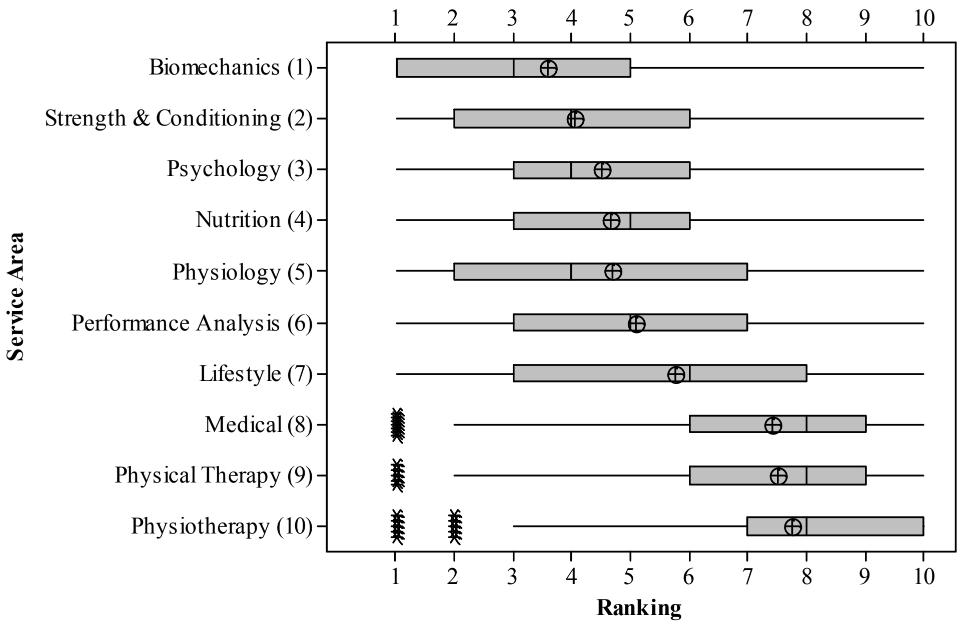

Figure 2.1. Box-plot summarising areas of sports science service provision ranked in perceived order of importance for inclusion in training programme (1 = most important; 10 = least important). Mean (⨁), median (|), interquartile range and outliers (*) are displayed.

Systems of analysis and key performance related parameters

Coaches were asked to provide details of the frequency of use of various systems available for analysing swimming performance and also what they regarded as key system requirements when choosing an analysis tool. Table 2.2 displays results of coaches' usage frequencies. Figure 2.2 provides a ranked order of system requirements, indicating that although more coaches ranked "accessibility" as their top priority, "ease of use" received a higher average ranking overall. A summary of the categories of performance measures reported by coaches as those most important to quantify in order to analyse swimming performance is shown in Table 2.3. The data highlight the central importance placed on temporal measures of performance. In fact, the category for start and turning related parameters reported were also mainly temporal in nature (i.e. breakout time, rotation time) but are grouped separately due to the high response rate amongst coaches, indicating a preference for assessing these key phases of swimming.

Table 2.2 Summary of the frequency of use of various systems available for swimming analysis. The most frequent response is highlighted in bold for each device. All values are percentages (%) based on the responses of coaches.

Analysis System	Daily	Weekly	Monthly	Quarterly	Annually	Less than annually	Not at all
Heart rate monitor	27.5	13.5	12.2	5.7	2.2	3.5	**35.4**
2D Video-based system	9.2	**38.8**	25.3	9.6	5.7	3.5	7.9
3D Video-based system	3.9	16.6	11.4	5.2	3.5	5.2	**54.2**
Inertial-sensor device	3.9	7.9	9.6	7.0	2.6	6.1	**62.9**
Physical activity monitor	3.9	3.9	6.1	5.7	1.7	3.5	**75.2**
Lactate monitor	2.6	10.9	16.6	8.7	1.7	4.8	**54.7**
Pressure sensor	1.7	3.5	6.6	7.9	1.3	5.2	**73.8**
Portable metabolic system	1.3	3.1	7.0	5.2	3.5	3.1	**76.8**
Tethered device (i.e. velocimeter)	0.9	12.2	14.4	10.0	4.4	3.9	**54.2**
Force platform	0.0	3.9	10.0	8.7	2.6	6.6	**68.2**

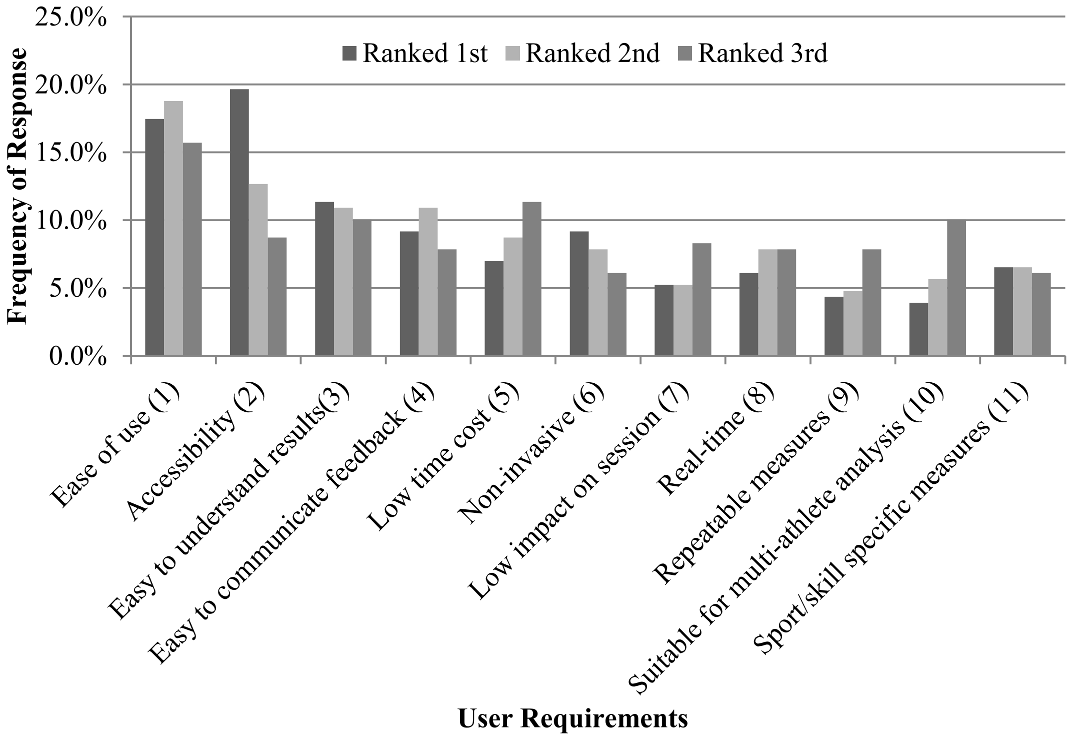

Figure 2.2. Ranking of the perceived most important system requirements reported when choosing an analysis tool. The frequency of response of coaches who ranked each category as one of their top three responses is included. Results indicate a preference for easy to use systems that can be implemented readily into training programmes.

Table 2.3. Summary of the self-selected performance indices reported by coaches as the most important parameters to measure in order to analyse swimming performance. Parameters are grouped into areas such as temporal, kinematic and kinetic parameters based on the specific responses provided.

System requirements	Frequency of response
Temporal parameters (i.e. stroke rate, splits)	41.3%
Body positioning	17.6%
Start & Turn specific parameters	14.8%
Kinematic parameters (i.e. stroke length, velocity, acceleration)	14.0%
Physiological variables (i.e. heart rate, lactate)	3.4%
Kinetic parameters (i.e. force)	3.7%
Psychological parameters	0.5%
N/A responses	4.7%

Video-Based Analysis

As shown in Table 2.2 video-based methods are used frequently by swim coaches, although the extent to which above-water and below-water cameras are used is not clear. Further questions were posed to gain additional insight into the type of analysis carried out using video (Figure 2.3). The expectation was that each category of analysis would be equally represented but a Chi-square goodness of fit test showed that a greater than expected proportion of qualitative analysis is taking place, with a subsequent under-representation of quantitative analysis (X^2 = 35.93, $p < 0.05$).

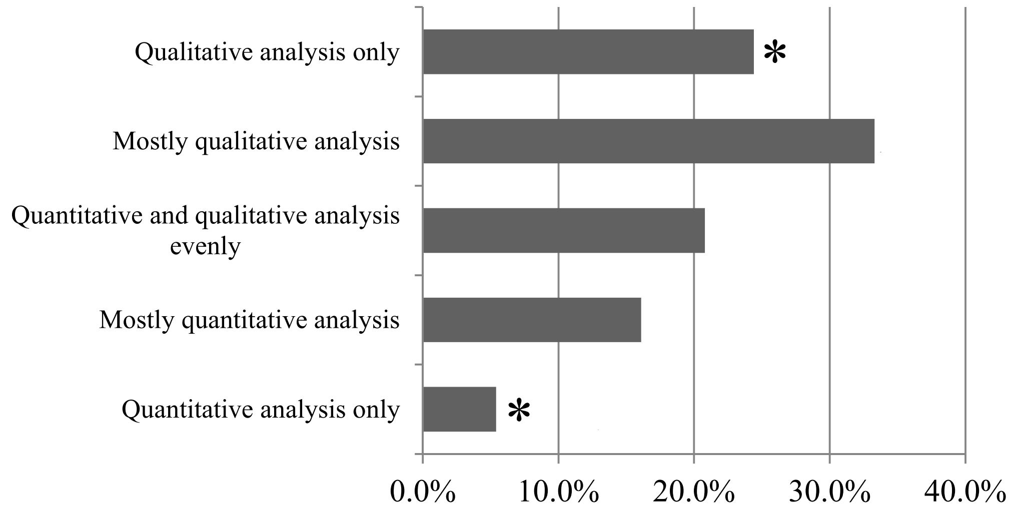

Figure 2.3. Comparison of types of video analysis most frequently carried out. Coaches were asked to state the relative proportions of both qualitative and quantitative analysis conducted within their training programmes. * The results indicate a significant over-representation of qualitative analysis and under-representation of quantitative analysis ($p < 0.05$).

Sensor-based technology

Sensor-based technologies are a topic of recent research attention. Therefore, further enquiry was made regarding familiarity with this emerging technology. Overall familiarity was found to be poor (Figure 2.4) and when subsequently asked explicitly if they had used the devices in the preceding six months a very low number of coaches reported that they had (N = 14). Figure 2.5 compares coaches' perceptions of key barriers to the use of both video and inertial-sensor-based systems.

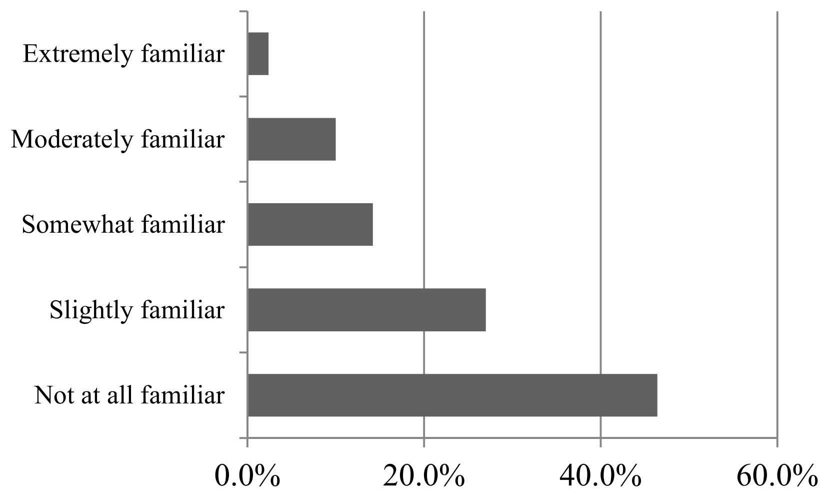

Figure 2.4. Familiarity amongst swimming coaches of the application of body worn sensor-based devices for the analysis of swimming performance, highlighting a lack of familiarity with the technology.

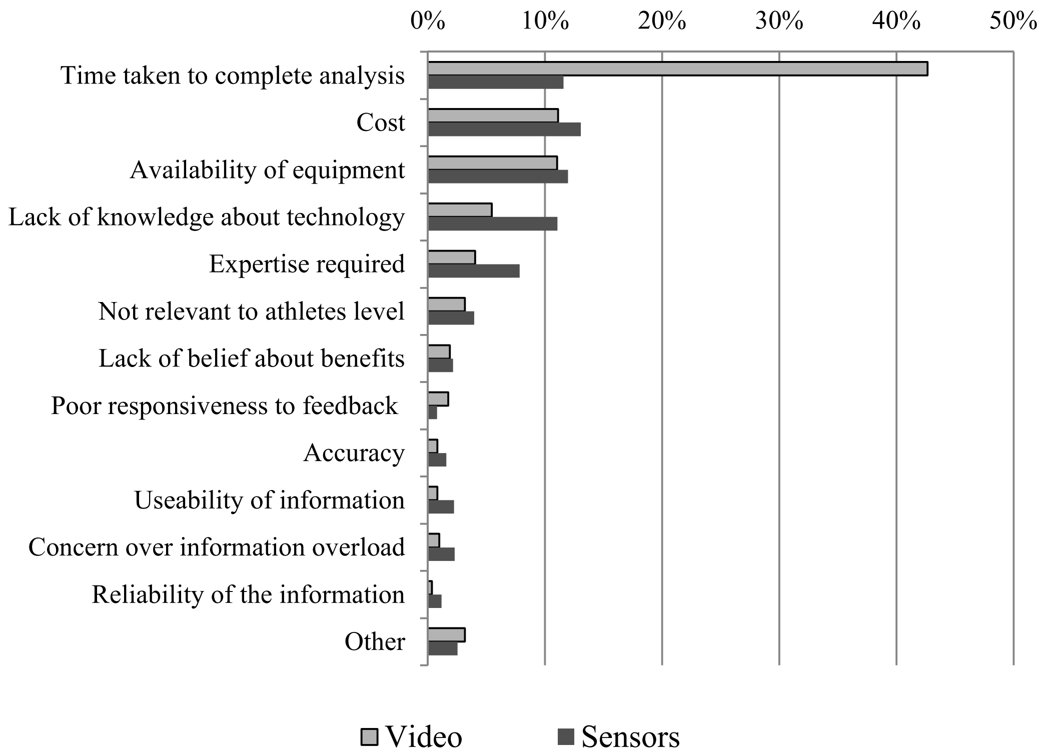

Figure 2.5. Comparison of perceived barriers to use of video-based methods and sensor-based technologies for the analysis of swimming performance. Common barriers exist for both systems, but the time taken to complete analysis is an additional barrier to more widespread use of video.

Information sources

Finally, coaches were asked about their preferred sources of information on swimming performance analysis when deciding what tools to use and what parameters to measure (Figure 2.6). Academic literature and input from a sport scientist ranked lowest. Instead, coaches opt for other information sources such as discussions with other coaches or their own coaching philosophy when making these decisions.

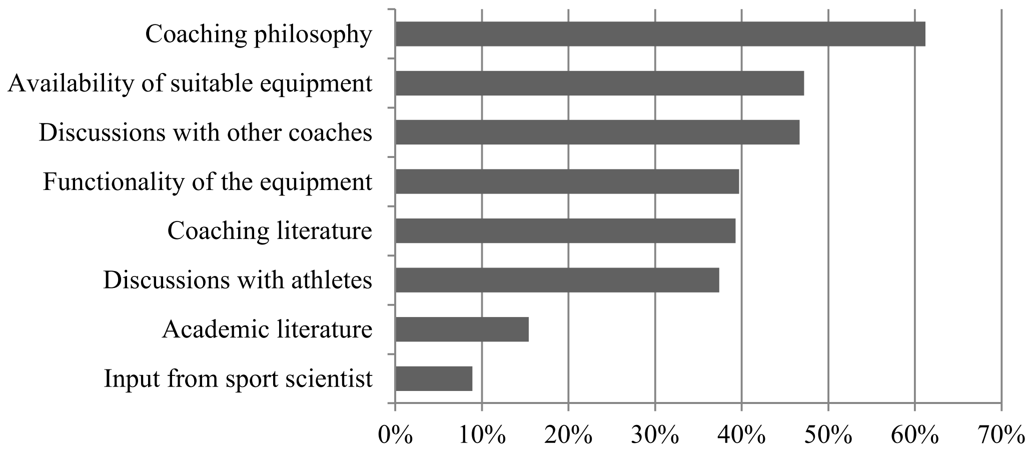

Figure 2.6. Ranked-order of the sources of information for coaches regarding factors that influence decision making regarding the methods of analysis used within their programmes. Academic and non-academic sources are included as well as user requirements for analysis equipment.

2.4 Discussion

The purpose of this research was to determine the practices and perceptions of elite swim coaches based in the United States regarding different performance analysis tools used in competitive swimming, with a specific focus on biomechanical analysis. It was found that coaches regard biomechanics as the most important area of sport science service provision, of the categories queried. This is likely a reflection on the importance of correct technique and also on an accumulation of knowledge emerging from several decades of research into the biomechanical principles governing the four competitive swimming strokes [4, 5, 27-29]. Coaches also indicated that in the majority of cases (196 of 298 respondents), they have sufficient control over how the services are implemented. Not surprisingly therefore, almost three quarters of respondents used video-based methods of analysis on a monthly basis and close to 50 % used video weekly. However, whilst the use of video was widespread, there was a disparity between the perceived importance of quantitative biomechanical data analysis and existing practice that largely employs qualitative analysis of video footage. One coached summed this up by stating:

> *"While biomechanics is an area that is a major focus, it's not always the first focus of either the swimmers or the coach."*
>
> [Male, 5-9 years' experience; swimmer ranked top-25 in world]

This disparity is consistent with previous research that has suggested that the development of video technology in coaching has had an emphasis on qualitative approaches in many sports [11], albeit with a lack of detailed information on specific methods used [12]. Moreover, other performance monitoring tools are much less seldom incorporated into coaching practices. Usage rates of inherently quantitative systems such as force plates, activity monitors and pressure sensors appear limited, suggesting that either significant barriers exist that prevent coaches from conducting such work more frequently or that quantitative data analysis is not considered important. When asked if actual provision mirrors their ideal or preferred provision as shown in Figure 2.1, less than half of respondents agreed (N = 136).

Barriers

According to the coaches surveyed, the main constraints preventing more widespread use of biomechanical tools in swimming were a lack of finances, time restrictions and accessibility to suitable testing equipment. Several coaches commented on the difficulties of balancing resources with requirements, hampering their ability to deliver the sports science services in an ideal manner. Additionally, coaches were often forced into balancing the needs of a group versus those of the individual.

> *"Time is always the culprit, we only have so much time and space so I must make the decisions to do what I think is best for the team and then the individual."*
>
> [Male, 20+ years' experience; swimmer ranked top-50 in world]

> *"Time and budget make it difficult to spend as much time analysing mechanics and performance data."*
>
> [Male, 0-4 years' experience; swimmer ranked outside top-250 in world]

Several coaches' remarks also indicated that in an ideal situation, without these constraints, they would perform more quantitative analysis, such as in-depth kinematical examination of specific skills; increased investigation into propulsive forces generated by individual athletes and acceleration profiling for different stroke phases. However such views were not universally held, with other coaches making reference to the experience and skill of the coach as the vital component in achieving swimming excellence.

> *"Swimming excellence is based on form feel and aggressive approach. I am not convinced that those things can be acquired by the majority, using [available] technologies."*
>
> [Female, 15-19 years' experience; swimmer ranked top-100 in world]

> *"Coaches are too hung up on technology and forgetting that we are artisans. There is no perfect scientific way to create a champion; it must happen between the ears, not with a magic box."*
>
> [Male, 5-9 years' experience; swimmer ranked outside top-250 in world]

Video-based analysis methods

Many coaches provided interesting insight into what can be considered the key advantages and disadvantages of using video. Interestingly, none of the advantages related to quantitative approaches. Instead, coaches' comments concur with research findings that the main feature promoting the use of video is the objective record of a swimmer's activity provided [11], from which both coach and swimmer can benefit. Visual feedback on performance is perceived to be vital for skill acquisition, with many coaches suggesting that swimmers' awareness of their movements in the water may be at odds with what they are actually doing much of the time. Manipulation of the video image using tools such as slow motion replay, frame by frame viewing or split screen comparisons are also perceived as important advantages. Most of the swimmers' movements occur under the water, causing difficultly for a coach to see what is going on, therefore the video appears to be just as important for the coach as for the athlete.

> *"[Video gives a coach the] ability to show the athlete what they are actually doing versus what they feel they are doing so your instructions are supported by fact in their minds."*
>
> [Male, 10-14 years' experience; swimmer ranked top-25 in world]

> *"[Video] truly helps a swimmer to see what they are doing or need to do. Sometimes telling them just doesn't work, but letting them watch it does. [Video] also helps to slow down a stroke and allow you to see things you could not see [otherwise]."*
>
> [Male, 0-4 years' experience; swimmer ranked outside top-250 in world]

Commonly perceived disadvantages to video analysis methods were clearly found from the results. Cost and availability are both important factors, however time delay has been found to be the most critical barrier. This may involve the time to complete data collection; time to interpret and analyse information or time lost from training to provide feedback information to swimmers.

> *“It is difficult to provide relevant information to a large group in a timely manner.”*
>
> [Male, 15-19 years’ experience; swimmer ranked top-50 in world]

> *“I love being able to offer [video analysis]; but it is extremely time consuming to provide good analysis to every swimmer. With even a small team of 40 athletes it can take me a week dedicated just to videotaping, analysing it for hours at home, and then with 15 minutes of feedback to the swimmer each, it takes me 10 hours to review with them all.”*
>
> [Female, 20+ years’ experience; swimmer ranked outside top-250 in world]

> *“Many programs that you can use (Dartfish for instance) offer great analysis, but are extremely labour intensive. The best programs offer immediate feedback for the athlete to make adjustments quickly.”*
>
> [Male, 10-14 years’ experience; swimmer ranked outside top-250 in world]

Time delay, too, is often cited as a disadvantage of video in research literature [30, 31]. Aside from the editing process, digitization and data processing for quantitative analysis is labour intensive and time consuming, thus reducing the effectiveness of the feedback. Guadagnoli, et al. [32] demonstrated that video is an effective method of producing changes in technique over and above verbal feedback. However, others have shown that quantitative feedback is also important for swimming analysis rather than using video purely to provide the visual record of performance [33]. Researchers have also questioned the accuracy of various video-based methods [34]. Moreover, video capture in aquatic environments has other inherent disadvantages, such as hidden or obscured body segments, water turbulence and issues with light refraction [30, 35], none of which was referenced by respondents to the survey.

Sensor-based technology

Comparison of the perceived barriers of video to those for sensor-based technology is of interest as inertial-sensors have been touted as a possible substitute for video-based analysis [30]. Cost and availability were commonly expressed as disadvantages, but for inertial-sensors a perceived lack of knowledge amongst coaches is clearly another important issue. Despite recent claims of the potential benefits of inertial-sensor-based systems, usage remains extremely low, with very few of the coaches surveyed (N = 14) using these systems within the previous six months. Close to half of respondents (N = 138) described themselves as "not at all familiar" with the technology, with coaches commenting:

> *"More literature needs to be published in the swimming community. As an everyday coach, if I have not heard of it, and I do more reading than the average coach, then there is a problem with the advancement of the technology right there."*
>
> [Male, 10-14 years' experience; swimmer ranked outside top-250 in world]

> *"[I would] need a demo of the technology and testimonies of people using it and making a difference."*
>
> [Male, 15-19 years' experience; swimmer ranked outside top-250 in world]

Swimming related applications for sensor-based technology have received much research attention recently [35-38] and some commercially available devices have recently emerged. The small number of coaches who have used sensors did provide insight into possible advantages of sensor-based technologies. They reference both the speed of feedback provided as well as the quantitative nature of the data obtained.

“[sensors provide] immediate feedback for multiple swimmers at once.”

[Male, 10-14 years’ experience; swimmer ranked top-100 in world]

“It is quantifiable.”

[Male, 20+ years’ experience; swimmer ranked top-100 in world]

“Information is collected automatically and feedback is given within seconds. Detailed information can be accessed [at a later time].”

[Male, 20+ years’ experience; swimmer ranked outside top-250 in world]

These sentiments echo the key conclusions of other researchers’ findings. Sensor-based systems have been developed to provide rapid feedback to swimmers on key performance indices such as lap times and stroke rates [36, 38]. Other research purported advantages include high levels of accuracy and potential for integration with other feedback systems [30, 35, 38]. Interestingly, some academic sources also refer to the low cost of sensor-based technology [39], which is at odds with perceived opinion amongst coaches.

Coaches’ perceptions of key performance related parameters

Biomechanical swimming research has found certain measureable parameters to have a significant influence on swimming performance. Therefore it is interesting to explore and compare coaches’ perceptions of the most important parameters and the data they most frequently collect. A common theme evident from results presented in Table 2.3 is that coaches consistently reported time-based parameters such as stroke rates or split times over and above other types of information as being of most importance to them. Temporal measures are useful benchmarks of performance but more in-depth analysis of the underlying kinetic and kinematic factors influencing this temporal outcome is recommended [3].

The analysis of starts and turns is recognised by coaches as a vital component of overall performance but again the remarks of coaches are focused on time-based parameters. For example, time to 15m is frequently used as a measure of starting performance but has been shown to be influenced by other underlying factors, such as the horizontal velocity at take-off or time spent in flight [40, 41].

Another theme that emerged was the perceived importance of body position, including streamlining, hand movements and joint angular positions. Coaches would appear to assess these areas through direct observation or qualitative examination of video footage to get a general picture of a swimmer's position in the water and coordination of various body segments, without typically relying on quantitative data to support their opinions. Therefore, the coaches view would be that sophisticated data analysis tools are not currently used to get the information that they are looking for.

User requirements

Comparisons of the findings in the present study with previous research exploring the main user requirements of coaches when selecting an analysis tool are of interest. The data presented in Figure 2.2 show that the main requirements are (i) ease of use; (ii) accessibility and (iii) ease of understanding, suggesting a preference for straightforward analysis systems that do not require complex implementation. Presumably, coaches are more concerned with the data output for use with their athletes. Surprisingly, coaches ranked real-time feedback eighth out of eleven use requirements, which is unexpected given their comments on the issue of time affecting their practices. These findings contradict previously reported user requirements that suggested skill specific measures and repeatability of measures to be the key user requirements [38]. User requirements had been determined through a similar methodology in this previous study, which involved interviews and questionnaires with coaches, biomechanists and swimmers, but the numbers involved were unreported. Contradictory findings such as these serve to highlight that the requirements for different end user groups may not always be the same.

Information sources

A potential explanation for the key findings of the present study lies in the sources of information used by swimming coaches. A coach's knowledge source will drive the coaching process by informing training plans [42]. Coaches would appear to rely on their own coaching philosophy, coaching literature and other coaches' opinions rather than academic or scientific sources when making decisions about technical analysis of swimming. Interestingly, time constraints have also been cited elsewhere as a reason for ignoring certain sources of information [25]. Although not considered in the present study, it would have been interesting to assess the academic background of respondents in addition to their vocational training, as access to such resources may also be a limiting factor.

A supportive coaching community working within a collaborative knowledge-sharing environment is to be welcomed. However, the results of the present study raise concerns that research led developments in elite assessment of swimming may not be filtering down to those on the side of the pool, a finding that is consistent with previous research [24, 25, 43]. Potentially, a situation may develop whereby coaches might not recognise how important certain kinetic or kinematic parameters are to measure or fully appreciate the link between these parameters and overall race performance.

2.5 Conclusion

The results of this survey highlight a disparity between ASCA Level 3 coaches' perceptions and their practices in monitoring and assessing technical aspects of swimming performance. On the one hand, the findings suggest an understanding of the importance of applying biomechanical principles in their training programmes. However, swim coaches have a clear focus on measuring temporal based parameters and place limited emphasis on the underlying principles influencing these. A variety of factors are at play, including constraints due to their personal situations (time, cost, availability); accepted coaching practice and their awareness and application of the findings of research studies.

What is unclear from this study is whether practices would change if the barriers were to be removed. Additional exploration of coaches' needs is warranted, to examine more fully the reasons for conducting different types of analyses with their swimmers. It would also be interesting to compare these findings against other prominent swimming nations. Additionally, gaining the opinions of elite swimmers would also allow further insight into what they consider to be the best methods of analysing their technique and what modes of feedback and instruction they would find most beneficial.

These findings have implications for coaches and researchers alike, as well as impacting on device development for swimming analysis. Enterprises concerned with new product development for swimming performance analysis can benefit from fresh insight into barriers against the use of existing technology and the key user requirements according to coaches. Poor crossover between research and applied practice is not unique to swimming. However, with such emphasis on technical development, it is important that swim coaches measure the parameters that will most impact performance. Coaching literature plays a large part in disseminating the information emanating from academic research and presenting findings to coaches in a convincing manner. Until such time that coaches fully appreciate the value of quantitative data it is likely coaches will continue to opt for traditional practices and their own intuition as the main means of assessing elite swimming performance.

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Chapter 3 – Review of Relevant Literature (Part 1: Video-Based Analysis of Swimming)

Published as:

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The results of the coaching survey, presented in Chapter 2 of this thesis, raised a number of important and relevant issues. Firstly, video-based systems were found to be very widely used for the analysis of swimming performance in applied settings. However, the scope of the use of video is limited largely to qualitative practices, with clear barriers towards the use of video for quantitative data collection. Additionally, little is known regarding the specific methodologies that are employed for using video in aquatic environments. Therefore it was deemed important to undertake a comprehensive review of the relevant literature in order to fully understand the use of video-based systems for the analysis of swimming performance. This is the focus of Chapter 3 of this thesis.

3.1 Introduction

Elite sporting success is achieved through gradual improvements over an extended period of time, to ensure that the athlete has achieved a sufficient level of physical conditioning and technical expertise. Central to this process is a detailed training plan which is prepared by the coach and monitored using a variety of means, with video-based analysis arguably the most common methodology employed in elite sport. Unsurprisingly therefore, many reviews have been published on the various applications of video in sport, including technical recommendations [1] applications in coaching and feedback [2-4]; human motion tracking and analysis [5-7]; and technological advances [8].

There are various methods by which video analysis is applied in different sports [2, 3]. A recent review of the development of video technology in coaching settings examined key questions about why and how sports coaches apply video-based methods [2]. That author proposed that the main reason why video is used is to provide an objective record of performance, providing evidence that can be reviewed and analysed. To further understand the application of video in particular situations, reviews have been carried out for specific sports such as soccer [9]; tennis [10] and golf [11]. Video analysis has been used for various purposes, including tactical; technical; physical and mental applications in different sports [12].

The use of video in competitive swimming is widespread, with close to three quarters of coaches based in the United States using video on a monthly basis [13]. This is not unexpected as underwater video cameras can be positioned in ways that can record what the coach cannot see from the pool deck, thus providing him/her with additional insight into the athletes' performances. This is essential to ensure that swimmers develop a good technique, not just for performance gains but also to reduce the risk of injury [14]. Previous research has shown that video is used by swimming coaches mainly as a qualitative tool [13]. This is intuitive as the qualitative process is more straightforward to implement in applied settings compared with quantitative practices. However, Lees [15] has argued that there is a lack of information regarding the specific qualitative methods used in elite sport and also a shortage of evidence of how successful this approach may be. In a swimming context, this appears to be valid, with a dearth of published research papers outlining the application of qualitative video analysis and providing evidence of the effectiveness of the approach.

Video is also widely utilised for quantitative purposes in swimming for various applications including assessing technique, for race analysis; as a teaching tool; or as part of a medical screening process. Additionally, video is the primary means by which data for swimming research are collected and has allowed researchers to greatly advance our understanding of the mechanics governing each of the four competitive swimming strokes [16-19]. Callaway, et al. [20] reviewed how our understanding of swimming mechanics developed through video analysis but focused on research breakthroughs, making comparisons with newer sensor-based technologies. Others have provided an extensive examination of the technical aspects of underwater videography, with an emphasis on calibration and reconstruction procedures [21-23].

No review has been published specifically assessing the processes by which video is captured in applied swimming settings. This may result in uncertainty amongst coaches and practitioners regarding the most appropriate methodologies to be adopted and the value of video in swimming. Additionally, it is the view of the authors that such a review could serve to provide recommendations for coaches, sports scientists and clinicians, given the challenges of working in an aquatic environment. This may lead to increased consistency in approaches to video analysis in competitive swimming to ensure the efficiency and effectiveness of coaching practices is maximized. The aim of this study is to systematically review the applications of video-based systems for the analysis of competitive swimming. The review will focus on the processes involved in video analysis in competitive swimming; the interpretation and feedback of data for technical analysis; and will outline future developments currently emerging in the literature.

3.2 Methods

A systematic review of the available literature on the application of video-based methods for the analysis of competitive swimming performance was conducted according to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines in an attempt to address the following review questions: (1) what are the processes involved in obtaining video-based data for swimming analysis, (2) how can the video footage be interpreted and presented for technical analysis of swimming performance and (3) what are the emerging advances in video-based technology for competitive swimming analysis. The electronic databases ISI Web of Knowledge, PubMed, Science Direct, Scopus and SPORTDiscus were searched for relevant publications over a five year period to the end of June 2015, using the following keyword search string: *(swim OR swimming OR swimmer) AND (performance OR analysis OR quantitative OR qualitative) AND (camera OR video)*. The inclusion criteria for these articles were: (1) that they provided sufficient detail regarding the equipment specifications and experimental setup; (2) that they include relevant data regarding the application of video-based methods for the analysis of competitive swimming performance; (3) that they were published in the last five years (1st July 2010 – 1st July 2015) to ensure that the most contemporary issues could be explored and (4) that they were written in the English language. Studies were excluded if they: (1) did not involve human competitive swimmers; (2) did not provide sufficient detail to answer at least one of the review questions and (3) were published as part of conference proceedings.

3.3 Results

The outcomes of the systematic search strategy process is summarised in Figure 3.1. The initial search identified 384 records. Reference manager software (EndNote X5, Thomson Reuters, Philadelphia, PA, USA) was used to collate results. Duplicates were removed and a screening process of both the title and abstract of the remaining records was subsequently conducted. The full-text of the remaining records was then assessed for relevance to the review. Following this procedure, 30 articles remained for the systematic review (Table 3.1).

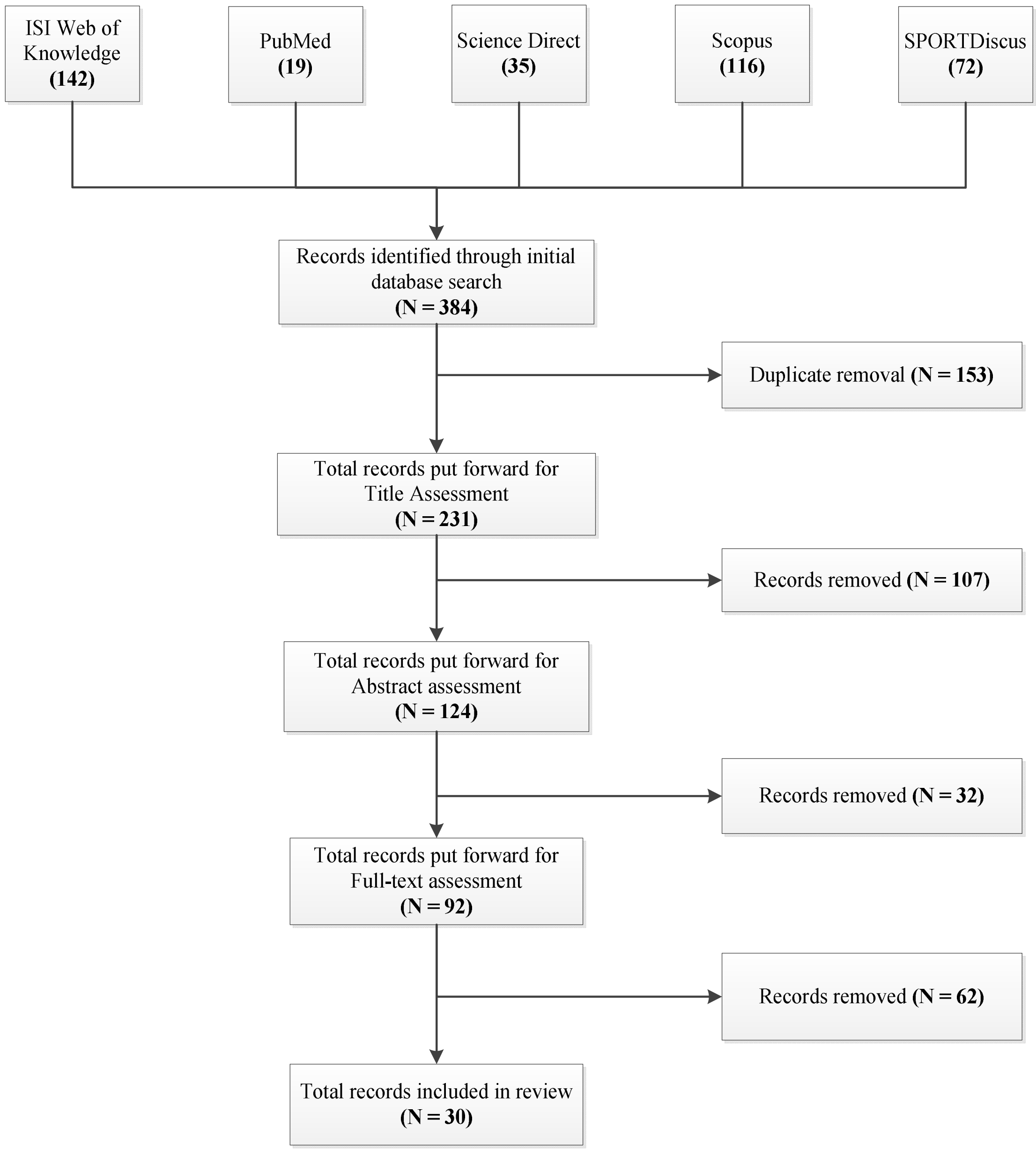


Figure 3.1 Flowchart of the systematic literature search.

Table 3.1 Results of systematic review search summarising studies conducted that apply video-based systems for the analysis of swimming performance. Results are presented in chronological order and include the purpose of the study; experimental and equipment details; the number of anatomical landmarks and the variables that were measured using the video footage. Abbreviations: UW = underwater; AW = above water; FoV = Field of view; Unrep. = Unreported; IdC = index of coordination.

Reference	Purpose of Study	Exp. Design	No. of cameras	Camera config.	Plane(s) of movement	Enclosures (for UW camera)	Frame rate	No. of anatomical landmarks	Camera positioning	Variables measured using video
Andrews, et al. [24]	Quantify shoulder kinematics in backstroke and compare between advanced and intermediate level swimmers	2D	1AW	Static	Frontal	Viewing window	50 Hz	4	2.3m above water FoV: 2x2m	Shoulder entry angles
Ceseracciu, et al. [25]	Analysis of freestyle kinematics using a markerless system	3D	6UW	Static	Sagittal, frontal	Waterproof housing	Unrep.	0	0.0-1.65m depth	Shoulder, elbow & wrist joint angles
Psycharakis and McCabe [26]	Examination of the effect of breathing patterns on freestyle swimming kinematics	3D	4UW 2AW	Static	Sagittal	Waterproof housing	50 Hz	19	UW: 8m from swimmer, 0.5-1.5m depth, 75-110° optical axis AW: 12m from swimmer, 100° optical axis FoV: 6.5m per camera	Shoulder & hip roll
de Jesus, et al. [27]	Effect of fatigue on kinematics of butterfly swimming	2D	1UW 1AW	Static	Sagittal	Waterproof housing	50 Hz	13	UW: 1.6m depth AW: 0.9m above water 2.1x3.0 calibration space 9m from plane of movement	Velocity, stroke length, stroke rate, intra-cyclic velocity variation, stroke duration, hand & foot displacement
Figueiredo, et al. [28]	Examination of the variability on arm coordination patterns in freestyle	3D	4UW 2AW	Static	Sagittal, frontal	Unrep.	50 Hz	21	UW: 75-110° optical axis AW: approx. 100° optical axis	Velocity, stroke length, stroke rate

Reference	Purpose of Study	Exp. Design	No. of cameras	Camera config.	Plane(s) of movement	Enclosures (for UW camera)	Frame rate	No. of anatomical landmarks	Camera positioning	Variables measured using video
Komar, et al. [29]	Analyse the effect of increased energy cost on kinematics of freestyle swimming	2D	1UW 1AW	Static	Sagittal	Waterproof housing	50 Hz	0	UW: 0.5m depth FoV: 5m	Stroke rate, stroke length, velocity, arm coordination, energy cost
McCabe and Sanders [30]	Analysis of kinematic differences in freestyle performance between sprint and distance swimmers	3D	4UW 2AW	Static	Sagittal	Waterproof housing	50 Hz	19	UW: 8m from swimmer, 0.5-1.5m depth, 75-110° optical axis AW: 12m from swimmer, 100° optical axis FoV: 6.5m per camera	Average velocity, stroke length, stroke rate, stroke duration, arm & foot displacement, shoulder, elbow & hip joint angles
Martens and Daly [31]	Qualitative analysis of breaststroke technique	2D	1UW	Static	Sagittal	Viewing window	25 Hz	0	Unrep.	Water displacement due to kicking patterns
Puel, et al. [32]	Kinematic and kinetic analysis of tumble turn performance	3D	5UW	Static	Sagittal, transverse	Waterproof housing	50Hz	17	0.7-2.0m depth 45-60° optical axis	Temporal, kinematic & kinetic parameters related to turn performance (integrated with force platform)
Takeda, et al. [33]	Effect of starting block setup on the kinematics of track start performance	2D	1AW	Static	Sagittal	N/A	125 Hz	14	2m from plane of motion	Block time, velocity (horizontal, vertical, resultant), flight distance, take off angle, rear foot take off time
Thow, et al. [34]	Comparison of different feedback methods on glide performance	2D	1UW 1AW	Static	Sagittal, frontal	Waterproof housing	50 Hz	5	UW: 10m from swimmer AW: 5m from swimmer FoV: 9m	Initial & average velocity, glide factor
Bideault, et al. [35]	Investigation of individual variations in limb coordination patterns	2D	2UW 1AW	Static, trolley	Sagittal, frontal	Waterproofed camera	50 Hz	0	UW: 0.4m depth FoV: 10m (side view)	Average speed, stroke length, stroke rate, IdC

Reference	Purpose of Study	Exp. Design	No. of cameras	Camera config.	Plane(s) of movement	Enclosures (for UW camera)	Frame rate	No. of anatomical landmarks	Camera positioning	Variables measured using video
Ceccon, et al. [36]	Kinematical analysis of arm motion in freestyle using CAST technique	3D	6UW	Static	Sagittal, frontal	Waterproof housing	Unrep.	31	0.0-1.65m depth	Shoulder & elbow joint angles
de Jesus, et al. [37]	Comparison of different backstroke starting techniques	2D	1UW 1AW	Static	Sagittal	Waterproof housing	50 Hz	13	UW: 0.3m depth AW: 0.3m above water 2.5m from head wall of pool 2.1x3.0 calibration space	Centre of mass position and velocity, contact time, take off angle, back angle arc, fight distance, start time
Gourgoulis, et al. [38]	Effect of resistance on propulsive forces during freestyle sprint swimming	3D	4UW	Static	Sagittal	Periscope	60 Hz	11	3x1x1m capture volume	Pitch & sweepback angles, hand velocity, propulsive forces
Silva, et al. [39]	Characterization of backstroke swimming kinematics at high intensity	2D	2UW	Static	Sagittal, frontal	Waterproof housing	50 Hz	12	6.3m^2 capture space	Average velocity, stroke rate, stroke length, stroke index, IdC
Strzala, et al. [40]	Investigation of correlation between technique with velocity profile in breaststroke swimming	2D	1UW 1AW	Trolley	Sagittal	Waterproofed camera	50 Hz	0	UW: 1.0m depth 5m from plane of motion	Stroke phase analysis (arms & legs), stroke rate, stroke length, IdC, speed
Veiga, et al. [41]	Analysis of the kinematics of backstroke turns	2D	4AW	Static	Sagittal	N/A	25 Hz	0	All cameras positioned 7m above and 7m away from pool 2 cameras fixed at ends of pool, perpendicular to plane of motion, 2 cameras fixed with	Turn time (7.5m round trip), distance in, UW distance, velocity, normalized velocity, stroke velocity

Reference	Purpose of Study	Exp. Design	No. of cameras	Camera config.	Plane(s) of movement	Enclosures (for UW camera)	Frame rate	No. of anatomical landmarks	Camera positioning	Variables measured using video
									optical axes crossed (one from 0-15m and the other from 10-25m)	
Atkison, et al. [42]	Examination of dolphin kicking performance	2D	1UW	Static	Sagittal	Waterproofed camera	30 Hz	12	0.5m depth, 7.5m from push-off wall, 4m from swimmers plane of motion	Kick symmetry, displacement, amplitude & frequency. Horizontal centre of mass velocity, relative angles for ankle, knee, hip, shoulder, elbow, wrist, upper waist, lower waist & chest.
Cohen, et al. [43]	Examination of the pitching effects of buoyancy using a markerless system	2D	2UW 1AW	Trolley, towing cable	Sagittal, transverse	Unrep.	50 Hz	0	Unrep.	Centre of mass & centre of buoyancy positions, buoyancy torques, moment of inertia
do Couto, et al. [44]	Effect of breathing patterns on freestyle swimming kinematics	2D	1AW	Static	Sagittal	N?A	50 Hz	2	2.35m above water Approx. 11.7m from swimmer FoV: 7.5m	Stroke rate, stroke length, velocity
Gourgoulis, et al. [45]	Assess the effect of leg kicking dynamics on freestyle kinematics	3D	4UW	Static	Sagittal	Periscope	60 Hz	6	3x1x1m capture volume	Stroke rate, stroke length, velocity, intra-cyclical hip velocity, IdC, pitch & sweepback angles
Monnet, et al. [46]	Determine the accuracy of a 3D kinematics system for swimming analysis	3D	8AW	Static	Sagittal, frontal	Viewing window	200 Hz	4	0.55-2.0m height 1.4-1.9m from viewing window 0.45-1.8m between cameras	Sweepback & pitch angles
Schnitzler, et al. [47]	Effect of aerobic training on freestyle kinematics	2D	2UW 1AW	Static & panning	Sagittal, frontal	Waterproof housing	50 Hz	0	UW: panning camera positioned at mid-pool, static camera captured frontal plane AW: profile view of entire swim trial	Stroke rate, stroke length, velocity, IdC, propulsive phase duration

Reference	Purpose of Study	Exp. Design	No. of cameras	Camera config.	Plane(s) of movement	Enclosures (for UW camera)	Frame rate	No. of anatomical landmarks	Camera positioning	Variables measured using video
Takeda, et al. [48]	Examination of the kinematics of the backstroke start technique	2D	1UW 1AW	Static	Sagittal	Viewing window	60 Hz	14	UW: 1.0m depth AW: 0.2m above water 7.5m from plane of motion	Hip & knee joint angles, angular velocity, hip & toe displacement, time to 5m
Seifert, et al. [49]	Assessing the relationship between coordination and energy cost of freestyle and breaststroke swimming	2D	2UW	Static	Sagittal, frontal	Unrep.	50 Hz	0	FoV: 10m, between 10 & 20m mark in 50m pool	Average velocity, stroke rate, stroke length, IdC, stroke phases, kick rate, arm & leg coordination
Veiga, et al. [50]	Analysis of kinematic parameters relevant to starts and turns, comparing national and regional level swimmers	2D	2AW	Static	Sagittal	N/A	25 Hz	0	Cameras positioned 7m above and 7m away from pool	Turn distance & velocity, start distance & velocity
Zatoń and Szczepan [51]	Examination of the impact of verbal feedback on technique	2D	1UW 1AW	Static	Sagittal	Waterproofed camera	50 Hz	3	Cameras fixed mid-pool FoV: 15m	Stroke rate, stroke length, velocity
Gatta, et al. [52]	Investigation of path linearity in elite freestyle swimmers	2D	2AW	Static	Sagittal	N/A	50 Hz	0	6m above water 15m from plane of motion FoV: 40m	Forward & lateral speed fluctuations
[53]	Examination of the effect of swim speed on coordination in Paralympic swimmers	2D	2 UW	Trolley	Sagittal	Waterproof housing	50 Hz	4	6.5m from swimmer (left and right sides), FoV: included whole body of participants, 10m test window	Arm and leg cycle phases, swim speed, stroke frequency, kick frequency, kick pattern, downbeat time, upbeat time, pull time, recovery time, leg to arm coordination

3.4 Discussion

3.4.1 Process of video capture

It has been found that technical examination of a swimmer in an applied setting can be undertaken using many different types of video setup and using various analysis methods (Table 1). For example, quantitative or semi-quantitative techniques involve an objective, deductive means of examining components of a performance using specialized instrumentation. Alternatively, a qualitative approach is more inductive in design and analysis is descriptive and subjective in nature [54]. Qualitative analysis can be carried out to assess the quality of the performance or technique but is also important as a method of identifying the key variables that need to be measured by quantitative means at a later stage [1]. Figure 3.2 provides an overview of the video analysis process. Three stages are involved: (i) camera selection and setup (ii) video capture and (iii) data processing and analysis. Following these three stages, a coach will interpret the results, provide feedback to the swimmer and decide on appropriate intervention strategies.

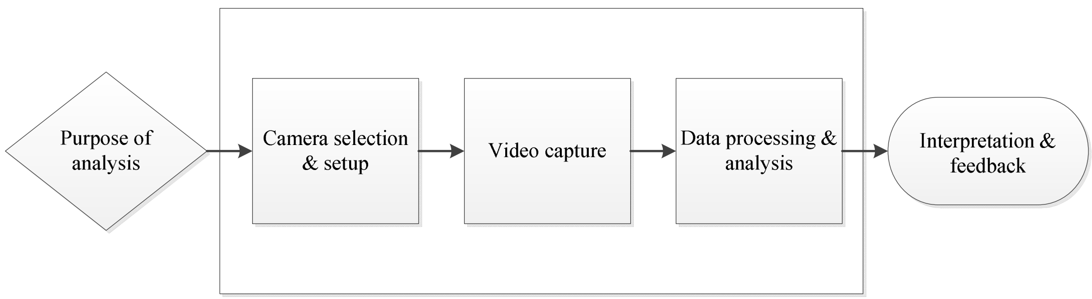


Figure 3.2 The process of video capture for swimming analysis involves three stages: (i) camera selection and setup; (ii) video capture and (iii) data processing and analysis. This may be conducted in either training or competition settings.

Camera selection and setup

Equipment specifications. Swimming presents unique challenges to the application of video that warrant consideration. Important issues to consider include light refraction and the effect of water turbulence such as bubbles and splash that are generated by a swimmers movements [20, 21]. Refraction can result in the distortion of an image when light passes from a fast medium (air) to a slow medium (water). An additional concern for underwater recording is water clarity and its effect on image quality. For example, a swimming pool that is excessively aerated will result in high levels of bubbles around the swimmer, making identification of anatomical landmarks on the swimmer difficult (Figure 3.3).

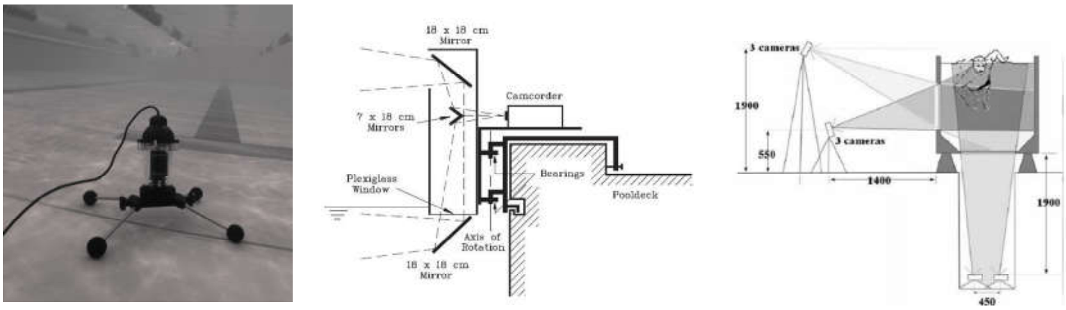
Figure 3.3 The motion of a swimmer in the water can cause turbulence resulting in bubbles that make identification of landmarks difficult. Rapidly moving body segments can also result in a blurred image.

There is a vast array of video cameras to choose from, with both under-water and above-water cameras available from all the major camera manufacturers. Studies that utilise only above-water cameras tend to be analyses based on competition footage [41, 50, 52]. However, for a thorough technical examination of swimming using video it is imperative for the swim coach to have an underwater view to fully assess a swimmer's movements. Specialist underwater equipment is available through dedicated manufacturers. Examples include SwimPro, SwimRight and Qualisys Oqus (Table 3.2). Some key parameters to consider when choosing a camera include the frame rate and shutter speed. Frame rate refers to the number of individual frames that comprise each second of video, also known as FPS (frames per second). Shutter speed refers to the amount of time that each individual frame is exposed for. It is generally advised that the denominator of your shutter speed should be at least double the number of FPS that you are recording. Consequently, a frame rate of between 25-50 Hz and a shutter speed of between 1/350s - 1/750s are recommended for swimming applications to maximise image quality [1]. These frame rates are reflected in the extant literature although some examples of higher values such as 125 Hz and 200 Hz can be found [33, 46].

Table 3.2 Comparison of technical specifications for various underwater cameras systems used in competitive swimming environments, highlighting that no common configuration has been established.

Camera System	Shutter Speed (s)	Frames per second (fps)	No. of Cameras	Resolution (Mpixel)	Min Illumination (Lux)
SwimRight *Shark Eye Coach*	1/50-1/10,000	25-30	1	0.3	1.0
SwimPro *IQ Recorder*	1/50-1/60,000	N/A	1-4	0.6	0.01
GoPro *Hero3*	1/1-1/8,192	12-240	1	0.4-12.0	1.4
Qualisys *Oqus*	N/A	180-10,000	1-24	0.3-12.0	0.0

Various solutions have been developed to record underwater motion, including placing the camera in a waterproof housing [25, 47, 53]; using an underwater viewing window [24, 31, 46] or alternatively a periscope system [38, 45] (Figure 3.4). Although periscope systems were frequently used in the past [55-58], waterproof camera housings would appear to now be the most popular choice and offer flexibility in positioning but have short camera to interface distances (the distance between the camera lens and the glass of the waterproof housing) which can result in reconstruction errors (Figure 3.5) [21]. Underwater viewing windows allow for increased camera to interface distances but video capture will be limited by access to a swimming pool or flume with built in windows included and may also result in issues with refraction. Inverse periscopes allow for cameras to be positioned above the water to record activity both above and under the water. The advantage of a periscope system is that it allows for a longer camera to interface distance compared to waterproofed camera housings. However, the mirrors used in periscope systems must be of a very high quality to ensure a good image and consequently periscope systems can be expensive compared with the alternative approaches [21].



(a) (b) (c)

Figure 3.4. To capture the underwater movements of the swimmer different options are available for the positioning of cameras including (a) using a waterproof housings such as the SharkEye system; (b) a periscope system or (c) placing cameras outside the water and tracking the swimmers as they pass underwater viewing windows. Reproduced from Yanai, et al. [56] (Figure 4b) and Monnet, et al. [46] (Figure 4c), with permission.

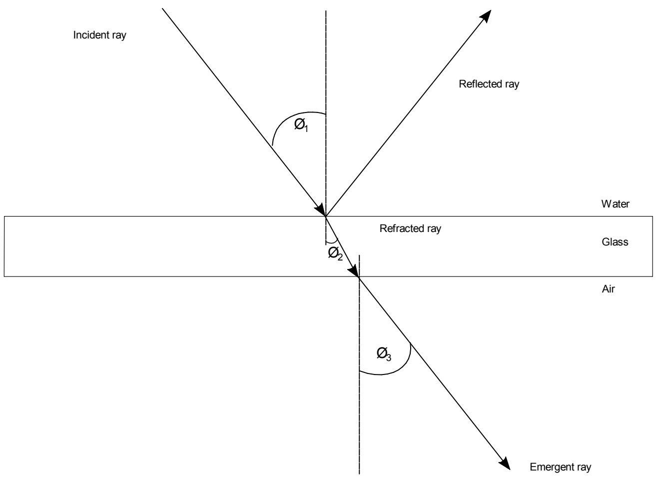
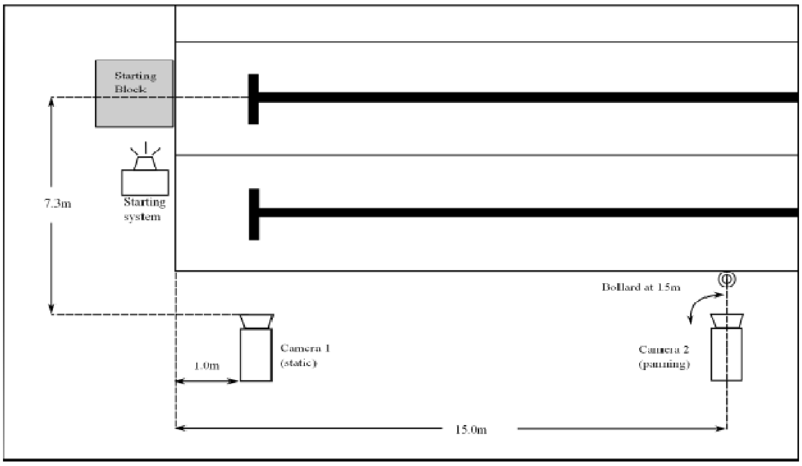


Figure 3.5. When using a waterproof housing, the distance between the camera lens and the glass of the housing is important as refraction at both the water-glass interface and glass-air interface will cause deformation of the image. The thickness of the glass will also affect the degree of refraction experienced.

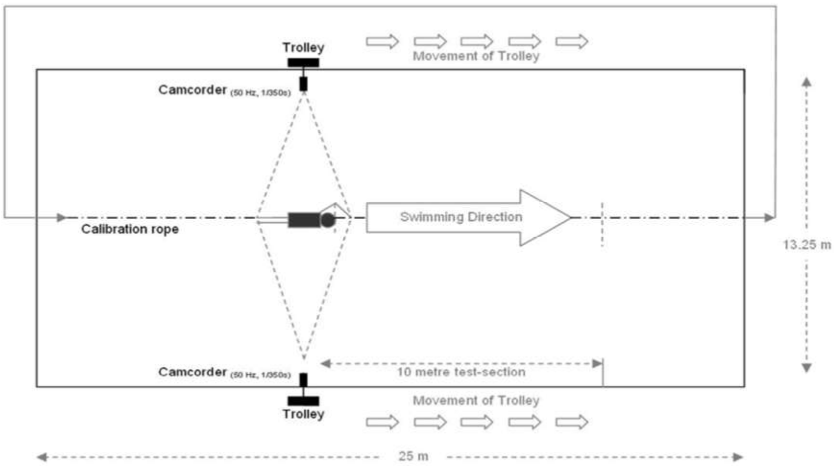
Camera configuration.

Using a single camera offers an ease of portability and setup, and can often be used for a rapid performance assessment [59]. Use of multiple cameras requires a more complex setup and requires images from different cameras to be synchronized. Between one and eight cameras have been used in studies capturing swimming footage, with various combinations of above-water and under-water cameras [31, 35, 46]. Cameras can be positioned to capture the swimmer when viewed from the front, side, above or below, or a combination of these views, depending on the analysis requirements [53, 60, 61] (Figure 3.6).

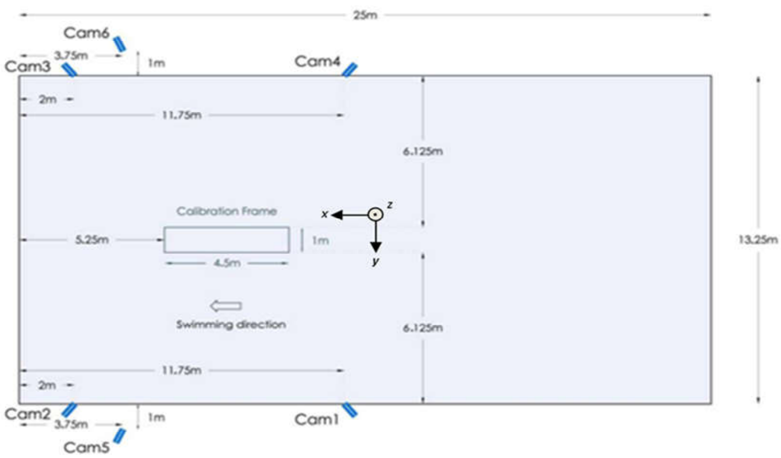
Payton [1] recommended that the size of the performer in view be maximized in order to reduce perspective error. Perspective error results in the size of an object changing with its distance from the lens and overcoming this is critical in measurement applications involving objects with depth or objects moving relative to the lens. This can be achieved through a combination of increasing the distance from the camera to the performer and choosing an appropriate zoom level. Whilst this is seldom an issue for above water cameras, when recording underwater this can present a challenge as it can often require several lanes of the pool to be left empty to avoid other swimmers from blocking the view. Moreover, underwater lenses typically have a fixed focal length (the distance between the centre of the lens and its focus) and do not always allow for adjustment in zoom or shutter speeds so it is necessary to increase the distance of the camera position in relation to the swimmer [1], which may be impractical for many training programmes.



(a)



(b)



(c)

Figure 3.6. Representative examples of different video setups and configurations for various quantitative analyses. (a) Two above water cameras, one static and one panning, for kinematic and temporal analysis of dive starting technique. Images from the static camera were used for

digitization of subjects during block and flight phases whilst the panning camera was used to measure temporal measures for the full 15m start phase. (b) A trolley system with underwater views from both sides of the pool facilitated following the swimmer over 10m to get three full stroke cycles for kinematic analysis. A graduated rope was fixed below the swimmer and within the field of view to facilitate calibration. (c) Multiple above and below water cameras around a calibrated space of known dimensions (4.5m x 1.5m x 1.0m) and control points distributed at regular intervals allows for a 3D analysis of swimming performance. Reproduced from Mooney [60] (Figure 6a); Osborough, et al. [62] (Figure 6b); Sanders, et al. [61] (Figure 6c), with permission.

Static cameras are typically used in order to allow for the movement to be assessed relative to an external reference [28, 34, 42]. The camera is fixed on a specific field of view and the footage is captured as the swimmer moves past. When using a smaller capture space, issues arise as only a short number of stroke cycles can actually be recorded within the capture space. This may limit the effectiveness of such an approach as it does not allow for variations in swimmers patterns of movement to be fully observed [63, 64].

Panning cameras introduce additional complexity for accurate measurement [56] but can be used to capture a swimmer's movements through a longer distance, for example over the full length of an Olympic distance pool [59]. Alternatively, tracking cameras allow the videographer to manually follow the swimmer throughout the length of the pool using a camera mounted on a trolley or similar device [40, 43, 53]. This increases the analysis potential beyond the limited capture volume possible with static cameras.

Calibration procedures. Calibration of a video image for a 2D quantitative analysis requires a scaling object and vertical reference to be recorded before video capture, to facilitate accurate extraction of variables during the digitization stage [1]. Typically, this is achieved using a metre stick. When conducting 3D analysis, a controlled volume is defined according to a calibration frame of known dimensions with control points positioned at known intervals and the calibration frame design must reflect its intended use.

Examples of differently sized calibration frames used in swimming can be found in the literature. Larger frames are capable of capturing the entire swimmer during one or more stroke cycles, with examples as large as 18 m^3 [22] and 25.2 m^3 [56] previously described. Others have used a calibration frame with dimensions of 4.5 m x 1.0 m x 1.5 m (6.75 m^3) which is also suitable for whole body analysis [26]. Cappaert, et al. [65] used a 5.6 m^3 calibration frame in a whole body swimming investigation. These researchers used digitized footage from four cameras (two below and two above the water) to determine changes in shoulder, hip and elbow angles throughout one stroke cycle, to compare the techniques of elite and sub-elite swimmers.

Conversely, smaller calibration frame sizes have also been utilized [45, 57, 58, 66, 67]. Payton, et al. [57] used a frame measuring 1.3 m x 0.93 m x 0.88 m (1.06 m^3) and digitized six anatomical landmarks on the shoulder, forearm and hand in order to determine the movements of one arm during a single stroke. Lauder, et al. [66] previously reported the smallest frame found in a swimming related study, measuring just 0.4 m^3 (1.0 m x 0.5 m x 0.8 m). These studies focused on specific aspects of swimmers' arm movements and the relationship of these with propulsion. Smaller frame sizes can result in lower reconstruction errors than larger frames [55]. These reconstruction error differences can be attributed to various factors, including the effects of light refraction; image deformation when recording; the relative size of the reproduced image in relation to the capture volume or issues with the reconstruction algorithms used [21, 55]. A trade off exists in deciding the appropriate calibration frame size and the resultant accuracy of the reproduced image, in addition to the precision with which anatomical landmarks can be digitized (both manually and automatically). Moreover, increasing the distance between the camera and the performer can help compensate for errors owing to larger frame sizes.

Video capture

Preparation of swimmers. There are various factors involved in preparing swimmers for video-based data collection. Some factors are common to both quantitative and qualitative analysis, but quantitative methods will require additional preparation. Swimmers may be required to wear specific clothing (such as different coloured hats or swim-suits to aid identification), have identification markers written on their skin, or some other markers for identifying body landmarks when conducting digitization procedures (Figure 3.7). Digitization involves the reconstruction of a swimmers body movement by tracking the displacement of markers placed at specific anatomical locations. Up to 31 landmarks have been included in the reviewed literature [36], although the number of specific locations of the markers will depend on the aims of the study. It is important to note that the swimmer cannot typically hear or see the videographer whilst performing trials so it is vital that instructions regarding the protocol are clearly communicated to the swimmer in advance to improve the efficiency and accuracy of data collection.

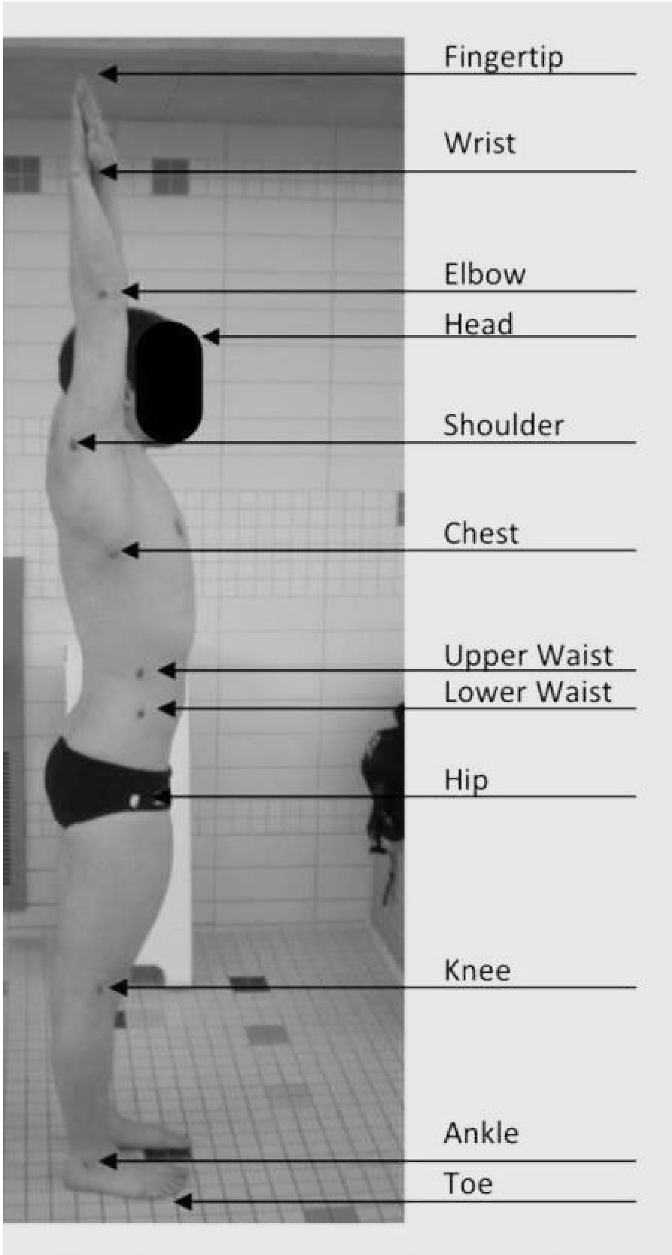


Figure 3.7. Representation of the anatomical locations of body segments used to facilitate the digitization process for kinematic analysis. The accuracy of the digitization process is dependent on anatomical knowledge when markings are made. Reproduced from Atkison, et al. [42], with permission.

Video storage and retrieval. Various software packages are available, including Dartfish; Kinovea; Quintic; APAS; Coaches Eye and Simi Motion, for video capture, editing and subsequent analysis. Video requires a large amount of storage space on a computer, with footage of a typical 200m race lasting 2-3 minutes taking up 250-300 MB. Recordings taken during a training activity are typically longer in duration and require much larger storage space.

A large volume of recording raises two concerns for the coach. Firstly, a suitable storage solution must be available with sufficient capacity for dealing with multiple recordings over an extended period of time. This may involve a physical hard drive or a cloud based solution. Advances in cloud based computing allow for vast storage and sharing solutions for coaches but this may also involve a lot of time for compressing, uploading and downloading of information when large squads of swimmers are involved. Secondly, a coach must have a system that allows for rapid retrieval of information at a later stage. This may involve manually indexing and tagging data, to attribute information related to a specific swimmer, event or analysis type conducted. Many software packages include features for this to be carried out or alternatively a coach may develop their own notational system. It is important that coaches and sports scientists working with the same group of swimmers follow a consistent approach for ease of retrieval at a later stage.

Data processing and analysis

For a qualitative analysis, it is typically only necessary to edit and store the files for later review. However, processing may involve merging of images from multiple views for thorough assessment. Data processing for quantitative analysis involves additional steps however. Digitization procedures are required to obtain the coordinates of body landmarks from recorded video and can be completed using manual or automatic methods. Manual methods involve an operator having to identify landmarks through visual inspection of each frame of the footage. In order to improve the consistency of the process, the same operator should perform all the digitizing for data to be analysed. Certain limb positions can be difficult to identify due to water turbulence or hidden body segments. Operators should have a sound anatomical knowledge and use markers on the skin only as a guide.

The scaling object or control points must be digitized with a high degree of accuracy as this process is used to generate all other outputs from the system [1]. It is also recommended to assess the level of systematic and random error involved. Errors can arise from various factors including the quality of the video image; the resolution of the digitization software; the size of the calibration volume and the skill of the operator [1]. Error estimation typically involves a both inter-operator and intra-operator reliability testing [68-70]. Reconstruction error for 3D analysis of less than 5mm for each axis is deemed acceptable [61, 71].

According to swim coaches, a key disadvantage to performing quantitative video analysis methods is the time taken to manually digitize the footage [13]. Coaches perceive that it takes too long to carry out quantitative analysis and this outweighs any perceived advantage of conducting such work. A recent study reported that it took approximately seven and a half hours to carry out manual digitization of a relatively small amount of footage, involving ten swimmers performing three dives each [72]. Magalhaes, et al. [73] also cite another example whereby it took 27 hours to digitize footage of four separate stroke cycles for one swimmer, involving images from six cameras, 19 anatomical landmarks and 1,620 frames in total [74].

Automatic digitization offers a clear time-saving advantage over manual methods. However, it is not always possible to complete automatic digitization as markers cannot always be placed on a performer (in a competitive setting for example) and in the water the negative drag effects of markers hinders the swimmers movements significantly. An increase of between 7-10% in passive drag was reported in one study which involved 24 markers, each 19mm in diameter [75]. Additionally, underwater and/or outdoor conditions lead to variations in the pixel contrast (the difference in luminance or colour that makes an object or its image representation distinguishable) between the markers and the background and air bubbles in the water can also introduce additional error in automatic procedures, rendering them impractical [1].

Based on the evidence presented in this review, the overall trend in video capture in swimming appears to be towards the use of multiple cameras and that both the underwater and above water images are important to the coach. This is logical as it allows for swimmers movements to be tracked through complete stroke cycles and from multiple planes of motion. Increased availability of low-cost equipment is also facilitating coaches in obtaining these multiple views. Additionally, whilst a number of 3D analysis setups are reported in the extant research, there is a much greater emphasis on 2D approaches, especially in applied practice.

3.4.2 Interpretation and feedback

Qualitative technical assessment

Commonly, a coach will conduct technical analysis using video as an aid to their own observations [2, 15]. This analysis is based on a coach's own knowledge and experience but video allows the coach to prepare, observe, assess and evaluate a swimmer's performance before taking what they consider to be the most appropriate action [54, 76]. A key advantage is that it is low cost and easy to implement with large numbers of athletes. Wilson [2] suggests that in coaching settings there is more of a focus on qualitative methods as it allows for rapid video feedback to be provided at any stage during a training session. Moreover, qualitative analysis is considered by some to be more intuitive for an athlete, compared with quantitative approaches [76]. Despite this, limited examples of qualitative swimming research using video can be found [31, 77, 78].

One recent study used a qualitative approach to assess different breaststroke techniques [31]. By using an underwater camera, researchers were able to use flow visualization techniques to assess the impact of different arm and leg movements (Figure 3.8). For example, it was found that supination of the foot at the end of leg extension resulted in increased displacement of the swimmer compared with leg extension without a corresponding foot supination.

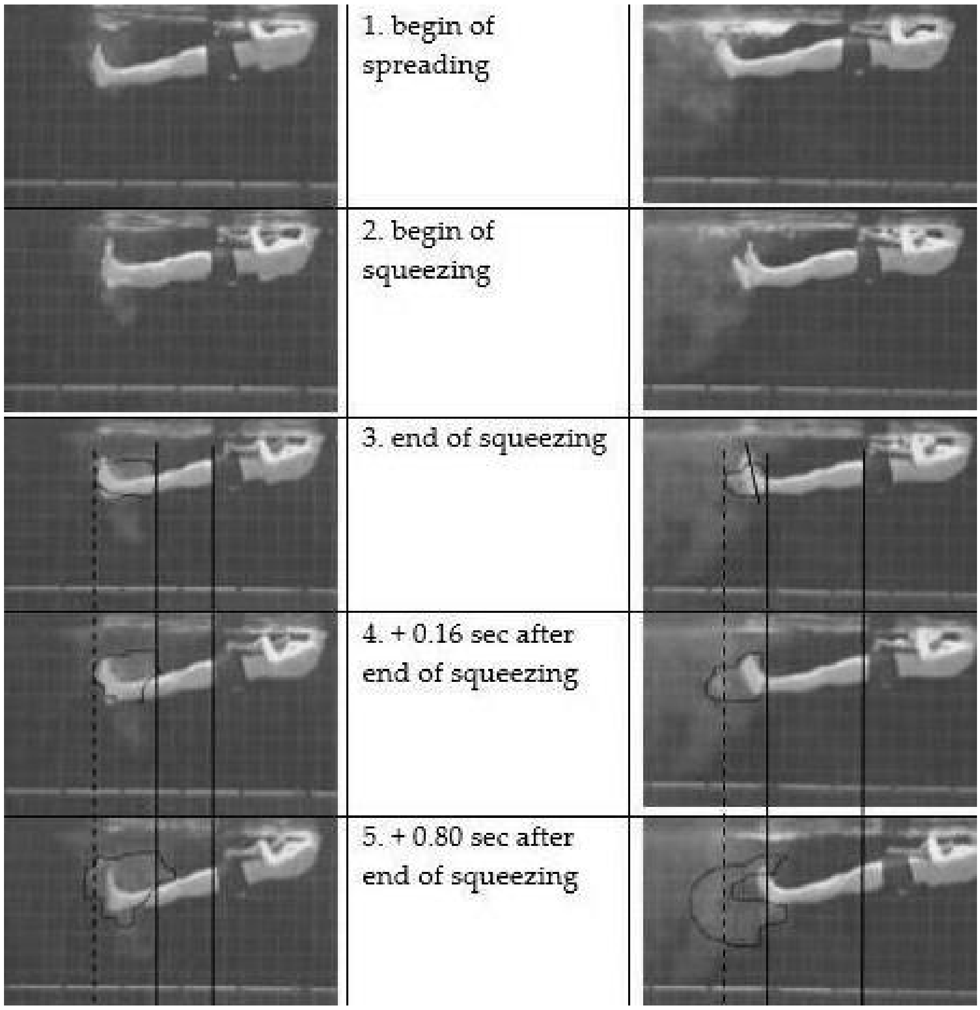


Figure 3.8. A qualitative assessment of breaststroke kicking action is facilitated through the use of underwater video footage. A fluorescent dye is used to assess the impact of foot supination at the end of leg extension (squeezing). The supinated position (on right) results in increased displacement of the swimmer as compared to the non-supinated position (on left). Reproduced from Martens and Daly [31], with permission.

Another example of the application of video for qualitative assessment is the use of self-modelling. Self-modelling is an observational technique based on preparing a video of an athlete's own performance that has been edited to show a performance level that is greater than what the athlete is currently capable of [79]. Such an approach has been implemented previously for the learning of swimming skills [78] and may also have relevance in competitive environments. This may involve taking video footage of a swimmers four best laps (from a longer race or from different performances) and editing them together with the swimmer's best ever start, turns and finish, to create a video file that the swimmer can then view. This approach has been used in competitive gymnastics and shown to significantly increase performance compared to when no video is provided to the athletes [80].

This visual feedback on performance is vital for skill acquisition, it raises a swimmer's awareness of their movements in the water and it is suggested that feedback should be provided as quickly as possible during the skill acquisition stage to maximise the learning effect [81]. Furthermore, it has been believed that the timing and content of feedback information should change as learning and skill development progresses [4, 8]. Video facilitates this augmented feedback approach just as readily.

Video allows for a thorough qualitative evaluation from any viewing angle to be conducted. As most of a swimmer's movements occur under the water it is difficult for a coach to see what is going on. Therefore underwater video appears to be just as important for the coach as it is for the athlete. Manipulation of the video image using tools such as slow motion replay, frame-by-frame viewing or split screen comparisons can be used to facilitate both observation and assessment of the performance and highlight issues that could be missed with the naked eye. Moreover, video footage can be used to compare the same swimmer on different occasions to check for changes in technique following a period of training or for the effects of fatigue.

The lack of qualitative swimming research highlighted in this review is of concern as it has been found that coaches most often employ qualitative procedures in their own environments [13]. However, without a strong evidential basis for its efficacy, it is possible that coaches are not making the best use of the methods, leading to poor practice and potentially in-efficient performance gains. Future research should focus on examining the merits of qualitative approaches in applied swimming settings.

Quantitative technical assessment

Alternatively, video may be used along with specialist equipment and software to assess swimming technique using quantitative or semi-quantitative means [30, 35, 61, 82, 83]. Whilst qualitative analysis using video has been shown to be an effective method of producing changes in technique compared with verbal coach feedback [11], it has been suggested that quantitative feedback is also important for improving technique rather than using video purely for qualitative analysis [34, 84]. Thow, et al. [34] reported significantly greater improvements in both initial and average velocity measurements in elite swimmers during the glide phase following a dive start when swimmers were provided with quantitative feedback to compliment the coach's instructions. Average velocity increased from 1.74 ±0.16 $m{\cdot}s^{-1}$ to 1.84 ±0.09 $m{\cdot}s^{-1}$ over a five week intervention period. Moreover, whilst the results also indicated that a qualitative feedback approach brought about significant gains in performance, the addition of quantitative data elicited faster improvement gains [34].

Video facilitates the quantification of key performance-related parameters, which have been shown to significantly influence overall performance. These quantitative methods can also be applied to injury prevention strategies. Ayyildiz and Conrad [85] used video to assess different phases of butterfly swimming technique in order to highlight how changes to technique can reduce the risk of injury by affecting the forces experienced by the swimmers' hands as they propel themselves through the water. Furthermore, video has been used to determine stroke asymmetries [86, 87] and has informed musculoskeletal screening procedures to help clinicians and coaches to identify such deficiencies [88].

The studies included in this review demonstrate that video has been used in a diverse number of ways for providing analysis in swimming. Whilst some differences can be attributed to the advancement of filming and computer technology, the review does highlight an apparent lack of common approaches for conducting quantitative video analysis in swimming, with different studies using different camera configurations to measure the same variables. What is also apparent is that in-depth quantitative video analysis does not always require a complex experimental setup.

For example, the pitch and sweepback angles of the hand are important factors for generating propulsion [38, 71]. Recent studies have used either two, four or eight cameras positioned either in waterproof housings, behind viewing windows or with a periscope system and have digitized between 4 and 12 anatomical landmarks in order to measure these angles [38, 46, 50, 66, 71]. Similarly velocity, stroke rate and stroke length have been variously derived using static cameras [29], or cameras with a trolley setup [53], both with and without [89] digitization procedures. Such diversity in approaches is undoubtedly due to the specific nature of different studies, but may lead to confusion among practitioners as to the best methods to employ in their own environments.

Turns are a vital component of swimming competition and have been shown to be significantly related to overall performance [32, 90] and as a result have received much research attention [32, 41, 50]. Puel, et al. [32] provided a comprehensive three-dimensional analysis of the key parameters related to successful performance of the freestyle tumble turn, using five underwater cameras and an integrated force platform to quantify 51 separate variables. In contrast, Veiga, et al. [50] recently also assessed turning performance in a group of elite swimmers but used just two above water cameras and measured only turning distance and velocity. Clearly the objectives of these studies differed but it is interesting to consider which study would be more likely to be replicated by a coach in their own environment.

3.4.3 Emerging advances in video technology

The criticisms of video appear to be commonly expressed by both researchers and coaches. A central theme of this criticism is the time required to carry out video-based procedures [13, 20, 91]. This is certainly limiting the frequency of quantitative video analysis performed in applied settings but is likely to also decrease qualitative video practices, given that video editing for multiple swimmers can be very labour intensive in its own right. It is unsurprising therefore that much research attention is currently focused on reducing the time taken to obtain pertinent information using video and on the automation of many of the laborious manual procedures involved [4, 6-8]. By way of example, one recently reported automated digitization approach claims to reduce processing time by a factor of ten over manual tracking methods [46].

Automated tracking systems

One such approach uses an array of LEDs mounted on flexible circuit board that was worn by the swimmer [92]. The system removes the requirement for manual digitization and initial testing suggests comparable accuracy to manually derived variables related to swimming starts and turns. Another automated tracking system recently described is based on the Calibrated Anatomical System Technique (CAST) [36]. The CAST system, frequently seen in clinical settings, estimates anatomical landmarks based on joint degrees of freedom and can be used to estimate the position of hidden landmarks [93]. Initial results indicate that this approach may be suitable for swimming applications [36, 73], although the procedures are still time-consuming and complex, with 31 anatomical landmarks required during swimmer preparation for one arm and a portion of the trunk to be digitized, which perhaps offsets the time gained elsewhere.

Marker-less analysis

Another emerging approach found in other sports is a marker-less 3D analysis method based on the extraction of a swimmer's silhouette from video images [25, 43]. Marker-less systems have an advantage over other techniques for swimming applications, as form and drag caused by markers are central concerns [75]. The results of initial investigations suggest that this method shows similar reliability to manual digitization approaches, but further investigation of system reliability has been suggested [46]. This method may help to reduce both participant preparation and processing time [94] and has also been investigated in other sports to provide real-time kinematic data on performance with promising results [95]. As with any new methodology, additional investigation is required to fully assess the merits and feasibility of any new approach for applied settings. For instance, the system described by Ceseracciu, et al. [25] was tested for one arm only and for front-crawl swimming, and it remains to be seen if the same level of accuracy would be achieved for whole body kinematic analysis and for other swimming strokes.

This trend towards automated procedures is likely to increase quantitative analysis practices as the time constraints associated with digitization are reduced. However, it could be reasonably argued that many of the automatic video analysis procedures are currently overtly costly to be applied in the majority of coaching settings, with one example costing over US$35,000 to purchase the equipment and software (ProAnalyst, Xcitex Inc., Woburn, MA, USA). Additionally, with a concurrent growth in interest in alternative methods of quantifying swimming performance, some have argued that more suitable solutions are starting to emerge, such as the use of low cost MEMS inertial sensor devices [20, 94, 96]. What is more likely is that integrated systems will become more prominent, with data measurements arising from multiple sources.

3.5 Conclusion

The aim of this study was to systematically review the process of applying video-based systems for the analysis of competitive swimming. It is clear that video can be used in a variety of ways to provide feedback, and to aid technical development and to reduce the risk of injury. Video allows a coach to review, reflect and evaluate the development of many aspects of athletic preparation and can be used to facilitate both qualitative and quantitative analysis.

Video capture in swimming shares many common characteristics with other sports, but with additional considerations for underwater filming. The aquatic environment adds to the time, cost and complexity of implementing video analysis. In using video to provide feedback to swimmers, coaches, sport scientists and researchers must make appropriate decisions regarding the equipment, camera configurations and processing methods involved, and ensure they follow key recommendations.

There are a large number of factors to be considered when using video analysis for swimming applications and no common specifications or methodologies appear to exist. It could be argued that this lack of consistency is hindering the effectiveness of the technique. A more consistent approach would remove some of the confusion around the process and could facilitate increased use of video. Figure 3.9 provides a detailed flowchart of the various stages involved and is intended to provide recommendations that may aid decision making and perhaps improve the effectiveness of video for coaching purposes.

It would appear that the key feature of video is its adaptability to various applications. Video analysis can be tailored to suit the specific needs at the time. If rapid feedback is required, video can facilitate instant review by both the coach and the swimmer. Additionally, video can be edited, processed and reviewed either qualitatively or quantitatively to provide an augmented feedback approach. Furthermore, video can be used to capture movement in both 2D and 3D for in-depth study or combined with other measurement tools. Finally, video can also be used in training, competition and research situations, and can capture movements both above and under the water. This versatility extends its application potential far beyond other analysis systems used in elite sport. With continued advances in video and software technology it is also likely that video will continue to remain an integral part of the elite training environment in future.

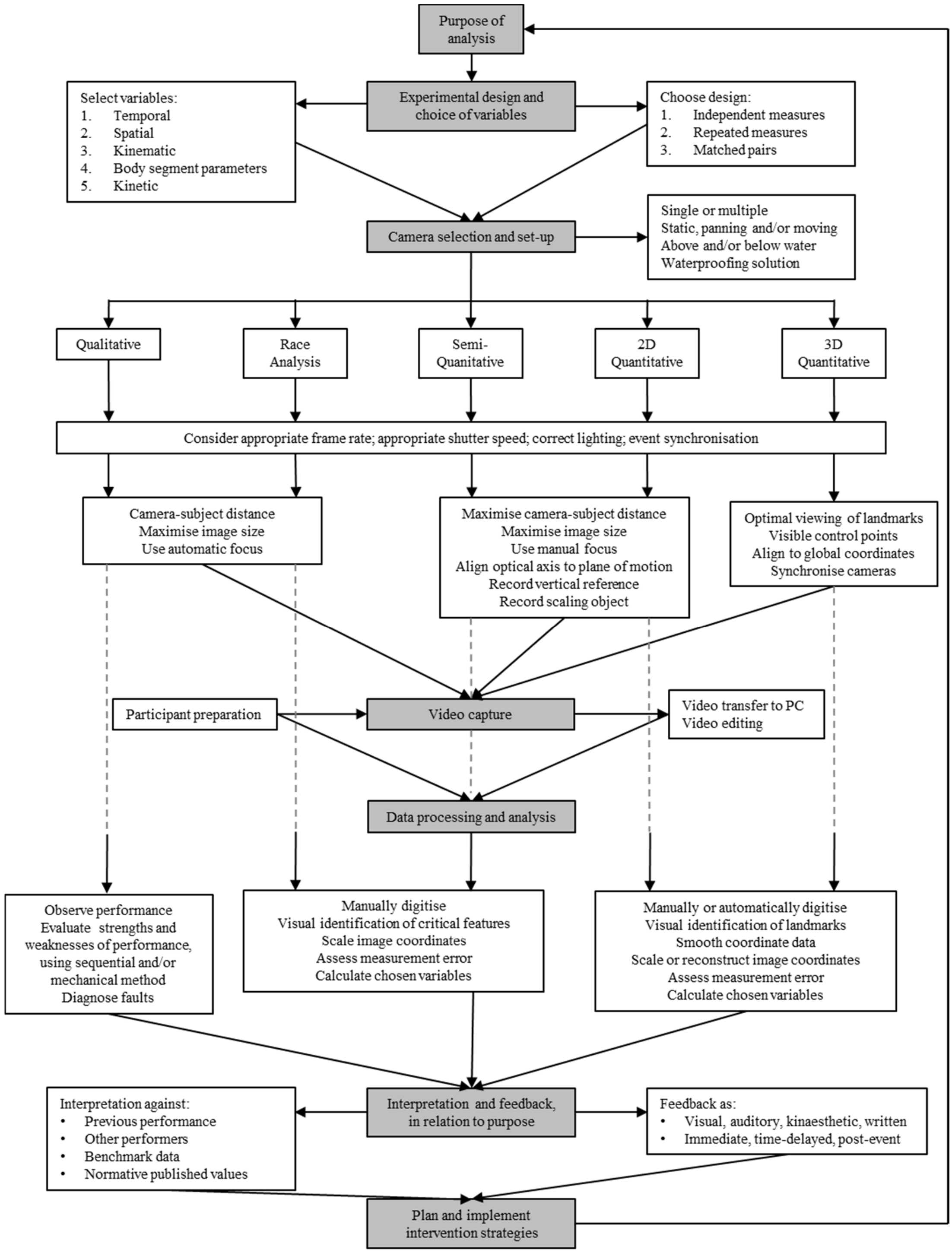


Figure 3.9. Flowchart detailing recommendations for the key steps to be followed and decisions to be made when undertaking video analysis in swimming.

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Chapter 4 – Review of the Relevant Literature (Part 2: Inertial Sensor-based Analysis of Swimming)

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The review conducted into the application of video-based systems for the analysis of swimming performance, presented in Chapter 3 of this thesis, has demonstrated that there are significant methodological and technical issues that must be considered. This, along with the findings of the survey what were presented in Chapter 2, demonstrates that traditional methodologies of conducting biomechanical analysis of swimmers are not ideal and solutions are required. As a consequence, several new technologies have been developed, including instrumented force platforms and pressure plates. The use of body worn inertial sensor technology has gained increased prominence in many sporting situations in recent years as an alternative to video-based approaches. In swimming, several research studies have described the application of these systems for the analysis of swimming. Additionally, a limited number of commercial systems have become available. However, to date, no attention has been paid to providing an evaluation of the accuracy of different feature detection algorithms described in the literature for the analysis of different phases of swimming, or the consequences associated with different sensor attachment locations. Therefore, a systematic review of the relevant literature was conducted and presented here as the next chapter of the thesis.

4.1 Introduction

Elite swimming is highly competitive, with world class athletes constantly challenging themselves against their rivals and tiny margins deciding the outcome of races. Consequently, swimmers and coaches continually strive for methods and strategies to optimise performance. A fundamental aspect of this preparation involves regular, quantifiable data measurement to assess skill acquisition and technical development.

Swimming is characterised by a sequence of coordinated actions of the trunk and limbs, in a repeated, synchronous pattern. Arm action during each of the four competitive swimming strokes comprises specific phases. It is typical to define these phases according to the various sweeps of the arms, which are specific to each stroke (Figure 4.1). For example downsweep; insweep; and upsweep movements are completed during frontcrawl [1]. Important kinematic variables such as velocity and acceleration fluctuate greatly throughout each phase, both for specific body segments and the body as a whole. Techniques for accurately determining this valuable information can therefore be used for quantitative biomechanical analysis and to inform the coaching process.

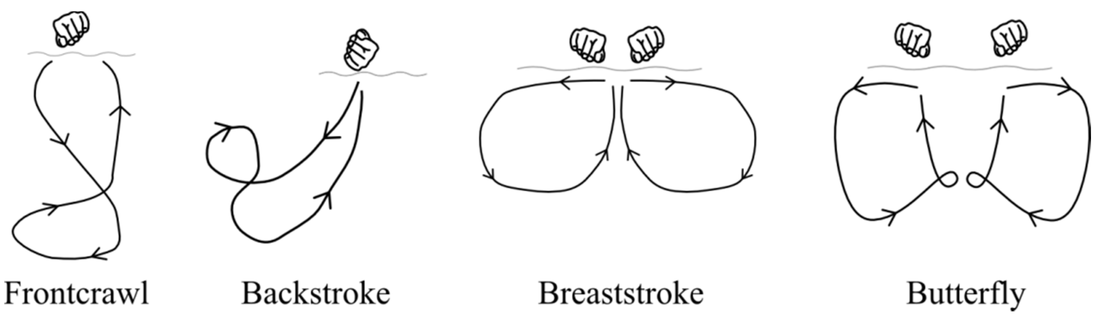


Figure 4.1. Representation of typical arm actions during swimming, viewed from the front, highlighting the characteristic patterns of movement and sweeps of the arms for each of the four competitive strokes. Adapted from Maglischo [1].

Competitive swimming can be broken down into specific segments to facilitate such analysis (Figure 4.2). Starts are typically defined as the duration from the starting buzzer until the swimmer reaches the 15 m mark. Turns are defined according to coaches' requirements and involve varying distances on approach to and leaving the wall after each lap. For example, competition analyses from major international competitions have defined this segment from 5 m before the wall to 5 m after the wall [2]. Finishes involve the final few metres (typically 5 m) before the wall is touched at the end of the race. Finally, free swimming is the term given to describe the regular swimming strokes performed during each lap that occurs outside of the other race segments. During each of these race segments, different categories of analysis are appropriate and can take place through the measurement of temporal, kinematic and kinetic variables. Examples of swimming variables related to each category are provided in Figure 2 and may be examined with various methods.

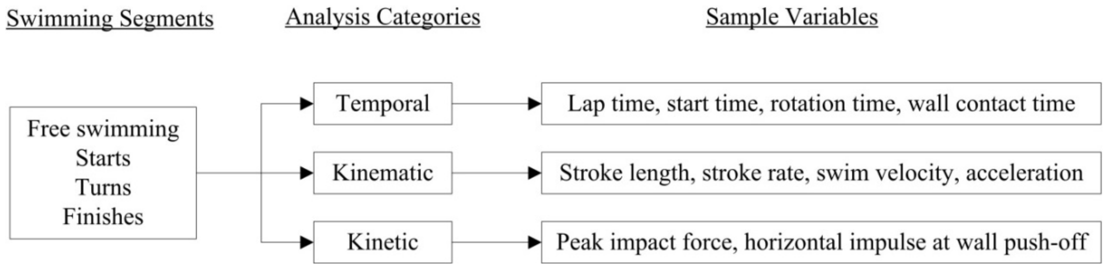


Figure 4.2. Swimming can be broken down into different race segments to facilitate technical analysis and different categories of performance related variables can be selected for measurement.

Predominant methods for extracting this quantitative information are video-based [3]. Images from cameras positioned above and/or below the water allow for the entire swimming stroke to be captured, yielding vast amounts of information such as velocity profiling [4] or joint angular kinematic analysis [5]. Video capture in aquatic environments has inherent disadvantages however, such as parallax error, hidden or obscured body segments and water turbulence. Moreover, the digitization and data analysis process associated with video analysis is labour intensive and time consuming, thus reducing its effectiveness as a feedback tool [6, 7]. A recent survey of swimming coaches also found that although quantitative analysis is perceived to be important, the time consuming nature of the process is limiting its application in practice [8].

Recent advances in the development of microelectromechanical systems (MEMS); wearable technologies and waterproofed coatings facilitate a potentially new approach to swimming coaching. These advances may allow for the development of new kinematic swim sensor technology which facilitates improved analysis of stroke mechanics, race performance and evaluation of exercise intensity thus enabling more efficient, competitive and quantitative coaching. This has led some to suggest that this technology may offer significant advantages over traditional video-based approaches [9].

A number of authors have developed the use of MEMS systems for measuring key performance related parameters in swimming [10-12]. An important consideration in this ongoing development work is feature extraction. However, a thorough evaluation of different feature detection algorithms described in the literature and the consequences associated with different sensor attachment locations is warranted and has been cited by Magalhaes, et al. [13] as an important gap in the literature. By way of example, various algorithms have been described for measuring the same parameter, such as velocity, and often using devices placed at different locations on the body; but the relative merits of these approaches has not yet been examined in detail. This has led to substantial ambiguity with respect to the optimal system design; the most suitable algorithms for a given parameter of interest and the best means of applying kinematic swim sensor technologies. All of which are significantly limiting the potential of sensor technology in applied settings.

Indeed it was suggested by Magalhaes, et al. [13] that there has been poor uptake of this technology by coaches for these reasons, with research evidence also supporting this claim [8]. The aim of this systematic review is to address these gaps in the literature and to provide further depth of understanding of this growing area of research. Additional information such as this should help practitioners to select the most appropriate systems and methods for extracting the key performance related parameters that are important to them for analysing their swimmers' performance and may serve to inform both applied and research practices.

4.2 Methods

4.2.1 Review questions

A systematic review of the literature into the application of inertial sensor technology for the analysis of swimming performance was conducted in an attempt to address the following review questions: (1) What signal processing methods have been utilised to measure parameters for the analysis of the different swimming race segments, including free-swimming, starts and turns? (2) What is the current functionality and performance of commercially available swimming sensor devices? (3) What are the implications for the placement of these sensors at different body sites on device functionality? (4) What technical specifications are required for the optimum design of kinematic swim sensor technologies?

4.2.2 Article selection

Article selection was based on a systematic search for publications following the PRISMA guidelines [14] of the following scientific databases: Embase; European Patent Office; IEEE Xplore; ISI Web of Knowledge; PatentScope (World Intellectual Property Organisation); PubMed; Science Direct; Scopus; SPORT Discus and the United States Patent and Trademark Office. These databases were chosen as the most relevant sources of information related to the areas of engineering; sports science and sports technology. All publications from January 2000 to May 2015 were included in the search. The keyword string used for the search was "(swimming OR frontcrawl OR freestyle OR backstroke OR backcrawl OR breaststroke OR butterfly) AND (accelerometer OR gyroscope OR inertial sensor OR IMU (Inertial Measurement Unit) OR MEMS OR acceleration OR angular velocity)". In this context, IMU and MEMS are commonly used acronyms for Inertial Measurement Unit and Micro Electro Mechanical Systems, respectively. The inclusion criteria were that the publication: (i) was written in English; (ii) appeared in a peer-reviewed academic source or patent; (iii) was related to the analysis of human competitive swimming. Exclusion criteria included: (i) animal studies and (ii) publications not directly related to the topics outlined in the review questions.

4.3 Results

The process flowchart detailing the results of the database search and article selection is provided in Figure 4.3. The initial search yielded 1498 results. Duplicates were removed and the title and abstract of each publication was reviewed and evaluated based on the relevance to the systematic review questions. The final number of publications included for this review was 87. Table 4.1 provides a summary of the publications selected and includes information related to the participants involved in these studies; the swimming strokes examined; the sensor output variables that were extracted; the phase of swimming that the variables are relevant to and the validation method used to verify the results of the study. Figure 4.4 details the body location and sensor configuration used in these studies.

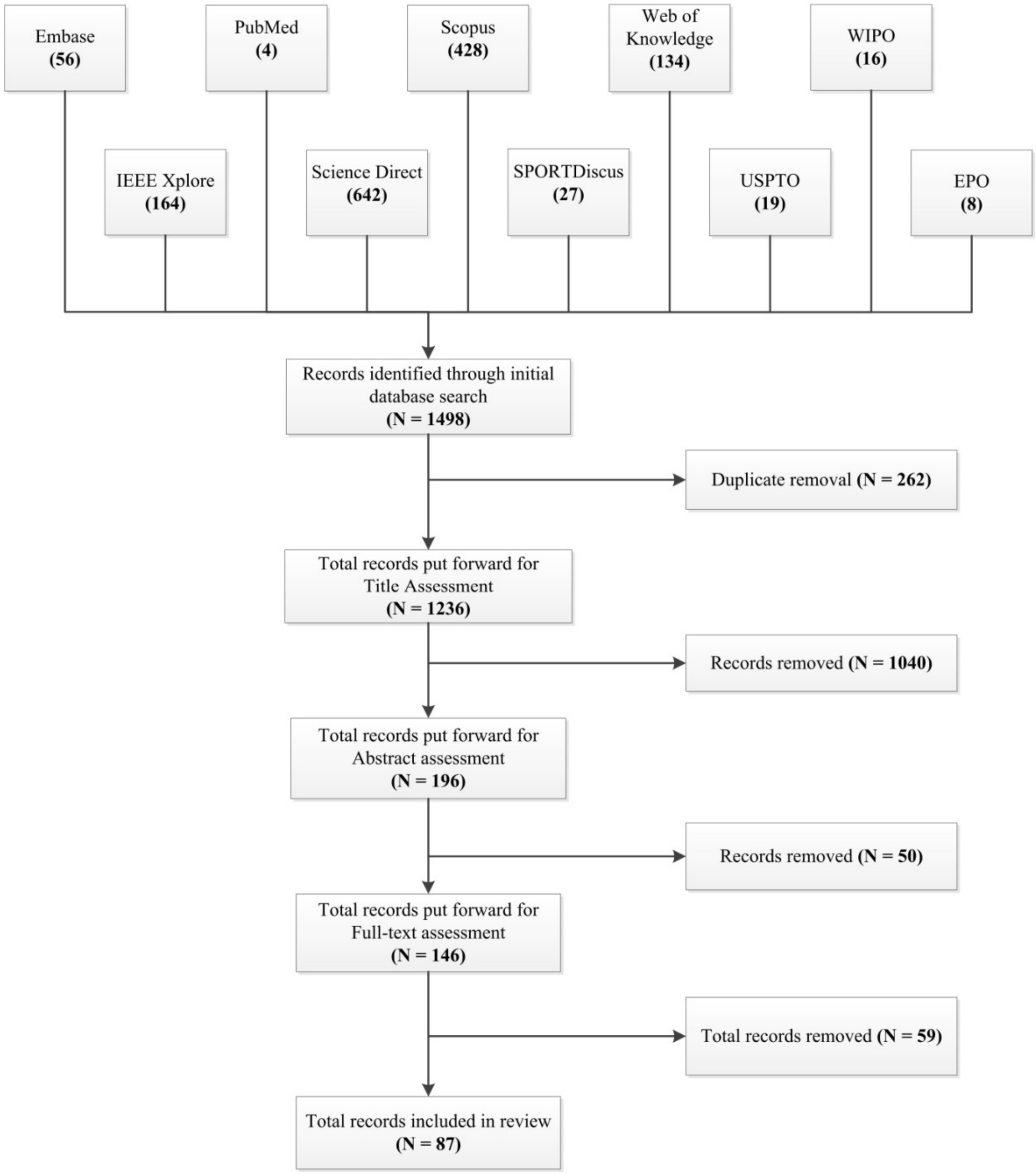


Figure 4.3. Systematic review search strategy and results.

Table 4.1. Summary of selected research studies investigating the use of inertial sensor technology for swimming analysis. References are presented in chronological order. Details included relate to the number of participants involved and their status (E: elite, C: competitive, R: recreational), swimming strokes examined (Fc: frontcrawl; Br: breaststroke, Bk: backstroke, Bf: butterfly); accelerometer and gyroscope sensor ranges; device size and mass; volume (where three dimensions are reported); sampling rate; filter design (LP: Low Pass, BW: Butterworth, HW: Hamming window, MA: Moving average); data storage; data transmission (RF: radio-frequency, IR: infra-red); output variables reported for different phases of swimming (F: free-swimming; S: starts; T: turns) and validation procedures. (Unrep = unreported).

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m \cdot s^{-2}$)	**Gyro.** ($rad \cdot s^{-1}$)	**(m x10^3)** **(kg x10^3)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[15]	2000	-	2	-	•				±490.5	N/A	Unrep 62	Unrep	Unrep	LP BW	Unrep	Unrep	stroke phase acceleration patterns	•			Video
[16]	2002	-	5	-	•	•			± 98.1	±26.2	142.8×23 78	Unrep	128	Unrep	128	Unrep	stroke phase acceleration & angular velocity patterns, effect of fatigue	•			Video
[17]	2002	-	5	-	•				±98.1	N/A	88×21 50	Unrep	128	LP BW	32	Unrep	stroke phase acceleration patterns, effect of fatigue	•			Video
[12]	2003	-	2	-		•			± 490.5	N/A	Unrep 62	Unrep	Unrep	LP BW (10 Hz)	Unrep	Unrep	stroke phase acceleration patterns	•			Video
[18]	2004	-	1	-	•	•	•	•	±19.62	N/A	Unrep	Unrep	150	LP HW (0.5 Hz)	Unrep	IR	stroke id, lap time, stroke count	•			Video& observation

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m \cdot s^{-2}$)	**Gyro.** ($rad \cdot s^{-1}$)	**(m x10^3) (kg x10^3)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[19]	2004	6	-	-	•				Unrep	Unrep	Unrep	Unrep	250	Unrep	Unrep	Unrep	Stroke id, stroke count	•			Video & observation
[20]	2004	-	5	-	•	•	•	•	±98.1	±26.2	142×23 78	Unrep	128	Unrep	128	Unrep	stroke phase acceleration patterns	•			Video
[21]	2005	-	1	-	•				±19.6	N/A	Unrep	Unrep	150	LP HW (0.5 Hz)	Unrep	IR	Lap time, stroke count, stroke rate	•			Video & manual
[22]	2006	-	4	-	•				±98.1	N/A	88×21 50	Unrep	128	LP BW	Unrep	Unrep	stroke phase patterns, arm joint angles	•			Video
[23]	2007	-	-	-	•	•	•	•	N/A	N/A	Unrep	Unrep	32	LP (5 Hz)	Unrep	Unrep	lap count, lap time, stroke count, swim speed, distance	•			Unrep
[24]	2007	-	-	-	-	-	-	-	Unrep	N/A	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Hip rotation	•			Unrep
[25]	2008	-	4	4	•				Unrep	N/A	Unrep	Unrep	256	LP BW (0.01 Hz)	1000 Flash	Unrep	Velocity, distance per stroke	•			Manual

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m \cdot s^{-2}$)	**Gyro.** ($rad \cdot s^{-1}$)	**(m x103) (kg x103)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[26]	2008	1	-	3				•	±14.7 – ±58.9	N/A	Unrep	Unrep	200	LP BW (10 Hz)	128 Flash	USB	stroke count, stroke rate, temporal stroke phase analysis	•			Video
[11]	2008	6	-	-	•	•	•	•	±19.6	N/A	Unrep	Unrep	150	LP HW (0.5 Hz)	Unrep	IR	stroke id, lap time, stroke count, stroke rate	•			Video & manual
[27]	2008	-	2	-	•	•		•	±19.6	±2.6	52×34×12 22	2.12×10^{-5}	150	LP HW (0.5 Hz)	128 Flash	RF, USB	acceleration, velocity	•			Tethered speed meter
[28]	2008	-	-	-	•	•	•	•	Unrep	N/A	Unrep	Unrep	100	LP BW (2.5 Hz)	Unrep	2.4 GHz RF	velocity, stroke rate, distance per stroke, intra stroke velocity	•			Unrep
[29]	2008	-	1	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Acceleration profile recognition	•			Video
[30]	2009	-	1	-	•				Unrep	N/A	36×42×12 34	5.14×10^{-5}	256	Unrep	1000 Flash	Unrep	Acceleration	•			Unrep

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m \cdot s^{-2}$)	**Gyro.** ($rad \cdot s^{-1}$)	**(m x103) (kg x103)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[31]	2009	7	-	15	•				±29.4	N/A	36×42×12 34	$5.14x10^{-5}$	256	LP BW (0.01 Hz)	1000 Flash MMC	USB	velocity, lap time, time per stroke, stroke length, orientation	•			Video & observation
[32]	2009	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Wi-Fi, Bluetooth, ANT or RF	stroke id, average speed, pace, distance, stroke count, swim distance, lap count	•			Unrep
[33]	2009	12	-	-	•				±19.6	>600	52×33×11 20.7	$1.89x10^{-5}$	100	LP BW (0.5 Hz)	256	USB	kick rate, kick count	•			Video
[34]	2009	14	-	-	•				±19.6	>600	52×33x11 20.7	$1.89x10^{-5}$	100	LP BW (0.5 Hz)	256	USB	kick rate, kick count	•			Stopwatch
[35]	2009	-	1	-	•				Unrep	N/A	Unrep	Unrep	128	Unrep	Unrep	2.4 GHz RF	Arm acceleration and timing profiles	•			Video
[36]	2009	-	-	-	•				Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Bluetooth, ZigBee or Wi-Fi	lap counter, lap time, stroke count, stroke length	•			Unrep

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m{\cdot}s^{-2}$)	**Gyro.** ($rad{\cdot}s^{-1}$)	**(m x103) (kg x103)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[37]	2009	-	-	-	•	•	•	•	Unrep	N/A	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	lap count, stroke count	•			Unrep
[38]	2010	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	30	LP (1 Hz)	Unrep	USB	stroke id, stroke count, stroke rate, stroke length, lap time, speed, force	•			Unrep
[39]	2010	-	-	-	•	•	•		Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	stroke count, lap count	•			Unrep
[40]	2010	-	1	-	•	•	•	•	±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (5 Hz)	4	RF	stroke count, stroke rate, lap count	•			Video
[41]	2010	-	1	-	•				±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (5 Hz)	4	RF	stroke count, stroke rate, lap count, start and turn phase analysis	•	•	•	Video
[42]	2010	-	-	-	•				Unrep	Unrep	Unrep	Unrep	Unrep	LP	Unrep	Unrep	body orientation, speed, lap time	•			Unrep

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	C	R	Fc	Br	Bk	Bf	Accel. ($m{\cdot}s^{-2}$)	Gyro. ($rad{\cdot}s^{-1}$)	(m x103) (kg x103)	(m^3)	(Hz)		(MB)			F	S	T	
[43]	2010	-	-	1	•	•			Unrep	Unrep	Unrep	Unrep	190	Unrep	Unrep	Wireless	stroke phase acceleration and angular velocity profiles	•			Unrep
[44]	2010	-	-	1	•	•	•		Unrep	N/A	Unrep 7	Unrep	Unrep	LP (5 Hz)	2	2.4 GHz RF	pitch and roll angles, breathing patterns	•			Unrep
[45]	2010	-	1	-	•				±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (5 Hz)	4	RF	acceleration profile during turns			•	Video
[46]	2010	3	-	-	•	•	•	•	Unrep	N/A	Unrep	Unrep	100	Unrep	Unrep	Unrep	stroke id	•			Video
[47]	2010	8	-	-	•	•	•	•	Unrep	Unrep	88x51×25 93	1.1×10^{-4} Unrep	100	Unrep	Unrep	Unrep	angular velocity, temporal phase assessment, stroke rate, r index	•		•	Video & stopwatch
[48]	2010	-	53	-	•				Unrep	N/A	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	speed, swim distance	•			Manual
[49]	2010	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	RF	stroke id, lap time, stroke count	•			Unrep

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	C	R	Fc	Br	Bk	Bf	Accel. ($m \cdot s^{-2}$)	Gyro. ($rad \cdot s^{-1}$)	(m x103) (kg x103)	(m^3)	(Hz)		(MB)			F	S	T	
[50]	2011	-	1	-				•	±14.7 – ±58.9	Unrep	Unrep	Unrep	200	LP BW (0.6 Hz)	512 Flash	USB	acceleration, angular velocity, pitch angle	•			Video
[51]	2011	12	-	-	•				±19.6	>600	52×33×11 20.7	$1.89x10^{-5}$	100	LP BW (0.5 Hz)	256	USB	kick rate	•			Video
[52]	2011	-	-	1	•				Unrep	N/A	Unrep	Unrep	50	Unrep	Unrep	RF	stroke phases	•			Unrep
[53]	2011	1	-	-	•				±78.5	±26.2	52×33×10 20	$1.72x10^{-5}$	100	LP HW (0.5 Hz)	1000	2.4 GHz RF	temporal stroke phase analysis	•			Video
[54]	2011	-	-	-	•				Unrep	Unrep	Unrep	Unrep	100	Unrep	Unrep	2.4 GHz RF	Unrep	•			Unrep
[55]	2011	-	-	6	•				Unrep	Unrep	Unrep	Unrep	200	Unrep	Unrep	Unrep	simulated arm stroke patterns	•			Video
[56]	2011	2	-	-	•				±78.5	±26.2	52×33×10 20	$1.72x10^{-5}$	100	LP HW (0.5 Hz)	1000	2.4 GHz RF	turn phase acceleration patterns			•	Video

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	C	R	Fc	Br	Bk	Bf	Accel. ($m \cdot s^{-2}$)	Gyro. ($rad \cdot s^{-1}$)	(m x103) (kg x103)	(m^3)	(Hz)		(MB)			F	S	T	
[57]	2011	-	2	-	•	•	•	•	±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (5 Hz)	4	RF	stroke count, stroke rate, stroke duration, lap count	•			Video
[58]	2011	-	-	-	•	•	•		Unrep	N/A	Unrep 18	Unrep	50	Unrep	Unrep	Unrep	stroke id	•			Unrep
[59]	2011	-	11	-	•	•	•		Unrep	N/A	Unrep	Unrep	50	MA	Unrep	Unrep	stroke id, stroke count, swimming intensity	•			Unrep
[60]	2011	-	1	-	•	•		•	Unrep	Unrep	57×91×24 65.6	$1.24x10^{-4}$	50	Unrep	Unrep	2.4 GHz RF	stroke id	•			Unrep
[61]	2011	-	-	1	•				±78.5	±26.2	53×33×10 20	$1.75x10^{-5}$	100	LP HW (0.5 Hz)	1000	2.4 GHz RF	mean velocity	•			Tethered speed meter
[62]	2012	7	-	11	•				±29.4	N/A	36×42×12 34	$1.81x10^{-5}$	256	LP BW (0.01 Hz)	1000 Flash MMC	USB	velocity, lap time, time per stroke, stroke length, orientation	•			Video & observation

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m\cdot s^{-2}$)	**Gyro.** ($rad\cdot s^{-1}$)	**(m x103) (kg x103)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[63]	2012	12	-	-	•				±19.6	>600	52×33×11 20.7	1.89x10^{-5}	100	LP BW (0.5 Hz)	256	USB	kick rate, kick count, breathing patterns	•			Video
[64]	2012	11	-	19	•				±107.9	±15.7	Unrep	Unrep	500	Unrep	Unrep	Unrep	instantaneous velocity, mean velocity	•			Tethered speed meter
[65]	2012	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	lap count, swim distance	•			Unrep
[66]	2012	-	-	-	•	•	•	•	Unrep	N/A	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	stroke rate	•			Unrep
[67]	2012	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	LP 0.5–5.0 Hz	Unrep	Unrep	stroke id	•			Unrep
[68]	2012	-	1	-	•				±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (1 Hz)	4	RF	start and turn phase acceleration patterns, stroke count, stroke duration	•	•	•	Video
[69]	2012	1	-	-	•				±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (1 Hz)	4	RF	turn phase acceleration patterns, temporal analysis			•	Video

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m \cdot s^{-2}$)	**Gyro.** ($rad \cdot s^{-1}$)	**(m x103) (kg x103)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[70]	2012	9	-	-	•				±78.5	±26.2	52×33×10 20	1.72×10^{-5}	100	HW FIR (0.5 Hz)	1000	2.4 GHz RF	arm symmetry, stroke rate	•			Video
[71]	2013	-	2	-	•	•	•	•	±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (1 Hz)	4	RF	stroke count, stroke rate, lap count	•			Video
[10]	2013	-	7	-	•				±98.1	±20.9	Unrep	Unrep	500	Unrep	Unrep	Unrep	temporal stroke phase analysis, arm coordination	•			Video
[72]	2013	-	20	-	•				±107.9	±15.7	50×40×16 36	3.2×10^{-5}	500	LP (100Hz)	Unrep	microSD	mean velocity	•			Tethered speed meter
[73]	2013	-	6	6	•				±107.9	±15.7	50×40×16 36	3.2×10^{-5}	500	LP (100Hz)	Unrep	microSD	energy expenditure, velocity, cycle velocity variation	•			Indirect calorimetry, lactate
[74]	2013	-	7	-		•			±98.1	±15.7	50×40×16 36	3.2×10^{-5}	100	Unrep	Unrep	Unrep	stroke phase acceleration patterns	•			Video

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	C	R	Fc	Br	Bk	Bf	Accel. ($m \cdot s^{-2}$)	Gyro. ($rad \cdot s^{-1}$)	(m x103) (kg x103)	(m^3)	(Hz)		(MB)			F	S	T	
[75]	2013	-	-	1	•	•	•	•	Unrep	N/A	Unrep	Unrep	50	Unrep	2	RF	stroke rate	•			Unrep
[76]	2013	-	-	1	•				Unrep	N/A	Unrep	Unrep	50	Unrep	2	2.4 GHz RF	stroke count, stroke length, stroke rate, velocity	•			Unrep
[77]	2013	-	-	1	•	•	•	•	Unrep	N/A	Unrep	Unrep	50	Unrep	2	2.4 GHz RF	stroke rate	•			Unrep
[78]	2013	-	12	-	•	•	•	•	±14.7	±8.7	Unrep	Unrep	200	MA	Unrep	SD	stroke id	•			Video
[79]	2013	-	-	1	•				±29.4	±8.7	150×90 Unrep	Unrep	50	LP BW (5 Hz)	4	RF	block time, entry time, kick initiation time, stroke initiation time, kick rate, stroke rate, stroke count		•		Video
[80]	2013	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	200	Unrep	Unrep	Bluetooth	stroke id	•			Unrep
[81]	2013	1	1	-	•				Unrep	±1500	Unrep	Unrep	100	LP BW (2 Hz)	Unrep	Unrep	body roll velocity	•			Video

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	C	R	Fc	Br	Bk	Bf	Accel. ($m \cdot s^{-2}$)	Gyro. ($rad \cdot s^{-1}$)	(m x103) (kg x103)	(m^3)	(Hz)		(MB)			F	S	T	
[82]	2013	1	2	4	•				±58.9	N/A	69×28×07 15	$1.59x10^{-5}$	100	HW FIR (0.5 Hz)	Unrep	Unrep	push-off velocity			•	Tethered speed meter
[83]	2013	8	9	-	•				±78.5	±26.2	53×33×10 20	$1.75x10^{-5}$	100	LP HW (0.5 Hz)	1000	2.4 GHz RF	mean velocity, stroke rate	•			Tethered speed meter
[84]	2013	-	53	-	•				Unrep	N/A	29×37×11 34	$1.18x10^{-5}$	32	Unrep	Unrep	Unrep	speed, distance	•			Stopwatch
[85]	2014	-	-	3	•	•	•		±19.6	N/A	5×58×25 Unrep	$7.25x10^{-6}$	Unrep	Unrep	Unrep	Bluetooth	stroke count, kick count, symmetry	•			Unrep
[86]	2014	-	21	-	•	•		•	Unrep	N/A	Unrep	Unrep	100	Unrep	Unrep	2.4 GHz RF	stroke count, mean velocity	•			Video
[87]	2014		9	9	•				±107.9	±15.7	50×40×16 36	$3.20x10^{-5}$	500	LP (100 Hz)	Unrep	microSD	energy expenditure, velocity, kick rate	•			Indirect calorimetry, lactate

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	C	R	Fc	Br	Bk	Bf	Accel. ($m \cdot s^{-2}$)	Gyro. ($rad \cdot s^{-1}$)	(m x103) (kg x103)	(m^3)	(Hz)		(MB)			F	S	T	
[88]	2014	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	stroke count, stroke id, lap count, lap time	•			Unrep
[89]	2014	-	2	-	•	•	•	•	±19.6	±4.4	16×12×10 Unrep	1.92×10^{-6}	100	MA	NOR flash memory 64	433 MHz RF	stroke id, breathing patterns	•			Unrep
[90]	2014	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	2.4 GHz RF	lap count	•			Unrep
[91]	2014	-	-	-	•	•	•	•	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	swim distance, lap count, lap time, stroke id	•			Unrep
[92]	2014	-	-	60	•				Unrep	N/A	Unrep	Unrep	Unrep	Unrep	Unrep	Unrep	energy expenditure	•			Cosmed
[93]	2014	-	45	-	•	•	•	•	±19.6	N/A	Unrep	Unrep	32	Unrep	Unrep	Unrep	stroke id	•			Video
[94]	2014	-	1	-				•	±9.8	±8.7	53×32×19 Unrep	3.22×10^{-5}	Unrep	Unrep	Unrep	Blue-tooth	joint angles during fly kick	•			Video
[95]	2014	-	1	1		•			Unrep	Unrep	Unrep	Unrep	Unrep	LP Fourier (8 Hz)	Unrep	Unrep	joint angles	•			Video

Table 4.1. *Cont.*

Ref	Year	Participants			Swim Strokes				Sensor Range		Size & Mass	Volume	Sample Rate	Filter Design	Data Storage	Data Trans.	Output Variables	Swim Phase			Validation Methods
		E	**C**	**R**	**Fc**	**Br**	**Bk**	**Bf**	**Accel.** ($m \cdot s^{-2}$)	**Gyro.** ($rad \cdot s^{-1}$)	**(m x103) (kg x103)**	**(m^3)**	**(Hz)**		**(MB)**			**F**	**S**	**T**	
[96]	2014	10	-	-	•	•	•	•	Unrep	N/A	30×30 33	Unrep	100	LP (2 Hz)	Unrep	Unrep	stroke id	•			Manual
[97]	2015	-	8	7		•			±107.9	±15.7	50×40×16 36	$3.2x10^{-5}$	500	LP (100Hz)	Unrep	microSD	mean velocity	•			Tethered speed meter
[98]	2015	-	-	3	•				Unrep	Unrep	Unrep	Unrep	50	Unrep	Unrep	Unrep	Positioning	•			Video

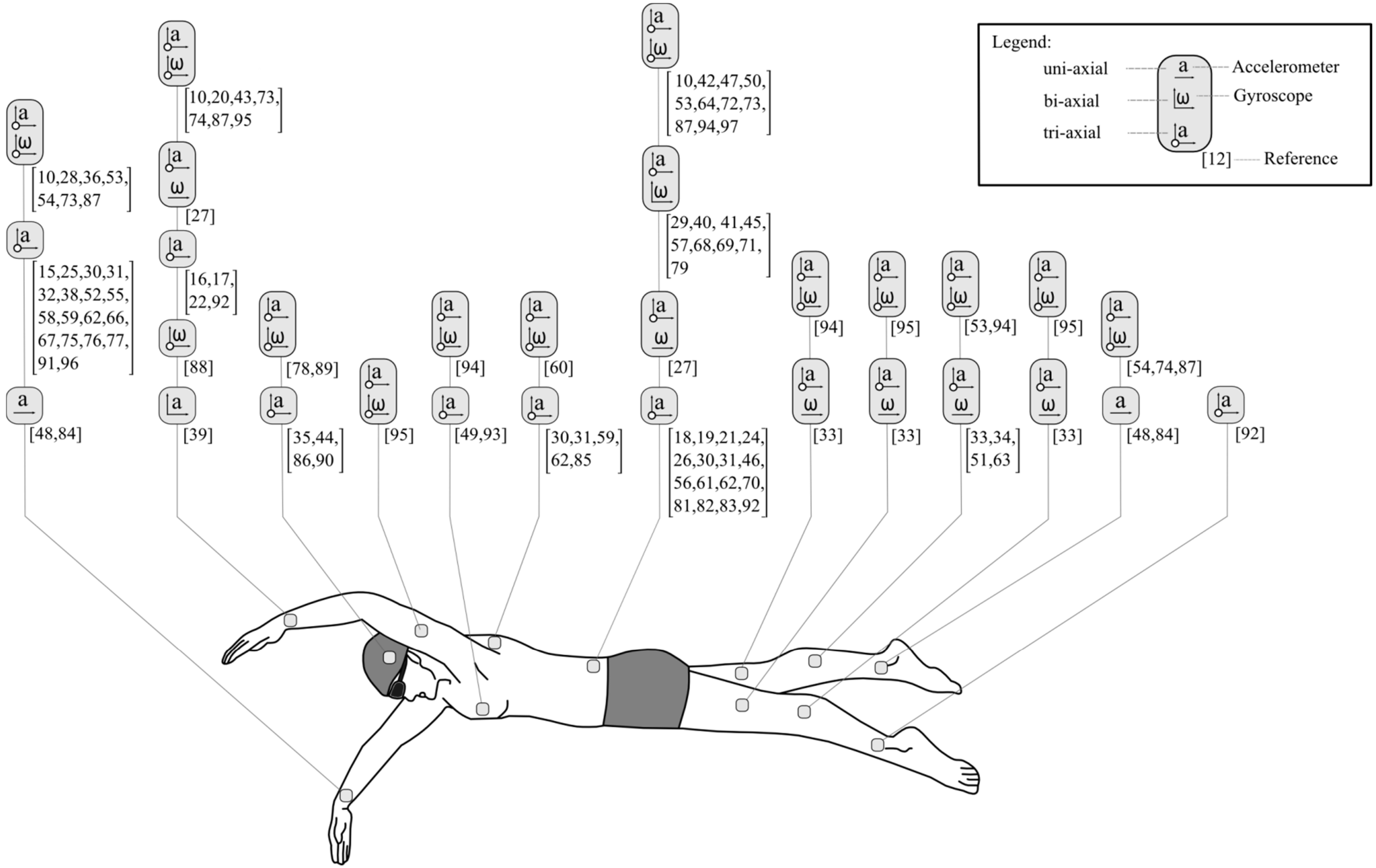


Figure 4.4. Locations and specifications of different inertial sensor units used in previous swimming related studies. Studies have used devices in both single and multiple sensor configurations. The most popular locations are the lower back and wrist/lower arm and the most prevalent sensor specifications incorporate a tri-axial accelerometer and tri-axial gyroscope.

4.4 Discussion

4.4.1 Parameters for Analysing Free-Swimming

Stroke Phase Analysis

In 2000, Ohgi and colleagues were the first to apply inertial sensor technology to identify swimming stroke phases during frontcrawl swimming from a wrist-worn accelerometer device sampled at 128 Hz [15, 17]. This work was soon expanded to include an analysis of other swimming strokes and also to combine the acceleration signal with angular velocity measurements from a gyroscope [12, 16, 20]. During a swimming stroke, a swimmer continuously alters shoulder, elbow and wrist joint angles, combined with actions of the rest of the body, to change hand position in the water and generate propulsive forces. This movement can be tracked by analysing the signal signatures from these inertial sensors and through comparison with video footage.

For example, a positive local acceleration maximum in the ulnar-radial direction (X-axis) seen in Figure 4.5 is indicative of the start of the insweep, which is followed by local minimum along the distal-proximal direction (Y-axis) at the beginning of the upsweep phase during frontcrawl [15]. These studies found that wrist acceleration ranges from -40 $m \cdot s^{-2}$ to +40 $m \cdot s^{-2}$ whilst angular velocity ranges from −10.5 $rad \cdot s^{-1}$ to +14.0 $rad \cdot s^{-1}$, with evident differences between strokes (Table 4.2). This early research confirmed that features of the acceleration signal output could potentially be used as a novel means of analysing a swimmer's technique.

Table 4.2. Indicative range of acceleration and angular velocity values recorded at the wrist during each of the four swimming strokes. Adapted from Ohgi [20].

Swimming stroke	Acceleration ($m \cdot s^{-2}$)	Angular velocity ($rad \cdot s^{-1}$)
Frontcrawl	−20 to +40	−7.0 to +8.7
Backstroke	−10 to +30	−10.5 to +10.5
Breaststroke	−20 to +40	−7.0 to +7.0
Butterfly	−40 to +40	−7.0 to +14.0

Additionally, this work highlighted an individual nature to signal signatures, albeit with limited subject numbers. To illustrate, Figure 4.6 compares the Z-axis acceleration profile for two swimmers during a frontcrawl stroke cycle. This palmar-dorsal direction can be related to the orientation of the wrist. Differences in the signals can be seen throughout the different phases. For example, it can be seen in Figure 6a that the Z-axis is close to 0 $m \cdot s^{-2}$ at the point of hand entry (at time zero). Conversely, the value at the same point in the stroke is much larger in Figure 4.6(b). Ohgi, et al. [15] postulated that this difference can be explained by the two swimmers displaying a different pitch of the hand at the point of entry, with swimmer (a) displaying a more ideal pitch as opposed to swimmer (b) who demonstrated a flatter hand entry. Furthermore, it has been found that the effects of fatigue can be seen in the acceleration signal. Reduced acceleration during the upsweep phase is indicative of poor elbow extension and this can be related directly to shorter stroke durations and reduced propulsive movements during the arm sweeps [17]. Differences such as these facilitate a detailed and specific analysis of a swimmers hand actions, but also lead to difficulties in identifying common features upon which to base automatic feature detection algorithms.

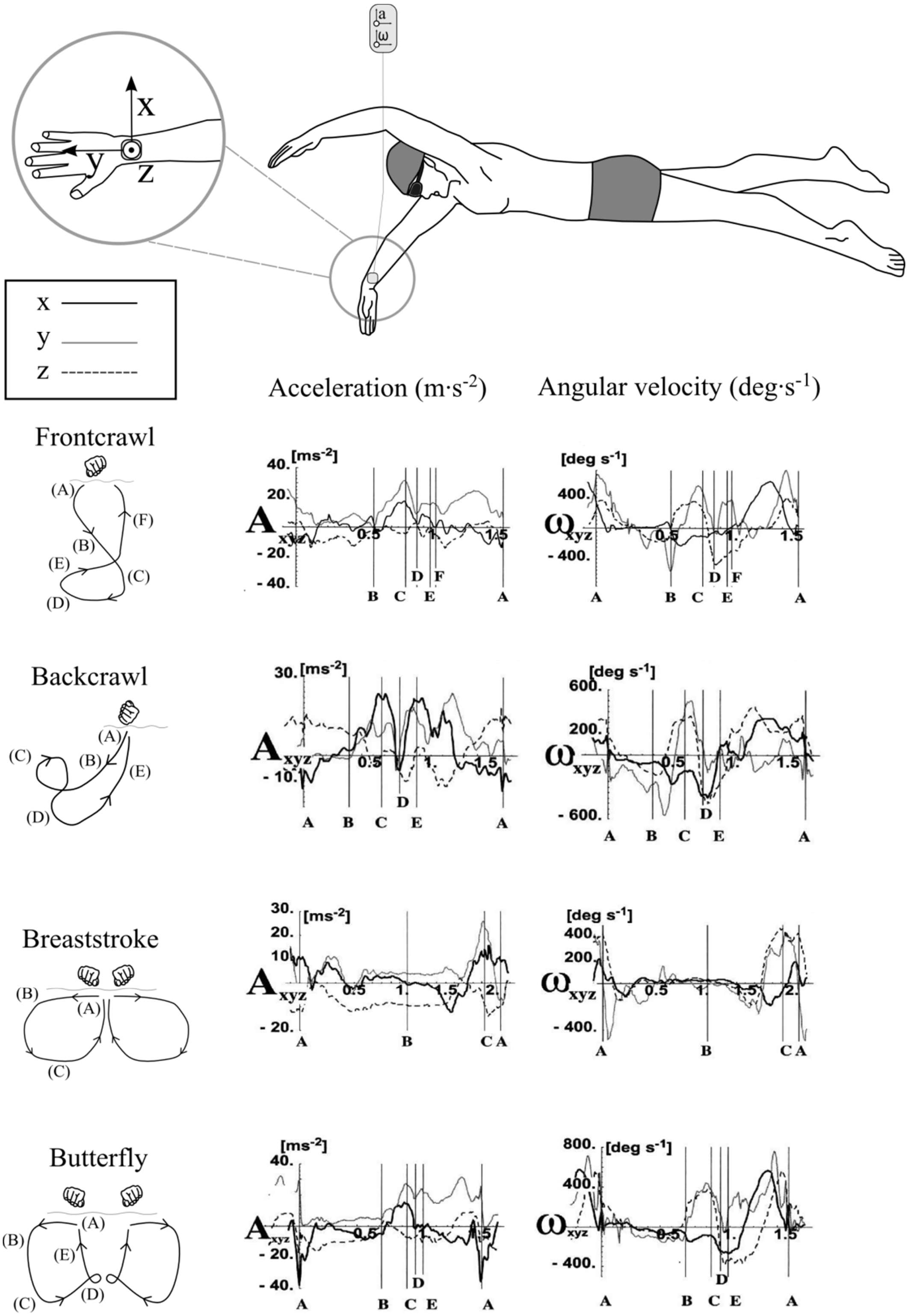


Figure 4.5. Different swimming styles will exhibit different acceleration (A) and angular velocity (ω) patterns. Representative signal output from the wrist is shown. Each signal begins from the point of hand entry into the water and the various phases of each stroke style are identified with vertical lines. Characteristic features of each signal allow researchers extract key performance related information. Adapted from Maglischo [1] and Ohgi [20].

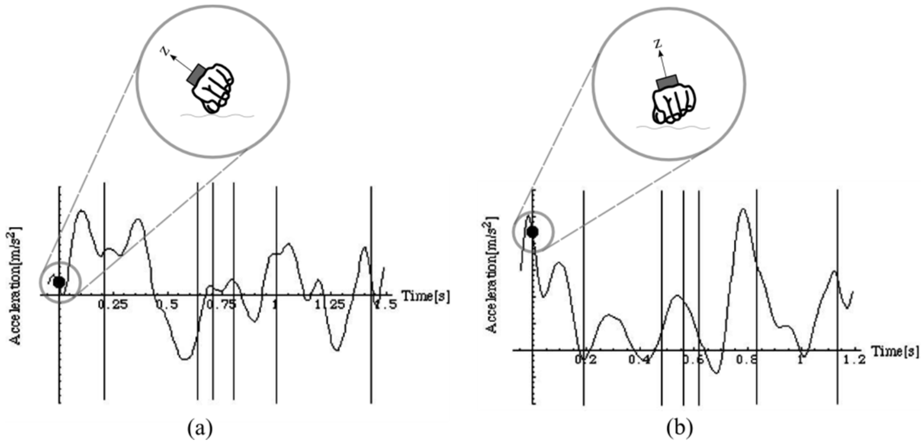


Figure 4.6. Features of the acceleration signal can be used to distinguish between different swimming techniques. Swimmer (a) demonstrates a more ideal pitch angle at the point of hand entry to the water and this is reflected in the Z-axis (palmar-dorsal) acceleration of approximately 0 m·s−2. In contrast, swimmer (b) has a much larger Z-axis acceleration at this point, which is indicative of a flatter hand entry to the water. Adapted from Ohgi, et al. [15].

An Australian research group, led by Davey and James, later combined the signals from both an accelerometer and a gyroscope in an attempt to more accurately define the phases of arm action during frontcrawl [53]. These events were identified and described through visual inspection of the sensor data in conjunction with video images. This work compared arm, back and leg worn sensors and argued that the primary signal of interest for stroke phase detection should be the medio-lateral signal of the gyroscope located on the wrist, which is indicative of pronation and supination of the forearm (Figure 4.7) Acceleration data were then used as a secondary confirmation of specific events such as the instant of hand entry. The authors acknowledged a previously highlighted issue that the point of hand exit from the water, marking the beginning of the recovery phase, was not easily identified and did not correspond with any particular spike in any of the three dimensional accelerometer or gyroscope sensor signals. Indeed, Ohgi and colleagues had combined the upsweep and recovery phases when determining the temporal durations of phases of arm actions for this reason [17]. This issue also raises concerns about feasibility testing of new technology using dry-land swim bench apparatus, as found in Lee, et al. [55], as the acceleration signal may not be consistent with that produced in the water, even if stroke patterns are reproducible.

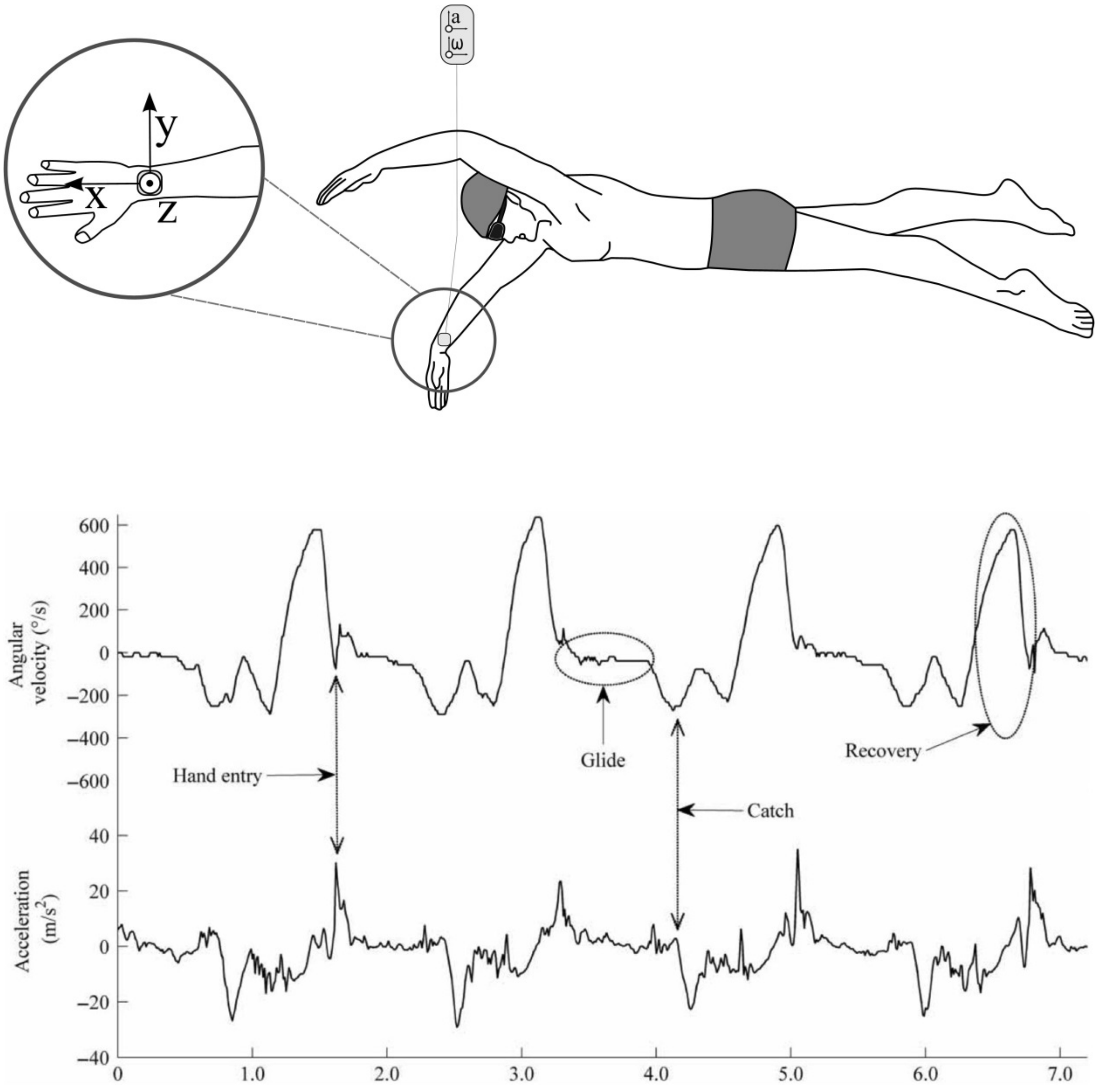


Figure 4.7. Comparison of signal output from both gyroscope and accelerometer sensors for four arm strokes. The signal displayed is from the Y-axis (ulnar-radial direction). It can be seen that the angular velocity pattern that is obtained is smoother and may facilitate easier feature detection of key events such as hand entry; glide; catch; and recovery. Reproduced with permissions from James, et al. [53].

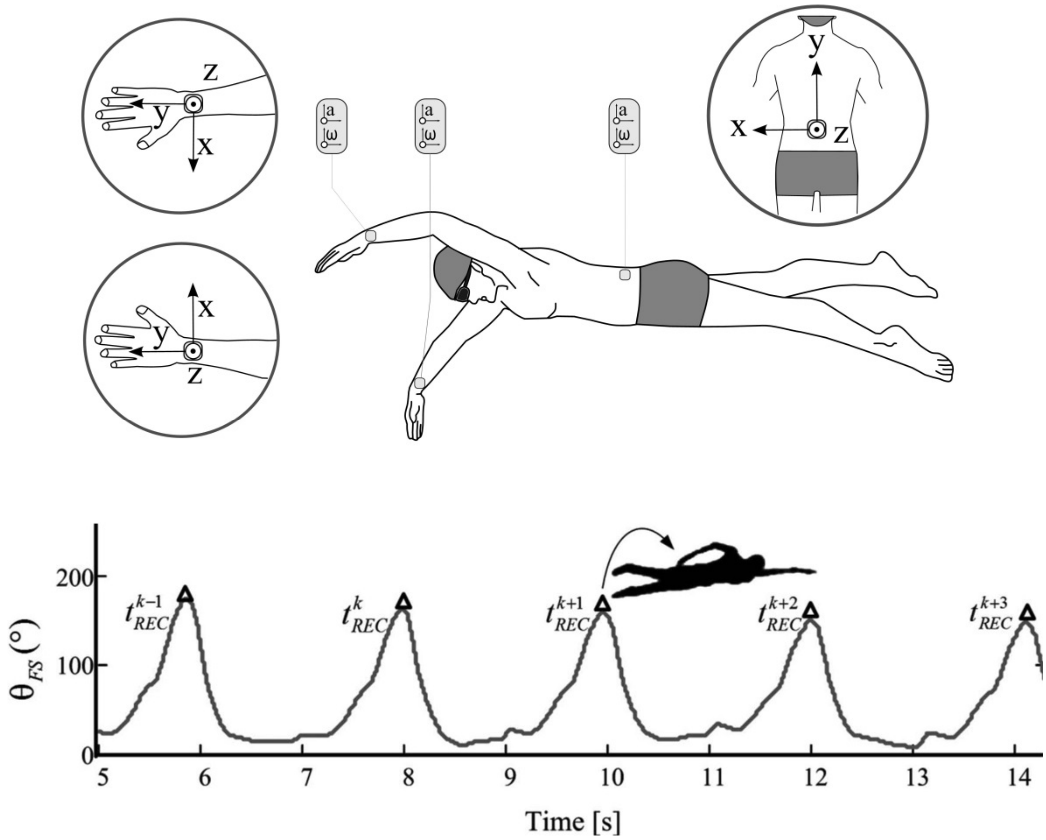


Figure 4.8. The changing angle between the Y-axis orientation of a sensor worn at the sacrum and a sensor worn at the forearm, measured using the gyroscopic signal and used to determine the start of the recovery phase, which occurs when the angle is at a maximum value. Reproduced with permissions from Dadashi, et al. [10].

A recent paper has suggested a possible solution for this. By using multiple sensors positioned on both forearms and on the swimmers lower back, researchers measured the changing angle between the sensors at the sacrum and the forearm throughout the stroke, calculated from the angular velocity signal. It was suggested that the start of the recovery phase occurs when this angle is at a maximum value of approximately 2.6 rad to 3.1 rad (150° to 175°), and a peak detection algorithm was used to track these points in the stroke [10].

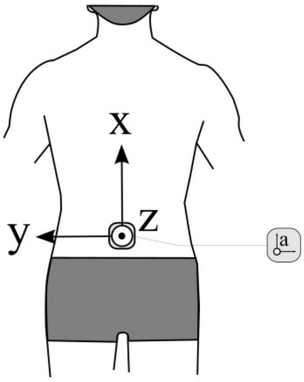
Furthermore, the authors developed a change detection algorithm to track the changing slope from both the accelerometer and gyroscope signals and were able to identify stroke phases as a result (Figure 4.8). By using sensors on both arms, this work also allowed for the measurement of the lag time between propulsive phases, termed the index of coordination (IdC), which previous research has found to correspond with skill level and swimming intensity and is traditionally measured using video [4, 99, 100]. The results demonstrated the validity of this approach, with a strong linear relationship found between the sensor derived data and the gold-standard data determined from video footage.

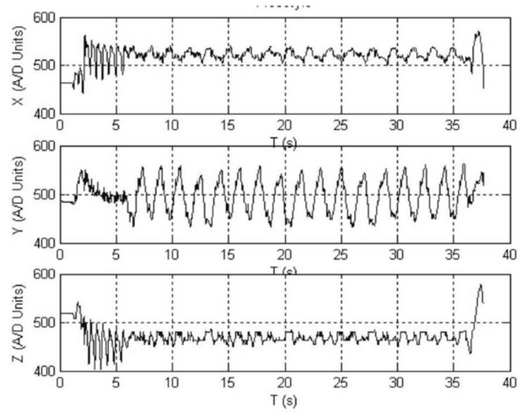
The research undertaken investigating how stroke phases can be determined using inertial sensors is important because it has provided coaches with a new way of analysing swimming techniques. This work has also demonstrated the potential for examining movement characteristics of both left and right arms independently [35] or to determine stroke rates and other performance related variables from regularly occurring patterns in the sensor signal, laying the foundations for future exploration in this field.

Stroke Type Identification

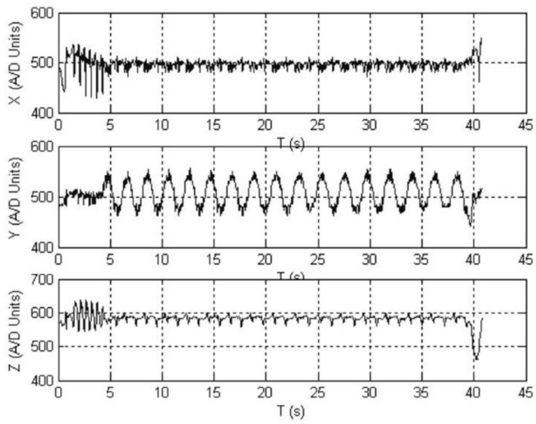
Specific characteristics of the acceleration profile for the four competitive swimming strokes allow for swimming stroke type to be detected. This functionality is important because feature detection algorithms frequently depend on knowledge of stroke type. Similar methodological approaches have been described in the literature that have detected stroke type using sensors positioned on the upper or lower back [11, 27, 59, 79, 101], wrist [27, 32, 59, 91], chest [85, 93] and head [78, 89]. Figure 4.9 provides a representation of a typical acceleration signal from the lower back over a full lap of swimming for each stroke [79]. A swimmer will lie in a supine position when performing backstroke. Consequently, the Z-axis signal (*i.e.*, acceleration in the anterio-posterior direction) outputs a value of approximately +1 g (+9.81 $m \cdot s^{-2}$) during backstroke. This is in contrast to the other three strokes in which the Z-axis tends towards −1 g (-9.81 $m \cdot s^{-2}$) as the swimmer is in a prone position when performing these strokes and the device will be orientated in the opposite direction. Additionally, whilst the X and Y axes during all four strokes appear to show similarities, there are differences in the magnitude and spread of the local maxima and minima that can be recognised.

Researchers have exploited these characteristics to develop methods which may be used to automatically detect the stroke type completed for any given lap [11, 46, 59, 60]. Davey & colleagues [11, 19] developed an algorithm that calculates sensor orientation and signal energy (Figure 4.10). The raw acceleration data were filtered using a low-pass Hamming window filter with a cut-off frequency of 0.5 Hz. The device orientation for each lap of swimming was determined using the Z-axis data as described above to first discriminate backstroke from the other three strokes. To distinguish further between strokes, thresholds were set for the three axes based on the magnitude of the filtered signal [11]. For example, it can be seen in Figure 9 that the amplitude of the Y-axis (medio-lateral direction) is large for frontcrawl and backstroke. This is because the body rotates along this longitudinal axis during each stroke cycle. In contrast, breaststroke and butterfly are known as short-axis strokes [1] and do not feature this rotation. Overall recognition accuracy across all strokes of 95% was reported when the data were compared to the prescribed swimming protocol. As such, it is not certain if there were any recognition issues due to specific stroke styles. Additionally, only six swimmers were included in the study so more rigorous testing of the algorithm would be necessary to offer a thorough evaluation of its reliability. That said this research did demonstrate for the first time that stroke type could be determined from the acceleration signal using straightforward signal processing and computational methods.

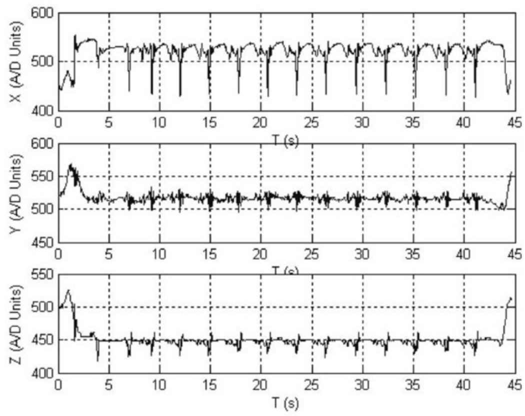




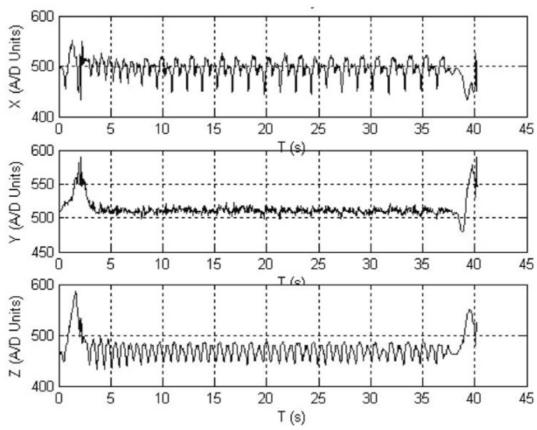
(a) Frontcrawl



(b) Backcrawl



(c) Breaststroke



(d) Butterfly

Figure 4.9. Sample acceleration output from a lower back worn sensor for each of the four competitive swimming strokes. Characteristic patterns of each stroke can be used to automatically identify stroke styles. The A/D (analog to digital) units referred to can be related to acceleration, such that 512 A/D units is representative of 0 g. Values greater than 512 A/D units are therefore positive g-values and values less than 512 A/D units are negative g-values. Reproduced with permissions from Davey [102].

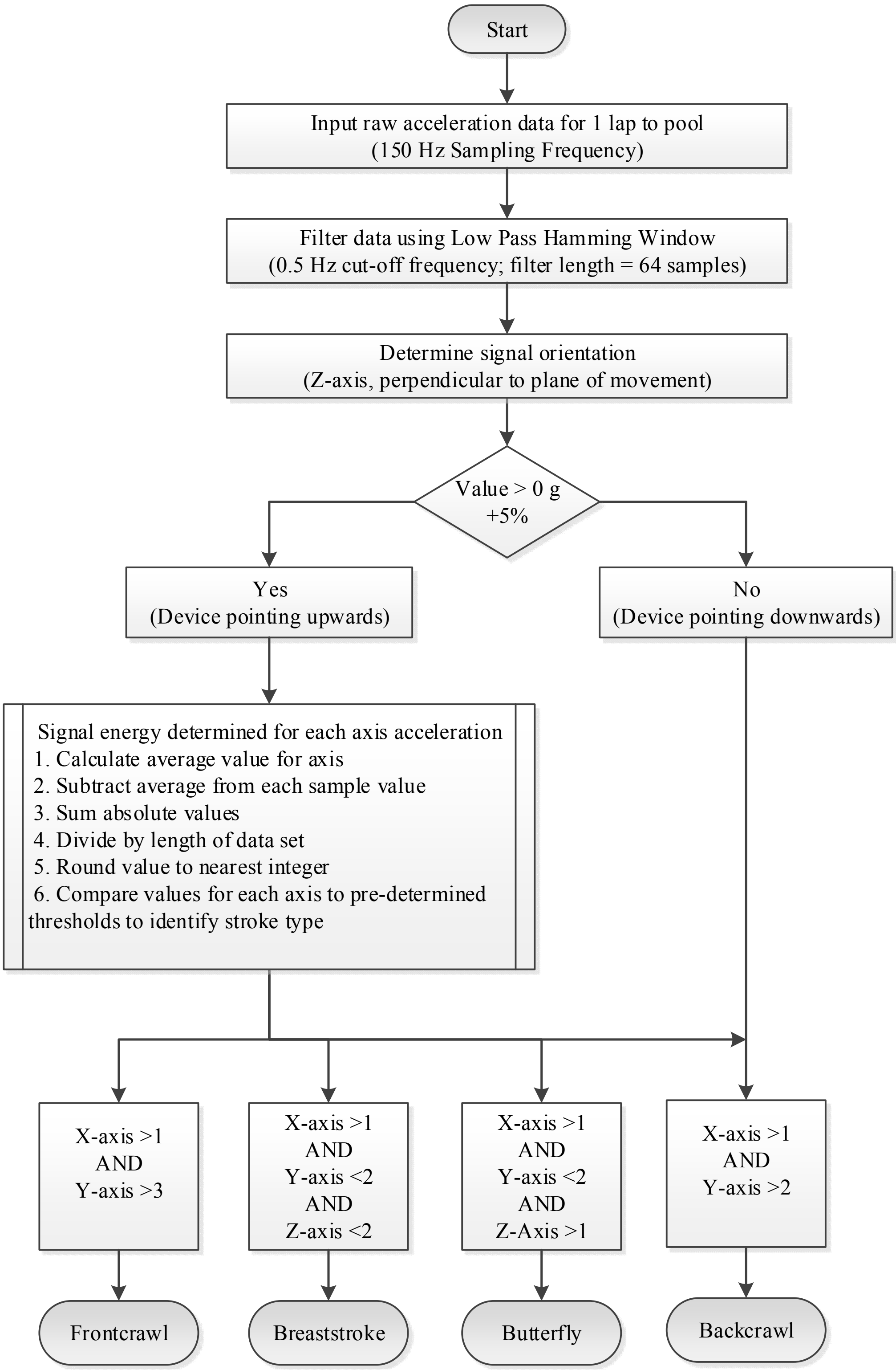


Figure 4.10. Flowchart for a stroke identification algorithm used to distinguish between each of the four competitive swimming strokes. Adapted from Davey, et al. [11].

Siirtola, et al. [59] utilised linear and quadratic classification methods and achieved comparable results to Davey, et al. [11]. The specific details of the methodology employed went unreported but it involved a sliding window technique to process the data using a window size of two seconds with an interval of half a second between windows. What is noteworthy about the study by Siirtola, et al. [59] is that comparisons were made of the accuracy of stroke identification: (i) for different sampling rates; (ii) between wrist and upper back worn accelerometer devices; and (iii) for three of the four competitive swimming strokes. The data were then resampled at 5, 10 and 25 Hz, to assess what effect this may have on detection accuracy. The results are summarized in Table 4.3 and indicate that the back worn sensor achieved better overall accuracy (95.3% at 25 Hz compared to 89.8% for the wrist). This was true at each of the sampling frequencies tested and for all three swimming styles included in the study. It is well established that the pattern of hand movement during swimming shows considerable variances owing to various factors including individual anthropometric and technique differences, skill level, swimming speed and fatigue [38, 100, 103]. It is possible that these variations are affecting the results of the wrist location. It was also found that sampling rates as low as 5 Hz can be used to accurately distinguish between styles and similar recognition rates were reported for each of the three strokes tested [59].

Table 4.3. Results of automatic stroke style identification, comparing different sensor locations and sampling frequencies. The back worn device produced more accurate results for all styles and sampling frequencies. Note that the results provided for the three swimming styles relate to data calculated at 5 Hz. Adapted from Siirtola, et al. [59].

Comparison Measure	**Recognition Accuracy**	
	Wrist	**Upper Back**
Sampling Frequency		
5 Hz	88.5%	95.1%
10 Hz	88.9%	95.4%
25 Hz	89.8%	95.3%
Swimming style		
Frontcrawl	90.8%	96.1%
Backstroke	88.8%	97.1%
Breaststroke	92.6%	96.7%

A recently published conference paper also using classification methods for automatic stoke identification was based on data mining procedures (neural network and decision tree) [93]. Using a chest mounted tri-axial accelerometer, descriptive information including the mean; variance and skewness of the acceleration data for all axes were examined to establish thresholds and used to distinguish between strokes (Figure 4.11). Results indicated an overall accuracy (91.1%) and this approach does warrant further examination as a much larger data set was involved than in previous studies discussed. It appears that the torso offers a more accurate location for stroke style identification compared with the wrist, but with a trade-off in terms of usability and user comfort. However additional investigation is warranted due to the limited research currently available. Other body locations, such as the head for example, may offer an alternative solution and convenient location.

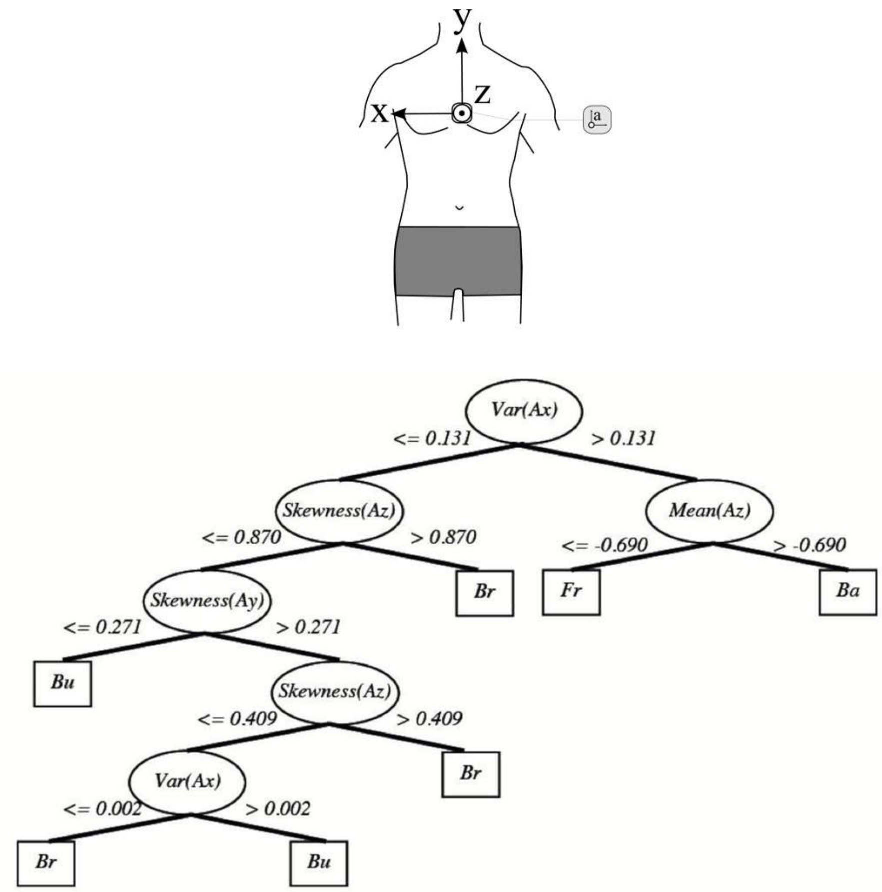


Figure 4.11. Stroke identification classification model based on descriptive statistical features of all three axes of the acceleration signal from a chest worn device. Thresholds were set to the data from each of the three axes (values in m·s-2) in order to classify stroke styles. Reproduced with permissions from Ohgi, et al. [93].

Much of the patent literature also features automatic stroke identification functionality and this is certainly an acknowledgement of the importance of this for applied use of inertial sensors in swimming settings [32, 38, 49, 67, 91]. Unfortunately, the accuracy of the approaches in the patent literature is untested and there is often insufficient information related to the specific system specifications and signal processing techniques. For example, Yuen [49] describes a method of distinguishing strokes that replicates that of Davey, using the polarity of the Z-axis channel to distinguish backstroke and then comparing the same individual axes to further distinguish between the other styles. However, the specifics regarding the threshold values employed are not described and no data are presented to explore the accuracy of the approach. Furthermore, in most instances, several embodiments may be suggested within a given patent, providing several potential methodologies.

One such example of this ambiguity is provided in Figure 4.12 [38], which describes the process of determining stroke type from a wrist worn tri-axial accelerometer device. In part (a), the raw acceleration signal is recorded at 30 Hz. A low-pass filter is applied with a cut-off of 1 Hz (b). In part (c) a peak detection algorithm is used to isolate maxima and minima along the X-axis, representing acceleration in the direction of swimming. This is achieved using a moving window technique with a window size of 1.5 s. Individual strokes are identified in part (d), using heuristic techniques, such as determining a sequence of maxima-minima-maxima. It is suggested that a threshold of greater than 1 g (9.81 $m{\cdot}s^{-2}$) in total acceleration within a three second duration is used, but it is not clear if these same sequences and values may be applied to all stroke types. Finally, in part (e), recognition models are applied to determine which of the competitive swimming types is involved. However, various possible options for conducting this process are mentioned, including linear discriminants, hidden Markov models and neural networks, but with no data presented to test any of these approaches.

Where reported, automatic stroke type identification algorithms appear to show good levels of accuracy and can be readily incorporated into embedded systems for applied use. However, this feature is not included in most research designs. This could be because the majority of studies are concentrated solely on frontcrawl and as such, no detection algorithm is necessary. Even where multiple strokes are included, study protocols are prescribed in advance so the sensor output can be manually attributed to a specific stroke [57, 76, 86, 101]. Whilst this may be expected of early exploratory research work in this area, it does call into question the robustness of these devices for use in applied settings, where all four strokes are used interchangeably, even for elite swimmers with specific stroke specializations. The requirement for the end user to manually input the swimming stroke completed for a given lap or training interval severely hampers the functionality of these systems. Additionally, without clear details of the methodology employed, it is difficult for researchers to fully assess the merits of any given approach or to arrive at a best-practice methodology for identifying stroke type.

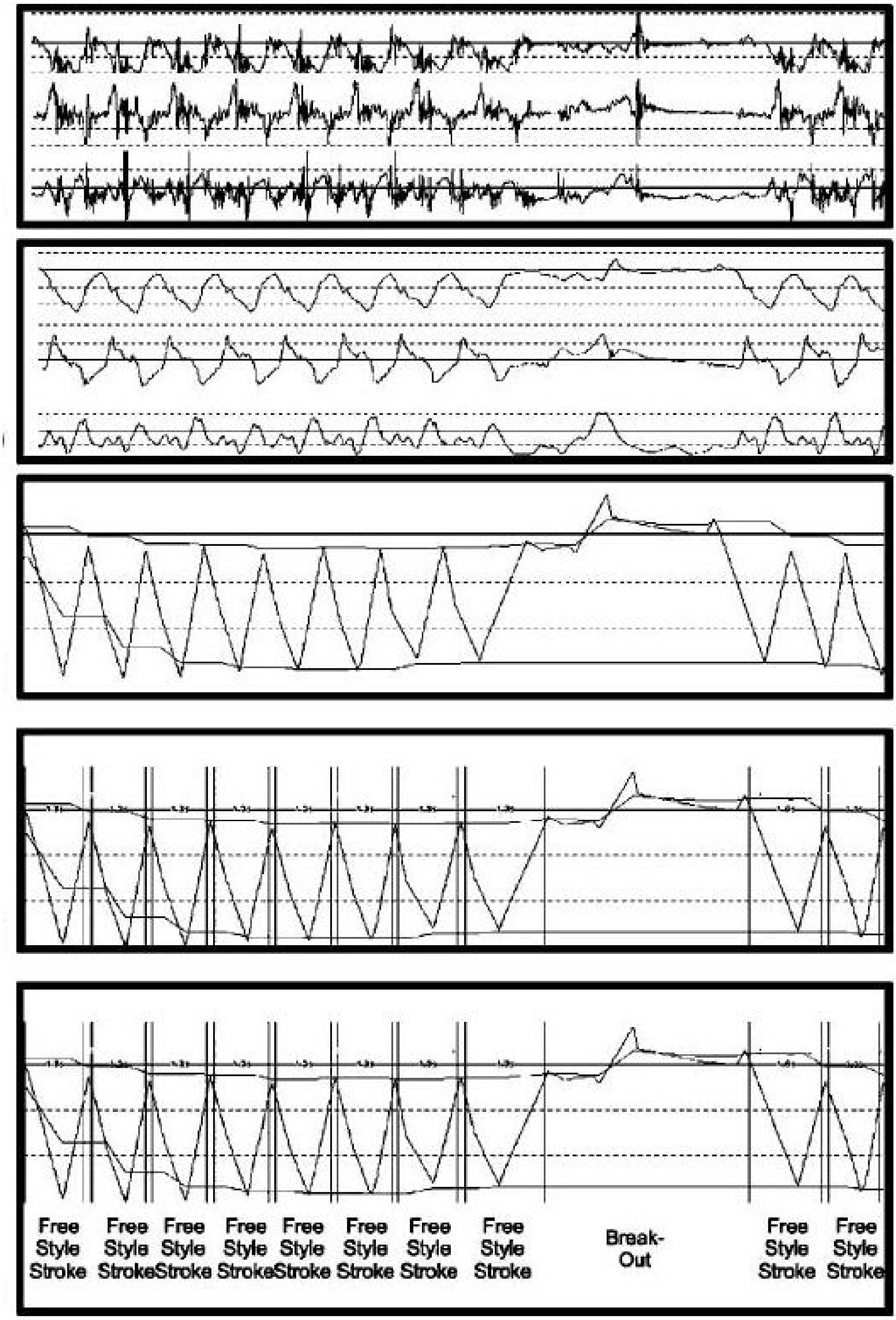


Figure 4.12. The process of determining stroke type from a wrist worn tri-axial accelerometer device: (a) raw acceleration signal; (b) low-pass filter with a cut-off of 1 Hz; (c) peak detection algorithm used to isolate maxima and minima; (d) individual strokes are identified; (e) recognition models applied to determine stoke type. Adapted from Anthony and Chalfant [38].

Lap Time

The ability to record lap times during swimming allows for the intensity of effort to be monitored closely. Measuring lap time requires the detection of events when the swimmer makes contact with the pool walls. Bächlin and Tröster [62] filtered the acceleration signal from the longitudinal axis of a wrist worn device using a low-pass 2nd order Butterworth filter with a cut-off frequency of 0.01 Hz. The resultant filtered data were used to determine events at the pool walls (Figure 4.13). A push-off was registered at the point of the first falling slope in acceleration, whereas a large impact peak and rising slope signified that a wall strike had occurred. The authors reported that values were within ±0.3 s of the criterion measure. Unfortunately, significance was not reported and the criterion used was a manual method using a stopwatch which itself is prone to human error.

Davey, et al. [11] describe algorithms for detecting two distinct types of wall push-off events with an accelerometer worn on the lower back, those following the commencement of swimming and those after turns (Figure 4.14). As the swimmer commences swimming from a standing start, a change in orientation from vertical to horizontal can be recognised. A turn can be detected using a zero-crossing algorithm about the perpendicular axis as the swimmer rotates in the water [11, 57]. Additionally, the wall push-off is characterised by a rapid increase in acceleration over a short interval, such as a 1 g rise over a 0.1 s duration. However, Davey, et al. [11] reported a significant difference ($p < 0.01$) existed in lap time calculations between the video and that of the accelerometer device (mean difference -0.32 ±0.58 s). Further analysis revealed that this was as a result of errors in the part of the algorithm that was used for the detection of the commencement of swimming as opposed to the algorithm used to detect turns or the end of the final lap. Lap time differences for the first 100 m of a 200 m swimming trial averaged -0.38 ±0.23 s (significantly different at $p < 0.01$) whilst no significant differences reported for the second 100m of the trial (0.05 ±0.45 s). The authors also reported that the offset was consistent, with the accelerometer tending to underestimate lap times [11].

An additional concern with the detection of wall contact is that the arms or legs will absorb the majority of the impact [11, 59], causing difficulty in setting threshold values for automatic detection of turns and the end of a swimming interval, especially with a sensor positioned on the torso. Furthermore, some have reported issues with detecting peaks during turns owing to individual differences in turning technique, such as gliding into the wall on approach [59]. Impact accelerations will be more clearly visible from wrist worn sensors at the end of a swimming interval [62] and during butterfly and breaststroke turns but the opposite is true during frontcrawl and backstroke as the arm will not make wall contact when performing flip turns.

It appears that the accurate determination of lap times using inertial sensors remains an area of ongoing research. Further empirical testing is necessary to ensure accuracy of this important parameter. The ability to detect wall contact events, and thus record lap times, is paramount, not just from a coaching point of view but also as many other variables are derived from this parameter such as average speed, stroke count, stroke rate and stroke length.

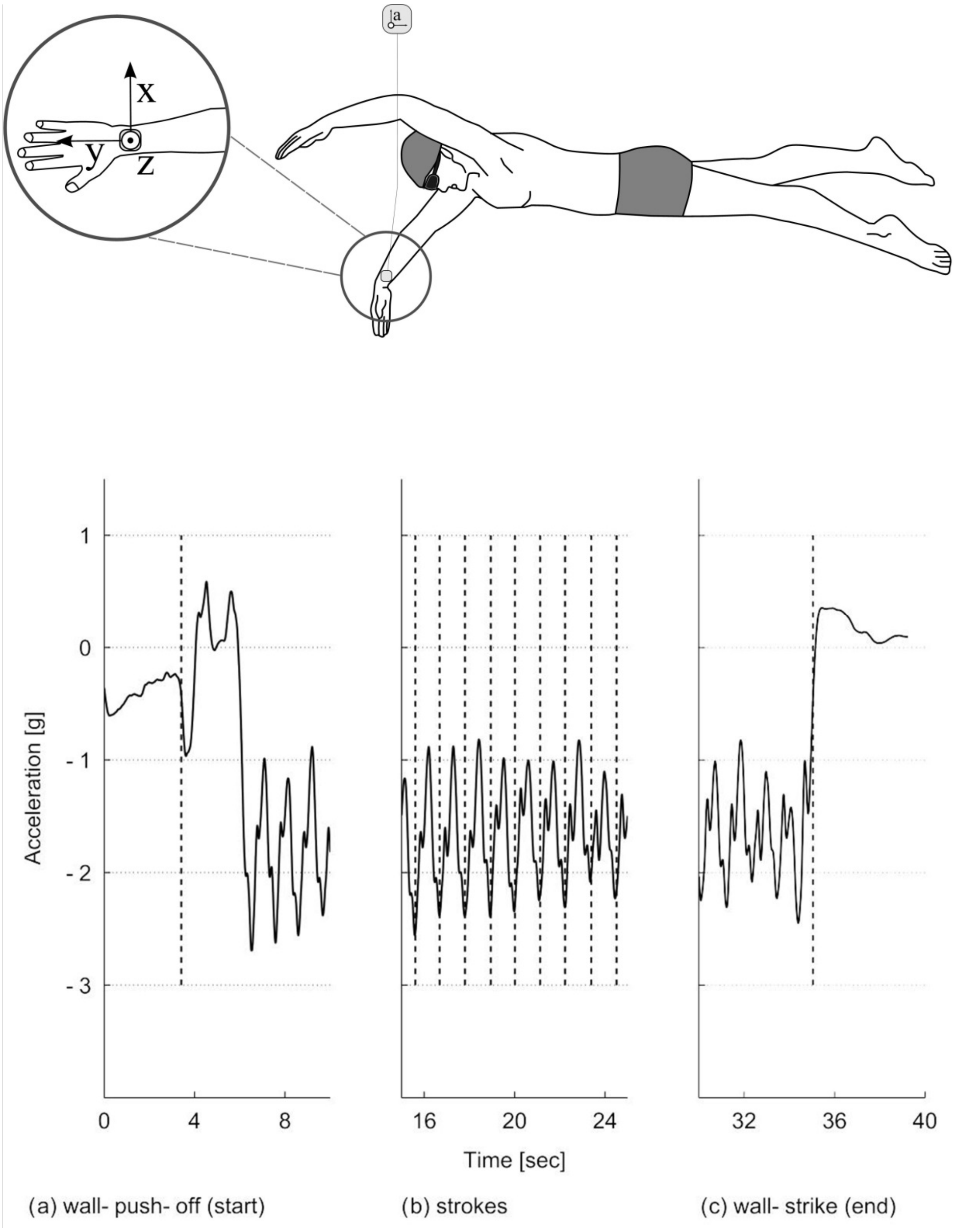


Figure 4.13. Lap times can be determined by identifying events at the pool walls. Both push-off and wall strike events result in rapidly changing slopes and a corresponding signal amplitude that exceeds that observed during mid-pool swimming. Reproduced with permissions from Bächlin and Tröster [62].

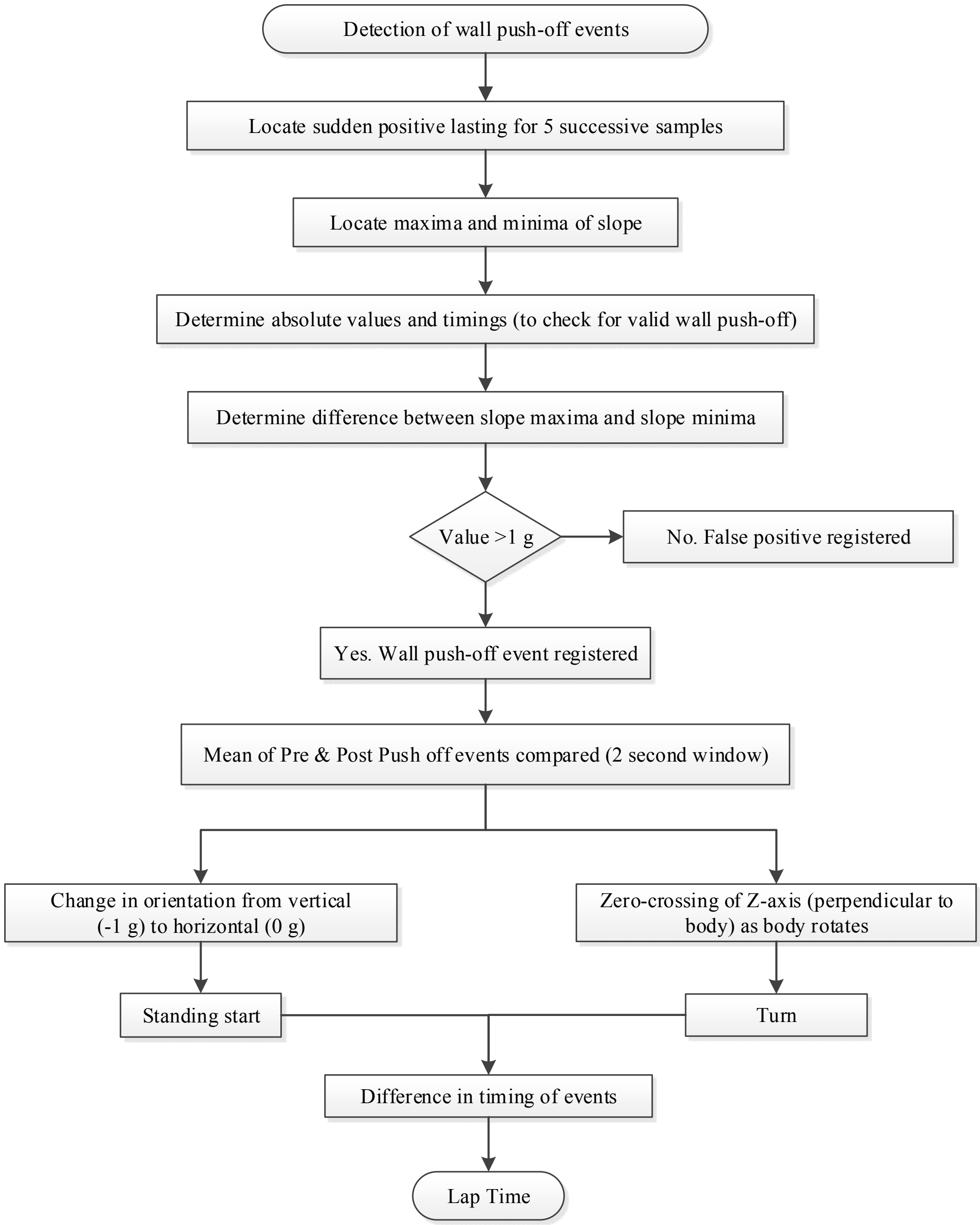


Figure 4.14. Flowchart for a lap time detection algorithm based on detection of wall push-off events. Adapted from Davey, et al. [11].

Swim Distance

The same methodology described above for identifying events at the pool walls to measure lap times can also be used in a more simple fashion to register that a lap has occurred. Subsequently, by knowing the length of the pool, swim distance is readily calculated by utilizing a lap counter function that is not dependent on determining the exact instant of wall contact or push-off. For example, Le Sage, et al. [57] described a lap counter algorithm that tracks when turns have been registered. Figure 4.15 shows how this was achieved. The raw acceleration data from the Z-axis (perpendicular to the plane of movement) was filtered using a low-pass Butterworth filter with a cut-off frequency of 2 Hz for frontcrawl swimming. The filtered data show clear local minima which are indicative of the swimmers transverse rotation during the flip-turn. A simple threshold was applied to these data to facilitate automatic counting of the laps performed [40, 57]. This process appears to be quite robust due to the clear amplitude difference observed during the turn but data were only provided for four consecutive laps of swimming so this requires further verification. Others did report an 88.9% accuracy in detecting that a turn had occurred using a similar process and using a slightly larger data set comprising of 12 swimmers each completing 400 m of swimming in total [78]. However, it could be argued that an error rate of greater than 10% is too high for this parameter given that coaches will typically prescribe the distance to be performed in a training session.

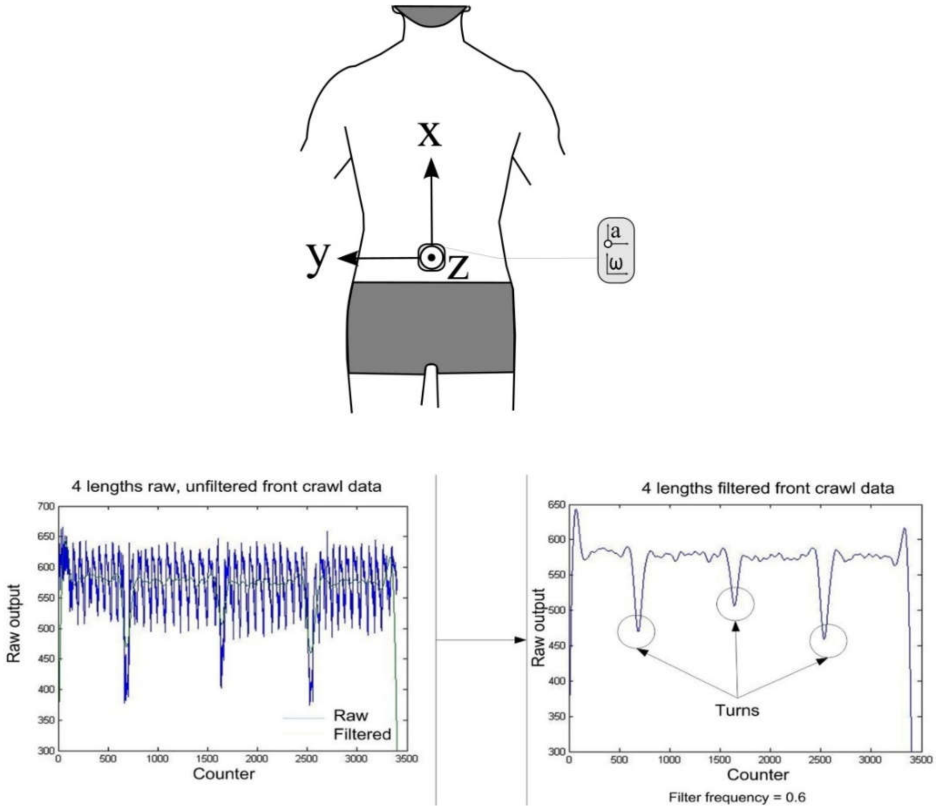


Figure 4.15. Turns performed during frontcrawl can be automatically detected by thresholding of the filtered acceleration signal from the axis perpendicular to the plane of movement as this undergoes a rapid change in acceleration as the swimmer rotates during the tumble. Reproduced with permissions from Le Sage, Bindel, Conway, Justham, Slawson and West [40].

Interestingly, Wright and Stager [84] recently reported an alternative method of recording swimming distance that does not rely on determining when events at the pool walls have occurred or prior knowledge of the pool length. Using a regression technique, the authors reported a statistically significant relationship between raw accelerometer output and actual swim distance completed ($R^2 = 0.9608$, $p < 0.05$), using a combination of wrist and ankle worn devices. This promising technique requires further study as the effects of different swimming styles are unknown but one drawback is that it cannot be used to determine lap times.

Swim distance is also probably of little importance in an elite swimming environment whereby training distances are prescribed by the coach in advance as part of the training plan. However it may have a useful application in open water swimming as an alternative to GPS tracking. Additionally, swimming distance is a more important functional consideration for sensor-based systems designed for recreational swimmers. This cohort do not have the benefit of a coach to monitor their training. In fact, a swim distance function may be used by some users as the primary determinant of whether training goals have been achieved, in much the same way as a recreational runner will wish to know the distance completed during a run without necessarily wanting to know any other information about the activity. Hence there is a greater prevalence of lap counter and swim distance functions in the patent literature [30, 32, 36, 39, 60, 65, 90, 91, 104].

Stroke Count and Stroke Rate

The most commonly calculated variables from inertial sensor devices are stroke count and stroke rate [11, 19, 26, 28, 32, 38, 39, 57, 59, 62, 65, 71, 77, 83, 85, 86], both key performance indicators in competitive swimming [1]. The back and wrist are the most prevalent locations and Table 4.4 shows that a similar approach to stroke count measurement can be taken at both body sites and this approach typically involves the detection and summation of acceleration peaks for a given lap.

Davey, et al. [11] isolated the medio-lateral acceleration signal (Y-axis) of a back worn device and identified peaks and troughs in the signal (Figure 4.16). This characteristic waveform is representative of the roll of the body about that axis and as such the strokes completed can be determined. The authors programmed their device to find the first peak and not count another peak until a trough had been registered. The results show very high recognition rates for stroke counts within one stroke of the criterion data [11, 71]. This suggests that the body roll action used may not always be indicative of an arm action, especially at the beginning and end of laps. Anthony and Chalfant [38] argue that similar issues may also arise from a single wrist worn device as the sensor will have to make an assumption regarding the movement of the other arm.

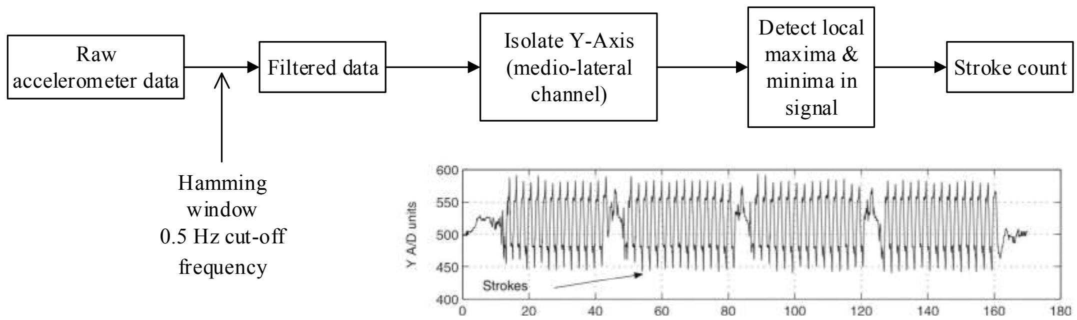


Figure 4.16. The regularly repeating pattern of swimming exhibited allows for a stroke count algorithm based on tracking peaks and troughs in the acceleration signal. Reproduced with permissions from Davey, Anderson and James [11].

Table 4.4. Details of various methods used for the detection of stroke count using inertial sensor devices, with validation methods and reported detection accuracy.

Ref.	Stroke Count Detection Method	Sensor Location	Protocol	Accuracy
[11]	Peak detection of medio-lateral acceleration signal	Lower back	N = 6; 4 × 50 m intervals (164 data sets analysed) Video and manual data used for comparison	All strokes: 90% ± 1 of actual. Frontcrawl: 65% accuracy, 100% ± 1 of actual.
[26]	Peak detection of anterio-posterior acceleration signal and zero-crossing of longitudinal signal	Lower back	N = 4; 4 × 25 m intervals of butterfly Video used as criterion measure	97.6% accuracy
[59]	Peak detection of acceleration signal with different threshold levels for each stroke. Different axes used for different strokes	Wrist & upper back	N = 11; Intervals completed at various speeds (up to 1053 data sets); Validation method not reported	All strokes: >99% accuracy
[25]	Peak detection of forward acceleration signal	Wrist	N = 8; 7 × 50 m frontcrawl intervals; Video and manual data used for comparison	Not reported
[62]	Zero crossing of acceleration signal with thresholding. Medio-lateral axis for frontcrawl and backstroke. Forward axis for breaststroke and butterfly	Lower back	N = 2; 4 × 25m each stroke	All strokes: 56% accuracy, 100% ± 1 of actual.
[71]	Peak detection of acceleration signal; GPS integration necessary	Head	N = 21; 3 × 100 m swims (1 each of butterfly, breaststroke & frontcrawl); Video data used for comparison	Butterfly: r = 1.00 (p < 0.05); Breaststroke: r = 0.99 (p < 0.05); Frontcrawl: stroke count was “not discernible” due to sensor location

Subsequently, some researchers chose to use multiple acceleration channels in an attempt to improve recognition accuracy [26, 59, 71]. Figure 4.17 describes the steps in this process used in one example for butterfly swimming [26]. The anterio-posterior axis signal is filtered using a 4th order low-pass Butterworth filter with a 10 Hz cut-off frequency. Local minima of this filtered signal are determined to create an envelope. The maxima of this envelope are then used to approximate the location of each stroke on the longitudinal axis and a zero-crossing algorithm of this axis is completed to identify the exact instant when each stroke begins. The authors reported an accuracy of 97.6% for strokes recorded by four swimmers each performing 100 m butterfly swimming.

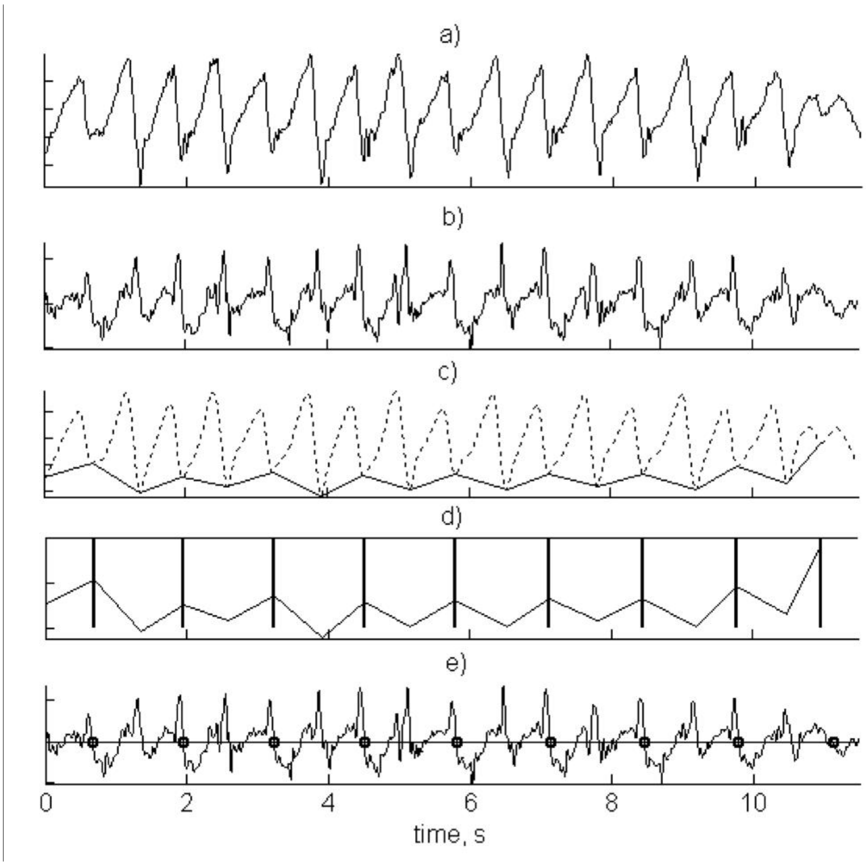


Figure 4.17. Stroke count detection method using back worn accelerometer: (a) raw vertical axis acceleration; (b) raw anterio-posterior axis acceleration; (c) filtered vertical axis acceleration; (d) filtered vertical axis acceleration with envelope applied; (e) stroke detection on anterio-posterior axis using peaks in envelope. Reproduced with permissions from Daukantas, Marozas and Lukosevicius [26].

Recent attempts to determine stroke count using a head mounted device have also been made [86]. Again a peak detection method was used to automatically count strokes completed, although the actual axis used for analysis was unspecified. Excellent accuracy was reported for butterfly and breaststroke swimming (Table 4.4). However, during frontcrawl and backstroke, swimmers will aim to keep their heads as static as possible and consequently the signal output did not demonstrate the patterns of repeated peaks and troughs to facilitate accurate stroke count recognition. Additionally, swimmers will use different breathing patterns which may not be synchronous with arm actions, further complicating this approach. The study was exploratory in nature and further investigation of a head worn device is warranted, including a thorough analysis of all three acceleration axes, to attempt stroke counting for all four swimming strokes. The inclusion of a gyroscopic signal may also aid this investigation. A head-mounted position has clear advantages for ease of positioning and is found to be quite unobtrusive to the swimmer in comparison to other locations.

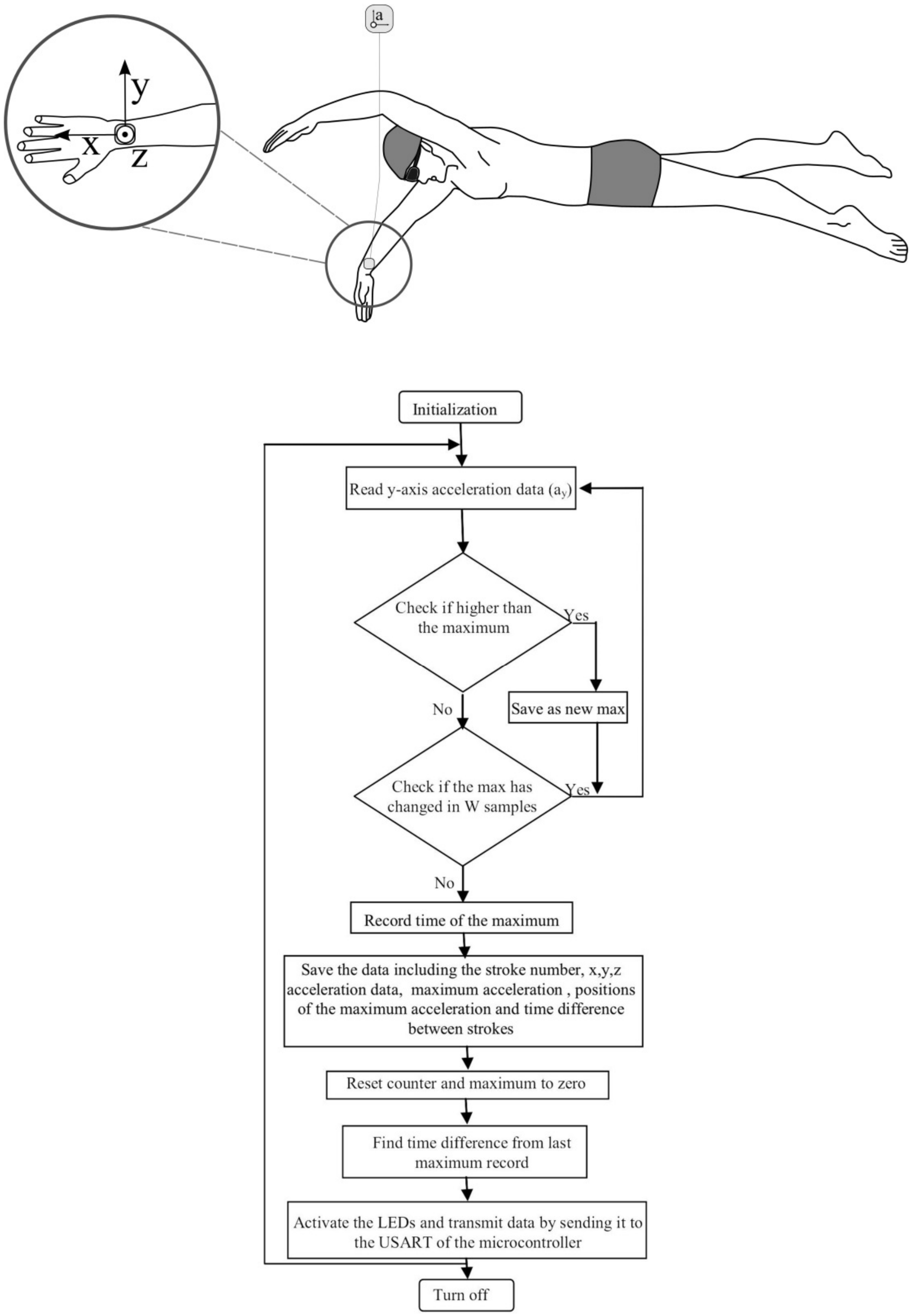


Figure 4.18. Flowchart of a stroke rate detection and transmission algorithm used to provide real-time feedback to a swimmer. Stroke rate is detected using a wrist worn accelerometer and information is provided to the swimmer via an LED based receiver system located in the goggles. Reproduced with permissions from Hagem, O'Keefe, Fickenscher and Thiel [77].

One study evaluated the accuracy of a zero-crossing algorithm for measuring stroke rate by comparing the performance of the algorithm against manually digitized video footage [71]. Differences with the criterion measure ranged from -0.25 strokes per minute (breaststroke) to +0.19 strokes per minute (backstroke). Within-subject reliability testing also showed positive results, although with low subject numbers. The interclass correlation coefficient for butterfly ranged from +0.74 to +0.91, with standard error of the mean of 1.2% to 1.6%. Finally, stroke rates over four lengths of frontcrawl were compared. The overall average was the same for both automatic and manually derived data (33.5 strokes per minute) although small differences were observed when each length was compared in isolation. Hagem, et al. [77] suggested that this approach is overly complex, in comparison to peak detection methods, requiring additional processing owing to signal offset and the fact that the signal may cross the zero point in either direction. Figure 4.18 provides an overview of their alternative methodology which involved the transmission of stroke rate values from a wrist worn accelerometer device to a receiver in the swimmers goggles to facilitate real-time feedback on performance [77]. However a thorough evaluation of the accuracy of this algorithm is not reported. Earlier work had investigated the accuracy of a peak detection based stroke rate measurement algorithm, comparing with both manually counted and video derived data, albeit for frontcrawl only [11]. Results showed a magnitude and spread of error similar to reference values. The stroke rate algorithm was accurate to within one stroke of the manually collected data for 90% of data sets.

At present, these algorithms all appear to determine stroke rate over the full lap of swimming, whereas the common convention in applied practice would be to calculate this parameter over three stroke cycles performed mid-pool to better reflect actual stroke rate during free-swimming [1]. An algorithm could be derived to facilitate a similar approach to bring these methodologies in line with coaching practices.

Swimming Velocity

Swimming velocity is a key performance indicator that has recently become the focus of attention in several studies [62, 64, 83, 86, 97], with a range of methodologies for its calculation previously reported (Table 4.5). In one study, mean velocity was calculated using the time taken to swim a known pool length of 50 m

[62]. The authors compared this automatic parameter extraction method against a standard manually calculated protocol involving repeated 50 m frontcrawl intervals with increasing velocity [105], with analogous results. However, manually calculated velocity was found to be lower than the automatic method. A possible explanation for this lies in the effects of increased velocity following the wall push-off when measured over the full 50 m pool length. An alternative approach negates this by only measuring velocity over a shorter mid-pool distance, thus the influence of the wall push-off is excluded. Hagem, et al. [76] calculated velocity by dividing stroke length by stroke rate. In this instance, the velocity measurement is more reflective of the speed achieved during the free-swimming phase.

Table 4.5. Details of various methods used for the detection of swimming velocity using inertial sensor devices and reported detection accuracy.

Ref.	Swimming Velocity Detection Method	Sensor Location	Accuracy
[62]	Average speed determined as time taken to cover known pool distance, recorded with accelerometer.	Wrist	1.67% upper bound error in velocity calculations 1.33% upper bound error in stroke duration calculations
[64]	Trapezoidal integration of forward acceleration. Geometric moving average change detection algorithm to account for integration drift. Determined both instantaneous and average velocity.	Lower back	Instantaneous velocity: RMS error = 11.3 $cm \cdot s^{-1}$ Average velocity: Spearman's Rho 0.94 ($p < 0.001$)
[72]	Gaussian process framework	Lower back	RMS error = 9.0 $cm \cdot s^{-1}$, $r = 0.95$ ($p < 0.001$)
[83]	Integration of acceleration signal with correction based on swimmers height. Five points on different axes and resultant acceleration determined	Lower back	1.08 $m \cdot s^{-1}$: bias 0.01 $m \cdot s^{-1}$; limits of agreement: −0.26 to 0.29 $m \cdot s^{-1}$ (94.75% of data points inside limits of agreement) 1.01 $m \cdot s^{-1}$: bias 0.02 $m \cdot s^{-1}$; limits of agreement: −0.17 to 0.20 $m \cdot s^{-1}$ (96.25% of data points inside limits of agreement)
[84]	Regression analysis and predictive equations based on output of two accelerometers	Wrist & ankle	$r = 0.76$, $R^2 = 0.57$, SEE = 0.14 $m \cdot s^{-1}$ ($p < 0.001$)
[86]	GPS positioning. 5 point moving average to smooth. Exclusion criterion included for manual inspection of velocity data.	Head	Butterfly: SEM = 0.18, 95% CI = 0.14-0.27 (Sig. difference with criterion, $p < 0.05$) Frontcrawl: SEM = 0.13, 95% CI = 0.10-0.19 (No sig. difference) Breaststroke: SEM = 0.12, 95% CI = 0.09-0.17 (No sig. difference)
[97]	Bayesian linear regression (BLR) compared against Linear least square estimator (LLS) and Gaussian process regression (GPR)	Lower back	LLS: RMS error = 17.7%, 14.4 $cm \cdot s^{-1}$, $r = 0.56$ ($p < 0.001$) GPR: RMS error = 9.2%, 6.1 $cm \cdot s^{-1}$, $r = 0.91$ ($p < 0.001$) BLR: RMS error = 9.7%, 6.2 $cm \cdot s^{-1}$, $r = 0.91$ ($p < 0.001$)

Another recently described method for calculating swimming velocity involves integration of the acceleration signal. Studies have attempted to validate this approach using back worn sensors and a tethered speed-meter as reference [27, 64, 83]. In one study, mean velocity was determined using peak detection algorithms for specific channels to identify five key data points in the acceleration signal [83]. Results of a Bland-Altman analysis indicated that mean velocity recordings were within 4% of the reference values and integration error was determined to be non-significant (0.002 $m \cdot s^{-1}$). Nonetheless, others have questioned the repeatability of this approach due to issues associated with resolving the sensors orientation with respect to gravity [97].

Instantaneous and mean velocity has also been determined using a geometric moving average change detection algorithm to account for integration drift – whereby errors in acceleration and angular velocity outputs are integrated into larger errors in velocity and position data. A two-fold validation procedure was completed and similar mean velocity accuracy to Stamm, et al. [83] was reported (3.5%). Instantaneous velocity displayed an RMS difference of 0.113 $m \cdot s^{-1}$, a relative error of 9.7% compared to the reference value [64]. The authors noted that some of the error may have been attributed to movement artefact owing to the modified swim suit design employed (Figure 4.19). Interestingly, the determination of instantaneous velocity allowed for intra-cycle velocity variations (IVV) to be assessed and the authors demonstrated that this variation is visible on the acceleration trace and can distinguish between elite and non-elite swimmers.

Recently, the same authors extended their investigations and compared different mathematical regression models for the determination of swimming velocity as an alternative to integration [72, 97]. Results for both Gaussian and Bayesian regression methods are comparable with a relative error of 9.2% and 9.7% respectively, suggesting that further development work is required before implementation in an applied setting. In contrast to earlier methods, these models do not require prior knowledge of the pool length, extending their applicability in real-world settings. Additionally, Bayesian regression can be performed without requirements for the inclusion of constraints related to the swimming stroke performed [97]. For example, the Gaussian method was tested during frontcrawl swimming and the algorithm assumes that the sacrum will roll about the longitudinal axis in a uniform manner so modifications would be necessary for other swimming strokes [72].

Figure 4.19. A modified swim suit design allows for accurate positioning of the sensor device but may result in unwanted sensor movement. Reproduced with permissions from Dadashi, et al. [97].

Much of this work has to date used a tethered speedometer as the criterion measure so results are only verified over a single lap of swimming at present [64, 72, 83, 97]. Tethered systems may also interfere with kicking action, further complicating the procedure. Two additional approaches have been reported for velocity measurement which overcome this constraint, but both have other disadvantages [84, 86]. A recent study described using accelerometry as a means of quantifying training load in competitive swimmers [84]. The algorithm involved the summation of raw accelerometer output from both wrist and ankle worn sensors, which were found to correlate positively with swim velocity and distance. Predictive equations were validated following linear regression analysis and showed a significant correlation between actual and predicted values for both distance and velocity, indicating that this approach may offer a sound method of quantifying velocity in applied settings. However, the authors note that there is a necessity for specific regression equations to be customised for individual swimmers, which would be essential for accurate measurements, requiring future experimental investigation. The other approach used GPS, rather than an accelerometer, for velocity measurements [86]. However, measurements were taken in an outdoor swimming pool, thus severely limiting the practical applicability of this approach except in warmer climates.

Kick Count and Kick Rate

Quantifying a swimmer's kicking pattern is a relevant concern for coaches as the action of the lower limbs helps to maintain body position, aids streamlining and contributes to propulsion [106]. Moreover, kicking patterns can be difficult to observe, even with underwater video, as the movements are rapid and water turbulence can obscure a coach's view. One author argued that kicking patterns may be observed on the medio-lateral axis of a back worn accelerometer [85]. However, no evidence was presented and it is unclear how the distinction would be made between the actions of the arms and legs in this instance. A more plausible approach to investigating leg action is to position the inertial sensor directly to the lower limb.

Fulton, et al. [33] utilised a gyroscope for this purpose, as opposed to analysing the acceleration signal, and assessed the reliability and validity of the process. Angular velocity of the lower limb was found to fluctuate in the range of approximately ±600 $rad \cdot s^{-1}$ during the upbeat and downbeat phases of the frontcrawl kicking action and a zero-crossing algorithm was used to detect each kick (Figure 4.20). The results indicated that the kick count measurements during frontcrawl swimming were correlated positively with the criterion values ($r = 0.96$, 90% confidence interval 0.95 to 0.97) and that the standard error of the estimate (SEE) for kick count, expressed as a coefficient of variation, was 5.9 ± 0.5%.

However, a single inertial sensor placed on the anterior or lateral sides of the swimmer's lower limb was found to be both uncomfortable and to interfere with streamlining [33]. A posterior placement on the leg however did not inhibit kicking movements and also allowed for clearer signal transmission. Researchers therefore positioned sensors on the calf of the dominant kicking leg in subsequent studies, but the effect of location on the subjects' comfort went unreported [51].

Fulton, et al. [34] next quantified kick count and kick rate in Paralympic swimmers and found that decreases of almost 11% in kick rate owning to fatigue were associated with diminished overall swimming times. Meanwhile, another study by the same research group aimed to optimise kicking patterns and found that a kick rate of approximately 150 kicks per minute was associated with peak swimming speed in a similar cohort of swimmers [51]. This study additionally evaluated the inclusion of inertial sensor technology as part of a combined, integrated performance monitoring system for use in elite swimming, which has been described elsewhere recently by others [53, 71]. Notwithstanding the fact that kicking patterns were only investigated for frontcrawl swimming, it is likely that a similar algorithm could be used to accurately examine kicking in other strokes.

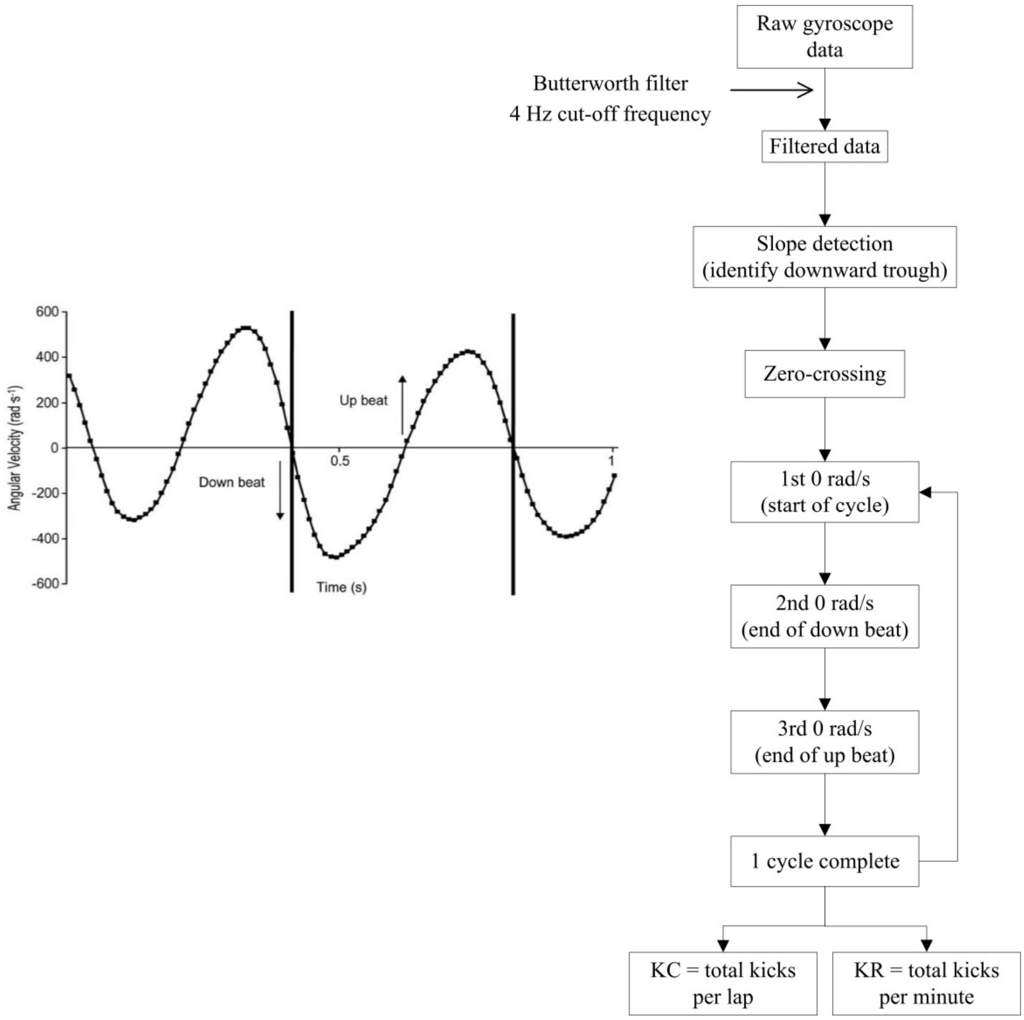


Figure 4.20. Process flowchart for detecting kick count and kick rate from angular velocity signals. Reproduced with permissions from Fulton, et al. [33].

Joint Angular Kinematics

The ability to measure joint angles during swimming is important to ensure that the correct movement patterns are performed; to monitor streamlining and to maximise propulsive forces [107, 108]. Important angle measurements include the elbow, shoulder and knee joints, as well as the pitch, roll and yaw angles of the torso. For example, Figure 4.21 compares the elbow angle of two swimmers during the in-sweep phase of frontcrawl. Previous research has shown that this elbow angle is important for maximising force production. It is suggested that elbow flexion of about 105° is optimal during this phase [107]. Therefore, whilst both of the swimmers in Figure 4.21 have an elbow angle greater than 105°, reducing the effectiveness of their stroke, the swimmer on the left has an elbow flexion much closer to what a coach would consider ideal. It can be difficult for a coach to observe these movements appropriately as they occur underwater and are fast moving so methods for obtaining these data are likely to be of significant interest to the coaching community.

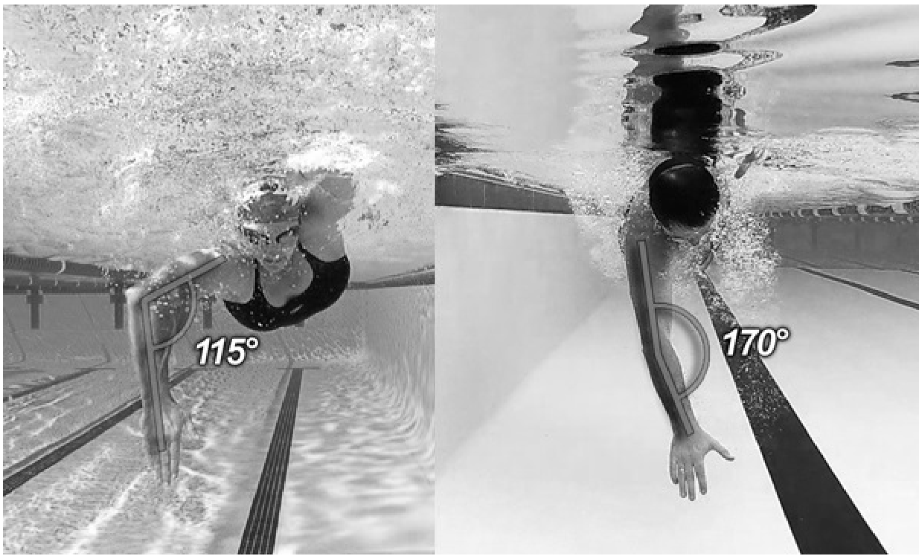
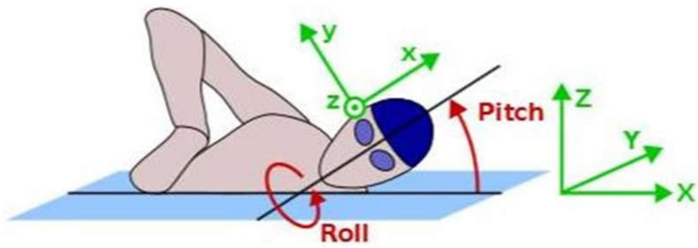


Figure 4.21. Comparison of different elbow angles produced during the insweep phase of frontcrawl swimming. Measuring these angles allows coaches to optimise technique and maximise propulsive force generation [109].

A limited number of examples of using inertial sensor technology to measure joint angles can be found in the literature [22, 44, 50, 94, 95]. Single sensor units have been used to determine the pitch and roll angles of the swimmer using positions on the head [44] and back [50] (Figure 4.22). These may be calculated from the measured acceleration signal using trigonometric functions as shown. The pitch angle is important as it relates to the swimmers streamlining in the water.

Additionally, the roll angle has been used to examine the effects of different breathing patterns [44]. Interestingly, Daukantas, et al. [50] used complementary filters in their algorithm to determine pitch angle. The acceleration signal was low-pass filtered, whilst the gyroscopic data were high-pass filtered. Validation methods suggest that errors in pitch angle estimation were less than 2° at a cut-off frequency of 0.6 Hz.



$$Pitch\ angle = -arcsin\frac{Ax}{g}$$

$$Roll\ angle = -arctan\frac{Ay}{Az}$$

Figure 4.22. Determination of pitch and roll angles using a head mounted sensor. Reproduced with permissions from Pansiot, et al. [44].

Other studies have used multiple sensors to measure joint angles [94, 95]. Processes typically involve methods to represent the three dimensional orientations and rotations of the swimmers' limbs, including a rotation matrix [44]; Euler angles [94] or quaternions [95] and these methods have been used to analyse human movement in other sporting and health related contexts [110-114]. Seifert, et al. [95] demonstrated how this approach could be used to enhance the coaching process by assessing different patterns of limb coordination. Using four inertial sensors, the authors extracted knee and elbow angles during breaststroke swimming (Figure 4.23). The data were sampled at 100 Hz and filtered using a low pass Fourier filter with an 8 Hz cut-off frequency. Unfortunately the specific axes orientations of the sensors used was not reported. It can be seen that the less proficient swimmer (on the left in Figure 4.23) displays almost simultaneous knee and elbow flexion and extension, whereas a more competent performer (on the right) has near maximum extension of the elbow when the knees are at full extension, allowing for swimming speed to be better maintained throughout the stroke cycle. Seifert, et al. [95] reported a variation of between 0.09 rad and 0.15 rad from the criterion measure using this method. Phillips, et al. [94] also used four sensor locations to measure joint angles, focusing on butterfly kicking technique. Using a similar method to Seifert, the results showed a very high accuracy for the knee joint (0.0019 rad accuracy) but less so for the hip joint (0.071 rad). It has been suggested that an error of 0.034 rad or less can be deemed acceptable but that errors of between 0.034 rad and 0.087 rad may require consideration when interpreting results [115].

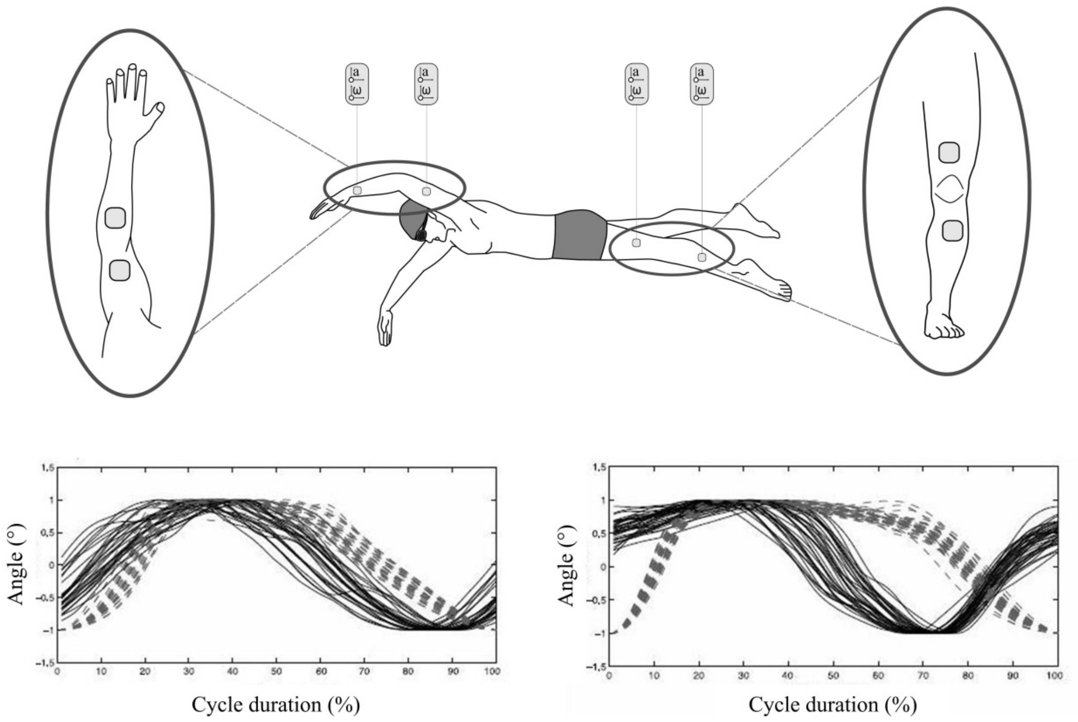


Figure 4.23. Comparison of changing joint angles produced during breaststroke stroke cycles measured using a multi-sensor system. The ideal pattern at the start of each cycle is for the knee joint (dashed line) to be at maximum flexion when the elbow joint (solid line) is near maximum extension. This is demonstrated on the right hand graph with data from an elite performer. The graph of the left hand side would be characteristic of a beginner who demonstrates near simultaneous knee and elbow movement patterns. In this example, joint angles have been normalised between −1 (maximum flexion) and +1 (maximum extension). Reproduced with permissions from Seifert, et al. [95].

Interestingly, the movement of the shoulder joint during swimming has not been investigated in the reviewed literature. This is surprising given the importance of shoulder kinematics for optimum stroke technique. A previous study did investigate the action of the shoulder using two inertial sensors to study the tennis serve [111]. Sensors were positioned on the upper arm and chest and comprised of a tri-axial accelerometer with a range of ±2 g (±19.62 $m{\cdot}s^{-2}$) and uni-axial gyroscope (±5.2

rad·s^{-1} range). Angular velocity was measured about the vertical axis and used to record shoulder abduction. A similar process could readily be applied in a swimming context although it is likely that a tri-axial gyroscope would be most appropriate in order to fully analyse all possible shoulder movements.

It is worth noting that the studies described that have measured angles are all from conference proceeding, where the level of detail is limited. Therefore, this avenue of research remains underdeveloped and it would not be advisable to draw conclusions regarding the merits or demerits of these approaches based on the limited information available. Certainly, the use of inertial sensors for measuring joint angular kinematics is commonplace in other sporting situations and high levels of accuracy have been achieved [111, 113, 116-118].

Kinetic Variables

Acceleration and deceleration signals are due to the forces exerted by the swimmer as well as the swimmer's interaction with the environment. However, none of the reported studies in this review use accelerometers for any kinetic analysis. This is unusual, given that acceleration directly relates to force production and kinematic swimming data can be used for kinetic analysis [119]. Additionally, previous work in related fields has shown that acceleration correlates positively with peak impact force ($r = 0.85$, $p < 0.05$); average resultant force ($r = 0.82$, $p < 0.05$); and peak loading rate ($r = 0.63$, $p < 0.05$) in adults for either hip or wrist worn accelerometers [120]. Others have found a similar association, with peak ground reaction force calculated from accelerometer counts during walking and running in children [121]. This relationship has also been acknowledged in other sporting situations [117, 118, 122-124]. Meamarbashi and Hossaini [118] measured kinetic parameters such as force, torque and angular impulse with an inertial sensor system to study kicking techniques in soccer and to compare dominant and non-dominant legs, drawing clear parallels with symmetry assessment in swimming. However, force plates and pressure sensors remain the most commonly used tools for kinetic analysis in pool swimming, even for systems that employ inertial sensors [71].

It is likely that the kinetic analysis potential of sensor-based systems will become more prevalent in future swimming research. Anthony and Chalfant [38] proposed that a "force-score" may be determined, for example to represent the force produced by the arm during the propulsive phase of the stroke. The process involves first determining the total acceleration (a_{total}) from each axis of a tri-axial accelerometer (Equation 4.1).

$$a_{total} = \sqrt{x^2 + y^2 + z^2}$$

[Equation 4.1]

Next, Newton's second law of motion is used to determine the force produced, F, (Equation 4.2), where m is the mass of the swimmer's arm and F_d is the drag force experienced as the arm is pushed through the water.

$$F = (m \cdot a_{total}) + F_d$$

[Equation 4.2]

Fd is derived from the drag equation (Equation 4.3), where ρ is the mass density of the fluid; v is the velocity; C_D is the drag coefficient and A is the surface area of the arm.

$$F_d = \frac{1}{2}\rho \cdot v^2 \cdot C_D \cdot A$$

[Equation 4.3]

Whilst this approach appears theoretically sound, it has not been empirically tested in a swimming context and it remains unclear if such an approach would prove accurate. One area of concern is how an automatic feature detection algorithm could account for the changing anthropometric characteristics of individual swimmers. That said, should future research work validate this method of kinetic analysis, it would offer an exciting alternative to existing practices. Current methods of measuring propulsive forces generated by the action of the arms, such as 3D video analysis or the MAD system (Measurement of Active Drag) [119] require complex and expensive equipment that is not accessible to the majority of coaches.

4.4.2 Parameters for Analysing Starts

As the technology of inertial sensors continues to develop, more detailed analysis of other aspects of swimming performance, such as starts and turns, should be possible but are currently quite limited. Findings of video-based studies with elite swimmers [125-127] suggest that the most statistically significant starting performance variables, based on correlation with overall start time, are block time; flight time; peak horizontal velocity at take-off and peak horizontal force, and it is recommended that swimmers and coaches focus on improving these variables during training to improve overall starting performance [128]. These key variables have been measured by only one group [41, 68, 129].

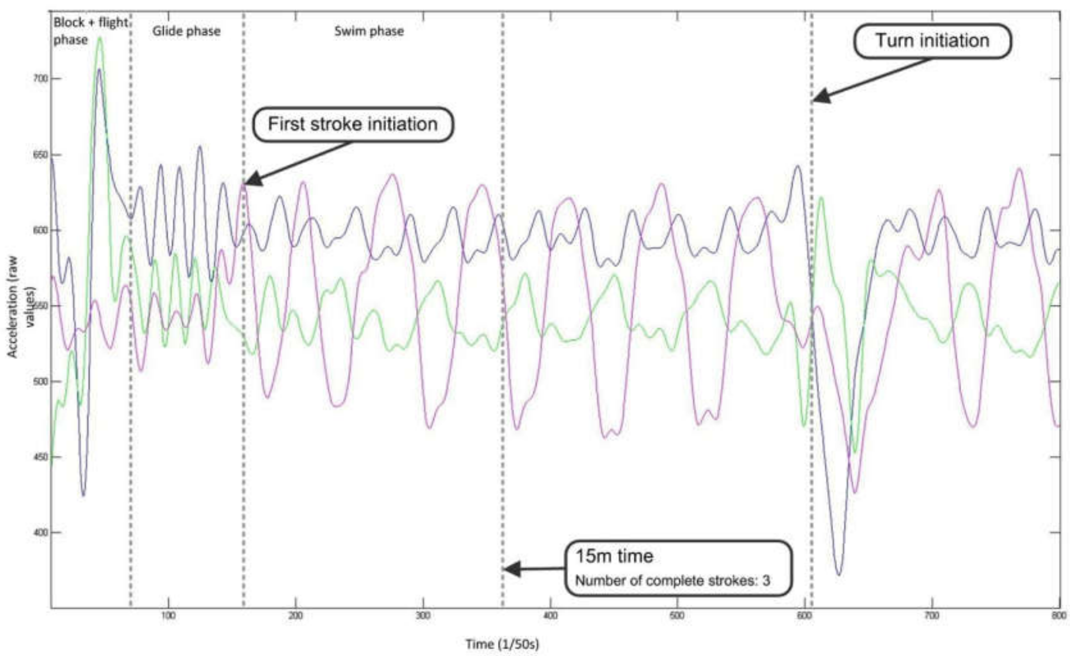


Figure 4.24. The acceleration signals from a back worn sensor device can be used to identify different phases (block, flight, glide, swim) of starts. Additional video input is necessary to determine the end of the start phase at 15 m. Reproduced with permissions from Le Sage, et al. [68].

For example in Figure 4.24 different phases of the start such as block, flight and glide phases were identified from the raw acceleration signal but this was only possible when the data were synchronised with video images [68], allowing for key performance related information to be extracted. Automatic detection of positional information, such as the determination of when the starting phase is completed (defined as the 15 m mark), is postulated by the authors through double integration of the acceleration signal using a Kalman filter and prior knowledge of the pool length but no empirical data have yet been published to verify this method. Another potential solution that requires further investigation is to include a photoelectric sensor to determine positional information and to help account for integration drift error [42]. Additionally, it is not clear how the phases of the start could be distinguished from these back-work sensor signals if treated in isolation. For example, there appears to be no obvious features in any of the three axes of acceleration to determine the point of entry at the end of the flight phase, based on the evidence presented thus far.

4.4.3 Parameters for Analysing Turns

In addition to starts, turns are also a vital aspect of competitive swimming performance and have been shown to be significantly related to overall performance [16]. As a consequence, much research using video-based systems has investigated the various turning techniques [16, 130, 131] and coaches will spend a considerable amount of time working on turns during training. Turns are usually assessed within specific set distances, such as from 5 m before the wall to 10 m after the wall. When analysing a swimmer's performance during a turn, it is also typical to break the turn down into specific phases to facilitate detailed assessment of a swimmers strengths and weaknesses and also to allow different turning techniques to be compared (Figure 4.25).

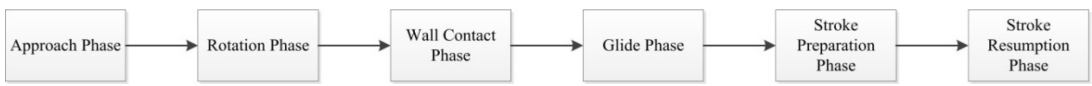


Figure 4.25. Swimming turns can be broken down into phases to facilitate a detailed quantitative analysis.

Only a small number of researchers have used inertial sensors to study turns in swimming, all using sensors positioned on the lower back [47, 56, 68, 69, 82]. One study demonstrated that key features of the frontcrawl flip turn such as the instant of wall push-off and rotation can be detected using an accelerometer [56]. It is suggested in the coaching literature that longitudinal rotation should occur after the wall push-off, in order to avoid reductions in angular velocity [1]. The researchers found that these features can be detected from a tri-axial acceleration signal sampled at 100 Hz, using the same system developed by Davey & colleagues [11] and compared the performances of two swimmers with marked differences in technique by way of example (Figure 4.26) [56]. The sensor was orientated such that the X-axis channel was representative of the direction that the swimmer was travelling in and was deemed to be most appropriate for recording the wall push-off. Additionally, the Z-axis (anterior-posterior direction) was chosen for analysing the rotation of the swimmer during the turn. This was a proof of concept approach to analysing turns and so no further assessment was conducted, such as breaking the turn down into phases or examining if the parameters could be detected automatically using software.

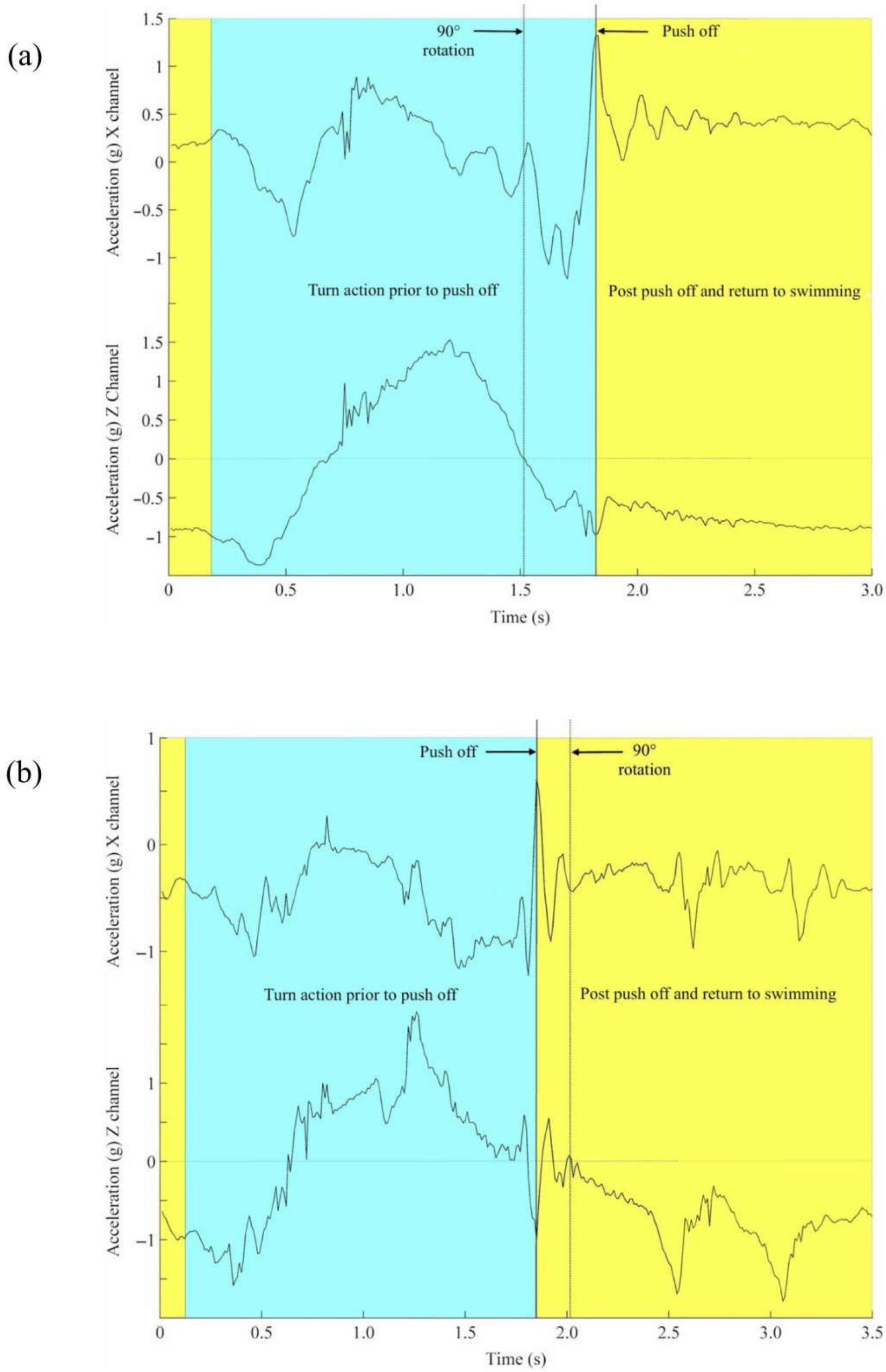


Figure 4.26. The analysis of swimming tumble turns is possible through examination of the acceleration signal. In this example, two swimmers rotation following the wall push-off are compared. In (a), it can be seen that the swimmer has rotated by 1.57 rad (90°) before the wall push-off whilst in (b) the push-off occurs before the swimmer reaches 1.57 rad (90°) of rotation. Reproduced with permissions from Lee, et al. [56].

Researchers at Loughborough University described a method by which these different phases of the frontcrawl turn can be extracted from accelerometry signals [41, 45, 68, 69, 132]. The accelerometer was positioned and orientated in a similar manner to Lee, et al. [56] (Figure 4.27). By using both peak detection and zero crossing methods, it was possible to automatically isolate the turn during each lap by marking the point when arm movements stop and resume again. This algorithm advanced the examination of turns using sensor-based systems as a temporal analysis of the different phases of a turn was now possible, albeit without the corresponding distance measurements. Variables such as time to rotation, wall contact time, glide time and stroke initiation time were measured with a high degree of accuracy, with an average difference from criterion measures of under 0.15 s [132]. Lacking from these works however is an examination of the features for other turn styles for the remaining swimming strokes, and with large groups of swimmers, as well as a lack of feature extraction methodologies to determine relevant parameters such as speed or distance.

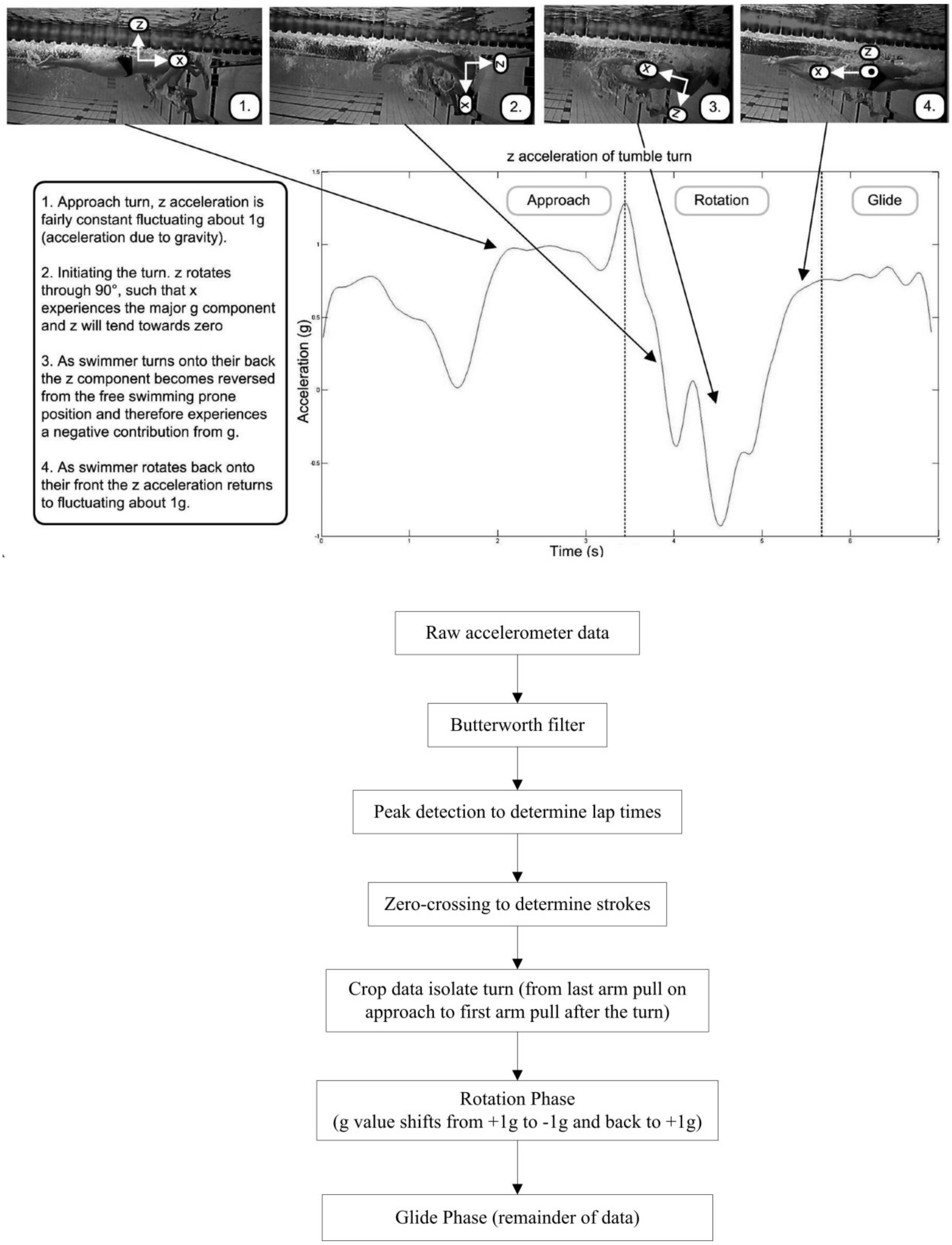


Figure 4.27. Flowchart of the process used to distinguish the approach, rotation and glide phases of the frontcrawl turn. Reproduced with permissions from Slawson, et al. [69].

Vannozzi, et al. [47] took an alternative approach and utilized the angular velocity signal from a tri-axial gyroscope to identify the rotation, glide and stroke resumption phases for turns performed during all four strokes. The algorithm was based on peak detection methods of analysing the signal from each of the three axes of rotation. The authors demonstrated that different signal features are indicative of different turns and also provided indicative angular velocity values for each stroke (Table 4.6).

Table 4.6. Angular velocity during turns. Sample data adapted from Vannozzi, et al. [47], providing indicative values of peak angular velocity (Pω) during turns performed for each of the four competitive swimming strokes.

Angular Velocity ($rad \cdot s^{-1}$)	Frontcrawl	Backstroke	Breaststroke	Butterfly
$P\omega_x$	−4.21	−6.14	−3.58	−4.01
$P\omega_y$	9.86	6.00	−6.61	−5.60
$P\omega_z$	−1.94	−0.31	−5.76	−4.54

Unfortunately, the authors did not provide any verification of their approach and there was insufficient detail regarding the signal processing methods involved. That said, the study does highlight some challenges that need to be overcome before automatic feature detection of turning performance may be possible. The signal output appears to be specific to individual turning techniques. For example, the sign of the angular velocity peak (Pω) in the X and Z axes depends on the direction of rotation. If a swimmer is performing backstroke and leads the rotation with the right arm, then $P\omega_x$ will be negative. However, $P\omega_x$ will be positive if the swimmer leads with the left arm. As seen in data in Table 6 above, $P\omega_x$ for backstroke for males was −6.14 $rad \cdot s^{-1}$. The corresponding value was +6.18 $rad \cdot s^{-1}$ for females in the study. This is not due to any gender differences but solely because the male participants happened to turn in one way and the females in the other direction. Furthermore, the representative peak values provided are also individually specific and will depend on other factors such as approach speed and as such no consistent pattern was discernible. This raises further challenges to setting threshold values for automatic detection. The study also highlights the importance of the Y-axis rotation in the analysis and identification of variables related to the turn as it shows a consistent pattern and will always be positive for the flip turn (performed during frontcrawl and backstroke) and negative for open turn (performed during breaststroke and butterfly). Moreover, the corresponding $P\omega_x$ will occur prior to $P\omega_y$ in backstroke and ideally after $P\omega_y$ in frontcrawl, further aiding automatic detection and temporal analysis.

Stamm, et al. [82] offered a novel methodology to provide a more specific analysis of aspects of the turn, using an acceleration signal to detect push-off velocity. In this study, the sensor was orientated such that the Y-axis represented the direction of travel and the total acceleration was also determined as part of the velocity determination process, which involved integration of the acceleration data (Figure 4.28). The researchers did highlight the potential for error using this integration method however, including issues with accumulated errors and gravitational concerns due to the changing sensor orientation, but the results provided correlated well with the gold-standard video measurements. This investigation could be extended to examine how the velocity fluctuates during other phases of the turn, such as on approach and also how the velocity can be maintained through rapid butterfly leg kicks following the glide phase.

Due to the central importance of starts and turns to overall performance it is expected that this research will become more prominent in the coming years and will focus on feature extraction methods for key performance related variables. For example, a recent video-based biomechanical study provided an extensive investigation of the most statistically significant variables related to the performance of turns during frontcrawl swimming [133]. Analysing a total of 51 temporal, kinematic and kinetic variables for correlation with total turning time, the authors found that the three most statistically significant variables were (i) maximizing the distance between the swimmers head and wall at the start of transverse rotation; (ii) a slower horizontal velocity at peak force production; and (iii) minimizing the turn distance, or 3D length of the path covered during the turn. These conclusions have also been backed up by other researchers [125, 134]. The collective of studies in these sections on starts and turns has thus far been largely exploratory in nature but does demonstrate that much of this important information may possibly be extracted using sensor-based systems. It is likely also that the combination of signals from accelerometers and gyroscopes represents the most sensible way forward, as has been found for the determination of free-swimming parameters.

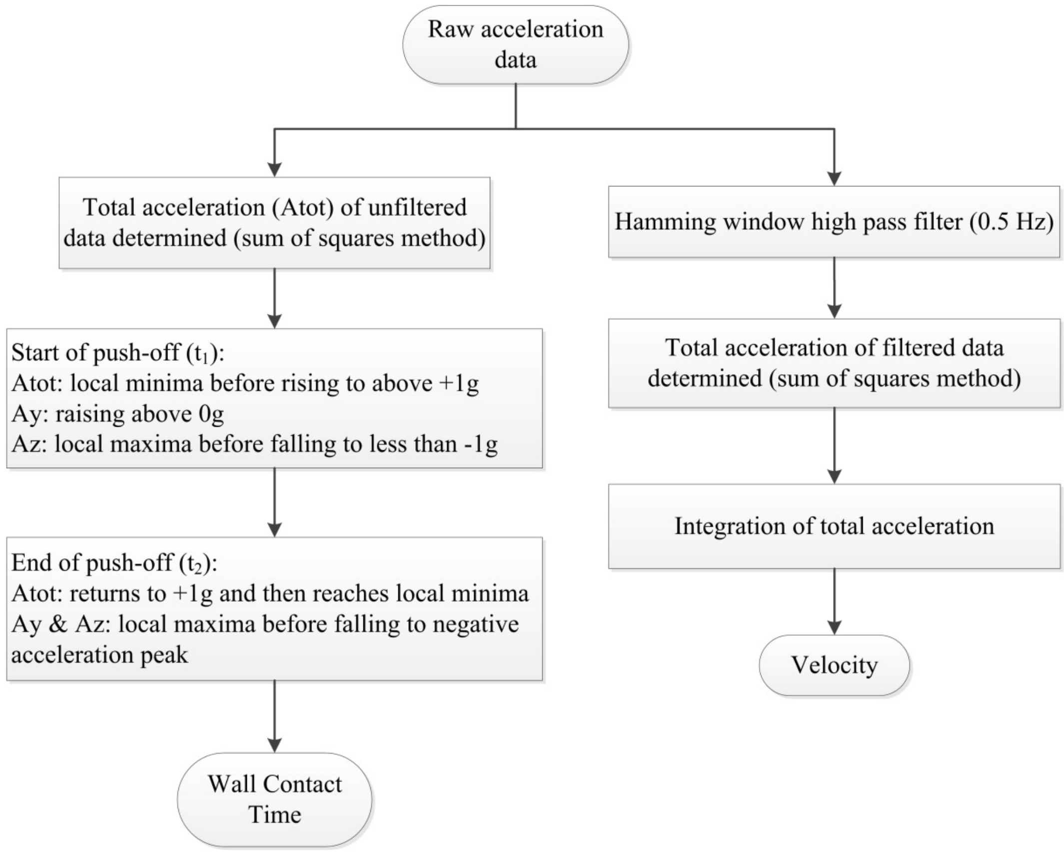


Figure 4.28. Method of determination of push-off velocity and wall contact time that utilizes all three acceleration signals and the resultant total acceleration. The raw unfiltered signal output is used to automatically determine the start and end of wall contact whilst the filtered signal was used to determine velocity during the push-off phase. Adapted from Stamm, et al. [82].

4.4.4 Commercially Available Swimming Sensor Devices

A number of commercially available swimming performance monitors have recently become available (examples include *AvidaMetrics*, AvidaSports LLC, Harper Woods, MI.; FINIS *SwimSense,* FINIS USA, Livermore, CA.; Garmin *Swim,* Garmin International Inc, Olathe, KS. and Swimovate *PoolMatePro*, Swimovate Ltd, Middlesex, UK. [135-138]). Wrist-worn designs are a common feature and allow for user interaction with the devices (Figure 4.29). These systems all feature similar processing methods; data are stored on-board for immediate review or later downloaded to system specific software for analysis. It is seen that some of the general performance related variables such as stroke count and stroke rate found in research studies are also key features of commercially available products (Table 4.7).

(i)

(ii)

Figure 4.29. Commercially available swimming sensor devices: (i) FINIS SwimSense [136], (ii) Swimovate PoolMatePro [138].

Table 4.7. Details of system functionality provided by commercially available swimming sensor devices. The features described are similar to those described in research studies for the analysis of swimming performance.

Measured Parameter	**AvidaSports** ***AvidaMetrics***	**FINIS** ***Swimsense***	**Garmin** ***Swim***	**Swimovate** ***PoolMatePro***
Time	•	•	•	•
Stroke identification	•	•	•	
Stroke count	•	•	•	•
Stroke rate	•	•	•	
Split times	•	•	•	
Distance per stroke	•	•		
Breakout	•			
Average speed	•	•	•	•
Kick count	•			
Kick rate	•			
Lap counter		•	•	•
Efficiency				•
Intervals		•	•	
Distance		•	•	•
Calories		•	•	•

The Garmin, FINIS and Swimovate products are geared towards a single user who wishes to gather useful performance related information when no coach is available. They would appear to be well suited to the task, especially for recreational swimmers, with their wrist worn design and interface. *AvidaMetrics* offers the potential to monitor activity of up to 25 athletes at one time, which is certainly attractive for gathering large scale training information and is more suited to competitive swim training. *AvidaMetrics* is the also the only commercially available system that featured a measure of lower limb activity. This system incorporates five sensors, two which are worn on the swimmers ankles, allowing this information to be gathered.

Certainly there is a growing interest in the commercialization of sensor-based methods of analysing swimming performance, as evident from the number of patent applications that have emerged in recent years [23, 24, 32, 36, 38, 39, 42, 49, 65, 67, 88, 90, 91]. Unfortunately, no published research material is currently available that investigates the accuracy, reliability or validity of these products. Additionally, only limited information regarding the feature detection algorithms is available for these devices. Future research is warranted to fully assess the merits/demerits of these systems and their applicability for real-world settings.

4.4.5 Sensor Attachment Locations

In selecting a sensor attachment location, it is important to have regard to the potential effects of that location on the desired measure of interest and on the quality of movement [139], as different measures are possible using different locations. Although the method of attachment is often unreported, attachment solutions include taping or strapping [62, 70, 83], wrist-watch style designs [12, 15, 32] or sensors incorporated into swim wear clothing [60, 64]). Sensor movement may be inevitable and result in measurement inconsistencies, affecting the ability of sensor algorithms to accurately measure body motion [139]. This has implications for how sensors are attached to body segments.

For research purposes, it seems reasonable to use taping or a flexible medical plaster to attach sensors to body segments, ensuring accurate positioning that can be individually adjusted to suit a subject's physique. In applied settings however a more convenient approach may be desired to ensure minimal set-up delay whilst also not significantly interfering with stroke mechanics. This is a key advantage of a wrist-watch styled approach; hence its popularity in commercially oriented monitors [32, 38, 91].

Unfortunately only a small number of papers discuss the relationship between comfort and sensor location or make attempts at quantifying the magnitude of measurement error introduced by sensor movement. An early prototype swim sensor described in 2008 by Davey, et al. [11] was attached to the lower back using a belt but swimmer feedback indicated that it was unsuitable and caused excessive movement, especially during tumble turns. Bächlin and Tröster [62] used multiple sensors and aimed to minimise the risk of sensor slippage by using a belt with elastic stretch bands, Velcro fasteners and additional harnesses for individual sizing. It is unclear if this approach was successful or otherwise. A custom designed swimming suit with the sensor located inside a sealed pocket offers an interesting alternative attachment solution [64].

Participants in this study included a mixture of male and female, elite and recreational swimmers (N = 30), with a diverse range of body size and stature reported. However, it was unclear if the same suit was used for all subjects. Such an approach would clearly affect the exact location on the sacrum that the sensor was located [64]. Moreover, whilst no negative drag as a result of the suit was reported, no objective measure of this was provided and importantly the majority of subjects were recreational swimmers who may not adequately perceive drag effects. A variety of housing solutions have also been discussed. Clearly the main feature is that the device is watertight, and a variety of rubberised or plastic casings have been used. However, as much of the published work is based on prototype designs, this area remains underdeveloped, with many housing options lacking consideration for drag effects. Prototype designs may be bulky by nature and the intention of this work has been on algorithm development so it is not appropriate to be critical of such designs.

However these clearly will impact on performance and it is a valid consideration for future development work.

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Upper Limb Locations

Swimming is an upper body dominant activity, with the majority of propulsion derived from the action of the upper limbs and the phases of arm movement result in changes in the acceleration of the entire body [1]. Therefore, in many of the reviewed studies, the authors chose to select locations on the arm, forearm or wrist [12, 15, 52, 53, 56, 62]. This location has been particularly useful in studies investigating the various acceleration patterns exhibited by different swimmers. However, the use of a single device on the arm has some limitations which must be considered. For example, it has been found that wrist worn devices do not appear to be as accurate as sensors positioned on the torso for stroke type identification. Moreover, as consistent coordination between left and right arms or upper and lower limb actions cannot be guaranteed, the positioning of a sensor on one limb will not give a full and accurate picture of actual activity. Several studies have objectively demonstrated that variations in inter-arm coordination exist in swimming owing to various factors including swimming speed [99, 140]; arm dominance [141]; physical disability [142]; energy cost [4]; exercise intensity [143] and skill level [140]. Furthermore, a similar variance exists between the coordination and synchronisation of the arms and legs for all swimming strokes [100, 144]. All of these factors have implications for the accuracy of feature detection algorithms when using wrist mounted devices.

Torso Locations

To investigate overall body motion a torso location provides a sensible alternative to the wrist. The back offers a practical solution towards balancing comfort with function, potentially minimizing the effect of drag and is found in a number of published studies [11, 53, 57, 62, 64, 70, 71, 83]. As the sensor is located in close proximity to the body mass centre, a lower back location can detect whole-body accelerations and provide a good indication for overall swimming parameters such as mean velocity [64]; stroke type detection [11] or stroke rate analysis [11]. The sacrum is most frequently chosen, resulting in minimal intrusion both to stroke mechanics and the effects of body roll on the acceleration direction [53, 56, 64, 70, 71, 83]. Back worn sensors are not well suited to a thorough kinematic analysis of upper or lower limb activity. A recent attempt was made to measure inter-arm stroke dynamics using acceleration and angular velocity recorded at the sacrum [70]. However, arm symmetry depends on many other variables other than just temporal characteristics, such as propulsive forces and the angular kinematics of the wrist, elbow and shoulder joints [1]. Recently, chest mounted sensors were described which demonstrated the benefits of back worn devices for monitoring whole-body motion, whilst also potentially allowing for integration of physiological data by incorporating an ECG sensor [49, 93].

Head Locations

Locating a sensor on the head has many advantages. Similar to back worn devices, measures of overall body motion can be readily determined at the head. Furthermore, a head mounted device will not affect drag to the same degree as other body locations and the issue of attachment can be overcome by using a swim cap or goggle strap, which can be tightly fixed and is unlikely to result in excessive movement. As a consequence of these potential advantages, several of the reviewed studies have followed this approach to measure a wide range of parameters [35, 44, 52, 78, 86, 89]. A possible concern could be that head movements or individual breathing styles may affect the output and make this location unsuitable, specifically for assessment of frontcrawl and backstroke as the head should remain relatively still. Another potential disadvantage of the head location is that motion of the head has six degrees of freedom, which may result in difficulty when extracting specific position or orientation based information, especially in developing swimmers who often struggle to maintain a static head positioning.

Multiple Sensor Locations

Whilst the majority of systems described utilise a single sensor setup, it is a logical progression in the development of the technology to combine measurements from multiple sensors located at two or more body segments. Multiple sensor configurations have been used successfully for other human motion tracking [145] and sports applications [146, 147]. Methods of handling large volumes of multi-sensor athlete data have also been described [148]. The potential benefit of a whole body system for biomechanical analysis in swimming includes increased functionality over other described systems, allowing for a more detailed and thorough kinematic analysis of performance. For example, it has previously been suggested that the action of the legs can alter the trajectory of the wrist underwater, effectively improving the propulsive action of the arm, specifically by increasing stroke length and forward arm motion and also reducing backward movement in the sagittal plane [149, 150]. Additionally, using multiple sensors allows for joint angular kinematical analysis to be carried out [94, 95]. However, there is a trade-off that must be considered, as increasing the number of sensors will lead to increased drag, swimmer discomfort, altered swim mechanics and more complex signal processing and data transmission [53].

Swimming speed depends on maximising propulsive forces whilst also minimising resistive drag forces [1]. Elite swimmers routinely remove body hair and devote much attention to improving their streamlining. Body worn sensors may negatively influence drag and potentially hinder stroke dynamics. Additionally, active and passive drag may result in sensor artefact due to movement through the water [53], potentially affecting algorithm accuracy, and should influence design decisions. However this important concern has been largely ignored by researchers. No study has yet objectively investigated the effects of drag due to body-worn systems, although some have reported subjective perceptions [33, 57, 62, 64] and made attempts at low profile enclosures [53, 62, 83]. This issue will become increasingly significant as the move towards multiple sensor systems continues.

4.4.6 Technical Specifications of Inertial Sensor Designs Used in Swimming

A range of components has been incorporated into inertial sensor designs. Most common is an accelerometer [11, 12, 15, 16, 31, 48, 52, 62, 79, 82, 93], but gyroscopes are also found, typically when used in combination [33, 51, 53, 56, 57, 64, 70, 71, 83, 94]. Acceleration has generally been measured along three axes for kinematic investigations, whereas gyroscopic information has been variously collected along either one [33, 51], two [57, 71] or three axes [53, 56, 64, 70, 83]. It was found that system designs have evolved from early models featuring uni-axial accelerometers to more recent devices where tri-axial accelerometers and tri-axial gyroscopes are now typical [10, 53, 83, 87]. The inclusion of a magnetometer is also becoming more prevalent [60, 90, 91, 99], whilst a recent study validated the use of a combined GPS and accelerometer device for kinematic analysis of swimming [73]. Integration of these sensors has also been attempted for physical activity monitoring [151, 152] and in other sports [153, 154], but the necessity to perform analyses in an outdoor environment limits functionality. Additionally whilst a magnetometer may increase the accuracy of the signal from the accelerometer and gyroscope, whose signals tend to drift, pool-operating machinery may hinder the magnetometer output [9].

Figure 4.30 provides an example of a typical system architecture which is emerging as a reference design for these systems and is reflective of the most commonly described systems in the literature. Many of the systems described are prototype systems that have been developed specifically for use in swimming research [53, 74, 83]. Additionally, various commercially available sensor devices such as Physilog (BioAGM, Switzerland) [64]; FreeSense (Sensorize, Italy) [47]; MinimaxX (Catapult Sports, Australia) [46, 86] and Shimmer (Shimmer, Ireland) [78, 94] have also been used. These platforms are not specifically designed for use in swimming; therefore various modifications to make them suitable for use in aquatic environments have been developed, specifically to provide waterproofing solutions.

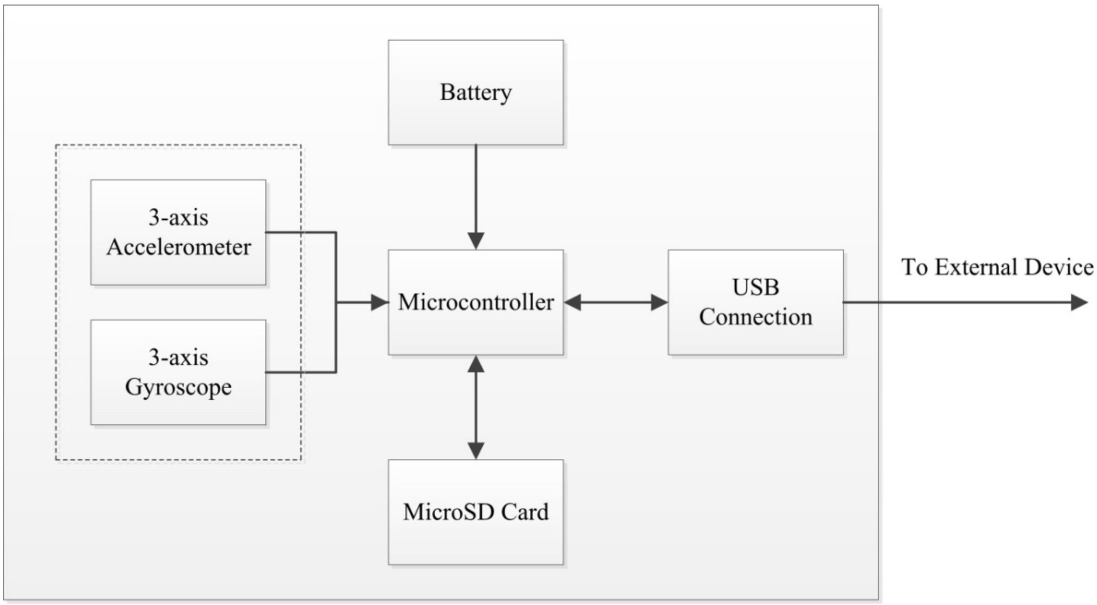

Figure 4.30. Example of typical system architecture found in inertial-sensor-based devices used for the analysis of swimming.

The selection of components should be dependent upon the desired output variable or the specific algorithm employed [139]. Whilst certain stroke mechanics may be analysed using only acceleration data [15, 62], orientation information may also be required for analysing other skills, such as turns, for example [56]. The raw signal generated must undergo processing procedures to allow interpretation and analysis. Typically post-processing is conducted following data download to an external computer but recently on-board, real-time data processing has been described [57, 71].

Measurement Range

An essential feature of any sensor is that it provides an accurate measurement of the frequency and amplitude of human movement. Therefore, knowing these ranges for a given activity is important and will inform the sensor selection process. Human movement is in general considered to be at the lower end of the range of possible accelerations, with values of between −0.3 g to 0.8 g (-2.94 $m{\cdot}s^{-2}$ to 7.85 $m{\cdot}s^{-2}$) reported for walking and between 0.8 g to 4.0 g (7.85 $m{\cdot}s^{-2}$ to 39.24 $m{\cdot}s^{-2}$) for running [155]. Human body acceleration due to swimming falls between these activities, with values less than 2 g (19.62 $m{\cdot}s^{-2}$) typical [57]. The measurement range of accelerometers reported in reviewed studies appears to cover this range appropriately, although agreement has not been reached on an optimum range and also outliers can be found [12, 15, 52]. The range of the gyroscope sensors varies between 8.7 and 26.2 rad$\cdot$s^{-1}, where reported. Measurement range may be influenced by sensor location, with more distally attached sensors requiring a greater range [139]. This is typical of gait analysis studies, whereby trunk worn devices have smaller ranges than those worn on the lower limbs [156, 157]. However in the swimming studies reviewed it appears that this recommendation is not followed, with no consistency between the range selected and the attachment location whilst studies involving multiple sensors had a fixed range [53, 62].

Sampling Frequency

There appears to be little consensus in the extant literature as to the optimal sampling rate to record swimming variables, with a wide range of sampling frequencies described. This disparity may be due to sensor locations of selected studies; however a lack of justification for sampling rates chosen is evident from the literature. Very high sampling rates have the benefit of increased reproduction fidelity but increase computational power, storage capability and energy demands. In some instances, higher rates may be required to extract specific movement characteristics [158]. The Nyquist Sampling Theorem states that the recording frequency should be at least twice bandwidth of the signal being recorded. Early studies suggested that the lowest sampling frequency advisable for the accurate recognition of human motion was 20 Hz [159, 160] although higher frequencies could be expected during limb movements [161]. By down-sampling accelerometer data originally sampled at 150 Hz, researchers have attempted to reduce the complexity of signal processing algorithms [162]. Although lower sampling rates achieved similar results in some cases, in general the lowest frequency (15 Hz) performed worst and accuracy and resolution decreased along with sampling frequency [162].

Signal filtering

Signal filtering processes are required as the signal to noise ratio can be low in a swimming setting [57]. Spectral analysis has revealed that a power peak frequency of approximately 6 Hz represents the movement of the arms and legs during a complete stroke cycle [163] and that frequencies in excess of 10 Hz are insignificant [164]. Butterworth and Hamming window filters are both commonly used in the extant literature. Butterworth filters provide a very flat frequency response in the passband and a key advantage over alternatives is that they do not require strict tolerances, unlike Chebyshev or Bessel filters [165]. Butterworth filters are also commonly used in other human movement related studies [122, 166, 167]. Some considered using a Chebyshev filter [57] but instead opted for a low pass Butterworth filter to avoid ripple voltages in the passband. A cut-off frequency of 2 Hz was applied to frontcrawl and backstroke, but this was deemed to smooth the data excessively for other strokes so higher frequencies (6 Hz for breaststroke; 8 Hz for butterfly) were chosen [57]. A Fourier filter has been shown to be accurate and effective for determining three dimensional orientations from a gyroscope in walking studies [168]. This method was also proposed for usage in swimming and one study followed this approach [95].

A common theme in the literature is that low pass filtering is conducted as the first stage of signal processing to remove unwanted noise components, owing to various factors including sensor movement, drag effects and skin wobble. However, it is important to note that there is a potential for valuable data to be lost if inappropriate filtering is adopted. Researchers should be aware of this fact and careful consideration should be given to the cut-off frequency employed as there is not a "one size fits all" solution to handling the raw data input. For example signals recorded from the back would have a much lower usable frequency content than those recorded from the arm and thus different cut-off frequency values would be used in a low-pass filter employed in these two cases.

Data Storage and Transfer

Advances in data storage technology allow for increasingly compact solutions, offering capacities that are more than sufficient for recording swimming data in training environments. A 1 GB microSD card will allow for over 200 hours of recording at 100 Hz [53]. For real-time systems, on-board storage is still required due to the volume of raw signal generated. One study incorporated 4 MB storage buffer, facilitating real-time implementation of data processing algorithms [57]. Interestingly though, raw acceleration signal was also transmitted along with the processed data, as both may be of relevance when a coach or sport scientist analyses performance. Real-time feedback is an exciting new area of research and will further enhance the standing of inertial sensor-based systems within coaching communities. Rapid feedback on performance is vital to skill acquisition and has been found to improve technical performance in swimming [169].

However, the range of transmission is quite low, less than two meters in one study using Radio Frequency (RF) [53] and just 0.7 m for an optical wireless link when operated in turbulent water [52], thus feedback can only be provided to the swimmer and not the coach. This setup may be appropriate for recreational swimming analysis but is unsuited to elite swimming environments. This is a limitation of the majority of the data transmission options described. One paper did report a tested RF transmission range of 35 m at 0.25 m water depth, but unfortunately without providing additional methodological details [57].

Power Supply

Power consumption of wearable sensor devices is an on-going area of investigation within the research community and as multiple sensor designs become more commonplace, so too will the requirement for balancing power consumption to avoid overload [170]. It has been suggested that the main constraint on the size and mass of MEMS systems is the power source, highlighting the requirement for low power signal processing methods [162]. Eight hours of battery life can be achieved using a high density lithium polymer cell incorporating sleep states and variable clock rates [53]. One system is capable of 48 hours of continuous recording across multiple sensors using a 250 mAh 3.7 V rechargeable battery [62]. Lithium ion batteries are not without limitations for use in aquatic environments due to the fire risk associated with damage or leakages. An alternative solution may include super-capacitors or carbon-nanotube based energy stores. Another potential lies in energy harvesting in the surrounding electromagnetic environment, but further research is required in these areas [170-174].

4.5 Conclusions

This paper aimed to provide a systematic and critical review of inertial sensor use within swimming, focusing on methods that have been described for extracting key performance related variables for different phases of swimming and the consequences of different sensor attachment locations. Of the 87 papers included in this review, 62 of them (71.3%) have been published since 2010. Consequently, this field of study is relatively new and rapidly expanding. The development of this technology has advanced from early prototype models capable of simple stroke recognition to more recent systems that have provided for temporal; kinematic; kinetic and physiological analyses. Systems have been described that are capable of analysing starts; turns and free swimming parameters for a range of swimming strokes.

Much of the work has focused on extracting variables using relatively simple processing techniques, such as peak detection and zero-crossing. This requires an understanding of the features of the raw acceleration and angular velocity signals and their relevance to swimming performance as well as an appreciation for individual differences in stroke mechanics. Detecting other variables requires more complex solutions. The accurate determination of swimming velocity, for example, is a current area of much research, with different methods being explored including integration and regression techniques. It remains to be seen which process will prove to be most appropriate. This is perhaps expected for a growing field of research but such inconsistency will undoubtedly result in confusion amongst coaches and sports scientists and also makes comparisons between studies difficult. It is important that best practice approaches to analysing swimming performance using inertial sensors are developed to ensure a greater adoption of the technology in applied settings and increased confidence in the accuracy of specific designs. Perhaps the greatest challenge at present when considering algorithm development is ensuring that the systems can robustly handle the individual movement characteristics of different swimmers and with high accuracy. It could be argued that the research community as a whole needs to move beyond low level signal processing techniques such as peak detection and move towards more complex signal processing and data analysis techniques in order to achieve solutions to these ongoing issues and to provide a greater depth of analysis potential to swimming coaches and practitioners.

It has also been found that many different sensor locations have been used to date. Advantages of choosing a single site include ease of use and reduced cost but with limitations on the depth of analysis possible. Moreover, many algorithms described are specific to the location chosen and once selected should not be used interchangeably [139]. Multiple sensors mounted on various body segments offer increased analytical potential as reflected in recent studies. Certainly, the selection of an appropriate location or locations must be related to the measurement variable of interest due to the specific mechanics and coordination patterns of the four competitive strokes. The same function, such as stroke count, cannot always be best measured for different strokes using the same location.

As would be expected in a new area of research, there remains a large number or directions for future work to exploit. The variety of system specifications described is vast but with little consideration for the potentially negative effects of drag owing to their design. The accuracy of some feature detection algorithms may be questioned, such as those for lap time and stroke count. There remains a need for more thorough validation of systems and processes as much work to date has involved low participant numbers and insufficient detail regarding validation procedures that have been carried out. The lack of statistical analysis performed in some of these studies to determine the significance of the findings is also a concern. For example, Siirtola, et al. [59] reported accuracy levels of greater than 99% for their stroke count algorithm but did not provide any statistical analysis and details of the method of validating the sensor data were not properly reported.

Several aspects of swimming analysis are largely unexplored but are vital from a coaching point of view. These include increasing the array of variables that can be measured, not just for free-swimming but also for the analysis of starts and turns which remains underdeveloped. Joint angular kinematics have not received sufficient research attention and to date no study has attempted to describe the action of the shoulder joint, which is paramount in swimming. Developing the kinetic potential of sensor-based technology would open up a new avenue for many coaches.

Future work also needs to focus on applied studies to demonstrate how this technology can be used to influence coaching practice. The work of Fulton & colleagues [33, 34, 51] into kicking patterns is important as they are utilising sensor-based technology to optimise performance in an elite coaching setting. Similar examples are lacking in the research literature. Future applied research investigating other swimming strokes and involving elite able-bodied swimmers as participants are warranted, in order to convince the coaching population that sensors have a place in swimming training. Currently, the awareness and usage of sensor-based technology in applied swimming programmes is very low [8].

Commercial systems appear to be more geared for a recreational swimmer and lack sufficient depth of analytical potential, as well as operational validity, to be of relevance currently in elite swimming. Additionally, research should look to include all four competitive strokes when validating feature detection algorithms in order to increase the applicability of this technology for real-world settings.

The evidence presented to date would suggest that inertial sensor technology has enormous potential to influence swim coaching practice in the coming years. Due to the difficulty in obtaining accurate data in aquatic environments, there is a strong demand for sophisticated analysis tools to quantify key performance related variables such as acceleration and velocity. MEMS based technology has the potential to deliver the required accuracy, precision and speed of feedback. Ultimately, however, this technology is competing against video-based analytical tools and researchers should continue to strive towards providing sufficient evidential basis of the merits of inertial sensors. Until such time, it is likely that coaches will continue to rely on traditional approaches for the analysis of swimming performance.

4.6 References

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Chapter 5 – Evaluation of Commercially Available Swimming Activity Monitors

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The systematic literature review of inertial sensor-based analysis of swimming performance, presented in Chapter 4, highlights several areas of interest and potential research development. It is apparent that the growth of interest in this area suggests that there is also significant commercial opportunity for new systems aimed at providing coaches with a means of analysing their swimmers' performance using sensor-based systems. However, before any effort can be made towards developing new technology, it is prudent to make a comprehensive assessment of currently existing commercially available swimming sensors. This assessment will help to identify areas of strength and weakness with existing technology and allow the opportunity to develop an important reliability testing protocol for use in aquatic settings that can be used in later stages of this research project. The findings are presented here as the next chapter of the thesis.

5.1 Introduction

Swimming ranks amongst the most popular leisure activities worldwide [1, 2]. The general health benefits of regular swimming are well established and swimming is one of the few sports that can be enjoyed during all stages of life [3]. Individuals who swim as a recreational activity for health and fitness can benefit from monitoring some basic indices of their performance. Parameters may include the time or distance completed; in much the same fashion as a recreational runner will use a stopwatch or GPS device. Indeed, research evidence suggests that better health outcomes can arise when levels of physical activity are quantified [4].

Additional benefits of quantifying swimming performance for health may include assisting with goal-setting, as an activity diary, as a means of monitoring trends in performance over time or as a motivational tool. In aquatic settings such variables would typically be measured using manual methods such as a stopwatch. However, manual methods are prone to inconsistencies and inaccuracies. Furthermore, recreational swimmers do not typically have the availability of a coach or other observer who can record this information for them, using video for example [5].

Wearable sensor technologies have gained popularity in many sporting settings and commercially available products have been validated for use across a range of physical activities [6-8]. With advances in MEMS-based kinematic sensing, swimmers can also now monitor their own activity in their normal training environment using wearable technologies [9]. Several prototype designs have been described and validated in the swimming literature [10-13]. Additionally, commercially available swimming activity monitors have gained prominence, including the Finis *Swimsense*® (FINIS USA, Livermore, CA, USA.) and Garmin *Swim*™ (Garmin International Inc, Olathe, KS, USA.).

These commercial activity monitors include features such as stroke counting and swim speed measurements and can identify the different strokes performed automatically. Feedback is provided either instantly on the wrist worn interface or by downloading the data to custom designed websites for a more detailed analysis once the swimming session has been completed. These devices are marketed directly at the swimmer and are primarily aimed for recreational, self-coached and amateur swimmers or triathletes as opposed to elite swimmers. These systems are seldom used by swim coaches for competitive swimming training and performance analysis [14]. These activity monitors offer significant potential in recreational swimming settings by providing swimmers with a method of quantifying and analysing their own training in the pool. However, to the author's knowledge, these devices have not yet received objective scrutiny to validate their performance. The activity monitors are designed for people who train in order to achieve personal swim training goals.

The aim of this paper is to assess the accuracy of the Finis *Swimsense* and the Garmin *Swim* activity monitors in providing accurate feedback on a range of swimming performance parameters for each of the four competitive swimming strokes.

5.2 Methods

5.2.1 Participants

Ten national level competitive swimmers were recruited to take part in the study (5 male, 5 female; 15.3 ±1.3 years; 164.8 ±12.9 cm; 62.4 ±11.1 kg; 425 ±66 FINA points (Fédération internationale de natation)). Competitive athletes were chosen over recreational swimmers in order to ensure that the participants would be fully competent in performing all four competitive swimming strokes in a highly consistent manner over the protocol distance. In doing so, it was expected to achieve the absolute best estimate of accuracy that could be attained from the activity monitors in a recreational setting. The study received approval (reference number 13/NOV/08) from the institutional ethics committee, NUI Galway Research Ethics Committee (REC), and followed the terms of the Declaration of Helsinki. The protocol was explained to the swimmers and their parents. Parental written consent was obtained and the participants provided written informed assent.

5.2.2 Procedures

Data collection took place in a temperature controlled 25 m indoor swimming pool (water temperature 29 °C), which was within the normal operating temperature for both swim monitors. Participants were fitted with a monitor on each wrist, which were allocated at random. Both devices feature tri-axial accelerometers to automatically track the acceleration of the wrist as the swimmer moves through the water. Pool length can be readily adjusted on both devices and was programmed to suit the 25 m environment. Settings were configured for each individual user (height, mass, age, wrist used) and the participants completed a self-directed warm up of 15 minutes duration to prepare physically and to habituate to wearing the devices whilst swimming.

Participants were instructed to complete a swimming session totalling 1,500 m (60 laps) comprising each of the four competitive swimming strokes, completed in individual medley order (i.e. butterfly, backstroke, breaststroke, frontcrawl). Butterfly was swum in 50 m intervals followed by 45 s rest, repeated six times. The other strokes were swum in 100 m intervals, again followed by 45 s rest, repeated four times. Two minutes of rest was included when transitioning between strokes, during which swimmers were instructed to remain still with their forearms resting on the pool deck. In total, 15,000 m of swimming were completed, generating 600 laps, or data sets, for statistical analysis. Swimming speed was self-selected during all trials.

Trials were simultaneously captured at 50 Hz using two fixed underwater cameras (GoPro Hero3+) positioned to record all events occurring at the pool walls in order to identify wall contact events and one panning video camera on the pool deck to record the participants throughout each lap (Sony Handycam HDR-XR550). Images from the three cameras were synchronised by interpolating the data according to the time lag between cameras using a blinking light source [15]. Video footage was subsequently used as the criterion measure to assess the performance of the swim activity monitors.

5.2.3 Data Processing & Analysis

Video files were stored on a portable hard drive and analysed with the use of Dartfish Video Software (ProSuite version 5.5; Dartfish, Fribourg, Switzerland) to allow for criterion measures of all variables to be determined through manual observation of the video footage.

Inter-operator and intra-operator reliability testing was carried out by calculating the intra-class correlation coefficient (ICC) on a segment of the video data for lap time and stroke count. ICC is used to interpret the relationship between two variables that record the same measurement [16]. This was a necessary step in order to ensure the accuracy of the criterion measure. The other variables measured in the study can be derived from these variables so this was deemed sufficient for reliability assessment of the criterion measure. Intra-operator reliability for lap time (ICC = 0.999) and stroke count (ICC = 0.972) were found to be excellent. Inter-operator reliability for lap time (ICC = 0.993) and stroke count (ICC = 1.000) were also found to be excellent [17]. These results indicate that the video footage is a valid criterion measure from which to compare the performance of the activity monitors.

Data from each activity monitor were downloaded and exported to Microsoft Excel (2010 version; Microsoft, USA) for collation and processing. Stroke type, swim distance, lap time, stroke count, and average speed were measured on both activity monitors. Additionally, stroke rate and stroke length were also recorded for the Finis *Swimsense*. These were not available features on the Garmin *Swim*.

Descriptive statistics (mean, standard deviation) were determined for all variables. The Kolmogorov-Smirnov test was used to assess if the data were parametric or non-parametric. Stroke identification data were categorical in nature and a Pearson's chi-square test was used to assess for agreement between values [16]. Wilcoxon signed-rank tests were conducted to compare the relationship between non-parametric data. The standard error of the mean was calculated to determine the standard deviation of the sample means. 95% limits of agreement were determined as the mean difference ±1.96 times the standard deviation of the difference. ICCs were determined as a measure of the reliability of the devices. A linear mixed model was used to generate limits of agreement for each set of comparisons for the lap time and stroke count data which account for the (linked) replicates within individuals across devices [18, 19]. These data (lap times and stroke counts) are the most critical and fundamental parameters measured here as these values are used in the determination of many of the other reported parameters. Data analyses were performed using Statistical Package for the Social Sciences for Windows (Version 21, SPSS Inc., Chicago, IL). A p-value of 0.05 was set for all statistical analyses.

5.3 Results

Table 5.1 compares the sensitivity and specificity of the stroke type identification function for both activity monitors. Sensitivity is a measure of the proportion of positives that are correctly identified (i.e. lap recorded by monitor as frontcrawl when actually performing frontcrawl), whilst specificity measures the proportion of negatives that are correctly identified (i.e. lap not recorded by monitor as frontcrawl when not actually performing frontcrawl). The Garmin *Swim* correctly identified which of the four competitive swimming strokes was performed for a given lap with 95.4% overall sensitivity rate whilst the Finis *Swimsense* was slightly more sensitive at 96.4% overall. It was also found that there was a significant correlation in stroke type identification between the activity monitors and video for each of the four strokes (Garmin: X^2 (3) = 31.292, $p < 0.05$; Finis: X^2 (3) = 33.004, $p < 0.05$). Taking each stroke in isolation, a sensitivity of 94% or greater was achieved in all but two cases; namely breaststroke when recorded with the Garmin (86.0%) and backstroke when recorded by the Finis monitor (88.9%). This is also reflected in the slightly lower specificity values for these two strokes.

The total distance recorded by each sensor was compared to the actual total distance completed. Both activity monitors performed with very high accuracy when measuring the total distance completed for all four swimming strokes. A cumulative total of 15,000 m was completed by the participants. The Garmin monitor registered a total of 14,925 m (99.5% detection accuracy), which was 75 m, or three laps, short. These missed laps were all for the frontcrawl stroke. The Finis registered exactly 15,000 m correctly, however inspection of the results showed small variations within strokes (-1 lap butterfly; -3 laps backstroke +1 lap breaststroke; +3 laps frontcrawl, giving an adjusted detection accuracy of 98.7%).

Table 5.2 and Table 5.3 provide a comparison of performance of the activity monitors for other variables in the study. Lap times; stroke count; average speed, stroke rate and stroke length were statistically significantly different from the criterion measure in the majority of cases for both activity monitors and for all four strokes.

Table 5.1. Sensitivity and specificity of stroke identification for Finis *Swimsense* and Garmin *Swim*. The actual stroke completed for each lap was compared against the success of the sensors to correctly identify each lap. For both devices, a significant association was found with the actual stroke completed. Sensitivity is a measure of the proportion of positives that are correctly identified, whilst specificity measures the proportion of negatives that are correctly identified. (Fly = Butterfly; Bk = Backstroke; Brs = Breaststroke; Fc = Frontcrawl; Miss = no lap registered).

	Sensitivity					**Specificity**
Garmin	Fly	Bk	Brs	Fc	Miss	
Fly	**94.9%**	0%	0.8%	4.2%	0%	100.0%
Bk	0%	**98.8%**	0%	1.3%	0%	95.8%
Brs	0%	13.2%	**86.0%**	0.7%	0%	99.8%
Fc	0%	0%	0%	**98.3%**	1.7%	98.1%
Finis	Fly	Bk	Brs	Fc	Miss	
Fly	**97.2%**	0%	0%	0.9%	1.9%	100.0%
Bk	0%	**88.9%**	10.4%	0%	0.7%	99.8%
Brs	0%	0.8%	**99.2%**	0%	0%	96.5%
Fc	0%	0%	0%	**100.0%**	0%	99.7%

Table 5.2. Comparison of results for lap time and stroke count. Mean score, standard deviation (SD), standard error of the mean (SE), 95% confidence intervals, interclass correlation coefficient (ICC), limits of agreement (LOA), mean absolute percentage error (MAPE) and the error range are presented for both Finis *Swimsense* and Garmin *Swim* monitors and compared with the criterion measures extracted from video footage. Values denoted with an asterisk (*) indicate that a significant difference exists between the sensor device and the criterion (p < 0.05).

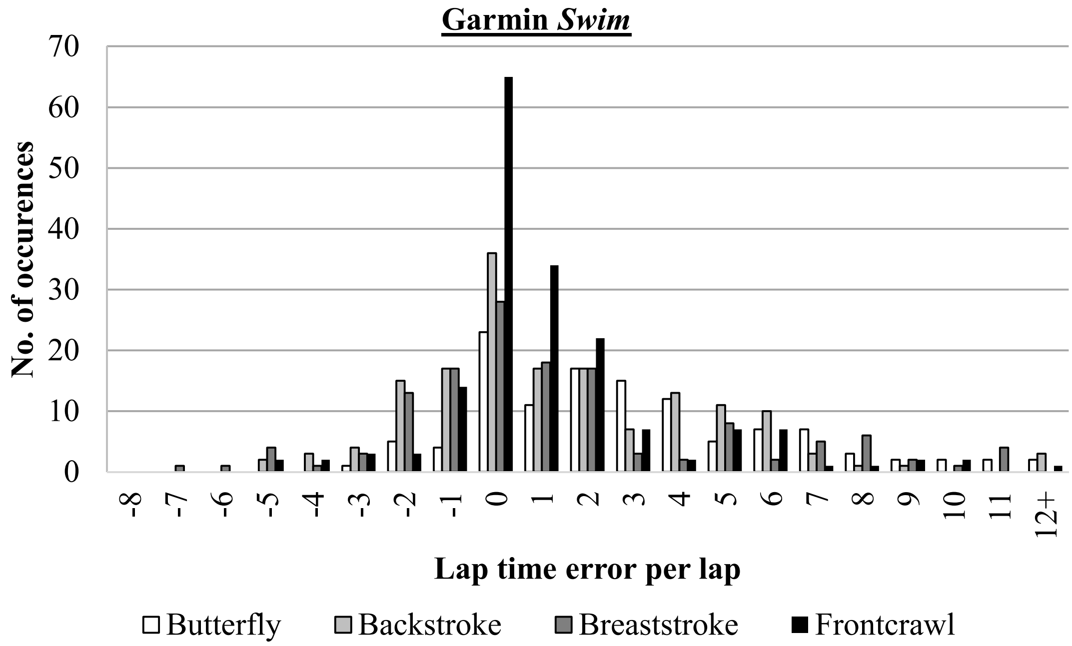
	Lap time (s)							**Stroke count**						
	Mean ±SD	SE	95% CI	ICC	LOA	MAPE (%)	Error Range (%)	Mean ±SD	SE	95% CI	ICC	LOA	MAPE (%)	Error Range (%)
Butterfly														
Video	20.31±2.46		(19.87-20.75)					12.2±1.8		(11.9-12.5)				
Garmin	23.33±3.49*	0.321	(22.70-23.96)	0.357	-8.293 – 5.199	17.2	(-13.6-114.5)	10.9±2.0*	0.183	(10.5-11.3)	0.295	-3.537 – 2.262	15.6	(-46.2-27.3)
Finis	23.30±5.28*	0.518	(22.29-24.31)	0.131	-7.046 – 4.521	20.6	(-20.7-117.7)	11.3±1.9*	0.186	(10.9-11.7)	0.758	-2.773 – 3.254	9.3	(-46.2-20.0)
Backstroke														
Video	22.38±1.38		(22.17-22.59)					8.9±1.1		(8.7-9.1)				
Garmin	23.93±3.24*	0.256	(23.43-24.43)	0.153	-8.293 – 5.199	11.6	(-22.4-74.1)	9.5±1.4*	0.110	(9.3-9.7)	0.453	-3.537 – 2.262	14.1	(-33.3-57.1)
Finis	23.64±2.91*	0.244	(23.16-24.12)	0.225	-7.046 – 4.521	9.7	(-18.6-69.4)	8.6±1.3	0.106	(8.4-8.8)	0.361	-2.773 – 3.254	12.0	(-40.0-62.5)
Breaststroke														
Video	25.23±2.05		(24.89-25.57)					9.9±1.6		(9.6-10.2)				
Garmin	26.59±3.10*	0.266	(26.07-27.11)	0.044	-8.293 – 5.199	11.2	(-28.1-48.9)	11.3±1.8*	0.152	(11.0-11.6)	0.542	-3.537 – 2.262	18.9	(-20.0-71.4)
Finis	26.48±3.07*	0.271	(25.95-27.01)	0.317	-7.046 – 4.521	9.7	(-20.7-47.3)	11.3±1.6*	0.145	(11.0-11.6)	0.650	-2.773 – 3.254	18.6	(-16.7-50)
Frontcrawl														
Video	21.24±1.76		(20.98-21.50)					9.3±1.2		(9.1-9.5)				
Garmin	22.33±5.18*	0.390	(21.56-23.10)	0.117	-8.293 – 5.199	8.4	(-24.2-50.6)	9.4±2.5	0.192	(9.0-9.8)	0.169	-3.537 – 2.262	11.4	(-50.0-58.3)
Finis	21.82±2.68*	0.202	(21.42-22.22)	0.635	-7.046 – 4.521	7.7	(-40.3-57.3)	9.8±1.3*	0.096	(9.6-10.0)	0.062	-2.773 – 2.262	14.4	(-44.4-62.5)

Table 5.3. Comparison of results for stroke rate, stroke length and average speed. Mean score, standard deviation (SD), standard error of the mean (SE), 95% confidence intervals, interclass correlation coefficient (ICC), mean absolute percentage error (MAPE) and the error range are presented for both Finis *Swimsense* and Garmin *Swim* monitors, where applicable and compared with the criterion measures extracted from video footage. Values denoted with an asterisk (*) indicate that a significant difference exists between the sensor device and the criterion (p < 0.05).

	Stroke rate (str/min)						**Stroke length (m)**						**Average speed (m/s)**					
	Mean ±SD	SE	95% CI	ICC	MAPE (%)	Error Range (%)	Mean ±SD	SE	95% CI	ICC	MAPE (%)	Error Range (%)	Mean ±SD	SE	95% CI	ICC	MAPE (%)	Error Range (%)
Butterfly																		
Video	46.1±5.4		(45.1-47.1)				1.64±0.18		(1.61-1.67)				1.24±0.14		(1.21-1.27)			
Garmin	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1.09±0.15*	0.014	(1.06-1.12)	0.327	13.2	(-53.5-16.5)
Finis	36.0±9.2*	0.903	(34.2-37.8)	0.135	20.8	(-73.0-6.2)	2.29±0.47*	0.046	(2.20-2.38)	0.127	40.9	(0.9-138.9)	1.12±0.20*	0.020	(1.08-1.16)	0.068	16.4	(-53.8-31.5)
Backstroke																		
Video	29.5±3.7		(28.9-30.1)				2.31±0.22		(2.27-2.35)				1.12±0.07		(1.11-1.13)			
Garmin	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1.06±0.13*	0.011	(1.04-1.08)	0.198	10.0	(-42.5-29.2)
Finis	24.0±4.1*	0.346	(23.3-24.7)	0.168	18.0	(-60.8-4.5)	2.95±0.46*	0.038	(2.87-3.03)	0.093	30.4	(-51.9-119.8)	1.08±0.12*	0.010	(1.06-1.10)	0.286	8.2	(-40.9-22.9)
Breaststroke																		
Video	29.6±3.2		(29.0-30.2)				2.04±0.28		(1.99-2.09)				1.00±0.08		(0.99-1.01)			
Garmin	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.95±0.12*	0.011	(0.93-0.97)	0.076	10.4	(-73.0-39.1)
Finis	27.1±3.3*	0.288	(26.5-27.7)	0.608	9.0	(-45.8-9.3)	2.26±0.33*	0.029	(2.20-2.32)	0.702	13.1	(-13.5-42.9)	0.97±.011*	0.010	(0.95-0.99)	0.286	8.6	(-31.1-36.2)
Frontcrawl																		
Video	33.4±4.4		(32.7-34.1)				2.15±0.21		(2.12-2.18)				1.19±0.10		(1.17-1.21)			
Garmin	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1.10±0.20*	0.015	(1.07-1.13)	0.258	7.3	(-33.7-30.7)
Finis	28.9±3.9*	0.296	(28.3-29.5)	0.455	12.9	(-50.4-10.3)	2.59±0.39*	0.029	(2.53-2.65)	0.292	21.2	(-11.2-117.1)	1.17±0.17*	0.013	(1.14-1.20)	0.613	7.4	(-36.2-68.2)

A comparison was performed of laps performed at the beginning of an interval (i.e. the first lap of four in a 100 m swim interval) to those performed during the middle of an interval and those performed at the end of an interval. The butterfly trials were omitted from this analysis as butterfly was completed in 50 m intervals and thus did not include a middle lap for comparison. Both activity monitors demonstrated a similar pattern of error in lap times, with a statistically significant difference found for laps performed at the beginning and end of an interval but no statistical difference found for those performed in the middle of an interval. For example, the average front crawl mid interval lap time was 21.03 ±4.27 s. The Garmin *Swim* averaged 21.53 ±2.17 s (+2.4%) and the Finis *Swimsense* averaged 20.91 ±4.48 s (-0.6%). However for laps performed at the start and end of an interval, the reported error was much larger, ranging from -13.4% to +33.5%.

The results showed that mid interval lap times were accurately recorded, the Garmin *Swim* showed a bias of -0.065s, a lower limit of agreement of -3.828s and an upper limit of agreement of 6.920s. For the same laps, the Finis *Swimsense* demonstrated a bias of -0.02s, a lower limit of agreement of -3.095s and an upper limit of agreement of 3.142s. For starting laps, the results for Garmin showed a bias of 4.608s (-4.855s – 14.070s limits of agreement) and for Finis showed a bias of 3.84s (-5.199s – 12.871s). Finally, for end laps, the results for Garmin showed a bias of 1.382s (-4.157s – 6.920s) and for Finis showed a bias of 0.77s (-5.679 – 7.217s).



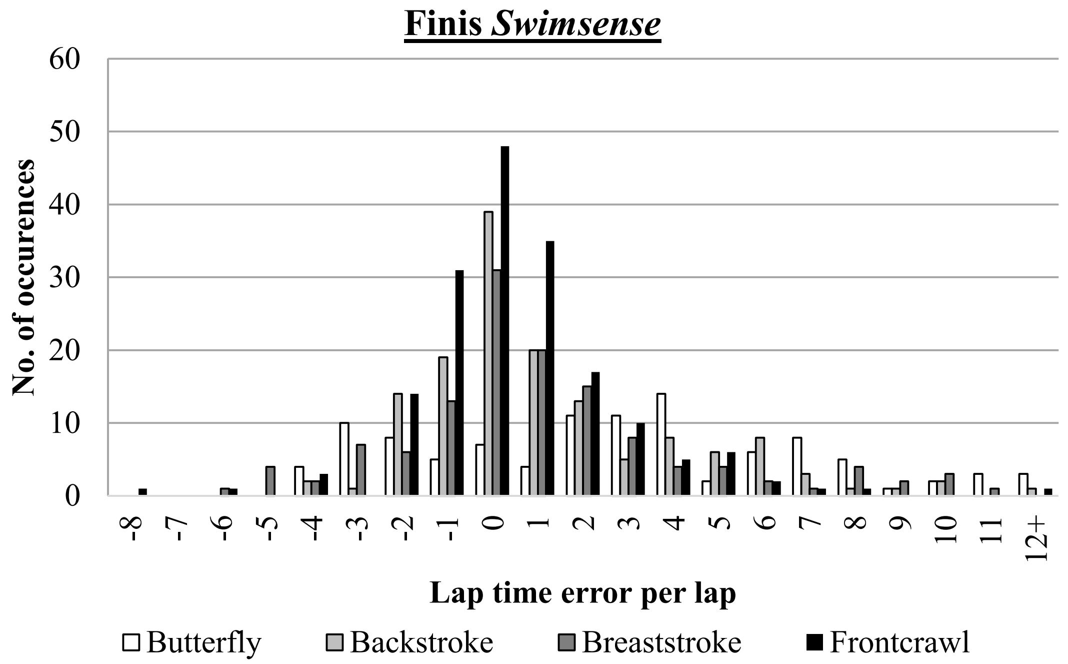
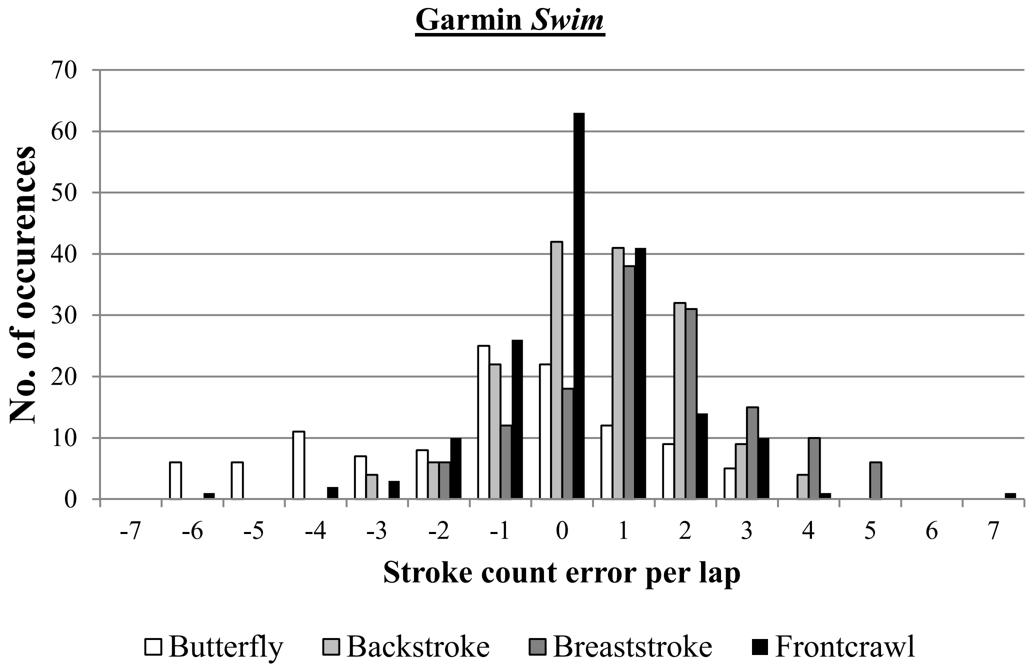


Figure 5.1. Comparison of overall frequency of error in the measurement of lap times for both Finis Swimsense and Garmin Swim.

Figure 5.2 highlights the results of the stroke count measurements, demonstrating an overall overestimation of stroke count for both activity monitors. Taking all four strokes combined, the Finis monitor correctly registered the stroke count to within one stroke of the actual stroke count in 62.2% of laps. Similarly, the Garmin monitor was within one stroke of the actual stroke count in 62.5% of laps. Looking at each stroke in isolation, the trend towards overestimation of stroke count was observed in all strokes except butterfly, which showed a tendency towards underestimation for both activity monitors. The results for stroke count were statistically significantly different from the criterion measure in all but two instances; in backstroke for the Finis monitor and in frontcrawl for the Garmin monitor.

The highest level of accuracy for the Garmin monitor was found for frontcrawl, with the stroke count within one stroke of the actual stroke count in 75.6% of laps. With the Finis monitor, the highest level of accuracy was found in the backstroke (73.4% ±1 of actual). Breaststroke demonstrated the lowest stroke count accuracy for both devices (Finis 40.6% ±1 of actual; Garmin 50.0% ±1 of actual). For the Garmin monitor, the long axis strokes performed better than the short axis strokes, but this was not observed in the Finis monitor.



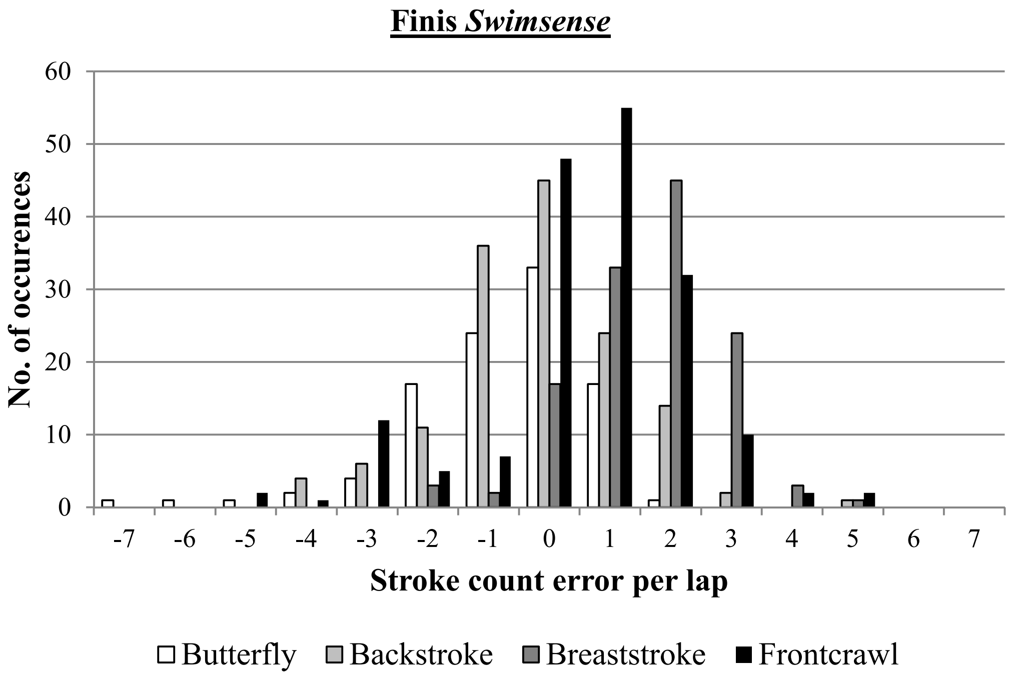


Figure 5.2. Comparison of overall frequency of error in the measurement of stroke count for both Finis Swimsense and Garmin Swim. The results indicate a significant overestimation of stroke count for both devices for all strokes except butterfly.

5.4 Discussion

The aim of this study was to assess the accuracy of the Finis *Swimsense* and the Garmin *Swim* activity monitors and to assess the validity of using these devices in recreational settings. It is well established that the pattern of hand movement during swimming shows considerable variances owing to various factors including anthropometrics, skill level and fatigue [20-22]. With recreational swimmers, there can be a very wide variation in skill level and fatigue, with consequent high levels of variation in swim performance in this group of swimmers. Conversely, competitive athletes display more consistent patterns of movement [23] and thus these athletes were used for testing in order to minimize variation in swimming performance. Thus the results obtained in this study would represent expected best case findings for these devices and it would be reasonable to expect that there would be a significant deterioration in the activity monitors' performance when used by recreational swimmers.

When assessing the performance of these activity monitors it is important to consider carefully what can be regarded as an acceptable performance level for different categories of users. Whilst some findings in the present study suggest that some parameters were statistically significantly different from the criterion measures, these differences, in a sporting context, may or may not be at a scale to be of concern to the intended users of these activity monitors [24]. A table of proposed system requirements for swimming activity monitors when used by either recreational or competitive swimmers is presented in Table 5.4, showing that these two groups will have very different requirements for the accuracy of feedback information provided to them on their swimming performance.

Table 5.4. The system requirements of recreational and competitive swimmers will differ and have an impact on the level of accuracy required of the swimming monitors.

System Parameter	Recreational Swimmer	Competitive Swimmer
Lap time	Accuracy required to within ±2 seconds to monitor trends over time. A variance of 2 seconds over a lap time of 30 seconds equates to a 6.7% error	Accuracy required to within ±0.3 seconds in order to be comparable with a stopwatch (current standard)
Stroke count	Accuracy within ±2 strokes sufficient to monitor trends over time	Accuracy required to no more than ±1 stroke per lap
Swim distance	Key determinant of training progression, accuracy required to within ±5% of actual (i.e. no more than 2 missed/additional laps included per 1,000 m completed in a 25 m pool)	Not applicable to user, training distances pre-prescribed and monitored by coach
Swim speed	Not applicable to user, lap times provide a sufficient metric	Accuracy within ±0.01 m/s required to relate to required lap time accuracy and also to compare with other reported methods. More concerned with instantaneous speed or speed during different race segments
Stroke rate	Not applicable to user, stroke counts provide a sufficient metric	Accuracy within ±5% adequate (i.e. ±2 str/min). More concerned with instantaneous stroke rate or stroke rate during different race segments
Stroke length	Accuracy within ±0.2 m sufficient and related to accuracy of stroke count measure	Accuracy close to 100% required (i.e. errors of no more than 0.1 m) and related to stroke rate measure. More concerned with stroke length during different race segments
Stroke identification	100% accuracy required as errors will be very apparent	100% accuracy required as errors will be very apparent

For example, a competitive swimmer or coach may require a lap time measure to be precise to within three tenths of a second in a training environment. This level of performance would effectively bridge the gap between the performance capabilities of a stopwatch and those of a video-based analysis system. The Garmin device registered the lap time to within 0.3 seconds on 18% of laps recorded. The Finis also showed a similar performance level (15%). The same could not be said for a recreational athlete, who would require a much less stringent level of lap time accuracy. Based on our experience working with both elite and recreational swimmers, lap time values of within one to two seconds of the actual time for a given lap would be appropriate for a recreational swimmer in order for them to gauge their performance level and to monitor gross improvements in performance over an extended period of time. In the present study, both devices registered the lap time within two seconds of the actual lap time on 67% of occasions.

Moreover, when measuring stroke count, recreational swimmers are likely to be more interested in monitoring the trends over a period of time, as opposed to monitoring the exact stroke count for each lap, in order to assess if training goals are being achieved and if swimming efficiency has improved. It was found that both devices registered the stroke count to within one of the actual stroke count on over 62% of laps recorded. In this context, both the Finis *Swimsense* and the Garmin *Swim* activity monitors would appear to provide recreational swimmers and triathletes a way of keeping a record of their training and progression. Without these types of devices, this would not be possible. Conversely, a competitive swimmer would have developed a consistent stroke count pattern through extensive training. These swimmers would have greater awareness of their stroke count for given laps and may deliberately make minor adjustments to their stroke count during training sets, in order to practice specific racing strategies for their different events, for example. As such, the stroke count accuracy would need to be very high for competitive swimmers.

The ability of such activity monitors to correctly identify the swimming stroke used in a given lap is a fundamental performance characteristic for monitoring both recreational and competitive activities. Notwithstanding the fact that the frontcrawl stroke may reasonably be assumed to be the most prevalent stroke in the majority of training settings, all four strokes may be used interchangeably during training, even for elite swimmers with specific stroke specializations. The results of the present study demonstrate that the Finis *Swimsense* performed slightly better than the

Garmin *Swim*, but both sensors reported very high overall sensitivity and specificity for stroke identification (Table 1), which is comparable with previous research [10, 25, 26].

Closer inspection of the results in the present study suggests that where errors did occur these errors appear to be attributable to individual swimmers. For example, the Finis monitor registered an entire backstroke set for one swimmer as breaststroke, whilst the Garmin monitor incorrectly recorded breaststroke as backstroke on 14 of the 16 laps for another swimmer. However, as backstroke is performed in a supine position, in contrast to other strokes, it should be possible to correctly identify when this is being performed. It is conceivable that the misidentification issue could be linked to clockwise and counter-clockwise movements about the shoulder joint. Backstroke arm pull is opposite in direction to frontcrawl and butterfly, whilst breaststroke swimming has a more backward and forward movement of the wrist. Another possible explanation is that activity during rest periods, such as slight arm movements when standing at the pool wall, may lead to errors in the algorithm for stroke type identification.

This large level of misidentification could be due to individual variances in stroke technique. It is reasonable to expect that this level of misidentification would increase when the devices are used by recreational swimmers rather than elite swimmers.

Both activity monitors measured swim distance with excellent accuracy across all strokes. The swim distance is derived in both devices by multiplying the number of laps completed by the length of the pool. Therefore, swim distance is a function of the accuracy of the lap counter algorithm, which relies on accurate detection of wall contact events. Three types of wall contact events can be detected; those at the start and end of a swimming interval and those after turns. Data from a wrist worn accelerometer can be used to determine these events as a large impact acceleration peak will signify that a wall strike has occurred [27]. From a practical point of view, accurately recording the distance completed during a training activity is a fundamental function for recreational swimmers. In fact, this function may be used along with the total time spent swimming by some users as the primary determinant of whether their training goals have been achieved.

The ability to record lap times during swimming allows for the intensity of effort to be monitored closely during training and to assess progression. Statistically significant differences in lap time measurements were found for all of the four swimming strokes for both the Finis and the Garmin monitors, with the devices overestimating the time to complete laps (Table 5.2). Ultimately, statistically significant differences in lap times may not be very relevant to a recreational swimmer, who may be satisfied with a close approximation. A two second error over a typical lap time of 25 seconds would represent an error of 8%. Both activity monitors were found to perform within these limits for frontcrawl swimming. However, this was not found to be the case for the other three strokes. The average error in frontcrawl lap time was 0.58s and 1.09s for the Finis and Garmin monitors, respectively, over an average lap time of 21.24s (i.e. 7.7 % and 8.4 % error). The maximum lap time error was found for the butterfly stroke (20.6 %). Additionally a large range of errors was found for all strokes.

By examining laps at the start, middle and end of intervals, it was found that statistically significant errors, found for the Finis and Garmin monitors could be attributed to the an overestimation in the time taken to complete the first and last laps in a given interval, whilst the middle laps were found to accurately reflect the actual lap time (Fig 2). This finding is consistent with previous research [10].

There are several factors which may help to explain the errors found in the lap times, which averaged over three seconds in some cases (Table 5.2). A strong push-off and finish are required to detect these events in order to maximise the accelerometer amplitude at impact [27]. Movement that occurs prior to wall push off may have caused the sensor to begin recording a new lap before it had actually begun. For example, a swimmer may position themselves underwater with their feet against the wall before initiating hip and knee extension, resulting in an overestimated lap time.

A similar scenario may also occur during rest intervals. Another legitimate concern is that these issues and resultant errors would be further exacerbated when the activity monitors are used by recreational swimmers. Finis' documentation recommends that the swimmer should remain static during rest intervals and that rest should be at least three to five seconds in duration to avoid the algorithm from registering a turn [28]. This raises an issue of practicality if the swimmer drinks from a bottle or adjusts their goggles during this time, for example. The Garmin monitor requires the user to manually pause and restart the timer to record intervals. This may result in an inevitable overestimation of first and last laps. The Finis monitor features automatic interval detection, but this was not found to lead to improved accuracy, but clearly is more convenient for the swimmer.

It should be noted that if the test protocol had included longer intervals then a greater proportion of the laps performed would have been mid swimming laps, which were found to be accurately registered by both activity monitors. This would have reduced the impact of the starting and ending laps on the overall statistical results. For example, in a 100m interval swim, half of the laps performed are mid swim laps. However, in a 400m interval, these laps would comprise 87.5% of the total laps performed. For recreational swimmers who chose to swim in a continuous manner, without taking frequent rest intervals, this would greatly improve the performance of the activity monitors during their swim. Swimming strokes can be identified from an accelerometer output as regularly occurring peaks in the signal signature, with local maxima and minima tracked and counted [10, 13]. The activity monitors tested in the present study were found to perform quite similarly for the stroke count measure (Figure 5.2). Both monitors showed significant differences from the criterion in stroke count on all but two occasions. The Finis was found to be significantly related to the criterion measure during backstroke only, whilst the Garmin monitor was significantly related for frontcrawl only. Outliers increased the spread of stroke count errors considerably for both activity monitors. Additionally, both activity monitors tended towards overestimation of the stroke count in all strokes except butterfly. The maximum reported error was found to be -7 strokes for the Finis and +7 strokes for the Garmin. That said, both monitors reported the stroke count to within one of the actual stroke count on over 62% of instances.

Previous studies have determined stroke count from either the back, wrist or head [9]. The tendency towards over estimation of the stroke count may be explained by an analysis of the action of the arm on which the sensor is placed. It is standard practice to only record full stroke cycles when determining stroke count. In frontcrawl and backstroke swimming, this means that both the left and right arms must complete a stroke for a cycle to be counted. However, the algorithms used by these devices record the movements of only one arm and multiply this by two to arrive at the stroke count [29]. Therefore, the activity monitors may report an incorrect stroke count depending on which arm is used for the first and last strokes of a given lap.

This would not explain the results for the short-axis strokes however. One possibility for the overestimation in breaststroke stroke count is that the arm action during the push-off and glide phase were erroneously counted as stroke cycles. Variations may also be due to action of the arms before and after a turn. It has previously been suggested that the first and final strokes of a given length can be difficult to record and are more prone to error than strokes performed mid-pool [27]. In butterfly, a swimmer will aim to finish the final stroke with their arms at full extension and as close to the wall as possible. This action may interfere with the stroke count algorithm as the signal may be distorted with the accelerations produced by the turning action of the swimmer. Again like other parameters, it would be expected that these errors would be greater when the devices are used by recreational swimmers.

Some of the issues with accuracy may arise from the wrist worn position of these devices. Consistent coordination between left and right arms or upper and lower limb actions cannot be guaranteed. Several studies have objectively demonstrated that variations in inter-arm coordination exist in swimming owing to various factors including swimming speed [22, 30]; arm dominance [31]; physical disability [32]; energy cost [33]; exercise intensity [34] and skill level [30]. Furthermore, a similar variance exists between the coordination and synchronisation of the arms and legs for all swimming strokes [23, 35]. All of these factors have implications for the accuracy of feature detection algorithms when using wrist mounted devices.

In the present study the average speed over a given length of the pool was determined by both the Garmin and Finis monitors by dividing the pool length (25m) by the time taken to complete each lap. Consequently it is unlikely that this parameter would be of interest to a recreational user as the lap time data would provide a sufficient metric. Ultimately, as a consequence of both activity monitors' inaccuracies in recording lap times; the results for speed are also significantly different (Table 5.2). This approach has been evaluated previously and found to overestimate speed [27]. An explanation for this lies in the effects of increased speed following the wall-push off when measured over the full pool length. It is more common in coaching practice for swimming speed to be measured over shorter distances to remove the influence of increased speed during wall push-off. This approach has been found to produce measures of average speed within 3.5% – 4.0% of the criterion values using inertial sensor-based systems [12, 36]. In the present study the mean absolute percentage error was found to be higher than this, ranging from 7.3 % to 16.4 %. This can be explained by the issues with the method of determining speed and also by the influence of poorly timed starting and ending laps in a given interval. Again like other parameters, we would expect that these errors would be greater when the devices are used by recreational swimmers.

Stroke rate is the number of strokes a swimmer takes per minute. A typical stroke rate during frontcrawl swimming would be between 35 – 50 strokes per minute. In comparison to the criterion measure, it was found that the Finis *Swimsense* significantly underestimated stroke rates for all four strokes (Table 5.3). The average differences ranged from -2.5 strokes per minute (breaststroke) to -9.9 strokes per minute (butterfly), resulting in a maximum expected error of 9.0 % and 20.8 % error, respectively.

Although specific details of the Finis algorithm are unclear, one possibility is that stroke rate is derived from the stroke count measurements, using the time taken to complete all strokes for a given lap. If this is the case, stroke rate can fluctuate during a lap so is highly dependent on when and how it is measured. In the present study, stroke rates were calculated from the video data using the standard method of measuring the time taken to complete three mid-pool stroke cycles [37]. This difference may go some way towards explaining the underestimated stroke rates registered by the Finis *Swimsense*. Secondly, the accuracy of stroke rate determination depends on the accuracy of the stroke count algorithm, which was found to be error prone. Additionally, small discrepancies in stroke count can lead to large changes in derived stroke rate. For example, if a lap of frontcrawl is completed in 21 seconds and the swimmer completed nine strokes in this lap then the stroke rate would be calculated as 25.7 strokes per minute. However, if the stroke count was overestimated by just one stroke to ten, then the stroke rate would be increased to 28.6 strokes per minute.

Garmin's documentation suggests that stroke rate is a built-in function of the device but the data provided were the average strokes per minute for the entire swimming session [38]. This information may be of benefit if swimming the same stroke throughout the entire session but not if changing strokes frequently and so is of little value in competitive settings.

The Finis activity monitor determines stroke length by dividing the length of the pool by the stroke count completed by the swimmer in one lap. However this method will overestimate the actual stroke length for the swimmer due to the influence of the wall push off and glide and has been recognised as an unsuitable methodology for some time [39, 40]. To illustrate, if ten strokes were completed in a given 25m lap, then the stroke length would be calculated as 2.5m using the Finis algorithm. However, it is typical that the swimmer would have pushed off from the wall and glided for several metres before initiating arm movements. As a result those ten strokes would actually be completed over a shorter distance. If, for example, the swimmer glided for five metres then the actual stroke length would be two metres. This has shown to be the case as the Finis result revealed a statistical difference with actual stroke length.

A more typical method of calculating stroke length (SL) is to using the formula $SL = V/(SR/60)$; thus relating it to the speed (V) and stroke rate (SR) measures [27, 41]. However, even had a direct comparison been made to calculate the stroke length from video footage using the Finis method, poor accuracy would still have occurred as the stroke count results for Finis were in themselves significantly different.

5.5 Conclusion

This is the first study to assess the accuracy of two commercially available swimming activity monitors; the Finis *Swimsense* and Garmin *Swim*. Both monitors were found to operate with a relatively similar performance level. However, as previously noted, with recreational swimmers there can be a very wide variation in skill level and fatigue, with consequent high levels of variation in swim performance in this group of swimmers. Conversely, competitive athletes display more consistent patterns of movement [23] and thus the results obtained in this study would represent expected best case findings for these devices and it would be reasonable to expect that there would be a significant deterioration in the activity monitors' performance when used by recreational swimmers.

Stroke identification and swimming distance were determined with high accuracy. This feedback alone is likely to be suitable for the majority of recreational swimmers seeking health benefits from swimming. For a recreational user, high precision in lap time measurements is not necessary. It is also important to note that issues with lap time measures are specific to laps performed at the beginning and end of a swimming interval and that lap times performed in the middle of an interval (i.e. during a lap that involves two turns) were measured accurately by both devices. Moreover, issues related to the accuracy of the lap time function are skewed due to the short intervals performed in this study. Improved overall accuracy in lap time measurements can be expected for longer distance swimming intervals.

These activity monitors are designed to be used by swimmers who do not have any means of recording this information or for monitoring trends in performance over time. Consequently, whilst this study has revealed statistical issues related to their performance, both devices offer the recreational user a new way of comprehensively monitoring their physical activity whilst swimming. Future research could aim to evaluate the performance of these devices with this specific cohort of swimmers, to assess how increased variability in stroke mechanics would affect the results. Ongoing developments by the manufacturers of both of these monitors are likely to address these issues, in what is a rapidly expanding area of both research and commercial exploration. Rigorous testing is also necessary to ensure that the devices offer a valid and reliable means of monitoring swimming performance. Such improvements would also increase their applicability for competitive swimming environments.

5.6 References

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Chapter 6 - Application of a User Centred Design Methodology in the Development of an Inertial Sensor Based System for the Analysis of Swimming Turns

There are a range of options available to sports scientists and coaches when choosing equipment for analysing athletic performance. However, dissatisfaction with a number of the most prominent systems currently available for the quantitative assessment of sports performance is limiting the extent to which quantitative analysis is taking place in applied settings, as highlighted in Chapters 2 and 3 of this thesis. Additionally, it was found in Chapter 5 that some commercially available swimming sensor devices cannot be regarded as being suitable for use in elite settings due to design choices made in the creation of those devices. Reflecting on these issues, it is proposed that a User Centred Design (UCD) methodology could be utilised for the development of a novel system for performance analysis in elite swimming. In doing so, it is hoped that many of the identified issues may be addressed, thus aiding a more widespread adoption of the technology with the intended user group. A Use Case was developed that details the concept for a new performance analysis system and describes how the intended end users (sports scientists, coaches and athletes) will interact with the system during the various stages of its operation. The findings of this study are presented here.

6.1 Introduction

Competitive swimming is considered to be highly technically demanding. It requires the coordinated and synchronized actions of all body parts in order to produce the movements necessary to perform each of the four competitive swimming strokes. The efficient performance of these strokes that is required to achieve elite status involves considerable technical expertise on the part of swimmers, coaches and their support teams. Coaches are highly reliant on the assessment of key indices to monitor athletic progression, affect change and to critique performance. Swimming can be broken down into specific segments to facilitate such analysis (Figure 6.1). These segments include starts, turns and finishes in addition to free swimming components. During each of these race segments, different categories of analyses are appropriate and can be undertaken through the measurement of temporal, kinematic and kinetic variables.

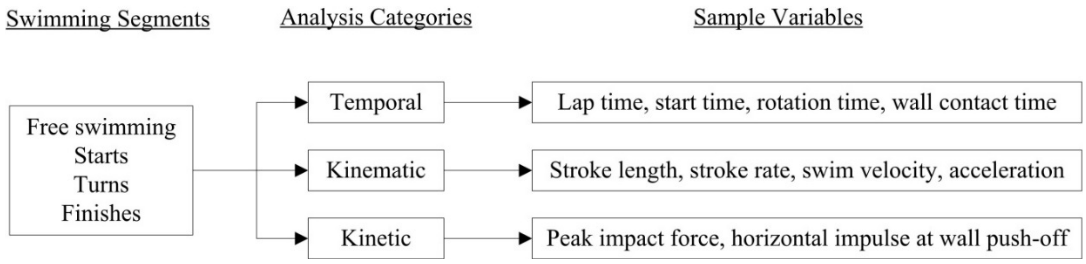

Figure 6.1. Swimming can be broken down into different segments to facilitate technical analysis and different categories of performance related variables can be selected for measurement.

Turns are a very important area of swimming performance, accounting for between 20-40% of the total racing time, depending on event and race distances [1, 2]. Moreover, coaches have confirmed that turns are an important aspect of their training plans [3] and much previous research has concentrated on examining this phase of swimming [1, 2, 4, 5]. Studies have shown that improving a swimmer's ability to effectively perform turns can reduce swim time by up to 0.2 s per lap [6] and that turning performance can be the difference between winning and losing in Olympic finals [7].

There are many variations of the turn in swimming, based on different swimming strokes and individual preferences. Flip turns are performed during frontcrawl and backstroke events, whilst open turns are used in breaststroke and butterfly [6]. Additionally, individual medley events involve different variations of these turns, in order to transition between strokes (from backstroke to breaststroke, for example). Therefore it is important for coaches to be able to fully understand what their swimmers are doing and how best to maximise improvements in their technique. As a consequence, a considerable coaching effort is required in order to improve the competency of their swimmers when performing these complex movements. This can be difficult to achieve with large squad numbers and limited resources.

Turns may be defined differently depending on coaches' requirements and can involve varying distances on approach to and leaving the wall after each lap. For example, competition analysis performed at major international competitions has defined this segment as being from 5m before the wall to 5m after the wall [8].

Irrespective of the distances used, turns themselves are comprised of separate phases for detailed analysis (Figure 6.2).

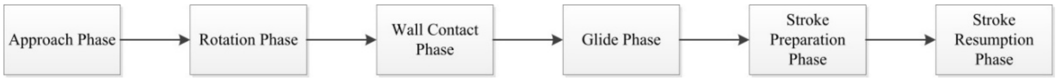

Figure 6.2. Swimming turns can be broken down into phases to facilitate a detailed quantitative analysis.

Traditionally, parameters of interest are measured using manual methods such as a stopwatch or by using video analysis [9]. However, manual methods are prone to inconsistencies and inaccuracies whilst video-based methods often require expensive equipment and involve significant time delay in providing feedback and are disruptive to regular training schedules. Furthermore, neither approach is well suited for monitoring large groups of swimmers. This is a problem, as these barriers have been found to limit the quantitative analyses being performed by elite swimming coaches, who consequently rely heavily on qualitative approaches [3]. This has led to efforts to provide alternative quantitative solutions for coaches and sports scientists.

Advances in the development of microelectromechanical systems (MEMS) facilitate a new approach to swimming coaching and technique analysis [10]. Kinematic swim sensor technology has emerged as a new method for facilitating the analysis of stroke mechanics; enabling an efficient means of providing quantitative information to inform coaching practices. This has led some to suggest that this technology may offer significant advantages over traditional video-based approaches [11] and several commercially available systems have recently gained prominence.

Feature detection algorithms for many important parameters have been described in the extant literature [12-14]. These algorithms mainly relate to free swimming components and include temporal and kinematic parameters such as lap times, stroke rates and swim speed. However, swimming turns have yet to receive the same level of attention in this research domain. Some early work has suggested the possibility of using sensor based technologies for the study of swimming turns [15, 16], but the accuracy and application of these approaches remains unexplored. This gap in the research is hindering coaches' ability to perform quantitative data analysis on swimming turns using inertial-sensor based systems.

Furthermore, it has been found that sensor based technologies are not in common use in elite coaching environments and that there is poor familiarity with these systems amongst the coaching community [3]. It could be argued that this is because currently available commercial systems do not adequately meet the needs of elite coaches who wish to perform quantitative data analysis [17]. Moreover, there remains a lack of research evidence that sensor based technologies can be used to change existing coaching practices, as the majority of research to date has focused on validation of new designs and extraction of new parameters, as opposed to field based implementation of the technology that takes into account the requirements of the end users of the system or product during the design phase and the context within which the technology is intended to be used. This has been acknowledged by others also as an essential area for future development [18].

An important consideration in the design of devices is the usability of those devices [19]. Usability is defined by the ISO (International Organization for Standardization, Geneva) as *"the extent to which a user can use a product to achieve specific goals with effectiveness, efficiency and satisfaction in a specified context"* (ISO 9241-11) [20]. The present study follows a User Centred Design (UCD) approach to the development of a sensor based system to be used for analysing swimming turns. UCD is defined as an *"approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying human factors/ergonomics and usability knowledge and techniques"* (ISO 9241-210) [21]. Once a system or device concept has been proposed, various methodologies can be used to define user requirements and establish context of use. From these requirements, design solutions are generated and then tested to assess whether it these meet these user requirements (Figure 6.3). These steps can be repeated using an iterative process until the desired outcome is achieved.

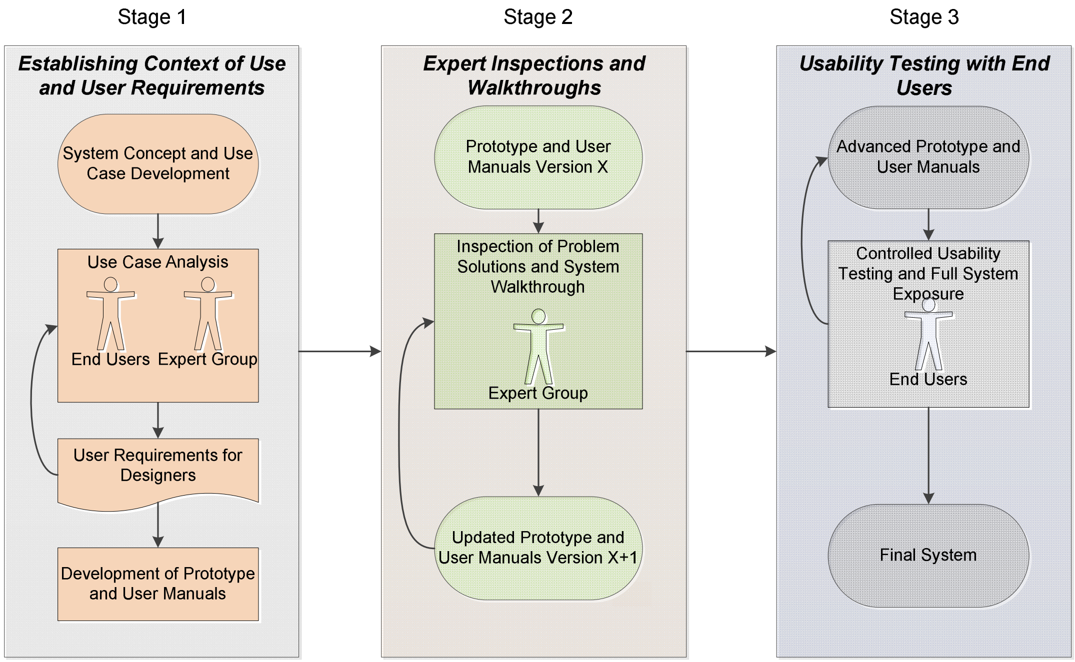

Figure 6.3. Standard User Centred Design (UCD) methodology [22].

A Use Case is a dynamic document which can be viewed by various stakeholders and is an effective way of gathering and defining user requirements and establishing the context of use. By providing the reader with a detailed description of the use and function of a device, the Use Case facilitates an exploration of individual views and gauges reaction to aspects of the design. This should ultimately lead to a final system that facilitates a user to achieve his/her goals in an efficient and effective manner and with satisfaction.

Use Cases have been used frequently, in particular during the development of medical devices for connected healthcare [23-26], or for assessing various computer applications [27, 28]. However, its use is less frequently reported for the design of sporting technology, with only limited examples of usability testing available in the extant literature [29-31] and none describing the application of the Use Case for this purpose. Salmon, et al. [32] discussed the importance of incorporating usability testing into sports technology device design, but unfortunately no relevant examples have been published. van Heek, et al. [33] reported that the context of use is a key component of UCD. Therefore, in a swimming context, the aquatic environment places significant challenges on users of technology and the process of analysing swimming performance when using these technologies. Several potential problems may result if system usability is not addressed, with the most relevant issue being that the system will not gain acceptance from end users who will subsequently be unlikely to incorporate the system into their coaching practices to any great extent.

The aim of this study is to describe the development of a Use Case document. This Use Case, which details the concept for a new system of analysing elite swimming performance, is specifically focused on quantifying swimmers' turns in a pool. The objectives of this study are to answer the following questions:

1. Is a system that is designed for the quantitative analysis of swimming turns of interest to coaches?
2. Is there agreement from potential end users that the head is an acceptable location for this system?
3. Can a list of quantitative feedback parameters be defined that are appropriate for the analysis of swimming turns?

The ability of the Use Case to accurately define user requirements and context of use will be examined and the implications of these findings will be considered, with an emphasis on future product development.

6.2 Methods

6.2.1 Participants

The primary potential end user of the swimming sensor device is the swim coach. The system is designed to support them in their work and thus coaches were the main participants in this study (N = 36, 22.6 ±12.7 years coaching experience). However, it is also important to get views of other potential groups who may interact with the system. Therefore, the participants used in this study also included a small number of sports scientists (N = 3, 11.7 ±11.0 years involvement in swimming) and competitive swimmers (N = 2, 13.0 ±1.4 years swimming experience). Sports scientists were included as it is important to get expert opinion from those regularly working with coaches and swimmers and skilled with using different technologies for collecting and interpreting data. Sports scientists may also be regarded as having a high level of appreciation for the value of quantitative data and the key performance related parameters that need to be improved in order to maximise swimming performance.

Competitive swimmers can provide insight into how they perceive the importance of data analysis for improving their own performance. Also, as the wearers of the device, it is vital to gauge opinion regarding the proposed location of the device and other related comfort issues. Table 6.1 provides further details regarding the participants in this study.

Table 6.1. Descriptive information for the participants of the study (N = 41), including gender breakdown, role, years of swimming experience, coaching qualifications (Based on ASCA system, if applicable), highest world ranking of athletes coached (if applicable) and location.

Gender	N=	Role	N=	Swimming Experience	N=	Coaching Qualifications	N=	Highest Swimmer World Ranking	N=	Location	N=
Male	34	Coach	36	0-4 years	2	Level 2	7	Top-25	9	USA	24
Female	7	Sport scientist	3	5-9 years	3	Level 3	13	Top-50	3	IRL	10
		Swimmer	2	10-14 years	10	Level 4	9	Top-100	3	UK	4
				15-19 years	7	Level 5	7	Top-250	5	CAN	2
				20+ years	19	N/A	5	> Top-250	16	ITA	1
								N/A	5		

6.2.2 Use Case

A Use Case was constructed in several phases, with input from coaching, engineering and scientific expertise. Multiple scenarios were explored and evaluated before arriving at an agreed version for use in data collection. The Use Case was created as an interactive, scenario driven, descriptive document. This facilitated a common platform for all project stakeholders to communicate their vision for the swimming sensor device and the interactions they would have with it during various stages of the use of the devices including (i) setup and configuration; (ii) pool-side preparation; (iii) data collection during swimming and (iv) data analysis. The concise and structured nature of the Use Case assessment allowed all participants to assess potential usability issues on a task-by-task basis. From this analysis a set of user requirements could be established to inform future development work. The full Use Case document is included in Appendix A of this PhD thesis.

6.2.3 Components of the system

It was proposed as a first iteration that the components of the swimming sensor device system would include the sensor unit, a tablet computer (such as an iPad) and an App to visualise and interact with the data (Figure 6.4). The sensor unit is designed to be waterproof, low profile and light weight, to minimize drag effects and interference with the swimmer. Conceptually, it weighs 30 g and has dimensions of 40 mm x 20 mm x 15 mm. The unit is designed to be positioned at the back of the head. It is held in position using the swimmer's own goggles and cap. Inside the unit are various electronic components, including an accelerometer, gyroscope, SD memory card, battery and a wireless Bluetooth connection. This sensor device is capable of measuring 3D acceleration and angular velocity, thus allowing for a swimmer's movement in the water to be recorded. The sensor unit has some external features including (i) a power button for turning the device on and off and (ii) an LED status light.

Sensor Unit Tablet Computer Analysis App

Figure 6.4. Description of the swimming sensor device system components.

A tablet computer is used to communicate with the sensor unit via Bluetooth. Data that are collected by the sensor during a swimming session can be uploaded to a tablet for processing and analysis. The sensor unit uses a custom software application that is used to visualise the data that are recorded. Feedback is designed to suit the coach's needs and includes both graphical and numerical data presentation.

6.2.4 Procedures

The Use Case involved both formative and summative phases. The formative phase comprised of two parts. Firstly, a pilot study was completed to finalise the first draft of the Use Case (N = 5). This was done to ensure clarity of instructions and to get some preliminary feedback on the overall satisfaction with the system. Modifications were made in an attempt to improve the overall satisfaction and level of agreement with the proposed functionality of the system. Subsequently, a second round of interviews was completed (N = 7) and some additional modifications to the Use Case were made. The modifications took many forms, including amendments to definitions of terms, changes to the actors involved and alterations to the system design. A detailed discussion of these changes is provided in the discussion section of this chapter. This led to the final version of the Use Case which was used for subsequent interviews as part of the summative phase of the process (N = 29).

Interviews with participants were conducted via video call using Skype (Skype Communications SARL, Luxembourg). Audio recordings of interviews were performed using Callnote (Kanda Software, Newton, MA) so that the interviews could be transcribed in order to clarify what was said and to collate opinions on a thematic basis. Figure 6.5, Figure 6.6 and Figure 6.7 below provide a sample of the storyboard images that were included at various stages of the Use Case.

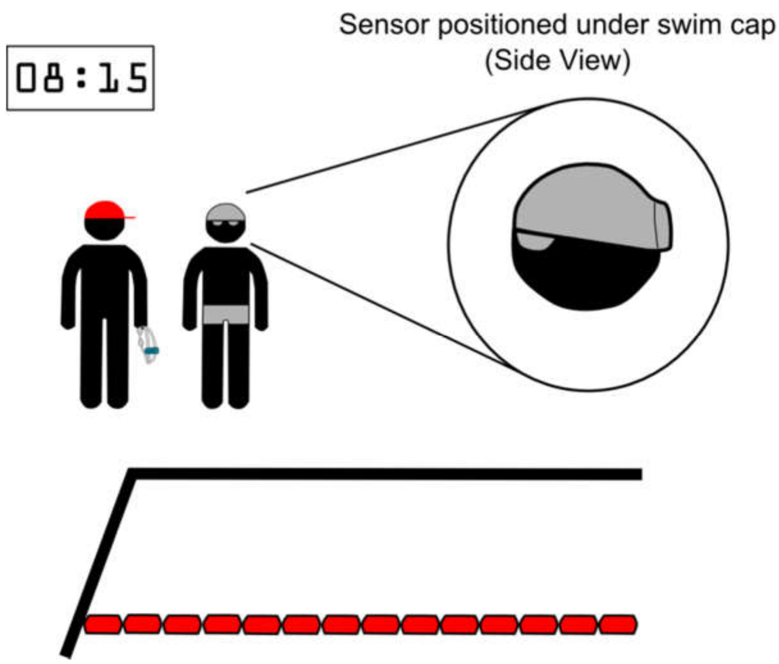

Figure 6.5. Sample storyboard image demonstrating the use of the sensor device and the interaction of the actors with the device. In this example, the coach is helping the swimmer to position the sensor unit correctly before use.

Figure 6.6. Sample storyboard image demonstrating the communication protocol between the sensor and the App on the tablet computer, which is achieved using a wireless connection.

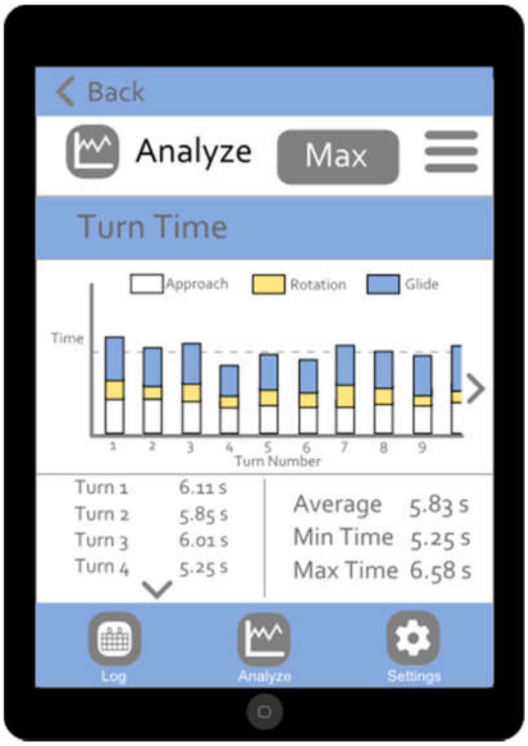

Figure 6.7. Sample storyboard image demonstrating the use of a tablet computer to visualise the data that have been collected by the sensor device.

After each scenario has been described, questions are put to the participant regarding their level of agreement with those aspects of the Use Case, using Likert type items.

A sample is provided in Table 6.2. Participants provided their level of agreement with the various statements and these responses were used to assess areas of the Use Case than need to be improved or altered. These questions related to various aspects of the Use Case, including the perceived importance of turns to swimming performance; aspects of system design, setup and use as well as an assessment of the relevance of the feedback that it was proposed to be provided. At each stage, an opportunity was provided for participants to talk freely, allowing them to expand on ideas and allowing the investigators to seek clarification on any aspect of the responses.

Table 6.2. Sample of the statements used to assess level of agreement after each stage of the Use Case.

Having read Section 7, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
I understand the procedures involved when collecting data during swimming using the sensor units					
Using the devices would not hinder my ability to carry out my normal training session with my entire swimming squad					
I would be comfortable carrying out these procedures myself and without any assistance					

Please wait for further instructions before reading any further.

6.2.5 Data analysis

Data analysis was performed using Statistical Package for the Social Sciences for Windows (Version 21, SPSS Inc., Chicago, IL). A p-value of 0.05 was set for all statistical analyses. Data from the Likert type items were scored from 0 (strongly disagree) to 4 (strongly agree) for each question and collated to produce the descriptive statistics for each question. The System Usability Scale (SUS) was also included at the end of the Use Case [34]. The SUS includes ten statements, to which respondents provide a level of agreement on a five-point Likert scale. Responses are scored on a range from zero to one hundred, with a higher score indicating a higher agreement [34]. This is an established process for measuring subjective assessments of usability [35] and provides a benchmark from which to compare results in the present study with other devices. Data for Likert items are presented using diverging stacked bar charts, as recommended by Robbins and Heiberger [36] as the most appropriate way of presenting the results of rating scales such as Likert scales. Using this method, positive and negative responses can readily be distinguished and the responses for different statements easily compared using the layout and colour scheme.

6.3 Results

The average score that was achieved for all statements included in the final revision of the Use Case was 3.4 ±0.2 (N = 29). This is on a five point Likert scale from 0 (strongly disagree) to 4 (strongly agree), indicating a very high overall level of agreement from respondents to the concepts outlined in the Use Case. 92.9% of total responses across all areas were ranked as either agree or strongly agree and on only 12 occasions (1.5%) did a respondent disagree or strongly disagree with a statement. The overall median score was 3.5 and the mode score was 3.6. The minimum average score received for an individual statement was 2.8, which related to the statement *"I currently have a method for measuring the quality of my swimmers' turns"*. The maximum average score of 3.9 was achieved for the statement *"Turns are a very important aspect of overall swimming performance"*.

A summary of the changing level of agreement amongst study participants to each revision of the Use Case is provided in Figure 6.8. It can be seen that the overall level of agreement was quite high at all stages, but that the spread of scores reduced for the final version of the Use Case. Additionally, higher maximum and minimum scores were also achieved due to revisions that were made.

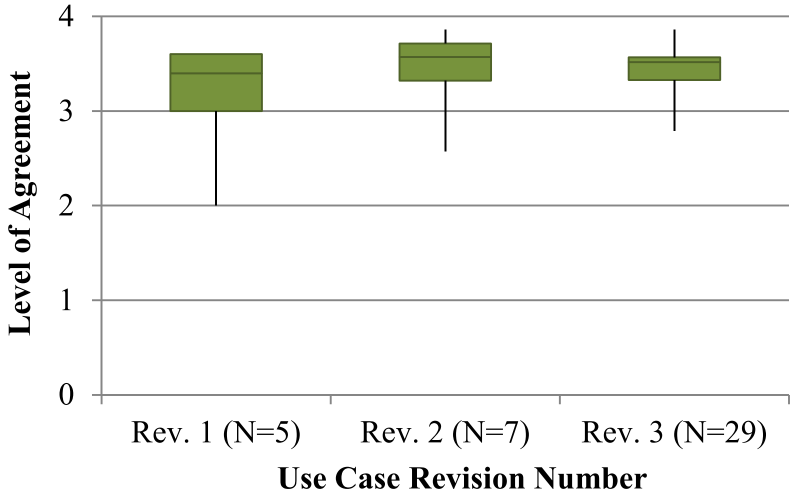

Figure 6.8. Box plot summarising the changing level of agreement amongst study participants to each revision of the Use Case. The formative stage comprised of revisions 1 and 2 whilst the summative phase comprised of revision 3.

6.3.1 Importance of turns

It is a fundamental consideration for the design of this system that the analysis of turns is considered to be a key area of interest to coaches. This is necessary in order to back up the findings in the literature and to provide justification in the system concept. Figure 6.9 provides a summary of the level of agreement of respondents to statements related to their perception of the importance of turns; the value of analysing turns and the methodologies used for such analyses. The results indicated a very strong level of agreement that the analysis of turns is important to coaches and that a system that can be used for this purpose would be of interest to them.

> *"I always tell my kids that 60% of a race is swimming, the other 40% is starts, turns and finishes – with turns being the main one."*
>
> [Male, 35 years' experience; swimmer ranked in top-25 in world]

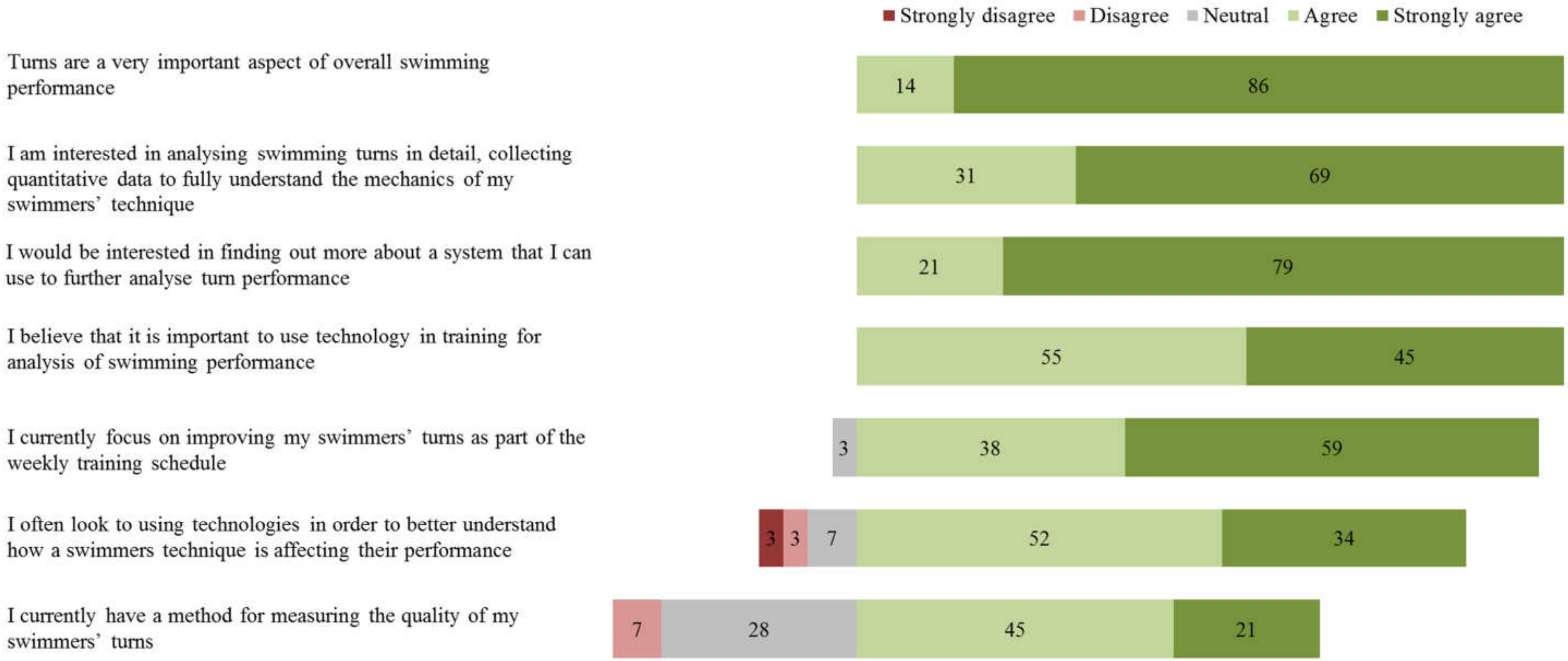

Figure 6.9. Respondents' level of agreement related to the importance of turns in swimming. All numerical values reported are percentages.

Some disagreement was found with statements related to current coaching practices, which indicates a level of dissatisfaction with currently available systems and methods for quantitative analysis of swimming performance. This was confirmed through follow up questioning, with coaches citing the time required to complete quantitative analysis as the major limiting factor. An additional reason, common to some coaches of younger age-group swimmers, for not conducting this type of analysis was that their squad of athletes was not at a sufficient level to warrant that level of analytical detail into their performance.

6.3.2 Description of system utilization

The system was described to respondents at various points throughout the Use Case. Figure 6.10 provides the level of agreement with various statements related to the proposed components of the system. The results appear to indicate that the system design as proposed would meet the coach's requirements in terms of the physical components involved for data collection, visualisation and analysis, with only limited neutral or negative responses received. Three respondents indicated neutral agreement with the proposed head-mounted positioning of the sensor device. Additional commentary from respondents regarding the head location elicited two categories of response. Firstly, many respondents remarked that a head position is suitable from the point of view of comfort and wearability issues, such as the convenience for swimmers and the minimal interference with normal swimming that would be expected with this sensor location. Other respondents focused on the technical aspects associated with a head-mounted device, such as how the flip turn is initiated from the head and how the movement of the head during a turn would be representative of the movement of the whole body during rotation. Respondents' level of agreement with how the system would be used can be further explored by analysing the questions related to (i) their understanding of the procedures involved in using the device; (ii) how comfortable they would be in carrying out these procedures themselves and (iii) their perception regarding how much of a hindrance to normal training use of the system would represent. These results are summarised in Figure 6.11.

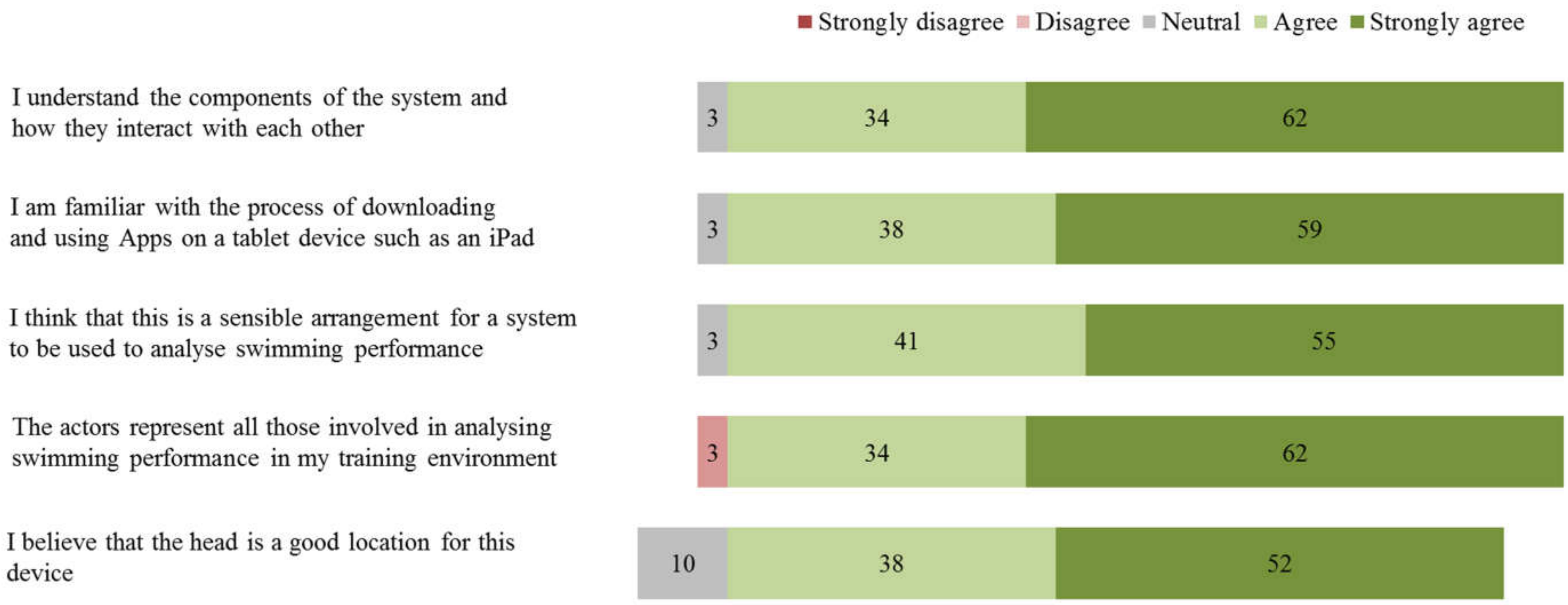

Figure 6.10. Respondents' level of agreement related to the description of the components of the system. All numerical values reported are percentages.

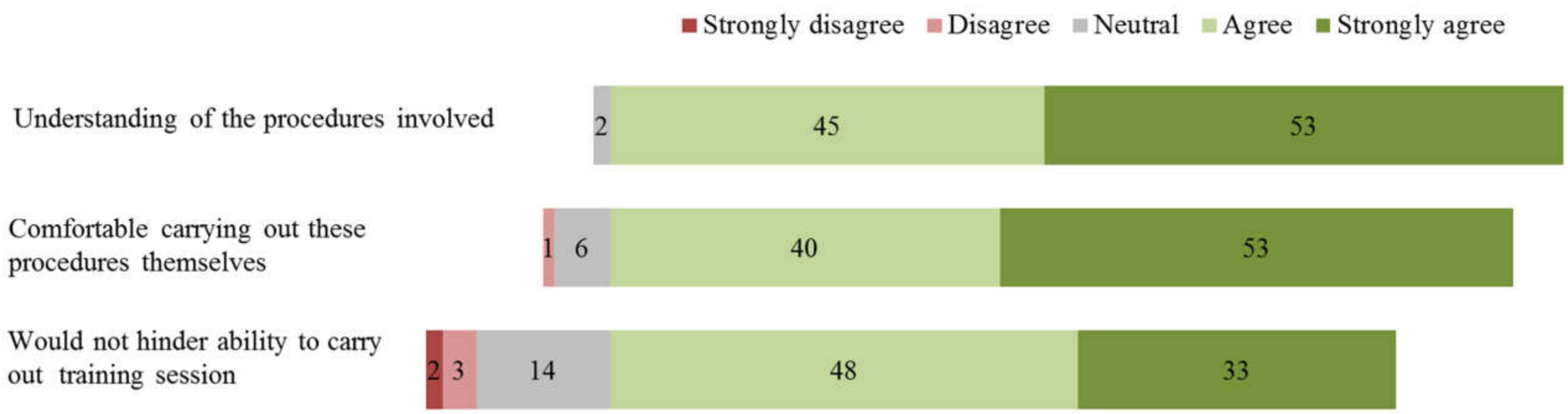

Figure 6.11. Respondents' level of agreement related to the system utilization and their perception of how they would feel when using the system in their own training environments. All numerical values reported are percentages.

It can be seen in Figure 6.11 that there is a high level of agreement regarding the respondents' understanding of the procedures required to use the device as they were described in the Use Case (98%) and their confidence in carrying out these procedures without assistance (93%). 81% agreement was reached that the system would not hinder the ability of a coach to carry out their coaching role. This was further explored and the reasons for this are that any form of analysis is deemed to be inherently distracting during a normal training session. Additionally, it was felt by some coaches that if large swimmer numbers were involved there may be time lost in setting up the devices for use.

> *"It's going to take time away from your job; you can't get away from that fact. But if it is important to you…then I will prioritise what I do."*
>
> [Male, 40+ years' experience; swimmer ranked in top-25 in world]

6.3.3 Quantitative feedback

Figure 6.12 provides the results of coaches' feedback to statements which explored the respondents' perceptions of the appropriateness of the quantitative performance related parameters included in the system concept which they can use to analyse turns performance. The results indicate a high level of confidence that the proposed system would provide the type of data that are of interest to coaches (96%). 82% of respondents felt that the proposed device does offer an advantage, largely because of its capacity to provide this quantitative data. Some negative opinion was received for the statement *"I believe that the swimming sensor unit offers an advantage over other methods of analysis"*, with four respondents neutral to this statement and one respondent strongly disagreeing. When further explored, a common perception from these respondents was that the quantitative data provided by the sensor unit must be taken in context and that a large emphasis should be put on the coaches' own subjective opinion of what is considered optimal technique based on their experience and observations.

"[The] data needs [sic] to mean something to me. So I think that rather than just having the data it would be very important to understand how that data [sic] correlated with what I have observed."

[Male, 10 years' experience; swimmer ranked outside top-250 in world]

The overwhelming majority (26 of 29 respondents) were also in agreement that an accuracy of one tenth of a second (0.1 s) would be sufficient for their needs.

"I am happy with the accuracy [of 0.1 s]. To me it is well within the parameters of what you are looking for."

[Male, 40+ years' experience; swimmer ranked in top-25 in world]

"I know that times are being measured to [0.01 s], but we're not going to be able to make a visual or a coaching change beyond a tenth of a second (0.1 s) with a swimmer."

[Male, 20+ years' experience; swimmer ranked outside top-250 in world]

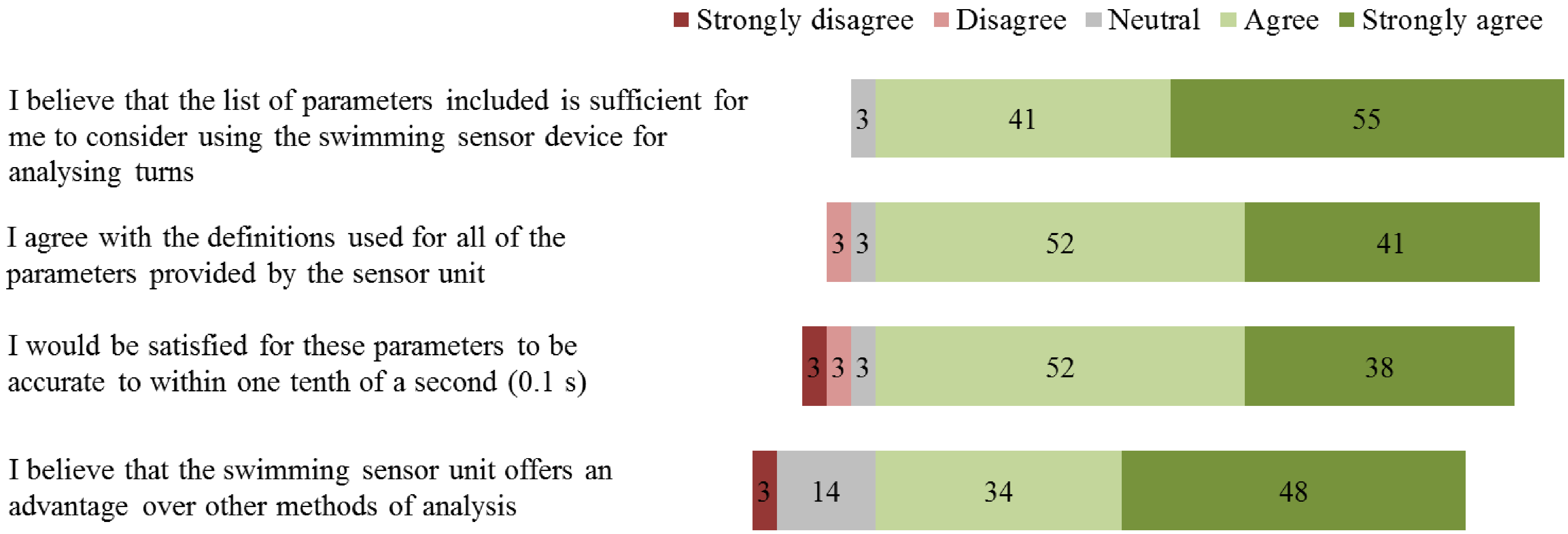

Figure 6.12. Respondents' level of agreement related to the parameters recorded by the device for providing quantitative feedback on a swimmers performance during turns. All numerical values reported are percentages.

6.3.4 Concerns raised

Respondents were prompted to highlight any concerns that they had with the procedures to use and interact with the proposed system as described in the Use Case. The concerns were recorded as open-ended questions to allow the respondents to express themselves fully and expand on any aspects that had been discussed during each stage of the Use Case. The results of this process are presented in Table 6.3. Concerns were collated, categorised and sub-categorised in order to determine common themes between respondents and assess the frequency of response for each category.

It can be seen in Table 6.3 that common concerns exist, which can be grouped into five categories. The main concern relates to time, which previous research has shown is a major issues for coaches [3]. These time-based issues can be related to the time required to carry out the various processes to obtain data and provide feedback as well as a concern regarding the need for real-time feedback to be incorporated into the system. Other categories of concern include various issues related to the value of quantitative data as part of the coaching process; specifics around the context of use for the system; technical issues and financial concerns.

Table 6.3. All areas of concern as highlighted by the survey respondents. Responses were categorised into five thematic areas and further sub-categorised as necessary in order to evaluate the frequency of response for different aspects of the system.

Category	Sub-category	Issue(s) raised
Time	Time involved to use the system	*"I would have a question about realistically how much time for setup and retrieval of the unit with or from the swimmer…we talked about how it becomes kind of an analysis session that is separate from training that you have to kind of take a break from the flow of what you are doing to get it setup."* *"It might take a long time to do the analysis and to review the data. The configuration process might take a while too."* *"Maybe the only thing I don't know yet is how quickly I can give them the information back – it looks like it is pretty quick."* *"I guess the only other thing I would say is the time involved, it sounds like it is quick, but I have been told that by other people too with certain things. Until I would see it, I would need to see it in action before I would feel comfortable with it, if it is definitely faster than some of the other things that I have tried."* *"Let's say I have ten [swimmers] and I am going to take all that data and then I am going to spend the rest of my day analysing it – am I going to be able, am I going to have the time to do that?"*
	Real time capability	*"Related to [another concern raised regarding time] would be the fact that it's not real time."* *"If I could look at this information live…I am buying the product tomorrow."* *"In my opinion the primary weakness of the product is the lack of real-time feed-back to the swimmer while wearing the device (e.g. vibration to indicate slowing velocity during Glide Time to help the swimmer learn the feel for the point where forward velocity starts to decrease indicating it is time to initiate underwater work (kicks or hand separation). By providing real time feedback the swimmer could use the device daily and thereby increase return on investment."*

Quantitative data	Over-reliance on quantitative analysis practices	*"[The] data needs [sic] to mean something to me. So I think that rather than just having the data it would be very important to understand how that data [sic] correlated with what I have observed."* *"I would have a concern about using the system in isolation, putting too much emphasis on the data if you know what I mean. I really like that it gives such detailed quantitative information, but that information would need to be put in context, like if it was integrated with some footage for example."* *"I do like technology, but I don't want to just coach numbers, I do want to rely a little on the qualitative side of things as opposed to just quantitative – I mean I would personally pair it with video from a race or from that training session.* *"It just so happens that I am working on using video to focus on turns – particularly flip turns. This will help analysing the techniques used."*
Context of use	Swimmer skill level	*"The value of the system really depends on the swimmer's level. I don't see this being a device that would have relevance for a younger, developing swimmer. I see it more as a tool for more elite athletes"* *"It's just trying to figure out who is going to use it."* *"I think to review like we have mentioned, if you are going to use this device to measure turns typically one day out of two weeks, [swimmers] are automatically going to try to do better turns."*
	Incorporating the system into current coaching practices	*"My only concern is - is it like a gadget that someone is going to get…and they don't use it properly so they…use it for the first six sessions and then they are not really using the data."* *The [concern] would be to actually measure it during a race or race pace major competition which you can't really on a major scale."*
	Initial training required to understand how to use system	*"I would need to use the system myself early on, to be sure that I am comfortable using the system, before I would let my swimmers use it."*

		"I don't know the method used to collect all the data."
	Data protection	*"There wasn't really anything that concerned me at all – it was just, the information staying in safe hands and things like that – that would be all."*
Technical	Sensor design	*"The clip. It really comes down to the stability of it. If I could see that it securely stayed on there. In looking at the way the clip is designed…it looks similar to the Tempo-trainer from Finis and I know placing that on the cap had issues- that it slips around and it comes undone because of tight streamlining."* *"[Swimmers] having electronic devices on deck! Dropping them, you know. That would probably be the biggest thing of everything that I have seen up there is that durability of that device. If I had to say anything - that would be my primary concern."*
	Accuracy and reliability of data	*"I think just verifying the accuracy and making sure that there is accurate information"* *"The only concern that I would have is… is the information we are getting valid and reliable."*
	Sensor location	*"I am not sure about the head position and if how movement of the head relates to movement of the body."*
	Wireless connectivity	*"It would just be with the Bluetooth sync'ing and things that are down the road from here."*
	Parameter definitions	*"The [concern] would be the three stroke [definition] that we talked about."*
Financial	Cost	*"The only thing that would ever concern me, if this thing was ever commercialised, would be the price."*

6.3.5 Key advantages

Understanding the perceived key advantages of the system is important as it can help to inform design decisions at a later stage and ensure that the device delivers in these key areas. These can also confirm that the key features proposed in the Use Case are of interest to the potential end users. As shown in Table 6.4, the advantages can be categorised in a similar way to the concerns, with four of the five categories replicated. It is interesting to compare these perceived advantages with the concerns raised. The most frequently perceived advantage that was provided related to the appeal of being able to measure quantitative data for analysis, with 13 respondents highlighting this area. Four respondents had noted that this quantitative information alone was a concern and would not be sufficient to perform a full analysis of turns and that the context of the analysis is also very important, which can be best achieved through video recording of the swimming.

Interestingly, the comments of seven respondents pointed to the time involved to use the system and provide feedback to swimmers as being a positive aspect of the system and was considered adequate to suit their needs. It may also have been reasonably assumed that similarly grouped coaches would have the same opinion, for example that the very elite and successful coaches would be the ones who prefer real time features. However, this was not borne out in the data. A broad consensus of opinion was found across all respondents; with a very closely matched level of satisfaction with the various system design features and the procedures involved with using the system.

Table 6.4. Aspects of the system that were highlighted by the survey respondents as the main advantages of the system. All responses were categorised into four thematic areas and further sub-categorised as necessary in order to evaluate the frequency of response for different aspects of the system.

Category	Sub-category	Issue(s) raised
Quantitative data	Appeal of quantitative data for analysis	*"The quantitative recording of data components that comprise the individual and collective pieces of swimming motions is very nice to have for comparison, analysis, training and coaching. If we can get this quantitative information about the specifics of the mechanics of what is going on, that would be wonderful; how great to be able to take the coaching up to that level."* *"The idea of having hard data rather than just observation is very appealing."* *"I am strongly interested in analysing the details and the data."* *"The level of detail provided would be great – that really appeals to me as a swimmer as I like to know this information."* *"I can collect data for quantitative analysis."* *"I like the idea of learning how to analyse and measure swimmers very accurately."* *"Just the amount of data that is there would absolutely immediately appeal to me because I like numbers, and it is things that I can show the athletes."* *"I just think the ability to look at hard data and say look, this is the time of your turn when you do it this way, this is the time of your turn when you are doing it that way and this is something that you need to consider."* *"I think the timing of the turns throughout the course of the event, seeing the second turn compared to the fourth turn or something like that is going to be the major difference because for example in a 200 [yard event in a 25 yard pool] it is often laps 5 and 6 that are going to be the slowest and to prove that with this data [sic] would help a lot."* *"I think probably breaking down the timing for each of those actions into the wall. Those specific parameters that*

		are being measured on the wall." *"For me I think the appeal would be to have measureable standards for each athlete… It sounds like you are able to collect a lot of data points with, frankly, not a lot of effort."* *"Timing the various parts of the turn is important – it will let me know where to focus changes with each swimmer."* *"It is the breaking down of the turns into all of those segments, because it is not just a single element – I love being able to say ok, how many kicks, how long was that glide, what was that turn rotation – all of those add up and some [swimmers] might be really good at the rotation but really terrible on their push-off or their kick."*
Time	Time involved to use the system	*"I think it is the real fast turnaround time of the data; it's the greater accuracy than a coach's stopwatch. For me the greatest limiting factor [with existing practices of analysis] is that I can do things accurately but it is making sure the feedback has the impact and by the time the swimmer has left the building it is too late."* *"There is no requirement for video to be setup so I can get the information faster."* *"The fact that I can get this information so much easier than I would be able to using video. I can get the information faster and with less effort on my part."* *"I think just the ease in response time to be able to give instant feedback. I think as a society we are all about instant feedback these days, nobody has patience to wait and so being able to have that access is really intriguing to me."* *"The immediate feedback – you know being able to take that data and within a very short period of time being able to pull that swimmer out and show them immediate results, I would call that immediate results versus me having to take a video like I do now with race analysis it's very cumbersome to do multiple swimmers and then supply that information with them. Immediate feedback is absolutely critical."* *"This is great as it would save me a lot of time because now if we are doing timed turns now it has to be one person at a time and it is very tedious so this would be fantastic and I could do it in combination with video and we can learn a lot in a very quick period of time and actually make changes in the same session."*

		"It seems to be timely… it is so important now to give feedback as soon as possible and so I think with that, with the information is uploaded and you can look at it pretty quickly and you could talk to [the swimmer] on the side of the pool-deck if you wanted to."
Context of use	Ease of use	*"It seems to be user friendly and would be good to have."* *"It seems like it is a turn-key [device]… we give [the swimmers] the sensor and off we go."* *"It sounds great and it sounds simple enough for most coaches to be able to follow along and do. It kind of appeals to me in general because I could just give it to my assistants and just say here do this and I could continue coaching or videoing or something else."* *"The ease of use, for the amount of technical data that it appears that you can get."*
	Specific to analysis of turns	*"What I like about it is that it is doing something very specific [to the analysis of turns] which is, especially swimming [in a short course pool], is very important."* *"The breakdown of the turn. I love that there is all those different components…because I don't have a way to do that easily, currently. This lets me tell [a swimmer] which specific parts of their turn are good and which specific parts we can improve"* *"I think the breakdown of the different segments of a turn definitely appeals to me – that is something that I do quite often and sometimes I have been told that I over analyse by doing that but I don't feel like it is, I feel like it's just like a stroke technique – you are breaking it down to what's the hand doing at the top, what's the hand doing at the bottom and in between – it's the different components that make it up."* *"The opportunity to improve, especially for short course swimming. I mean any turn is important but we swim short course yards over here and short course metres a lot – and [turns] can be 60% of the race, so I am so excited to see that we can tackle in a very scientific manner how to improve."*
	Comparison between swimmers	*"I can get an accurate and fast representation of how a swimmer is doing relative to other swimmers and more importantly…there is an historical analysis that can be done…so I can demonstrate to [a swimmer] that he is or is not improving in his turn capability as well as looking within a particular swim to the decrement of turns or to the*

		fact that they are staying static and that has a tremendous amount of value." *"I think the other very appealing part for us and for our team would be that competition aspect between, you know, this is what your team mates are able to do, where do you stand compared to your peers."*
	Involvement of different people in analysis	*"The fact that the information gets sent to other people at the same time like your scientists…so they can all measure it and see it as well as the swimmer."*
	Multi swimmer analysis	*"I like the fact that you, be able [sic] to monitor multiple [swimmers] and then have that information quickly so that."*
	Training tool versus analysis tool	*"It would make a good training tool if it was used on a regular basis."*
Technical	User interface	*"The presentation in graph form and the visual evidence that you can see and show it to the swimmer"* *"I really like the read-out after the session."* *"The ability to use a tablet or laptop is very appealing."*

6.3.6 System Usability Scale

The System Usability Scale (SUS) was included as part of the Use Case in order to get an overall satisfaction rating for the design concepts presented. The SUS is scored on a scale, with 100 the maximum score achievable. The SUS allows for the current system design to be compared against benchmark values achieved from a range of different products and areas of industry. The final version of the Use Case achieved an average SUS score of 79.4 ±12.3. The average SUS score also increased between formative and summative phases (Figure 6.13). McLellan et al. (2012) suggested that a score of less than 65 can be considered as "not acceptable", between 65 and 84 is "acceptable" and 85 or greater is "excellent". This would suggest that the current system design has performed well, albeit with a caveat that this is a concept Use Case so users do not have hands on experience of the procedures and interactions involved. Therefore other potential issues that may arise when physically using the device are not taken into account which could affect the overall result. That said, the SUS score achieved for the concept device could be directly compared with the score achieved after a prototype device was used by coaches, providing directly comparable results of the concept and physical product and could serve to highlight specific areas of concerns for end users and technical limitations of the system.

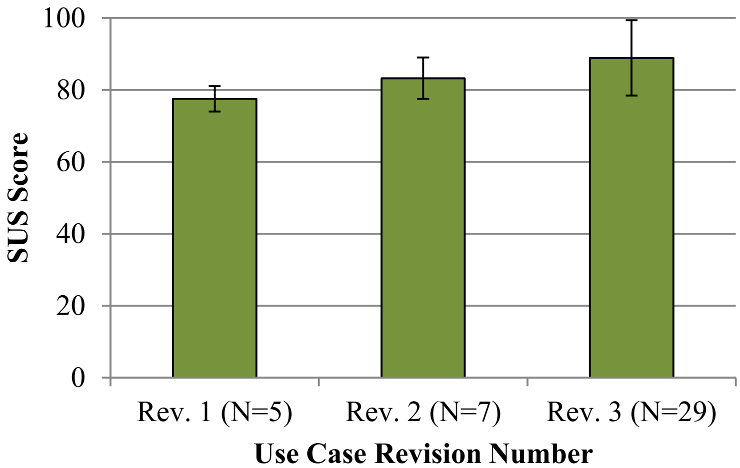

Figure 6.13. Summary of the changing scores achieved on the System Usability Scale for each revision of the Use Case.

6.4 Discussion

The aim of this paper was to describe the development and evolution of a Use Case that details the concept for a system for the analysis of swimming turns. The results presented show a positive level of agreement with the system concepts, the system design and a good understanding of the procedures and interactions involved with using this system. This would appear to indicate that the multiple iterations of the Use Case that have evolved as part of this process have adequately responded to the views of potential end users of the system and that the system concepts do meet user requirements and that the context of use has been established and verified by the respondents of this study. Three specific objectives were also established in order to focus the research effort on important system concepts that will ultimately inform future development work. The objectives are discussed below and changes that were made to the Use Case in an attempt to achieve these objectives are also examined.

Objective 1: Is a system that is designed for the quantitative analysis of swimming turns of interest to coaches?

It has been confirmed that coaches do regard turns as important, they do focus on improving their swimmers' turns frequently and they are interested in using technology for quantitative analysis of turns (Figure 6.9). This finding is critical as it provides justification for the system concept presented in this Use Case. At a fundamental level, it is an essential user requirement that the user is interested in what the system does, irrespective of how it looks or how it is operated.

It is well established that existing technology, such as video-based methods, are not adequately servicing the needs of coaches and that this is limiting the extent to which quantitative practices are being performed [3, 9]. As a consequence, current methods employed are mainly focused on the use of a stopwatch, observational techniques or the use of video for qualitative analysis. This would suggest that a need exists in the swim coaching community but this need is not currently being adequately addressed using existing technologies. Therefore, a system that can be used for quantification of key parameters related to the performance of turns may be relevant to coaches, but this system must overcome the limitations of other technologies – which mainly relate to the time involved in gathering meaningful data.

As shown in Figure 6.11, respondents were asked to state their level of agreement with how well they understand the procedures involved in using the proposed system; how comfortable they would be carrying out these procedures themselves and if they feel that using the system would hinder normal training activities. These questions were repeated after different points of the Use Case in order to isolate issues to specific stages of use. Although there is a perception that any form of analysis is inherently disruptive to normal training, the responses obtained were very positive for these areas. This is an important point in relation to the intended context of use of the device. Should the system be designed so that it can be deemed as a training tool, as opposed to an analysis tool, then it is postulated that this would increase usage rates.

Changes were made to enhance the system usability during the evolution of the Use Case. An early revision of the Use Case described how the system would be operated with one coach working with a squad of swimmers. This was done as it was initially envisaged that the processes involved could be managed by a single person. However, a poor level of agreement was received on this point. Coaches suggested that they are likely to include additional personnel when analysing performance in their own environments, such as an assistant coach or a sports scientist. It is important to note that this question was put to respondents prior to describing the current system so this negative feeling may be a response to current methods of analysis, such as video, which will often require additional personnel due to the time and logistical constraints involved. However a change to the Use Case was made to include two coaches and this resulted in an increased level of agreement; with an average score of 3.6 ± 0.7 achieved (Figure 6.10).

There would appear to be a perception that any form of quantitative analysis is inherently time consuming and will distract from normal training procedures. As a result of which, a coach will need extra support in order to be able to conduct data collection. An additional consideration is that the size of the swimming squad may dictate the numbers of coaches/support personnel required. The Use Case describes a system that is intended to be used by multiple swimmers simultaneously and in this case a coach may perceive that this would require more than one individual in order to manage the process.

Further changes were made related to the way that devices are allocated to the squad of swimmers. In an early iteration, the devices were largely handled by the coach as part of the poolside setup, with the coach heavily involved in turning the unit on, attaching the device to the goggles and ensuring the devices were correctly positioned before data collection commenced. Several coaches commented on this, with concerns about dealing with large squad numbers and how this would effect a training session. Consequently, changes were made to involve the swimmers more in getting the devices ready to be used. It may also be possible to carry out these procedures without the requirement for the swimmers to exit the pool, thus further speeding up the process and helping to integrate the system into normal training activity.

Finally, a change was made to increase the functionality of the system so that in addition to having devices pre-allocated to squad members, devices could also be used interchangeably between swimmers. This issue was raised as a concern regarding the costs associated with needing to purchase multiple devices. In this context, additional steps would be involved as the coach would be required to keep track of which device is used by which swimmer and when data are synchronised with the App the coach would then need to assign the data retrospectively to a particular swimmer. However, this issue was not raised again by subsequent respondents once the change had been made.

Objective 2: Is there agreement from potential end users that the head is an acceptable location for this system?

Various body locations were considered for the positioning of the sensor unit, with advantages and disadvantages associated with each. These include the head, chest, upper back, lower back, wrist and ankle. The most frequently described locations in the extant literature include the wrist and lower back [10]. For the analysis of turns, the wrist can be excluded as the movement of the arms is not representative of the rotational movements involved. The lower back can be considered a good option as it is located close to the centre of mass. However attachment solutions that involve a swimmer wearing a belt will cause unwanted drag effects. A custom designed swim suit with a pocket for the sensor unit would alleviate this issue, but interestingly comments from some coaches raised concerns regarding inappropriate physical contact between the coach and swimmer if assistance were needed when positioning the units at this location. Additionally, a custom designed suit would also add additional complexity to the system and reduce its universality.

When considering the best location, it is important to balance comfort issues with technical concerns. From a comfort point of view, positioning the device at the back of the head, under the swim cap is an ideal location as it is unobtrusive and will not interfere with the swimmers movements in any way. Additionally, coaches remarked that a flip turn is initiated from the head, and the head is also used by coaches when timing a turn using a stopwatch or video. It is unsurprising therefore, that 90% of respondents agree or strongly agree that the head is a good location for the device (average score 3.4 ± 0.7) (Figure 6.10). Interestingly, coaches' remarks highlighted both the comfort and technical issues when further questioned, although the majority leaned towards comfort as the main issue. This location also resonates with coaches who are familiar with other devices such as the Tempo Trainer (FINIS USA, Livermore, CA, USA) which is head mounted.

A change was made to the attachment method of the device as part of the iteration process of the Use Case. Initially, the device featured two guide holes through which the goggle straps would be fed (Figure 6.14a). In response to user feedback regarding the ease of use and time required to do this, it was changed to a clip-on device (Figure 6.14b).

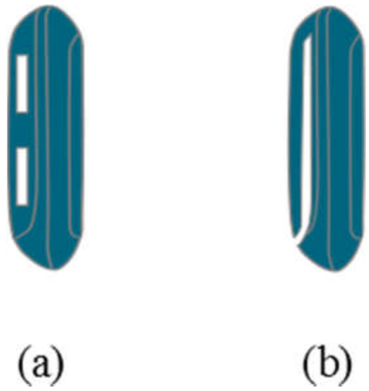

Figure 6.14. Changes to the sensor unit attachment method.

<u>Objective 3: Can a list of quantitative feedback parameters be defined that are appropriate for the analysis of swimming turns?</u>

The parameters that the sensor unit will measure are important to define and will have clear implications for algorithm development. It is vitally important to understand what can be regarded as a suitable range of feedback parameters, from a coaching point of view, and how these parameters should be defined. The results presented in Figure 6.12 show a positive level of agreement to the parameters included. However, several amendments to the Use Case were necessary to achieve this result, as outlined in Table 6.5. These changes were based directly on respondents' feedback to the Use Case.

The most important change made was to the *Turn Time* parameter. This is defined as the time from the start of the third last arm stroke on approach until the end of the third arm stroke after push-off. Originally only one arm stroke on either side of the wall was included in this definition. However, additional strokes were deemed necessary as respondent feedback suggested that these arm strokes are important to thoroughly assess the quality of a swimmer's technique. Another change to the parameters was the inclusion of a new variable, *Kick Time*, which was added during the evolution of the Use Case. The number of kicks performed after push-off and before stroke resumption is a key parameter for developing fast turns. However, it is not just the number of kicks that are performed but also how long it takes to perform them that are relevant.

Table 6.5. Revisions made to the definition of terms for each of the feedback parameters.

Parameter	Original Definition	Revised Definition
Turn time	Time from last arm stroke on approach to first arm stroke after push-off	Time from the start of the 2nd (Breaststroke / Butterfly) or 3rd (Frontcrawl / Backstroke) last arm stroke on approach until the end of the 2nd or 3rd arm stroke after push-off
Approach time	Time from last arm stroke on approach to wall contact	Time from the start of the 3rd last arm stroke on approach to wall contact
Rotation time	Time from initiation of rotation with head to wall contact	Time from start of last arm stroke to wall contact (Frontcrawl / Backstroke)
Wall contact time	Time from first contact with wall to push-off	No change
Hands to feet contact time	Time from first contact with wall with hands to first contact with feet (Breaststroke/ Butterfly)	No change
Glide time	Time from push-off to first dolphin kick	No change
Kicks off wall	Number of dolphin kicks performed after push-off and before stroke initiation	No change
Kick time	This parameter was not originally included	Time taken for the dolphin kicks after push-off from the wall to be performed
Breakout time	Time from push-off to first arm stroke	No change
Length time	Time to complete each lap performed	“Lap time” changed to “Length time” as a lap could be considered as 2 lengths of the pool.
Average speed per length	Average speed of swimmer (m/s) to complete each length of the pool	No change

No distance related parameters are included in the system design. This is because the unit is designed to monitor the movements of the swimmer but not those movements relative to any fixed point such as the pool wall. As such, it cannot be stated with any level of confidence that accurate measures of a swimmer's displacement can be made using this device. Surprisingly, this did not cause any issue for the respondents of the survey and no respondent referred to this as a gap in the feedback potential of the system.

A level of accuracy of one tenth of a second (0.1 s) is deemed satisfactory for this system. This can be regarded as more accurate than a stopwatch, which anecdotally is accurate to two tenths of a second (0.2 s). The sensor unit has an additional benefit of also being able to monitor multiple swimmers at the same time, which can be difficult when using stopwatches for timing turns. A 50 Hz video camera can provide a maximum resolution of two hundreds of a second (0.02 s), far greater than the proposed system. However, the key advantage of the proposed system is that this information is provided much quicker than would be possible using video and without the requirement for much processing of the data on the part of the user. Therefore the sensor unit, as described in this Use Case, would appear to alleviate the main shortcomings of the current most commonly used methods for quantitative analysis of swimming turns.

6.5 Conclusion

Turns are an important component of competitive swimming performance but the analysis of turns is difficult to implement in applied settings, largely owing to the limitations of existing methods. Wearable sensor based technologies offer a potentially new approach to allow coaches to conduct in-depth quantitative analysis of their swimmers turns. However, this remains an unexplored area in both research and commercials domains.

A User Centred Design approach has been followed based on the principles of ISO 9241-210 [21]. This has proven to be an effective framework for conducting a thorough assessment of the proposed system. The Use Case provided a common methodology for various potential end users, including coaches, sports scientists and swimmers, to provide input into the design of the different aspects of the system. These respondents were able to identify potential design problems regardless of explicit experience with the proposed technology or with usability analysis. The use of Likert scales allowed for constraints to be placed on specific aspects of the scenarios and interfaces that required feedback from respondents. Meanwhile, the use of open-ended questions allowed for expansion of respondents' thinking regarding key areas. Important user requirements have been elicited and the preferred context of use has been established following an iterative evaluation-driven process informed by end users.

The Use Case analysis has proven to be effective for a number of reasons. The analysis did not require any prototype development or specialised equipment to be used. This is important as there were some key concepts that required confirmation from potential end users, specifically the focus on turns; the head positioning used for the sensor unit and the range of feedback parameters to be included. These concepts were tested out and fully considered without the requirement for extensive development work to be carried out in advance. It is recommended that future sports technology development would continue to follow this UCD methodology in order to maximise end user satisfaction and increase the likelihood of the adoption of new technology into existing practices of analysing sports performance in applied settings.

This study has produced a proposed system design concept which has gained a sufficiently high level of agreement from potential end users to confidently state that the main objectives of this study have been achieved. This also provides justification for the development and validation of feature detection algorithms for the analysis of swimming turns from a head worn inertial sensor device. Full implementation of the proposed system has a high level of complexity, involving various components that need to be optimised for use in aquatic environments; a wireless interface; multiple signal inputs and a custom designed user interface.

Despite the efforts made to ensure a high quality and detailed presentation of the system concepts, the Use Case document remains limited by the fact that it is essentially a paper prototype and not a physical entity that a respondent can fully examine and interact with in a real world setting. This raises some limitations as to how a respondent can perceive the various stages of system utilisation. Additionally, despite the positive results reported, there remain a number of key concerns from potential end users. The main issue is one of time and it is imperative for wide scale acceptance of the system that the time required for using the device and obtaining feedback is minimised. It would be necessary to repeat the Use Case analysis with a functioning prototype system in an applied training setting in order to be confident that these issues have been adequately addressed and to re-assess end user satisfaction.

6.6 References

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Chapter 7 – Swimming Sensor Prototype Development

The work described in Chapter 6 of this thesis has demonstrated that a wearable, inertial-sensor based system focused on the analysis of swimming turns is of interest to elite coaches. Following multiple iterations of the Use Case, it was found that the final version received widespread acceptance from the study participants. There are various key components of this system that are of most importance in terms of delivering such a system. Of central importance is the capacity of the system to break down a swimmer's turns into various component parts for detailed examination – thus extending the use of sensor based technology beyond the generic, high-level feedback capabilities of existing systems (such as those described in Chapter 5) and moving towards a system that is of greater relevance in an elite setting. These component parts constitute the key performance parameters necessary for a thorough evaluation of a swimmer's performance of turns in each of the four competitive swimming strokes. However, existing systems described in the extant literature lack such performance capabilities. Therefore, the next stage of this process was to develop a prototype swimming analysis system which closely replicates the design and functionality described in the Use Case. The work completed in developing a prototype hardware platform is described below in Chapter 7 of this PhD thesis.

7.1 Introduction

MEMS based inertial sensor technologies have been incorporated into a number of analysis systems for use in aquatic environments [1-3]. A key advantage of this technology is that it has the capability of providing quantitative feedback to the coach and swimmer far quicker than traditional video-based methods, thus driving the recent expansion of research and commercial interest in this area of study. The majority of these systems are based on the use of accelerometer and gyroscope sensors and a range of swimming parameters have been reported and validated in the literature, such as stroke counts and lap times [4]. Consequently, many of the key hardware design considerations that are relevant for using these technologies in aquatic environments have already been well described in the extant literature [4]. The aim of this study is to leverage this existing knowledge in order to describe the development of a suitable hardware platform that can determine quantitative parameters related to the analysis of swimmers' movements, and specifically the analysis of swimming turns. This prototype device is intended to store the raw output signal recorded from a head-mounted position on a swimmer as they complete successive laps of a swimming pool.

As a starting point in the development of this prototype system, it is necessary to identify the important features to be included. These features are based primarily on the results of the User Centred Design study described in Chapter 6 of this thesis, as well as the in-depth knowledge gained from thoroughly investigating prior research literature in this area. The features relate to the technical specifications, positioning, size and attachment of the system itself, in addition to the functionality of the system and the output information provided. The specifications of the prototype system were developed from this list of features in addition to consultation with swim coaches and swimmers. A system that can meet all of the user requirements identified will provide detailed quantitative feedback to the end user about a swimmer's performance of turns in a swimming pool, information that is not currently available using a sensor based system. This chapter will focus on providing a comprehensive description of the functionality of a prototype sensor, in order to assess the suitability of the hardware platform for use in experimental data collection for swimming applications.

7.2 Prototype Hardware System Development

A prototype hardware platform was developed in order to record the swimmers' movements in the pool. The platform closely resembles many reported system designs used in research studies and available commercially [4]. The microcontroller used was the small but powerful Teensy 3.0 (PJRC LLC, Sherwood, OR, USA). The Teensy 3.0 is provided with a Freescale microprocessor (MK20DX128VLH5) that has a 32-bit ARM architecture. Specifically, it is a Cortex-M4 with DSP, 128 KB of program flash memory and 50 MHz of maximum CPU frequency. There are two types of communication integrated, the I²C and the SPI, that are used to manage the sensors and micro SD Card. Both communication protocols are used by microcontrollers for communicating with one or more peripheral devices rapidly over short distances. However, whilst I²C allows multiple masters and slaves on the bus, SPI can only work with one master device controlling multiple slaves. In addition, there is a MINI54TAN that is a small microprocessor used to support the USB communication, running up to 24 MHz with an ARM Cortex M0. By integrating both Teensyduino and Teensy Loader software packages into the Arduino IDE, it is possible to program the MK20DX128VLH5 using the micro USB connection. Moreover, the Teensy 3.0 has a total of 34 digital I/O and some of them have specific specializations, including 14 analog inputs, ten PWM (Pulse Width Modulation, used for obtaining analog results with digital methods), three UART units (ports for serial communication), one SPI, one I²C, one USB, and others functionalities. At the end of the board, there is a LED in the pin 13, and a reset button.

The microcontroller connects to various other hardware components as part of the prototype system design. The Inertial Measurement Unit (IMU) comprises of a tri-axial accelerometer and a tri-axial gyroscope. Raw, tri-axial acceleration and angular velocity data that are read by the sensors are stored in a buffer and transferred to an 8 GB microSD Card when the buffer is full. Data are then retrieved using a USB connection for post processing. A rechargeable polymer lithium ion battery (280 mAh, 3.7 V) is used to power the device. A MicroSD adapter has been used as the mount for the SD Card. Figure 7.1 provides a block diagram with an overview of the system configuration. Table 7.1 provides details of the specifications for both sensor components of the IMU, including resolution, range and sensitivity.

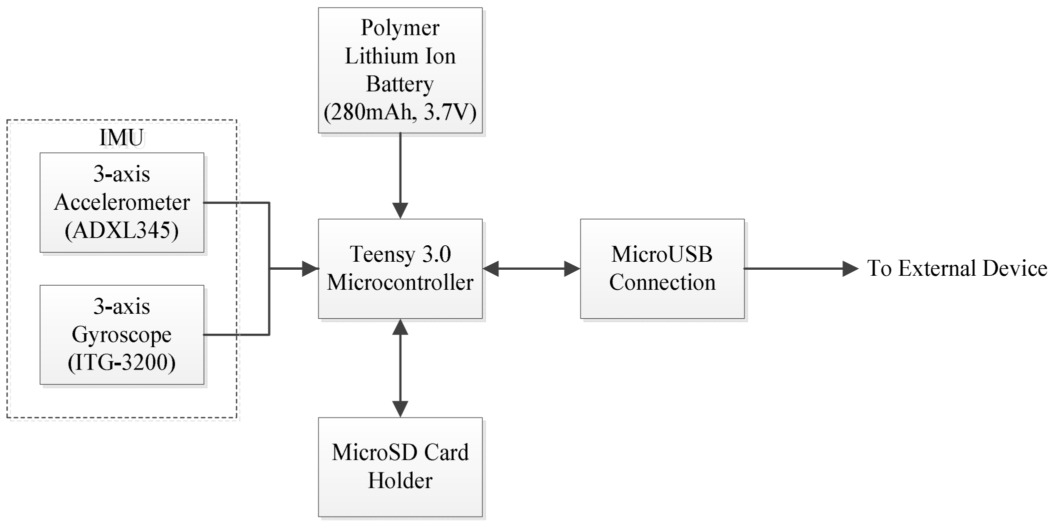

Figure 7.1. Block diagram of system hardware components.

Table 7.1. System specifications for the MEMS accelerometer (ADXL345) and gyroscope (ITG-3200) used in the prototype system.

Parameter	Accelerometer (ADXL345)	Gyroscope (ITG-3200)
Axes	3	3
Resolution	10-bit	16-bit
Range	±2 g	±2000 °/s
Operating Temperature	-40 – +85 °C	-40 – +85 °C
Sensitivity	256 LSB/g at ±2 g range	0.1°/s/g
Scale Factor	3.91 mg/LSB at ±2 g range	14.375 LSB/(°/s)
Nonlinearity	±0.5%	0.2%
Offset v. Temperature	±0.8 mg/°C	-13,200 LSB
0g Bias Level	±40 mg (X axis & Y axis) ±80 mg (Z axis)	

The system is housed in a low-profile plastic enclosure (Figure 7.2) with dimensions of 70mm x 51mm x 21mm (New Age Enclosures S1A-272008). The device is to be placed at the back of the swimmers head, under their swimming cap. For data collection purposes in a swimming pool, the prototype device is waterproofed using a re-sealable dry bag (LOKSAK Inc., Naples, FL). Testing of the device was also carried out using an electronics breadboard, with the same hardware configurations and specifications as described above. This allowed for rapid diagnostics of issues for debugging purposes.

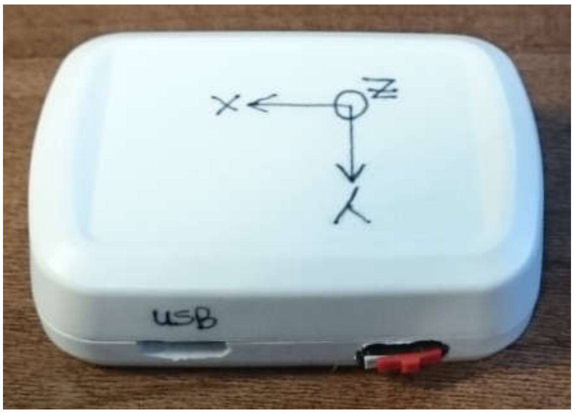

Figure 7.2. Image of the prototype enclosure.

7.3 Microcontroller Code Overview

The code for the microcontroller was written in C programming language using the Arduino IDE. The process is comprised of a setup stage to initialise and configure the sensor components and to call functions which have been declared as part of the program and a loop which continuously reads the tri-axial acceleration and angular velocity, and saves the values to an SD Card at intervals, as determined using an interrupt timer function. The loop continues indefinitely until the device is switched off. Testing of the device's functionality is achieved using the serial monitor that is built into the Arduino IDE, with additional testing using Visual Studio with the VisualMicro add-on to allow for Arduino programs to be run in the Visual Studio environment. A process flowchart for the data logging function of the prototype system is presented in Figure 7.3, as an overview of the process. Further detailed description of each stage of this process follows. A complete version of the microcontroller programming code is included in Appendix B of this PhD thesis.

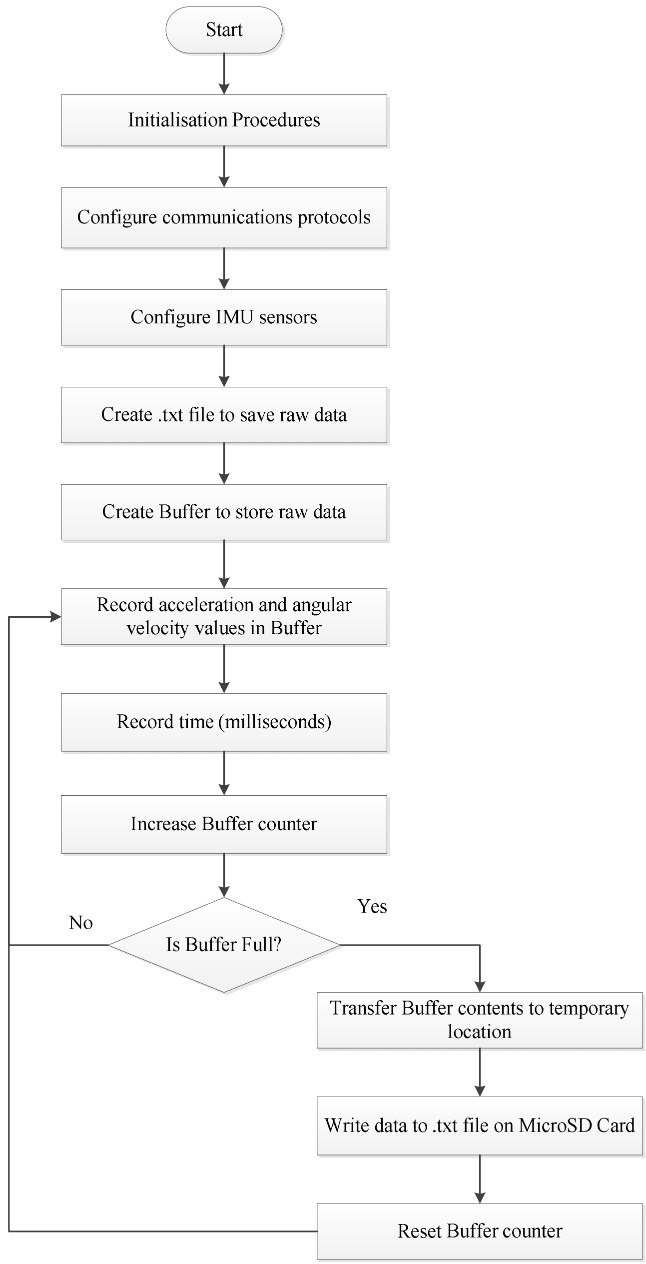

Figure 7.3. Process flowchart describing the data logging capability of the prototype device.

7.3.1 Initialisation Procedures

The first step in the programming code involves three steps, as summarised in Figure 7.4. Standard libraries that are needed for the correct functioning of the microcontroller must be included in the program, in addition to defining the size of a data storage buffer and creating an LED status indicator.

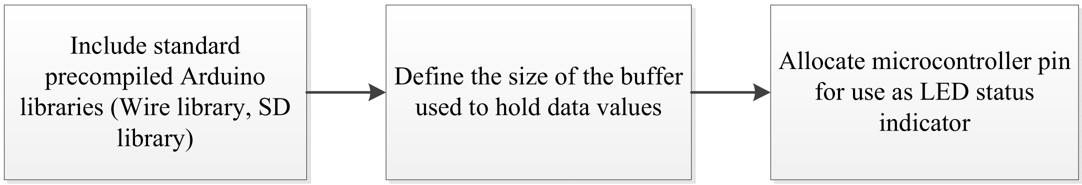

Figure 7.4. Initialisation procedures flowchart.

A number of libraries come installed with the Arduino IDE, including the Wire library and the SD library. The Wire library allows for communication with I^2C devices. The SD library allows for reading from and writing to SD Cards. The library supports FAT16 and FAT32 file systems on standard SD Cards. The communication between the microcontroller and the SD Card is via an SPI protocol.

A data buffer is required in order to allocate a portion of the physical memory storage to temporarily store data that are recorded from the IMU before the contents of the buffer are saved onto the SD Card. The size of this buffer is defined as a constant value (2,628 bytes) before the program is compiled. The buffer itself will be created later in the programme as part of the SD Card initialisation. When data are stored, there will be six gyroscope bytes, six accelerometer bytes, two control characters and four time characters, giving a total of 18 bytes. Therefore, 146 readings (2,628/18 = 146) will be stored in the buffer. The size of the memory that is allocated for this buffer capacity has implications for the amount of memory that is used and memory that is available for the program to run. When the program is compiled with the buffer size set to 2,628 bytes a total of 20,848 bytes (15%) of program storage space is used. The maximum available is 131,072 bytes. Global variables use 8,904 bytes (54%) of dynamic memory, leaving 7,480 bytes for local variables. Therefore, although the buffer size can be adjusted to suit the application, this needs to be considered carefully in order to allow for optimal performance of the prototype.

The final part of this stage in the process is to allocate a pin on the microcontroller that can be used as a status indicator during various stages of the device's function.

This LED will be used at various stages during the program and can be useful as a status indicator and also to highlight if errors have occurred.

7.3.2 Accelerometer Initialisation

Accelerometers, such as the ADXL345, measure acceleration and deceleration that is applied to the device in three dimensions. These MEMS devices operate on the principle of a suspended spring mass, such that when acceleration is applied, a small mass within the accelerometer responds by applying a force to a spring, resulting in compression or stretching. The displacement of the spring can be measured and used to calculate applied acceleration. The output voltage is proportional to the acceleration that is experienced [5, 6]. MEMS accelerometers such as the ADXL345 have been used frequently in swimming applications. During the accelerometer initialisation stage, various registers need to be defined in order to determine how the sensor will behave and hold data that represents the measured acceleration that is experienced. A summary of this process is provided in Figure 7.5, with details of the specific registers that are defined in the program subsequently discussed.

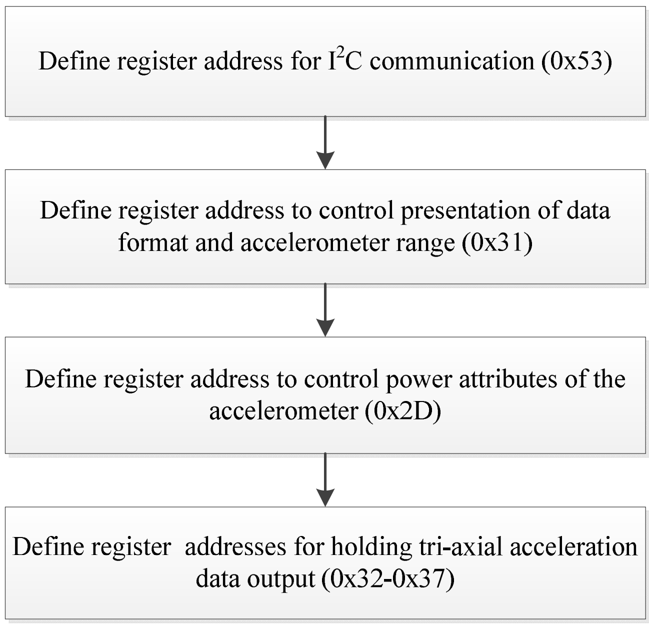

Figure 7.5. Accelerometer initialisation flowchart.

The first register that is defined is the accelerometer address during the I²C communication (Register 0x53). The microcontroller must be directed to communicate with either the accelerometer or the gyroscope when communicating with the IMU and this sets the address for the accelerometer. It supports standard (100 kHz) and fast (400 kHz) data transfer modes if the timing parameters are given in and are met. Single- or multiple-byte reads/writes are also supported.

Register 0x31 is used to control the presentation of data to Registers 0x32 to 0x37 (representing the tri-axial acceleration data, discussed below), as well as being used for setting the range of the accelerometer. The specific settings will be selected in the accelerometer configuration function and discussed further in that section. The range of the accelerometer can be set to different values according to the desired application. This will be done as part of the accelerometer configuration function.

Register 0x2D allows for power saving features of the device to be selected. This register is used to put the accelerometer into measurement mode when required. This will be completed in the accelerometer configuration function.

Register 0x32 through to Register 0x37 inclusive are six bytes which are eight bits each and hold the output data for each axis of acceleration, with two bytes associated with each axis. The output data are in two’s complement format, which is binary format that is used to represent signed integer values. Register 0x32 and Register 0x33 hold the output data for the x-axis. Register 0x34 and Register 0x35 hold the output data for the y-axis. Register 0x36 and Register 0x37 hold the output data for the z-axis. This is the end of the accelerometer initialisation step. The next part of the process is the gyroscope initialisation.

7.3.3 Gyroscope Initialisation

Gyroscopes, such as the ITG-3200, measure the angular rate of change, or angular velocity. The angular velocity is measured in reference to each of three axes, namely pitch, yaw and roll. The operating principle of MEMS gyroscopes is that a vibrating element is contained within a frame of reference. Rotation causes the element to vibrate out of plane, and this motion is sensed using a capacitor, with the output voltage proportional to the angular velocity experienced [6, 7]. MEMS gyroscopes, such as the ITG-3200, have been used frequently in swimming applications. During the gyroscope initialisation stage, various registers need to be defined in order to determine how the sensor will behave and hold data that represent the measured angular velocity that is experienced. A summary of this process is provided in Figure 7.6, with details of the specific registers that are defined in the program subsequently discussed.

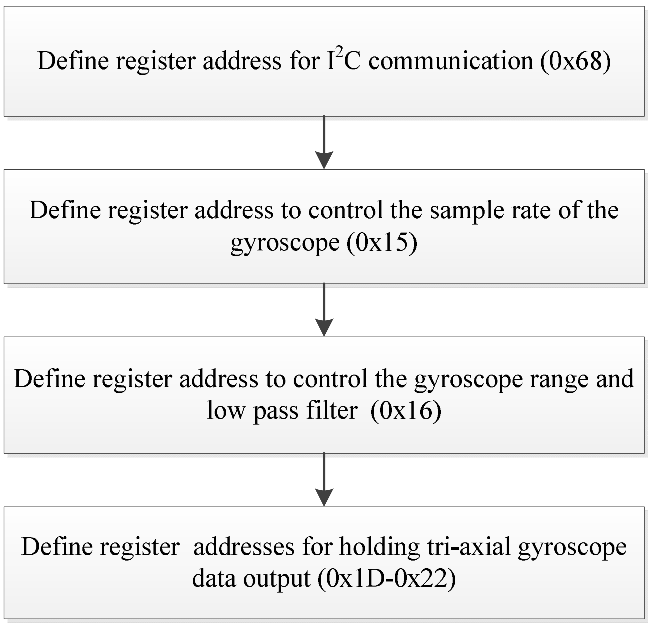

Figure 7.6. Gyroscope initialisation flowchart.

The first register that is defined is the gyroscope address during the I²C communication (Register 0x68). I²C is a two wire interface comprised of the signals serial data (SDA) and serial clock (SCL). With I²C communication, attached devices can act as either a master or a slave. The ITG-3200 always operates as a slave device when communicating to the system processor, which thus acts as the master. The maximum bus speed is 400 kHz. Register 0x15 is used to determine the sample rate of the gyroscope. The gyroscope outputs are sampled internally at either 1kHz or 8kHz. These samples are then filtered digitally and delivered into the sensor registers after the number of cycles, which are determined by this register. The specific sample rate used in this program will be selected in the gyroscope configuration function. Register 0x16 is required in order to set different configurations that are related to how the data are acquired from the gyroscope, including the scale range and low pass filter configuration. The specific settings used in this program will be selected in the gyroscope configuration function and discussed further in that section.

Register 0x1D through to Register 0x22 inclusive are six bytes which are eight bits each and hold the output data for each axis of angular velocity, with two bytes associated with each axis. In a similar manner as for the accelerometer, the output data are in two’s complement format. Register 0x1D and Register 0x1E hold the output data for the x-axis. Register 0x1F and Register 0x20 hold the output data for the y-axis. Register 0x21 and Register 0x22 hold the output data for the z-axis axis. This is the end of the gyroscope initialisation step. The next part of the process is the SD Card initialisation for data storage.

7.3.4 SD Card Initialisation

The next stage in the program involves the initialisation of variables that will be used for the SD Card function, in order to facilitate the transfer of data to the SD Card from the microcontroller’s memory buffer. A summary of this process is provided in Figure 7.7.

The first part is to configure the physical hard wired connection. The name of a control line on the SD Card used to facilitate the microcontroller to select and communicate with the SD Card in order to write data to the card is slave select (SS). A buffer variable is created (called *buf*). This buffer will hold values taken from the sensor devices, along with the time stamp of each reading, before they are written to the SD Card. The size of the buffer has already been allocated above in the initial step in this program. Another buffer variable is next created (called *bufTemp*). This is a temporary buffer that will be used to hold values taken from the sensor devices during the time when a write to the SD Card occurs, to avoid any loss of data during this stage of the program. An integer variable (*count_buf*) is created and is going to be used to know how much the buffer (*buf*) capacity has been used up. In the loop, *count_buf* will increment by one every time a reading from the sensors is taken. The size of *count_buf* can then be checked against the overall capacity of the buffer, to determine if a write to the SD Card is required or if the buffer has capacity remaining to accept further sensor readings.

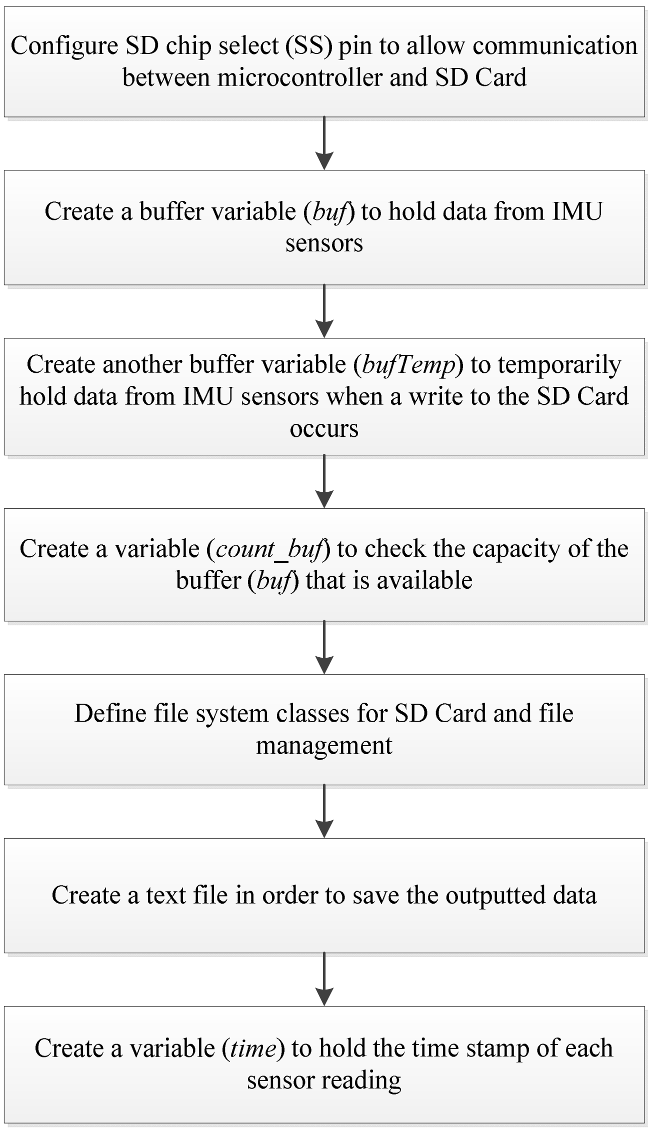

Figure 7.7. SD Card initialisation flowchart.

File system classes for the SD library are defined. These are required in order to start and stop transmission to the SD Card so that data can be written to the card. They are also required to create, open, close and write to a file on the SD Card. The output of the program will be a text file (*file_name.txt*), which is created next. The time of each sensor reading must be recorded to allow for analysis of the signal output and also in order to verify that the desired sampling rate has been achieved. A variable *time* is created in order to hold this temporal information. A pointer is used to manipulate the time data and will be described further in a later section of the program code, when it is implemented. This is the end of the SD Card initialisation step. The next part of the process is the function that will be used to configure the accelerometer for data logging.

7.3.5 Accelerometer Configuration Function

A function is created that will be called as part of the setup and is used to configure the accelerometer and establish the various operating settings, such as the range and data format. A summary of this process is provided in Figure 7.8.

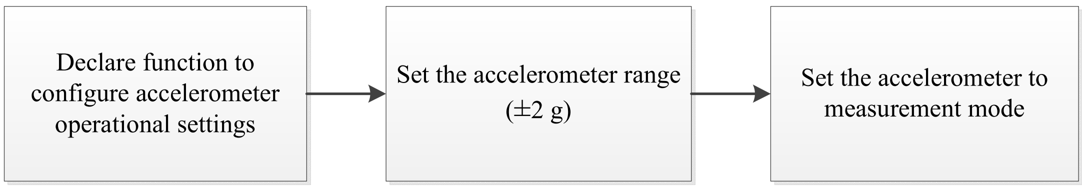

Figure 7.8. Accelerometer configuration function flowchart.

As part of this function the register addresses that were previously defined are configured to suit the desired application. This is done in order to set the range of the sensor. The range can be set to either ±2 *g*, ±4 *g*, ±8 *g* or ±16 *g*. Previous research has shown that a range of ±2 *g* is appropriate for swimming related activities [4, 8]. The accelerometer operates with 10-bit resolution, therefore the full scale range is 2^{10} = 1,024 levels. This is divided by two as acceleration can have both positive and negative values within its measurement range. Therefore the maximum positive value is 511 (+2 *g*) and the maximum negative value is -512 (-2 *g*). Consequently, 1 *g* (9.81 m/s^2) corresponds to 256 bits. Finally the accelerometer is put into measurement mode. By default, the sensor is already in 100 Hz sample rate giving a bandwidth of 50 Hz.

7.3.6 Gyroscope Configuration Function

A function is created that will be called as part of the setup and is used to configure the gyroscope and establish the various operating settings, such as the range, digital low pass filter and sampling rate. A summary of this process is provided in Figure 7.9.

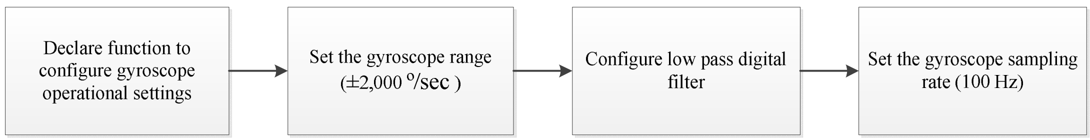

Figure 7.9. Gyroscope configuration function flowchart.

Once the function has been declared a command instructs the microcontroller to set the gyroscope to full scale range, which is ±2,000 °/sec. This command will also configure the digital low pass filter, setting the low pass filter bandwidth to 42 Hz and the internal sample rate to 1 kHz. The gyroscope operates with 16 bit resolution; therefore the full scale range is 2^{16} = 65,536 levels. This is divided by two as angular velocity can have both positive and negative values within its measurement range. Therefore the maximum positive value is 32,767 (+2,000 °/sec) and the maximum negative value is -32,768 (-2,000 °/sec). The next command determines the sample rate of the gyroscope. The gyroscope outputs are sampled internally at 1 kHz. These samples are then filtered digitally and delivered into the sensor registers after a number of predetermined cycles, according to the sample rate. For this application, the sample rate is set to 100 Hz to match the accelerometer.

7.3.7 Communication Protocol Functions

The communications protocol between all components is achieved using an I²C digital connection. In order for this protocol to correctly operate, two functions are required, one to instruct the microcontroller to write information to the sensors and one to instruct the microcontroller to read information from the sensors. The specific instructions within these functions are all part of the Wire library described earlier. A summary of these processes are provided in Figure 7.10.

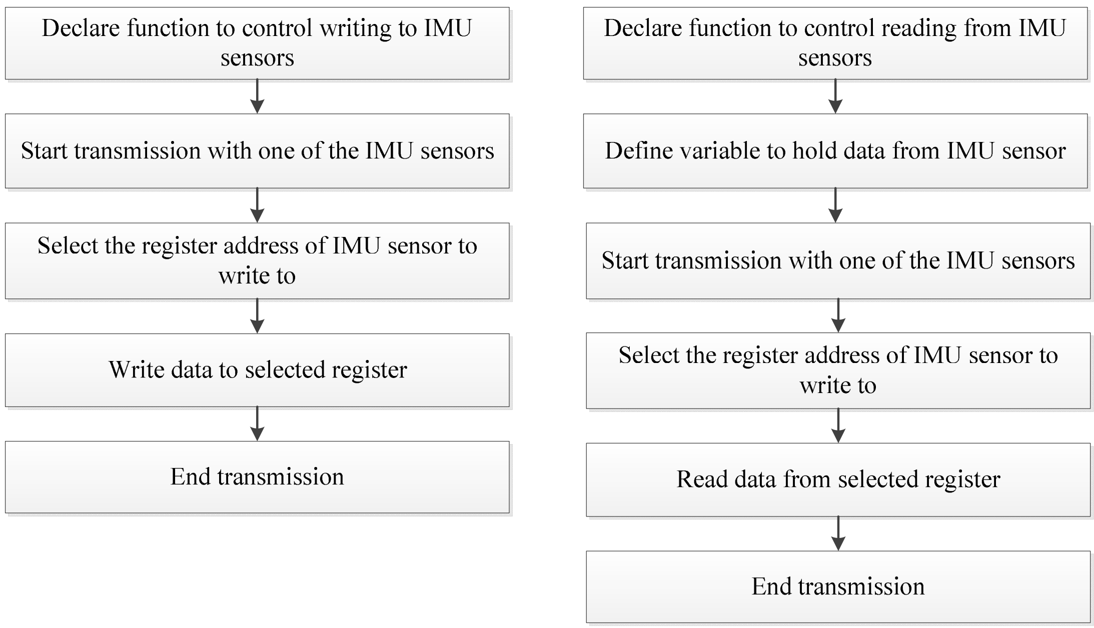

Figure 7.10. Communication protocol functions flowchart.

First, the function to control writing to the IMU sensors is created. The function will output the address of either the accelerometer or gyroscope, the address of the specific register to be accessed and the numerical value that is to be set in the register. This function is called in both the accelerometer and gyroscope configuration functions that were described above. Another function is created in order for the microcontroller to be able to read data from the two sensors. This function can return one or more bytes of information, depending on what data are available within the registers that are accessed. However, it is expected that only one byte will ever be available within the sensor registers under normal functionality of the program. The function returns the device and register address that has been accessed. A Boolean operator is used to check if data are available or not and the number of bytes that will be requested from the device. A buffer is used to temporarily store data from the sensors in the event that the Boolean condition is not met and there is not one byte of data available. This would be considered to be an abnormal condition for the code and is included as a test condition in order to notify the operator if an error has occurred.

7.3.8 Setup

In the Arduino IDE, the *setup()* function is called when a program starts. It is used for tasks such as initializing variables, pin modes and in-built libraries. The setup function will only run once, after each power up or reset of the Arduino board. A summary of this process is provided in Figure 7.11. In order to be able to test the program is functioning correctly at different stages of operation; it is useful to use the inbuilt LED on the microcontroller. The LED is turned on and set to stay on for a period of 5 seconds (5,000 ms). This is performed as a visual indictor that the setup has begun. Next the serial transmission is setup. Serial is used for communication between the Arduino board and a computer or other devices. This is required in order to be able to communicate with the SD Card and can also be used to output to the in-built Serial Monitor within the Arduino IDE, for testing of the program's functionality and performance. The I^2C communication is used for communication with the sensor devices and is also started. Next the two functions that were declared in order to configure the IMU sensors are called. A description of these functions and their operation was provided earlier.

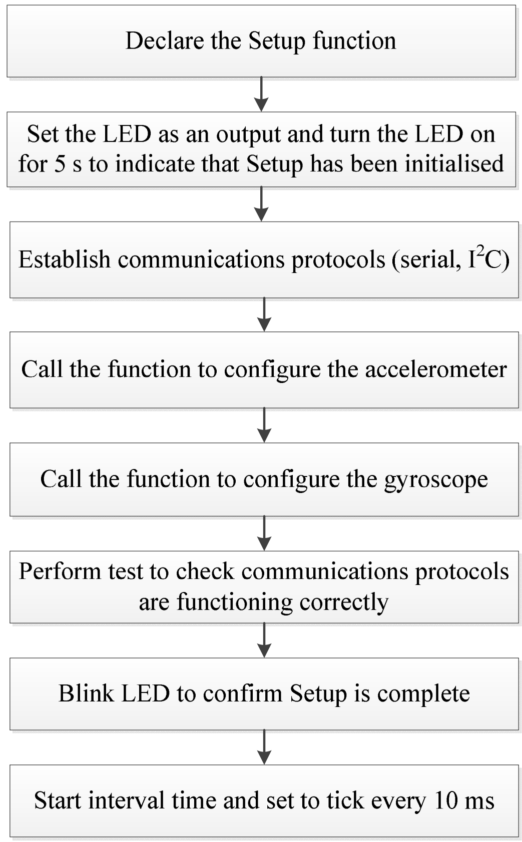

Figure 7.11. Setup function flowchart.

A test is completed in order to check that communication with the SD Card is working correctly and that a file has been created to store the sensor data. This is necessary in case there is an issue, for example if the SD Card is not inserted correctly. The test will instruct the microcontroller to stop the setup and produce an error message to the user if a fault has occurred. At this stage, the LED is set to blink to provide a visual indicator that the setup process is complete and that the loop is about to begin. Finally, an interval timer is created. This timer uses interrupts to call a function at a precise timing interval and will be used in order maintain the desired sampling frequency of 100 Hz. The timer is started and is scheduled to increment every 10 ms. This is the end of the Setup phase of the program.

7.3.9 Interrupt Timer Function

An interrupt timer function is now created. This function will be used for reading values from the sensors and is programed to run as long as there is capacity in the buffer to continue reading values. This function is called before the loop and will run continuously for the duration of the program. A summary of this process is provided in Figure 7.12.

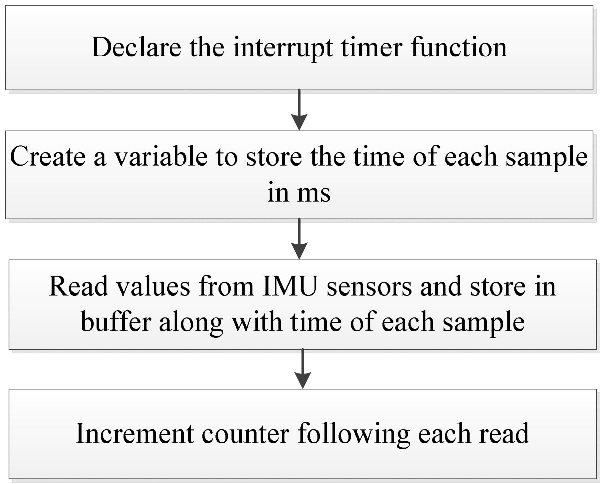

Figure 7.12. Interrupt timer function flowchart.

To ensure that the sampling rate is accurately recording at 100 Hz, all data within each iteration of the loop must be recorded in time windows of 10 ms. To make sure that the frequency is precise, a function called *millis()* is used. This function returns the time in milliseconds since the beginning of the program. This value will be assigned to the variable time that was initialized as part of the SD Card initialisation stage described earlier.

Data are saved in the buffer in a specific sequence. It starts with two delimiter characters and after that the data from both sensors and finally the time. As a result, the bytes are organized in the file following a defined logic which is important to have in order to secure and fast data acquisition. This logic can be described as $\underline{CC}D_1D_2D_3D_4D_5D_6D_7D_8D_9D_{10}D_{11}D_{12}\underline{TTTT}$, which represents the binary combination that data are registered in the file. $\underline{CC}$ are the delimiters characters, used in order to be able to distinguish each line of data within the resulting .txt file. The twelve D_X values are the data from the sensors, whereby D_1D_2 = Gyroscope x-axis; D_3D_4 = Gyroscope y-axis; D_5D_6 = Gyroscope z-axis; D_7D_8 = Accelerometer x-axis; D_9D_{10} = Accelerometer y-axis and $D_{11}D_{12}$ = Accelerometer z-axis. The four $\underline{T}$ values together form the time given in ms. After each byte is written in the buffer, it is necessary to increase a counter to move along the buffer to continue to write the data from the sensors. This interrupt function will run continuously for the duration of the program, storing values from the sensors into the buffer. The loop function, described below, will be used in order to control this interrupt and configure the saving of data to the SD Card when necessary.

7.3.10 Loop

After the interrupt timer function has commenced, the *loop()* function starts and loops consecutively, allowing the program to change and respond once sensor data are started to be recorded. This is used to actively control the microcontoller. A summary of this process is provided in Figure 7.13.

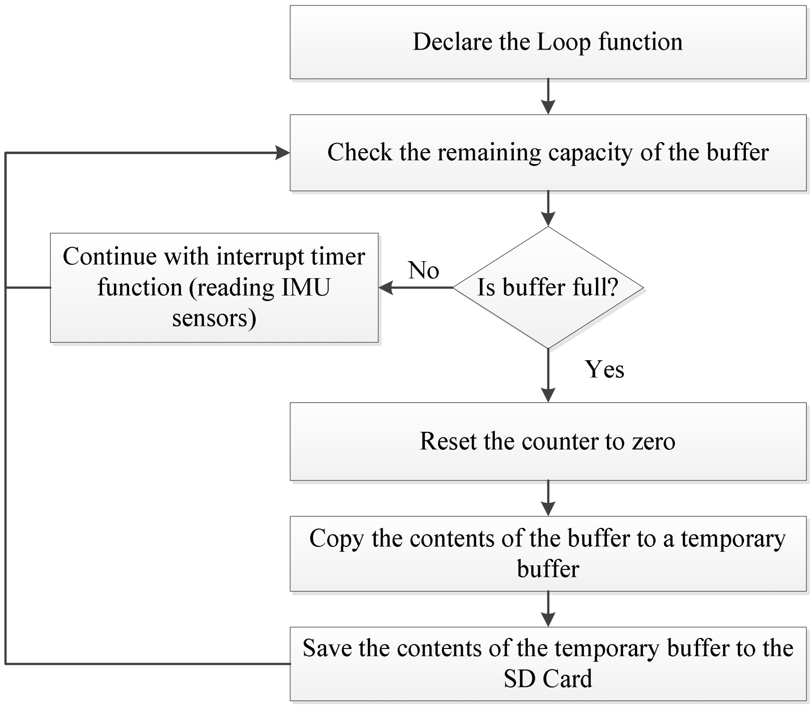

Figure 7.13. Loop function flowchart.

An *if/else* statement is used in order to determine the program flow. This statement is based on the remaining capacity of the data buffer. If there is remaining capacity, then the data from the sensors will continue to be stored in the buffer, as described in the interrupt timer function above. Otherwise, if the buffer has no remaining capacity, then the instructions to save the data to the SD Card will be carried out and the buffer counter is reset. The value of the incremental buffer counter is reset to zero, so that once the data in the buffer have been cleared, it is ready to be used again.

Prior to writing to the SD Card, the contents of the buffer (*buf*) will be copied to the temporary buffer (*bufTemp*). This command allows for the sensor readings to continue to be taken from the sensor devices whilst writing to the SD Card, thus avoiding any loss of data during the SD Card write. The time required for the SD Card write contains a latency of approximately 30-40 ms. Therefore, approximately three to four samples would be missed every time a write to the SD Card is completed. This could have unwanted consequences for the accuracy of the prototype device when used for analysing swimming performance, as key events may occur during these missed samples. However, with the inclusion of the interrupt timer function, the sampling frequency of 100 Hz can be maintained even when writing to the SD Card.

A representative output of the program can be seen in Figure 7.14. The values 35 and 64 are repeated at the start of each sample reading. These are ASCII characters representing the two delimiters that are used at the start of each sample so that each sample can be distinguished. 35 is the ASCII character for "#", whilst 64 is the ASCII character for "@". In this figure, the device is lying flat. It can be seen that the acceleration z-axis values (in the two rightmost columns) are close to 255 in the low byte, indicating that the value is close to 1 *g*. Additionally, the values for the acceleration x-axis and y-axis are both close to 0 (0 *g*). These values are not exactly 1 *g* and 0 *g*, but the slight offsets experienced will be determined and eliminated in post-processing. The angular velocity values are all close to zero as the device is static at this point. Two's complement format is followed. For example, the gyro z axis values are 255 (high) and 248 (low). As the values can have both positive and negative numbers, which are stored in a two's complement format, this number is actually a small negative number. The values are actually -256 + 248 = -8. Again, the gyroscope offset will be determined during post-processing.

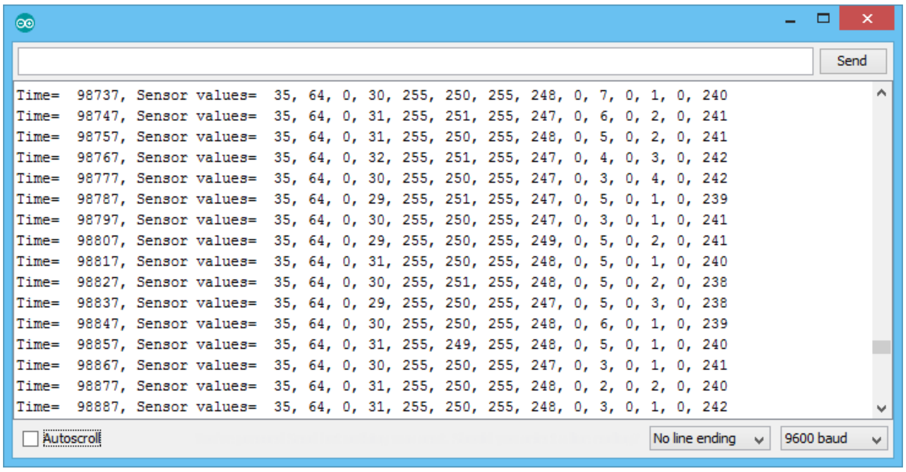

Figure 7.14. Sample output from the prototype device, showing the time in ms of each sample taken (every 10 ms), the delimiter characters and the values recorded for both sensors, including three axis gyroscope data and three axis accelerometer data.

Finally, in Figure 7.15 below, a similar sample output can be seen, this time with the device experiencing movements. The values for each of the sensor registers can be seen to be dynamically changing as the samples are recorded every 10 ms.

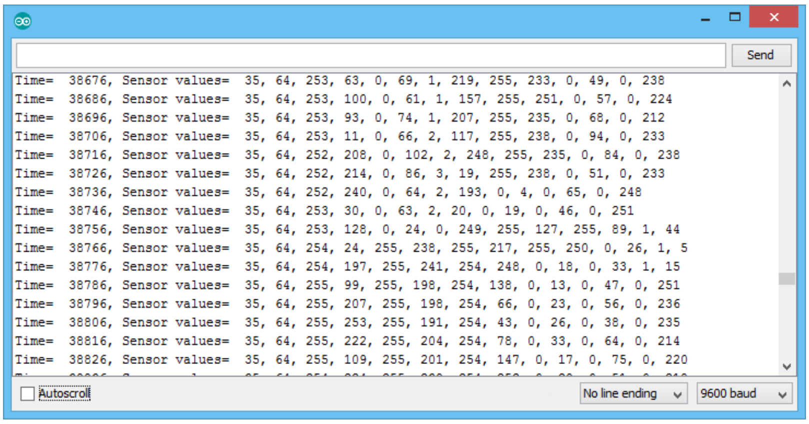

Figure 7.15. Sample output from the prototype device, when experiencing motion.

7.4 Conclusion

The aim of this study was to describe the development of a suitable hardware platform for use in experimental data collection of human swimming. A prototype hardware platform was developed in order to record the swimmers movements in the pool. The platform closely resembles many reported system designs used in research studies and available commercially. A key feature of this hardware platform is the small size of the unit, made possible due to the components selected, leading to improved user comfort. The prototype system has been found to be functioning as intended and can be deemed suitable for data collection in applied settings. Future developments in the hardware platform may include the development of a custom designed board, as opposed to off-the-shelf components, thus leading to a smaller overall system size and potentially also enhanced processing power, all of which would improve the applicability of the system in applied settings.

7.5 References

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Chapter 8 – A Method for the Analysis of Swimming Turns using a Head-Worn Inertial Sensor

The work described in Chapter 7 of this thesis has demonstrated that the prototype hardware platform is functional and provides a suitable system for the accurate acquisition of acceleration and angular velocity data in an aquatic environment. The prototype hardware system also meets many of the user requirements identified in Chapter 6, including factors such as the enclosure size, positioning at the back of the head and minimizing any interference with respect to the ability of the swimmer to perform their normal swimming activities. Therefore, the next stage of this PhD programme of research was to develop feature detection algorithms that can extract automatically the parameters that are of interest to elite coaches. Previous research has largely focused on high-level analyses of swimming performance, such as lap times and stroke counts. Whilst this information is of value, a more detailed and forensic analysis of specific components of swimming is regarded as being an essential evolution in the development of this technology. This will facilitate a more widespread acceptance in elite settings. Swimming turns are one such area of swimming performance that has been identified as being of vital importance to elite swimmers and coaches. The work described in this chapter therefore describes the development of feature detection algorithms for the purpose of analysing swimming turns, based on signals recorded with the prototype hardware platform described in the previous chapter of this thesis.

8.1 Introduction

The analysis of swimming turns has received much research attention as swim coaches and sports scientists have tried to understand the factors involved and how best to maximise the performance of the different variations of turns that are associated with competitive swimming events [1-3]. Swimming turns can be broken down into phases to facilitate a detailed quantitative analysis (Figure 8.1). Swimming coaches devote much training time to improving the quality of their swimmer’s turns during these phases but have expressed dissatisfaction with current technologies for supporting their efforts, which rely heavily on time-consuming video-based systems [4, 5]. This is of concern as the needs of coaches are not being met and they are unable to perform their coaching roles adequately. Ultimately, coaches are heavily reliant on their own subjective interpretation of a swimmer's turn technique. This may result in inefficiencies in training and consequently may delay a swimmer's technical development and skill acquisition.

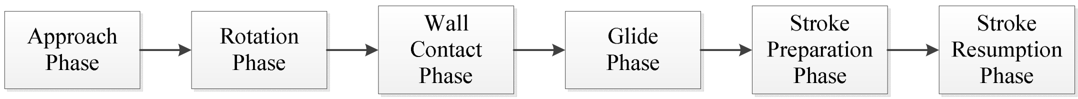


Figure 8.1. Swimming turns can be broken down into phases to facilitate a detailed quantitative analysis.

Emerging MEMS-based inertial sensor technologies have been incorporated into a number of analysis systems for use in aquatic environments [6-9]. Systems are largely based on the use of accelerometer and/or gyroscope sensors. A range of swimming parameters have been reported and validated in the literature, such as stroke counts and lap times [10]. A key advantage of this technology is that it has the capability of providing quantitative feedback to the coach and swimmer more rapidly than with traditional video-based methods. Consequently, this is an active area of ongoing commercial and academic research activity [10, 11].

As research developments in this area continue, it is likely that MEMS-based technologies will be utilised for ever more specific and detailed analyses of swimming performance. Currently, this gap in the research knowledge is hampering their applicability in elite settings. One such area that offers potential is in the analysis of turns and some preliminary studies have suggested the possibility of such an approach [12, 13]. Lee, et al. [13] demonstrated that key features of the frontcrawl turn such as the instant of wall push-off and rotation can be detected using an accelerometer and that differences in turning technique between swimmers of differing abilities can also be detected. Other research examined the potential to measure variables such as rotation time, wall contact time and glide time, again during a frontcrawl turn [14]. Lacking from these early works however was an examination of turns for the other swimming strokes and an objective assessment of the accuracy of the algorithms through experimental testing. Importantly, recent research indicates that such a system would be of interest to elite coaches, who are as yet reluctant to adopt sensor based technologies in their own training environments [4]. However, to date few attempts have been made at developing feature detection algorithms for the purpose of quantifying variables related to the performance of the turn, based on the signal output of a MEMS system. Consequently, there remains a knowledge gap regarding the feasibility of this approach. Therefore, the aim of this study is to describe the development of feature detection algorithms that can determine quantitative parameters related to swimming turns based on the output signal recorded from a head worn inertial sensor device.

8.2 Post-Processing of Raw Output Signal

Data used for algorithm development were obtained from national level competitive swimmers (N=12, 8 male, 4 female; 17.8 ± 2.3 years; 1.71 ± 0.08 m; 69.5 ± 11.3 kg). Raw data related to swimming activity were stored on the MicroSD card of the prototype system described in Chapter 7 of this PhD thesis. These raw data are imported into MATLAB for post-processing (R2013a, MathWorks Inc., Natick, MA.). Once these data are imported into MATLAB, further signal processing and analysis can take place in order to extract meaningful information from the original raw signal values that are measured with this prototype device.

8.2.1 Calibration Procedure

A calibration method was performed in order to determine the offset and sensitivity of the sensors. This procedure involved recording the voltage output on a flat surface under static conditions and with the device orientated sequentially about each of the axes, following industry standard recommendations [15, 16]. The offset is the voltage output when acceleration is at 0 g. The sensitivity is the relationship between the changes in output for a given change in input. Acceleration ($m \cdot s^{-2}$) values were calculated from the ADC output, with angular velocity ($deg \cdot s^{-1}$) determined using a similar method using a scale factor determined during the calibration process.

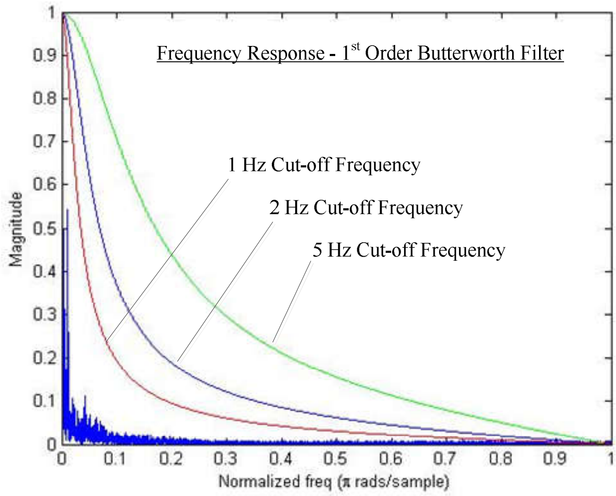
$$Sensitivity = \frac{(V(+1g) - V(-1g))}{2}$$

$$Acceleration\ (\mathrm{m \cdot s^{-2}}) = \frac{(Voltage - Offset)}{Sensivity} \cdot (9.81)$$

$$Angular\ Velocity\ (\mathrm{deg \cdot s^{-1}}) = \frac{(Voltage - Offset)}{Sensivity} \cdot (Scale\ Factor)$$

8.2.2 Filtering Procedure

A filtering process of the raw data is necessary to remove unwanted noise components from the signal. During the prototype development process, different low-pass filter design parameters were considered through examination of various filter responses and power spectral density analysis, as shown in Figure 8.2. The raw signal was characterised by low frequency components associated with swimming activities. Ultimately, data were filtered using a low pass 1st order Butterworth filter with a cut-off frequency of 1 Hz. These filter parameters are appropriate for a head mounted device and are consistent with previous research [10, 17]. The filter removes high frequency information that may occur as a result of vibrations or other rapid movements, leaving only the information of interest. A comparison of the raw and filtered signal, for different frequencies, is presented in Figure 8.3. These filtered acceleration and angular velocity signals that are obtained can now be used for the development of feature detection algorithms, in order to obtain swimming related parameters of interest. The cyclical, regular and repeating pattern of movements found during each of the four competitive swimming strokes is a key feature that allows MEMS technology to offer such potential in the sport for analytical purposes. Researchers can exploit the regular pattern to automatically detect parameters of interest, as has been already documented for parameters such as lap time and stroke count, for example [18, 19]. It is postulated that the same is also true during the different types of turns that can be performed; that there is a characteristic pattern of acceleration and angular velocity arising from the swimmers movement during a turn that can be recognised from the signal output of a sensor based system.



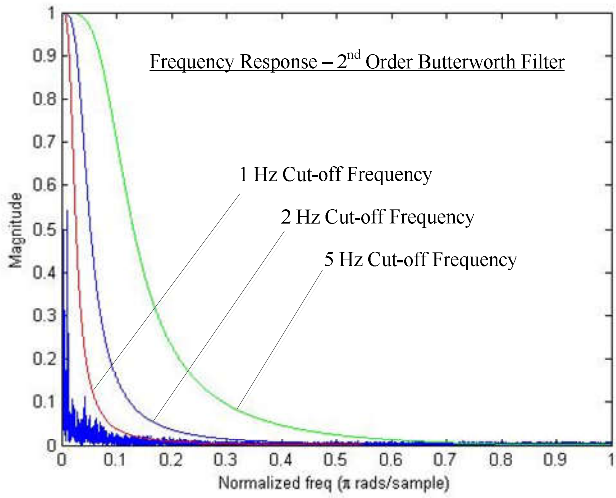


Figure 8.2. Comparison of the frequency response to different low pass filter designs.

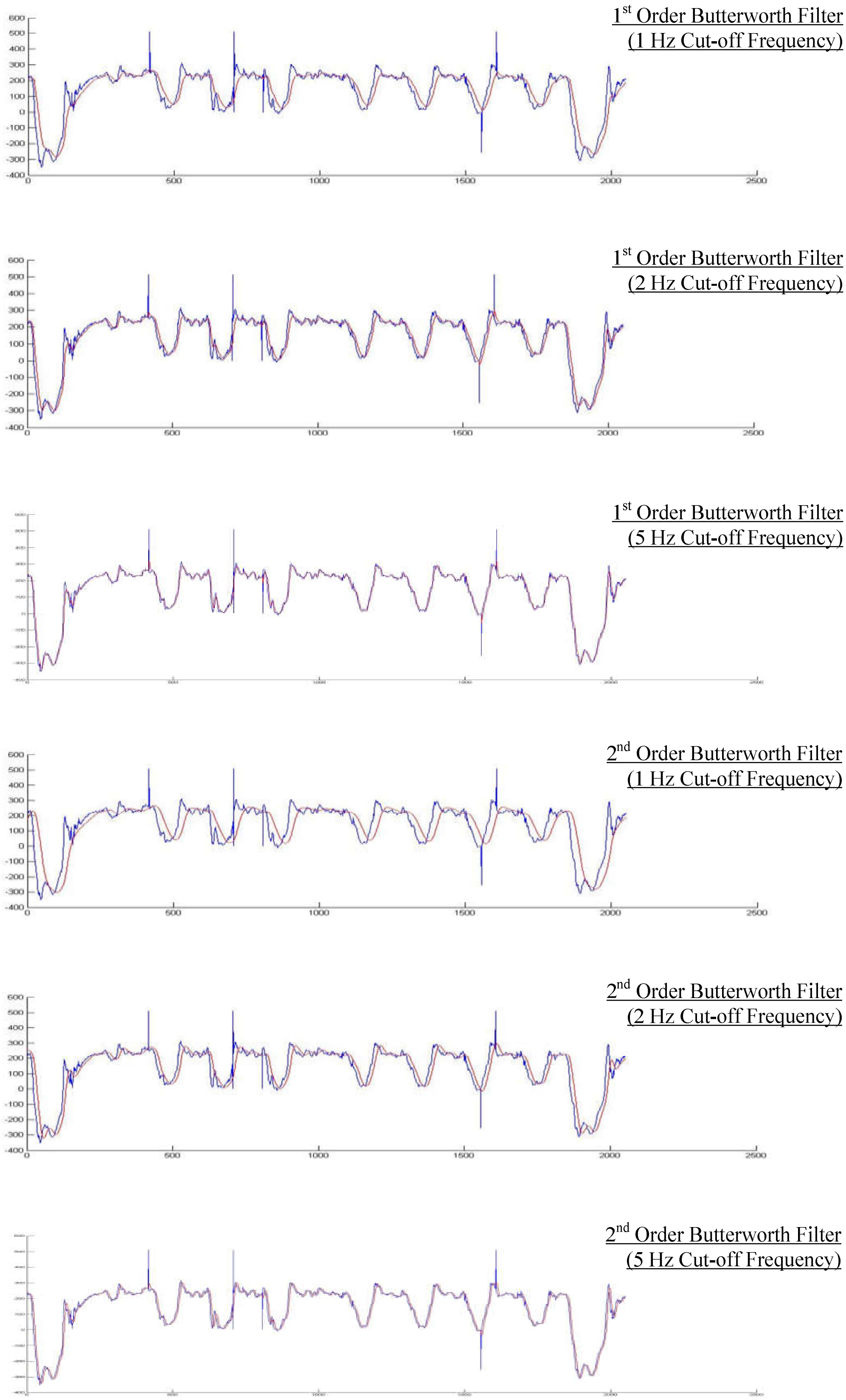


Figure 8.3. Comparison of the raw (blue) versus filtered (red) signal output for various filter options. Data were ultimately filtered using a 1st order low pass Butterworth filter with a 1 Hz cut-off frequency.

8.3 Feature Detection Algorithm Development

Figure 8.4 illustrates the feature detection algorithm development process utilised. By positioning the prototype system at the back of a swimmers head, the device records the three dimensional acceleration and angular velocity profile of the swimmer as they perform multiple laps of the pool. These recordings can be imported into a signal processing software such as MATLAB and swimming intervals can be readily distinguished due to the regular and repeating nature of the signal signatures obtained. Each turn that is performed can be isolated from these data sets. Different segments of a turn, including the approach, rotation, glide and stroke resumption phases, can then be identified through the comparison of the output signals with video footage. By developing feature detection algorithms to process these signals, it is possible to automatically generate performance related information for swimmers' turns. The software implementation required to run these algorithms were developed as part of this thesis specifically for this purpose.

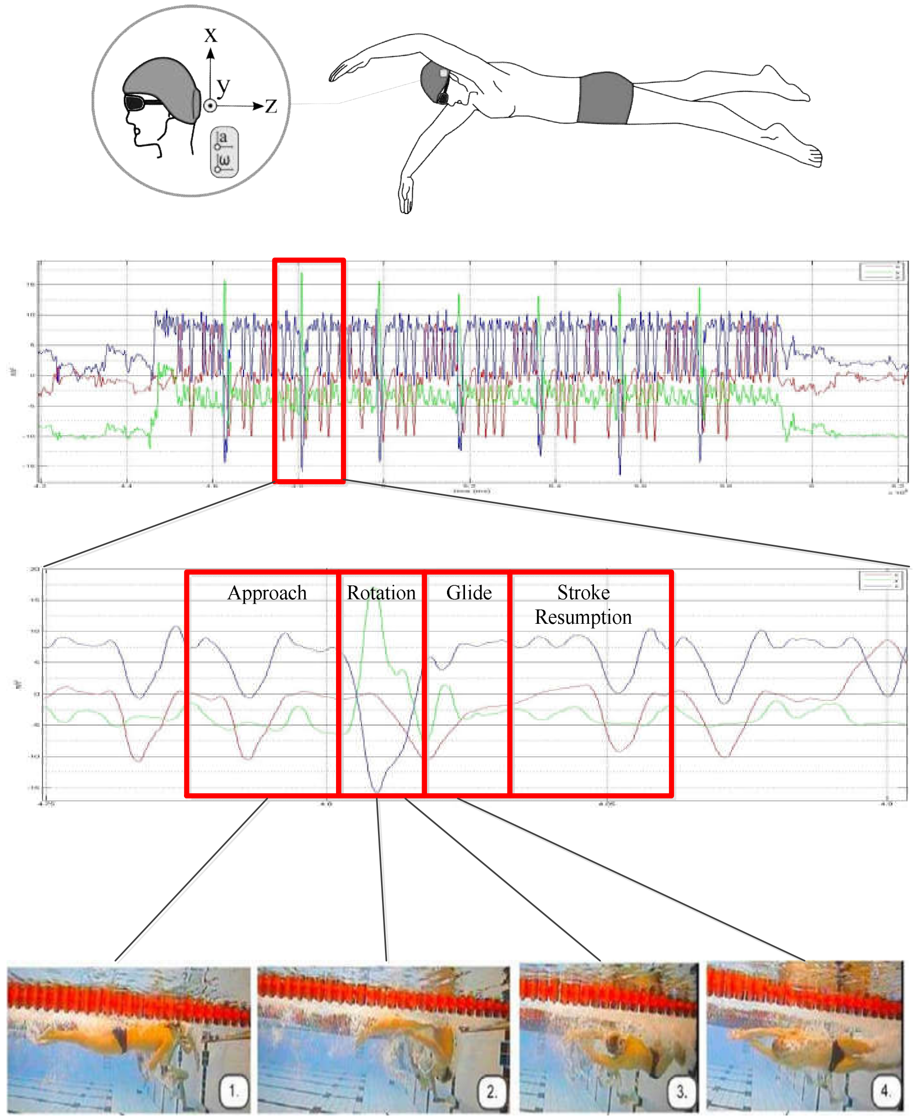


Figure 8.4. Representation of the process of obtaining an output signal from a head worn inertial sensor device. The sensor is worn at the back of the head whilst the swimmer completes the swimming interval. The signal output is obtained and each turn can be extracted so that the phases of the turn can be distinguished through comparison with video images. Photographic images reproduced with permission from Slawson, et al. [12].

The algorithmic process of extracting useful performance related information from signals recorded using the head-worn prototype hardware platform involves several distinct steps and is summarised in Figure 8.5.

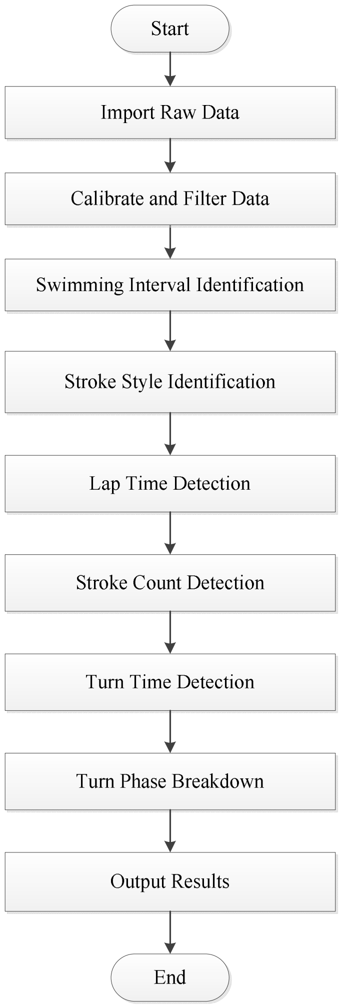


Figure 8.5. Overview of the feature detection process.

The imported acceleration and angular velocity data typically involve data acquired over several minutes of recording, which includes both swimming and rest intervals. Therefore the first stage in the process is to identify and isolate the swimming intervals. These swimming intervals may involve several laps of swimming. For each interval, it is important to identify which of the four competitive swimming strokes is performed as subsequent signal processing steps are stroke dependent. Once the stroke style has been identified, the next stage in the process is to determine the lap time for each of the laps performed. This process is also important as the wall contact events that represent each turn performed are also identified using this algorithm. The number of strokes performed for each lap is then determined. This allows for the turn phases to be identified and isolated for any given swimming interval. The next process involves assessing each of the identified turn phases and calculating key performance related parameters by breaking down the turn into its component parts, such as the approach, rotation and glide phases. The calculated parameters, with their definitions, are summarised in

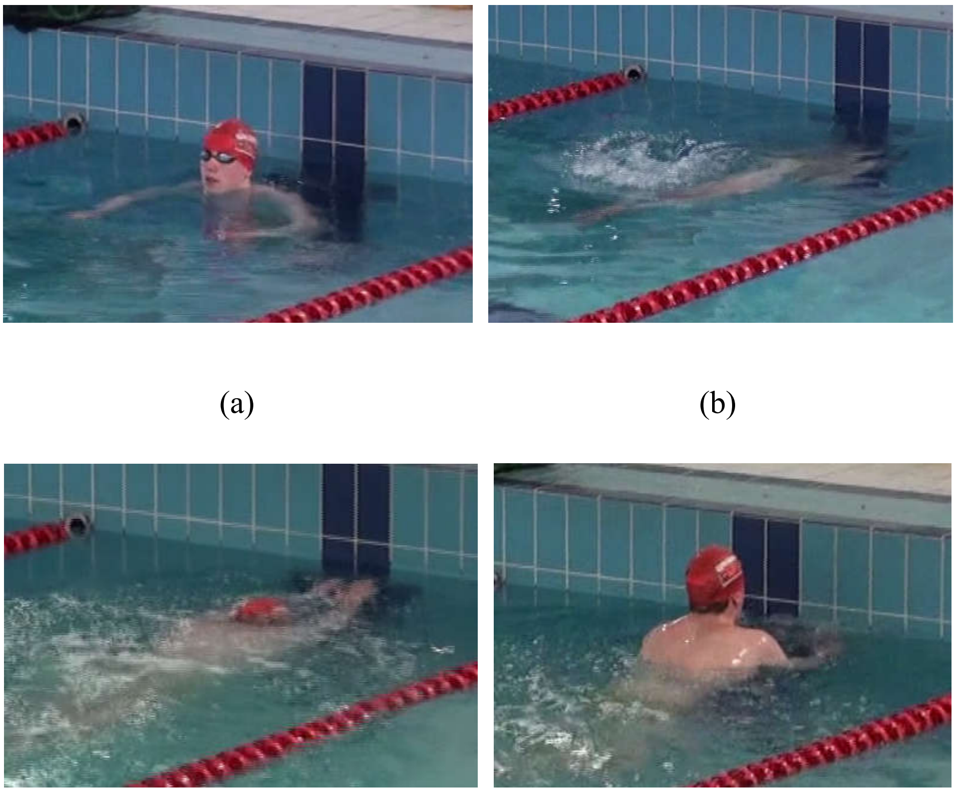
Table 8.1. Finally, these parameters are output from the system in a suitable format for review by the coach and swimmer.

Table 8.1. Definition of terms for each of the feedback parameters determined using the feature detection algorithms. Parameters which do not relate to all four swimming strokes are highlighted in parenthesis.

Parameter	Definition
Lap time	Time to complete each pool length performed
Stroke count	The number of arm strokes performed for a given lap of the pool
Turn time	Time from the start of the 2nd / 3rd last arm stroke on approach until the end of the 2nd / 3rd arm stroke after push-off (2nd: breaststroke / butterfly; 3rd: frontcrawl / backstroke)
Time in	Time from the start of the 2nd/3rd last arm stroke on approach to wall contact
Time out	Time from push-off to the end of the 2nd / 3rd arm stroke
Breakout time	Time from push-off to 1st arm stroke
Rotation time	Time from start of last arm stroke to wall contact (frontcrawl / backstroke)
Wall contact time	Time from 1st contact with wall to push-off
Hands to feet time	Time from 1st contact with wall with hands to first contact with feet (breaststroke / butterfly)
Feet contact time	Time from 1st contact with wall with feet to push-off (breaststroke / butterfly)
Turn direction	Direction of the swimmers movement during rotation (backstroke / breaststroke / butterfly)
Glide time	Time from push-off to first dolphin kick
Pulldown time	Time to complete the pulldown and arm recovery phase (breaststroke)
Kick count	Number of dolphin kicks performed after push-off and before stroke initiation (frontcrawl / backstroke / butterfly)
Kick time	Time taken for the dolphin kicks after push-off from the wall to be performed

8.3.1 Swimming Interval Identification

The first stage in the feature detection process is to isolate swimming intervals from periods of rest or other unwanted data. This is achieved by exploiting the changing orientation of the swimmer as they transition from a vertical position (when standing or floating during rest) to a horizontal position (when swimming), as shown in Figure 8.6. The swimming interval identification algorithm exploits these transitions to get a rough estimate of the beginning and end times of each swimming interval. A more precise determination of the start and end points is established at a later stage to allow for lap times to be calculated.



(a) (b)

(c) (d)

Figure 8.6. Swimming intervals can be distinguished from the changing orientation of the swimmers head at the start (a, b) and end (c, d) of a swimming interval.

The algorithm, which is described in Figure 8.7, finds the points where this orientation change occurs using a thresholding method applied to the X-axis acceleration (forward acceleration, or acceleration in the direction of movement), and creates an array of time stamps that approximate the start and end of each swimming interval.

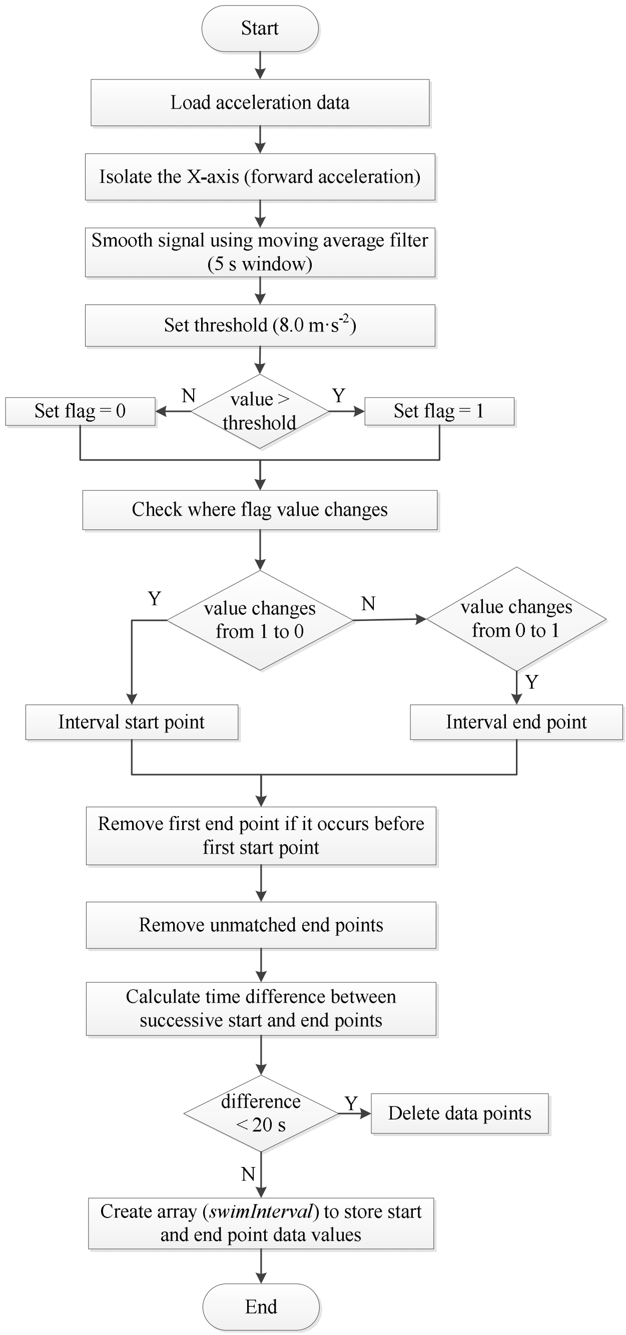


Figure 8.7. Flowchart of the swimming interval identification algorithm.

A 5 s moving average filter is applied to the X-axis acceleration signal prior to interval identification to facilitate ease of identification of these intervals. In Figure 8.8, regular swimming action results in acceleration values repeatedly approaching 9.81 m·s^{-2} (1 g). After the moving average filter is applied, the smoothing effect eliminates this unwanted noise (Figure 8.9).

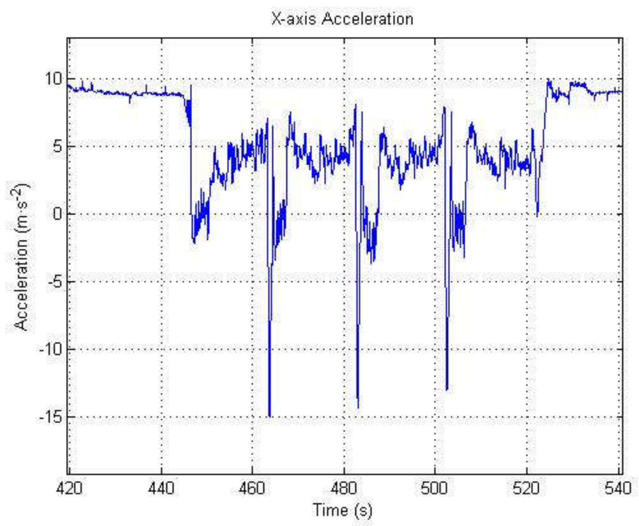


Figure 8.8. Sample X-axis acceleration data for a swimming interval. Periods of rest can be seen at the start and end of the interval, when the acceleration value approximates 9.81 m·s^{-2} (1 g), as the swimmer's head is vertically orientated. Swimming activity can be readily identified by tracking the change in the acceleration value across a moving window.

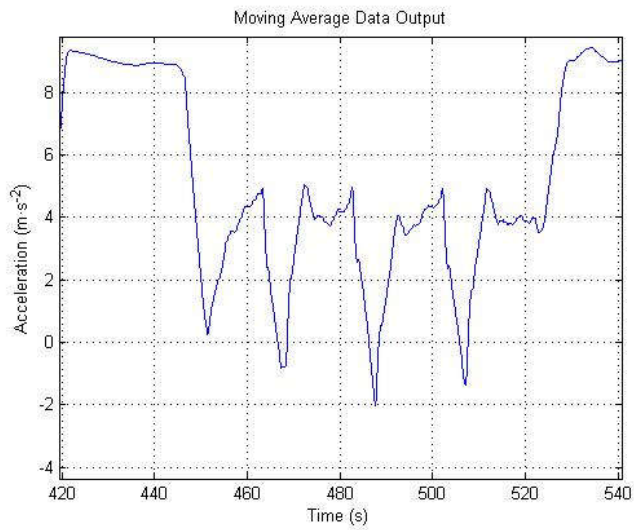


Figure 8.9. Calculating a moving average over a 5 s window creates a smoother signal, aiding the identification of rest periods from swimming activity.

A threshold value of 8.0 m·s^{-2} was selected because when a swimmer is standing or has their head upright then the value of the X-axis acceleration will be approximately

1 g. This value quickly drops when a swimmer transitions to a swimming posture. The opposite occurs at the end of a swimming interval as the swimmer returns to a vertical position. The algorithm sets flags for when the threshold is crossed, with the flag set to 0 when the signal value is less than the threshold and the flag is set to 1 when the value is greater than the threshold. This creates a signal shown in Figure 8.10. Unwanted data, such as movements that occur at the beginning of data collection before any swimming has commenced or at the end of the activity before the prototype is switched off, need to be removed. This can readily be seen in Figure 8.10 with a large number of rapid fluctuations in the signal between 0 and 1 on the left hand side of the image, which occurred as the swimmer entered the water and prepared for the swimming activity to follow.

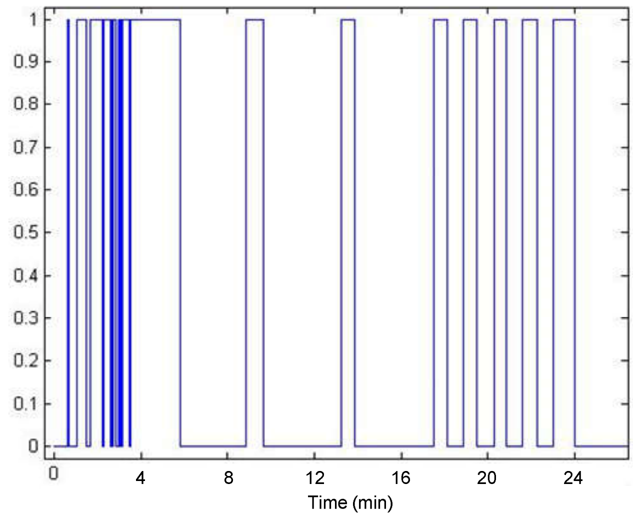


Figure 8.10. Sample output of the interval identification process, showing a large sample of the swimming session that was completed. A threshold value is established that can track when a swimmer's head is vertical (during rest) and when the swimmers orientation changes at the start and end of a swimming interval. This is used to automatically track the start and end points of each interval. Rapid fluctuations on the left side of the image represent movement that occurs when the prototype is first positioned on the swimmer's head and the swimmer first enters the water and readies themselves for swimming. Swimming intervals can be identifed, with three 100 m distance intervals first completed (in the middle of the image), followed by four shorter 50 m intervals (towards the right of the image).

These unwanted data points are eliminated using a three stage process. Firstly, if the first identified end point occurs before the first identified start point, then this first end point is removed. Secondly, the total number of end points is compared to the number of start points and any additional end points are removed if necessary to ensure an equal number of start and end points is achieved. Thirdly, a test for a minimum interval duration of 20 s is conducted and any start/end point pair that is not found to be of at least 20 s in duration is eliminated. This time value represents the minimum time that it would take a competitive swimmer to complete two lengths of a 25 m pool. The algorithm then tracks when the flag values are changing, with a change from 1 to 0 indicating an interval start point, whilst a change from 0 to 1 is indicative of an interval end point (Figure 8.11).

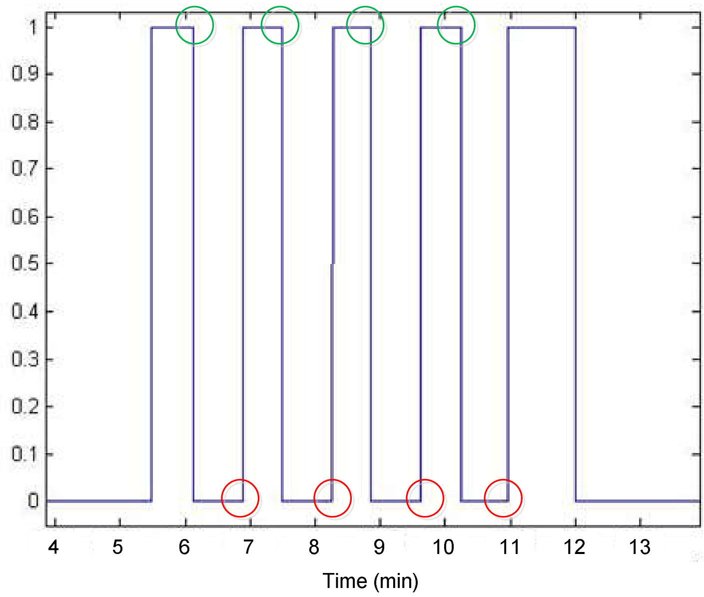


Figure 8.11. Representative sample of the output of the interval identification process. Swimming and resting activities can be distinguished to automatically track the start (green circles) and end (red circles) points of a swimming interval.

Finally, an array is created, called *swimInterval*, which contains the time stamp data values for all intervals performed (Figure 8.12). The algorithm then determines how many intervals were completed and automatically names each interval as "Interval 1"; "Interval 2", etc. These time stamp data are then used in subsequent stages of the feature detection process to extract the data of interest from the acceleration and angular velocity recordings (Figure 8.13).

swimInterval =

$$\begin{bmatrix} 28868 & 44034 \\ 48111 & 66203 \\ 69134 & 87427 \\ 90604 & 94399 \\ 97422 & 101333 \\ 104292 & 108044 \\ 111269 & 114862 \\ 120068 & 137008 \end{bmatrix}$$

Figure 8.12. An array of time stamps (in ms) that are associated with the start (left hand column) and end (right hand column) points of each of the detected swimming intervals. In this example, there were eight intervals performed by the swimmer.

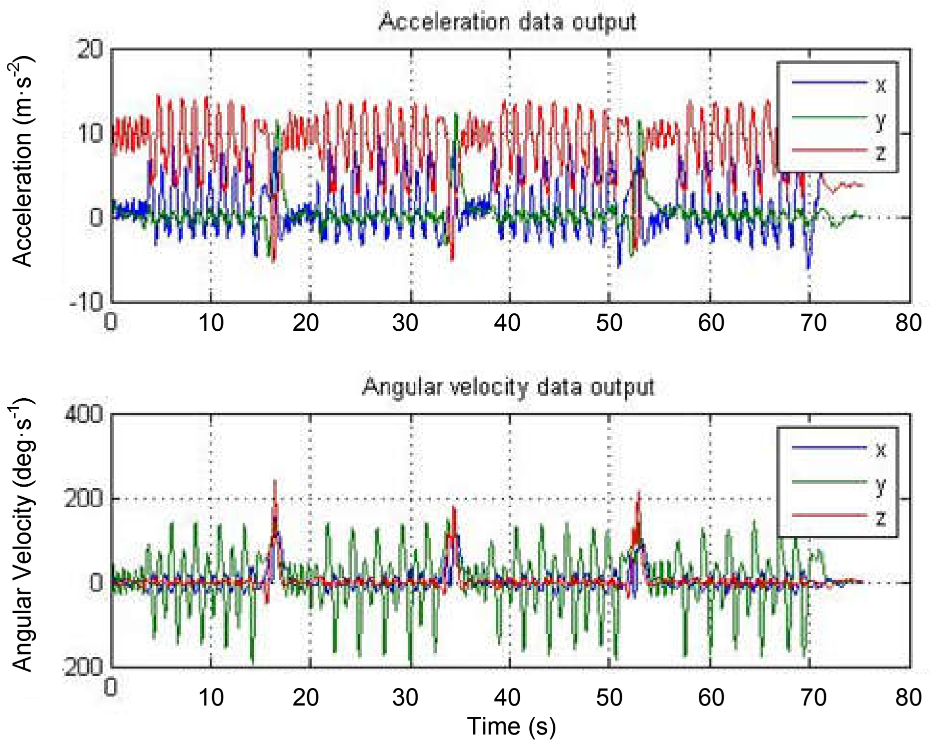
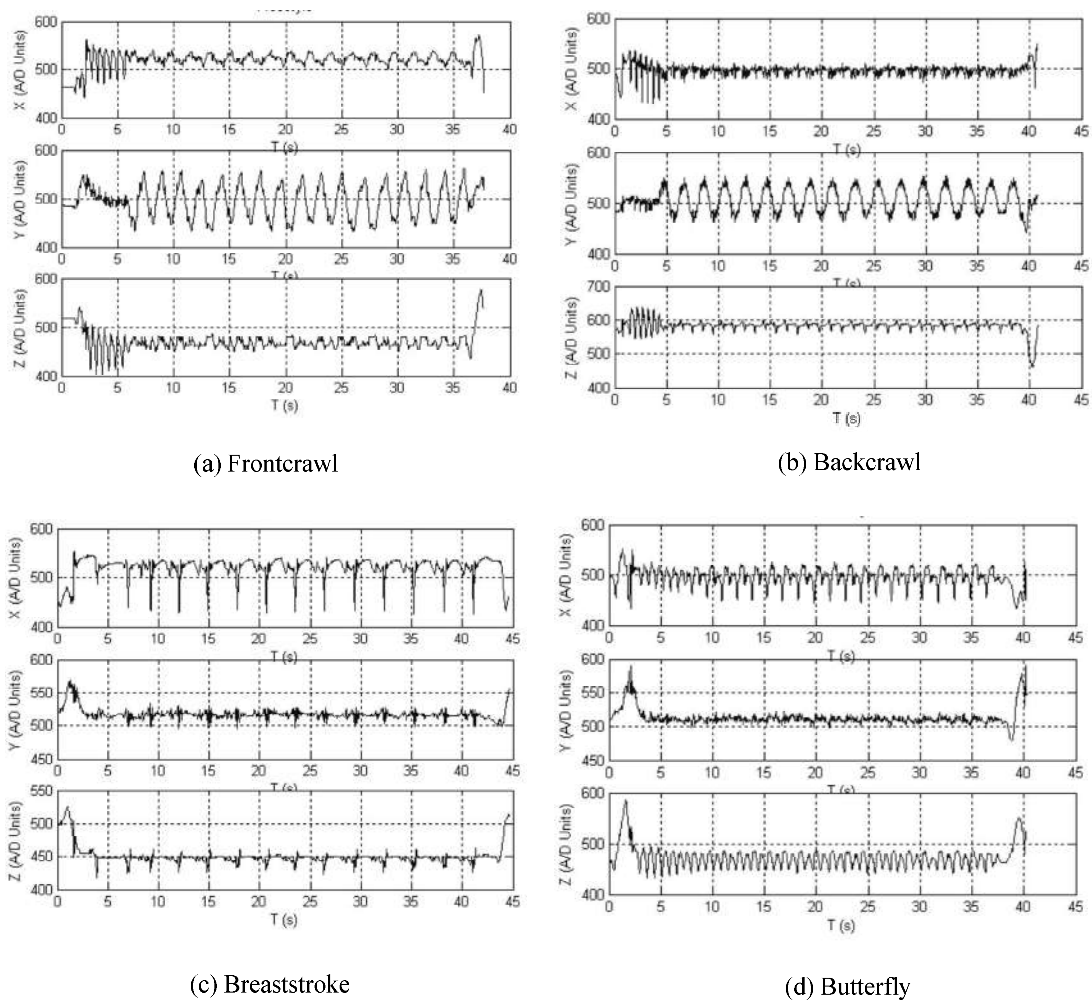


Figure 8.13. Values in the swimInterval array are used to extract swimming intervals from the filtered acceleration and angular velocity signal for all three axes. A sample of butterfly swimming interval is provided here, which contains four laps of swimming (100 m total). Three turning events can also be readily seen.

8.3.2 Stroke Style Identification

The next stage in the feature detection algorithm development is to determine which swimming stroke has been performed for any given interval. Specific characteristics of the acceleration profile for the four competitive swimming strokes allow for swimming stroke type to be detected, as each stroke displays unique features for each of the three axes of acceleration (Figure 8.14).



(a) Frontcrawl

(b) Backcrawl

(c) Breaststroke

(d) Butterfly

Figure 8.14. Sample acceleration output for each of the four competitive swimming strokes. Characteristic patterns of each stroke can be used to automatically identify stroke styles. Reproduced with permissions from Davey, et al. [20].

The developed algorithm uses a combination of established methodologies [18, 21] , with appropriate modifications made to reflect the different sensor placement position of the prototype device. Davey, et al. [18] demonstrated that as a swimmer lies in a supine position when performing the backstroke, then consequently the Z-axis signal (i.e., acceleration in the anterio-posterior direction) outputs a value of approximately +1 g (+9.81 m·s^{-2}) during this stroke. This is in contrast to the other three strokes in which the Z-axis tends towards −1 g (-9.81 m·s^{-2}) as the swimmer is in a prone position when performing these strokes and the device will be orientated in the opposite direction (Figure 8.15). Additionally, whilst the X and Y axes during all four strokes appear to show similarities, there are differences in the magnitude and spread of the local maxima and minima that can be recognized [18, 21]. Ohgi, et al. [21] determined that these differences could be exploited by calculating simple descriptive statistical measures, such as mean and variance. Stroke identification is then performed by comparing these values against pre-determined threshold values (Figure 8.16).

	Channel Orientation			Channel Energy		
Stroke Type	AX	AY	AZ	AX	AY	AZ
Freestyle	–	–	−1 g	>1	>3	–
Backstroke	–	–	+1 g	1	>2	–
Breaststroke	–	–	−1 g	>1	<2	<2
Butterfly	–	–	−1 g	>1	<2	>1

Figure 8.15. Threshold values used in a stroke identification algorithm to distinguish between each of the four competitive swimming strokes. . Reproduced with permissions from Davey, et al. [18].

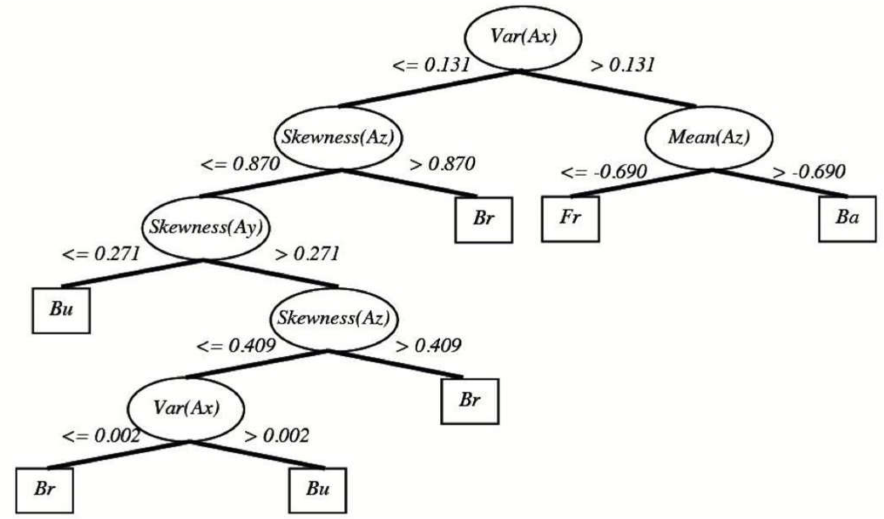


Figure 8.16. Stroke identification classification model based on descriptive statistical features of all three axes of the acceleration signal from a chest worn device. Thresholds were set to the data from each of the three axes (values in m·s^{-2}) in order to classify stroke styles. Reproduced with permissions from Ohgi, et al. [21].

The algorithm developed in this thesis work combines these two approaches and the algorithm process flowchart is shown in Figure 8.17. Definitions for each of the descriptive statistical features used in the stroke style identification algorithm are provided in Table 8.2.

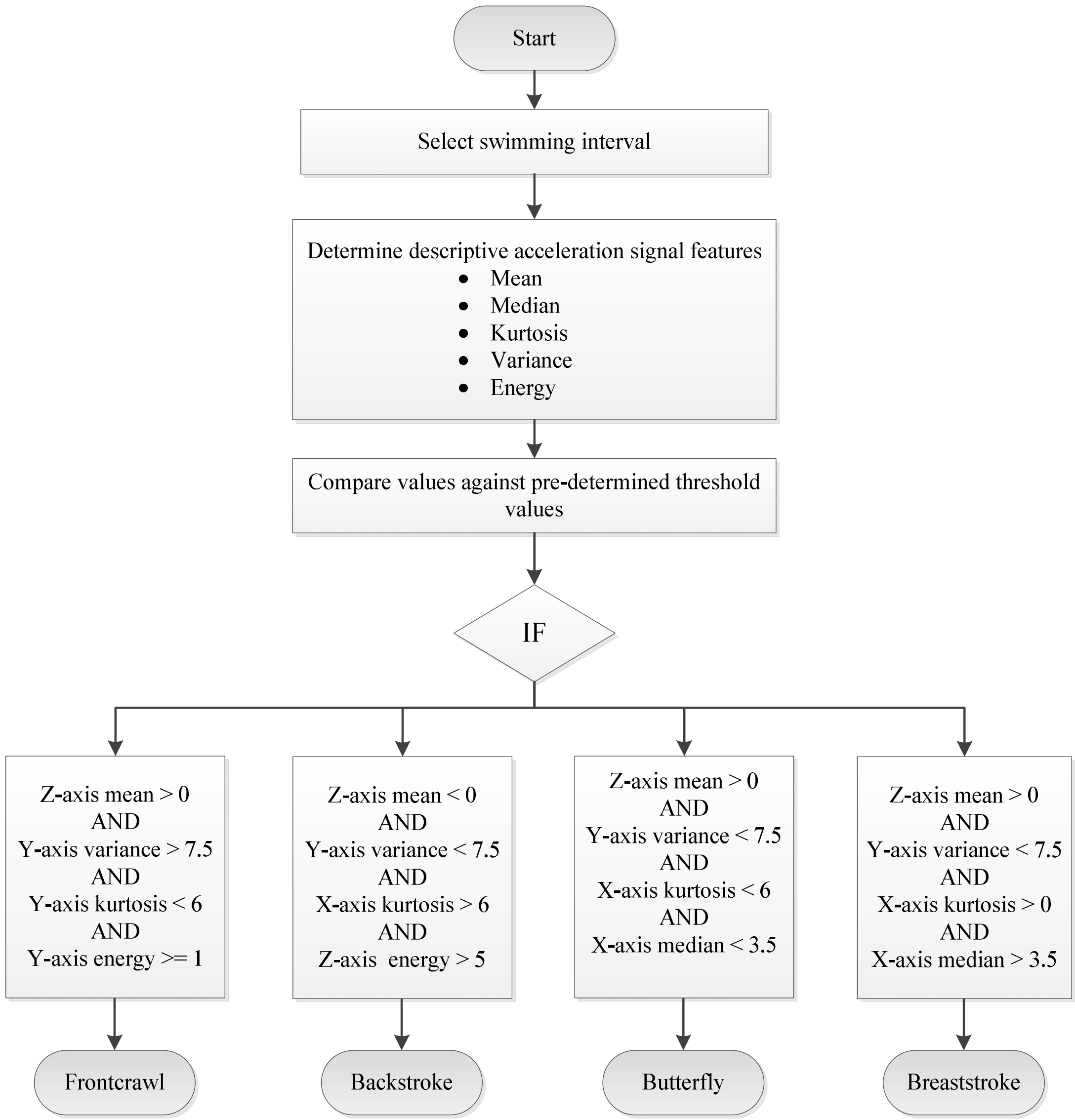


Figure 8.17. Flowchart of the stroke style identification algorithm. All threshold vaues shown are acceleration values ($m{\cdot}s^{-2}$).

Table 8.2. Definition of terms for each of the descriptive statistical features used in the stroke style identification algorithm.

Feature	Definition of term
Mean	The sum of the sampled values divided by the number of items in the sample. $$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n}$$
Median	The middle value of a data set, i.e., the value separating the higher half of a data sample from the lower half.
Kurtosis	The sharpness of the peak of a frequency-distribution curve. A measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. Where μ_4 is the fourth central moment and σ is the standard deviation. $$Kurt[X] = \frac{\mu_4}{\sigma_4}$$
Variance	Measurement of how far a set of numbers are spread out from the mean value. Where the variance of a random variable X is the expected value (E[X]), of the squared deviation from the mean of X (μ = E[X]). $$Var[X] = E[(X-\mu)^2]$$
Energy	Measurement of signal energy determined for each axis of acceleration. Determined by calculating the average value for the axis, subtracting the average from each sample value, summing the absolute values, dividing by the length of the data set and rounding to the nearest integer value. $$SE = \left(\frac{\sum(\lvert X - \bar{x}\rvert)}{n}\right)$$

The mean value for the Z-axis acceleration (acceleration in the anterio-posterior direction) reflects the position of the swimmer in the water whilst swimming (Figure 8.18). When the swimmer is prone, during frontcrawl, breaststroke and butterfly swimming, this value will be greater than 0 $m \cdot s^{-2}$. Conversely, when the swimmer is in a supine position during backstroke the value for the Z-axis mean will be less than 0 $m \cdot s^{-2}$. By comparing the calculated value for the Z-axis mean for a given swimming interval, backstroke can readily be distinguished from the other strokes using this metric.

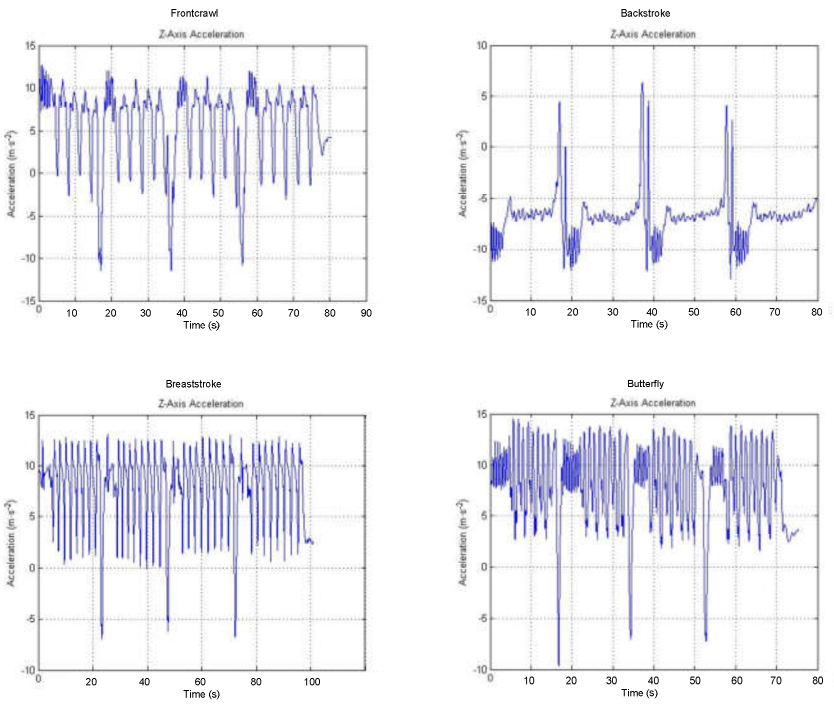


Figure 8.18. Comparison of Z-axis acceleration signals.

The next step is to calculate and compare the other descriptive information, including median, kurtosis and variance. In Figure 8.19 it can be seen that the X-axis acceleration signal appears to be similar for frontcrawl/backstroke and also for breaststroke/butterfly. Moreover, the Y-axis signal for breaststroke/butterfly also appears to be very similar on visual inspection (Figure 8.20). However determination of the descriptive information for all three axes of acceleration allows for automatic identification to take place (Table 8.3).

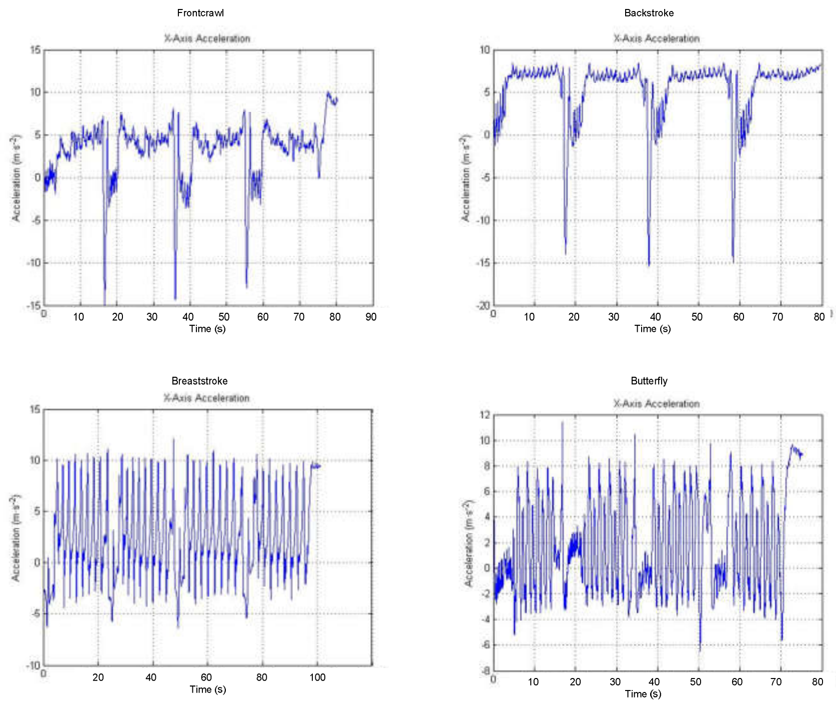


Figure 8.19. Comparison of X-axis acceleration signals.

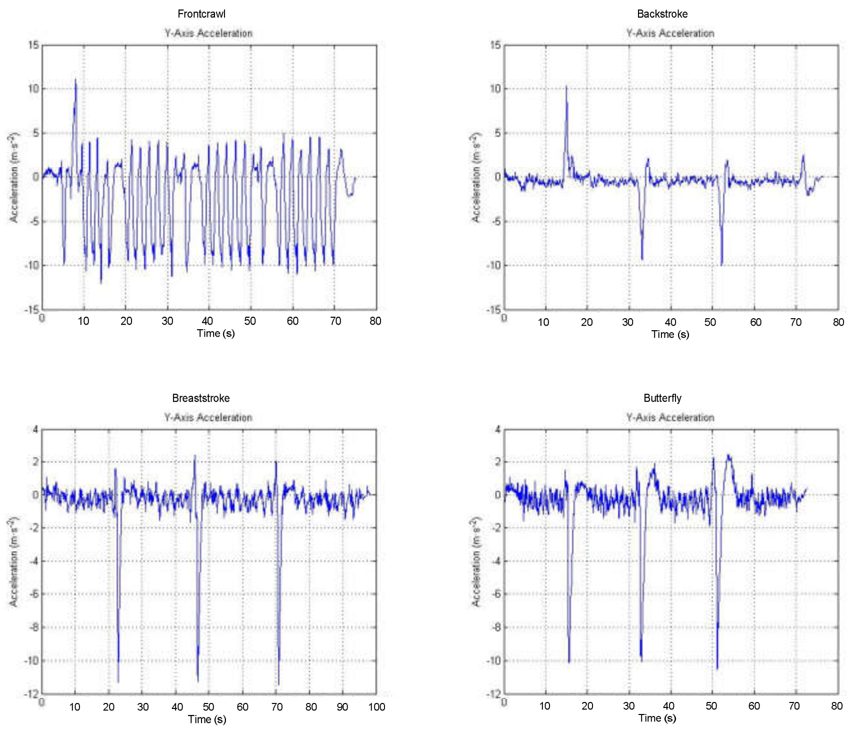


Figure 8.20. Comparison of Y-axis acceleration signals.

Table 8.3. Descriptive statistical information (mean ±SD) related to the acceleration signal for all four swimming styles. Data used to set thresholds in the stroke style identification algorithm are underlined. All values are in m·s^{-2}.

	Frontcrawl	Backstroke	Breaststroke	Butterfly
Mean				
X-axis	3.9 (0.6)	5.2 (1.1)	4.3 (1.1)	3.6 (1.1)
Y-axis	0.7 (1.1)	-0.7 (1.1)	0.2 (0.5)	0.3 (0.6)
Z-axis	5.1 (1.1)	-7.0 (1.3)	6.9 (0.6)	7.3 (0.6)
Median				
X-axis	4.5 (0.5)	6.1 (1.6)	4.6 (1.8)	3.1 (1.4)
Y-axis	0.5 (0.3)	-0.6 (1.2)	0.5 (0.5)	0.4 (0.4)
Z-axis	7.0 (1.1)	-7.2 (1.3)	8.2 (0.7)	8.2 (0.5)
Kurtosis				
X-axis	13.6 (4.0)	18.8 (5.7)	2.7 (0.3)	2.4 (0.2)
Y-axis	3.9 (0.7)	17.2 (5.9)	23.7 (7.9)	17.4 (2.4)
Z-axis	4.0 (1.4)	11.6 (2.6)	4.0 (0.9)	4.9 (1.0)
Variance				
X-axis	11.7 (0.5)	11.1 (2.5)	14.6 (3.4)	11.4 (3.2)
Y-axis	16.0 (3.7)	2.0 (0.5)	2.7 (0.6)	3.0 (0.6)
Z-axis	21.2 (6.2)	6.5 (1.8)	13.8 (5.1)	15.1 (1.8)
Energy				
X-axis	1.0 (0.0)	1.0 (0.0)	0.4 (0.5)	0.4 (0.5)
Y-axis	2.3 (1.5)	2.0 (1.7)	0.8 (0.4)	0.6 (0.5)
Z-axis	1.3 (0.6)	14.0 (2.0)	0.2 (0.4)	0.0 (0.0)

For example, by collating data for multiple swimmers during the development phase, it was found that the X-axis kurtosis averaged 13.6 ±4.0 m·s^{-2}, 18.8 ±5.7 m·s^{-2}, 2.7 ±0.3 m·s^{-2} and 2.4 ±0.2 m·s^{-2}, for frontcrawl, backstroke, breaststroke and butterfly, respectively. Furthermore, the average value for the Y-axis kurtosis was found to exceed 17.0 m·s^{-2} in all strokes except for frontcrawl, which had an average Y-axis kurtosis value of 3.9 ±0.7 m·s^{-2}. These differences allow for thresholds to be established. Ohgi, et al. [21] had previously also determined the signal skewness. However, in this thesis work, this was not found to provide a sufficiently stable and unique level of measurement to be used in this algorithm.

The signal energy, previously described by Davey, et al. [18], was not used in the decision making process for determining butterfly or breaststroke swimming as it was not found to improve the distinction between these strokes, possibly owing to the head mounted sensor position. Instead, the signal median was determined and used as a method of differentiating breaststroke from butterfly. The signal energy was however successfully used in the determination of both frontcrawl and backstroke.

It has been found that a head worn sensor device can be used to determine swimming styles by adapting existing methodologies to this sensor location and through the modification of threshold values. The correct determination of stroke style is important as all subsequent processes are tailored to suit the identified style. The next stage in the feature detection algorithm development process is to determine lap times.

8.3.3 Lap Time Detection

Several procedures for determining lap times have been described in the literature and typically involve detecting peaks in the acceleration signal that correspond to wall contact events [10]. These peaks can be seen readily in Figure 8.18, for example, with three visible peaks representing the three turns performed during a 100 m swimming interval. A similar process for determining lap times has been followed in this thesis work, albeit with modifications to allow for lap times to be determined for all four swimming strokes. The process flowchart is illustrated in Figure 8.21. The algorithm involves three stages; (i) identification of the precise start of a swimming interval; (ii) identification of the wall contact events that are associated with turns during a swimming interval and (iii) identification of the precise end of a swimming interval when a swimmer returns to contact the wall.

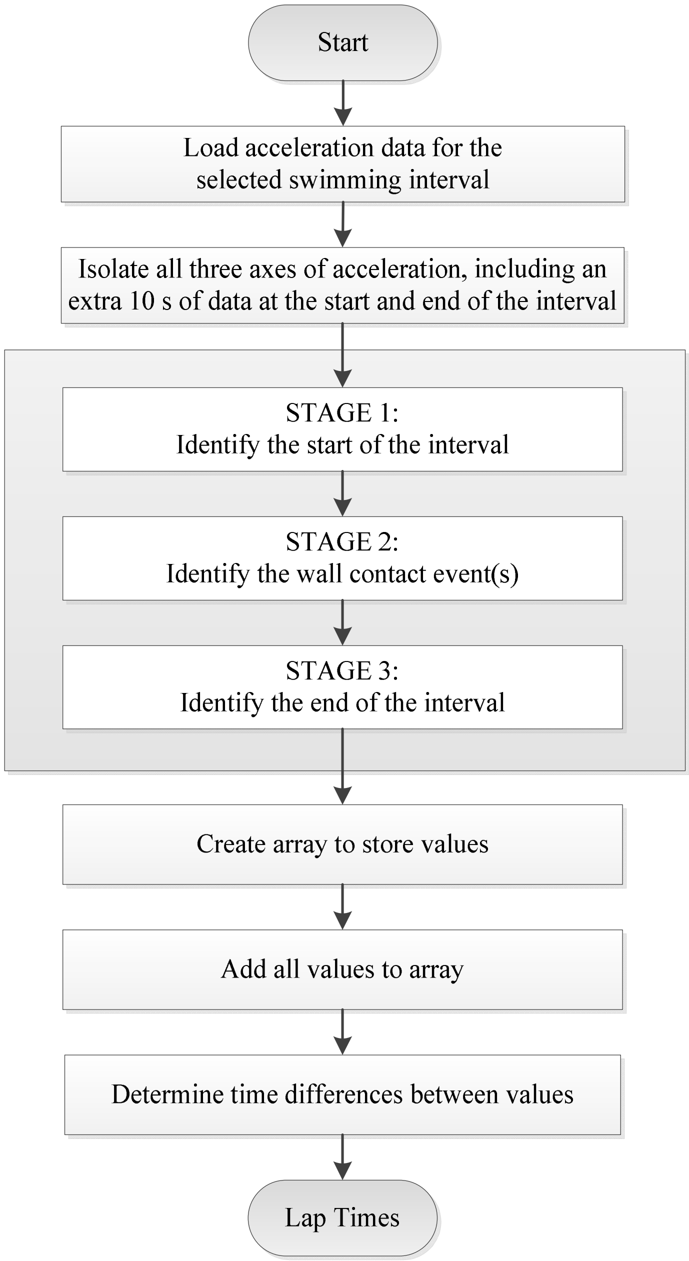


Figure 8.21. Lap time algorithm overview flowchart.

As described, the start of the first lap is characterised by a changing orientation of the swimmer as they commence swimming activity. Stage 1 of the lap time algorithm determines a more precise time for this event compared with the earlier approximation that was determined in the swimming interval identification algorithm. The algorithm process flowchart for Stage 1 is illustrated in Figure 8.21.

The algorithm first isolates a 40 s window in the X-axis acceleration signal where the start occurs (Figure 8.23). This window begins 10 s prior to the time stamp value associated with the close approximation, as determined by the interval identification algorithm (shown in Figure 8.12 above). Therefore, the window also includes 30 s of data after this approximation.

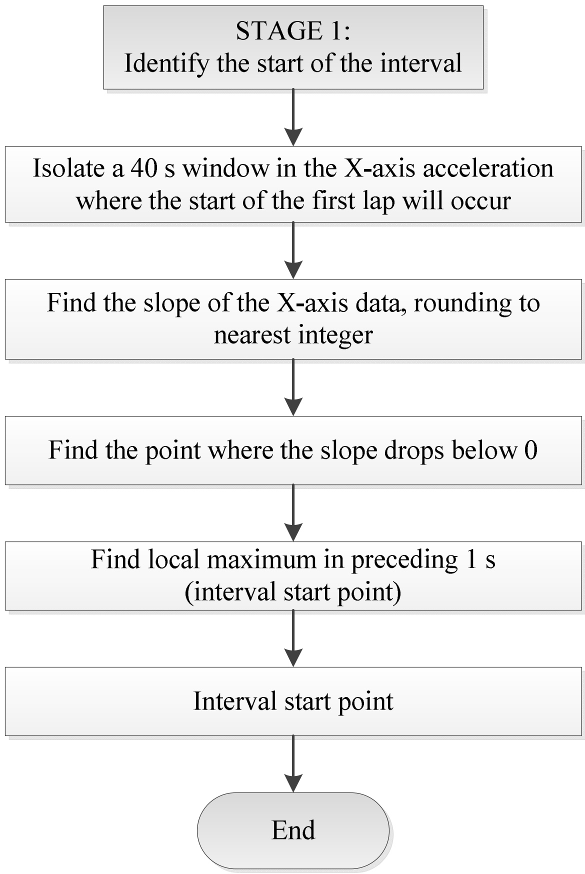


Figure 8.22. Flowchart describing Stage 1 of the lap time algorithm.

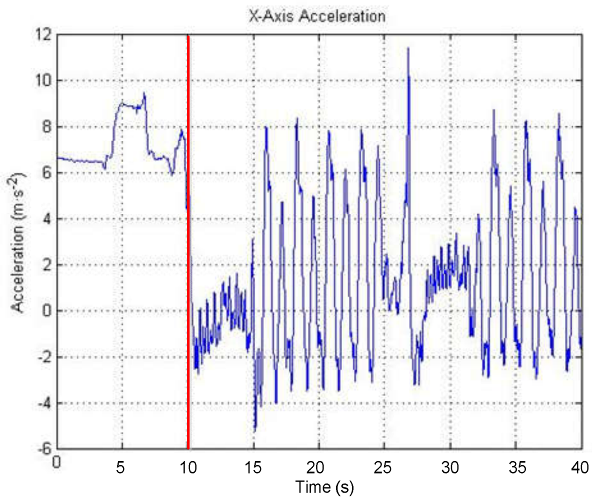


Figure 8.23. A 40 s window in the X-axis acceleration data is isolated to determine where the start of the first lap in a swimming interval occurs. The red line indicates the point where the close approximation of the lap start was originally determined as part of the swimming interval identification algorithm.

Next the slope of the data during this window is calculated. The slope values are determined over three sample points and rounded to the nearest integer in order to eliminate rapid local slope fluctuations that naturally occur in the signal, as can be seen by comparing Figure 8.24 and Figure 8.25. The rounding process isolates only the most rapidly changing slope values. The algorithm selects the first such occurrence when the slope value is -1. This can be seen in Figure 8.25 at 10.2 s.

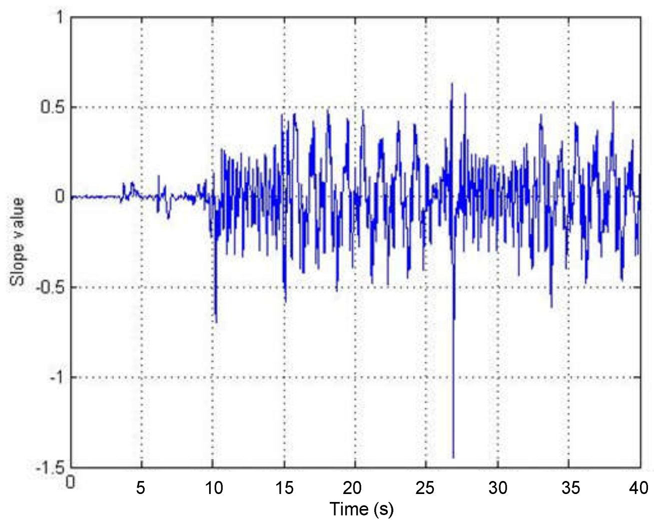


Figure 8.24. Values for the slope of the X-axis signal without rounding of the data values.

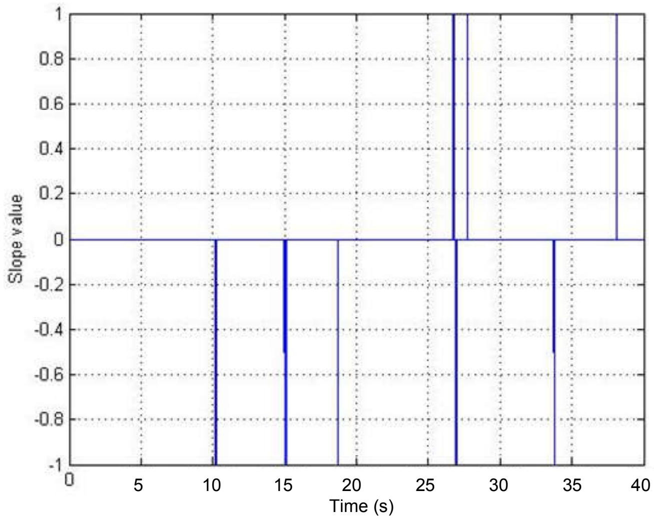


Figure 8.25. Values for the slope of the X-axis signal with rounding of the data values. The first occurance of a slope value dropping below 0 to -1, at 10.2 s, is the point of interest.

Once the rapidly falling slope is found, the algorithm then finds the largest local acceleration peak that occurs within the preceding 1 s of this point, which is then determined to be the start of the first lap. In this representative example, this yields a start point of the first lap that is different from the close approximation determined earlier by 0.46 s, as seen in Figure 8.26.

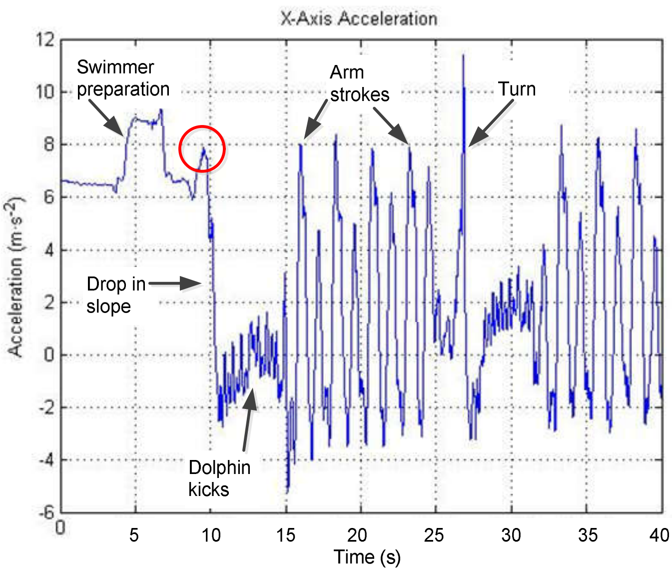


Figure 8.26. The location of the start of the first lap is identified as the local maximum in the X-axis acceleration signal that preceeds the rapid fall in acceleration that is associated with the changing orientation of the swimmer. This occurs at 9.54 s (red circle)

The second stage of the lap time detection algorithm involves the identification of wall contact events that occur as a swimmer performs a turn at the end of a lap. These wall contact events are readily detected using a peak detection algorithm, identifying the minimum peaks in the signal that represent the rapidly changing orientation of the swimmer as they rotate during a turn (Figure 8.27). This approach has been described frequently in the extant literature [14, 22]. Adaptations to the algorithm are required for specific strokes. The algorithm flowchart for Stage 2 is illustrated in Figure 8.28 below.

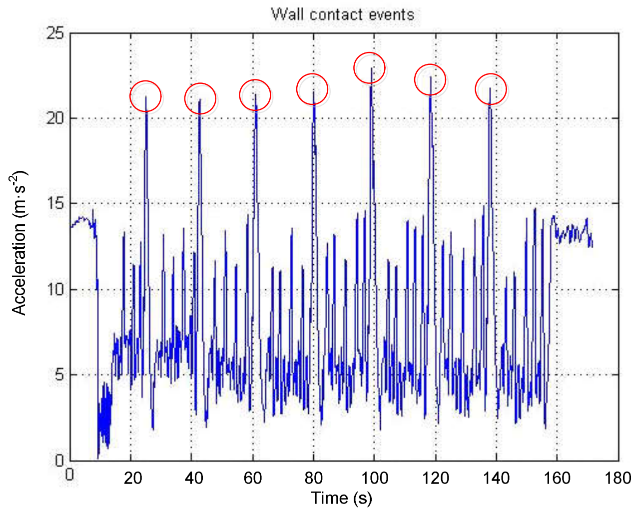


Figure 8.27. Wall contact events (circled in red), which are representative of turns that are performed during a swimming interval, can be identified using a peak detection algorithm. In this example, seven wall contact events (or turns) were detected during this 200 m frontcrawl interval performed in a 25 m pool.

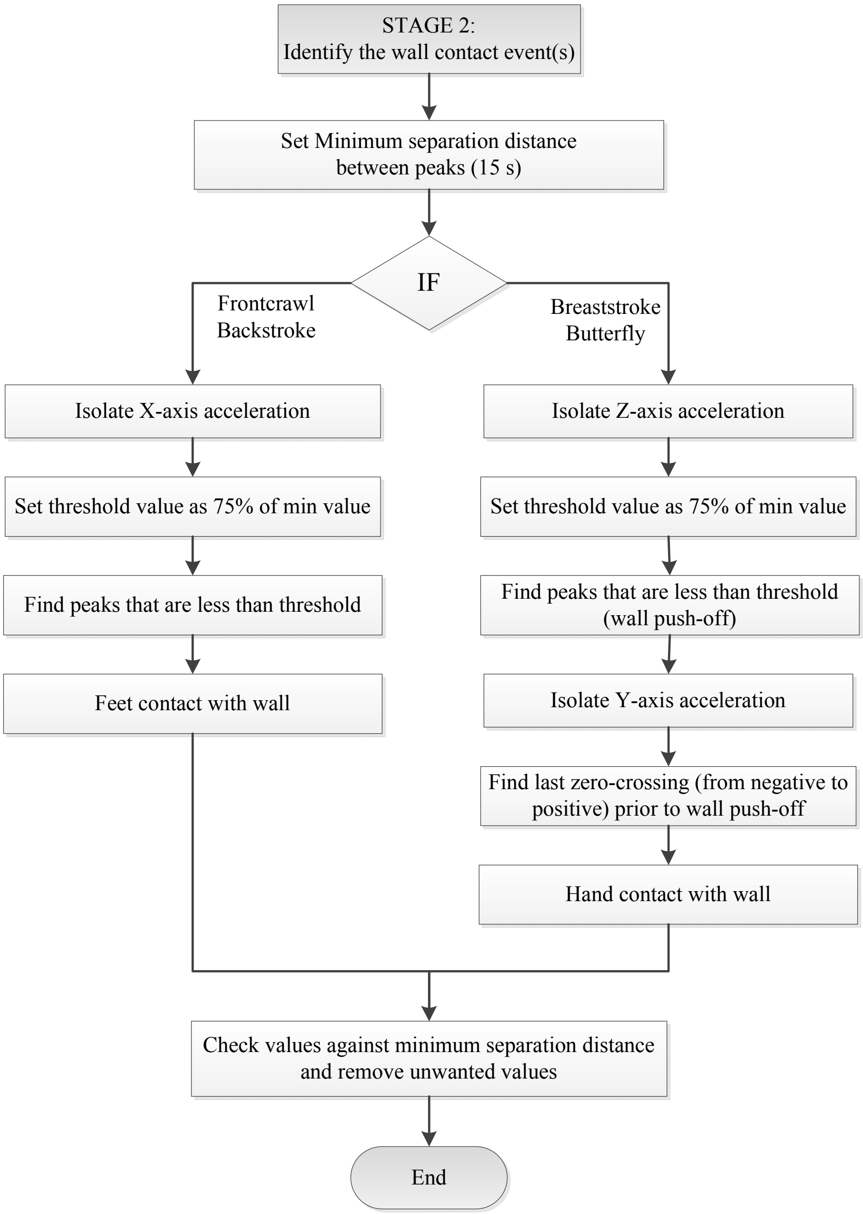


Figure 8.28. Flowchart describing Stage 2 of the lap time algorithm.

A minimum separation distance of 15 s is first defined to ensure that only wall contact events related to turns are identified and so that in the instance of a local maximum occurring as a result of normal swimming activity it is eliminated. For frontcrawl and backstroke the X-axis signal is used to identify the instant that the swimmers feet make contact with the wall (Figure 8.27). The maximum value is found, which represents the largest peak in the signal, and a threshold value is set to 75% of this maximum. This is completed in order to identify only those peaks associated with turning events and not local peaks of smaller magnitude that are associated with regular swimming activity. The values are also compared against the minimum separation distance to ensure that they are valid wall contact events. In the case of frontcrawl and backstroke, this will be the instant of feet making contact with the wall.

In contrast, butterfly and breaststroke swimming involve open turns during which the swimmer touches the wall with the hands first and then the feet. It is the instant of wall contact with the hands that marks the end of the lap for timing purposes. Therefore a modification to the previously described process is required. For these swimming strokes, peak detection along the Z-axis acceleration is employed. Again, the maximum value is found and used to establish a threshold. Peaks with a magnitude value exceeding 75% of this maximum are detected. These peaks mark the incidences of wall push-off. The algorithm then works back from this point to find the location of hand contact. This is achieved using a zero-crossing algorithm applied to the Y-axis acceleration signal for the 5 s that precedes the wall push-off. The zero-crossing process identifies when the acceleration changes from negative to positive, with the last such change that occurs prior to the wall push-off determined to be the instant of hand contact with the wall (Figure 8.29).

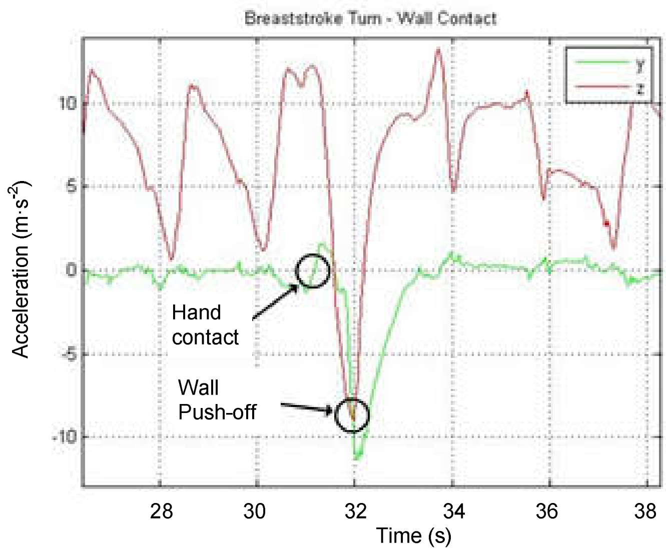


Figure 8.29. For breaststroke and butterfly turns, the identification of wall contact first requires the identification of the push-off using peak detection along the Z-axis. From this point, it is possible to work back to the zero-crossing event on the Y-axis that corresponds to the hand contact with the wall.

Stage 3 of the lap time detection algorithm involves locating the end of the final lap of swimming. The algorithm process flowchart is illustrated in Figure 8.30. The end of an interval is determined in a similar fashion to the identification of the interval start. Firstly, a window is examined where the event is likely to have occurred. This window starts 10 s after the final turn event identified in Stage 2 and continues until the end of the interval. The slope of the signal is again determined, using the same process as described earlier. The only change in this case is that it is the rising slope, not the falling slope, which is of interest. Once this is located, the next local maximum in the signal that exceeds the 8.5 $m \cdot s^{-2}$ threshold is determined to be the final wall contact event as the swimmer's head orientation changes after wall contact is made (Figure 8.31). Subsequent to this the X-axis value returns to a relatively steady state output of approximately 9.81 $m \cdot s^{-2}$, as the swimmer's head returns to a vertical position.

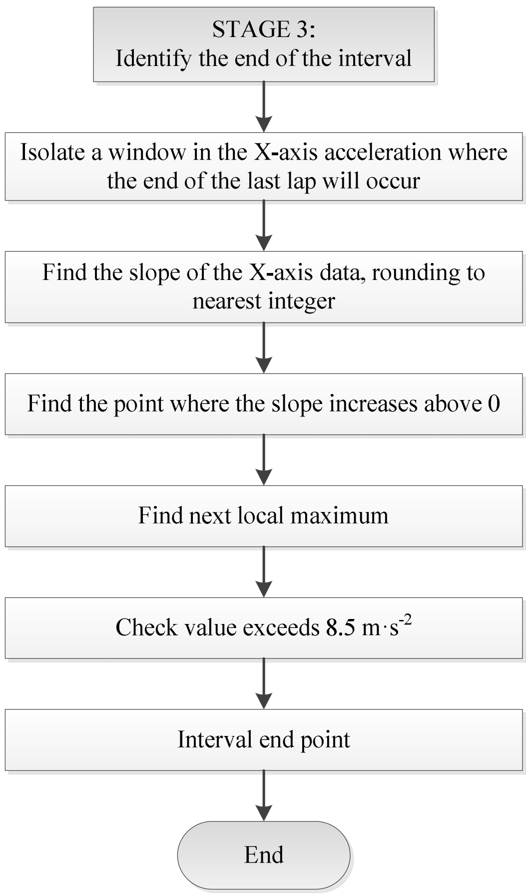


Figure 8.30. Flowchart describing Stage 3 of the lap time algorithm.

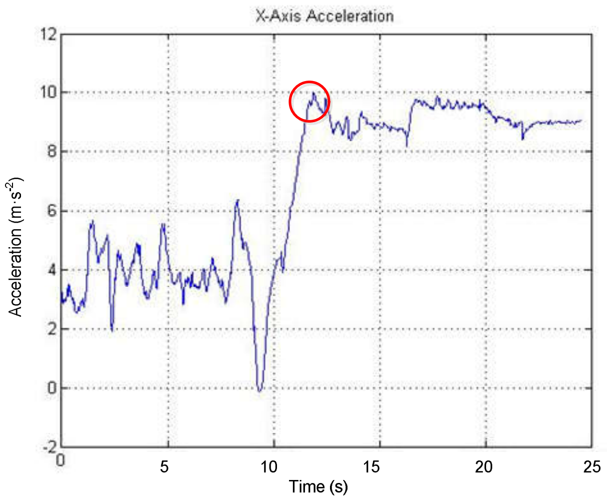


Figure 8.31. Identification of the end of a swimming interval, which is characterised by a rapid change in acceleration about the X-axis as the swimmer changes their orientation in the water. The peak in the signal following this orientation change is highlighted with the red circle.

Once the data for these three stages of wall contact events have been determined, the time stamps for these data are put into an array and then the time between each of these events is calculated. A sample of the output of the lap time algorithm is provided in Figure 8.32 below. An array of times is created, representing the calculated lap time for each lap performed in the swimming interval that was selected. The average speed is also calculated and reported. This is determined by dividing the pool length (25 m in this study) by the time taken to complete each lap.

Lap Times	Average Speed
Lap 1 Time = 15.9 s	1.57 m/s
Lap 2 Time = 17.6 s	1.42 m/s
Lap 3 Time = 18.35 s	1.36 m/s
Lap 4 Time = 19.11 s	1.31 m/s
Lap 5 Time = 18.94 s	1.32 m/s
Lap 6 Time = 19.36 s	1.29 m/s
Lap 7 Time = 19.51 s	1.28 m/s
Lap 8 Time = 18.29 s	1.37 m/s

Figure 8.32. The output of the lap time algorithm. An array of lap times for each lap performed during the selected swimming interval is produced. The swimmer's average speed is also reported for each lap.

8.3.4 Stroke Count Detection

Stroke counts are not a primary objective in this study but rather are required in order to define the turn phase. During the development of the use case, described in Chapter 6, swim coaches agreed that a definition of a turn that is based on a set number of strokes performed both before and after the turn itself is acceptable. This definition is required as it is not possible to accurately determine a swimmer's position in the pool or the distance they have travelled during a given lap using the prototype system. Consensus was reached that three strokes be used in the case of frontcrawl and backstroke, whilst two strokes were appropriate for breaststroke and butterfly. Interestingly, this also is perceived by coaches to provide an approximation of five metres from the wall on approach, equating well with a standard definition of the turn phase based on distance. The time of the breakout stroke is also included as it is another important parameter to evaluate with analysing turn performance. Similar to the lap time, accurate detection methods for determining stroke count are well described in the literature [18, 23, 24]. Stroke counts are important coaching parameters and methods may involve either a zero-crossing approach [25, 26] or the detection and summation of acceleration peaks for a given lap [18, 24]. The majority of previous studies have focused on frontcrawl stroke count methods, typically involving the medio-lateral acceleration signal [18, 26] (Figure 8.33). However, this axis is not suitable in all cases and for all sensor locations and therefore different acceleration axes are required for the other three swimming strokes [25, 27]. A similar approach has been taken in this PhD work by selecting the most suitable axis for a given swimming style. The algorithm process flowchart is illustrated in Figure 8.34.

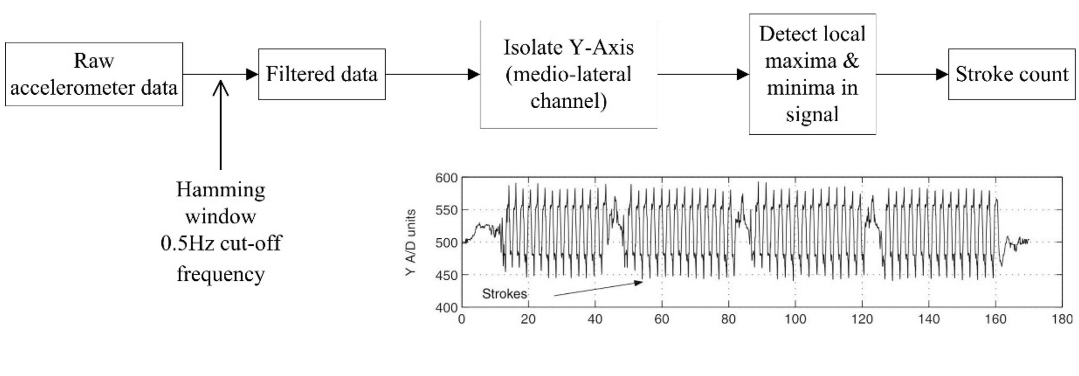


Figure 8.33. The regularly repeating body roll during frontcrawl swimming allows for a stroke count algorithm based on tracking peaks and troughs in the medio-lateral acceleration signal. Reproduced with permissions from Davey, Anderson and James [18].

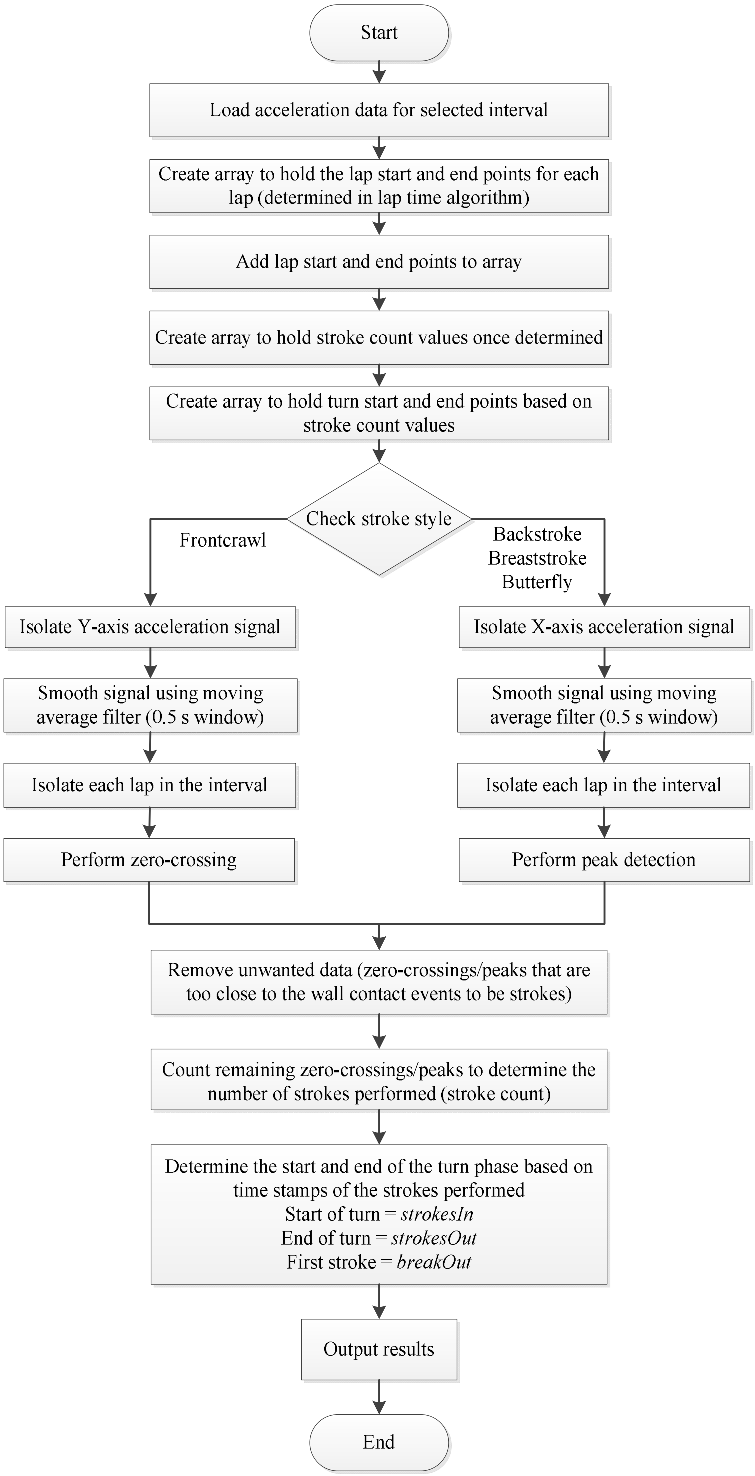


Figure 8.34. Stroke count detection algorithm. This process determines the number of strokes performed during each lap and is also used to define the turn phase based on when a set number of strokes are performed both before and after the wall contact event. For frontcrawl and backstroke, the turn phase is from the 3rd last stroke on approach to the 3rd stroke after the push-off. For breaststroke and butterfly, two strokes are used.

The algorithm takes inputs from the previous lap time detection algorithm, using the identified wall contact events to create an array of the start and end points of each lap that were performed in the selected swimming interval. Two further arrays are also defined. The first is created to store the number of strokes completed for each lap, once determined. A second array is created that will hold the time stamps for the start and end point of each turn. These time stamps are determined based on the number of strokes for each lap. For example, if a swimmer completes two laps of frontcrawl and performs ten strokes for each lap, then the turn phase is defined as being from the third last stroke in lap one to the third stroke in lap two. The algorithm involves a zero-crossing calculation in the case of frontcrawl or peak detection methods for the other three strokes. If frontcrawl swimming is detected, the Y-axis acceleration signal is analysed. In the case of the other strokes, it is the X-axis acceleration that is used. Once the stroke style has been checked, the data is smoothed out using a moving average filter across a 0.5 s window. This is necessary as the initial signal contains small local fluctuations that make identification of each peak, representing the arm strokes, difficult, as seen in Figure 8.35. In contrast, the filtered version of the same data signal demonstrates a smoother pattern in Figure 8.36. Each peak, which is representative of individual strokes, can then be more readily determined and counted.

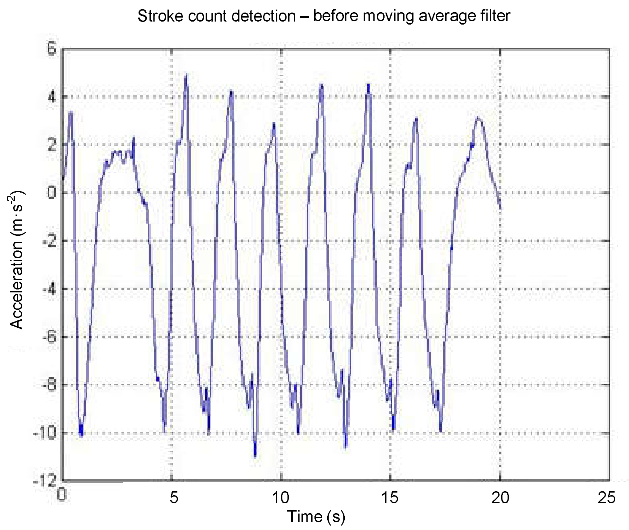


Figure 8.35. Stroke count detection involves the identification of peaks in the X-axis acceleration signal that occur during each lap of the swimming interval.

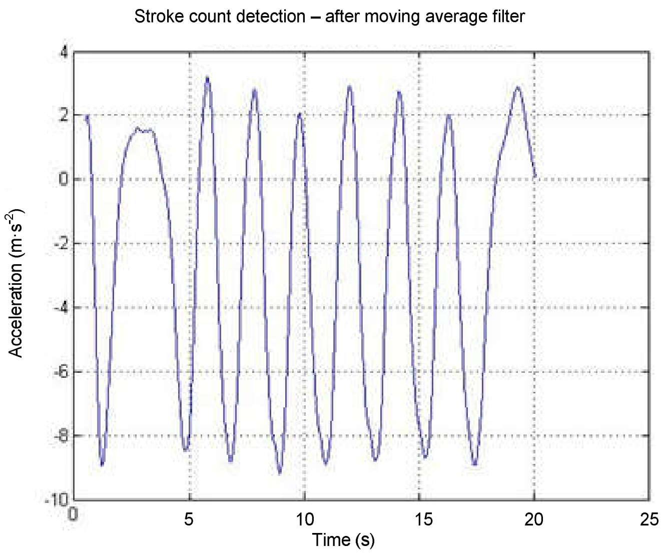


Figure 8.36. The detection of each peak in the X-axis acceleration signal for stroke count determination is made easier by using a moving average filterover a 0.5 s window to smooth out the signal.

Once the filtered signal has been obtained, each lap performed is processed in turn, using the appropriate method based on the stroke style. The process for three of the strokes (butterfly, breaststroke, backstroke) involves peak detection of the X-axis acceleration. Different thresholds were used for each stroke. The threshold was set to 10% of the maximum value in butterfly as the peak amplitude alternates between a large peak and a small peak (Figure 8.37). This occurs as a result of the requirement for swimmers to lift their head to breathe, usually every two strokes. The algorithm detects the number of peaks that exceed the threshold. Any peaks that occur as a result of the turn are removed. Dolphin kicks performed following the push-off can also be identified but do not produce the amplitude of signal necessary to exceed the threshold.

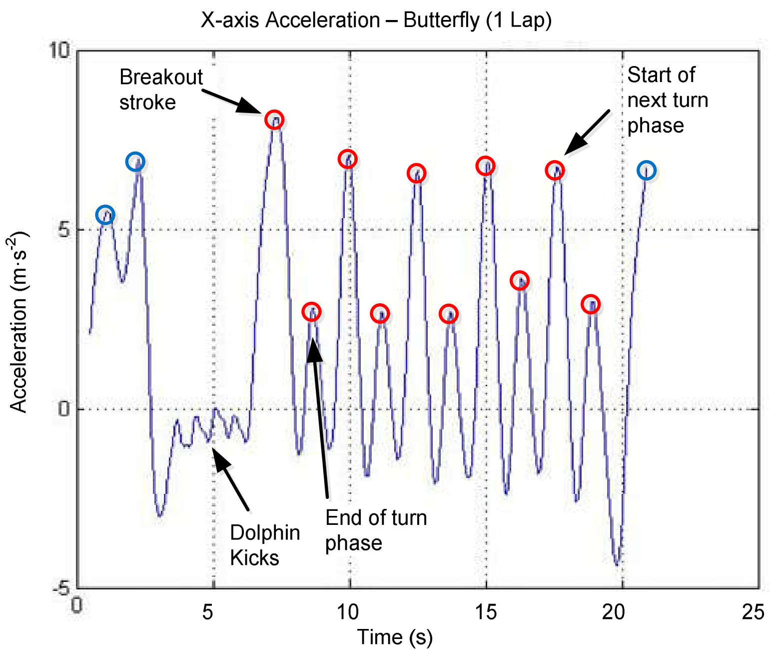


Figure 8.37. Peak detection is performed on the X-axis acceleration signal to determine the number of strokes performed during a lap of butterfly swimming. The strokes performed are highlighted in the red circles, whilst unwanted data (blue circles) at the start and end of the lap are identified and removed.

For breaststroke, the threshold was 60% of the maximum value as the peak amplitude is more consistent owing to the fact that swimmers breathe following every stroke performed (Figure 8.38). The pulldown stroke can also be recognised in the signal, occurring following the push-off from the wall. The amplitude of this signal feature was not found to be sufficient to exceed the 60% threshold.

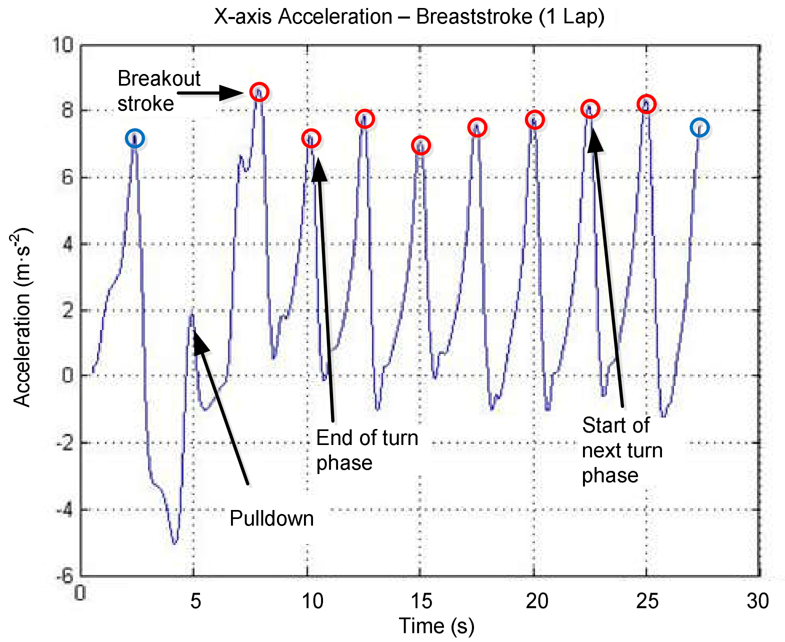


Figure 8.38. Peak detection is performed on the X-axis acceleration signal to determine the number of strokes performed during a lap of breaststroke swimming. The strokes performed are highlighted in the red circles, whilst unwanted data (blue circles) at the start and end of the lap are identified and removed.

In the case of backstroke the threshold was not established in relation to a maximum value. Instead, the threshold was set to 4.0 $m{\cdot}s^{-2}$. The reason for this is that because the swimmer aims to keep the head steady the signal output for the head worn prototype is relatively stable and consistently greater than this threshold (Figure 8.39). Additionally, dolphin kicks that are performed do not produce this amplitude of signal.

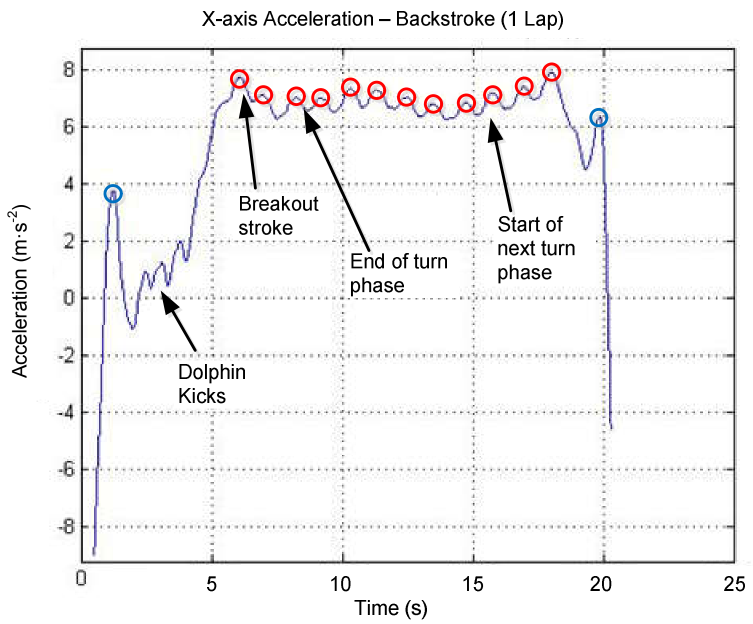


Figure 8.39. Peak detection is performed on the X-axis acceleration signal to determine the number of strokes performed during a lap of backstroke swimming. The strokes performed are highlighted in the red circles, whilst unwanted data (blue circles) at the start and end of the lap are identified and removed.

For frontcrawl, rather than performing peak detection, a zero-crossing detection algorithm on the Y-axis acceleration is performed. The reason for not using the X-axis can readily be seen in Figure 8.40 as no discernible pattern related to specific arm strokes can be distinguished.

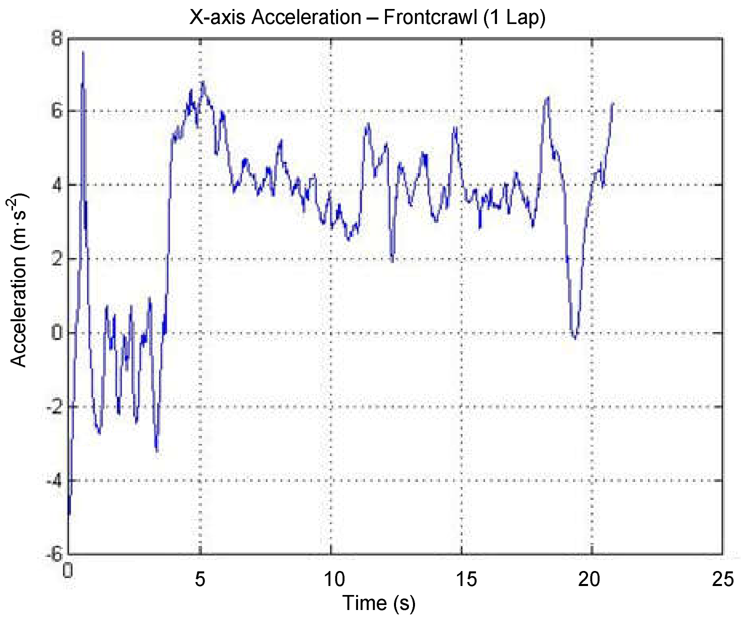


Figure 8.40. X-axis acceleration signal during a lap of frontcrawl swimming.

The Y-axis acceleration is affected by the longitudinal rotation of the swimmer as they move from side to side during frontcrawl (Figure 8.41). This signal output therefore provides a more stable method of determining the number of strokes performed. It could be possible to count the peaks in this signal using a similar methodology described above except for the fact that the signal magnitude is altered depending on whether a breath is taken. As shown in Figure 8.41, when a swimmer takes a breath the signal amplitude is magnified. Additionally, the direction of this signal (either positive or negative) depends on which side the swimmer turns to breathe. As a consequence, a zero-crossing approach was deemed more appropriate. Tracking the zero-crossing events should also prove more accurate, as this relates to the point when the swimmer is flat in the water, which should correspond to the point of hand entry. The algorithm counts the number of times the Y-axis acceleration value crosses the 0 $m \cdot s^{-2}$ acceleration line. This initial count is then modified if any of the zero-crossings were deemed to occur within the first 3 s of a lap or the last 1 s of a lap as this would indicate that the event is part of a turn as opposed to a stroke. Once the final stroke count is established, the time stamps associated with the first stroke (breakout), third stroke (end of turn) and the third last stroke (start of the next turn) are determined and used to define the turn phase.

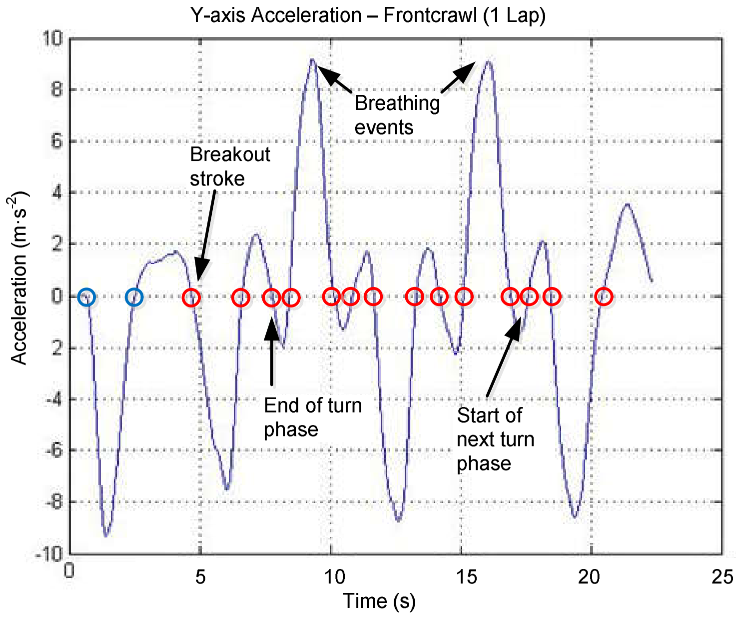


Figure 8.41. Zero-crossing detection is performed on the Y-axis acceleration signal to determine the number of strokes performed during a lap of frontcrawl swimming. The strokes performed are highlighted in the red circles, whilst unwanted data (blue circles) at the start and end of the lap are identified and removed.

A sample of the output of the stroke count algorithm is provided in Figure 8.42. An array of stroke count data is created, representing the calculated number of strokes performed for each lap of the swimming interval that was selected. These values can be compared to the manually recorded stroke count values from the video footage to check for accuracy. The time stamps for each stroke are also recorded, so that the turn phase can be determined in the next stage of the feature detection process.

$$\begin{bmatrix} \text{Lap 1 Stroke Count} = 9 \\ \text{Lap 2 Stroke Count} = 12 \\ \text{Lap 3 Stroke Count} = 11 \\ \text{Lap 4 Stroke Count} = 10 \\ \text{Lap 5 Stroke Count} = 11 \\ \text{Lap 6 Stroke Count} = 13 \\ \text{Lap 7 Stroke Count} = 10 \\ \text{Lap 8 Stroke Count} = 9 \end{bmatrix}$$

Figure 8.42. The output of the stroke count algorithm is an array of strokes performed for each lap performed during a selected swimming interval.

8.4 Turn Phase: Algorithm Development

The final stage in the algorithm development is to quantify the performance related parameters that can be used by a coach and swimmer to conduct a detailed analysis of each turn. To reach this stage in the process, the development work has focused largely on the use of previously described techniques, such as the calculation of stroke style, lap times and stroke counts, with appropriate modifications made to suit the head worn position of the prototype device. This work has facilitated the detection and timing of the turn phase. Moreover, once the turn phases are identified, the potential for a detailed quantitative analysis of each turn may be explored.

8.4.1 Turn Time Detection

Once the lap time and stroke count have been calculated for each lap, it is straightforward to determine the turn time for each turn, along with other parameters that make up this turn, namely time in, time out and breakout time. Figure 8.43 provides a schematic representation of the process that will be carried out. In this example four laps are completed. Therefore three turns will be performed. The turn phase is determined using the stroke counts already identified for each lap. For example, the start of *Turn 1* is the second/third last stroke performed in *Lap 1*. The end of *Turn 1* is the second/third last stroke performed in *Lap 2*. The breakout stroke is the first stroke performed in each lap. The wall contact events that were identified as part of lap time detection are also input to the algorithm.

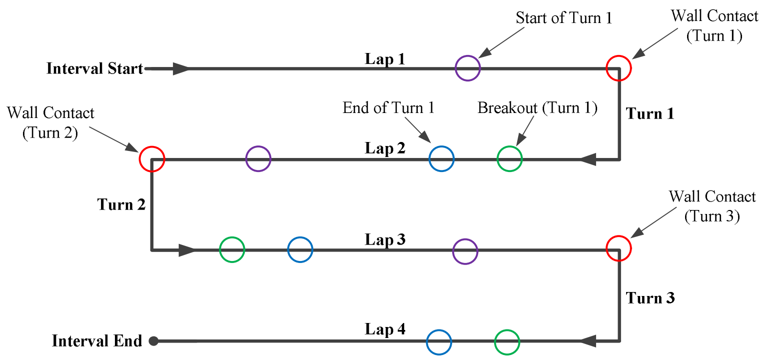


Figure 8.43. Schematic representation of the turn phase detection within a swimming interval. The interval contains four laps and three turns. The end of each lap is identified by the wall contact events (red circles). Each turn is defined according to a set number of strokes

performed both before (purple circles) and after (blue circles) each wall contact event. The breakout stroke is also identified (green circles).

The algorithm process flowchart for determining these parameters is illustrated in Figure 8.44. The algorithm takes inputs from the previous stages to create an array of time stamp values for the *turnStart*, *turnEnd*, *breakOut* and *wallContact* parameters. Next, a simple arithmetic is performed to calculate the turn times for all turns performed in the swimming interval. Finally, the results are displayed for review, as shown in Figure 8.45.

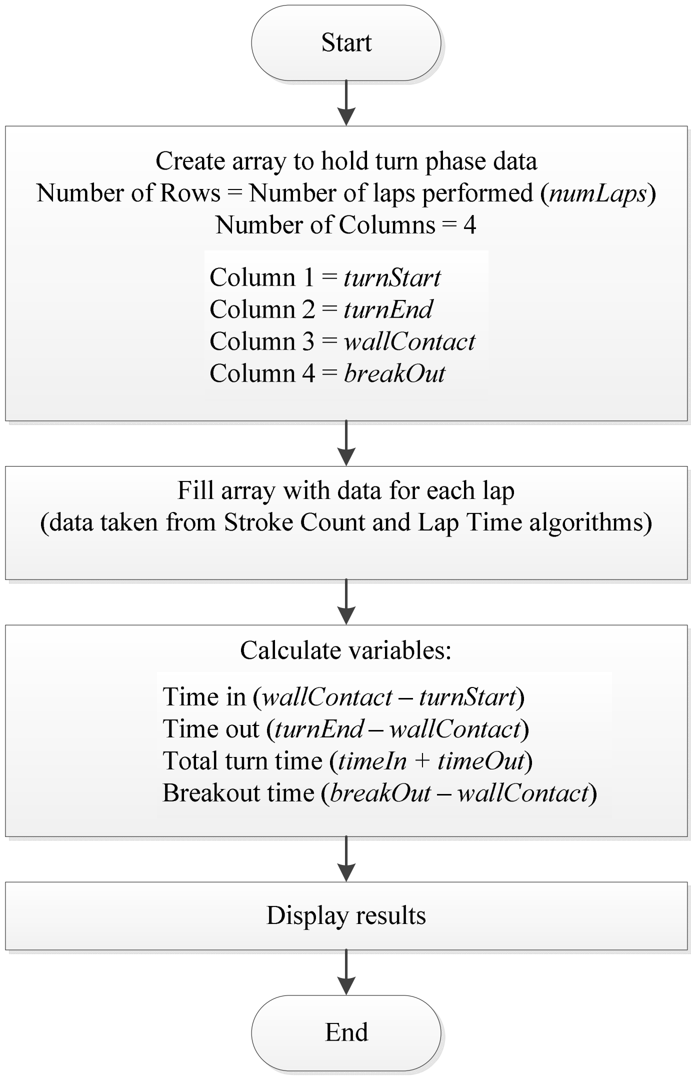


Figure 8.44. Turn time detection algorithm. The process takes inputs from the lap time algorithm and the stroke count algorithm and outputs the temporal turn phase variables based on these values.

Turn	Turn Time	Time In	Time Out	Breakout
Turn 1	10.45 s	5.48 s	4.97 s	2.28 s
Turn 2	11.78 s	5.91 s	5.87 s	2.17 s
Turn 3	11.69 s	5.52 s	6.17 s	2.69 s
Turn 4	11.66 s	5.82 s	5.84 s	2.73 s
Turn 5	12.15 s	5.82 s	6.33 s	3.03 s
Turn 6	9.13 s	3.56 s	5.57 s	2.76 s
Turn 7	12.15 s	5.98 s	6.17 s	2.97 s

Figure 8.45. The output of the turn time detection algorithm. Total turn time, along with time in, time out and breakout times are determined for each turn performed in an interval.

Once the turn phase has been identified, the acceleration and angular velocity signals can be visually inspected and compared with the corresponding video footage to gain an understanding of how the signal outputs relate to the movements of the swimmer. Temporal information related to the analysis of the turn, including parameters such as wall contact time, rotation time and glide time can be determined once the time stamps of each of these key events are known. The parameters included in this study are listed in Table 8.4. Whilst some of the parameters are relevant to all four swimming strokes, others are specific to certain strokes, such as transverse rotation time for example, which is a parameter of interest in backstroke and frontcrawl swimming only.

The specific algorithm that is performed depends on the type of turn that is executed. In pool swimming, there are two main types of turns that can be performed, open turns and flip turns. An open turn, performed during breaststroke and butterfly swimming, involves the swimmer touching the wall first with their hands and then rotating in a tuck-like position to bring their legs up to touch the wall. The swimmer then turns on the wall to face the opposite end of the pool and pushes off to begin a new lap. A flip turn (also known as a tumble turn) is performed during frontcrawl and backstroke. As the swimmer approaches the pool wall they perform a tuck and a forward flip, touching the wall with their feet, before pushing off to begin the next lap.

Table 8.4. Parameters that are measured using the prototype system for each of the four competitive swimming strokes. Items that are listed as not applicable (N/A) signify parameters that are not relevant to the analysis of turns during that particular swimming stroke.

	Open Turns		Flip Turns	
Parameter	**Breaststroke**	**Butterfly**	**Frontcrawl**	**Backstroke**
Lap time	•	•	•	•
Stroke count	•	•	•	•
Turn time	•	•	•	•
Time in	•	•	•	•
Time out	•	•	•	•
Breakout time	•	•	•	•
Transverse rotation time	N/A	N/A	•	•
Longitudinal rotation time	N/A	N/A	N/A	•
Wall contact time	N/A	N/A	•	•
Hands to feet time	•	•	N/A	N/A
Feet contact time	•	•	N/A	N/A
Turn direction	•	•	N/A	•
Glide time	•	•	•	•
Pulldown time	•	N/A	N/A	N/A
Kick time	N/A	•	•	•
Kicks count	N/A	•	•	•

8.4.2 Open Turns (Breaststroke and Butterfly)

The sequence of actions during an open turn can be seen in Figure 8.46. During breaststroke and butterfly swimming, swimmers must touch with two hands [28], then one arm is dropped into the water to begin the turn while the other arm moves over the head to complete the turnaround from the wall. At the same time, the swimmer gets into a tuck position and rotates to get their feet to contact the wall [29]. The swimmer will then push-off into a streamlined position and glide until initiation of the dolphin kick (butterfly) or pulldown stroke (breaststroke) occurs.

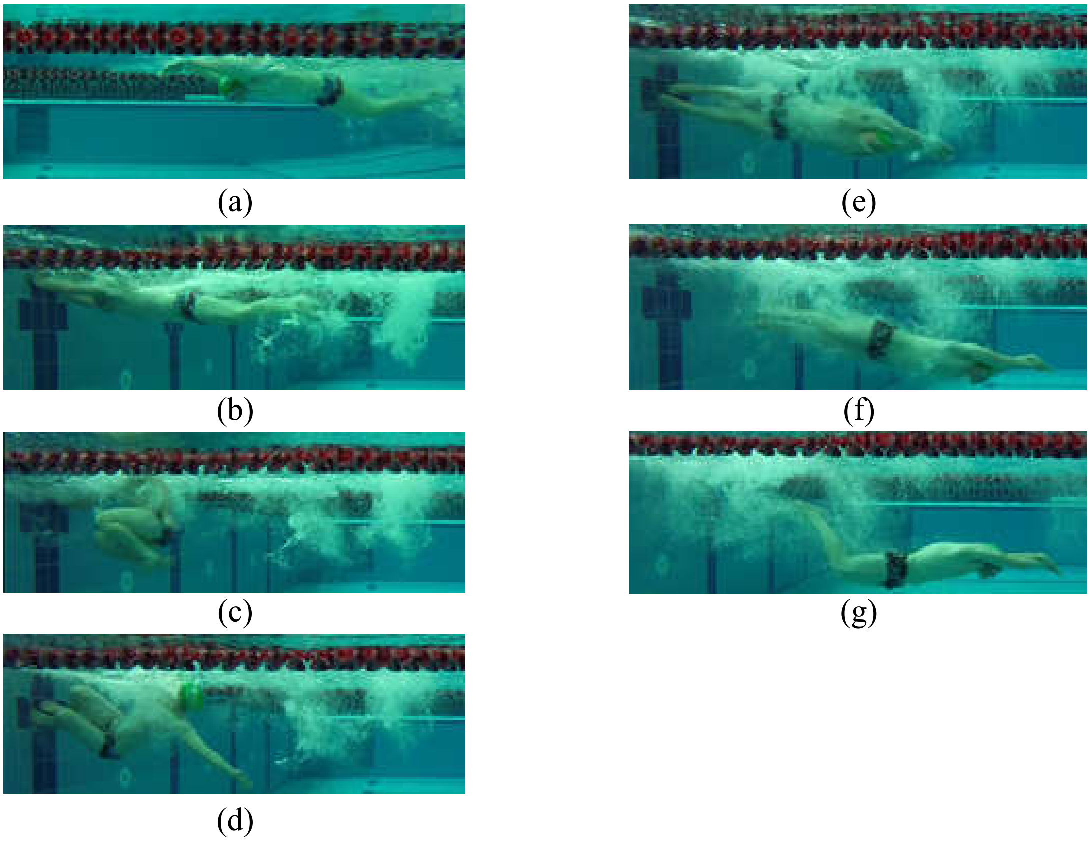


Figure 8.46. Open turn sequence, performed during breaststroke and butterfly. (a) approach, (b) hand contact, (c) tuck and rotation, (d) feet contact, (e) push-off, (f) glide, (g) kick.

Key features of the open turn that determine successful performance in a competitive setting include the time taken from touching the wall with the hands (Figure 8.46b) to touching with the feet (Figure 8.46d). This is known as hands to feet time and a time of 0.7 s is considered to be of an elite standard [30]. Information such as this is used by coaches in order to assess technical proficiency.

The next step is to examine what the turn signal looks like, in order to determine if the parameters of interest can be identified. Figure 8.47 provides a representative example of the acceleration and angular velocity signal output for one swimmer performing an open turn. Rotational events corresponding to the movements during the turn can be seen in the centre of these plots and are distinguishable from the swimming activity performed at the start and end of the turn phase. The point of wall push-off, which was identified earlier as part of the lap time detection algorithm, corresponds to the minimum peak found in the Z-axis acceleration.

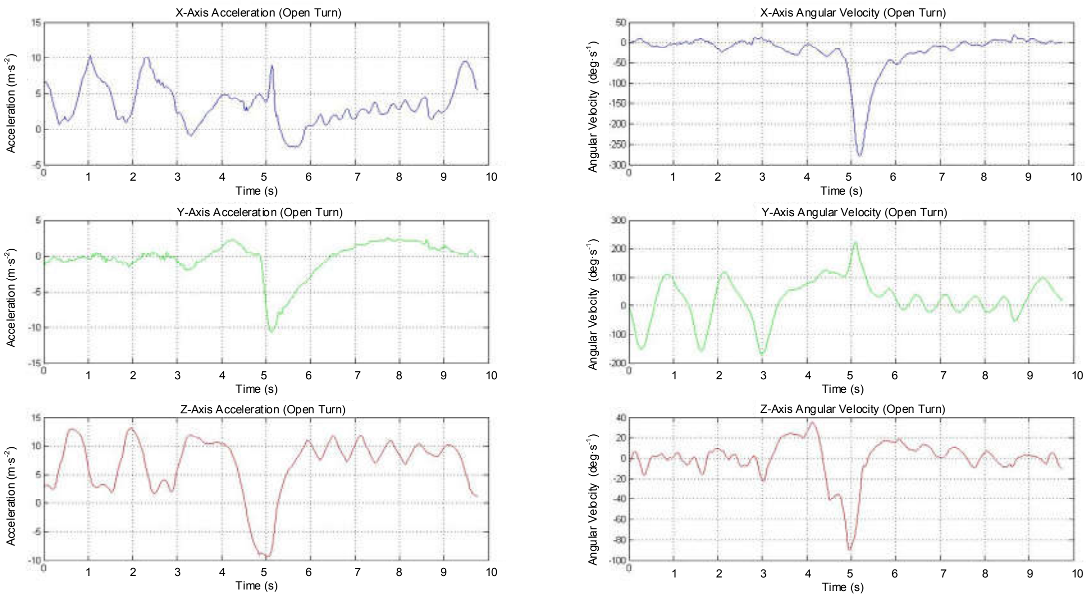


Figure 8.47. Acceleration and angular velocity signal output for an open turn.

Before algorithm development can be commenced it is vital to ensure that the signal output shown in Figure 8.47 is repeatable between subjects and within subjects. This will help ensure that feature detection is based on repeatable and reproducible signal features, thus improving the likelihood of accurate detection in a broad range of competitive swimmers. The repeatability/reproducibility of this signal output for the open turn is shown in Figure 8.48, featuring the signal output from multiple turns performed by different swimmers. Both breaststroke and butterfly turns are included and all turns are centred on the point of wall push-off.

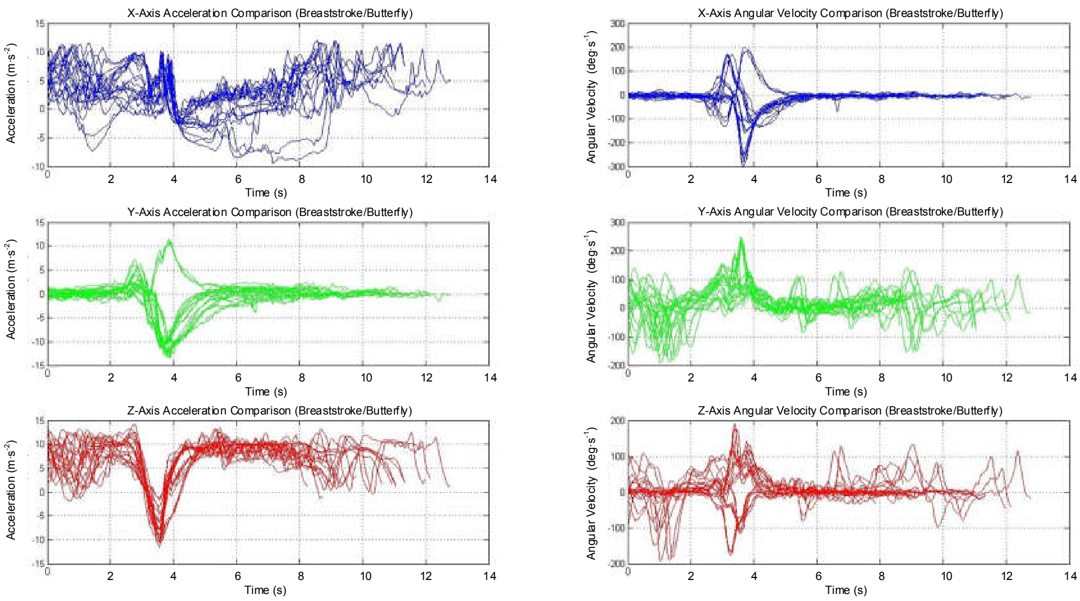


Figure 8.48. Repeatability of acceleration and angular velocity profiles for the open turns performed during the breaststroke and butterfly turn phase.

It can be seen that there are several common features in the various signal profiles as well as some inconsistent features. The X-axis acceleration appears to display a very inconsistent signal profile during the entire turn phase. However, a consistent feature is a positive peak in the signal during the wall contact phase (occurring at approximately 4 s), which appears to be common between swimmers. The signal before and after the wall contact phase is considerably influenced by the duration of the entire turn phase and by the timing of the arm strokes in relation to the turn itself.

The Y-axis acceleration displays a very consistent signal profile. Before and after the turn, the signal output centres on 0 $m \cdot s^{-2}$ as the swimmer does not rotate from side to side during breaststroke or butterfly. During the turn, a small positive (or negative) peak is observed, relating to the initial body actions from the point of hand contact with the wall. A zero-crossing detection algorithm was used in Section 8.3.3 during lap time detection to determine wall contact with the hands. This signal feature corresponds with the head lifting out of water to breath and starting to rotate to the side. The value of this initial peak is approximately 6 $m \cdot s^{-2}$. Next a second, larger peak, approximating to 12 $m \cdot s^{-2}$ occurs in the opposite direction. This peak is related to the longitudinal rotation occurring as the swimmer prepares for and executes the push-off. The Y-axis acceleration appears to show enough consistency to allow for feature detection algorithms to be based on this signal output. The direction of the Y-axis acceleration peaks (either positive or negative) is related to the direction that the swimmer turns. If the larger peak is positive, the turn is to the right. If the larger peak is negative, the turn is performed to the left side.

The Z-axis acceleration also displays a very regular pattern around the wall contact phase of the open turn. This large negative acceleration peak has already been identified at the instant of wall push-off as part of the lap time detection algorithm. Actions before and after the wall contact events display significant variability between subjects, owing to contrasting stroke timings during the turn phase. However, as will be described later, the Z-axis acceleration does prove useful for examining the dolphin kicks performed during butterfly turns and the pulldown stroke performed during breaststroke.

Inspection of the angular velocity profiles also displays both similarities and differences between trials. Examination of the X-axis angular velocity shows that the rotation of the swimmer during the turn can be observed as the signal deviates and returns to the 0 $deg \cdot s^{-1}$ seen during swimming. What is different between subjects is how the timing of this rotation relates to the push-off event, with some swimmers fully returning to a prone position before push-off, whilst others will push-off whilst still on their side. The Y-axis and Z-axis angular velocity profiles do appear to display a small degree of commonality between subjects in the signal characteristics, but this level of consistency is not as high as for other axes described above.

By zooming in on the wall contact events (Figure 8.49) it is possible to relate the signal output to the video images more clearly. Key distinguishable features in these signals are highlighted, together with associated video images, allowing for performance related parameters to be determined. As discussed, the push-off is the determined from the Z-axis acceleration. The points of hand contact and feet contact are identified using the Y-axis acceleration (Figure 8.50).

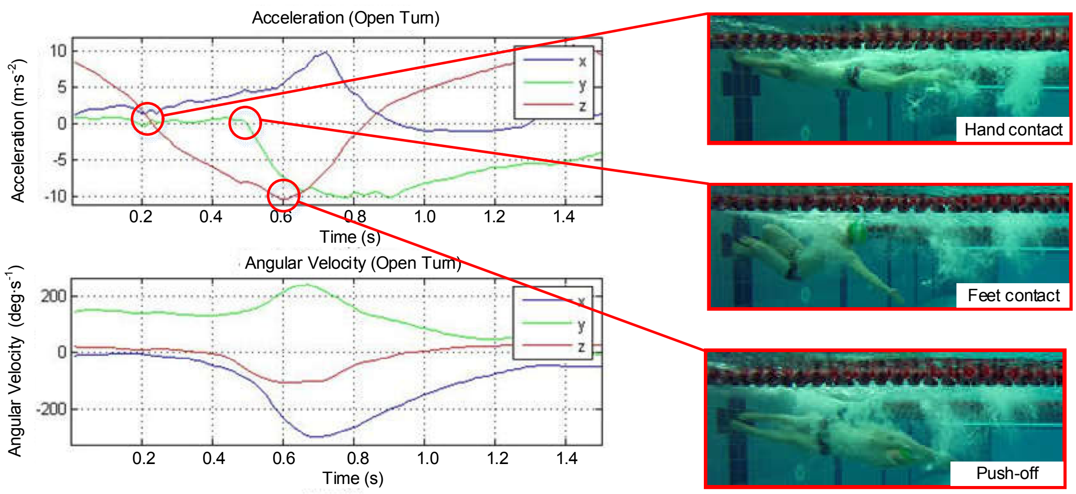


Figure 8.49. Wall contact phase of open turn.

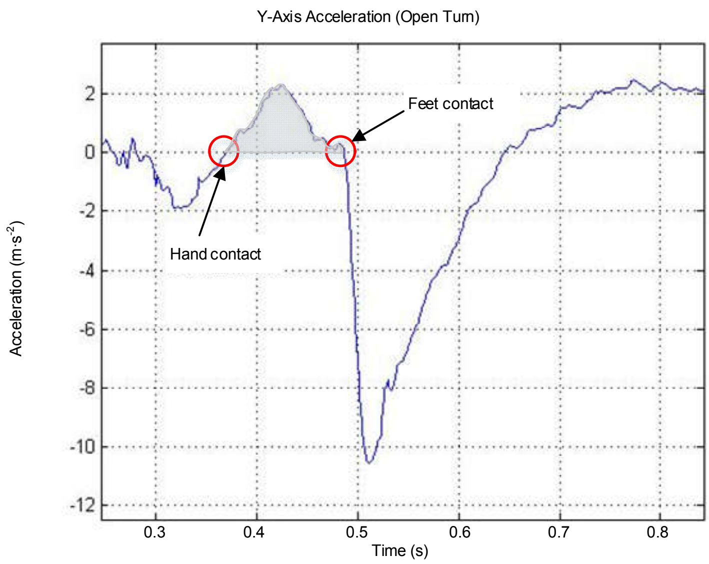


Figure 8.50. Hand and feet contact can be identified in the Y-axis acceleration using a zero-crossing algorithm. The shaded area represents the initial movement of the swimmer as they lift their head to breathe and rotate towards feet contact.

The process involves tracking the zero-crossing events that immediately precede the push-off from the wall. It was necessary to identify hand contact earlier as part of the lap time algorithm. A zero-crossing process identifies when the acceleration changes from negative to positive, with the last such change that occurs prior to the wall push-off determined to be the instant of hand contact with the wall. Feet contact is then identified as the next zero-crossing event in the opposite direction (from positive to negative in this example). Once these three points are known, hands to feet contact time, feet contact time and wall contact time can all be readily determined.

Turn direction can be identified using the X-axis angular velocity signal. In Figure 8.51, a large negative angular velocity peak is shown. This indicates that the turn is performed to the left side. If the peak were a positive value, the turn would be to the right.

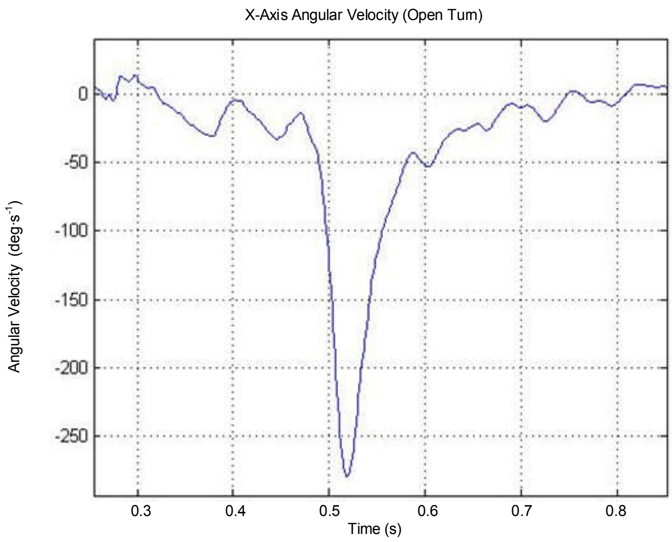


Figure 8.51. The X-axis angular velcoity signal is used to identify turn direction. A large negative peak indicates the turn is performed to the left side.

Following push-off from the wall, the sequence of movements differs between butterfly and breaststroke swimming. In butterfly, the swimmer performs a number of dolphin kicks whilst in a streamlined position. In contrast, in breaststroke a pulldown and arm recovery stroke is performed, during which a single dolphin kick is permitted [28]. This leads to a different signal output. However the process of determining some of the key parameters has common features.

The first dolphin kick in butterfly can be identified by first isolating a window in the Z-axis acceleration signal (Figure 8.52). This window is from the point of push-off to the breakout stroke. During this window the swimmer glides for a period and then initiates the dolphin kicking action. Peak detection during this window facilitates the kick count to be determined. Glide time is calculated as the time from the push-off to the time of the first kick. Kick time is therefore the time from the first kick until the breakout stroke.

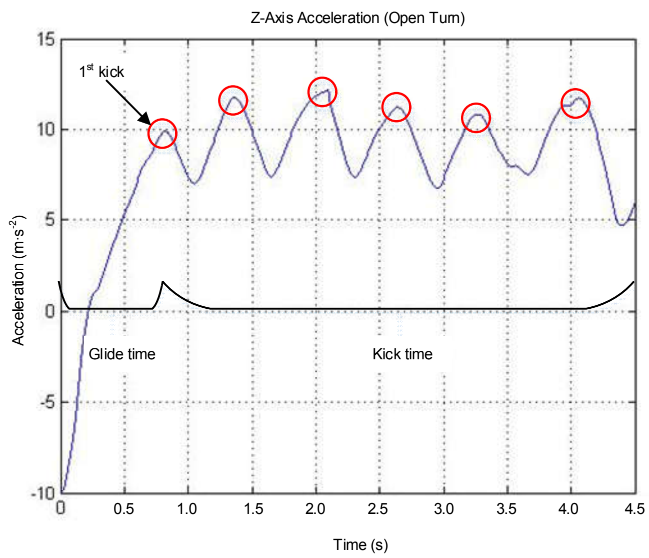


Figure 8.52. The Z-axis acceleration signal is used to identify the glide time and the number of dolphin kicks performed prior to the first arm stroke in butterfly. Six kicks (red circles) are identified in this example.

In breaststroke swimming a window in the Z-axis acceleration signal from the point of push-off to the breakout stroke is again determined (Figure 8.53). During this window the swimmer glides for a period and then initiates the pulldown and arm recovery action. Peak detection during this window facilitates the determination of the point where the pulldown stroke commences. Glide time is calculated as the time from the push-off to the time of the pulldown stroke. Pulldown time is the time from this action until the breakout stroke.

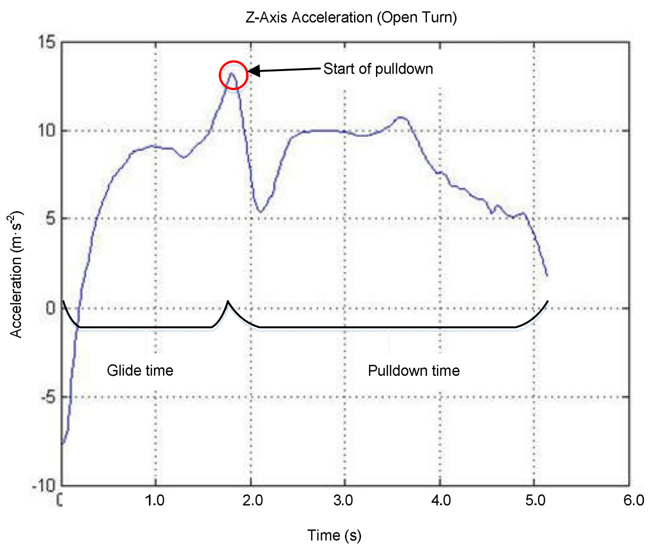


Figure 8.53. The Z-axis acceleration signal is used to identify the glide time and pulldown time prior to the first arm stroke in breaststroke.

All of the key features required for the analysis of open turns are now identified and can be provided to the coach and swimmer as feedback. A summary of the algorithm process flowchart is illustrated in Figure 8.54.

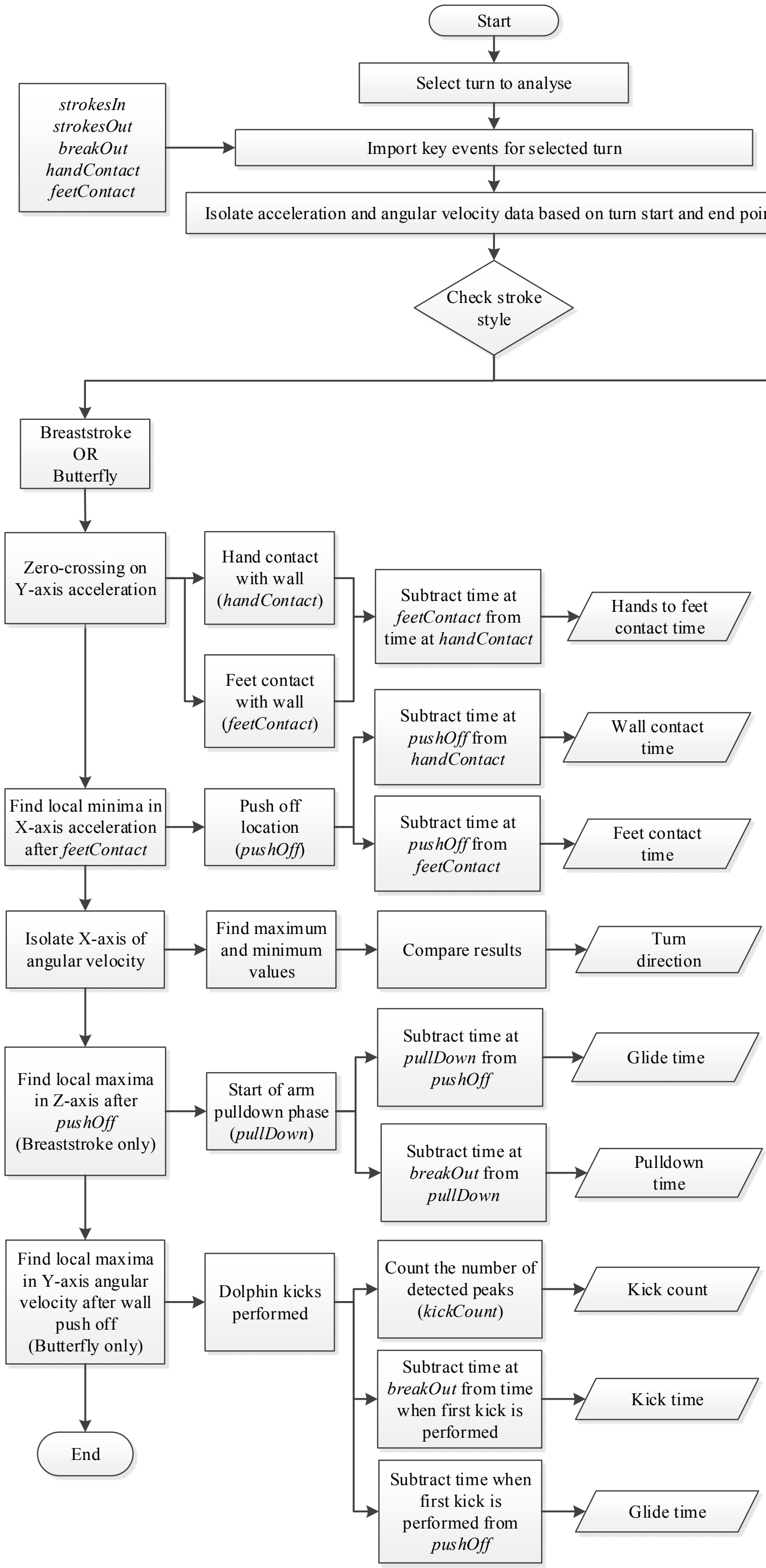


Figure 8.54. Turn phase analysis algorithm process flowchart, highlighting the feature detection process for open turns performed duing breaststroke and butterfly swimming.

8.4.3 Flip Turns (Frontcrawl and Backstroke)

The sequence of actions during a frontcrawl flip turn can be seen in Figure 8.55. As the swimmer approaches the pool wall they perform a tuck and transverse rotation. This is followed by touching the wall with the feet, before pushing off in a streamlined position and performing dolphin kicks until swimming is resumed [29]. The push-off is typically, although not always, performed when the swimmer is on their side (Figure 8.55d), with the swimmer then rotating to a prone position during the glide phase.

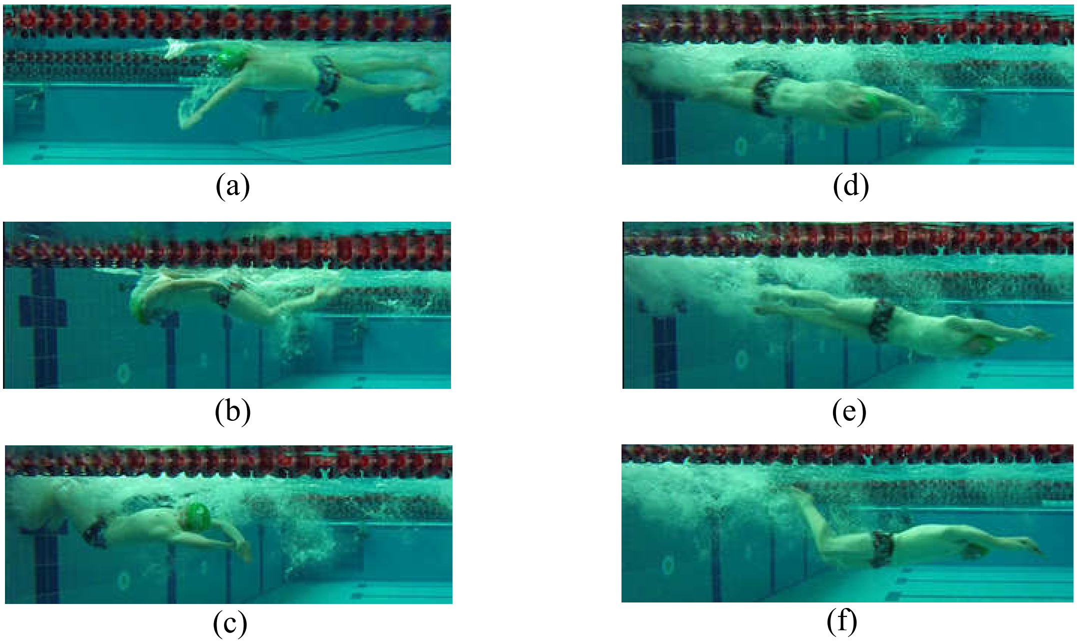


Figure 8.55. Flip turn sequence, performed during frontcrawl. (a) approach, (b) transverse rotation, (c) feet contact, (d) push-off, (e) glide, (f) kick.

The sequence of actions during a backstroke flip turn can be seen in Figure 8.56. As the swimmer approaches the wall in a supine position, a longitudinal rotation must first be performed immediately prior to the tuck and transverse rotation. Following push-off, a swimmer will remain in a supine position when gliding, dolphin kicking and resuming their arm action.

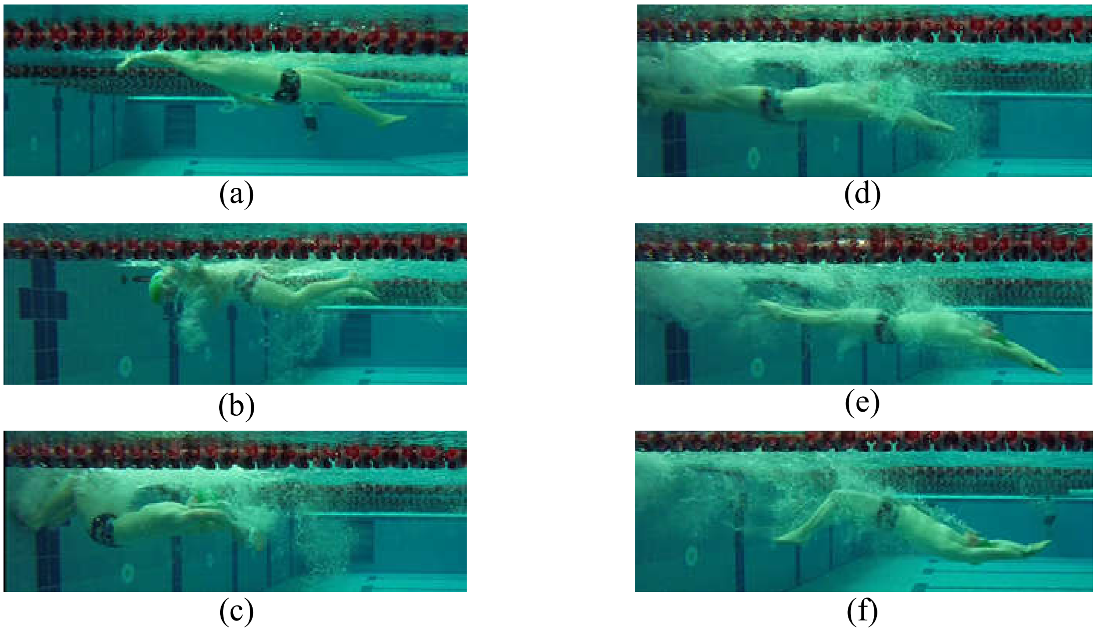


Figure 8.56. Flip turn sequence, performed during backstroke. (a) approach, (b) transverse rotation, (c) feet contact, (d) push-off, (e) glide, (f) kick.

Figure 8.57 provides a representative example of the acceleration and angular velocity signal output for one swimmer performing a flip turn. Similarly to the open turns, rotational events corresponding to the movements during the turn can be seen in the centre of these plots and are distinguishable from the swimming activity performed at the start and end of the turn phase.

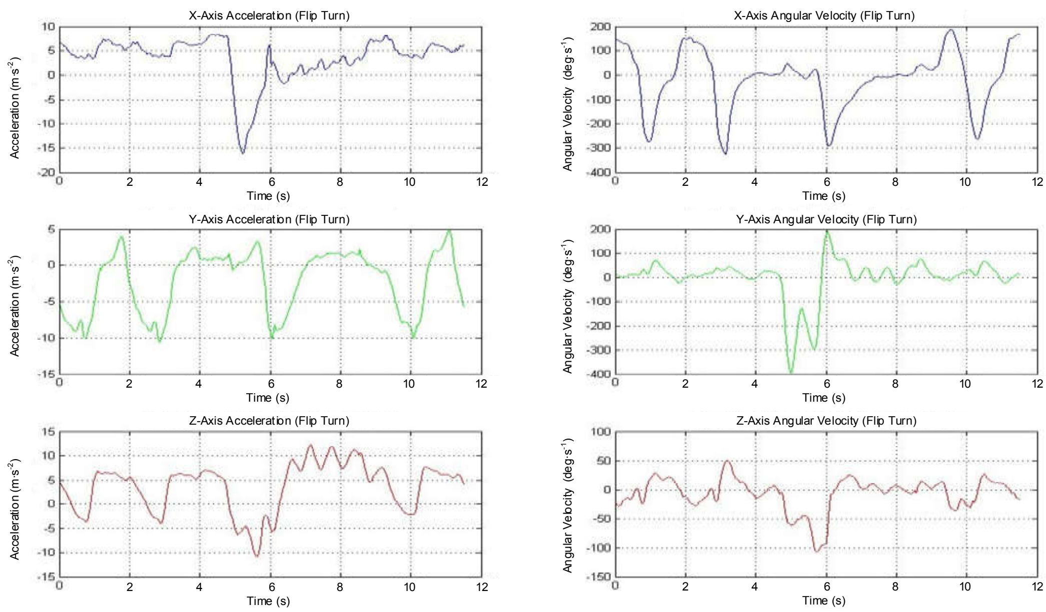


Figure 8.57. Acceleration and angular velocity signal output for a flip turn.

The repeatability/reproducibility of this signal output for the flip turn is shown in Figure 8.58, featuring the signal output from multiple turns performed by different swimmers. Both frontcrawl and backstroke turns are included and all turns are centred on the point of wall contact.

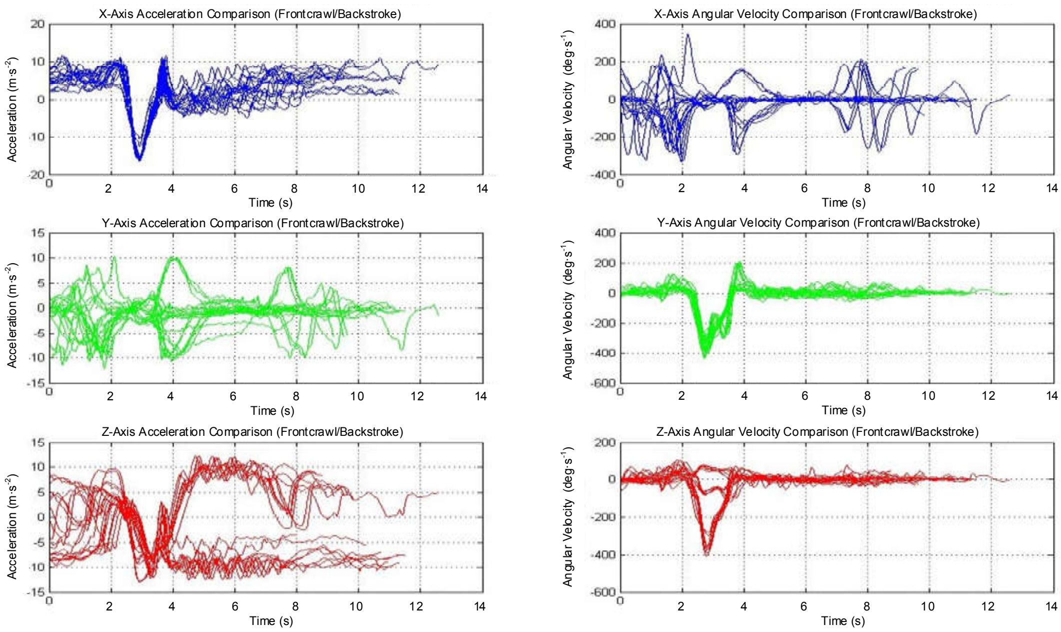


Figure 8.58. Repeatability of acceleration and angular velocity profiles for the flip turns performed during the frontcrawl and backstroke turn phase.

The point of wall contact, which was identified earlier as part of the lap time detection algorithm, corresponds to the minimum peak in the X-axis acceleration. The movements during the turn are represented on the X-axis acceleration as the swimmer tucks and rotates before wall contact is made, leading to a rapid negative acceleration peak. The X-axis acceleration appears to display a very consistent signal profile during the entire turn phase. The acceleration signal before and after the wall contact phase is relatively stable and consistently positive. This represents the forward acceleration of the swimmer as they progress down the pool. The increasing acceleration following push-off can also be seen as they transition to swimming after the glide phase.

The Y-axis acceleration profile is influenced by the side to side movements of the swimmer as they perform arm strokes. This signal does not display a level of consistency required during the turn phase to be of value for algorithm development. However, what can be seen in this signal is whether the swimmer is performing the glide phase on their back or on their side. The value will approximate 0 $m \cdot s^{-2}$ when in a prone or supine position. If the swimmer is on their left or right side during the glide this can be determined as the Y-axis acceleration value approaches +10 $m \cdot s^{-2}$ if the swimmer is on their right side (right hip closer to the pool floor than left hip) or -10 $m \cdot s^{-2}$ if the swimmer is on the opposite side. This can be seen at approximately 4 s on the Y-axis acceleration plot (Figure 8.58). Whilst not used in this study for feature detection purposes, this does represent interesting information for qualitative analysis.

The point of push-off from the wall following a flip turn can be determined by tracking the minimum peak in the Z-axis acceleration signal, just as for open turns. Additionally, the rotational events during the flip turn display a strong consistency and are useful for feature detection. The pattern of the Z-axis acceleration signal differs between frontcrawl and backstroke. The differences are due to the opposite orientation of the swimmer between these strokes. In the Z-axis acceleration plot, the value increases to approach +10 $m \cdot s^{-2}$ post push-off during frontcrawl but will approach -10 $m \cdot s^{-2}$ post push-off during backstroke.

The X-axis angular velocity is of value for feature detection as it is influenced heavily by how still the swimmer keeps their head when swimming and, like the Y-axis acceleration, can be of use in determining the direction of rotation. Positive angular velocity values before wall contact events indicate a turn to the right side whilst negative values indicate a turn to the left side. The Y-axis angular velocity displays a very consistent pattern during flip turns and can be used to assess the transverse rotation of the swimmer when performing the flip. This signal can also be used to determine the dolphin kicks performed post push-off. In contrast the Z-axis angular velocity signal is dependent on the head movements of individual swimmers. Ideally there should be little or no movement about this axis during the turn. The negative peaks sometimes seen in the Z-axis angular velocity plot prior to wall contact represent unwanted head movements and are not of use for feature detection.

By zooming in on the wall contact events it is possible to relate the signal output to the video images more clearly (Figure 8.59). Key distinguishable features in these signals are highlighted, together with associated video images, allowing for performance related parameters to be determined. As discussed, the transverse rotation can be identified in the Y-axis angular velocity. Wall contact with the feet is represented by the negative peak in the X-axis acceleration and the Z-axis acceleration can be used to identify the wall push-off. Wall contact time is the time difference between the negative peaks in the Z-axis acceleration (push-off) and X-axis acceleration (wall contact) values. In competitive swimming, a value of 0.3 s is regarded as adequate [30] in order to both minimise the time spent in contact with the wall whilst also generating impulse to maximise push-off velocity.

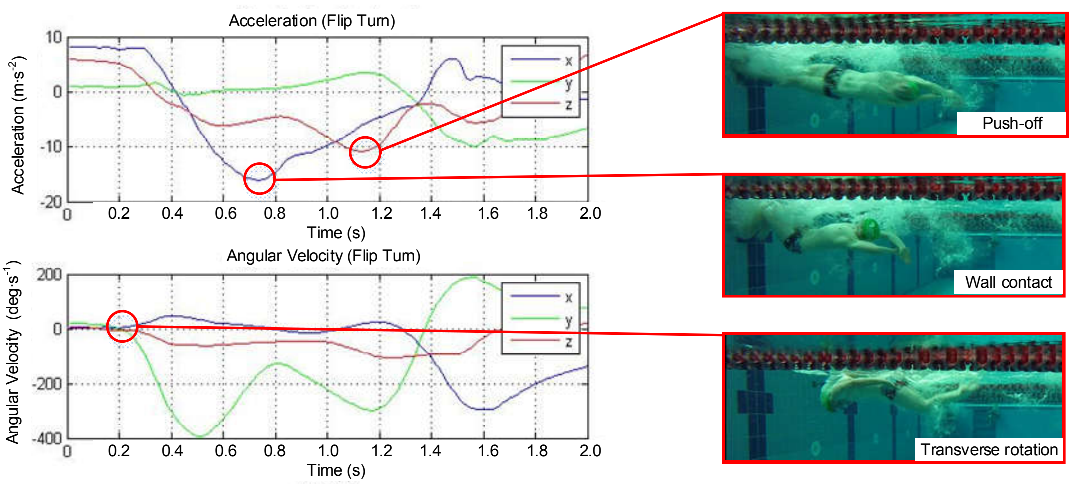


Figure 8.59. Wall contact phase of flip turn.

Transverse rotation time can be determined using a peak detection method on the Y-axis angular velocity signal. All peaks in this signal that are greater than 0 deg·s^{-1} that occur prior to the wall contact event are identified. The final identified peak is then regarded to be the point of the start of the transverse rotation (Figure 8.60).

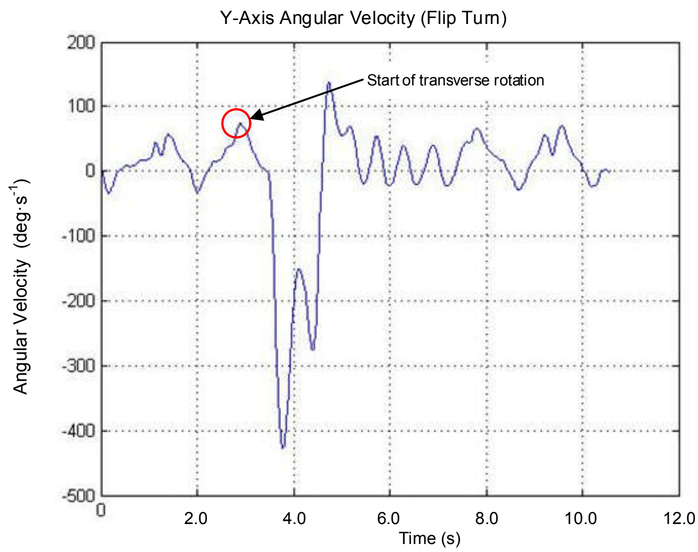


Figure 8.60. Start of transverse rotation during a flip turn.

In backstroke swimming, the longitudinal rotation time on approach to the wall can also be identified. This is commonly known as the “turnover stroke” in coaching and represents the movement of the swimmer from a supine position to a prone position as they prepare for the flip turn. This can be identified on the X-axis angular velocity using a zero-crossing method (Figure 8.61). The direction of the longitudinal rotation can also be identified using the same signal. A large negative angular velocity indicates that the turn is performed to the left side whilst a positive peak value indicates that the turn is to the right.

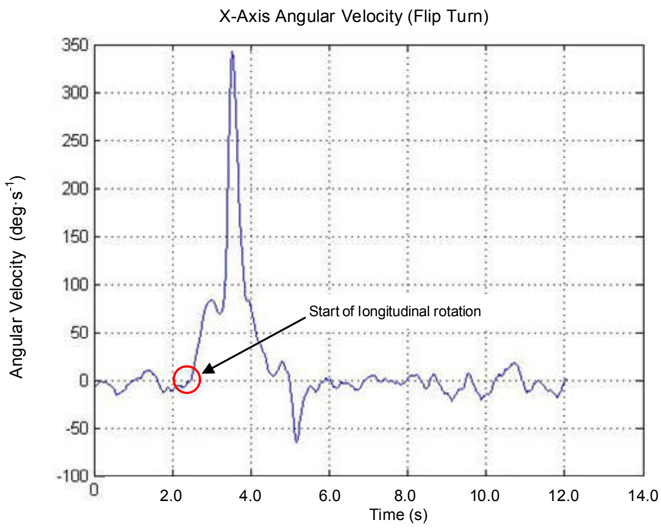


Figure 8.61. Start of longitudinal rotation during a backstroke flip turn.

The first dolphin kick in frontcrawl or backstroke can be identified by first isolating a window in the Y-axis angular velocity signal (Figure 8.62). This window is from the point of push-off to the breakout stroke. During this window the swimmer glides for a period and then initiates the dolphin kicking action. Peak detection during this window facilitates the kick count to be determined. Glide time is calculated as the time from the push-off to the time of the first kick. Kick time is the time from the first kick until the breakout stroke. A large peak can be seen initially in this signal. This peak is associated with the rotational movements of the swimmer and is not a kicking action. Therefore, this first peak is not included in the kick count calculation.

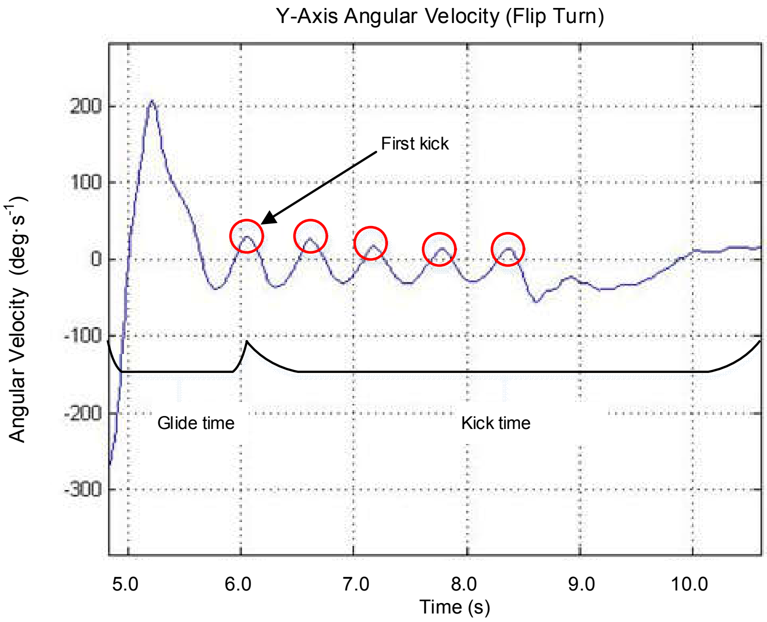


Figure 8.62. The Y-axis angular velocity signal is used to identify the glide time and the number of dolphin kicks performed prior to the first arm stroke in frontcrawl and backstroke. Five kicks (red circles) are identified in this example.

Once all of the key features required for the analysis of flip turns are identified then quantitative feedback can be provided to the coach and swimmer. A sample of the output that is produced by this algorithm is shown in Figure 8.63. These data can be used by the coach and swimmer to analyse the swimmers performance. A summary of the algorithm process flowchart is illustrated in Figure 8.64.

Results for Turn Number: 1
Longitudinal Rotation Time = 0.98 s
Transverse Rotation Time = 0.76 s
Wall Contact Time = 0.47 s
Glide Time = 1.06 s
Kick Time = 3.8045 s
Kicks off Wall = 6
Turn Direction = Left

Figure 8.63. Sample output of the turn phase breakdown algorithm. Results for each turn performed are provided in a list wise fashion and can be used to analyse the swimmers performance.

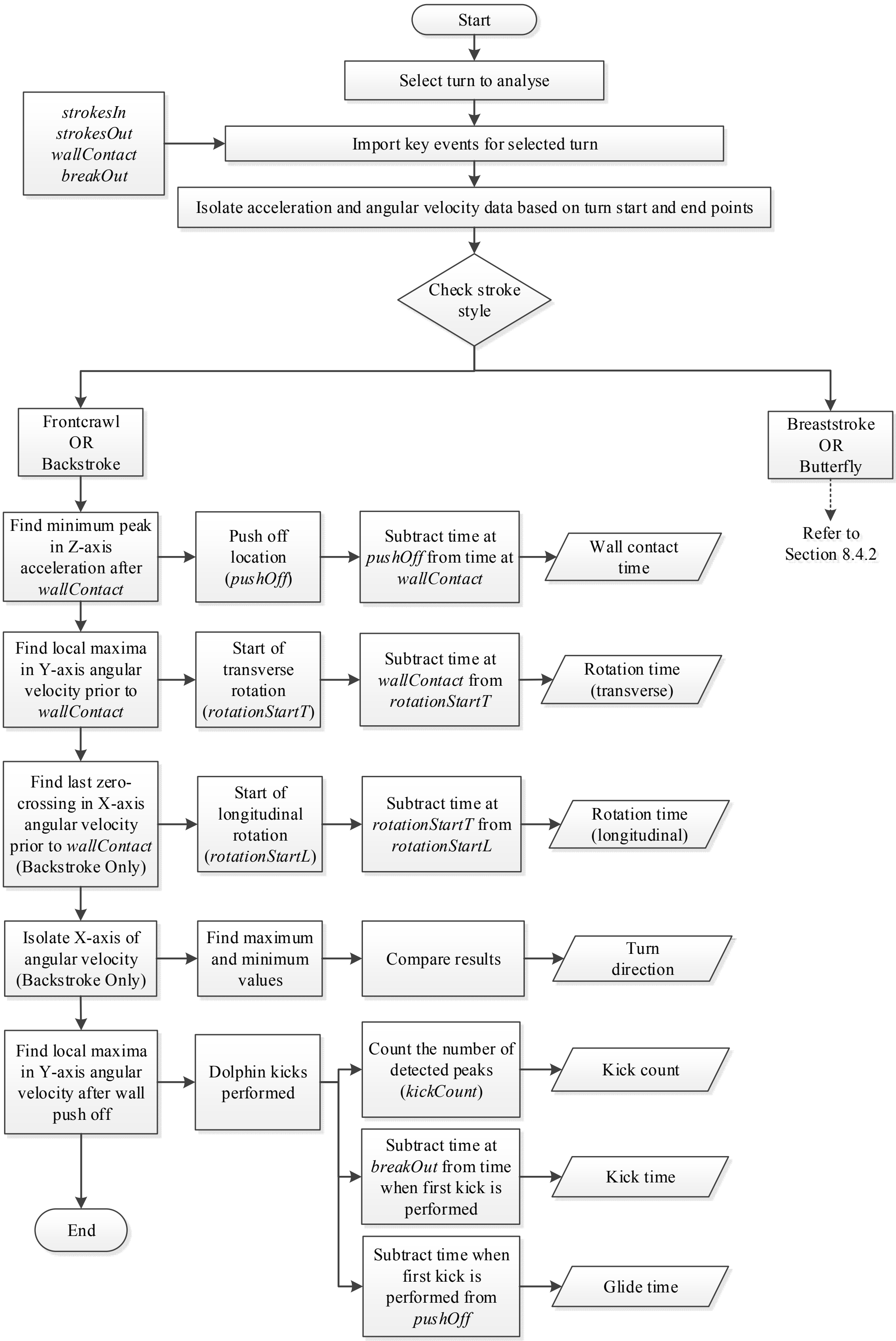


Figure 8.64. Turn phase analysis algorithm process flowchart, highlighting the feature detection process for flip turns performed duirng frontcrawl and backstroke swimming.

8.5 Conclusion

The aim of this study was to assess the feasibility of using MEMS technology to develop feature detection algorithms that can determine parameters related to the analysis of swimming turns. The prototype system described in Chapter 7 was used to record swimmers' movements in the pool. These recordings provided acceleration and angular velocity signals for analysis in MATLAB. Examination of these signals highlights both common and unique characteristics associated with each stroke style and each turn type.

No previous research work has attempted to incorporate MEMS inertial sensor technology for the purpose of quantifying and automatically measuring parameters related to the analysis of swimming turns. It has been found that a large number of parameters related to the performance of turns during each of the four competitive swimming strokes appear to be possible to identify in a repeatable and reproducible manner. Moreover, it is likely to be possible to provide rapid quantitative feedback to both coach and swimmer with this system, overcoming a major limitation of existing analytical methods. The implications of the findings suggest that such an approach offers real potential for application in an applied coaching environment. However, further work is required in order to experimentally validate the accuracy of these feature detection algorithms. This will be discussed in the Chapter 9 of this PhD work.

8.6 References

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Chapter 9 – Evaluation of the Feasibility of Applying MEMS Inertial Sensor Technology for the Analysis of Swimming Turns

The work described in Chapter 8 of this thesis has demonstrated that the acceleration and angular velocity profiles recorded during swimming turns display a consistency between swimmers. Importantly, it has also been determined that key performance related parameters may be extracted based on these signal features. The ability to rapidly and accurately obtain these performance related parameters in an applied setting would represent a significant advance in the analytical potential of elite swimming coaches. Such an approach, if proven feasible to implement, would also overcome many of the issues associated with traditional methods of analysis. Therefore, the final stage of this PhD was to experimentally assess the accuracy of the feature detection algorithms that were described in Chapter 8. Additionally, the implications of the findings obtained will be discussed with regard to their applicability in an elite coaching environment.

9.1 Introduction

Swimming races are comprised of various segments, including starts, turns and finishes. Turns are a very important segment of the race, contributing approximately one third to the overall race time and have a large influence on overall performance, especially in longer events and in short course pools [1]. Therefore, it is essential for elite and competitive swimmers to be proficient in performing swimming turns during pool swimming. A recent relevant example that serves to highlight the critical importance of the turn phase can be found in the Men's 400 m individual medley final at the 2016 Olympic Games [2]. A difference of 0.7 s separated the gold and silver medal winners in this race, with a winning time of 4 minutes 6.05 seconds. An analysis of the respective performances of these two swimmers revealed that the second placed swimmer consistently had a higher average swimming speed throughout each lap of the race. However, this swimmer's turns were performed slower than his rival and as a consequence of this, he was unable to capitalise on his superior swimming speed. Other similar examples are also frequently found at both international and national level competitions.

Traditional methods of analysing swimming turns involve the use of video-based systems [3]. However, there are inherent disadvantages to this approach and alternative solutions are warranted [4]. The application of MEMS based inertial sensor technologies offers a potential solution to the analysis of turns. By recording and analysing the acceleration and angular velocity profile of swimmers as they perform turns in a swimming pool, it has been possible to develop novel feature detection algorithms that can automatically extract key performance related parameters. However, it is essential that the accuracy of this novel approach is examined experimentally in order to prove that the concept is of merit in an applied setting. If such a solution were to prove successful, this may lead to positive implications for elite coaches and swimmers, who would be able to rapidly obtain important quantitative data related to their technique and performance. The aims of this study were to determine the accuracy of the prototype system and to discuss the implications of the findings with regards to their applicability in an elite coaching environment.

9.2 Methods

9.2.1 Participants

A total of seven national level competitive swimmers were recruited to take part in the study (6 male, 1 female; 16.9 ± 1.8 years; 1.76 ± 0.11 m; 72.0 ± 11.1 kg). The study received approval from the NUI Galway Research Ethics Committee and followed the terms of the Declaration of Helsinki. The protocol was explained to the swimmers and the parents of those participants under 18 years of age. Parental written consent was obtained and the participants also provided written informed assent.

9.2.2 Procedures

Data collection took place in a 25 m indoor swimming pool. Following a self-directed warm up, Participants were instructed to complete a swimming session totalling 400 m comprising each of the four competitive swimming strokes. 100 m of each stroke was performed in individual medley order (i.e. butterfly, backstroke, breaststroke, frontcrawl), with a minimum rest interval of one minute included between intervals. This resulted in 16 lengths of the pool per swimmer, with a total of 112 lengths and 84 turns that could be used in order to test the accuracy of the feature detection process. Participants were fitted with the prototype sensor device, positioned at the back of the head and held in place with the swimmer's goggle straps and swimming hat, following the concept developed as part of the Use Case. Swimmers wore two swimming hats in order to minimize the possibility of any unwanted sensor movement. Trials were simultaneously captured at 50 Hz using two fixed underwater cameras (GoPro Hero3+) positioned to record all events occurring at the pool walls in order to identify wall contact events and one panning video camera on the pool deck to record the participants throughout each lap (Sony Handycam HDR-XR550). Images from the three cameras were synchronised by interpolating the data according to the time lag between cameras using a blinking light source [5]. Video footage was subsequently used as the criterion measure to assess the performance of the swim activity monitors.

9.2.3 Data Processing & Analysis

Video files were stored on a portable hard drive and analysed using Dartfish Video Software (ProSuite version 5.5; Dartfish, Fribourg, Switzerland) to allow for criterion measures of all variables to be determined. Data from each activity monitor were saved on a MicroSD card and these comma separated values (.csv) files were imported into MATLAB (R2013a, MathWorks Inc., Natick, MA.) for post-processing and feature detection. Table 9.1 provides a list of parameters that were determined from both the criterion and prototype systems along with definitions of all terms.

Table 9.1. Definition of terms for each of the feedback parameters that will require feature detection algorithms.

Parameter	Definition
Lap time	Time to complete each pool length performed
Stroke count	The number of arm strokes performed for a given lap of the pool
Turn time	Time from the start of the 2nd / 3rd last arm stroke on approach until the end of the 2nd / 3rd arm stroke after push off (2nd: breaststroke / butterfly; 3rd: frontcrawl / backstroke)
Time in	Time from the start of the 2nd/3rd last arm stroke on approach to wall contact
Time out	Time from push-off to the end of the 2nd / 3rd arm stroke
Breakout time	Time from push-off to 1st arm stroke
Rotation time	Time from start of last arm stroke to wall contact (frontcrawl / backstroke)
Wall contact time	Time from 1st contact with wall to push-off
Hands to feet time	Time from 1st contact with wall with hands to first contact with feet (breaststroke / butterfly)
Feet contact time	Time from 1st contact with wall with feet to push-off (breaststroke / butterfly)
Turn direction	Direction of the swimmers movement during rotation (backstroke / breaststroke / butterfly)
Glide time	Time from push-off to first dolphin kick
Pulldown time	Time to complete the pulldown and arm recovery phase (breaststroke)
Kick count	Number of dolphin kicks performed after push off and before stroke initiation (frontcrawl / backstroke / butterfly)
Kick time	Time taken for the dolphin kicks after push-off from the wall to be performed

Descriptive statistics were determined for all variables. The Kolmogorov-Smirnov test was used to assess whether the data were parametric or non-parametric. Stroke identification data were categorical in nature and a Pearson's chi-square test was used to assess for agreement between values [6]. Data were found to be non-parametric and the Wilcoxon signed ranked test was used to assess for differences between data sets [6]. Agreement between variables were assessed through the use of Bland-Altman plots [7] and 95% limits of agreement were determined as the mean difference ±1.96 times the standard deviation of the difference. Data analyses were performed using Statistical Package for the Social Sciences for Windows (Version 23, SPSS Inc., Chicago, IL). A p-value of 0.05 was set for all statistical analyses.

9.3 Results

Swimming intervals were identified with 86% accuracy. The algorithm tracks the changing orientation of the swimmer at the beginning and end of the swimming interval. This represents 24 out of 28 intervals performed by the participants in the study. There were no missed intervals for butterfly, one missed interval for both backstroke and frontcrawl and two missed intervals for breaststroke. Additionally, on two occasions a false positive was registered, whereby movement of the sensor during an activity other than a swimming interval was incorrectly registered as an interval.

It was found that there was a significant correlation in stroke type identification between the prototype and the actual stroke performed for each of the four strokes (X^2 (3) = 19.802, $p < 0.05$). Overall, 89% accuracy in stroke identification was achieved. Table 9.2 provides specific detail of the sensitivity and specificity of this algorithm on a stroke by stroke basis. Frontcrawl and backstroke were readily identified and easily distinguished from one another owing to the different orientation of the swimmer during these stroke styles. Conversely, the signal output descriptors for butterfly and breaststroke swimming were found to be quite similar, leading to reduced sensitivity of the algorithm performance for these strokes. This is also reflected in the slightly lower specificity values for these two strokes.

Table 9.2. Sensitivity and specificity of stroke identification algorithm. The actual stroke completed for each swimming interval was compared against the ability of the prototype sensor to correctly identify each interval. A significant association was found with the actual stroke completed. Sensitivity is a measure of the proportion of positives that are correctly identified, whilst specificity measures the proportion of negatives that are correctly identified. (Fly = Butterfly; Bk = Backstroke; Brs = Breaststroke; Fc = Frontcrawl; Error = no stroke registered).

	Sensitivity					**Specificity**
	Fly	Bk	Brs	Fc	Error	
Butterfly	**71%**	0%	29%	0%	0%	95%
Backstroke	0%	**100%**	0%	0%	0%	100%
Breaststroke	14%	0%	**86%**	0%	0%	90%
Frontcrawl	0%	0%	0%	**100%**	0%	100%

Table 9.3 provides an overall summary of the results for the performance related parameters included in this study. Values for the mean, standard deviation and 95% confidence intervals are provided for both the criterion measure (video) and the prototype system. Additionally, the average difference is presented, both in temporal terms and as a percentage. Of the 15 parameters measured using the prototype system, 11 were found to be determined accurately, with no significant difference with the criterion measure. Those that were found to have a significant difference were lap time; kick time; kick count and longitudinal rotation time. Six of the parameters were measured to within 0.1 seconds of the actual value, identified by coaches as being important for use in an applied setting. A further five parameters were measured to within 0.3 seconds of the actual value.

Table 9.3. Summary of results for parameters measured in the study, including values for mean, standard deviation and 95% confidence intervals. All values are in seconds, with the exception of stroke count and kick count. Parameters marked with an asterisks (*) were found to be significantly different from the criterion measure (p < 0.05). The average difference and percentage difference to the criterion value are also reported.

	Criterion		Prototype				
	Mean ±SD	**95% CI**	**Mean ±SD**	**95% CI**		**Difference**	**Difference (%)**
Lap Time	19.81 ±2.37	(18.36 to 20.25)	20.05 ±2.64	(19.55 to 20.54)	*	0.24	1.2
Stroke Count	11.22 ±3.00	(10.66 to 11.79)	11.12 ±2.96	(10.56 to 11.67)		0.10	0.9
Turn Time	12.12 ±2.07	(11.67 to 12.57)	12.06 ±2.47	(11.52 to 12.60)		0.06	0.5
Time In	4.63 ±0.97	(4.42 to 4.85)	4.79 ±1.16	(4.53 to 5.03)		0.16	3.5
Time Out	7.41 ±1.49	(7.08 to 7.73)	7.21 ±1.82	(6.82 to 7.61)		0.20	2.7
Breakout Time	4.90 ±1.42	(4.59 to 5.21)	5.05 ±1.88	(4.64 to 5.46)		0.15	3.1
Hands to Feet Time	1.10 ±0.12	(1.07 to 1.14)	1.12 ±0.85	(0.86 to 1.39)		0.02	1.8
Feet Contact Time	0.30 ±0.09	(0.28 to 0.32)	0.37 ±0.29	(0.30 - 0.43)		0.07	23.3
Wall Contact Time	1.45 ±0.12	(1.42 to 1.49)	1.53 ±0.88	(1.26 to 1.81)		0.08	5.5
Glide Time	1.18 ±0.57	(1.06 to 1.30)	1.39 ±1.25	(1.11 to 1.66)		0.21	17.8
Pulldown Time	3.03 ±0.87	(2.64 to 3.43)	3.10 ±1.33	(2.49 to 3.71)		0.07	2.3
Kick Time	3.37 ±1.01	(3.11 to 3.62)	2.66 ±1.44	(2.30 to 3.02)	*	0.71	21.1
Kick Count	3.65 ±1.17	(3.36 to 3.94)	3.06 ±2.02	(2.51 to 3.52)	*	0.59	16.2
Longitudinal Rotation Time	0.84 ±0.18	(0.76 to 0.92)	1.28 ±0.79	(0.92 to 1.64)	*	0.44	52.4
Transverse Rotation Time	1.39 ±0.42	(1.26 to 1.52)	1.51 ±0.62	(1.32 to 1.70)		0.12	8.6

Bland-Altman plots were constructed for each parameter, highlighting the variance between the criterion and measured scores. These plots, together with the remaining results of this study, are presented from Figure 9.1 through to Figure 9.9, inclusive. The results show that the prototype recorded lap times were found to be significantly different from the criterion, when all laps for all strokes are assessed together. In order to understand what factors are resulting in these issues with detection accuracy, the lap times were split into those performed at the start/end of an interval and those performed in the middle of an interval (Figure 9.2). For example, in a 100 m swimming interval performed in a 25 m pool, laps one and four are considered to be start/end laps, whilst laps two and three are the middle laps. When this distinction is made, it was found that there was no significant difference in laps performed in the middle of an interval but that there was a significant difference for the start/end laps. Lap time data are also presented on a stroke by stroke basis (Figure 9.3), showing the error in measurement per lap performed. It was found that that the algorithm performed with a similar level of accuracy for all four strokes, with a tendency towards overestimation of the lap times recorded. Data for the stroke count measures are also presented on a stroke by stroke basis (Figure 9.5), showing the error in measurement per lap performed. The algorithm performed best for butterfly and breaststroke, with the number of laps with the stroke count recorded to within one of the actual stroke count found to be 85.7% for butterfly and 92.9% for breaststroke. The corresponding values for backstroke and frontcrawl were 60.7% and 67.9%, respectively.

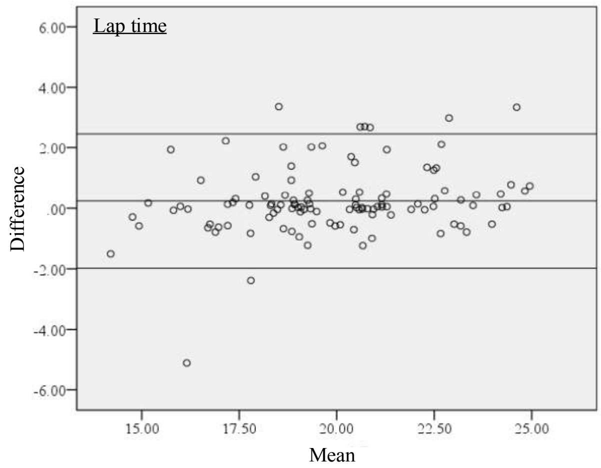

Figure 9.1. Bland-Altman plots for lap time data, showing the level of agreement between video and the data obtained from the prototype sensor. The results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

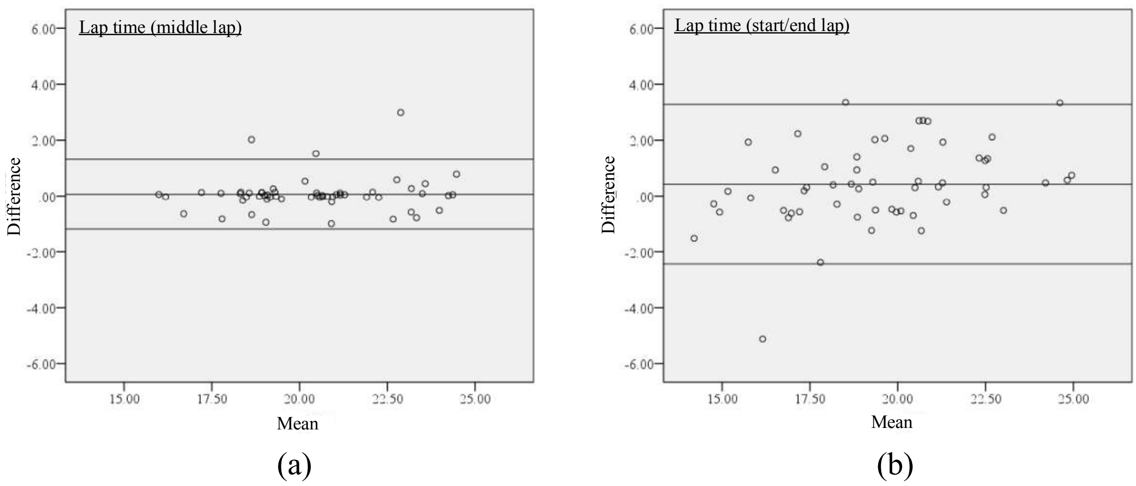

Figure 9.2. Bland-Altman plots for lap time data, separating out (a) laps performed during the middle of a swim interval and (b) laps performed at the start or end of an interval. The level of agreement between video and the data obtained from the prototype sensor is displayed and the results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

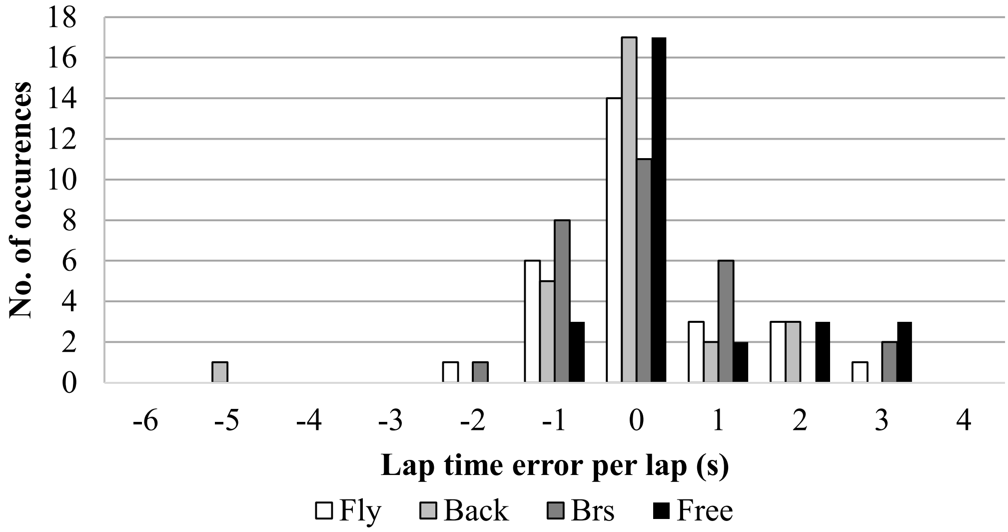

Figure 9.3. Comparison of the overall frequency of error in the measurement of lap times.

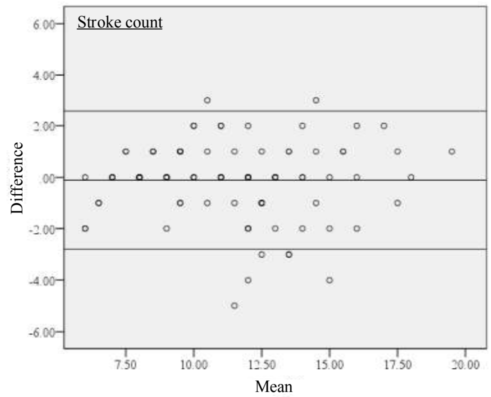

Figure 9.4. Bland-Altman plots for stroke count data, showing the level of agreement between video and the data obtained from the prototype sensor. The results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

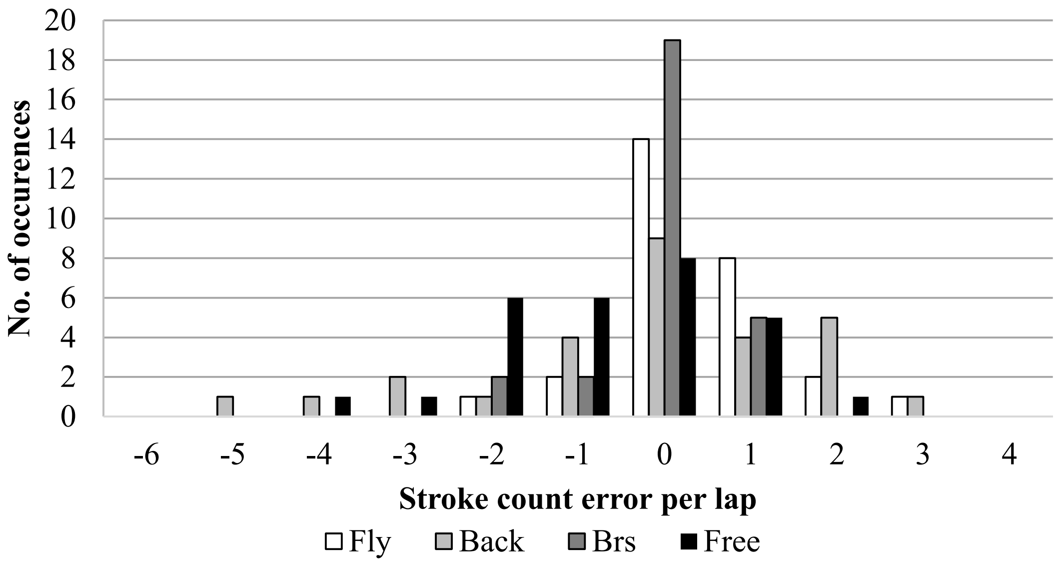

Figure 9.5. Comparison of the overall frequency of error in the measurement of stroke count.

No significant differences were found in the measurement of any of the key turn phase parameters, namely turn time; time in; time out and breakout time (Figure 9.6). Additionally, parameters measured during the wall contact phase (wall contact time; feet contact time; hands to feet time) were all found to be recorded accurately, with no significant difference from the criterion measures (Figure 9.7). The rotational parameters displayed contrasting accuracy. Longitudinal rotation time, performed only during a backstroke turn, was found to be significantly different from the actual. In contrast, transverse rotation time, performed during backstroke and frontcrawl, displayed no significant difference with the criterion values (Figure 9.8). Following wall push-off, four further parameters were recorded (glide time; kick time; kick count; pulldown time). Of these, glide time and pulldown time were measured accurately (Figure 9.9). Finally, the turn direction was identified with 100% accuracy.

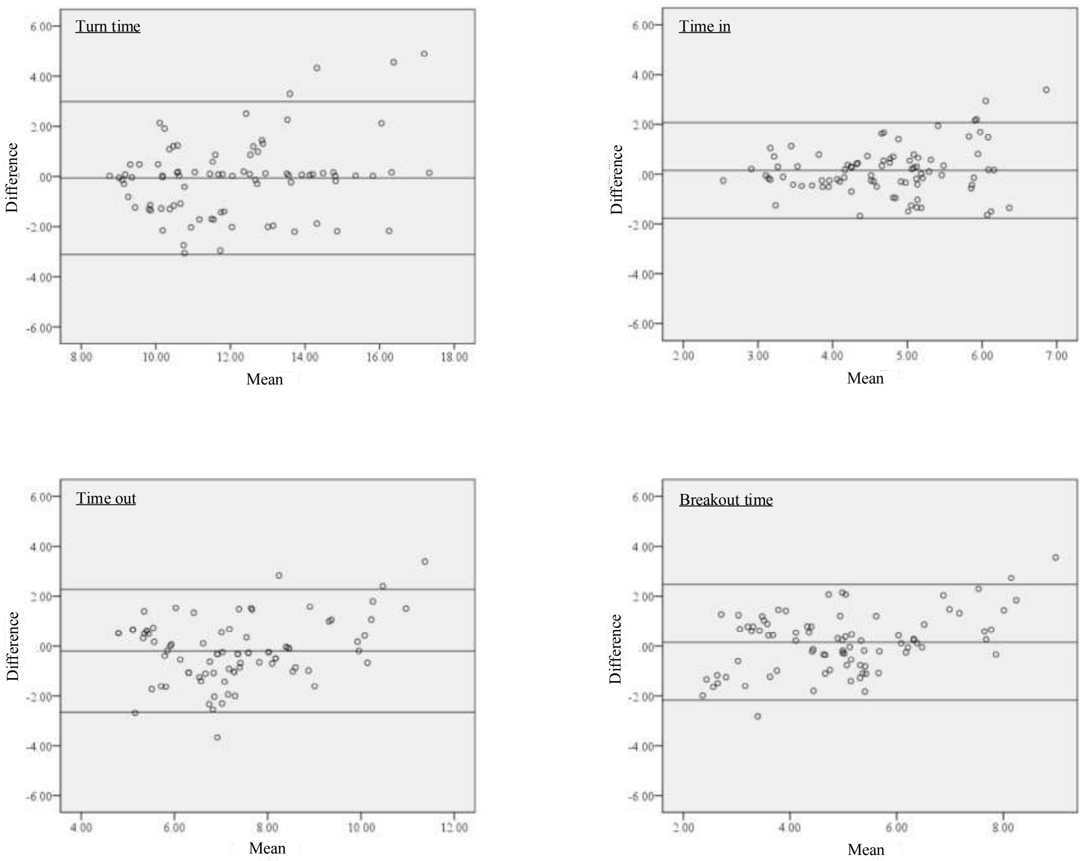

Figure 9.6. Bland-Altman plots for of turning phase parameters, including turn time; time in; time out and breakout time, showing the level of agreement between video and the data obtained from the prototype sensor. The results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

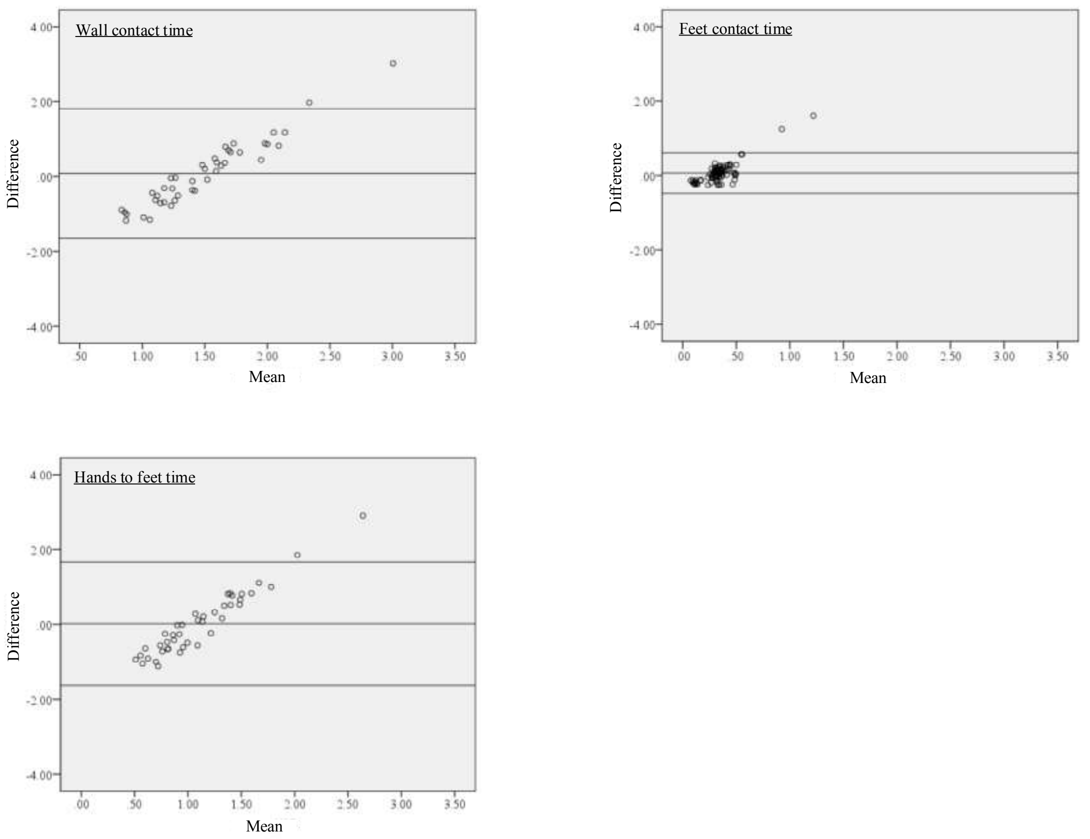

Figure 9.7. Bland-Altman plots for of wall contact phase parameters, including wall contact time; feet contact time and hands to feet time, showing the level of agreement between video and the data obtained from the prototype sensor. The results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

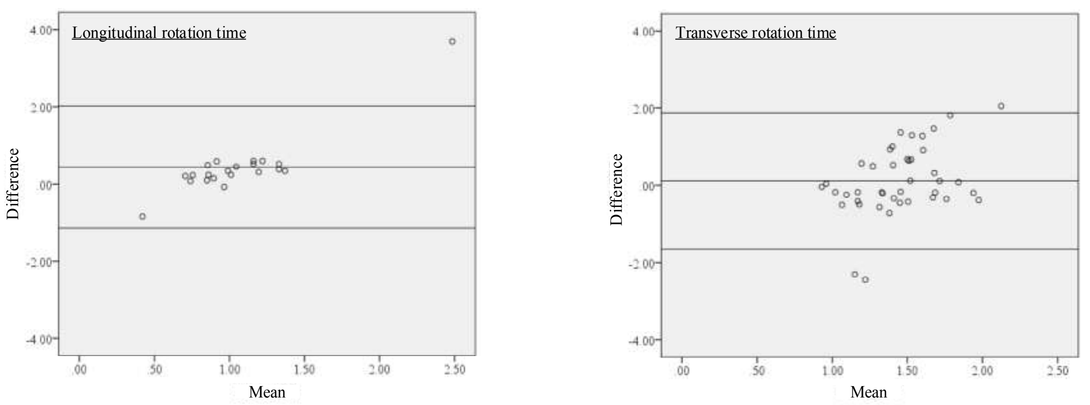

Figure 9.8. Bland-Altman plots for of rotational parameters, including longitudinal rotation time and transverse rotation time, showing the level of agreement between video and the data obtained from the prototype sensor. The results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

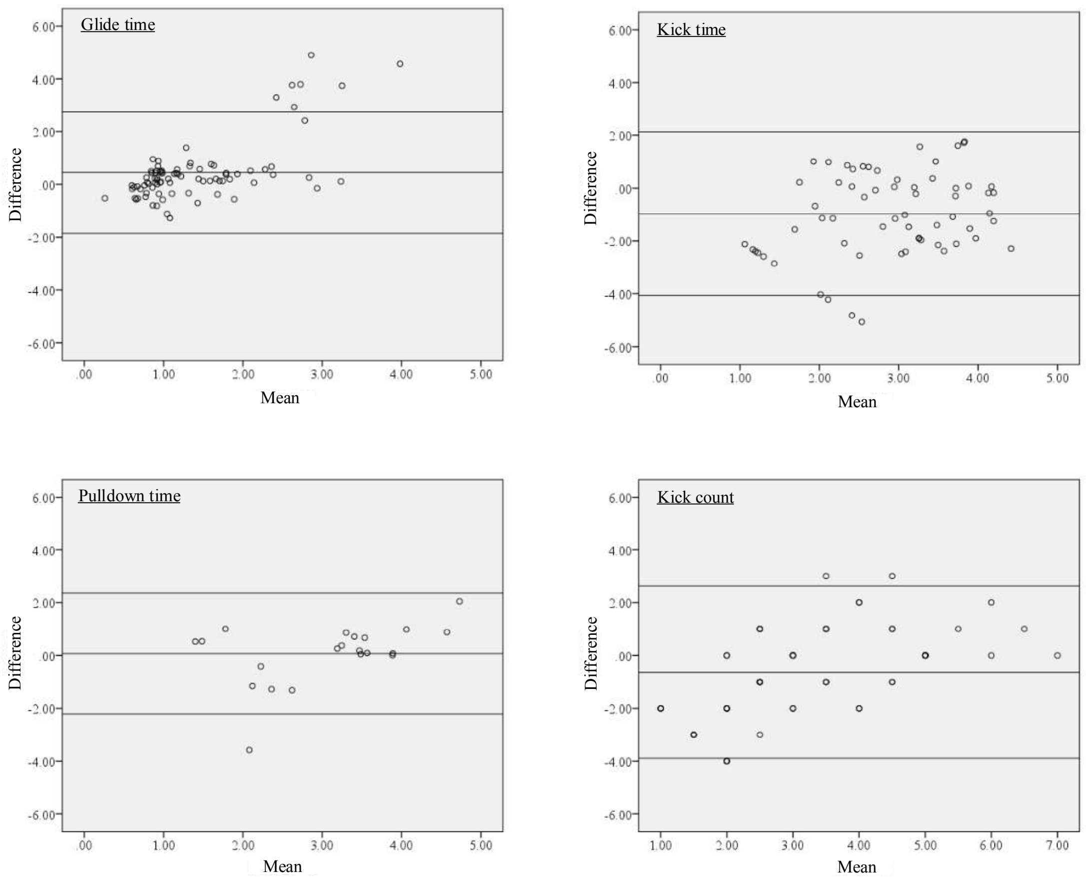

Figure 9.9. Bland-Altman plots for of post-push-off parameters, including glide time; kick time; kick count and pulldown time, showing the level of agreement between video and the data obtained from the prototype sensor. The results show the mean difference and 95% limits of agreement between the algorithm performance and the criterion measure.

9.4 Discussion

The primary aim of this study was to determine the accuracy of the prototype system for the accurate determination of key quantitative measures related to the analysis of swimming turns. It has been found that the developed algorithms have performed well for many of the parameters defined in this study. The swimming interval identification process was found to be highly accurate. The process is based on a simple concept of tracking the change in the swimmers orientation from standing at rest to a horizontal position when swimming, with a threshold value used to monitor this change. A key component of this algorithm is the determination of the moving average over a five second window and this smoothing of the signal removes instances where the threshold is crossed owing to swimming. Although many studies have previously used similar experimental protocols involving multiple swimming intervals, none has reported the inclusion of an automatic method for identifying these or documented the accuracy of such an approach. Therefore, there are no available data with which to compare these findings. However, in an applied training environment, coaches design training sessions around repeated swimming intervals and rest periods. As a consequence, it is important that these intervals can be identified automatically as this reduces the requirement for manual identification of intervals from the output signal.

Similarly, a very high accuracy was achieved for the stroke style identification algorithm. This level of accuracy is comparable with previous research. Davey, et al. [8] reported a 95% recognition accuracy when stroke type was identified with a back worn accelerometer device. Unfortunately this was an overall result so therefore it is not certain if there were any recognition issues due to specific stroke styles. A chest mounted accelerometer location has been found to achieve overall accuracy levels of 91.1% [9], with recognition issues related mainly to backstroke and breaststroke, similarly to the findings of a more recent study [10]. Siirtola, et al. [11] reported that a back worn sensor achieved better overall accuracy (95.3%) compared to a wrist worn sensor location (89.8%). In the present study, issues that arose were related to the similarity of signal profiles for both breaststroke and butterfly. This has been acknowledged previously [8, 9] and leads to difficulties in establishing threshold values that can fully distinguish between these strokes.

The measurement of lap times is not a central aim of this project as many other research studies have investigated this area [8, 12]. However, the detection of wall contact events, which are used to determine lap times, is important as these lap times are needed in order to segment swimming intervals into each lap performed. Additionally, when a coach analyses a swimmer’s performance during a turn, they often do so in the context of the entire lap or series of laps that were performed. For example, a coach may be interested in understanding what percentage of the lap time was taken up by the turn phase. The average lap time recorded by the video was

19.81 ± 2.37 s, with the average value by the prototype of 20.05 ± 2.64 s. As previously highlighted [8, 10], issues with the identification of the start and end of an interval can lead to inaccurate measurements. This is mainly due to the individual variances in swimmers movements during this time. There can be unwanted movement that will result in difficulties in ensuring that the identified peak really relates to the instant of wall push off. However, it cannot be expected that a swimmer working in an applied setting would keep themselves perfectly still during this time and as such the algorithm has to account for these movements. As the present study was focused on the analysis of turn events, inaccuracies with the timing of the first and last lap of swimming intervals was not found to negatively affect the performance of other feature detection algorithms.

Similarly to the measurement of lap times, there are many previously reported studies that have described the development and accuracy of stroke count algorithms [11, 13-15]. The methods used in the present study reflect those previously reported methods and as such the stroke count algorithm was found to work with high accuracy. Swimming strokes can be identified from an accelerometer output as regularly occurring peaks in the signal signature, with local maxima and minima tracked and counted [8, 16]. In the context of analysing the turn phase, the accurate identification of strokes performed during each lap is very important as the accuracy of this will have direct influence on the accuracy of the timing of the turn phase. This is because the turn phase is defined according to a set number of strokes performed both before and after wall contact. For frontcrawl and backstroke this is the time taken from the start of the third last stroke before wall contact to the end of the third stroke after wall contact. For butterfly and breaststroke swimming, the turn is defined according to two strokes before and after the wall, following consultation with coaches. This is because the overall numbers of strokes performed during butterfly and breaststroke may be as low as five to six strokes in a 25 m pool for an elite performer. Furthermore, the use of two or three strokes for different swimming styles closely corresponds to distances of five metres before the turn and ten metres after the turn; which relates well with how a turn is typically defined using a distance measurement.

Accuracy issues could potential have arisen from the head worn position of the device. During backstroke and frontcrawl a swimmer will aim to keep their head steady as they complete their strokes, which could result in difficult in peak detection. One previous study determined stroke count from head worn sensor [16]. Beanland, et al. [16] reported a strong relationship in stroke count calculation for breaststroke ($r = 0.99$, $p < 0.05$) and butterfly ($r = 1.00$, $p < 0.05$), but reported that no clear pattern could be discerned for frontcrawl. These researchers did not include backstroke in their study protocol. However, this was not found to be the case in the present study, with a zero-crossing algorithm was used for frontcrawl as an alternative to peak detection.

The determination of turn times based on the use of a MEMS inertial sensor device has never been reported previously so there are no results available to allow for a comparison of the accuracy found in the present study. This process is highly reliant on the correct identification of wall contact and the end of each lap, in addition to accurately recording the number of strokes performed by the swimmer. It has been found that this system can record turn time; time in; time out and breakout time with a high degree of accuracy, as shown in Table 9.3 and Figure 9.6. For example, the average turn time, as recorded with the video system, was found to be 12.13 ± 2.07 s. The average turn time, recorded by the prototype system, was 12.06 ± 2.47 s. Positive results such as these points to the potential of using MEMS devices in applied coaching settings in order to monitor key performance parameters related to turns. By way of comparison, a typical frontcrawl turn time at international level (defined as the time from when the swimmers head passes from five meters before the wall to ten meters after the push-off) would be approximately eight seconds for male competitors and nine seconds for female swimmers [17].

In addition to the dearth of research exploration in this area, no commercially available swimming sensor system provides features to allow for an analysis of turns that would be suitable for competitive swimmers. One slight exception is the *TritonWear* system (TritonWear Inc., Kitchener, ON, Canada). This device features a head worn sensor unit and provides a "*Turn Time*" variable as part of its suite of features, which it defines as the time from the initiation of rotation to the point of wall contact (comparable with the transverse rotation time parameter of this present study). However, this parameter alone would not be sufficient for a thorough analysis of the full turn phase. This parameter is also not relatable to turns performed during breaststroke and butterfly. Furthermore, no objective evaluation of the accuracy of the *TritonWear* device has yet been made available.

The final stage of the feature detection process involves analysing each turn that was performed and providing detailed feedback on the performance of that turn through the measurement of nine further parameters. Typical values for some of these parameters can be very small. For example the average values for feet contact time was found to be 0.30 ± 0.09 s in duration, whilst the average hands to feet time was recorded as 1.10 ± 0.12 s. It has been reported that a world class standard for hands to feet time is 0.80 s or less [3, 18]. Despite such short durations, many of these parameters were found to be recorded with no significant difference from the criterion, including hands to feet time, feet contact time, wall contact time, glide time, pulldown time and transverse rotation time (Table 9.3).

This is the first study to attempt to derive these variables using MEMS devices. Therefore there is a lack of findings upon which to compare these results. Events that occur during wall contact are important parameters for generating force in order to produce high velocity at the push-off [19]. These data were found to be accurately measured with the prototype device. It would be interesting to match the time spent on the wall with the peak force produced, in order to determine the impulse generated by the swimmer, for a more in-depth analysis. However, the determination of such kinetic parameters has yet to be explored using inertial sensor technology [20].

There were issues found in determining the number of kicks performed after wall push-off, as well as the time taken to perform these kicks. Often the last dolphin kick may occur at or very close to the breakout stroke and this transition to swimming can cause additional peaks in the signal which may be interpreted as a kick. Furthermore, some swimmers begin their dolphin kicks with vigorous leg action whilst others have a tendency towards a less powerful leg action, and thus are more difficult to identify in the acceleration signal. Previously Fulton, et al. [21] had described an algorithm for counting the number of kicks performed during a length of the pool but this did not include dolphin kicks performed after wall push-off.

Transverse rotation time is recorded during backstroke and frontcrawl and was found to be accurately determined. However, there were issues found in the determination of longitudinal rotation time, which is performed only during a backstroke turn. This may be a consequence of this smaller data set but is was found that the point where the swimmer completes the longitudinal rotation, which is defined as the point of the last hand entry into the water, may occur when the swimmer has not yet fully rotated onto their front, hence leading to issues in pinpointing this instant on the signal output (Figure 9.10). Another parameter which incorporated a smaller data set is the pulldown time, as this is related to breaststroke only. Additionally, there are different styles of pulldown that can be performed, with some swimmers opting to kick first whilst others will move their arms first. Both of these styles were seen by the participants in this study, although this did not have a negative impact on the results on this occasion.

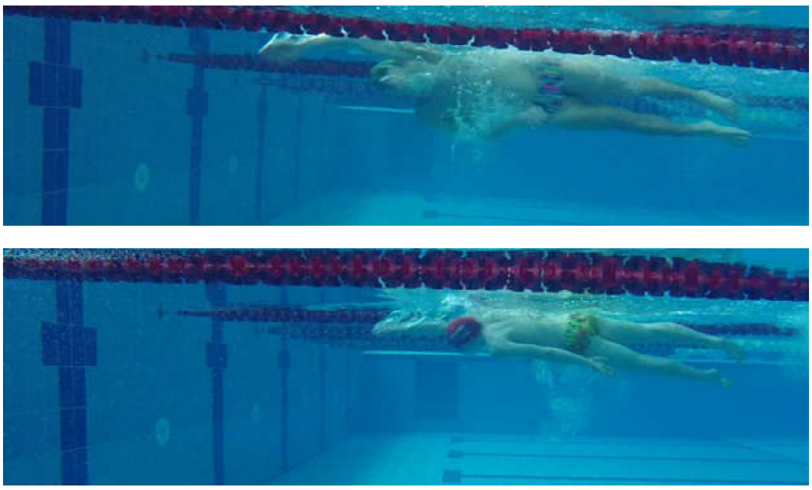

Figure 9.10. Differences in body position at the end of the longitudinal rotation during backstroke led to issues with algorithm accuracy.

9.5 Conclusion

The feature detection algorithms performed well for the analysis of swimming turns, with the majority of the parameters included in this study being identified with a high level of accuracy. This would appear to confirm that such an approach is feasible and warrants further research examination. However, this study represents a starting point towards fully exploring this area and validating the approach. It is likely that future work is required, to test the algorithms on larger groups of athletes, including swimmers with different levels of ability. That said, this study included a larger data set than can be found in the large majority of previous work in this area, involved multiple strokes and attempted to validate a large number of performance related parameters. Future work could also test other body locations, such as the lower back, to assess if accuracy could be improved. However, a head worn sensor is likely to be the most suitable location due to the ease of positioning, the stability and of the device which is held securely by the goggle strap and swim hat and also the preference from swimmers and coaches alike for this location as it is out of the way an does not interfere with normal swimming activity.

The use of sensor based technologies in swimming is rapidly advancing and offers clear advantages over video-based approaches. In the present study, only a matter of minutes was required to extract the data from the prototype sensor once the swimmer exits the pool. This includes the post processing methods involved in converting and importing files into MATLAB and running through the various algorithms. This compares very favourably to the time it take to get this information from video-based systems, which was approximately three and a half hours per study participant in this instance in order to edit, process and interrogate footage from multiple above and underwater cameras. Further development work could reduce the sensor processing time further, potentially offering a real time solution for coaches on pool side. This would represent a significant advancement in the analytical potential of elite swimming coaches when working with swimmers in a training environment. This faster dissemination of information affords coaches more time to spend interpreting the data in order to maximise the performance gains and better understand their swimmers' activities. The implications of this study are that inertial sensor technology does have the potential to provide accurate quantitative analysis of swimming turns, therefore strengthening the claim for the increased incorporation of this technology in elite settings to inform the coaching process.

9.6 References

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Chapter 10 – Discussion and Conclusion

10.1 Discussion

Swimming is a complex human activity. Significant technical proficiency is required on the part of the swimmer to be successful in the sport. Consequently, elite swimming coaches continually strive towards improving their swimmers' ability. At the elite level, performance gains through technical development will be small but yet still can have a dramatic impact on competitive performance, as fine margins will decide the outcome of competition. Central to this process of technical development is the requirement to quantify various aspects of a swimmer's performance in their training environment in order to determine the athlete's readiness for competition.

Elite swimming relies more and more on technology to make these small gains. Analyses have traditionally been conducted using video-based methods. However, the limitations of these traditional methods are hindering elite coaches in their ability to perform the extent of quantitative analysis that is warranted at this level of competition. Consequently, alternative technologies are required to ensure that the needs of coaches can be better met in the future. Ideally, performance testing should be completed in a swimmer's natural training environment. Advancements in technology allow for new methods of testing in aquatic settings, specifically through advances in MEMS inertial sensor technology. This approach offers many potential benefits that may help to overcome the limitations of video-based approaches, allowing for more in-depth analysis and more rapid quantitative feedback on performance. Key factors that make this approach so attractive for sports scientists and coaches alike include the potential for reduced data processing time; the ability to monitor multiple swimmers simultaneously; the capacity for monitoring performance over multiple laps; the reduced complexity of using the technology and the likely reduced cost of the equipment that is required.

The thesis outlined the potential contribution of inertial sensor technologies to the analysis of swimming performance. A specific focus was placed on the feasibility of applying the principles of inertial sensor technology in elite settings, to facilitate a detailed quantitative analysis of swimming performance. To achieve this aim a number of studies were carried out. This chapter summarises the main findings of each of the studies conducted and provides suggestions for future avenues of research.

The first investigative step involved a comprehensive survey of elite swimming coaches internationally. This survey was facilitated by the American Swim Coaches Association (ASCA). The primary motivation for conducting this study was to quantify, for the first time, the practices of elite coaches working at the highest levels of the sport worldwide. This study, which is described in Chapter 2, served as an important starting point for this thesis as it determined exactly what equipment swim coaches use and what factors are important to them when attempting to improve or review their swimmers' performance capabilities. This study revealed that a disparity exists between the perceived importance of quantitative biomechanical analysis and existing practices that largely employ qualitative methods of analysis. The implications of these findings are that existing technologies, which typically involve video-based methods, may not be adequately serving the needs of elite coaches. The major limiting factors were found to be time, cost and the availability of suitable equipment that is required to conduct quantitative analysis. Moreover, the survey also revealed a very poor awareness of inertial sensor technology amongst elite swimming coaches, indicating that despite the purported advantages of this technology, it has not gained much traction in elite settings. The comprehensive nature of this survey is such that it makes a strong contribution to the field and this chapter has been published in the *Journal of Sports Sciences* (2016;34:997-1005) and has received significant interest in the research and coaching community.

Following the survey, it was considered prudent to fully explore the state of the art of video-based methods for the analysis of competitive swimming performance, through a systematic review of the literature. This review contributes to the research domain as it provides an exploration of the use of video-based methods in swimming, specifically in aquatic environments, for the first time. The review, presented in Chapter 3, highlighted that the process of using video in aquatic settings is complex, with little consensus amongst coaches regarding a best-practice approach, potentially hindering usage and effectiveness. This uncertainty surrounding the most appropriate methodologies to be adopted and the value of video in swimming helps to understand the reasons for the disparity in perception and practice. An additional novel contribution of this work was that different methodologies were assessed and recommendations for coaches, sport scientists and clinicians were provided. It was concluded that video is an extremely versatile tool. In addition to providing a visual record, it can be used for qualitative and quantitative analysis and has applications in both training and competition settings. Cameras can be positioned to gather images both above and below the water. Ongoing advances in automation of video processing techniques and the integration of video with other analysis tools suggest that video analysis will continue to remain central to the preparation of elite swimmers. However, due to the limitations of video-based systems, most notably the time required to conduct quantitative analyses, it is likely that the primary purpose of video will remain to be the provision of the visual image, and that alternative analysis tools will serve to provide the quantitative data analysis to complement these images. This chapter makes an important contribution to the field and has been published in the *Sport and Exercise Medicine Open Journal* (2015;1:133-150).

Novel methods of analysis, incorporating body worn inertial sensors have received much attention recently from both research and commercial communities as an alternative to video-based approaches. A systematic review aimed at exploring the application of inertial sensor technology for the technical analysis of swimming performance was conducted and is presented in Chapter 4 of this thesis. This work provides an important contribution to the research domain as it delivered the first comprehensive systematic review of this technology in swimming, following 15 years of research activity in the area. The review focused on providing a detailed evaluation of the accuracy of different feature detection algorithms described in the literature for the analysis of different phases of swimming, specifically starts, turns and free-swimming. The primary conclusion of this study was that this technology may allow for improved analysis of stroke mechanics, race performance and energy expenditure, as well as providing real-time feedback capabilities to the coach, potentially enabling more efficient, competitive and quantitative coaching. However, many important areas of research investigation remain unexplored. The consequence of this is that this technology may not currently offer the level of functionality to be of relevance in elite settings. Furthermore, it was concluded that there was a lack of objective validation of existing sensor based systems and a clear need to thoroughly evaluate existing technology to assess its suitability in elite swimming. This work provides a valuable contribution to this field, has received significant interest in the research community and has been published in *Sensors* (2015;16:1-18).

In Chapter 5, an assessment of prominent, commercially available swimming activity monitors was conducted. The primary aims of this study were to evaluate the validity of these monitors for quantifying temporal and kinematic swimming variables. This work provides an important contribution as these monitors had not previously been subjected to independent scrutiny, despite being available for sale and marketed as a suitable training aid for the swimming community. It was concluded that both monitors operate with a relatively similar performance level and appear suited for recreational use. However, issues with feature detection accuracy may be related to individual variances in stroke technique. It was postulated that this level of error would increase when the devices are used by recreational swimmers rather than elite swimmers. Therefore, further development to improve accuracy of feature detection algorithms, specifically for lap time and stroke count, was recommended. Such improvements were also deemed essential in order to increase their suitability within elite settings. Additionally, it was felt that current systems lack the depth of analysis required by coaches and swimmers operating at the highest levels of the sport. This study also proved beneficial in providing a means of establishing a robust, peer-reviewed, experimental testing protocol that would ultimately be used for the validation of a new prototype design at a later stage in this project. Additionally, the work provided an opportunity to explore the context of use of this technology in swimming and design considerations for future development work. This chapter has been published in *PLoS ONE* (2017;12:1-17).

The next step in the project was to attempt to address some of the issues that had been raised. Specifically, was it feasible to use inertial sensor technology for conducting the depth of analysis necessary that would make this approach relevant in an elite setting? One such gap in the research knowledge, with major relevance to elite swimming, was the analysis of turns. This area became the next focus of the programme of research. The aim of the next study in this thesis, described in Chapter 6, was to describe how a User Centred Design (UCD) methodology was used for conceptual development of novel system of performance analysis in elite swimming. UCD is a framework of iterative processes, which facilitates the design of a product, service or method in a powerful manner to ensure that the usability of the device is maximised and that it satisfies user requirements. Incorporating a UCD methodology into this thesis helped to maximise potential end user satisfaction and increase the likelihood of the adoption of the new technology into existing practices of analysing swimming in applied settings. This work provides an important contribution as UCD methodologies are seldom reported in the extant literature for the development of technology for use in sport. What was learned from this study was that the proposed concept had merit. Important design and functionality considerations were also established, such as what body location on the swimmer was deemed most suitable and importantly, what variables are coaches interested in reviewing when analysing turns. The findings presented in Chapter 6 showed the clear potential of MEMS inertial sensor technology if properly applied for the benefit of elite swimmers and coaches and brought the project onwards to the subsequent implementation phase with increased clarity regarding the key design requirements of the proposed system.

Chapter 7 described the development of the prototype system, including both hardware and software components. The prototype is based on off-the-shelf hardware components and the software incorporates a data logging algorithm designed to obtain acceleration and angular velocity measurements from a swimmer. This chapter is important in the context of the thesis for several reasons. Firstly, it was vital that the hardware components and enclosure were developed and tested such that the prototype could be worn comfortably when swimming and not encumber the swimmer in performing their normal activities in the pool. Additionally, several technical specifications related to the design required careful consideration in light of the end user requirements elicited as part of Chapter 6. Finally, it was essential that the performance of the prototype device was adequately tested to ensure that the data logging capabilities were functioning correctly and that the acceleration and angular velocity signal obtained represented a true reflection of the swimmers movements. Each of these aims was successfully achieved, providing confidence that the prototype system could prove suitable for experimental data collection.

In Chapter 8 of this thesis the development of novel feature detection algorithms for the analysis of swimming turns was described. The algorithms were developed such that turns performed when swimming each of the four competitive swimming strokes could be analysed. The features chosen for detection were based on the key performance related parameters identified by coaches, including turn time, wall contact time, glide time and breakout time. The prototype system described in Chapter 7 was used to record swimmers' movements in the pool. These recordings provided acceleration and angular velocity signals for post-processing and analysis. A specific aim of this development work was to focus on isolating the features of the acceleration and angular velocity signals that are common between swimmers. It was demonstrated that the signal profiles when performing turns are consistent and it has also been determined that key performance related parameters may be extracted based on these signal features. A number of important research contributions are described in this chapter. These include adaptations and improvements to methods of detecting lap time, stroke identification and stroke count. Furthermore, several novel feature detection algorithms for the detailed quantitative analysis of turns are described.

The final aim of this thesis was to test the feasibility of incorporating these novel feature detection algorithms for the analysis of swimming turns in an applied environment. A particular emphasis was placed on ensuring that the level of accuracy achieved in feature detection was sufficient to allow for data to be used for feedback and analysis purposes and in agreement with coaches' requirements. It was found that the majority of the parameters included were identified with no statistically significant difference, when compared to the criterion measure. However, from a practical point of view, several issues with accuracy do remain.

Notably, the coaches' requirement for an accuracy level of 0.1 s has not been met. Ultimately, this area of research remains a complex and challenging issue as the time intervals comprising the various components of a turn are so small. However, the study would appear to confirm that such an approach is feasible and does warrant further research examination. This study has developed a framework for this future work, including both development and testing methodologies, as well as identifying the parameters of interest and confirming end user requirements. The implications of this study are that inertial sensor technology does have the potential to provide accurate quantitative analysis of swimming turns, therefore strengthening the claim for the increased incorporation of this technology in elite settings to inform the coaching process.

10.2 Limitations

There is one main limitation to the work presented in this thesis. Crucially, the needs of coaches clearly focus on real-time data analysis. This was confirmed and repeated by coaches involved in this project at all stages. Whilst there may be some confusion amongst coaches about the exact meaning of "real-time" and some debate in the extant literature regarding the efficacy of real-time feedback for eliciting performance gains in sporting activity it remains clear that any novel technological solution that is to be successfully incorporated into elite swimming environments must be capable of providing quantitative feedback rapidly to the coach. The prototype system developed as part of this project does not currently provide this functionality. Instead, the prototype is based on post-processing techniques following a manual data transfer process between the hardware and a laptop computer. Furthermore, analysis and feedback are completed using technical software as opposed to a custom designed software application specific to the purpose. The reasons for this is that a key component of the project was in understanding if the feature detection algorithms had any merit for analysing swimming turns. Once it has been confirmed that such an approach is feasible, future work can focus on ensuring that all end user requirements, including real-time feedback, custom designed software applications and a smaller system architecture are incorporated into future iterations of the system.

10.3 Closing Remarks and Future Work

In summary, this thesis described a series of studies that aimed to investigate the role of MEMS inertial sensor technology in swimming. It was intended to demonstrate the feasibility and the practicality of this approach for use in elite environments. By applying MEMS technology to this area, it has been shown that there are several potential advantages of this approach over traditional methodologies. Ultimately, in order for wearable sensor-based systems to become more widely accepted by swimming coaches working in elite environments as a suitable analysis method for their own use, additional research work is necessary. Future work should focus specifically on applied studies, demonstrating the use of the technology in coaching settings. Although confident that the experimental validation of the feature detection algorithms was rigorous, it is suggested that a larger sample and a repeated measures design would confirm this hypothesis. It is envisioned that future research would extend the work described in Chapter 9 of this thesis by applying MEMS technology in other applied swimming studies, with focus on different levels of swimmer ability and longitudinal study designs to provide additional evidence of the validity of the methods and the embedded algorithms. Modifications to the algorithms should also allow for turns performed during individual medley swimming to be analysed. Additional work could also focus on further developing the hardware and software components, including the provision of a more streamlined low-profile design, multiple user capability, real-time feedback potential and custom designed software applications for data visualisation and interrogation by end users. Indeed it is not just the analysis of turns that requires further research consideration. Several other areas of research were identified as being underdeveloped and are fundamental to the advancement of this area of research. These include the analysis of starts, for example, which is another key area of elite swimming performance that has received little attention in the extant literature. Ultimately it is intended that future studies would establish effective methods of analysing swimming performance in elite swimming environments, based on MEMS technology, thus providing the foundation to increase use beyond current levels.

The analysis of swimming technique remains a complex issue, with performance outcomes decided by fractions of seconds. However, despite this challenge, performance gains continue to be made by swimmers and their coaches, often with the aid of technology. It is intended that work presented in this thesis will provide a strong basis for the development of a highly effective new system for the analysis of elite swimming in the future. In conclusion, the studies described in this thesis demonstrates the practical application of inertial sensor technology as a suitable tool for use in elite swimming analysis. Furthermore, it is believed that this work lays the foundation for future meaningful and exciting work in this field.

Publications Arising from this Project

Journal Publications

R. J. Mooney, G. Corley, A. Godfrey, C. Osborough, J. Newell, L. R. Quinlan, and G. ÓLaighin, "Analysis of swimming performance: perceptions and practices of US-based swimming coaches," Journal of Sports Sciences, vol. 34, pp. 997-1005, 2016.

JOURNAL OF SPORTS SCIENCES, 2015
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Analysis of swimming performance: perceptions and practices of US-based swimming coaches

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ABSTRACT

In elite swimming, a broad range of methods are used to assess performance, inform coaching practices and monitor athletic progression. The aim of this paper was to examine the performance analysis practices of swimming coaches and to explore the reasons behind the decisions that coaches take when analysing performance. Survey data were analysed from 298 Level 3 competitive swimming coaches (245 male, 53 female) based in the United States. Results were compiled to provide a generalised picture of practices and perceptions and to examine key emerging themes. It was found that a disparity exists between the importance swim coaches place on biomechanical analysis of swimming performance and the types of analyses that are actually conducted. Video-based methods are most frequently employed, with over 70% of coaches using these methods at least monthly, with analyses being mainly qualitative in nature rather than quantitative. Barriers to the more widespread use of quantitative biomechanical analysis in elite swimming environments were explored. Constraints include time, cost and availability of resources, but other factors such as sources of information on swimming performance and analysis and control over service provision are also discussed, with particular emphasis on video-based methods and emerging sensor-based technologies.

ARTICLE HISTORY
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KEYWORDS
Swimming; coaching; biomechanics; video analysis; inertial sensor

Introduction

The preparation of elite swimmers for competition is characterised by detailed annual training plans designed to improve all aspects of performance. Central to these preparations are processes of regular testing and measurement as a method to assess and monitor progression. The swimming coach plays the vital role in the training process, with responsibility for instigating a positive change in a swimmer's performance. This is achieved by implementing a structured, periodised programme of training and competition that simultaneously addresses physical, mental, tactical and technical components (Bompa & Haff, 2009; Dick, 2002). Consequently, control over the nature of sports science service provision typically lies with the coach.

Ultimately, an extensive range of resources must be considered to decide the appropriate method of analysis for any given training environment. A comprehensive review of the area summarised that performance analysis of competition using video is the most complete method available, providing a method of analysing the outcome of a performance that incorporates all the factors necessary for that performance (Smith, Norris, & Hogg, 2002). Performance analysis can be defined as the provision of objective feedback to athletes and coaches through the use of different means, typically involving video analysis and statistical information. The analysis can then be used to (i) make a permanent record of performance; (ii) monitor progress; (iii) track changes in performance-related variables; and (iv) identify strengths and weaknesses of both the athlete and opposition. However, many other analysis options exist. These include force platforms, tethered devices and recently developed inertial-sensor-based technologies for biomechanical assessment; physiological tools such as heart rate and lactate monitors; as well as an assortment of systems and methods for assessing other areas including psychology, nutrition, and strength and conditioning. What is unclear is the extent to which coaches incorporate these various tools when analysing their swimmers' progression.

Competitive swimming is a highly researched area and technological developments have aided advances in the understanding of the biomechanical principles that underpin these elements and govern propulsion through the water (Payton, Baltzopoulos, & Bartlett, 2002; Sanders et al., 2006; Toussaint & Truijens, 2005). Deterministic models have been developed through biomechanical research to highlight the interplay between various temporal, kinematic and kinetic principles during swimming performance (Chow & Knudson, 2011; Grimston & Hay, 1986; McLean, Holthe, Vint, Beckett, & Hinrichs, 2000; Sanders, 2002). These models serve to identify the key parameters that practitioners could monitor to assess improvements when conducting performance analysis.

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R. J. Mooney, G. Corley, A. Godfrey, C. Osborough, L. Quinlan, and G. OLaighin, "Application of video-based methods for competitive swimming analysis: A systematic review.," Sport and Exercise Medicine, vol. 1, pp. 133-150, 2015.

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Review

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Application of Video-Based Methods for Competitive Swimming Analysis: A Systematic Review

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ABSTRACT

This paper explores the application of video-based methods for the analysis of competitive swimming performance. A systematic search of the existing literature was conducted using the following keywords: *swim*, performance, analysis, quantitative, qualitative, camera, video* on studies published in the last five years, in the electronic databases ISI Web of Knowledge, PubMed, Science Direct, Scopus and SPORT discus. Of the 384 number of records initially identified, 30 articles were fully reviewed and their outcome measures were analysed and categorised according to (i) the processes involved, (ii) the application of video for technical analysis of swimming performance and (iii) emerging advances in video technology. Results showed that video is one of the most common methods used to gather data for analysing performance in swimming. The process of using video in aquatic settings is complex, with little consensus amongst coaches regarding a best-practice approach, potentially hindering usage and effectiveness. Different methodologies were assessed and recommendations for coaches, sport scientists and clinicians are provided. Video is an extremely versatile tool. In addition to providing a visual record, it can be used for qualitative and quantitative analysis and is used in both training and competition settings. Cameras can be positioned to gather images both above and below the water. Ongoing advances in automation of video processing techniques and the integration of video with other analysis tools suggest that video analysis will continue to remain central to the preparation of elite swimmers.

KEYWORDS: Swimming; Video analysis; Coaching; Biomechanics; Qualitative; Quantitative.

ABBREVIATIONS: PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-analyses; MEMS: Micro-Electro-Mechanical Systems.

INTRODUCTION

Elite sporting success is achieved through gradual improvements over an extended period of time, to ensure that the athlete has achieved a sufficient level of physical conditioning and technical expertise. Central to this process is a detailed training plan which is prepared by the coach and monitored using a variety of means, with video-based analysis arguably the most common methodology employed in elite sport. Unsurprisingly therefore, many reviews have been published on the various applications of video in sport, including technical recommenda-

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sensors

MDPI

Review

Inertial Sensor Technology for Elite Swimming Performance Analysis: A Systematic Review

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Abstract: Technical evaluation of swimming performance is an essential factor of elite athletic preparation. Novel methods of analysis, incorporating body worn inertial sensors (*i.e.*, Microelectromechanical systems, or MEMS, accelerometers and gyroscopes), have received much attention recently from both research and commercial communities as an alternative to video-based approaches. This technology may allow for improved analysis of stroke mechanics, race performance and energy expenditure, as well as real-time feedback to the coach, potentially enabling more efficient, competitive and quantitative coaching. The aim of this paper is to provide a systematic review of the literature related to the use of inertial sensors for the technical analysis of swimming performance. This paper focuses on providing an evaluation of the accuracy of different feature detection algorithms described in the literature for the analysis of different phases of swimming, specifically starts, turns and free-swimming. The consequences associated with different sensor attachment locations are also considered for both single and multiple sensor configurations. Additional information such as this should help practitioners to select the most appropriate systems and methods for extracting the key performance related parameters that are important to them for analysing their swimmers' performance and may serve to inform both applied and research practices.

Keywords: swimming; inertial sensor; accelerometer; gyroscope; kinematics; stroke analysis; MEMS; biomechanics; performance analysis

1. Introduction

Elite swimming is highly competitive, with world class athletes constantly challenging themselves against their rivals and tiny margins deciding the outcome of races. Consequently, swimmers and coaches continually strive for methods and strategies to optimise performance. A fundamental aspect of this preparation involves regular, quantifiable data measurement to assess skill acquisition and technical development.

Swimming is characterised by a sequence of coordinated actions of the trunk and limbs, in a repeated, synchronous pattern. Arm action during each of the four competitive swimming strokes comprises specific phases. It is typical to define these phases according to the various sweeps of the

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R. J. Mooney, G. Corley, A. Godfrey, C. Osborough, L. Quinlan, and G. ÓLaighin, "Assessment of the validity of the Finis Swimsense and the Garmin Swim activity monitors for recreational and competitive swimming," PLoS ONE, vol. 12, pp. 1-17, 2017.

PLOS | ONE

RESEARCH ARTICLE

Evaluation of the Finis Swimsense® and the Garmin Swim™ activity monitors for swimming performance and stroke kinematics analysis

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Competing interests: The authors have declared that no competing interests exist.

Abstract

Aims

The study aims were to evaluate the validity of two commercially available swimming activity monitors for quantifying temporal and kinematic swimming variables.

Methods

Ten national level swimmers (5 male, 5 female; 15.3±1.3years; 164.8±12.9cm; 62.4±11.1kg; 425±66 FINA points) completed a set protocol comprising 1,500m of swimming involving all four competitive swimming strokes. Swimmers wore the Finis *Swimsense* and the Garmin *Swim* activity monitors throughout. The devices automatically identified stroke type, swim distance, lap time, stroke count, stroke rate, stroke length and average speed. Video recordings were also obtained and used as a criterion measure to evaluate performance.

Results

A significant positive correlation was found between the monitors and video for the identification of each of the four swim strokes (Garmin: X^2 (3) = 31.292, $p<0.05$; Finis: X^2 (3) = 33.004, $p<0.05$). No significant differences were found for swim distance measurements. Swimming laps performed in the middle of a swimming interval showed no significant difference from the criterion (Garmin: bias -0.065, 95% confidence intervals -3.828–6.920; Finis bias -0.02, 95% confidence intervals -3.095–3.142). However laps performed at the beginning and end of an interval were not as accurately timed. Additionally, a statistical difference was found for stroke count measurements in all but two occasions ($p<0.05$). These differences affect the accuracy of stroke rate, stroke length and average speed scores reported by the monitors, as all of these are derived from lap times and stroke counts.

Conference Publications

R. J. Mooney, G. Corley, L. R. Quinlan, and G. ÓLaighin. (2015). "Validation of Finis Swimsense and Garmin Swim swimming activity monitors." Presented at the 2015 All-Ireland Postgraduate Conference in Sport Sciences and Physical Education, University of Limerick.

R. J. Mooney, G. Corley, A. Godfrey, C. Osborough, J. Newell, L. R. Quinlan, and G. ÓLaighin. (2016). "The use of technology for the analysis of swimming performance: Implications for device design." Presented at the 2016 Bioengineering In Ireland Conference (BINI22).

R. J. Mooney, G. Corley, A. Godfrey, C. Osborough, L. R. Quinlan, and G. ÓLaighin. (2016). "Evaluation of the accuracy of two activity monitors for performance assessment in swimming." Presented at the 2016 Bioengineering In Ireland Conference (BINI22).

R. J. Mooney, L. R. Quinlan, and G. ÓLaighin. (2016). A user centred design methodology for the development of sports performance analysis technology. Presented at the 2016 International Society for Performance Analysis in Sport (ISPAS) Conference.

Invention Disclosures

R. J. Mooney, G. ÓLaighin, L. R. Quinlan, and G. Corley. (2017). "Feature detection algorithm for the measurement of parameters related to the performance of swimming turns using a MEMS inertial sensor based system." Technology Transfer Office, NUI, Galway.

R. J. Mooney, G. ÓLaighin, L. R. Quinlan, and G. Corley. (2017). "User centred design methodology applied to the development of a MEMS inertial sensor based system for the analysis of swimming turns." Technology Transfer Office, NUI, Galway.

R. J. Mooney, G. ÓLaighin, L. R. Quinlan, and G. Corley. (2017). "Perceptions and practices of swimming coaches in relation to the analysis of elite swimming performance." Technology Transfer Office, NUI, Galway.

Appendix

SWIMMING SENSOR DEVICE USE CASE

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Revision History

Rev.	Date	Partner	Description	Name
1.0	19.01.15	NUIG	Initial draft of Use Case for Swimming Sensor Device	Robert Mooney
2.0	29.09.15	NUIG	Update of Use Case following expert review	Robert Mooney
3.0	16.10.15	NUIG	Update of Use Case following supervisory review	Robert Mooney
4.0	19.11.15	NUIG	Further update of Use Case following supervisory review	Robert Mooney
5.0	24.11.15	NUIG	Finalised Use Case for implementation with end users	Robert Mooney
5.1	05.12.15	NUIG	Minor revisions based on pilot study	Robert Mooney
5.2	07.12.15	NUIG	Updated based on user feedback	Robert Mooney
5.3	10.12.15	NUIG	Updated based on user feedback	Robert Mooney

1. General background

A Use Case is an interactive system analysis tool which can be viewed by various stakeholders and is an effective way of gathering and defining user requirements. The purpose of this Use Case document is to provide the reader with a detailed description of the use and function of a new Swimming Sensor device that is currently under development at the National University of Ireland, Galway. This new technology is intended to be used in competitive swimming training environments to provide a swim coach with a new method for quantifying a swimmers performance specifically during the various types of turns performed in a pool.

Currently, the most common method for analysing swimming performance is to use underwater video cameras. In order to obtain detailed quantitative data, it is necessary to digitize this footage using specialised software. This process has been found to be costly, complex and labour intensive and therefore may not fully meet the needs of a swim coach who has limited time and resources available and who has to ensure that the needs of the group are addressed as well as those of individual swimmers. This has led to efforts to provide alternative solutions for coaches and sports scientists.

A recently completed survey of swim coaches based in the United States found that turns are regarded as an important aspect of swimming performance. Both open and flip turns are highly technical skills, with variations based on different swimming strokes and individual preferences. Therefore it is important for coaches to be able to fully understand what their swimmers are doing and how best to maximise improvements in their technique. This can be difficult to achieve with large squad numbers and limited resources.

The researchers involved in developing this new technology are following a procedure known as "*User Centred Design*". User Centred Design is a framework of iterative processes in which the needs, wants, and limitations of end users of a product, service or method are given extensive attention at each stage of the design process. Changes or suggestions made by one potential end user may be used to update the use case before presenting it to another end user. In this context, the end users may represent a swimming coach, swimmer or sports scientist.

This Use Case document is intended to explore your views as a coach and to gauge your reaction to aspects of the design. This may ultimately lead to a final system that should best facilitate a coach to achieve his/her goals in an efficient and user-friendly manner.

Please note that the information contained in the document is confidential in nature and the reader is referred to the signed Confidential Disclosure Agreement for details of their responsibilities under this agreement.

Having read Section 1, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
Turns are a very important aspect of overall swimming performance					
I currently focus on improving my swimmers' turns as part of the weekly training schedule					
I would be interested in finding out more about a system that I can use to further analyse turn performance					
I currently have a method for measuring the quality of my swimmers' turns					

Please wait for further instructions before reading any further.

2. The swimming sensor device system

The components of the swimming sensor device system include the sensor unit, the coaches tablet computer or laptop, and an App to visualise the data.

Sensor Unit

The sensor unit is designed to be waterproof, low profile and light weight, to minimize drag effects and interference with the swimmer. It weighs 30g and has dimensions of 40mm x 20mm x 15mm. The unit is designed to be positioned at the back of the head. It is clipped to the goggle straps and held in position using the swimmers goggles and hat. Inside the unit are various electronic components, including an accelerometer, gyroscope, SD memory card, battery and a wireless Bluetooth connection. This sensor device is capable of measuring acceleration and angular velocity, thus allowing for a swimmer's movement in the water to be recorded. The sensor unit has some external features including (i) a power button for turning the device on and off and (ii) an LED status light. For the purposes of this Use Case, please assume that the device is capable of running continuously for several months without any requirement to change or recharge the battery.

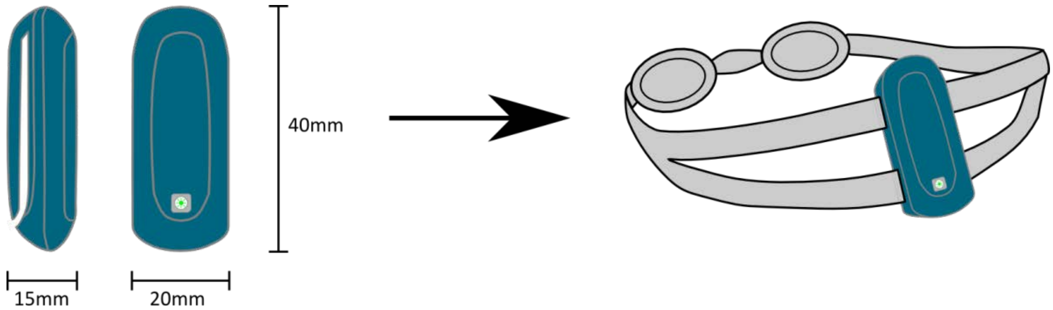


Figure 1: Sensor unit design, highlighting sensor dimensions and positioning on a swimmer's goggles.

Tablet computer/laptop

A tablet computer (such as an iPad) is used to communicate with the sensor unit via Bluetooth. Data that are collected by the sensor during a swimming session can be uploaded to an iPad for processing and analysis.

App

The sensor unit uses a custom software application that is used to visualise the data that are recorded. Feedback is tailored to suit the coach's needs and can include graphical, visual and numerical data presentation. The software also allows for video images to be synchronised with the sensor data.

(Sensor Unit) (Tablet Computer) (Analysis App)

Figure 2: Description of the swimming sensor device system components.

Having read Section 2, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
I understand the components of the system and how they interact with each other					
I think that this is a sensible arrangement for a system to be used to analyse swimming performance					

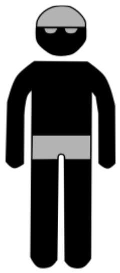
Please wait for further instructions before reading any further.

3. Role naming & description

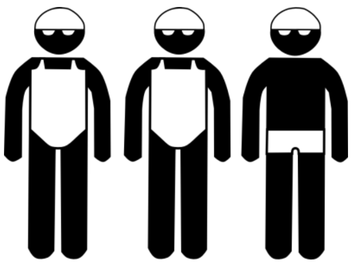
The Use Case will contain a number of people who interact with the Swimming Sensor device. These people are all referred to as actors. Each actor has a varying degree of interaction with the system. They have been given names to make it easier to follow the story and a brief description of each actor is provided below.

John
John is a swimming coach. He holds a Level 3 qualification from the American Swim Coaches Association and has been coaching for 15 years. He is the Head Coach at Laser Swimming Club and works with his senior squad of 30 athletes.

Andrea
Andrea is the Assistant Coach at Laser Swimming Club and supports Head Coach John. She is also a qualified Sports Scientist and often helps John with data collection for technique analysis.



Max
Max is a senior squad member at Laser Swimming Club and is coached by John. He has been swimming competitively for 10 years.



Other squad members
Max is part of a squad of multiple swimmers who train with him on a daily basis.

Having read Section 3, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I understand the roles of each of the actors described above					
The actors represent all the people who may be involved in analysing swimming performance in my own training environment					

Please wait for further instructions before reading any further.

4. Description of system utilisation

At a recent swim meet Max unexpectedly failed to make the final in the 200m frontcrawl event and was 3% off his personal best time. John suspects that the swimmers turns were a major factor for this poor performance. John decides to analyse the video footage of the race to check.

John's suspicions were correct. The time taken for Max to complete his turns were significantly longer in duration than his competitors and this was the difference that kept him from the final. John concludes that there is a technical issue with Max's frontcrawl turns that needs to be rectified.

John contemplates on the best course of action and decides to use a new Swimming Sensor device, which can collect quantitative data regarding Max's performance and can be used to analyse Max's technique. John also feels that multiple swimmers in his squad could benefit from such an analysis.

The following week, as part of the annual training plan for his squad, John has planned a swimming session that he feels is a good opportunity for collecting some data from his swimmers.

Having read Section 4, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

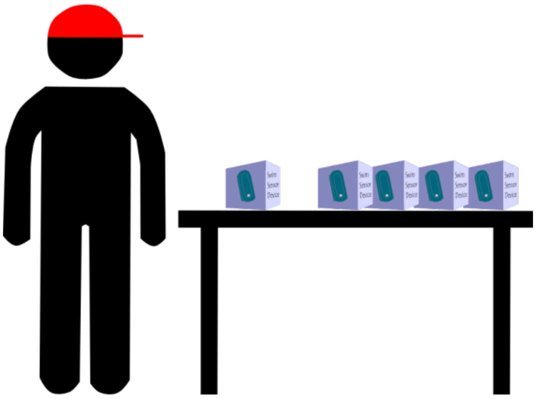
	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
The scenario described above closely resembles situations that I have had in the past with my swimmers					
I often look to using technologies in order to better understand how a swimmers technique is affecting their performance					
I believe that it is important to use technology in training for the analysis of swimming performance					

Please wait for further instructions before reading any further.

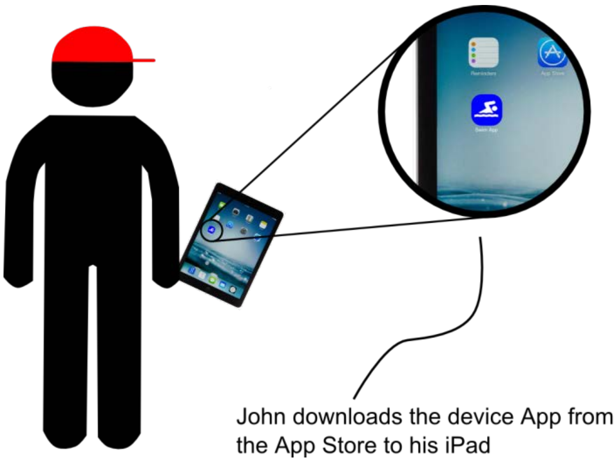
5. Device setup and configuration

A1 John has purchased multiple swimming sensor units and is ready to complete the system setup.

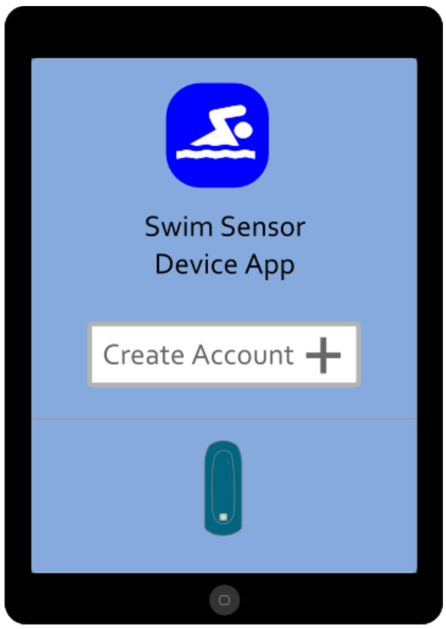
The units have arrived already engraved with individual identification markings, which were chosen by John when making his purchase.



A2 John downloads the App from the App store.

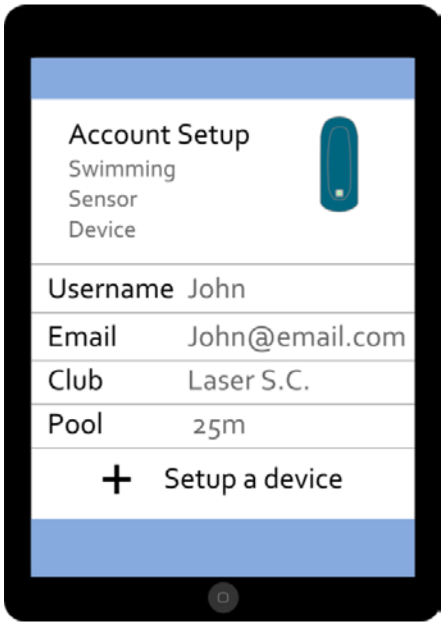


A3 Once downloaded John launches for the App for the first time and is prompted to create his own personal account.



A4 John is able to configure the App to his regular training location and set the pool size. He can add additional training locations at a later stage, for example if he were to use a 50m pool for some training sessions.

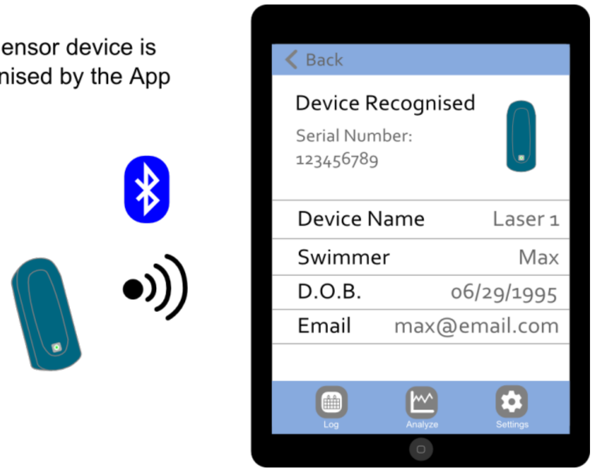
He is now ready to add some sensor units to his account.



A5 John configures each of the units separately. He turns the first device on and a green LED flashes. John brings it close to the iPad with the App running. The sensor unit is recognised from its serial number via Bluetooth.

John allocates the first device to Max and enters some personal information.

The Sensor device is recognised by the App

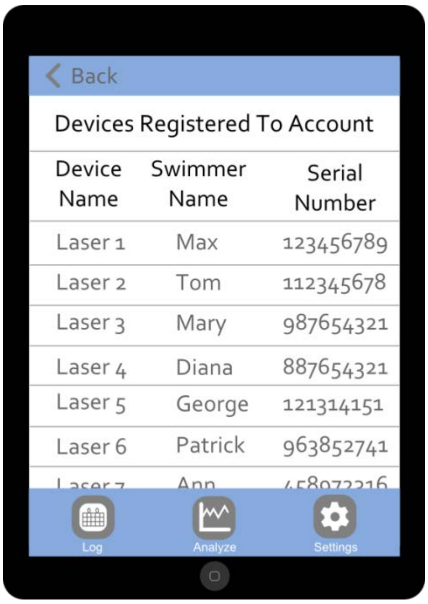


A6 John allocates the next device to another swimmer, and so on in a similar fashion until all devices have been configured for swimmers in his squad.

This allows for a log of data to be built up for each user and reviewed over time.

If he wishes, John can re-allocate a device to another swimmer in the future if necessary.

John could also have configured the devices so that a sensor unit could be used interchangeably between different swimmers.



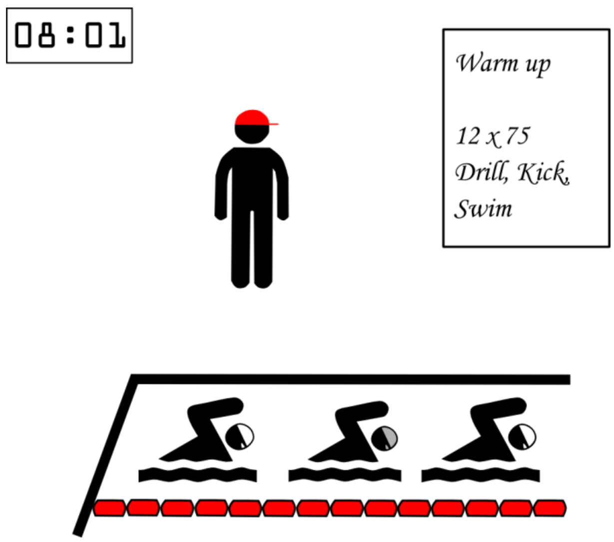
Having read Section 5, please indicate your level of agreement with the following statement(s).

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
I am familiar with the process of downloading and using Apps on a tablet device such as an iPad					
I understand the procedures involved in configuring the sensor units for use					
I would be comfortable carrying out these procedures myself and without any assistance					

Please wait for further instructions before reading any further.

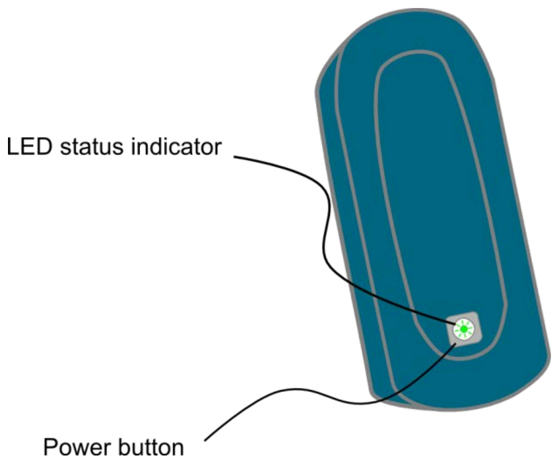
6. Pool-side preparation

B1 It is 8AM on Monday morning and training has gotten underway. John is on poolside and the squad of swimmers are warming up in the pool.

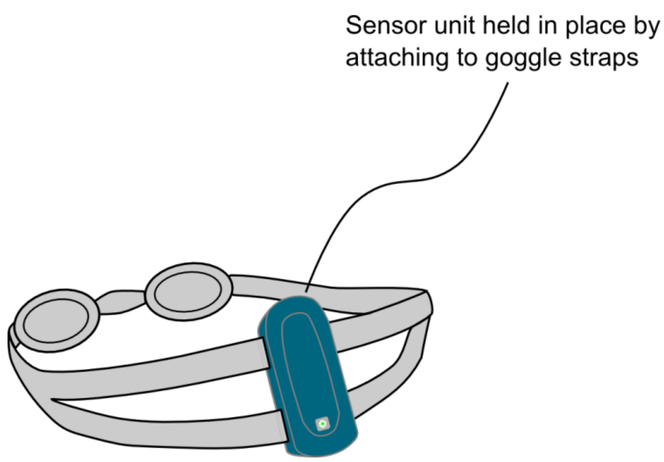


B2 When the warm-up is over the swimmers exit the pool and remove their hats.

John hands out the units to the swimmers. The swimmers turn the units on by pressing the power button and a green LED light blinks to indicate initialization. When the LED stops blinking and remains solidly lit green the device is ready to use.



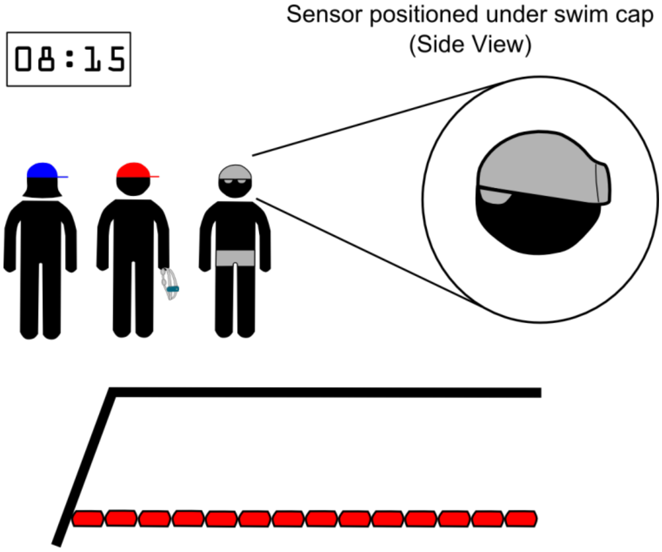
B3 The swimmers clip the unit into their swimming goggles, using the goggle straps to hold the unit in place.



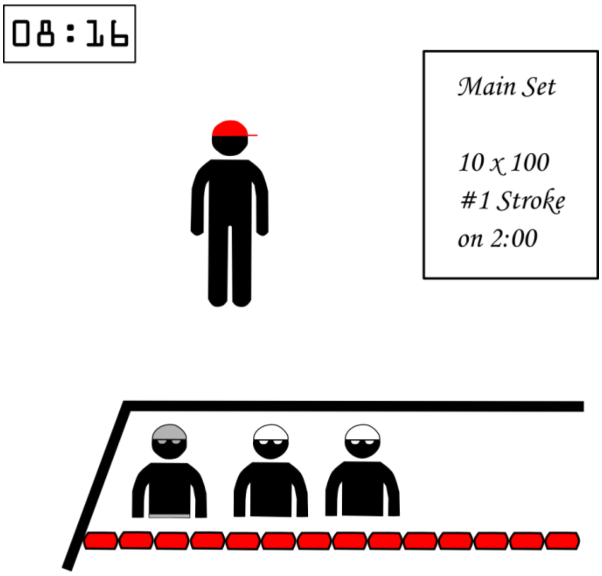
B4 The swimmers put back on their hats.

John and Andrea can supervise this and help the swimmers if required to ensure a secure, comfortable fit with the sensor unit correctly positioned under the swimming cap.

The setup of the devices has taken only a couple of minutes for the entire squad.



B5 The swimmers return to the pool and John issues instructions to the entire squad on the swimming training to be completed. On this occasion, the main set will comprise of 10 x 100m intervals, with each swimmer swimming their best stroke.



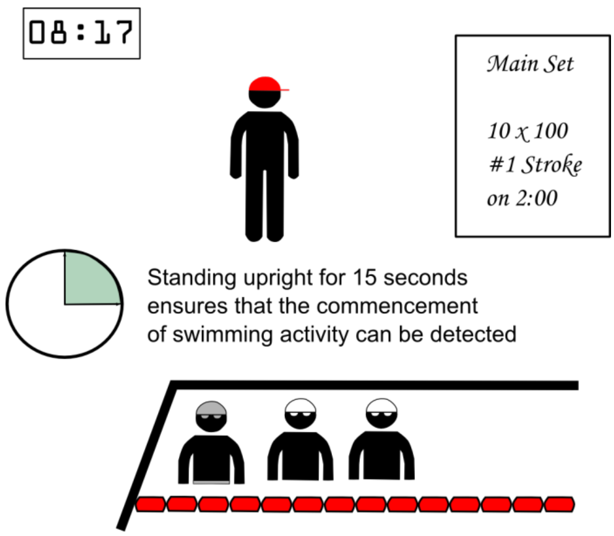
Having read Section 6, please indicate your level of agreement with the following statement(s).

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I understand the procedures involved when setting up the sensor unit for use					
I would be comfortable carrying out this setup procedure myself and without any assistance					
I believe that the head is a good location for this device					

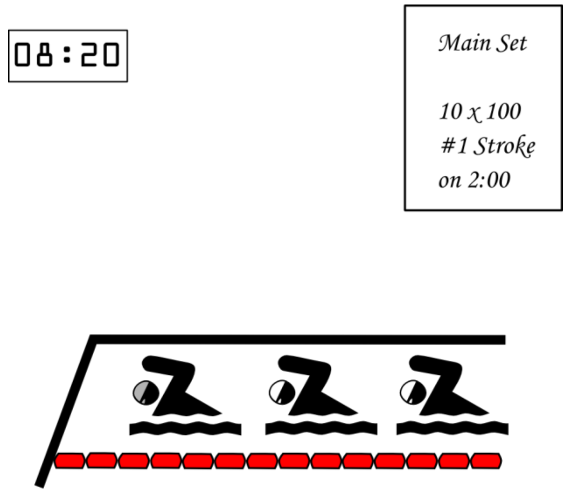
Please wait for further instructions before reading any further.

7. Data collection

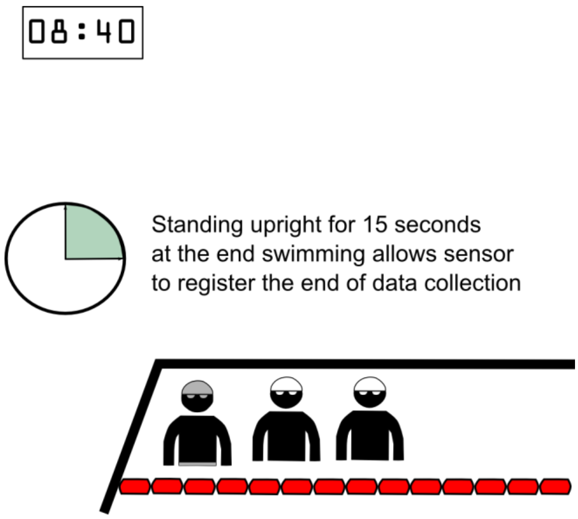
C1 Before starting to swim, The swimmers must stand upright and remain relatively still for approximately 15 seconds. This is done whilst the instructions from the coach about the training set are provided and ensures that the sensor units can detect when swimming activity is commenced.



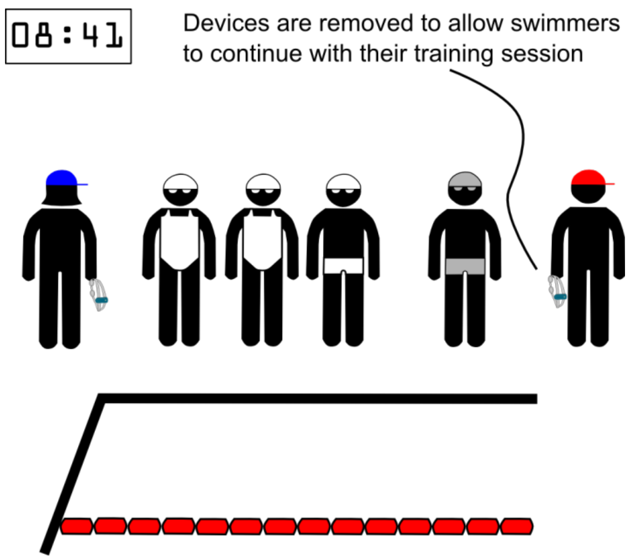
C2 The swimmers complete the set. Max completes the 10 x 100m intervals whilst swimming frontcrawl. Other swimmers swim different strokes based on their preference. As they are swimming in a 25m pool, they each complete 30 turns in total.



C3 When finished, the swimmers again stand in an upright stationary position for approximately 15 seconds so that the sensor unit can register that the swimming phase has been completed.

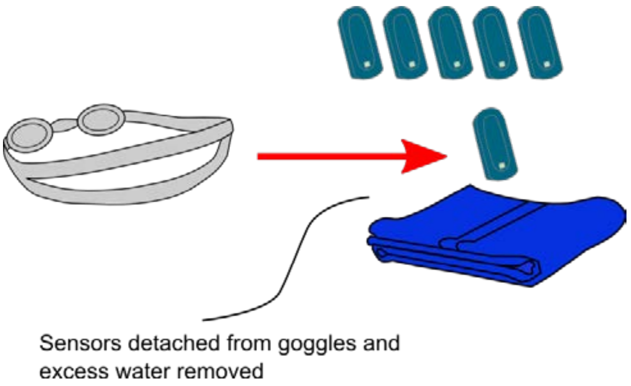


C4 The swimmers then exit the pool so that the devices can be removed.



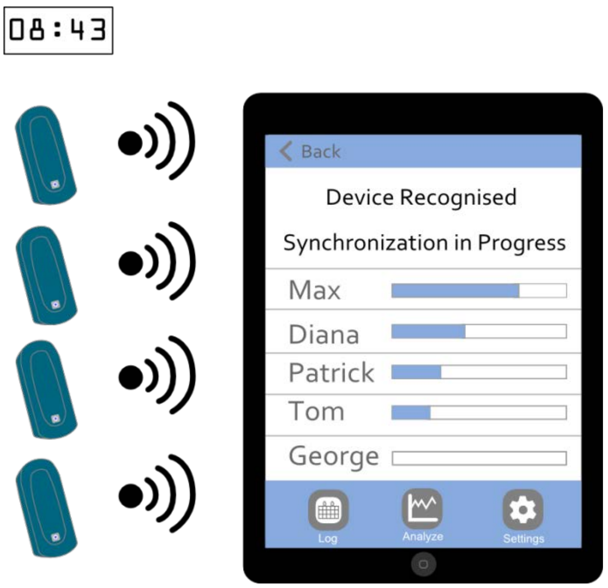
C5 John and Andrea can help the swimmers to remove the sensor units from the goggles. Andrea then pats the units dry with a cloth to remove excess water.

The swimmers are now free to continue with the training session.

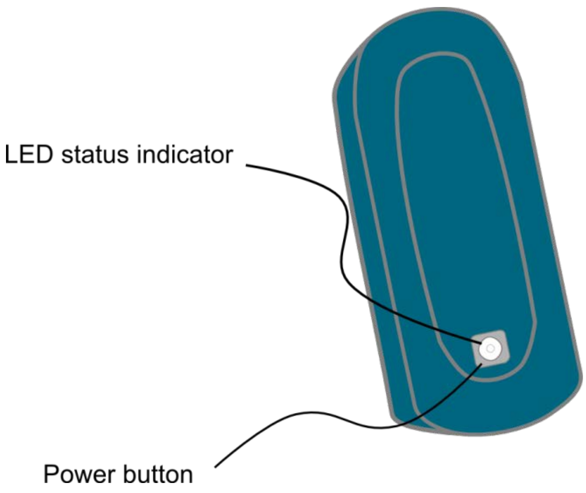


C6 As John continues with the training session, Andrea gets the iPad and launches the App. She then positions the sensor units in the vicinity of the iPad.

The devices are recognised and data synchronization starts automatically for each unit. The LED light blinks blue during this time. This is completed in less than 1 minute.



C7 Once the data has been transferred for all devices, Andrea powers off the sensor units by pressing and holding the power button until the LED light goes out. The units can now be stored until it is next required.



Having read Section 7, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

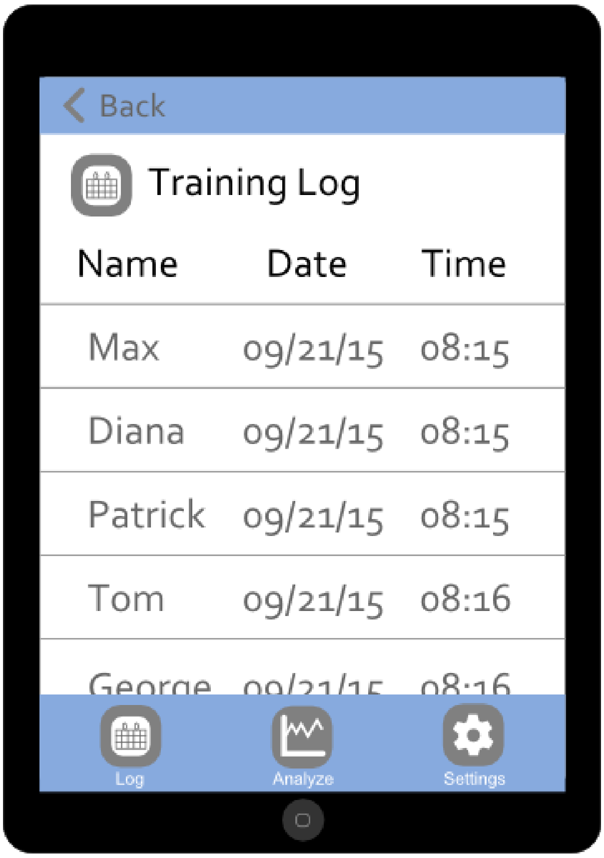
	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
I understand the procedures involved when collecting data during swimming using the sensor units					
Using the devices would not hinder my ability to carry out my normal training session with my entire swimming squad					
I would be comfortable carrying out these procedures myself and without any assistance					

Please wait for further instructions before reading any further.

8. Data analysis

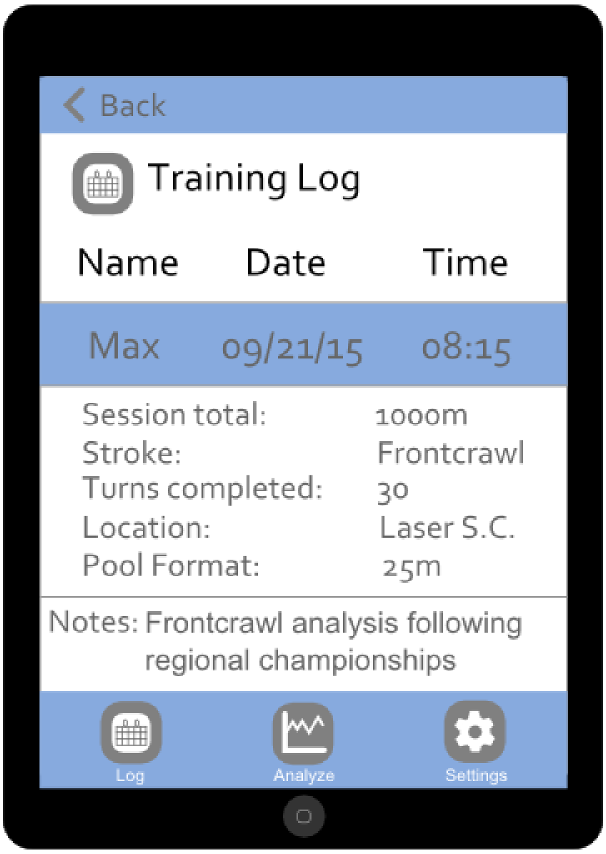
D1 Once the data synchronisation is complete John is able to start analysing the data.

John selects the *Training Log* tab to view a list of saved swimming sessions.



D2 John selects the data for Max and some summary information about the session is displayed.

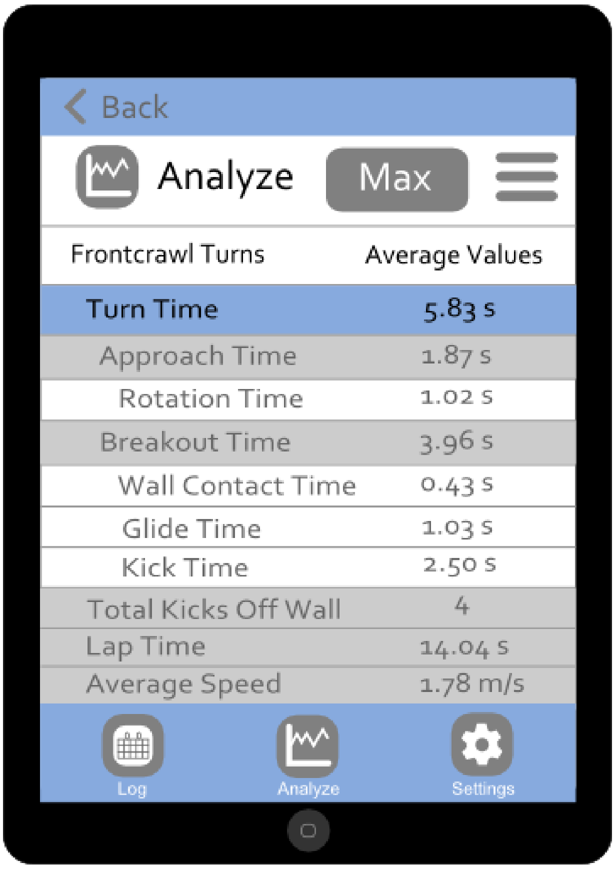
John is also able to manually input some notes about the session for future reference.



D3 John now selects the *Analyze* tab in order to get a detailed breakdown of Max's performance.

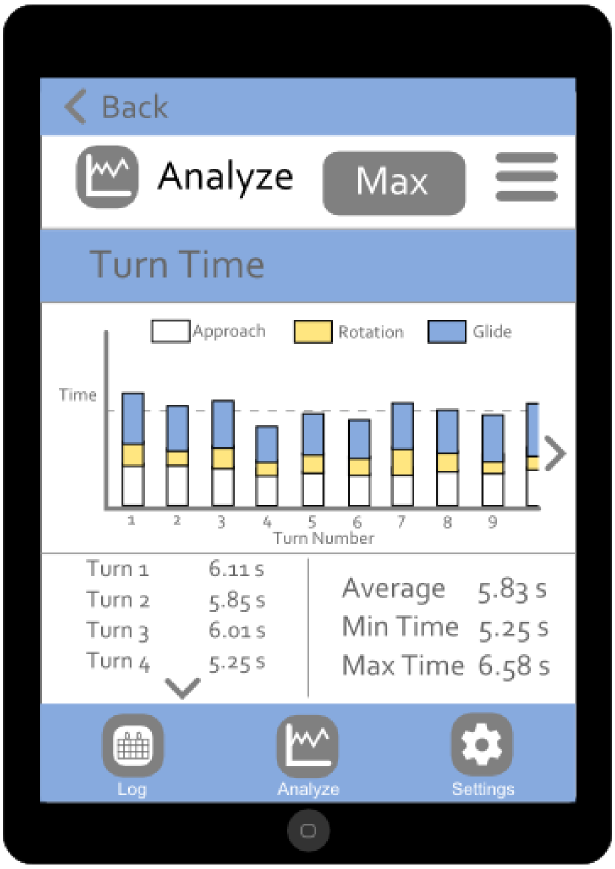
The information provides the average scores for a range of performance related variables, such as total turn time and times for different turn phase components.

The unit also provides information on lap times and the average swimming speed during each lap.

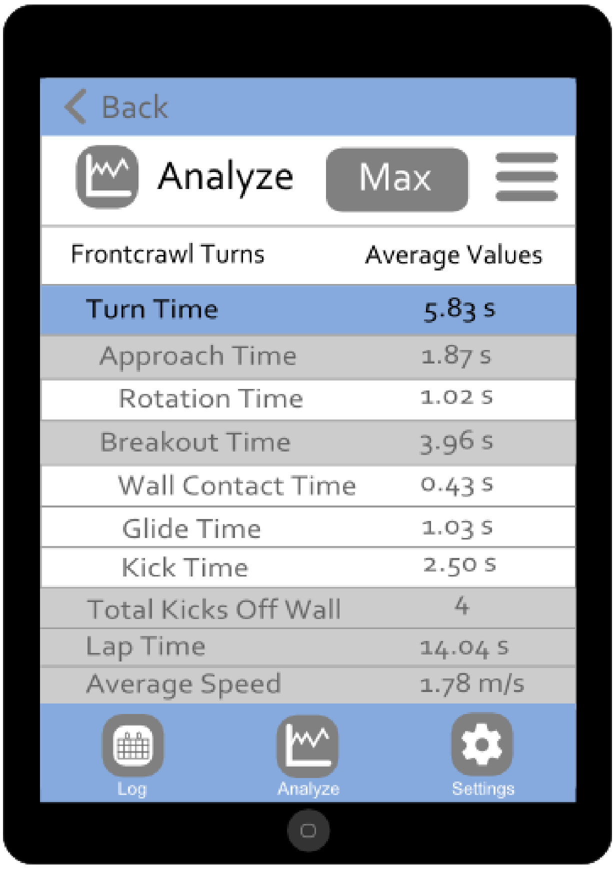


D4 John selects the *Turn Time* in order to further assess Max's performance. John can now review the results for each turn individually and get details of the time spent during different phases of the turns such as approach, rotation and glide.

John can scroll across and down the screen to get information for all turns performed during the session.



D5 John hits *Back* to return to the summary results screen

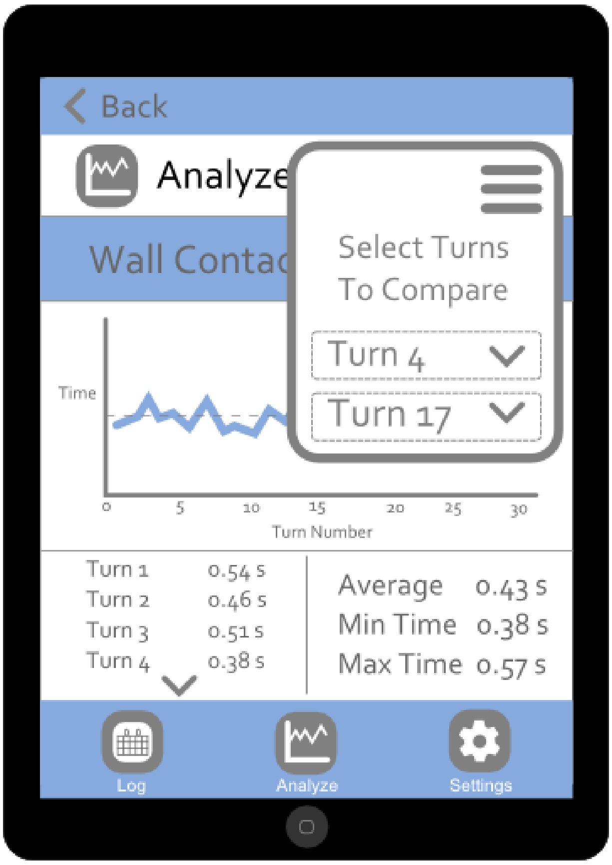


D6 Next, John views the *Wall Contact Time* results. These results are presented in a similar format to the *Turn Time*.

John can see that the times for this variable started to increase as the session progressed, possibly due to swimmer fatigue.

D7 John decides to compare two of Max's turns side by side. He opens the drop-down menu and makes his selections.

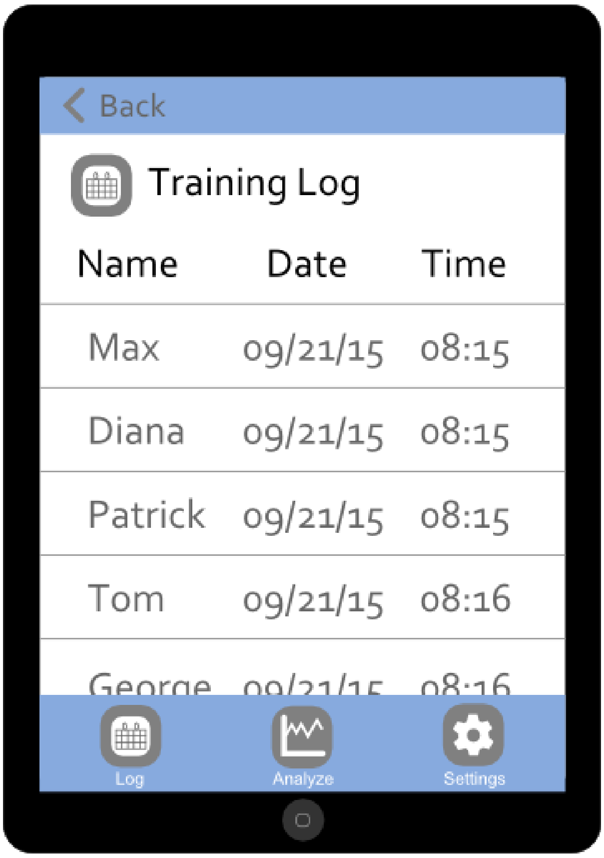
On this occasion he selects the fastest and slowest turns from swimming session, to see what differences there may be.



D8 The data is presented for him to review. John could also have chosen to compare against turns during a previous session, or those performed by a different swimmer in his squad.

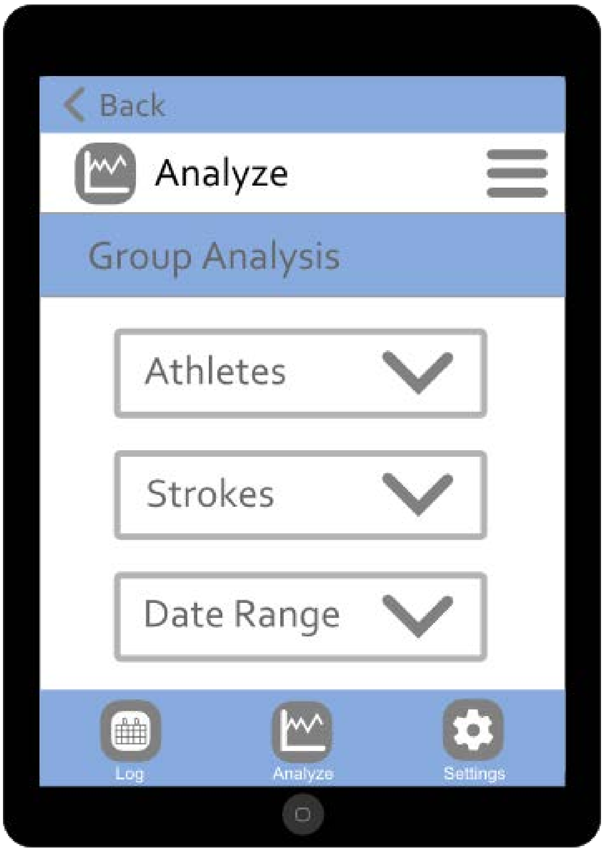
D9 John goes back to the *Training Log* and repeats the process described above to look at the individual results for some other swimmers.

John then decides to compare the results of the group.

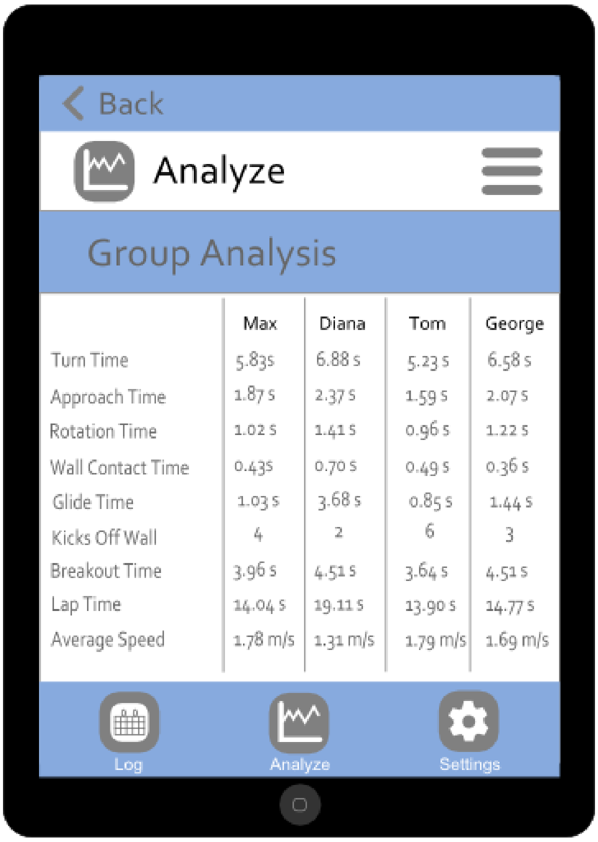


D10 John selects the *Analyze* tab and is prompted to select which athletes he would like to include in his group analysis. He can also filter by swimming stroke and is also able to select a date range if he wanted to include historical data.

On this occasion, John wants to compare only the swimmers who performed frontcrawl during the morning session and makes the appropriate selections.

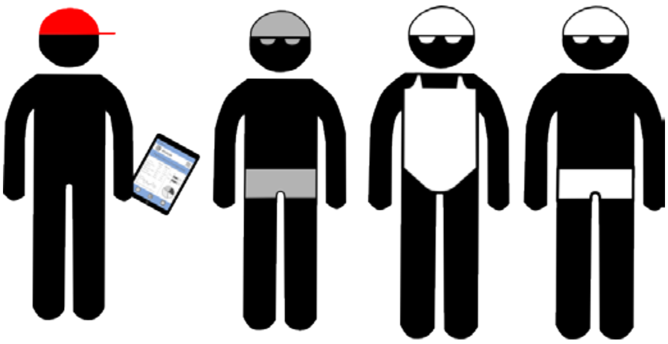


D11 John is presented with the data he wants and can now assess the performance of his swimming squad.



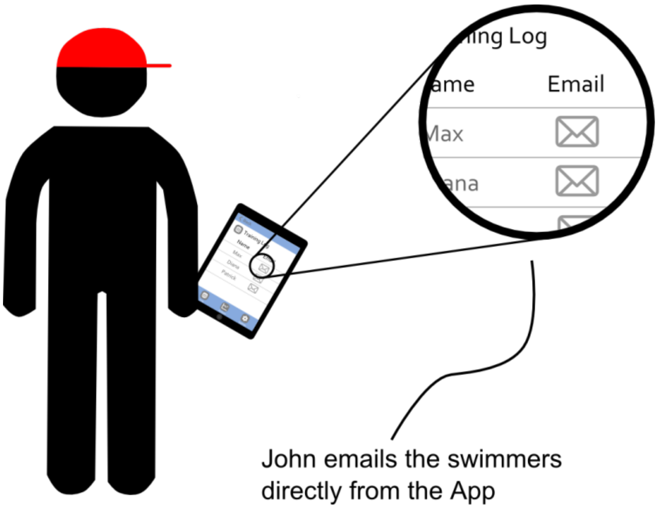
D12 After the swimming session, John meets with his squad and discusses the results.

They examine the information and decide how this can be used to inform future training and they discuss drills that can be practiced that will help to improve the performance of turns.



D13 Finally, John emails the reports to his swimmers directly from the App so that they can review a summary of their performance themselves in their own time.

John can also access the data himself later on that day if he wishes to spend more time analyzing the information.



Having read Section 8, please indicate your level of agreement with the following statement(s) by placing an X in the box which reflects your response to each statement.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I understand the procedures involved when downloading data and extracting information					
I think that the system would not interfere with my ability to do my job as a swim coach					
I am interested in analysing swimming turns in detail, collecting quantitative data to fully understand the mechanics of my swimmers' technique					
I believe that the swimming sensor unit offers an advantage over other methods of analysis					

Please wait for further instructions before reading any further.

The swimming sensor unit is designed to provide data for the following list of parameters for analysing turns:

- Turn time (Time from the start of the 3rd last arm stroke on approach until the end of the 3rd arm stroke after push off)
- Approach time (Time from the start of the 3rd last arm stroke on approach to wall contact)
- Rotation time (Time from start of last arm stroke to wall contact; Frontcrawl/Backcrawl)
- Wall contact time (Time from first contact with wall to push-off)
- Hands to feet contact time (Breaststroke/Butterfly)
- Glide time (Time from push-off to first dolphin kick)
- Number of dolphin kicks after push off
- Breakout time (Time from push-off to first arm stroke)
- Lap time
- Average speed per lap

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
I believe that the list of parameters included is sufficient for me to consider using the swimming sensor device for analysing turns					
I agree with the definitions used for all of the parameters provided by the sensor unit					
I would be satisfied for these parameters to be accurate to within one tenth of a second (0.1s)					

Please wait for further instructions before reading any further.

9. Conclusion

The information that was generated in the scenario described above has revealed that Max and the other swimmers have some technical areas to work on in order to improve their turns. John designs subsequent training sessions that allow for them to work on their turns regularly in an effort to improve performances. Six weeks later, John does a follow up analysis, again using the Swimming Sensor device to collect data. The results revealed a significant improvement in many key areas.

Max performs well at the next competition, qualifying for the 200m frontcrawl final and improving is personal best time in the process. After analysing the race performance, it was found that Max's turn times accounted for the majority of the improvement in his race time. Many other swimmers in the squad also showed similar improvements.

Having now read through this Use Case, are they any aspects of the procedures and interactions described that immediately appeal to you?

Additionally, are they any aspects of the procedures and interactions described that immediately concern you?

Please wait for further instructions before reading any further.

Having now read through the full Use Case, place an X in the box which reflects your response to each statement below. Don't think too long about each statement. Please respond to every statement.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
I think that I would like to use this system frequently					
I found the system unnecessarily complex					
I think this system would be easy to use					
I think that I would need the support of a technical person to be able to use this system					
I found the various functions in this system were well integrated					
I thought there was too much inconsistency in this system					
I would imagine that most people would learn to use this system very quickly					
I think this system would be cumbersome to use					
I would feel very confident using the system					
I would need to learn a lot of things before I could get going with this system					

```
//The Wire library is used for I²C communication

#include <Wire.h>


//standard SD libraries are used to control SD card function

#include <SdFat.h>

#include <SdFatUtil.h>


//Define the size of the buffer. There will be 6 gyroscope, 6
accelerometer, 2 control characters and 4 time characters, giving a total
of 18 x 292 = 5256

#define BUF_SIZE 5256


//Allocate a Pin out to use the LED as a status indicator

#define PIN_OUT 13


///////////////////////////////////////////////////////////////////////////
//                                                                       //
//                     ACCELEROMETER INITIALISATION                      //
//                                                                       //
///////////////////////////////////////////////////////////////////////////


//Accelerometer address during the I²C communication. The microcontroller
must be directed to communicate with either the accelerometer or the
gyroscope when communicating with the IMU and this sets the address for the
accelerometer (Refer to page 10 of ADXL345 datasheet for further
information)

#define ACCELEROMETER_ADDRESS 0x53


//Register for the data range. DATA_FORMAT also controls the format of the
data output from registers 0x32-0x37 (Refer to page 17 of ADXL345 datasheet
for further information)

#define ACCELEROMETER_DATA_FORMAT 0x31


//Management of the power attributes of the accelerometer. This is need to
set the accelerometer into measurement mode (Refer to page 16 of ADXL345
datasheet for further information)

#define ACCELEROMETER_POWER_CTL 0x2D


// include the six bytes needed to hold the output for the x, y and z axes.
The output is 2’s complement, DATAx0 is least significant byte and DATAx1
```

```
is most significant byte (Refer to page 18 of ADXL345 datasheet for further information)

//Low part of the x axis

#define ACCELEROMETER_XOUT_L 0x32

//High part of the x axis

#define ACCELEROMETER_XOUT_H 0x33



//Low part of the y axis

#define ACCELEROMETER_YOUT_L 0x34

//High part of the y axis

#define ACCELEROMETER_YOUT_H 0x35


//Low part of the z axis

#define ACCELEROMETER_ZOUT_L 0x36

//High part of the z axis

#define ACCELEROMETER_ZOUT_H 0x37



////////////////////////////////////////////////////////////////////////////
//                                                                        //
//                         GYROSCOPE INITIALISATION                       //
//                                                                        //
////////////////////////////////////////////////////////////////////////////

//Registers are parameters that determine how the sensor will behave and can hold data that represent the sensors status.

//Gyroscope address during the I²C communication. The microcontroller must be directed to communicate with either the accelerometer or the gyroscope when communicating with the IMU and this sets the address for the gyroscope

#define GYRO_ADDRESS 0x68


//Define the sample rate divider register so that the required sample rate can be configured.

#define GYRO_SAMPLERATE_DIVIDER 0x15
```

```
//Define the register that will be used to set the scale range and low pass
filter configurations.

#define GYRO_SCALERANGE_DIGITALFILTER 0x16



//include the six bytes needed to hold the output for the gyroscope output.
(Registers 29-34 p27)

//High part of the x axis

#define GYRO_XOUT_H 0x1D

//Low part of the x axis

#define GYRO_XOUT_L 0x1E


//High part of the y axis

#define GYRO_YOUT_H 0x1F

//Low part of the y axis

#define GYRO_YOUT_L 0x20


//High part of the z axis

#define GYRO_ZOUT_H 0x21

//Low part of the z axis

#define GYRO_ZOUT_L 0x22



///////////////////////////////////////////////////////////////////////////
//                                                                       //
//                           SD CARD INITIALISATION                      //
//                                                                       //
///////////////////////////////////////////////////////////////////////////



//SD chip select pin, Pin 10 on Teensy 3.0

const uint8_t chipSelect = SS;


//Buffer for storing sensor values. The size of the buffer has already been
allocated above

unsigned char buf[BUF_SIZE];
```

```
//Temporary buffer for writing to the SDcard. The size of the buffer has
already been allocated above

unsigned char bufTemp[BUF_SIZE];


//A variable called count_buf is created and is going to be used to know
how much the buffer capacity has been used up

int count_buf = 0;


//SDcard management


SdFat sd;


//File management

SdFile file;


//Create a file name for saved data. The file name must be 10 characters

char file_name[10] = {'T','R','N','0','0','1','.','T','X','T'};


//Time from the beginning of the program

unsigned long time = 0;


//Converting the unsigned long into four unsigned char

unsigned char *pt, byte_t0, byte_t1, byte_t2, byte_t3;


///////////////////////////////////////////////////////////////////////////
//                                                                       //
//                      ACCELEROMETER CONFIGURATION                      //
//                                                                       //
///////////////////////////////////////////////////////////////////////////


//This function will be called as part of the Setup and is used to
configure the accelerometer and establish the various operating settings

void configuration_of_accelerometer(void){
```

```
// setting the Data format register to 00 will put the device into +-2g
range (01 for +-4g; 10 for 8g and 11 for 16g). (Refer to page 17 of ADXL345
datasheet for further information).

write_to_device(ACCELEROMETER_ADDRESS, ACCELEROMETER_DATA_FORMAT, 00);



// setting the power control to 8 (binary = 0000 1000) sets the D3 bit
high, turning on measurement mode (p16)

// By default, the sensor is already in 100 Hz sample rating giving a
bandwidth of 50 Hz. This can be changed in Register 0x2C-BW_RATE if
necessary (p16 of datasheet)

write_to_device(ACCELEROMETER_ADDRESS, ACCELEROMETER_POWER_CTL, 8);



//delay just for precaution

delay(1000);

}



///////////////////////////////////////////////////////////////////////////
//                                                                       //
//                         GYROSCOPE INITIALISATION                      //
//                                                                       //
///////////////////////////////////////////////////////////////////////////



//This function will be called as part of the Setup and is used to
configure the gyroscope and establish the various operating settings

void configuration_of_gyro(void) {



//Set the gyroscope scale for the outputs to +/-2000 degrees per second and
the digital low pass filter to 42 Hz. The output is 16 bits, the max value
for positive value is 32767, and the max negative value is -32768

// setting this to 27 (binary = 0001 1011) sets the gyro to Full Scale
select and the filter in one Register (Refer to page 24 of the datasheet
for further information)

write_to_device(GYRO_ADDRESS, GYRO_SCALERANGE_DIGITALFILTER, 27);
```

```
//Fsample = Fint / (divider + 1) where Fint is 1kHz, so sample rate
(Fsample) =  1kHz (Fint) / (9+1), giving 100 Hz operation. (Refer to page
23 of the datasheet for further information).

write_to_device(GYRO_ADDRESS, GYRO_SAMPLERATE_DIVIDER, 9);




//delay just for precaution

delay(1000);

}

}



///////////////////////////////////////////////////////////////////////////
//                                                                       //
//                       COMMUNICATION PROTOCOLS                         //
//                                                                       //
///////////////////////////////////////////////////////////////////////////



//This function will be used to transfer data to the SD card. This method
is available in a library for different types of Arduino boards.

//It is necessary to include the device and register address and the value
to be returned.

void write_to_device(uint8_t device_address, uint8_t register_address,
uint8_t value){



//start a transmission with one of the sensors.

Wire.beginTransmission(device_address);




//select the register to be written to.

Wire.write(register_address);



//write data to the selected register.

Wire.write(value);
```

```
//end the transmission.

Wire.endTransmission();

}




//This method is flexible and can be used to return one or more bytes,
depending on the available data

unsigned char read_from_device(uint8_t device_address, uint8_t
register_address, boolean with_return = true, uint8_t num_bytes = 1,
unsigned char buffer[] = {0}) {


//data is zero, if still zero then this may be a signal that a problem has
occurred

unsigned char data = 0;


//start transmission to the device

Wire.beginTransmission(device_address);


//sends address to read from

Wire.write(register_address);


//end transmission

Wire.endTransmission();


//start transmission to device

Wire.beginTransmission(device_address);


//request num_bytes bytes from device

Wire.requestFrom(device_address, num_bytes);


//if just one byte is available; data is going to receive a value from the
device

if(with_return) {
```

```
//if the device has some data to return
if(Wire.available()) {

//save the data sent from the I²C device
data = Wire.read();
}
}

//if there is more than one byte, keep in the loop
else {


// device may send less than requested (but not expected to occur)
int i = 0;


// device may send less than requested (but not expected to occur)
while(Wire.available()) {

//receive a byte
buffer[i] = Wire.read();

//increase the counter
i++;


//if this is more than was requested, there is a problem so stop the
operation
if(i > num_bytes) break;
}
}

//end transmission
```

```
Wire.endTransmission();


//return the data

return data;

}


// Create an IntervalTimer object

IntervalTimer sampleTimer;



//////////////////////////////////////////////////////////////////////////////
//                                                                          //
//                                  SETUP                                   //
//                                                                          //
//////////////////////////////////////////////////////////////////////////////


// create the setup function

void setup() {


//set the LED as an output

pinMode(PIN_OUT, OUTPUT);




//turn the LED on

digitalWrite(PIN_OUT, HIGH);




//leave the LED on for 5 seconds

delay(5000);


//turn the LED off

digitalWrite(PIN_OUT, LOW);


//begin the serial transmission

Serial.begin(9600);
```

```
//delay for 5 ms
delay(5);

//begin the I²C transmission
Wire.begin();

//delay for 5 ms
delay(5);

//call the function in order to configure the accelerometer
configuration_of_accelerometer();

//call the function in order to configure the gyroscope
configuration_of_gyro();

//Check that communication has started with the SD card holder in order to
write the information to the card
if (!sd.begin(chipSelect, SPI_FULL_SPEED)) sd.initErrorHalt();

//Create the file
if (!file.open(file_name, O_CREAT | O_WRITE)) {

//If something is wrong the LED will turn on
digitalWrite(PIN_OUT, HIGH);

//Stay here if an error has been detected
while(1) {

//Send an error through the serial
Serial.write("Error in creating file\n");
```

```
//delay for 1 sec
delay(1000);
}
}

//Synchronization of the file
file.sync();

//Close the file
file.close();



//turn the LED on
digitalWrite(PIN_OUT, HIGH);



//leave the LED on for 100 ms
delay(100);

//turn the LED off
digitalWrite(PIN_OUT, LOW);

// tick to run every 0.010 seconds
sampleTimer.begin(tick, 10000);
}


///////////////////////////////////////////////////////////////////////////////
//                                                                           //
//                         INTERRUPT TIMER FUNCTION                          //
//                                                                           //
///////////////////////////////////////////////////////////////////////////////


//start the interrupt timer function
void tick(void) {
```

```
//This variable stores the time at the beginning of each sample
time = millis();


//A pointer is declared to be used to divide the time in four bytes
pt =(unsigned char *) &time;


//Each part receives 8 bits
byte_t0= *(pt+0);
byte_t1= *(pt+1);
byte_t2= *(pt+2);
byte_t3= *(pt+3);


//First character for initialization of the buffer
buf[count_buf] = '#';


//After each byte written in the buffer, it is necessary to
//increase the counter to move along the buffer
count_buf++;


//Second character to check the initialization of the buffer
buf[count_buf] = '@';


//increase the counter to move along the buffer
count_buf++;


//From here is recorded the data of the gyro and accelerometer, at the
total of 12 bytes
```

```
// Gyro x-axis (high)
buf[count_buf] = read_from_device(GYRO_ADDRESS, GYRO_XOUT_H);

//increase the counter to move along the buffer
count_buf++;


// Gyro x-axis (low)
buf[count_buf] = read_from_device(GYRO_ADDRESS, GYRO_XOUT_L);

//increase the counter to move along the buffer
count_buf++;


// Gyro y-axis (high)
buf[count_buf] = read_from_device(GYRO_ADDRESS, GYRO_YOUT_H);

//increase the counter to move along the buffer
count_buf++;


// Gyro y-axis (low)
buf[count_buf] = read_from_device(GYRO_ADDRESS, GYRO_YOUT_L);


//increase the counter to move along the buffer
count_buf++;


// Gyro z-axis (high)
buf[count_buf] = read_from_device(GYRO_ADDRESS, GYRO_ZOUT_H);

//increase the counter to move along the buffer
count_buf++;
```

```
// Gyro z-axis (low)

buf[count_buf] = read_from_device(GYRO_ADDRESS, GYRO_ZOUT_L);


//increase the counter to move along the buffer

count_buf++;



// Accelerometer x-axis (high)

buf[count_buf] = read_from_device(ACCELEROMETER_ADDRESS,
ACCELEROMETER_XOUT_H);


//increase the counter to move along the buffer

count_buf++;



// Accelerometer x-axis (low)

buf[count_buf] = read_from_device(ACCELEROMETER_ADDRESS,
ACCELEROMETER_XOUT_L);


//increase the counter to move along the buffer

count_buf++;



// Accelerometer y-axis (high)

buf[count_buf] = read_from_device(ACCELEROMETER_ADDRESS,
ACCELEROMETER_YOUT_H);


//increase the counter to move along the buffer

count_buf++;

// Accelerometer y-axis (low)

buf[count_buf] = read_from_device(ACCELEROMETER_ADDRESS,
ACCELEROMETER_YOUT_L);


//increase the counter to move along the buffer
```

```
count_buf++;


// Accelerometer z-axis (high)

buf[count_buf] = read_from_device(ACCELEROMETER_ADDRESS,
ACCELEROMETER_ZOUT_H);


//increase the counter to move along the buffer

count_buf++;


// Accelerometer x-axis (low)

buf[count_buf] = read_from_device(ACCELEROMETER_ADDRESS,
ACCELEROMETER_ZOUT_L);


//increase the counter to move along the buffer

count_buf++;


//The time is divided in 4 bytes and they are arranged in reverse order

//first is byte_t3

buf[count_buf] = byte_t3;


//increase the counter to move along the buffer

count_buf++;


//next is byte_t2

buf[count_buf] = byte_t2;


//increase the counter to move along the buffer

count_buf++;


//next is byte_t1

buf[count_buf] = byte_t1;
```

```
//increase the counter to move along the buffer
count_buf++;


//next is byte_t0
buf[count_buf] = byte_t0;

//increase the counter to move along the buffer
count_buf++;

}


//////////////////////////////////////////////////////////////////////////////
//                                   LOOP                                   //
//                                                                          //
//                                                                          //
//////////////////////////////////////////////////////////////////////////////


//start the loop
void loop() {


//Check the size of the buffer
// If capacity remains, then continue to read sensor values
if(count_buf < BUF_SIZE) {



//If all the buffer is full then the data is saved to the SD card
else {



//Turn the counter to zero again
count_buf = 0;
```

```
// copy contents of buffer into bufTemp
memcpy( bufTemp, buf, BUF_SIZE*sizeof(char) );

//Open the SDcard
if (!sd.begin(chipSelect, SPI_FULL_SPEED)) sd.initErrorHalt();


//Now the file is going to receive more data, so appended mode is used
if (!file.open(file_name, O_APPEND | O_RDWR)) {


//If something is wrong the LED is turned on
digitalWrite(PIN_OUT, HIGH);


//Stay here if an error has been detected
while(1) {


//Send an error through the serial
Serial.write("Error when re-opening file\n");


//delay for 1 sec
delay(1000);
}
}

//Write all the buffer in the SDcard
if (file.write(bufTemp, sizeof(bufTemp)) != sizeof(bufTemp)) {

//If something is wrong the LED is turned on
digitalWrite(PIN_OUT, HIGH);
```

```
//Stay here if an error has been detected
while(1) {

//Send an error through the serial
Serial.write("Error during write to file\n");

//delay for 1 sec
delay(1000);
}
}

//Synchronization of the file
file.sync();

//Close the file
file.close();

}
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                     %
%                      ACCELEROMETER CALIBRATION                      %
%                                                                     %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clc;
clear all;

% Import raw data file
raw_data = dlmread('CAL004.csv',';',1,0)';

% Isolate each axis (acceleration)
Ax = raw_data(4,:);
Ax = (Ax)';
Ay = raw_data(5,:);
Ay = (Ay)';
Az = raw_data(6,:);
Az = (Az)';

% convert time to sec
time = (1:length(Ax))/100;

% plot raw data
figure;
hold on;
plot(Ax, 'b'); plot(Ay, 'g'); plot(Az, 'r');
legend('x','y','z');
grid on;

% isolate acceleration output for each axis when orientated at +1g and -1g
x_pos = Ax(2000:3000);
y_pos = Ay(5000:6000);
z_pos = Az(7000:8000);
x_neg = Ax(9000:10000);
y_neg = Ay(11000:12000);
z_neg = Az(13000:14000);

% calculate acceleration sensitivity
x_sens = (mean(x_pos) - mean(x_neg)) / 2;
y_sens = (mean(y_pos) - mean(y_neg)) / 2;
z_sens = (mean(z_pos) - mean(z_neg)) / 2;

% calculate acceleration offset
% x-axis offset
x_off1 = mean(Ax(5000:6000));
x_off2 = mean(Ax(7000:8000));
x_off3 = mean(Ax(11000:12000));
x_off4 = mean(Ax(13000:14000));
x_off_array = [x_off1 x_off2 x_off3 x_off4];
x_off = mean(x_off_array);

% y-axis offset
y_off1 = mean(Ay(2000:3000));
y_off2 = mean(Ay(7000:8000));
y_off3 = mean(Ay(9000:10000));
y_off4 = mean(Ay(13000:14000));
y_off_array = [y_off1 y_off2 y_off3 y_off4];
y_off = mean(y_off_array);
```

```
% z-axis offset
z_off1 = mean(Az(2000:3000));
z_off2 = mean(Az(5000:6000));
z_off3 = mean(Az(9000:10000));
z_off4 = mean(Az(11000:12000));
z_off_array = [z_off1 z_off2 z_off3 z_off4];
z_off = mean(z_off_array);

% conversion of acceleration values into m/s-2
ax = 9.81*(raw_data(4,:) - x_off)/x_sens; % remove 9.81 to get g-values
ay = 9.81*(raw_data(5,:) - y_off)/y_sens;
az = 9.81*(raw_data(6,:) - z_off)/z_sens;

% plot the calibrated acceleration data
figure;
hold on;
plot(ax, 'b'); plot(ay, 'g'); plot(az, 'r');

% create array of  calibration variables
% these can be passed into the filtering process
calAccArray = [x_off x_sens y_off y_sens z_off z_sens];
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                      %
%                       GYROSCOPE CALIBRATION                          %
%                                                                      %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clc;
clear all;

% Import raw data file
raw_data = dlmread('CAL030.csv',';',1,0)';

% isolate each axis (angular velocity)
Gx = raw_data(1,:);
Gx = (Gx)';
Gy = raw_data(2,:);
Gy = (Gy)';
Gz = raw_data(3,:);
Gz = (Gz)';

% convert time to sec
time = (1:length(Gx))/100;

% plot raw data
figure;
hold on;
plot(time, Gx, 'b'); plot(time, Gy, 'g'); plot(time, Gz, 'r');
legend('x','y','z');
grid on;

% calculate gyroscope offset
% rotation was about z-axis so only this required
Gz_off1 = mean(Gz(800:1200));
Gz_off2 = mean(Gz(1900:2200));
Gz_off3 = mean(Gz(3000:3300));
Gz_off_array = [Gz_off1 Gz_off2 Gz_off3];
Gz_off = mean(Gz_off_array);

% subtract offset from raw data
Gz1 = Gz - Gz_off;

% calculate angular velocity values (deg/s)
Gz_sens = 16.384; % 16-bit (2^16=65535); +/-2000deg/s
Gx = (Gx - Gz_off)/Gz_sens;
Gy = (Gy - Gz_off)/Gz_sens;
Gz = (Gz - Gz_off)/Gz_sens;

% plot the angular velocity values (deg/s)
figure;
hold on;
plot(time, Gx, 'b'); plot(time, Gy, 'g'); plot(time, Gz, 'r');
legend('x','y','z');
grid on;

% calculate the gyroscope scale factor through integration
% isolate the rotation phases
Gz_int1 = Gz(1400:1800); % 1st 90 deg rotation
Gz_int2 = Gz(2300:2700); % 2nd 90 deg rotation
```

```
% perform the integration
time_int1 = (1:length(Gz_int1))/100;
time_int2 = (1:length(Gz_int2))/100;

int1 = trapz(Gz_int1, time_int1);
int1 = 90 / int1;
int2 = trapz(Gz_int2, time_int1);
int2 = 90 / int2;
G_SF = (int1 - int2)/2;     %G_SF is Gyroscope Scale Factor

% create array of  calibration variables
% these can be passed into the filtering process
calGyroArray = [Gz_off Gz_sens G_SF];
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                    %
%                       LOW PASS FILTER                              %
%                                                                    %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clc;
clear all;

% Import raw data file
raw_data = dlmread('EGR002.csv',';',1,0)';

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                Load calibration data for RM_Prototype1             %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% Accelerometer calibration array
load('calAccArray.mat');
x_off = calAccArray(1);
x_sens = calAccArray(2);
y_off = calAccArray(3);
y_sens = calAccArray(4);
z_off = calAccArray(5);
z_sens = calAccArray(6);

% Gyroscope calibration array
load('calGyroArray.mat');
Gz_off = calGyroArray(1);
Gz_sens = calGyroArray(2);
G_SF = calGyroArray(3);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                Convert values to correct units                     %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% calculate acceleration values (m/s2)
Ax = 9.81*((raw_data(4,:) - x_off)/x_sens); % remove 9.81 to get g-values
Ay = 9.81*((raw_data(5,:) - y_off)/y_sens);
Az = 9.81*((raw_data(6,:) - z_off)/z_sens);
Ax = (Ax)';
Ay = (Ay)';
Az = (Az)';

% calculate angular velocity values (deg/s)
Gz_sens = 16.384; % 16-bit (2^16=65535); +/-2000deg/s
Gx = G_SF*((raw_data(1,:) - Gz_off)/Gz_sens);
Gy = G_SF*((raw_data(2,:) - Gz_off)/Gz_sens);
Gz = G_SF*((raw_data(3,:) - Gz_off)/Gz_sens);
Gx = (Gx)';
Gy = (Gy)';
Gz = (Gz)';

% convert time to sec
time = (1:length(Ax))/100;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                Apply a Low Pass Butterworth filter                 %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
% Filtered signal using 1st Order 0.02 BW filter (1 Hz Cut-off Freq)
% Fs = 100Hz. 100/2 = 50Hz. 50x0.02 = 1Hz
[b a] = butter(1, 0.02, 'low');

% Filter acceleration data
Ax_filtered = filter(b, a, Ax);
Ay_filtered = filter(b, a, Ay);
Az_filtered = filter(b, a, Az);

% Filter angular velocity data
Gx_filtered = filter(b, a, Gx);
Gy_filtered = filter(b, a, Gy);
Gz_filtered = filter(b, a, Gz);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                Plot to compare raw vrs filtered data               %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% for acceleration
Ax_raw = raw_data(4,:);
Ax_filt = filter(b, a, raw_data(4,:));
figure;
hold on;
plot(time, Ax_filt, 'r'), plot(time, Ax_raw, 'b');
legend('Filtered','Raw');
title('Comparison of raw and filtered acceleration data');
xlabel('Time (sec)'), ylabel('Acceleration (m/s-2)');
grid on;

% for angular velocity
Gx_raw = raw_data(1,:);
Gx_filt = filter(b, a, raw_data(1,:));
figure;
hold on;
plot(Gx_filt, 'r'), plot(Gx_raw, 'b');
legend('Filtered','Raw');
title('Comparison of raw and filtered angular velocity data');
xlabel('Time (sec)'), ylabel('Angular Velocity (deg/s)');
grid on;

% create acceleration array of filtered values for later use
AC = [Ax_filtered, Ay_filtered, Az_filtered];
AV = [Gx_filtered, Gy_filtered, Gz_filtered];

% isolate 1 length of Frontcrawl swimming for assessment of filter design
AC_lap = AC(47000:49000, 1:3);
AV_lap = AV(47000:49000, 1:3);
timeLap = time(47000:49000);
figure;
subplot(2,1,1), plot(timeLap, AC_lap); title('Filtered acceleration data
output for 1 length of Frontcrawl');
xlabel('Time (sec)'), ylabel('Acceleration (m/s-2)');
legend('x','y','z');
grid on;
subplot(2,1,2), plot(timeLap, AV_lap); title('Filtered angular velocity
data output for 1 length of Frontcrawl');
xlabel('Time (sec)'), ylabel('Angular Velocity (deg/s)');
legend('x','y','z');
grid on;
```

```
% plot output from filter process
figure;
subplot(2,1,1), plot(time, AC); title('Filtered acceleration data output');
xlabel('Time (sec)'), ylabel('Acceleration (m/s-2)');
legend('x','y','z');
grid on;
subplot(2,1,2), plot(time, AV); title('Filtered angular velocity data
output');
xlabel('Time (sec)'), ylabel('Angular Velocity (deg/s)');
legend('x','y','z');
grid on;
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                    %
%                  SWIMMING INTERVAL IDENTIFICATION                  %
%                                                                    %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% load filtered acceleration and angular values
AC = [Ax_filtered, Ay_filtered, Az_filtered];
AV = [Gx_filtered, Gy_filtered, Gz_filtered];

% isolate the x axis. When swimmer is vertical this will be approx 1g
ACx = AC( :,1);

% calculate a moving average for the data
MA = tsmovavg(ACx,'s',500,1);

% set a threshold for this moving average
MAthreshold = 7.5; % was 7.5 - THIS MAY NEED TO CHANGE

% find where data exceeds/ does not exceed threshold
MAvalue = zeros(1,length(MA));
for i = 1:(length(MA));
    if MA(i) >= MAthreshold;
       MAvalue(i) = 1;
    elseif MA(i) < MAthreshold;
       MAvalue(i) = 0;
    end;
end;

% find where the slope of the MA changes
MAchange = zeros(1,length(MAvalue));
for i = 6:1:(length(MAvalue) - 1)
    MAchange(i) = round(MAvalue(i) - MAvalue(i-1));
end

% find where slope is increasing and decreasing
indx_up = find(MAchange>0);
indx_down = find(MAchange<0);
indx_up = (indx_up)';
indx_down = (indx_down)';

% swim intervals will begin with an index down so if the first data point
% is an index up then remove it
if indx_up(1) < indx_down(1);
    indx_up(1) = [];
end

% Also need to ensure that both indx's are the same length
if length(indx_up) < length(indx_down);
    indx_down = indx_down(1:length(indx_up));
end

% find difference between values
lengthCheck = indx_up - indx_down;
minIntervalDuration = 2500; % min time to complete 2 lengths is 25s

% remove unwanted data
unwantedData = find(lengthCheck < minIntervalDuration);
indx_up(unwantedData) = [];
```

```
indx_down(unwantedData) = [];

% remove noise from start of recording (1 min)
if indx_down(1) < 6000;
    indx_down(1) = [];
    indx_up(1) = [];
end

% create array of the swimming intervals
swimInterval = [indx_down indx_up];
disp(['Number of intervals performed: ' num2str(length(swimInterval))]);

% label each swim interval
for i = 1:length(swimInterval)
    eval(sprintf('Interval%d = [swimInterval(i,1) swimInterval(i,2)]', i));
end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                    %
%                    SWIMMING STROKE IDENTIFICATION                  %
%                                                                    %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% select interval of interest
 currentInterval = Interval2;

% isolate the acceleration data according to the selected interval
 strokeIdData = (AC(currentInterval(1,1):currentInterval(1,2), 1:3));

% isolate the axes of interest
x = strokeIdData( :,1);
y = strokeIdData( :,2);
z = strokeIdData( :,3);


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                    DETERMINE SIGNAL FEATURES                       %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% calculate the Mean
xMean = mean(x);
yMean = mean(y);
zMean = mean(z);

% calculate the Median
xMedian = median(x);
yMedian = median(y);
zMedian = median(z);

% calculate the Skewness
% (a measure of symmetry in the sginal)
xSkew = skewness(x);
ySkew = skewness(y);
zSkew = skewness(z);

% calculate the Kurtosis
% (the sharpness of the peak of a frequency-distribution curve
% a measure of whether the data are heavy-tailed or light-tailed relative
% to a normal distribution)
xKurt = kurtosis(x);
yKurt = kurtosis(y);
zKurt = kurtosis(z);

% calculate the Variance
xVar = var(x);
yVar = var(y);
zVar = var(z);

% calculate the Max and Min values
xMax = max(x);
yMax = max(y);
zMax = max(z);

xMin = min(x);
yMin = min(y);
zMin = min(z);
```

```
% calculate the Signal Energy (per Davey)
% (calculated by removing the average value from each data point, summing
% the absolute values, and normalising against the length of the data set)
xValue = abs(x) - xMean;
xEnergy = round(sum(xValue) / length(x));
yValue = abs(y) - yMean;
yEnergy = round(sum(yValue) / length(y));
zValue = abs(z) - zMean;
zEnergy = round(sum(zValue) / length(z));


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%              DETERMINE STROKE ID USING DECISION TREE               %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% set markers for each of the strokes
unknown = 0;
Backcrawl = 1;
Frontcrawl = 2;
Breaststroke = 3;
Butterfly = 4;
currentStroke = unknown;

% check data against thresholds to decide which stroke was performed and
% display result
if zMean < 0 && yVar < 7.5 && xKurt > 6 && zEnergy > 5
    disp('Backcrawl');
    currentStroke = 1;
elseif zMean > 0 && yVar > 7.5 && yKurt < 6 && yEnergy >= 1
    disp('Frontcrawl');
    currentStroke = 2;
elseif zMean > 0 && yVar < 7.5 && xKurt > 0 && xMedian > 3.5
    disp('Breaststroke');
    currentStroke = 3;
elseif zMean > 0 && yVar < 7.5 && xKurt < 6 && xMedian < 3.5
    disp('Butterfly');
    currentStroke = 4;
else
    disp('Error');
end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                      %
%                       LAP TIME CALCULATIONS                          %
%                                                                      %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% isolate the data of interest based on the selected interval
intervalAC = AC(currentInterval(1,1)-1000:currentInterval(1,2)+1000, 1:3);
intervalAV = AV(currentInterval(1,1)-1000:currentInterval(1,2)+1000, 1:3);
intervalTime = time(currentInterval(1,1)-1000:currentInterval(1,2)+1000);

% isolate relevant axes of acceleration
ACx = intervalAC( :,1);
ACy = intervalAC( :,2);
ACz = intervalAC( :,3);


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%           PART 1: IDENTIFY THE START OF A SWIMMING INTERVAL          %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% isolate a small sample of where start should occur
startApprox = ACx(1:4000);

% find the slope of the data
for i = 4:1:(length(startApprox) - 1)
    mTemp(i) = round(round(startApprox(i) - startApprox(i-3)) / 3);
end

% find the point on the slope where it is starting to go down
value = find(mTemp < 0);
closeApprox = value(1);

% check back for closest previous local max in ACx
localMaxValue = 0;
for j = (closeApprox-100):1:closeApprox % changed -100 from -200
    if startApprox(j) > localMaxValue
        localMaxValue = startApprox(j);
        lapStart = j;
    end
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                 PART 2: IDENTIFY WALL CONTACT EVENTS                 %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% Use peak detection to find acceleration peaks corresponding to wall
contact events

% peaks can't be closer than 15s apart
separation = 1500;

% check which stroke is performed first
if  currentStroke == 1 % Backcrawl
    % inverse of data so min peaks can be found
    ACInv = 1.01*max(ACx) - ACx;

% establish a threshold value based on the max value associated with a turn
```

```
    thresh = max(ACInv)*0.75;
    [pks,locs] = findpeaks(ACInv(1:end),'MINPEAKHEIGHT',thresh,
'MINPEAKDISTANCE', separation);
    feetContact = locs;

    % if the last wall contact is actually the lap end then remove it
    if length(ACInv) - feetContact(end)  < 1500
        feetContact(end) = [];
    end

    % for backcrawl, need to hone in on the start and end of the interval
     using a zero crossing
    p = diff(sign(ACz));
    indx_up = find(p>0);
    indx_down = find(p<0);

    % isolate only the wall contact events of interest
    feetContact=feetContact(feetContact>=indx_down(1) &
    feetContact<=indx_up(end));
    wallContact = feetContact;

elseif  currentStroke == 2 % Frontcrawl
    % inverse of data so min peaks can be found
    ACInv = 1.01*max(ACx) - ACx;

    % establish a threshold value based on the max value associated with a
turn
    thresh = max(ACInv)*0.75;
    [pks,locs] = findpeaks(ACInv(1:end),'MINPEAKHEIGHT',thresh,
'MINPEAKDISTANCE', separation);
    feetContact = locs;
    wallContact = feetContact;

elseif currentStroke == 3 % Breaststroke
    % inverse of data so min peaks can be found
    ACInv = 1.01*max(ACz) - ACz;
    % establish a threshold value based on the max value associated with a
turn
    thresh = max(ACInv)*0.75; % was 60%
    [pks,pushOff] = findpeaks(ACInv(1:end),'MINPEAKHEIGHT',thresh,
'MINPEAKDISTANCE', separation);

    % if the first wall contact is actually the interval start then remove
it
    if abs(lapStart - pushOff(1))  < 500
        pushOff(1) = [];
    end

    % if the last wall contact is actually the lap end then remove it
    if length(ACInv) - pushOff(end)  < 1500
        pushOff(end) = [];
    end

    % preallocate variables to match the size of the pushOff matrix
    handContactLoc = zeros(size(pushOff, 1),1);
    feetContactLoc = zeros(size(pushOff, 1),1);

    for k = 1:length(pushOff)
```

```
        % create a small window where the push off occurs for easier
identification
        pushOffWindow = ACy(pushOff(k)-500:pushOff(k));

        % perform the zero crossing
        q = diff(sign(pushOffWindow));
        indx_up = find(q>0); % from negative to positive
        indx_down = find(q<0);

        % sort the data in cronological order
        qData = sort([indx_up; indx_down]);
        handContactLoc(k) = qData(end-1);
        feetContactLoc(k) = qData(end);
    end

    % determine wall contact events (with hands)
    handContactLoc = 501 - handContactLoc; % 501 needed to offset
pushOffWindow
    handContact = pushOff - handContactLoc;
    wallContact = handContact;

    % calculate wall contact events (with feet)
    feetContactLoc = 501 - feetContactLoc;
    feetContact = pushOff - feetContactLoc;

elseif currentStroke == 4 % Butterfly
    % inverse of data so min peaks can be found
    ACInv = 1.01*max(ACz) - ACz;
    % establish a threshold value based on the max value associated with a
turn
    thresh = max(ACInv)*0.75;
    [pks,pushOff] = findpeaks(ACInv(1:end),'MINPEAKHEIGHT',thresh,
'MINPEAKDISTANCE', separation);

    % if the first wall contact is actually the interval start then remove
it
    if abs(lapStart - pushOff(1))  < 500
        pushOff(1) = [];
    end

    % if the last wall contact is actually the interval end then remove it
    if length(ACInv) - pushOff(end)  < 1500
        pushOff(end) = [];
    end

    % preallocate variables to match the size of the pushOff matrix
    handContactLoc = zeros(size(pushOff, 1),1);
    feetContactLoc = zeros(size(pushOff, 1),1);

    for k = 1:length(pushOff)
        % create a small window where the push off occurs for easier
identification
        pushOffWindow = ACy(pushOff(k)-500:pushOff(k));

        % perform the zero crossing
        q = diff(sign(pushOffWindow));
        indx_up = find(q>0); % from negative to positive
        indx_down = find(q<0); % am interested in these values now!
```

```
        % sort the data in cronological order
        qData = sort([indx_up; indx_down]);
        handContactLoc(k) = qData(end-1);
        feetContactLoc(k) = qData(end);
    end

    % calculate wall contact events (with hands)
    handContactLoc = 501 - handContactLoc;
    handContact = pushOff - handContactLoc;
    wallContact = handContact;

    % calculate wall contact events (with feet)
    feetContactLoc = 501 - feetContactLoc;
    feetContact = pushOff - feetContactLoc;

else
    disp('Error in Part 2');
end

% first peak may be close to lapStart so check and remove if needed
if wallContact(1) - lapStart < 1000
    wallContact(1) = [];
    feetContact(1) = [];
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%           PART 3: IDENTIFY THE END OF A SWIMMING INTERVAL          %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% approximate the lap end location
endApprox = ACx((wallContact(end)+1000):end);

if  currentStroke == 1 % Backcrawl
    threshEnd = 9;
    separationEnd = 10; % make this separation small to ensure i get the
first peak
    [pksEnd,locsEnd] = findpeaks(endApprox,'MINPEAKHEIGHT',threshEnd,
'MINPEAKDISTANCE', separationEnd);
    lapEnd =  (wallContact(end)+1000 +locsEnd(1));

elseif  currentStroke == 2 % Frontcrawl
    threshEnd = 9;
    separationEnd = 200;
    [pksEnd,locsEnd] = findpeaks(endApprox,'MINPEAKHEIGHT',threshEnd,
'MINPEAKDISTANCE', separationEnd);
    lapEnd =  (wallContact(end)+1000 +locsEnd(1));

elseif  currentStroke == 3 % Breaststroke
    endApproxInv = 1.01*max(endApprox) - endApprox;
    threshEnd = 6;
    separationEnd = 50;
    [pksEnd,locsEnd] = findpeaks(endApproxInv,'MINPEAKHEIGHT',threshEnd,
'MINPEAKDISTANCE', separationEnd);
    lapEndApprox = locsEnd(end);
    [pks,locs] =
findpeaks(endApprox(lapEndApprox:end),'MINPEAKHEIGHT',threshEnd,
'MINPEAKDISTANCE', separationEnd);
    lapEnd =  (wallContact(end)+1000 +lapEndApprox +locs(1));
```

```
elseif  currentStroke == 4 % Butterfly
    endApproxInv = 1.01*max(endApprox) - endApprox;
    threshEnd = 8;
    separationEnd = 10;
    [pksEnd,locsEnd] = findpeaks(endApproxInv,'MINPEAKHEIGHT',threshEnd,
'MINPEAKDISTANCE', separationEnd);
    lapEndApprox = locsEnd(end);
    [pks,locs] =
findpeaks(endApprox(lapEndApprox:end),'MINPEAKHEIGHT',threshEnd,
'MINPEAKDISTANCE', separationEnd);
    lapEnd =  (wallContact(end)+1000+ lapEndApprox +locs(1));

else
    disp('Error in Part 3');
end

% peak may be close to wallcontact peaks so check and remove if needed
if  lapEnd - wallContact(end) < 1000
    wallContact(end) = [];
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                PART 4: DISPLAY LAP TIME RESULTS                       %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% put all values into a matrix
wallContactValues = [lapStart; wallContact; lapEnd]; % NEED TO RENAME
PUSHOFF AS WALLEVENT
lapTime = (diff(wallContactValues)/100);

% add average speed to the matrix
averageSpeed = 25 / lapTime;
precision = 3;

% print out the values
disp('Lap Times                Average Speed')
for k = 1:length(lapTime)
    averageSpeed(k) = 25 / lapTime(k);
    disp(['Lap ' num2str(k) ' Time = ', num2str(lapTime(k)), ' s', '     ',
num2str(averageSpeed(k),precision), ' m/s'])
end;
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                     %
%                     STROKE COUNT CALCULATIONS                       %
%                                                                     %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% determine the number of laps in the interval
numLaps = length(wallContactValues) - 1;

% create a matrix to hold the lap start and end points
lapMatrix = zeros(numLaps, 2);

% add all lap times to the matrix
for i = 1:numLaps
    lapMatrix(i,1) = wallContactValues(i);
    lapMatrix(i,2) = wallContactValues(i+1);
end

% create matrix to hold stroke count values
strokeCount = zeros(numLaps, 1);

% pre-allocation of variables to hold turn start and end points - works but
not the correct sizes
    turnMatrix = zeros((length(wallContactValues)-2), 2);
    strokes_in = zeros(length(turnMatrix), 1);
    strokes_out = zeros(length(turnMatrix), 1);
    break_out = zeros(length(turnMatrix), 1);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%              DETERMINE STROKE COUNT BASED ON STROKE TYPE            %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

if  currentStroke == 1 % Backstroke
    for k = 1:numLaps

% isolate each lap in turn
  ACxLap = ACx(lapMatrix(k,1):lapMatrix(k,2));

% calculate the moving average
movingAve = tsmovavg(ACxLap,'s',50,1); % 0.5s window

% perform the peak detection
threshSC = 4; % use this to determine threshold
separationSC = 50; % add a separation to distinguish pull from kick
 [pksSC,locsSC] = findpeaks(movingAve(1:end),'MINPEAKHEIGHT',threshSC,
'MINPEAKDISTANCE', separationSC);

% remove first index if they are too close to the push off
excludeValuesStart = locsSC < 400;
locsSC(excludeValuesStart) = [];

% remove last index if they are too close to end of lap
excludeValuesEnd = locsSC > (length(ACxLap) - 150);
locsSC(excludeValuesEnd) = [];
% determine breakout location
D = diff(locsSC);
meanD = mean(D);
break_out(k) = locsSC(1) - meanD;
```

```
% calculate the number of strokes performed
strokeCount(k) = length(locsSC);
% and the time stamps for each stroke
strokes = locsSC;

% calculate the 3 strokes in/3 strokes out times for backcrawl
strokes_in(k) = strokes(end-3);
strokes_out(k) = strokes(3);

% output the results
disp(['Lap ' num2str(k), ' Stroke Count = ', num2str(strokeCount(k))]);
end

elseif  currentStroke == 2 % Frontcrawl
    for k = 1:numLaps
        % isolate each lap in turn
        ACyLap = ACy(lapMatrix(k,1):lapMatrix(k,2));
        % calculate the moving average
        movingAve = tsmovavg(ACyLap,'s',50,1); % 0.5s window

        % check the max and min values to see if breathing is bi-lateral
        if max(movingAve) > 5 && min(movingAve) < -5
            range = (max(movingAve) - abs(min(movingAve)))/2;
            % if breathing is bilateral then need to adjust the signal to
suit
            if range > 0
                movingAve = movingAve - range;
            elseif range < 0
                movingAve = movingAve + range;
            end
        end

        % perform the zero crossing
        q = diff(sign(movingAve));
        indx_upSC = find(q>0);
        indx_downSC = find(q<0);

        % get the time stamps for all strokes performed
        strokes = sort([indx_upSC; indx_downSC]);

        % remove first index if it is too close to the push off
              excludeValuesStart = strokes < 300;
      strokes(excludeValuesStart) = [];

        % remove last index if it is too close to end of lap
        excludeValuesEnd = strokes > (length(ACyLap) - 100);
        strokes(excludeValuesEnd) = [];

        % determine the number of stroke completed
        strokeCount(k) = length(strokes);

        % determine breakout location
                break_out(k) = strokes(1);

        % calculate the 3 strokes in/3 strokes out times for frontcrawl
        strokes_in(k) = strokes(end-3);
        strokes_out(k) = strokes(3);

        % output the results
```

```
        disp(['Lap ' num2str(k), ' Stroke Count = ',
num2str(strokeCount(k))]);
    end;

elseif  currentStroke == 3 % Breakstroke
    for k = 1:numLaps
        % isolate each lap in turn
        ACxLap = ACx(lapMatrix(k,1):lapMatrix(k,2));

        % calculate the moving average
        movingAve = tsmovavg(ACxLap,'s',50,1); % 0.5s window

        % perform the peak detection
        lapXmax = max(movingAve);

      threshSC = lapXmax * 0.60; % use this to determine threshold
      separationSC = 100; % add a separation to distinguish pull from kick
        [pksSC,locsSC] =
findpeaks(movingAve(1:end),'MINPEAKHEIGHT',threshSC, 'MINPEAKDISTANCE',
separationSC);

        % remove first index if it is too close to the push off
              excludeValuesStart = locsSC < 500;
      locsSC(excludeValuesStart) = [];

        % determine the number of stroke completed
        strokeCount(k) = length(locsSC);

        % calculate the 2 strokes in/2 strokes out times for breaststroke
        strokes_in(k) = locsSC(end-2);
        strokes_out(k) = locsSC(2);

        % determine breakout location
        break_out(k) = locsSC(1);

        % output the results
        disp(['Lap ' num2str(k), ' Stroke Count = ',
num2str(strokeCount(k))]);
    end;

elseif  currentStroke == 4 % Butterfly
    % use peak detection to determine number of strokes completed
    for k = 1:numLaps
        % isolate each lap in turn
        ACxLap = ACx(lapMatrix(k,1):lapMatrix(k,2));

        % calculate a moving average to smooth out the signal
        movingAve = tsmovavg(ACxLap,'s',50,1); % 0.5s window
        % perform the peak detection
       lapXmax = max(ACxLap); % find maximum peak value
        threshSC = lapXmax * 0.1;
        separationSC = 100; % add a separation to distinguish pull from
kick
        [pksSC,locsSC] =
findpeaks(movingAve(1:end),'MINPEAKHEIGHT',threshSC, 'MINPEAKDISTANCE',
separationSC);

        % remove first index if it is too close to the push off
```

```
        excludeValuesStart = locsSC < 500;
locsSC(excludeValuesStart) = [];

        % determine the number of stroke completed
        strokeCount(k) = length(locsSC);

        % calculate the 2 strokes in/2 strokes out times for butterfly
        strokes_in(k) = locsSC(end-2); % 2 strokes in
        strokes_out(k) = locsSC(2); % 2 strokes out

        % determine breakout location
        break_out(k) = locsSC(1);

        % output the results
        disp(['Lap ' num2str(k), ' Stroke Count = ',
num2str(strokeCount(k))]);
     end;
else
    disp('Error');
end;
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                    %
%                     TURN PHASE CALCULATIONS                        %
%                                                                    %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% extract and arrange the relevant turn start and end points
turnData = zeros(numLaps-1, 4);
for n = 1:(numLaps-1)
    turnData(n, 1) = [strokes_in(n)];
    turnData(n, 2) = [wallContactValues(n+1)];
    turnData(n, 3) = [strokes_out(n+1)];
    turnData(n, 4) = [break_out(n+1)];
end

% calculate the turn times (in, out, total, breakout)
disp('Turn    Turn Time    Time In    Time Out    Breakout')
for i = 1:(numLaps-1)
    lapLength(i) = wallContactValues(i+1) - wallContactValues(i);
    timeIn = (lapLength(i)-turnData(i,1))/100;
    timeOut = turnData(i,3)/100;
    turnTime = timeIn + timeOut;
    breakoutTime = turnData(i,4)/100;
    disp(['Turn ' num2str(i) '   ', num2str(turnTime, '%.2f'), ' s', '
', num2str(timeIn, '%.2f'), ' s', '     ',num2str(timeOut, '%.2f'), ' s', '
',num2str(breakoutTime, '%.2f'), ' s'])

      % determine start and end points for each turn on the interval time
      range
    turnStartLoc(i) = turnData(i,2) - (timeIn*100);
    turnEndLoc(i) = turnData(i,2) + turnData(i,3);
end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                    %
%                      TURN PHASE BREAKDOWN                          %
%                                                                    %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% select turn of interest
turnNumber = 3;

% determine points of interest for the turn
startPoint = turnStartLoc(turnNumber);
endPoint = turnEndLoc(turnNumber);

% isolate relevant axes of acceleration
ACxTurn = intervalAC(startPoint:endPoint,1);
ACyTurn = intervalAC(startPoint:endPoint,2);
ACzTurn = intervalAC(startPoint:endPoint,3);

AVxTurn = intervalAV(startPoint:endPoint,1);
AVyTurn = intervalAV(startPoint:endPoint,2);
AVzTurn = intervalAV(startPoint:endPoint,3);

if  currentStroke == 1 % backcrawl

    % import the data that is already known
    wallContactTurn = wallContact(turnNumber);
    breakOutTurn = wallContactTurn + break_out(turnNumber+1);

    % find push off (min peak in z-axis after wall contact)
    ACzInv = 1.01*max(ACzTurn) - ACzTurn;
    thresh = max(ACzInv)*0.8;
    [pks,locs] = findpeaks(ACzInv,'MINPEAKHEIGHT',thresh);

    % in case of any peaks early in the window - remove them
    timeInTurn = (lapLength(turnNumber)-turnData(turnNumber,1));
    excludeValues = locs < timeInTurn;
    locs(excludeValues) = [];
    pushOffTurn = locs(1);

    % find wallContactTime
    wallContactTime = (pushOffTurn - timeInTurn) /100;

    % determine the direction of turn and longitudinal rotation time
    [AVxMax, locAVxMax] = max(AVxTurn);
    [AVxMin, locAVxMin] = min(AVxTurn);

    if AVxMax > abs(AVxMin)
        turnDirection = 'Left';

        % find start of longitutinal rotation
        % perform the zero crossing
        qq = diff(sign(AVxTurn));
        indx_upRot = find(qq>0);

        % find the zeroCross of interest
        zeroCross = (locAVxMax - indx_upRot);
        excludeValues = zeroCross < 0;
        zeroCross(excludeValues) = [];
        rotationStartLong = indx_upRot(length(zeroCross));
```

```
        % find end of longitutinal rotation
        [maxACy, locACy] = max(ACyTurn);
        rotationEndLong = locACy;

    elseif AVxMax < abs(AVxMin)
        turnDirection = 'Right';

        % find start of longitutinal rotation
        % perform the zero crossing
        qq = diff(sign(AVxTurn));
        indx_downRot = find(qq<0);

        % find the zeroCross of interest
        zeroCross = (locAVxMin - indx_downRot);
        excludeValues = zeroCross < 0;
        zeroCross(excludeValues) = [];
        rotationStartLong = indx_downRot(length(zeroCross));

        % find end of longitutinal rotation
        [maxACy, locACy] = max(abs(ACyTurn));
        rotationEndLong = locACy;

    end

    % Determine longitudinal rotation time
    rotationTimeLong = (rotationEndLong - rotationStartLong) /100;

    % Determine transverse rotation time
    rotationTimeTrans = (timeInTurn - rotationEndLong) / 100;

    % find first kick
    AVyInv = 1.01*max(AVyTurn) - AVyTurn;
    separation = 50;
    thresh = 90;
    [pksAVyInv,locAVyInv] =
findpeaks(AVyInv(pushOffTurn+50:(pushOffTurn+break_out(turnNumber+1))),'MIN
PEAKHEIGHT',thresh, 'MINPEAKDISTANCE', separation);
    kickData = diff(locAVyInv);
    excludeKickValues = kickData > 75;
    kickData(excludeKickValues) = [];

    if kickData >0;
        firstKick = locAVyInv(1)+50;

        % determine number of kicks performed
        kickCount = size(kickData);
        kickCount = kickCount(1);

        % glide time = first kick - push off
        glideTime = firstKick /100;

        % kick time = breakout - first kick
        kickTime = (break_out(turnNumber+1) - firstKick)/100;

    else
        glideTime = break_out(turnNumber+1) /100;
        kickTime = 0;
```

```
        kickCount = 0;
    end

    % determine angular velocity during transverse rotation
    resAV = (AVxTurn .^2) + (AVyTurn .^2) + (AVzTurn .^2);
    resAV = sqrt(resAV);
    maxAV = max(resAV(rotationEndLong:pushOffTurn));

    % display results
    disp(['Results for Turn Number: ' num2str(turnNumber)]);
    disp(['Longitudinal Rotation Time = ' num2str(rotationTimeLong), '
s']);
    disp(['Transverse Rotation Time = ' num2str(rotationTimeTrans), ' s']);
    disp(['Wall Contact Time = ' num2str(wallContactTime), ' s']);
    disp(['Glide Time = ' num2str(glideTime), ' s']);
    disp(['Kick Time = ' num2str(kickTime), ' s']);
    disp(['Kicks off Wall = ' num2str(kickCount)]);
    disp(['Maximum Angular Velocity = ' num2str(maxAV), ' deg/s']);
    disp(['Turn Direction = ' num2str(turnDirection)]);


elseif  currentStroke == 2 % frontcrawl

    % import the data that is already known
    wallContactTurn = wallContact(turnNumber);
    breakOutTurn = wallContactTurn + break_out(turnNumber+1);

    % find push off (min peak in z-axis after wall contact)
    ACzInv = 1.01*max(ACzTurn) - ACzTurn;
    [pks,locs] = max(ACzInv);
    pushOffTurn = locs;

    % find wallContactTime
    timeInTurn = (lapLength(turnNumber)-turnData(turnNumber,1));
    wallContactTime = (pushOffTurn - timeInTurn) /100;

    % Determine transverse rotation time
    % first find all peaks in signal
    separation = 100;
    thresh = 0;
    [pksRot,locsRot] = findpeaks(AVyTurn,'MINPEAKHEIGHT',thresh,
'MINPEAKDISTANCE', separation);

    % relate these peaks to the push off
    rotData = (pushOffTurn - locsRot);

    % peak prior to push off is start of rotation
    excludeValues = rotData < 0;
    rotData(excludeValues) = [];
    rotationStartTrans = locsRot(length(rotData));

    % peak after push off is end of rotation
    rotData = (pushOffTurn - locsRot);
    excludeValues = rotData > 0;
    rotData(excludeValues) = [];
    rotEndPoint = rotData(1);
    rotationEndTrans = pushOffTurn - rotEndPoint;
    rotationTimeTrans = (rotationEndTrans - rotationStartTrans) / 100;
```

```
    % find first kick
    AVyInv = 1.01*max(AVyTurn) - AVyTurn;
    separation = 50;
    thresh =
max(AVyInv(pushOffTurn+50:(pushOffTurn+break_out(turnNumber+1))))*0.5;
    [pksAVyInv,locAVyInv] =
findpeaks(AVyInv(pushOffTurn+50:(pushOffTurn+break_out(turnNumber+1))),'MIN
PEAKHEIGHT',thresh, 'MINPEAKDISTANCE', separation);

    % determine number of kicks performed
    kickData = diff(locAVyInv);
    excludeKickValues = kickData > 75;

    if kickData >0;
        firstKick = locAVyInv(1) +50;
        kickCount = size(locAVyInv)- sum(excludeKickValues);
        kickCount = kickCount(1);

        % glide time = first kick - push off
        glideTime = firstKick /100;

        % kick time = breakout - first kick
        kickTime = ((break_out(turnNumber+1)) - (firstKick))/100;

    else
        glideTime = break_out(turnNumber+1) /100;
        kickTime = 0;
        kickCount = 0;
    end

    % determine angular velocity during transverse rotation
    resAV = (AVxTurn .^2) + (AVyTurn .^2) + (AVzTurn .^2);
    resAV = sqrt(resAV);
    maxAV = max(resAV(rotationStartTrans:pushOffTurn));

    % display results
    disp(['Results for Turn Number: ' num2str(turnNumber)]);
    disp(['Rotation Time = ' num2str(rotationTimeTrans), ' s']);
    disp(['Wall Contact Time = ' num2str(wallContactTime), ' s']);
    disp(['Glide Time = ' num2str(glideTime), ' s']);
    disp(['Kick Time = ' num2str(kickTime), ' s']);
    disp(['Kicks off Wall = ' num2str(kickCount)]);
    disp(['Maximum Angular Velocity = ' num2str(maxAV), ' deg/s']);


elseif currentStroke == 3 % breaststroke

    % import the data that is already known
    wallContactTurn = wallContact(turnNumber);
    feetContactTurn = feetContact(turnNumber);
    pushOffTurn = pushOff(turnNumber);
    breakOutTurn = wallContactTurn + break_out(turnNumber+1);

    % find wallContactTime
    wallContactTime = (pushOffTurn - wallContactTurn) /100;

    % find Feet Contact Time
    feetContactTime = (pushOffTurn - feetContactTurn) /100;
```

```
    % find hands to feet contact time
    handsFeetContactTime = (feetContactTurn - wallContactTurn) /100;

    % find the start of the pull down phase
    glideWindow = ACz(pushOffTurn:breakOutTurn);
    [pks, locmax] = max(glideWindow);
    pullDownStart = locmax;

    % glide time = first kick - push off
    glideTime = pullDownStart /100;

    % find duration of pull down phase
    pullDownTime = (break_out(turnNumber+1) - (wallContactTime*100) -
pullDownStart)/100;

    % determine the direction of turn
    [AVxMax, locAVxMax] = max(AVxTurn);
    [AVxMin, locAVxMin] = min(AVxTurn);

    if AVxMax > abs(AVxMin)
        turnDirection = 'Right';
    elseif AVxMax < abs(AVxMin)
        turnDirection = 'Left';
    else disp('Error');
    end

    % determine angular velocity during transverse rotation
    resAV = (AVxTurn .^2) + (AVyTurn .^2) + (AVzTurn .^2);
    resAV = sqrt(resAV);
    maxAV = max(resAV);

    % display results
    disp(['Results for Turn Number: ' num2str(turnNumber)]);
    disp(['Hands to Feet Contact Time = ' num2str(handsFeetContactTime), '
s']);
    disp(['Feet Contact Time = ' num2str(feetContactTime), ' s']);
    disp(['Wall Contact Time = ' num2str(wallContactTime), ' s']);
    disp(['Glide Time = ' num2str(glideTime), ' s']);
    disp(['PullDown Time = ' num2str(pullDownTime), ' s']);
    disp(['Maximum Angular Velocity = ' num2str(maxAV), ' deg/s']);
    disp(['Turn Direction = ' num2str(turnDirection)]);


elseif currentStroke == 4 % butterfly

    % import the data that is already known
    wallContactTurn = wallContact(turnNumber);
    feetContactTurn = feetContact(turnNumber);
    pushOffTurn = pushOff(turnNumber);
    breakOutTurn = wallContactTurn + break_out(turnNumber+1);

    % find wallContactTime
    wallContactTime = (pushOffTurn - wallContactTurn) /100;

    % find Feet Contact Time
    feetContactTime = (pushOffTurn - feetContactTurn) /100;

    % find hands to feet contact time
    handsFeetContactTime = (feetContactTurn - wallContactTurn) /100;
```

```
    % find first kick
    glideWindow = ACz(pushOffTurn:breakOutTurn);
    separation = 25;
    thresh = 7.5;
    [pks,locs] = findpeaks(glideWindow,'MINPEAKHEIGHT',thresh,
'MINPEAKDISTANCE', separation);
    kickData = diff(locs);
    excludeKickValues = kickData > 75;


    if kickData >0;
        firstKick = locs(1);
        kickCount = size(locs)- sum(excludeKickValues);
        kickCount = kickCount(1);

        % glide time = first kick - push off
        glideTime = firstKick /100;

        % kick time = breakout - first kick
        % kickTime = ((break_out(turnNumber+1)) - (firstKick))/100;
        kickTime = (breakOutTurn - pushOffTurn - firstKick)/100;

    elseif kickData == 0;
        glideTime = break_out(turnNumber+1) /100;
        kickTime = 0;
        kickCount = 0;
    end

    % determine angular velocity during transverse rotation
    resAV = (AVxTurn .^2) + (AVyTurn .^2) + (AVzTurn .^2);
    resAV = sqrt(resAV);
    maxAV = max(resAV);

    % determine the direction of turn
    [AVxMax, locAVxMax] = max(AVxTurn);
    [AVxMin, locAVxMin] = min(AVxTurn);

    if AVxMax > abs(AVxMin)
        turnDirection = 'Right';
    elseif AVxMax < abs(AVxMin)
        turnDirection = 'Left';
    else disp('Error');
    end

    % display results
    disp(['Results for Turn Number: ' num2str(turnNumber)]);
    disp(['Wall Contact Time = ' num2str(wallContactTime), ' s']);
    disp(['Hands to Feet Contact Time = ' num2str(handsFeetContactTime), '
s']);
    disp(['Feet Contact Time = ' num2str(feetContactTime), ' s']);
    disp(['Glide Time = ' num2str(glideTime), ' s']);
    disp(['Kick Time = ' num2str(kickTime), ' s']);
    disp(['Kicks off Wall = ' num2str(kickCount)]);
    disp(['Maximum Angular Velocity = ' num2str(maxAV), ' deg/s']);
    disp(['Turn Direction = ' num2str(turnDirection)]);


else
```

```
    disp('Error');
end
```

RESEARCH ETHICS COMMITTEE APPLICATION FORM

For Applicant to complete:

Applicants' Name:	Prof. Gearóid ÓLaighin
Title of Project:	Reliability and accuracy assessment of commercially available swimming performance monitors.

For Ethics Committee use only:

Reference Number: ☐ *Date r* ☐

Review Date: ☐ *Outcome:*

☐ Approval
☐ Provisional Approval
☐ Deferral
☐ Approval Declined

Applicant informed (Date): ☐

Please complete form and select YES/NO options as appropriate. An electronic version of this form is also available on the NUI Galway website (**http://www.nuigalway.ie/research/vp_research/ethics.htm*****).***

An application will only be accepted for review by the NUI Galway Research Ethics Committee (REC) if it is completed fully and the relevant enclosures are received. Refer to the accompanying Guidance Notes when completing the form and complete the checklist on the next page before submitting the form. Where you have received permission to do this, or similar research in another institution, please provide evidence of permission with this application.

Please submit your completed application: application form; protocol; participant consent form(s); patient information sheet(s); Questionnaire(s); as one single PDF document.

Address to send application: (Hard copy with signatures)	**NUI Galway Research Ethics Committee Office of the Vice-President for Research Science and Engineering Technology Building NUI Galway**
Email address: (pdf)	**eithne.oconnell@nuigalway.ie**

SUBMISSION CHECKLIST

Please indicate if the following have been enclosed by selecting YES/NO/Not applicable options below.
Please forward copies of the form and relevant enclosures required as outlined below.

		YES	NO
1	Electronic Copy of **complete** application. (single PDF document – with **all** relevant attachments)	x	
1	Hard Copy of **complete** application form (with **all** attachments)	x	

		Electronic Copy YES	Hard Copy YES	NO	Not applicable
1	Copy of protocol **(No more than 4 A4 pages)**	x	x		
1	Participant consent form(s)	x	x		
1	Participant information sheet(s)	x	x		
1	Copy of Confirmation of Garda vetting			x	
1	Sample letters (GP, Recruitment etc)				x
1	Copy of Risk Assessment Form**				x
1	Copy of Principal Applicant CV **(2A4 pages max)** (plus that of primary supervisor if principal applicant is a PhD student)	x	x		
1	Annex 1**				x
1	Annex 2***				x
1	Annex 3**** (1 copy per procedure for which risk identified)	x	x		

* *Please indicate if not yet finalised.*
** *If the study involves the use of a new medicinal product or medical device, or the use of an existing product outside the terms of its product licence*
*** *If the study includes the use of ionizing or non-ionising radiation, radioactive substances or X rays*
**** *Please complete for each hazardous procedure*

STUDY DESCRIPTORS

Select all descriptors that apply to this study:

Competent volunteer	X	Cross-over		Biological material	
Healthy volunteer	X	Case-study		Foetal material	
Patient volunteer		Longitudinal		Hazardous materials	
'Incompetent' patients		Cross-sectional		Invasive procedures	
Children (under 18 yrs)	X	Placebo		Devices (in licence)	X
Observational		Therapeutic		Medicinal products (in licence)	
Interview		Controlled	X		
Questionnaire		Double-blind		Devices (outside licence)	
Record-based		Single-blind			
Randomised		Prospective		Medicinal products (outside licence)	
Non-randomised	X	Retrospective			

SECTION 1 Applicant(s) Details

1. Title of project:

Reliability and accuracy assessment of commercially available swimming performance monitors.

2. Principal Applicant: *(All correspondence will be sent to this address unless indicated otherwise.)*

Family Name: ÓLaighin **Forename**: Gearóid **Title**: Prof

Contact address *(for correspondence regarding application)*:
College of Engineering and Informatics,
National University of Ireland, Galway,
University Road, Galway.

Tel: 091-492685 (Ext: 2685) **Fax**: **Email**: gearoidolaighin@nuigalway.ie

Mobile Number / Other Contact Number:

Present appointment of PA: Head of Electrical & Electronic Engineering

3. Other Investigator(s):

Family Name: Mooney **Forename**: Robert **Title**: Mr

Department: Electrical and Electronic Engineering

Institution: NUI Galway

Tel: **Fax**: **Email**: r.mooney4@nuigalway.ie

Present appointment: PhD student

Qualifications: BSc Sport & Exercise Science

Family Name: Quinlan **Forename**: Leo **Title**: Dr

Department: Physiology

Institution: NUI Galway

Tel: 091 493710 **Fax**: **Email**: leo.quinlan@nuigalway.ie

Present appointment: Lecturer, Physiology

Qualifications: PhD

Family Name: Corley **Forename**: Gavin **Title**: Dr

Department: Electrical and Electronic Engineering

Institution: NUI Galway

Tel: **Fax**: **Email**: gavin.corley@nuigalway.ie

Present appointment: Postdoctoral researcher

Qualifications: PhD

4. Other workers and departments/Institutions involved:

Name	Department/Institute	Appointment
Robert Mulcahy	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Nicola O'Sullivan	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Dylan Ryan	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Kevin McGlade	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Ciaran Walsh	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Jason O'Halloran	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Brendan Gilbert	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Laura Hanlon	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Ruairi Kehoe Clarke	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Sinead Cailleau	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Sean Moran	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)
Adam Scally	Electrical & Electronic Engineering	3rd Year Undergraduate (SEE)

These undergraduate students are taking part in this research to fulfil the requirements of a third year project as part of their Sport and Exercise Engineering course. Student will be split into groups and involved in the early phase of the study, assisting the PI and PhD student. They will gain experience in data collection, experimental design and statistical analysis and will write up their project based on the first set of data collected (N=4 subjects). The groups will be based on each of the four competitive swimming strokes (Frontcrawl, Backstroke, Butterfly, Breaststroke), with each group only focused on their specific stroke as assigned. As engineering students, they will also consider operational aspects of the monitors in question, such as the algorithms used to derive the outputs investigated. The undergraduates' involvement in this project will finish before the end of Semester 2, 2014.

5. Funding Sources:

(i) Has any funding been obtained/sought by the investigator in respect of this study?

Funding applied for:	YES [x]	NO [ ]	Not applicable [ ]
Funding secured:	YES [x]	NO [ ]	Not applicable [ ]

(ii) Name of sponsoring organisation from which funding has been obtained/sought?

Irish Research Council / Swim Ireland

(iii) Does the Investigator(s) have any direct involvement in the sponsoring organization?

e.g. financial, share-holding etc: YES [ ] NO [x] Not applicable [ ]

If YES, give details:

NOTE: Where the research programme has already received funding approval, please attach the letter of offer to this application.

6. Proposed start date and duration of study:

Proposed Start date: 9th December 2013

Duration (months): 12 Months

7. Signature of relevant personnel:

Principal Applicant declaration

The information in this application form is accurate to the best of my knowledge and belief and I take full responsibility for it.

I understand that it is my responsibility to obtain institutional approval where appropriate before the project takes place.

I agree to supply interim and final reports to the Research Ethics Committee from which approval was granted for this project.

I agree to advise the Research Ethics Committee from which approval was granted for this project and any local researchers taking part in the proposal of any material changes to the proposal or any adverse or unexpected events that may occur during this project.

I agree to advise the Research Ethics Committee in the event of premature termination, suspension or deferral of this project and to provide a report outlining the circumstances for such termination, suspension or deferral.

Signature of Principal Applicant: ______________________________ **Date**: ____________

Co-Signed by Supervisor where the P.A. is a Student: ________________ **Date:** ____________

Head of Department/Supervisor

I am fully aware of the details of this project and agree for it to continue as outlined here. I can confirm that the necessary facilities and resources are available to the researcher.

Name: ______________________________ **Department**: ______________________

Signature: ___________________________ **Date**: ____________________________

SECTION 2 Study Details

This section must be completed. A copy of the protocol should be enclosed with the application form but it is ***not*** *sufficient to complete questions by referring to the protocol.*

8. Aims and objectives of study (i.e. what is the intention of the study, key research questions?)

The aims of this study are:
1) To test the reliability and accuracy of the *Garmin Swim* and *Finis Swimsense* devices in order to comprehensively evaluate the devices' performance on all four competitive swimming strokes.
2) To test if these devices can be used by elite swimmers for training to improve technical performance.

9. Scientific/theoretical background[1] to study (Approx. 250 words)

Swimming is the largest participation sport in Ireland, with 6.7% of adults over 16 years (approximately 270,000 people) participating weekly (Kelly & Lunn, 2012). At an elite level, a traditional reliance on intermittent coaching feedback through video analysis methods has limited competitiveness and training efficiency. Kinematic stroke analysis is now considered essential to the training and preparations in elite swimming, to identify individual stroke variations and assess performance. Recent advances in the miniaturization of electronic wearable technologies, hydrophobic coatings enabling their use in water and the increasing availability of kinematic motion sensors facilitate a new approach to swimming coaching. This allows for improved analysis of stroke mechanics, race performance and energy expenditure as well as real-time feedback to the swimmer, thus enabling more efficient, competitive and quantitative coaching. Some preliminary work has demonstrated the feasibility of this approach using early prototype sensors (Davey et al., 2008). Commercially available swimming sensors include the Garmin Swim and FINIS Swimsense. However to date, no efforts have been made to objectively evaluate the performance of these devices in a competitive training environment. Such analysis is warranted, to test claims provided by the manufacturers regarding their accuracy and reliability. Output from sensors will vary depending on the swimming stroke employed. The four strokes (front crawl, backstroke, breaststroke, butterfly) are anatomically very different. A key question that remains unanswered is whether these devices can provide accurate data analysis across all four swimming strokes.

10. Brief plan of investigation[2] (i.e. what do you intend to do?) (Approx. 250 words)

Participants will be recruited from the Swim Ireland/NUIG Connacht Performance Centre, based at the Kingfisher on the NUIG campus. Data collection will take place on two occasions, separated by seven days, during the participants normal training schedule. Following a coach led warm up routine and collection of preliminary personal information, participants will be required to perform a prescribed swimming protocol, encompassing variations of speed and stroke style, whilst wearing swimming performance monitors on each forearm. Simultaneous video recordings will be obtained and used as a criterion measure. Following data collection, the results will be analyzed to assess the performance of each device against that of the criterion measures.

11. List procedures or investigations involving risks to participants' well-being or safety (what, when, how often and <u>risks</u> associated with all procedures)

The swimming protocol to be carried out is designed to be typical of an actual swimming session carried out as part of the participants' regular training schedule and as such involves minimal risk to those involved. Participants will be informed of data collection procedures beforehand and all data will be anonymized.

[1] A succinct background to be provided and to include reference to published work
[2] Please append detailed study protocol to this application; this brief description summarizes protocol only.

12. Study design (tick as appropriate)

Survey/Questionnaire	
Case Study	
Observational	X
Action research	
Record based	
Cohort	
Case control	
Other	X

(please specify)
Reliability assessment

Interviews	
• individual	
• group	
• person-to-person	
• telephone	
• electronic	
Forms of Recording	
• Video	X
• Audio	
• Photography	
• Notes	X
• Electronic recording	X

13. Size of the study (including controls):

(i) How was the size of the study determined?

The size of the study was determined based on the availability of testing equipment

(ii) Was there formal statistical input into the overall study design? NO

(iii) What method of analysis will be used?

Video analysis

14. Where[3] will the study take place and in what setting?

NUI Galway Sports Centre, using the 25m swimming pool facility

15. Does the study involve:

(i) distribution of a questionnaire? YES: [x] NO: [ ]

If YES, please append a copy of the questionnaire to this application. Please indicate whether the appended questionnaire is: Non-validated: [x] Validated: [ ]

(ii) the use of a existing medicinal product or medical device? YES [ ] NO [x]

If YES, is this medical product or device being used within the terms of its current product licence? YES [ ] NO [ ]

If NO, please complete **Annex 1** of this application.

(ii) the use of a new medicinal product or medical device? YES [ ] NO [x]

If YES, please complete **Annex 1** of this application.

(iii) the use of ionising or non-ionising radiation, radioactive substances or X rays?

YES [ ] NO [x] If YES, please complete **Annex 2** of this application.

[3] Geographical location; laboratory, hospital, general practice, home visits etc.

16. Peer Review/Critique[4]

Has the protocol been subject to peer review? YES [x] NO [ ]

If the review formed part of the process of obtaining funding, please give the name and address of the funding organisation:

Irish Research Council
Brooklawn House
Shelbourne Road
Dublin 4

If the review took place as part of an internal process, please give brief details:

In addition to the principal investigator, the protocol was subject to review by the Head Swimming Coach involved with the participants.

If no review has taken place, please explain why and offer justification for this:

N/A

17. Does the study fall into any of the following categories?

Pilot:	YES [ ]	NO [ ]	Not applicable [x]
Multi-centre study	YES [ ]	NO [ ]	Not applicable [x]

If this is a multi-centre study, please complete the following details, otherwise go to question 17.

(i) Which centres are involved?

Contact Name	Department/Centre

(ii) Which ethics committees have been approached, and what is the outcome to date?

(iii) Who will have overall responsibility for the study?

[4] *If you are in possession of any referee or other scientific critique reports relevant to your proposed research, please forward copies with your application form.*

(iv) Who has control of the data generated?

SECTION 3 Recruitment of participants

18. Who is being studied?

If non-competent persons are being studied, please give details of reasons for non-competence

N/A

19. How will be the participants in the study be:
(i) Selected?

Members of the Swim Ireland/NUIG Connaght Performance Centre squad are eligible to participate in the study.

(ii) Recruited? (Please append advertisement materials to application)

Recruitment will be through invitation of swimmers selected in consultation with Head Swimming Coach

20. What criteria will be used for inclusion and exclusion of participants?
(i) Inclusion criteria:

Members of the Swim Ireland/NUIG Connaght Performance Centre squad are eligible to participate in the study.

(ii) Exclusion criteria:

N/A

21. How many participants will be recruited and of what age groups?

N=20
The age group of the participants will be from 15-21 years

22. If applicable, how will the control group in the study be:
(i) Selected?

N/A

(ii) Recruited? (please append advertisement materials to application)

N/A

23. What criteria will be used for inclusion and exclusion of the control group?
(i) Inclusion criteria:

Only swimmers who are members of the Swim Ireland / NUIG Connacht Performance Centre swimming squad will be eligible to take part in the study.

(ii) Exclusion criteria:

N/A

24. If applicable, how many controls will be recruited and of what age group?

N/A

25. Are the participants/controls included in this study involved in any other research investigation at the present time?

YES: [ ] NO: [x]

If YES, please give details

N/A

26. Will participants receive any payment or other incentive to participate?

YES: [ ] NO: [x]

(i) If YES, give details of incentive per participant?

N/A

If YES, what is the source of the incentive?

N/A

SECTION 4 Consent

27. Is written consent for participation in the study to be obtained?

YES: [x] NO: [ ]

If YES, please attach a copy of the consent form to be used *(Guidance on consent is given in the Guidance Notes)*

If NO written consent is to be obtained, please explain why

N/A

28. How long will the subject have to decide whether to take part in the study?
(If less than 24 hours, please justify)

Participants will be notified at least two weeks prior to the commencement of the study.

29. Does the study include participants for whom English is not a first language?

YES: [ ] NO: [x]

If YES, give details of special arrangements made to assist these participants

N/A

30. Please attach a copy of the written participant information sheet
If NO information sheet is to be given to participants, please justify

31. If you are recruiting from a vulnerable groups (Children under 18 years of age; People with learning difficulties; Unconscious or severely ill participants; Other vulnerable groups e.g. dementia, psychological disorders, etc.), please specify and justify

Some of the participants will be under 18 years of age. Swimming is considered an early specialization sport, with the majority of athletes of a younger age group. Also, the majority of athletes who are members of the Swim Ireland / NUIG Connacht Performance Centre are under 18 years of age.

(ii) What special arrangements have been made to deal with the issues of consent and assent for vulnerable participants e.g. is parental or guardian agreement to be obtained, and if so in what form?

Parental consent will be required from all participants under 18 years of age.

(iii) In what way, if any, can the proposed study be expected to benefit the individual who participates?

New performance monitoring tools in swimming offer the participants the opportunity to gain greater insight into their swimming performance.

32. *Answer this question only where invasive or other interventions are planned which could be a risk to a pregnancy*
Are women of childbearing potential included in this study?

YES: ☐ NO: ☐

If YES, does the protocol/participant information sheet address the following:

- scientific justification
- negative teratogenic studies
- warning participants that foetus may be damaged
- requirement for initial negative pregnancy test
- forms of contraception defined
- duration of use to exceed drug metabolism
- exclude those unlikely to follow contraceptive advice
- notify investigator if pregnancy suspected.

If NO, please explain

SECTION 5 Details of interventions

33. Does the study involve the use of a new medicinal product or medical device, or the use of an existing product outside the terms of its product licence?

YES: [ ] NO: [x]

If YES, please complete Question 33 and Annex 1 of the Application Form.

34. Does the study involve investigations and/or interventions on either participants or controls?

(Please tick YES/NO as appropriate. If YES, details should be available in the protocol)

Investigation/Intervention	X	YES		NO
Self completion questionnaires		YES	X	NO
Interviews/interview administered questionnaires		YES	X	NO
Video/audio tape recording	X	YES		NO
Physical examination		YES	X	NO
Internal physical examination		YES	X	NO
Venepuncture*		YES	X	NO
Arterial puncture*		YES	X	NO
Biopsy material*		YES	X	NO
Other tissue/body sample*		YES	X	NO
Imaging investigation (not radiation)		YES	X	NO
Other investigations not part of normal care		YES	X	NO
Additional out patient attendance		YES	X	NO
Longer inpatient stays		YES	X	NO
Local anesthesia		YES	X	NO
General anesthesia		YES	X	NO

Other – please detail

N/A

Please indicate and justify where treatment is withheld as a result of taking part in the project.

N/A

35. Will any ionising or non-ionising radiation, or radioactive substances or X-Rays be administered to a participant?

YES: [ ] NO: [x]

If YES, please compete Annex 2 of the Application Form.

36. Where research conducted in a general practice setting, will all GPs whose patients will be involved, be required to sign to indicate that they are aware of and in agreement with the planned project?

YES: [ ] NO: [ ] Not applicable: [x]

* *Please see Guidance Notes*

If NO, please explain why not

N/A

SECTION 6 Risks and ethical problems

37. Are there any potential risks to participants?

YES: [ ] NO: [x]

If YES, please complete **Annex 3** for each procedure for which a potential risk occurs.

38. Could this study cause any discomfort or distress, either physical or mental?

YES: [x] NO: [ ]

If YES, estimate the degree and likelihood of discomfort or distress entailed and the precautions to be taken to minimise them.

Physical discomfort due to participants undertaking a prescribed swimming routine. The routine will be similar in nature to normal training activities so is not considered out of the ordinary for the participants.

Please include other potential embarrassments to the subject that should be explained prior to obtaining consent (e.g. state of undress etc)

39. What particular ethical problems or issues do you consider to be important or difficult with the proposed study?

Parental consent required from participants under 18 years of age.

(i) Will treatments provided during the study be available if needed at the end of the study?

YES: [ ] NO: [ ] Not applicable: [x]

(ii) If NO, is this made clear in the participant information sheet?

YES: [ ] NO: [ ]

If NO, please give reasons

SECTION 7 Indemnity

Product liability and consumer protection legislation make the supplier and producer (manufacturer) or any person changing the nature of a substance, e.g. by dilution, strictly liable for any harm resulting from a consumer's use of a product.

(Please refer to Page 8 of the '*Guidance Notes on Completing the Application Form*' for information on indemnity.)

40. Arrangements for indemnification[5]/compensation

(i) What arrangements have been made to provide indemnification and/or compensation in the event of a claim by, or on behalf of, a participant for negligent harm?

NUI Galway Professional Indemnity Cover

(ii) What arrangements have been made to provide indemnification and/or compensation in the event of a claim by, or on behalf of, a participant for non-negligent harm?

NUI Galway Professional Indemnity Cover

(iii) Will an undergraduate student be involved directly in conducting the project?

YES: [x] NO: [ ]

41. In cases of equipment or medical devices, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: [ ] NO: [ ] Not applicable: [x]

If YES, please give details and enclose a copy of the relevant correspondence with this application

N/A

42. In cases of medicinal products, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: [ ] NO: [ ] Not applicable: [x]

If YES, please give details and enclose a copy of the relevant correspondence with this application

N/A

[5] *Where there is more than one institution /organisation involved in the study, each institution /organization is responsible for its own indemnity cover, and confirmation of such cover must be appended to the application.*

SECTION 8 Confidentiality

43. Will the study include the use of any of the following?

Audio/Video recordings YES: x NO:

Observation of participants: YES: x NO:

If YES to either:

(i) How are confidentiality and anonymity to be ensured?

Participants will be assigned a number for identification purposes and all data will be anonymized. All data will be stored centrally with the PhD student, Robert Mooney. Upon publication, data will be destroyed.

(ii) What arrangements have been made to obtain consent for these procedures?

Participant information sheet will outline the procedures to be carried out and detail methods of ensuring confidentiality

(iii) What will happen to the tapes at the end of the study?

All data and video recordings will be deleted at the end of the study.

44. Will the study data be held on computer?

YES: x NO:

If YES, will the data be held so that participants cannot be identified from computer files (i.e. no name, address, medical chart number or other potential identifier such as GMS or RSI number?

YES: x NO:

If NO, please give reasons

45. Will records (preferably paper records) linking study participant ID with identifying features be stored confidentially? (Please refer to the REC policy on Data Retention: http://www.nuigalway.ie/research/vp_research/documents/ethics_committee_docs/datapolicy.pdf)

YES: x NO:

Please give details of arrangements for confidential storage

All data will be stored centrally with the principal applicant. Only summary data, which is non identifiable, will be shared with others involved.

For how long will records be retained prior to destruction?

Records will be deleted following publication of the findings of the research

46. Will the participants' medical records be examined by investigators in the study?

YES: ☐ NO: x

If YES, will information relevant **only** to this study be extracted: YES: ☐ NO: ☐ Not applicable: x

(i) If extra information is extracted, please justify

N/A

(ii) What, if any, additional steps have been taken to safeguard the confidentiality of personal medical records?

N/A

47. Will research workers outside the employment of NUI Galway examine medical or other personal records?

YES: ☐ NO: x

If YES, it is the responsibility of the Principal Applicant to ensure that research workers understand that: Information obtained about and from research participants is confidential to the study and must not be divulged except in legitimate methods of study data presentation or exceptional circumstances as discussed and agreed with the principal investigator.

Please ensure that you complete the checklist on the front cover of this application form and include all relevant enclosures.

THANK YOU.

ANNEX 1

This form is to be used if the study involves the use of a new medical product or medical device, or the use of an existing product outside the terms of its product licence.

(i) Does this project have Irish Medicines Board approval or has an application been made?

YES: ☐ NO: ☐ Not applicable: ☐ Application is at present with IMB: ☐

If approval applied for, state date of application: ☐

(ii) Is a pharmaceutical or commercial company arranging this trial?

YES: ☐ NO: ☐

If YES, attach indemnification.
If NO, has the licensing authority been notified? YES: ☐ NO: ☐

(iii) Does the drug(s) or medical device have a product license(s) for the purpose for which it is to be used?

YES: ☐ NO: ☐

If YES, please give details

☐

(iv) Is any drug or medical device being supplied by a company with a Clinical Trial Exemption Certificate or in response to an investigator with a Clinical Trial Exemption, or Doctors' Exemption?

YES: ☐ NO: ☐

If YES, give details of:

Clinical Trial Certificate Number: ☐

Clinical Trial Exemption Number: ☐

Doctors' Exemption Number: ☐

(v) Details of drug use or medical device *(please complete the table below)*

Approved name: ☐

Generic name: ☐

Trade name: ☐

Strength	Dosage	Frequency	Route	Duration of course

(vii) Who will administer the drug or fit the medical device?

☐

(viii) If a medical device, has the device been through acceptance and safety testing?
YES ☐ NO ☐

Please give details

(ix) Who is supplying the drug(s)/medical device? (If imported, name country)

(x) Who will dispense the drug(s)/medical device?

What is their qualification to dispense the drug(s)/medical device?

(xi) Does the organisation and performance of this trial conform to European Directives on Good Clinical Practice?
YES ☐ NO ☐

If no, please detail and explain

ANNEX 2

This form is to be used if the study involves the use of ionizing or non-ionising radiation, radioactive substances or X-Rays. A competent Radiation Protection Advisor must be involved in implementing this section.

A. RADIOACTIVE SUBSTANCES

(i) Details of substances to be administered *(please complete the table below)*

Investigation	Radionucleide	Chemical form	Quantity of radioactivity to be administered (MBq)	Route	Frequency

(ii) Estimated Effective Dose (Effective Dose Equivalent) (mSv)
(Please supply source of reference or attach calculation)

(iii) Absorbed dose to organ or tissues concentrating radioactivity (mGy) (Specify dose and organ)
(Please supply source of reference or attach calculation)

(iv) Administration of Radioactive Substances Advisory Committee certificate holder to oversee/administer substance

Name of Person:

Position:

Certificate No.:

I have assisted in and approve the protocol and arrangements that have been made in this project for the administration of the radioactive substance(s).

Signature: ______________________________ Date: __________

B. X-RAYS

(i) Details of radiographic procedures *(please complete the table below)*

Investigation	Organs	Frequency

(ii) Estimated Effective Dose (Effective Dose Equivalent) (mSv)
(Please supply source of reference or attach calculation)

C. NON IONISING RADIATION

(i) Details of procedures *(please complete the table below)*

Investigation	Organs	Frequency

(iv) Who has given safety advice?

Name of Person:	
Position:	
Qualification to advise:	

I have assisted in and approve the safety of the protocol and arrangements that have been made in this project

Signature: ______________________________ Date: ____________

ANNEX 3

Risk Assessment Form – Procedures Involving Human Subjects

Procedure no.:	
Title of Procedure:	Reliability and accuracy assessment of commercially available swimming performance monitors.
Name of Assessor(s):	Prof Gearóid ÓLaigin
Assessment Date:	9th December 2013

Does this procedure already have ethical approval? YES [ ] NO [x]

If YES, enter Approval No. and Expiry Date: Approval No: [ ]

Expiry Date: [ ]

1. Please provide a brief description of the procedure;

Participants will be recruited from the Swim Ireland/NUIG Connacht Performance Centre, based at the Kingfisher on the NUIG campus. Data collection will take place on two occasions, separated by seven days, during the participants normal training schedule. Following a coach led warm up routine and collection of preliminary personal information, participants will be required to perform a prescribed swimming protocol, encompassing variations of speed and stroke style, whilst wearing swimming performance monitors on each forearm. Simultaneous video recordings will be obtained and used as a criterion measure. Following data collection, the results will be analyzed to assess the performance of each device against that of the criterion measures.

2. Location in which the Procedure will take place

(e.g. Research Laboratory – Room No. , Teaching Laboratory – Room No., Hospital clinic – specify, etc)

NUI Galway Sports Centre, using the 25m swimming pool facility

3. Subject(s) to be used

How many human participants?	20

(tick as appropriate)

Undergraduate student(s)	x
Postgraduate student(s)	
University staff or campus personnel	
Members of the general public	x

4. What is the level of any potential risks for participants?
[To be explained BEFORE obtaining consent]

None	
Minimal only	x
Moderate	
Significant	

(ii) If the risk is other than minimal, please give details and likelihood of risk occurrence

(ii) If the risk is other than minimal, please give details of precautions taken to minimise the risk

5. Actions to be taken in the event of adverse response or medical emergency

Please provide details of arrangements to deal with adverse events, including reporting to the relevant authorities and follow-up

Staff at NUI Galway Sports Centre will be available during data collection in the event of a medical emergency.

6. Appropriate level of supervision required for procedure (please tick as appropriate)

Post-graduate researcher	x
Research/ lecturing Staff	
Paramedical personnel	
Medical personnel – Nurse	
Medical personnel – Doctor	
Medical personnel – Other	

If other personnel, please specify title and/or required qualification

Head Swimming Coach, Swim Ireland/NUIG Connacht Performance Centre

7. Other documentation required for this assessment

Pre-test subject questionnaire	
Detailed protocol	
Other	x

If other documentation is required, please describe

questionnaire

8. Signature

Signed: ______________________________ **Date:** ____________

Signature of Principal Applicant

FOR COMPLETION BY HEAD OF DEPARTMENT

Risk Assessment Form – procedures involving human subjects

In the Department/ Institute/ Center of: Electrical & Electronic Engineering

Procedure no.:

Title of Procedure: Reliability and accuracy assessment of commercially available swimming performance monitors.

Name of Assessor(s):

Assessment Date: 9th December 2013

9. Approval of Procedure

- [x] Granted
- [ ] Subject to conditions (see below)
- [ ] Refer to Hospital Ethics Committee

Other, please specify

10. Comments and/or conditions

11. Signature

Signed: ______________________________ **Date:** ______________

Signature of Head of Department/Centre

(Please copy this Annex as necessary)

Study Protocol

NUI Galway, Electrical & Electronic Engineering
Principal Investigator's Name: Prof. Gearóid ÓLaigin
Project Title: Reliability and accuracy assessment of commercially available swimming performance monitors.

A 15 Minute coach led warm-up routine will be carried out prior to commencement of the data collection phase, which is outlined below.

50 Fly moderate pace	*Butterfly Distance Swum:*	100 X 3 = 300 meters
Rest 30		
50 Fly sprint swim		
Rest 30		
X 3		2.20 min X 3 = 7 min + 2 min
Rest 2 min	*Estimated Time:*	= 9 min

100 BS moderate pace	*Backstroke Distance Swum:*	200 X 2 = 400 meters
Rest 30		
100 BS sprint swim		
Rest 30		
X 2		4 mins X 2 = 8 min + 2 mins
Rest 2 min	*Estimated Time:*	= 10 mins

100 BRS moderate pace	*Breastroke Distance Swum:*	200 X 2 = 400 meters
Rest 30		
100 BRS sprint swim		
Rest 30		
X 2		4.30 min X 2 = 9 min + 2 min
Rest 2 min	*Estimated Time:*	= 11 min

100 FS moderate pace	*Freestyle Distance Swum:*	200 X 2 = 400 meters
Rest 30		
100 FS sprint swim		
Rest 30		
X 2		3.30min X 2 = 7 min + 2 mins
Rest 2 min	*Estimated Time:*	= 9 mins

Total Estimated Time = 39 min X 2 for two swimmers = 78 mins + 15 mins warm up equals 93 mins. The protocol will be repeated on two occasions, one week apart.

<u>Participant Information Sheet</u>

NUI Galway, Electrical & Electronic Engineering
Principal Investigator's Name: Prof. Gearóid ÓLaigin
Project Title: Reliability and accuracy assessment of commercially available swimming performance monitors.

You are being invited to take part in a research study. Before you decide, it is important for you to understand why the research is being done and what it will involve. This Participant Information Sheet will tell you about the purpose, risks and benefits of this research study. If you agree to take part, we will ask to ask you to sign a Consent Form. If there is anything that you are not clear about, we will be happy to explain it to you. Please take as much time as you need to read it. You should only consent to participate in this research study when you feel that you understand what is being asked of you, and you have had enough time to think about your decision. Thank you for reading this.

Purpose of the study:
The analysis of a swimmer's technical performance is typically carried out using video based methods such as underwater camera's. Recently, a new approach to this analysis has been developed that involves the use of body worn sensors. Examples of this include products such as the *Garmin Swim* and *FINIS Swimsense* devices. This research is been carried out to assess how accurately these devices perform in a competitive swimming environment. You have been invited to participate in this study as you are a member of the Connacht Performance Centre (CPC) swimming squad and in consultation with the CPC Head Coach.

Taking part – what it involves
Do I have to take part?
It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and be asked to sign a consent form. If you decide to take part you are still free to withdraw at any time and without giving a reason. A decision to withdraw at any time, or a decision not to take part, will not affect your rights in any way.

What will happen to me if I take part?
If you decide to take part you will be asked to perform a set swimming protocol whilst wearing the *Garmin Swim* and *FINIS Swimsense* devices so that performance related measurements can be obtained and compared. A digital video of the swimming session will also be taken as a benchmark so that results from the sensor devices can be compared to video recordings. Participants will be assigned a number for identification purposes and all data will be anonymized. All data, including video recordings will be stored centrally with Robert Mooney. Video will be edited to obtain only the specific information of interest. Once the data is extracted from the video recordings, these images will not be used for any other purpose and will not be shared with any other parties.

How long will my part in the study last?
You will be required to perform the same swimming protocol on two occasions, one week apart. The exact time and date of the sessions will be confirmed at a later date but will take place during your regular training schedule at the CPC. Each session will last approximately one hour.

What do I have to do?
There are no restrictions to you either before or after the study. You are free to carry out your normal daily dietary, lifestyle and medical routine.

What is the procedure being tested?
The procedure being tested is whether the *Garmin Swim* and *FINIS Swimsense* devices can accurately record key variables related to swimming, such as stroke rate and swim speed. The routine outlined below will be repeated on two occasions, one week apart.

Following a coach led warm-up routine; you will be fitted with two sensors, one on each wrist. You will be asked to swim the following routine.

1. 50 metre butterfly moderate pace, rest 30 seconds, 50 metre butterfly sprint, rest 30 seconds, repeated 3 times, 2 minutes rest interval.
2. 100 metre backstroke moderate pace, rest 30 seconds, 100 metre backstroke sprint, rest 30 seconds, repeated 2 times, 2 minutes rest interval.
3. 100 metre breaststroke moderate pace, rest 30 seconds, 100 metre breaststroke sprint, rest 30 seconds, repeated 2 times, 2 minutes rest interval.
4. 100 metre freestyle moderate pace, rest 30 seconds, 100 metre freestyle sprint, rest 30 seconds, repeated 2 times, 2 minutes rest interval.

What are the possible benefits in taking part?
Should these devices prove accurate and reliable then there is potential for such instruments to be used as part of your regular training routine, so that you can obtain key information related to your swimming performance on an on-going basis.

What are the possible disadvantages and risks of taking part?
There are no risks to your involvement in this study. The swimming protocol does not involve undertaking any activity outside of your normal training routines.

What happens if I change my mind during the study?
You are free to withdraw your participation at any stage, without the requirement to provide reasons for your withdrawal.

Whom do I contact for more information or if I have further concerns?
If you have any further questions or concerns then please contact:

Robert Mooney
Bioelectronics Research Cluster,
Electrical and Electronic Engineering,
NUI Galway,
University Road, Galway.
Tel: 085-7173744
E-mail: r.mooney4@nuigalway.ie

What happens at the end of the study?
At the end of the study the data collected with be summarised and analysed to draw conclusions regarding the suitability of the devices for use in competitive training environments. All data and video recordings will be treated in strict confidence and will be deleted upon completion of this study.

If you have any concerns about this study and wish to contact someone independent and in confidence, you may contact:
Chairperson of the NUI Galway Research Ethics Committee,
c/o Office of the Vice President for Research, NUI Galway, ethics@nuigalway.ie.

Confidentiality
All information that is collected about you during the course of the research will be kept strictly confidential and will not be shared with anyone else. The information collected in this research study will be stored in a way that protects your identity. The original recordings will be stored securely for the duration of the study, after which they will be destroyed. Results from the study will be reported

as group data and will not identify you in any way.

Summary

Please feel free to contact Robert Mooney if you wish to clarify any points which remain unclear to you. Please note that you are free to refuse to take part in the study without any disadvantage and that should you agree to take part, you can change their mind at any point during the study and decide not to continue in the study without any disadvantage.

Thank you for your interest in taking part in this study.

Robert Mooney

____

Robert Mooney
Bioelectronics Research Cluster,
Electrical and Electronic Engineering,
NUI Galway,
University Road, Galway.
Tel: 085-7173744
E-mail: r.mooney4@nuigalway.ie

Date: 8th January 2014
Version Number: 2.0

NUI Galway
OÉ Gaillimh

Participant Questionnaire

Please respond to the following statements, by indicating your level of agreement in the space provided.
1 = completely disagree
7 = completely agree

I found the FINIS watch comfortable to wear whilst swimming	1	2	3	4	5	6	7
I found the Garmin watch comfortable to wear whilst swimming	1	2	3	4	5	6	7
The FINIS watch interfered with my swimming stroke	1	2	3	4	5	6	7
The Garmin watch interfered with my swimming stroke	1	2	3	4	5	6	7
I would consider using the FINIS watch in future	1	2	3	4	5	6	7
I would consider using the Garmin watch in future	1	2	3	4	5	6	7
I believe that the FINIS watch could benefit my swimming performance	1	2	3	4	5	6	7
I believe that the Garmin watch could benefit my swimming performance	1	2	3	4	5	6	7

Do you have any other comments to make regarding these swimming sensors?

Participant / Parental Consent Form

NUI Galway, Electrical & Electronic Engineering

Principal Investigator's Name: Prof. Gearóid ÓLaigin

Project Title: Reliability and accuracy assessment of commercially available swimming performance monitors.

Please tick each box:

1. I confirm that I have read the information sheet dated 5th November 2013 (version 1.0) for the above study and have had the opportunity to ask questions. ☐

2. I am satisfied that I understand the information provided and have had enough time to consider the information. ☐

3. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my legal rights being affected. ☐

4. I agree to take part in the above study. ☐

Participant Name: ________________________ Signature: ___________________________

Date: ____________________

If the Participant is under 18 years of age, consent is also required from a parent/guardian

Parent/Guardian Name: ___________________ Signature: ___________________________

Date: ____________________

Researcher Name: ________________________ Signature: ___________________________

Date: ____________________

CURRICULUM VITAE

Prof. Gearóid Ó Laighin

POSITION:	Head of Discipline & Professor of Electronic Engineering (2007-present), Electrical & Electronic Engineering, College of Engineering & Informatics NUI Galway
QUALIFICATIONS:	B.E. Electrical Engineering (First Class Honours) (UCC), M.Eng.Sc. (Microelectronics) (UCC), Ph.D. (NUI Galway)
MEMBERSHIP OF PROFESSIONAL BODIES:	FIEI, C.Eng., FIET, SMIEEE
PROFESSIONAL EXPERIENCE:	2 years in the automation industry, Dublin, Ireland 5 years in the microelectronics industry, California, USA 17 years as an academic at the University of Limerick and 7 years as a Professor at NUI Galway
TEACHING AREAS AND SPECIALITIES	Biomedical Instrumentation, Kinesiology of Human Movement, Medical Electronics
RESEARCH ACTIVITIES	Principle Investigator, Bioelectronics Research Cluster,NCBES Biomedical Electronics with a specialism in Neuromuscular Electrical Stimulation and Kinematic Sensing of Human Movement 14 PhD students as lead supervisor to graduation. NUI Galway PI on FP7 project REMPARK NUI Galway PI on CIP project FATE NUI Galway PI on CIP E-NO FALLS NUI Galway PI on USA DoD project PI on EI Commercialisation Project VASGARD PI on EI Commercialisation Project VSENSE 6 PhDs students currently under supervision 60+ peer reviewed international journal papers >70 conference papers Total citations = 2848 h-index = 26 Top cited paper in last ten years in *Medical Engineering & Physics* Top cited paper in *Gait & Posture* over a ten year period. Full list of Google Scholar indexed publications showing citations in Google Scholar http://scholar.google.com/citations?user=j4btiysAAAAJ&hl=en