THE DESIGN, DEVELOPMENT AND VALIDATION OF A WEARABLE BEHAVIOUR MONITOR FOR THE AUTONOMOUS ASSESSMENT OF THE FUNCTIONAL HEALTH OF OLDER ADULTS

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Dedicated to my parents,
Brendan and Helen Lowe.
For your limitless support and unending encouragement,
this was possible because of you.
Thank you.

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Abstract

Functional ability describes a person's capability to perform those tasks that are necessary to live independently. It is a proven predictor of functional decline, the need for hospitalisation and institutionalisation and for morbidity and mortality. For this reason, assessment of functional ability has been integrated into standard geriatric care. These assessments are typically performed using questionnaires or observation of the patient and rarely integrate information and communications technology. Devices that monitor a person's performance of activities of daily living have begun to be introduced but have not gained widespread traction in clinical assessment practice.

This thesis describes the development and validation of a wearable device for the contextualised monitoring of the performance of activities of daily living. This device is specifically designed to be useful in the domain of functional assessment. Algorithms to combine a range of parameters monitored by the device into a clinically meaningful output are developed and validated. This output is designed to require the minimum possible change in clinical practice.

The set of studies described in this thesis test the validity of the data generated by the device in terms of sensitivity and specificity. This testing was performed by comparing device output with video of participants performing activities of daily living in real time. The algorithms used to generate clinically meaningful data were validated in comparison to conventional questionnaire based assessments. Data were also collected on older adults wearing the device in an assisted living facility over a two week period.

Results indicated that the device developed in this thesis is an accurate platform for the monitoring of activities of daily living. The data regarding outputs for functional health assessment indicate that the device may perform valid assessments for three different domains of functional health i.e Mobility, Disability and Risk of hospitalisation. Furthermore participants indicated that with slight modifications the device would be acceptable for long term use.

Chapter 1

Introduction

1.1 Functional Decline

Functional decline describes the deterioration of a person's ability to perform activities of daily living that are necessary to survive and thrive independently. These activities of daily living cover a broad range of activities such as eating, shopping, toileting, grooming, mobility and several others. Functional decline usually precedes a more serious degradation in health and has been shown to be predictive of falls, hospitalisation, institutionalisation and mortality [2, 3, 4]. Functional ability can broadly be divided into two categories: Basic Activities of Daily Living (BADL) and Instrumental Activities of Daily Living (IADL). BADLs are those activities required to survive independently in the home such as feeding or toileting [5]. IADLs describe activities that are necessary to thrive in the community such as using public transport, or grocery shopping [6]. The loss of functional ability has been shown to broadly follow a hierarchical path, with people loosing the ability to perform certain instrumental activities of daily living before basic activities are lost as shown in Figure 1.1 [1] . Therefore, if a decline in functional ability is recognised early, and relevant interventions are put in place, a further decline and more serious health events may be delayed or avoided.

Aging is often recognised as the most common cause of functional decline. However, recent research has suggested that aging in itself does not necessarily cause any loss in functional ability directly; rather factors such as genetics, lifestyle and environment seem to be more significant causes of functional decline [7, 8]. Chronological age, as measured in years, and physiological age, as measured in functional ability do not always coincide [9]. While aging itself may

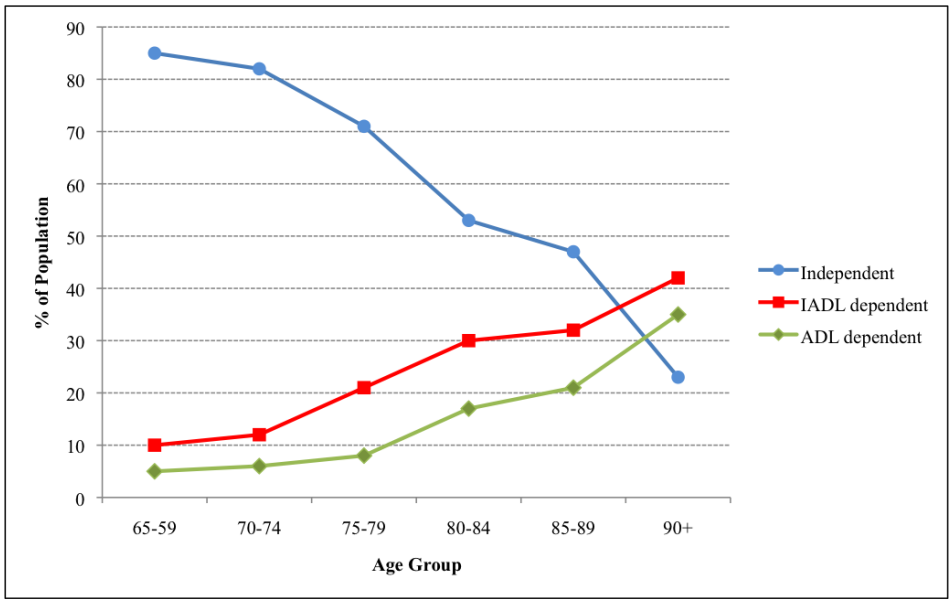

Figure 1.1: ***Hierarchical relationship between loss of IADL and BADL abilities. Across all age groups of older adults, people tend to become dependent in IADLs before BADLs (Adapted from [1]).***

not be the cause of functional decline, several factors related to functional ability do often coincide with increasing age.

Several physiological changes that often occur with increased age can directly affect a person's ability to perform certain daily activities. The cardiovascular system becomes less efficient as the heart muscle has to work harder to pump the same amount of blood, muscle atrophy becomes common and people often become less co-ordinated and have trouble balancing. The digestive system can be effected by multiple conditions, changes in diet or use of diuretics causing constipation and other toileting issues. Loss of urinary continence is also common among older adults. Reductions in social and mental activity can lead to cognitive impairments, making it more difficult to learn new things or access memories. Eyesight and hearing are often reduced with age. Weight levels become more difficult to maintain as muscle atrophy leaves older adults with reduced muscle mass and increases in fat. The cumulative effects of several of these factors can lead to a significant reduction in the ability to perform activities of daily living. However, most of these phenomenon are not necessarily a direct result of aging. In fact, the majority of these effects can be significantly slowed down with careful regulation of physical activity levels and mental stimulation [10, 11, 12, 13, 14]. In addition to physiological changes seen as people age, environmental and social

changes can also have a profound effect on a person's functional ability. The death of spouses or friends can lead to a social isolation of a person. This isolation, can lead to a deficit in mental stimulation which has been shown to be a leading cause of cognitive impairment [15].

Therefore, in several ways it is the reduction in the practice of functional tasks that often leads to the decline in functional capacity (i.e. The "use it or lose it" principle). This relationship means that one of the most useful methods of assessing and predicting levels of functional ability is to measure the current levels of performance of these functions. This technique of assessing the "activities of daily living" was first mentioned in 1949 by Edith Buchwald as the population of older adults was growing rapidly, with the first formal assessment scale introduced fourteen years later [16]. These conventional assessments consisted of questionnaire-based tools, which involved asking the person questions regarding their functional performance in daily life. Later, in addition to these questionnaire-based assessments, techniques involving the observation of the performance of functional tasks were introduced in the 1980's as discussed in Chapter 2 of this thesis. These methods of assessment have been widely validated using a wide range of statistical tests. Several new instruments have been introduced with improved validity, reliability or responsiveness, but all still rely on the basic concepts of questionnaires or observation of performance. While both questionnaire and performance based techniques have considerable advantages, they both retain sources of inherent error and both require significant resources to administer [17].

Despite this inherent error, the core technique for assessing functional ability has not seen any drastic changes since the introduction of performance based testing in the 1980's.

1.2 Activity Monitoring Technology

With the advent of modern sensing technologies, the ability to monitor and detect the performance of human activities has emerged. These systems can be based on a wide array of sensing technologies including body sensor networks, "smart homes" and several other implementations. The availability of this monitoring capability has paved the way for this thesis to explore the possibility of introducing a third, technology-based technique for functional assessment. This technique involves the use of continuously collected data as the medium for per-

forming assessments of functional health. This investigation is achieved through the design, development and validation of a wearable behaviour monitor for the performance of autonomous functional assessments.

1.3 Thesis Outline

The work outlined in this thesis describes the design, development and validation of a behavioural monitor based on wearable electronics for use in the functional assessment of older adults. This thesis is comprised of six chapters.

- Chapter 1 – Introduction: introduces the concept of functional decline and gives an overview of the entire thesis.
- Chapter 2 – New Technology-Based Functional Assessment Tools Should Avoid the Weaknesses and Proliferation of Manual Functional Assessments: provides a detailed overview and analysis of conventional functional assessment methodologies in use from the beginnings of the field in the 1960's to the present day. The different types of assessment methodology as well as their corresponding strengths and weaknesses are discussed. A possible role for technology in improving these assessments is also introduced. The contents of this chapter have been accepted for publication in the Journal of Clinical Epidemiology.
- Chapter 3 – Monitoring Elderly Human Behaviour in Their Living Environment: A Technological Review: gives an overview of the field of activity monitoring. Several technological approaches such as image processing, "smart homes", physiological and inertial sensing are discussed and evaluated for their potential to perform functional assessments. This is intended to be background information provided prior to describing the developed behaviour monitor in Chapter 4. The contents of this chapter have been submitted for publication to the Journal of Medical Engineering and Physics.
- Chapter 4 – The Development of a Wearable Behaviour Monitor: describes the design and development of a wearable behaviour monitor specifically designed to fit into clinical practice. The design not only focuses on classifying the current activity being performed, but also seeks to contextualise

this activity into behaviour using indoor and outdoor localisation. The behavioural data generated by the system are input into a "Functional Assessment Engine" which is trained in Chapter 6. Concerns such as ergonomics, comfort, power efficiency and other aspects relevant to medical device design are discussed.

– Chapter 5 – Primary Validation of a Wearable Behaviour Monitor in a Laboratory Setting: describes the results of a mock-apartment based protocol for testing the validity of the device described in Chapter 4 which was carried out with healthy volunteers. The protocol involved comparing the device' output to a video feed of participants performing a wide range of simulated activities of daily living.

– Chapter 6 – Predicting Functional Health Using a Wearable Behaviour Monitor incorporating a Functional Assessment Engine: A Proof of Concept Study: presents the development and validation of predictive equations for functional health using data collected by a wearable activity monitor. Older adults were asked to wear the device for a period of two weeks. Data collected were used as the input for a multiple linear regression analysis. The generalisation of the models is then examined using cross validation. Usability and comfort data were also collected from participants after this two-weeks of use.

The thesis finishes with Conclusions and Discussions.

Chapter 2

New Technology-Based Functional Assessment Tools Should Avoid the Weaknesses and Proliferation of Manual Functional Assessments

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2.1 Introduction

The health of older adults varies by degree and nature compared to that of the young, and can be further complicated by limitations in function that may not be symptomatically apparent. According to the National Pharmacy Claims Database, 86% of elderly people suffer from a chronic condition [18], it has also been shown that 39%, 16%, and 10% of people over the age of 75 suffer from mild, moderate, and severe/extreme disability respectively [19]. A system that consists of treatment of a patient's symptoms alone may not be optimal for an older population. As a matter of social policy, given the demographic changes, it is vital that the health system look beyond the objective of preserving life in the elderly population and that it also strives to maintain and add to the quality of that life. This can be seen in the way in which the WHO classifies a person's health and related domains. The International Classification of Illness Disability and Health (ICIDH) framework was first developed in 1980. This model put an emphasis on the consequences of disease. In contrast to this, when the ICIDH was revised in 2001 (renamed the ICIDH-2), it was designed to focus on the components of health. The ICIDH-2 deals with any disability in the same manner, regardless of the cause. The ICIDH-2 describes health under the following headings: 1) Health Condition, 2) Impairment, 3) Activity Limitation and 4) Participation Restriction. The traditional focus of medicine on the levels of health condition and impairment has lead to the tools and knowledge used for pathological diagnoses evolving to such a state that standardised, gold standard diagnostic tools and methods have been adopted across the medical profession. For example, Random Plasma Glucose (RPG) testing can be considered a gold standard test for diabetes as it is commonly used across the medical community throughout the developed world.

Older adults typically experience far more activity limitations than younger people do, which often cannot be cured pathologically. In fact, it has been shown that 15% of the elderly population experience limitations in basic activities of daily living (e.g. eating, dressing, bathing), 47% have difficulties in instrumental activities of daily living (e.g. shopping, using public transport), 20% have limitations of upper or lower limb function, and only 17% show no functional limitations [20]. Despite its increasing importance and in contrast to the extremely well developed field of pathological diagnosis, assessment of activity limitations and participation restriction boast no gold standard assessment tools. While there has been considerable attention paid to this field, as of yet, no assessment tool

has been widely implemented across the medical profession to a comparable degree as some of the gold standards of pathological diagnosis [21].

Functional assessment is a method used to assess activity limitation and participation restriction. A person's functional health describes their ability to perform those tasks that are necessary to survive independently in modern society. As well as a direct evaluation of activity limitation and participation restriction, the assessment of functional health has also been shown to be predictive of morbidity and mortality [2], as well as functional decline, need for home care assistance, hospitalisation and institutionalisation [3, 4]. Due to this range of predictive outcomes, functional assessment has emerged as being important in several different areas such as planning public health policies, quantifying the impact of a present illness, helping to guide the decision process, establishing care plans, tracking changes and evaluating the effectiveness of an intervention [22]. In fact, because functional assessment has shown to be so effective in assessing older adults, it has been incorporated as one of the main components in the Comprehensive Geriatric Assessment (CGA). The CGA provides a systematic approach to the collection of data about a geriatric patient and is the main instrument used in geriatric care [23]. The CGA is a much wider framework of assessment than the tools used in this paper, and so is not discussed further. Over the decades, there have been a multitude of instruments introduced, several of which overlap considerably, but few of which have been comprehensively evaluated to the point that they can be considered a gold standard.

There have been attempts to review available assessment tools in the past [21, 24, 25], however, in the near future technologies capable of monitoring human movements will become available. The potential to closely monitor a person's performance of ADLs in their daily lives could have significant applications in functional assessment. Therefore, it is possible that new functional assessments could be developed to take advantage of this new resource potentially resulting in more accurate or cost effective assessments tools. These assessment instruments could be very useful tools in a clinician's assessment methodology. Because of the potential for new assessments, it is important that new developments in functional assessment will be properly informed by the experience gained with the existing functional assessment tools. With this in mind, rather than trying to assist the reader to choose a scale to put into use, this review will seek to document the evolution of the field of functional assessment. It is the authors' view that by outlining the significant points in its evolution, this review can

be used to inform the development of new tools and to assist in the development of new standardised assessments of function.

2.2 Methods

2.2.1 Compiling a List of Assessment Instruments

A search was conducted of the Medline, CINHAL and Science Direct databases using the following search terms: (“Functional ability" OR "Activities of daily living" OR "Functional status") AND ("Assessment" OR "Measurement" OR "Performance") AND ("Physical" OR "Morbidity") AND ("Scale" or "Tool" or "Questionnaire") AND (“Elderly” or “Older Adults”)

2.2.2 Inclusion/Exclusion of Instruments

Results found using the search terms outlined were then evaluated based on titles and abstracts in order to generate a list of functional assessment tools. Tools that focused on a single functional ability (e.g. mobility) were excluded from this review because the result of such assessments cannot claim to represent a person’s functional health. An exception to this exclusion is if the scale has been shown to be valid as an assessment of total functional status through correlation with other existing assessment tools or otherwise. After this inclusion logic had been applied, the assessment instruments remaining were included in this review.

2.2.3 Evaluation of Instruments

Instruments were evaluated under the following performance properties: 1) reliability, 2) validity, 3) responsiveness, 4) time taken to administer and 5) contribution to the advancement of the field.

1) Reliability:

- Inter-rater reliability (the ability of the instrument to result in similar scores for different administering people)
- Test-retest reliability (the ability of the instrument to result in similar scores when administered by the same person with the same subject)

- Internal reliability (the extent to which an instrument is consistent within itself).

2) Validity:

- Concurrent validity (the extent to which the instrument correlates to existing proven methods of assessment)
- Predictive validity (the extent to which the instrument can forecast an oncoming illness or a decline in functional health).

3) Responsiveness:

- The ability of the scale to detect clinically significant changes in the person's functional health. This can be measured against any of several criteria such as a clinician's opinion of improvement or a patient's or family member's general perception of health.

4) Time taken to administer:

- The time taken to administer a scale is significant in the decision of whether it is used.

2.2.4 Evaluation Scale for the Performance Properties of Reviewed Instruments

Each of the performance properties 1 to 3 described in Section 2.2.3 can be evaluated in several different ways and using any of a number of different statistical tests. Reporting the properties of each of the instruments reviewed, using a wide range of these tests, may not lend itself to creating a clear comparison of each scale. To combat this, a five point rating scale from 0 to 4 for each property was designed to show how well each measurement has performed in evaluations. This should produce a more concise and easy to understand report than if the specific validation data were reported for a multitude of tools with different statistical tests. The design of this rating scale is outlined in Table 2.1.

		1	2	3	4
Reliability	Inter Rater	Poor: correlation < 0.4	Acceptable: 0.4> correlation <0.6	Good: 0.6 > correlation < 0.8	Excellent: correlation > 0.8.
	Test-Retest	Poor: correlation < 0.4	Acceptable: 0.4> correlation <0.6	Good: 0.6 > correlation < 0.8	Excellent: correlation > 0.8.
	Internal	Poor: correlation < 0.4	Acceptable: 0.4> correlation <0.6	Good: 0.6 > correlation < 0.8	(3.5) Good but may contain redundency: correlation > 0.95 Excellent: 0.8 > correlation < 0.95.
Validity	Concurrent	Scale has shown not to be concurrently valid	Conflicting reports on the concurrent validity of the scale	Scale has shown to have moderate concurrent validity	Scale has been proven concurrently valid.
	Predictive	Scale has not shown predictive validity	Conflicting reports on the predictive validity of the scale	Scale has shown to be moderately predictive	Scale's predictive validity has been proven
Responsiveness		Scale has shown not to be responsive	Conflicting reports on the responsiveness of the scale	Scale has shown to have moderate responsiveness	Scale has been proven responsive.

Table 2.1: ***Performance property evaluation criteria***

2.3 Results

The initial search yielded 1236 results. After the titles and abstracts of these papers had been reviewed, 474 relevant papers remained. These papers mentioned 166 different functional assessment tools. Of these, 41 assessment instruments, shown in Figure 2.1, remained after applying the inclusion logic. A timeline of the evolution of the tools used in functional assessment was developed. This timeline suggests that the area of functional assessment gradually evolved from assessing a person's ability to perform the most basic everyday tasks required to survive independently to studying a wide range of aspects of the person's life including cognitive, emotional and social abilities. The timeline of the instruments developed using the search strategy in Section 2.2, is shown in Figure 2.1. The trend in the categories of assessment can be seen to change from the early days of the field to the present day. These categories and the change in trends are discussed further in Sections 2.3.1-2.3.5.

Table 2.2 illustrates the different characteristics that were assessed as the field evolved. The depth and comprehensiveness of each type of assessment can clearly be seen.

2.3.1 Activities of Daily Living

The timeline in Figure 2.1 begins in the 1960's with the introduction of instruments to assess activities of daily living (ADL). ADLs are defined as those activities whose performances are required in order to survive independently. The concept of the basic ADLs (BADL's) was first introduced by Edith Buchwald in an assessment checklist in 1949 [26]. Fourteen years later Katz et al published the first instance of a formal framework for assessing a person's ability to perform BADL's [16]. As seen in Table 2.2, BADL scales tend to be short and do not tend to vary much between scales in the characteristics they assess. Two of the most widely published BADL scales, chosen by number of publications in the papers identified using the search strategy of Section 2.2, were chosen for inclusion in Table 2.3. Though this strategy of choosing scales to include is skewed towards the older scales, the authors' feel this method results in prominent scales that broadly represent the field.

A significant advantage of these types of scales is that they can often be administered through the observation of the performance of tasks or as a reported

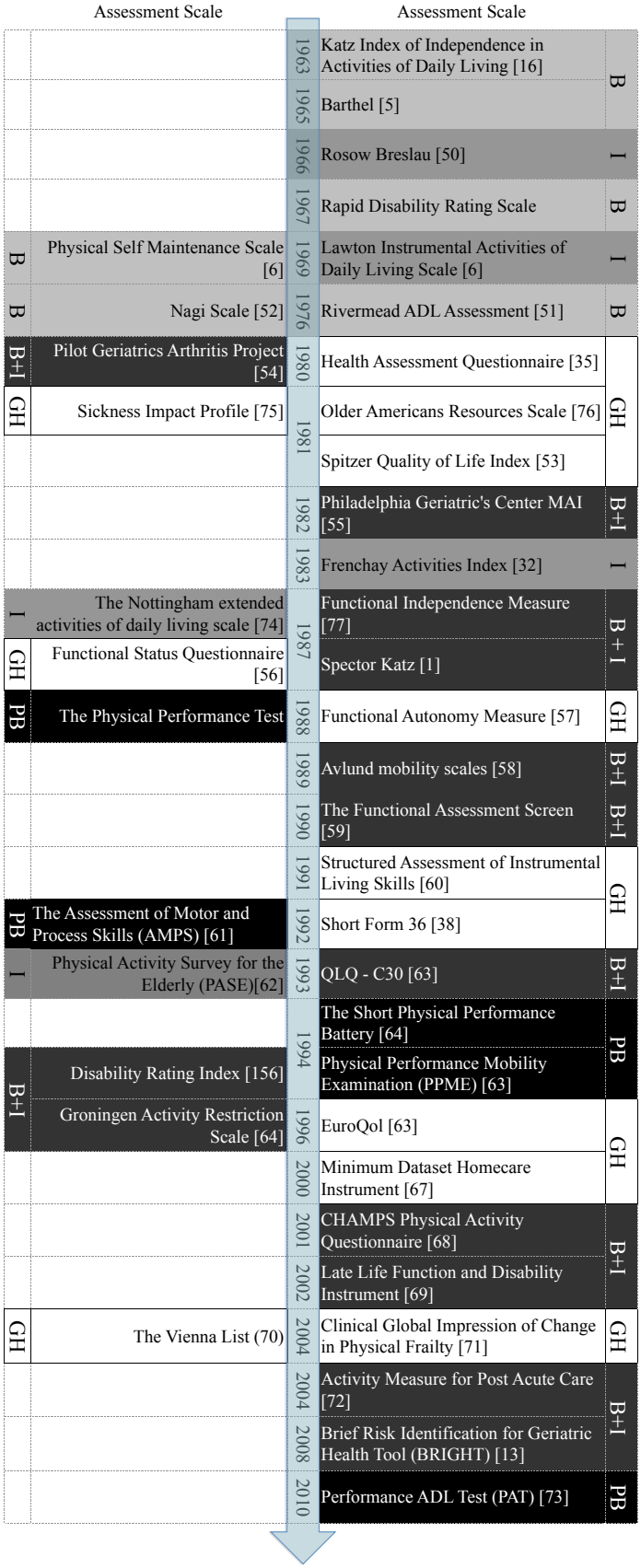

Figure 2.1: ***Timeline of assessment instruments***

Characteristic	ADL			IADL			Global Health				Combination		
	Katz ADL Index	Barthel Index	PSMS	Lawton	FAI	NEADL	HAQ	SIP	OARS	SF-36	Spector	FIM	GARS
Bathing	X	X	X				X	X	X	X	X	X	X
Continence	X	X	X					X	X			X	
Dressing	X	X	X				X	X	X	X	X	X	X
Feeding	X	X	X			X	X		X		X	X	X
Grooming		X	X						X			X	X
Toileting	X	X	X				X	X	X			X	X
Walking		X	X										
Wheelchair Use		X	X										
Ascend/Descend Stairs		X				X	X	X		X		X	X
Food Preparation				X	X	X			X				X
Gardening/DIY					X	X		X					
Get in / out of car						X							
Handling Finances				X		X		X	X				
Hobbies					X	X		X					
Housekeeping				X	X		X	X	X				X
Laundry				X	X	X		X					X
Paid Work					X		X	X		X			
Reading Books					X	X							
Responsibility for medication				X					X				
Shopping				X	X	X	X		X		X		X
Social Outings					X	X							
Transport				X	X	X			X		X		
Walking Outside					X	X	X	X	X	X		X	
Washing Up					X	X							
Activity							X	X	X				
Alchohol Consumption									X				
Anxiety about health								X					
Assistive Devices							X		X				
Bending/Kneeling							X						
Carrying Objects							X						
Cognitive Health								X	X			X	
Confinement								X					
Confusion								X					
Current ill-nesses/disabilities									X				
Dexterity								X					
Economic Resources									X				
Emotional Health							X	X	X	X		X	
Grip							X						
Health Perception							X		X	X			
Irritability								X					
Living Situation									X				
Medical History							X		X				
Medications							X		X				
Nutrition								X					
Pain							X			X			
Reach							X						
Self imposed isolation								X					
Sexual Activity								X					
Sleep								X					
Social Difficulties (Emotional)							X	X		X			
Social Difficulties (Physical)							X	X		X			
Social Resources									X				
Socioeconomic standing									X				
Telephone Use				X		X			X				
Use of mental health services									X				
Use of services available									X				
Communication								X				X	
Mobility								X	X	X		X	X
Social Interaction												X	
Swallowing												X	
Transferring	X	X	X				X	X	X		X	X	X

Table 2.2: ***Different categories of assessment characteristics***

		Barthel	Katz
Reliability	**Inter Rater**	Shown to be good [27]	Shown to be excellent [28]
	Test-Retest	Shown to be good [29]	
	Internal		Shown to be excellent [28]
Validity	**Concurrent**		
	Predictive	Found to correlate with both mortality and clinicians' evaluation [30]	Predictive validity shown to be good
Responsiveness		Evaluated using three methods (16) - t-statistics, p-values and ROC curves. Shown to be responsive using t-statistic but not using p-value or ROC curve.	Conflicting reports on the responsiveness of the scale
Introduction	**Time**	Originally known as the Maryland Disability Index First Published in 1965 [5]	Developed in the 1950s and first published in 1963 [16]
	Reason		First study to introduce a formal scheme for the assessment of BADLs
Assessment Methodologies		Interview with patient, interview with proxy, self-report, performance based test.	Interview with patient, interview with proxy, self-report, performance based test.
Time taken to administer		5 mins > <20 mins	5 mins > <20 mins
Scoring		Patient is scored in each task as independent, needs help or dependent. Each category is given a different score.	Patients are scored as dependent or independent in each BADL
Significant Notes		Probably the most widely used scale for assessing BADLs. An extended version has been introduced assessing similar activities as the Functional Indepence Measure but using the Barthel scoring system. Extended version has shown better responsiveness than the original [30].	Established the field of functional assessment

Table 2.3: ***BADL assessment scales***

measure as is the case with both the Barthel index and the Katz scale. The validity and responsiveness of these scales suffer from significant floor and ceiling effects, meaning a large proportion of patients are either so low functioning that they score the minimum, or so high functioning that they score the maximum score. These instruments cannot distinguish between people's functional health once they go into these brackets. For example, it has been reported that, for an elderly population, between only 2% and 8% are shown to be dysfunctional on a BADL scale **(author?)** [1]. Therefore, assessing BADL's will give an adequate assessment for only a small portion of the population.

2.3.2 Instrumental ADLs

To combat the ceiling effects of BADL instruments, Lawton et al introduced the concept of Instrumental ADL (IADL) [6]. IADL assessments were designed to measure a person's capacity to perform more complicated tasks both in the home and in the community. As shown in Figure 2.2, a person's ability to perform IADLs usually decreases before their BADL capabilities decrease. Though the person may be at too high a level of functioning for any functional deficits to be shown by a BADL scale, deficits may appear in a higher-level IADL. IADL assessments may also flag an oncoming degradation in functional health before a BADL instrument can. Again the two most published IADL instruments in the search results are outlined here in Table 2.4.

2.3.3 Global Health Instruments

Assessing a person's ability to perform IADLs was a useful method of gauging their role and status in the community and the home. However, it did not give the full picture of the person's health. This led to the integration of functional assessment measures into larger multidimensional "global health" instruments. These instruments not only measure a person's ability to perform everyday tasks, they also examine the person's mental capacity, emotional wellness, social involvement and several other characteristics. However, these instruments contain functional assessment sections so are included in this review. These tools tend to assess far more characteristics about a person's health, and often, these characteristics are assessed by numerous questions. While this leads to a more in depth, comprehensive assessment of the person's health, it requires significantly more time to administer than the previous BADL and IADL. The extent of these

		Lawton	Frenchay Activities Index
Reliability	**Inter Rater**	Good - correlation coefficient of 0.85 [6]	
	Test-Retest		Poor reliability when tested with Bland and Altman tests [29]
	Internal		Good [29]
Validity	**Concurrent**	Significant correlation ($p<0.05$) with the Physical Classification (6 point rating scale of functional health rated by a physician based on a complete medical history, physical exam and laboratory studies), Mental Status Questionnaire (10 item test of orientation and memory) and the Behaviour Adjustment rating scales (6 point scales measuring intellectual, personal, behavioural and social adjustment)	Moderately correlated with both the Barthel Index and the Sickness Impact Profile with Pearson's correlation co-efficient of 0.66 and 0.14-0.73 respectively
	Predictive		
Responsiveness			Less responsive than both the Barthel Index and the Functional Independance Measure in a population with lateral sclerosis
Introduction	**Time**	Introduced in 1969 [6]	Introduced in 1983 [31]
	Reason	First scale to introduce the notion of Instrumental Activities of Daily Living (IADL) [6]	Focuses on the pre-morbid lifestyle of patients. Hypothesis is that because a person's reduction in ability is often gradual, the patient may describe the activities they have done for years, though they may not have performed these activities for some time. This can lead to overestimation of rehabilitation goals after a traumatic event
Acceptability		Instrument takes between 10 and 15 minutes to administer [32]	
Scoring		Sections have between between 3 and 5 levels of dependence, each with a corresponding score	
Significant Notes		Despite widespread use, performance properties have not been extensively examined	Authors make the point that BADL scales may evaluate a person's capacity for self care rather than representing the actual activities they typically perform. Aim of this tool is to assess a persons lifestyle instead of their functional capability

Table 2.4: ***IADL assessment scales***

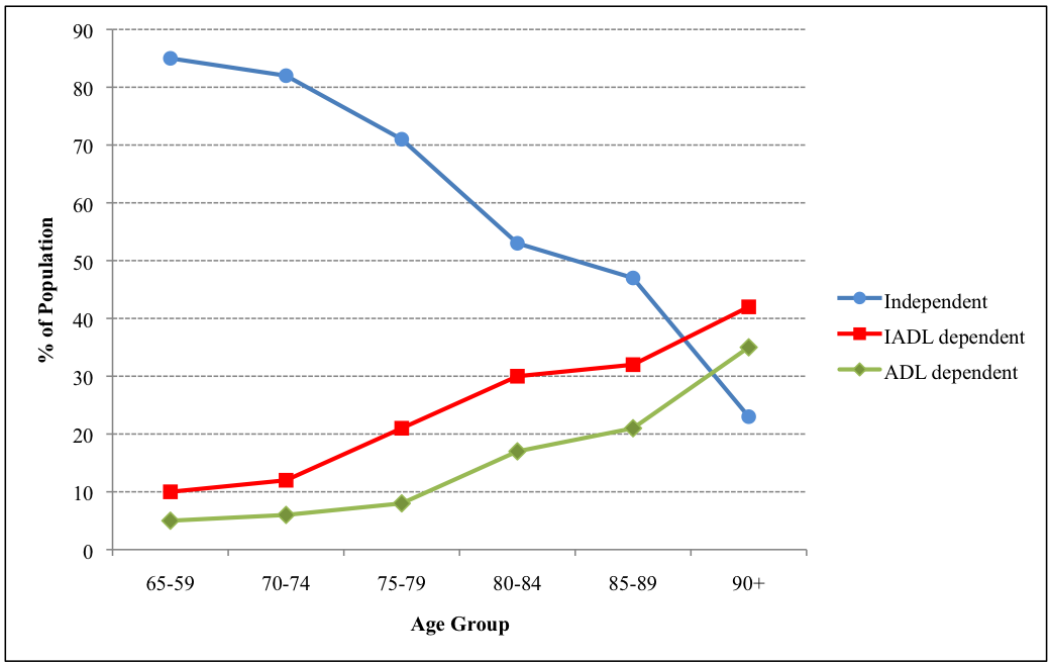

Figure 2.2: ***Hierarchical relationship between ADL and IADL (adapted from [1])***

instruments in comparison to BADL and IADL tools can clearly be seen in Table 2.2. Once again, the most published global health instruments from the search in this review are outlined in Table 2.5.

2.3.4 Expanded IADL + BADL Instruments

In recent times, the trend of functional assessment has moved towards a combination of basic ADL assessment and IADL assessment. These scales often incorporate other areas of health, as are featured in global health scales. However, they are less in depth, and more acceptable for everyday use. These scales do not contain any completely new concepts, they simple merge previously introduced concepts into single scales and so are not discussed in any further detail here.

2.3.5 Performance Based Functional Assessments

Assessments based on observation of the performance of specific tasks have also been introduced. These tests may include performing ADL tasks such as eating or walking and generate a functional assessment score, or as in the case of the TUG (Timed Up and Go) test generate a score that has been used as a measure of function in the literature. These tests require the health care worker to be

		Health Assessment Questionnaire (HAQ)	The Short Form 36 (SF-36)
Reliability	**Inter Rater**		
	Test-Retest	Correlation coefficient of 0.87 - 0.99	High using Bland and Altman tests [33]
	Internal	Good [34]	Good for all sections except social functioning [33]
Validity	**Concurrent**		Validity has been examined in comparison to the Nottingham Health Profile [33]. SF-36 distinguished between different demographic groups as expected.
	Predictive		
Responsiveness		Using standardised effect sizes, the HAQ-DI was shown to be more responsive than the WOMAC physical function scale (Western Ontario and McMaster Universities index of Osteoarthritis, a scale for the functional assessment of people with osteoarthritis of the knee or hip joints) in assessing disease progression for people with osteoarthritis [35]	SF-36 was shown to be responsive when tested with people who had one of four common conditions - back pain, menorrhagia, suspected peptic ulcer and varicose veins [36]. Responsivness has also been shown to equal that of the Sickness Impact Profile (a much longer global health measure)
Introduction	**Time**	Originally known as the Arthritis Assessment Questionnaire. Introduced in 1980 [34]	Introduced in 1992 [37] as on of several iterations in the development of the this tool
	Reason	Introduced because authors felt that any existing measures had not been adequately validated, were not sensitive enough and, due to time and training requirements, were not acceptable [34]	Designed to bridge the gap between lenghty global health instruments and the more coarse assessments available at the time
Assessment Methodologies			Interview with patient, interview with proxy, self-report.
Time taken to administer			~ 5 minutes
Scoring			
Significant Notes		Shorter "two page" version has been developed containing only the HAQ-disability index, the visual analog pain scale, and the visual analog global health scale.	Probably the most acceptable and valid of the global health measures discussed in this review

Table 2.5: ***Global health assessment scales***

present and to watch the person physically perform the tasks. However, results from these tests can still be compared to the results of questionnaire-based assessments and so these tests must be considered in any review of the evolution of the field. These functional assessments can avoid the error, due to biased answers or poor recollection, which can be present in questionnaire-based assessment. However, performance assessments can represent the person's capacity to perform a task to the best of their ability at the time of the test rather than their typical everyday performance of the tasks. Two of the most widely studied performance based tests are outlined in Table 2.6.

It should be noted that several of the questionnaire-based assessments discussed in Sections 2.3.1-2.3.4 are often implemented as performance based tests also **(author?)** [44], incorporating both the advantages, such as removal of bias, and disadvantages, such as labour costs, seen with the tools discussed in Section 2.3.5.

2.3.6 Evaluation of Categories of Assessment

Several of the existing instrument's characteristics have been rated using the method described in Section 2.2.3 and presented in Table 2.7. This table shows the performance properties of each of the five categories of assessment with the aim of outlining the strengths and weaknesses of each category. Concurrent validity is good across all five categories though it improves in the more in depth global health and combination scales. Predictive validity is not widely studied, however for those that have been shown, as with concurrent validity, predictive validity has also shown to improve for the longer Global Health and Combination of BADL + IADL scales over that in the short BADL scales. Internal, inter-rater and test retest reliability has been shown to be excellent across all categories in almost all scales assessed. As with the validity of the scales, responsiveness is shown to improve in the more detailed assessment scales with the global health scales performing best. This poorer performance of the shorter BADL and IADL scales could be due to the floor and ceiling effects that are experienced with these scales. Performance based tests show good performance properties, however, their reduced acceptability is clear. While the performance properties of the longer scales have been shown to be better, this comes at a cost of acceptability. The Global Health scales are the best performing assessments however they are the least acceptable. The combination of BADL + IADL scales maintain some of

		The Physical Performance Test (PPT)	**The Timed Up and Go Test (TUG)**
Reliability	**Inter Rater**	Excellent [38]	Excellent [39]
	Test-Retest	Excellent - interclass correlation coefficient of 0.895 [40]	Excellent [39]
Validity	**Internal**	Excellent [38]	
	Concurrent	PPT has shown high correlations with the Rosow Breslau scale (6 item questionnaire assessment of functional health of older peopler focusing on IADL activities) as well as several other BADL and IADL items [38]	Correlates poorly with Groningen Activity Restriction scale. Correlates moderatly to only two of the six subscales of the Sickness Impact Profile 68 [41]
	Predictive		Not predictive of length of stay in hospital (36) or of falls [41]
Responsiveness			Shown to be sensitive to change when applied to group data using standarised response means and responsiveness index. When applied to individuals, TUG shown not to be responsive [42]
Introduction	**Time**	One of the earliest physical performance assessments of functional ability, introduced in 1988 [43]	Introduced in 1991 as a modification to the original "Get up and go" test [44]
	Reason		Introduced to improve upon "get up and go" test
Acceptability		Requires observation of participant while performing activity	Requires observation of participant while performing activity. However, has the advantage of being one of the most straight forward of the performance based measures
Scoring		Patient is timed while performing nine tasks. Each task is given a rating of between 1 and 4 depending on how much time is taken to complete the task	Patient starts from sitting, walks three meters, turns, walks back to the chair and sits again. The time taken is the outcome of this test
Significant Notes		One of the first performance based tests of function	Test is a measure of mobility. Has been validated as a functional assessment tool. Very widely used in clinical practice

Table 2.6: ***Performance based assessment scales***

the better performance properties of the Global Health scales but are also more acceptable.

2.4 Discussion

This review has outlined the development of several influential instruments in the advancement of the assessment of functional health. A literature search was performed to compile a list of the assessment scales used to assess function. The list of instruments was extensive, with several tools included that overlapped with those already available. In fact, even in the early stages of functional assessment there had already been several instruments introduced that may not have added any significant value to the field. This was emphasised by Lawton et al. in their introduction of their IADL scale in 1969, just six years after Katz et al. published the first formal ADL assessment – "The present state of the trade seems to be one in which each investigator or practitioner feels an inner compulsion to make his own scale and to cry that other existent scales cannot possibly fit his own setting." [6]. In this review, the existing instruments were studied to build a picture of the important points in the evolution of the field. Using the knowledge gained in this process, the most relevant, widely used, studied and influential instruments were chosen for review.

2.4.1 Assessment Methodologies

Among all of the functional assessment instruments discussed, there are several different assessment methodologies used to administer the tests. As shown in Tables 3-6 some scales can be administered in several different ways. This is a significant advantage in the acceptability of the tools. The reason behind the assessment as well as the resources available will largely dictate which methodology is best and, in some cases, which instrument is used. There are three different methodologies used to administer functional assessment instruments: Self or proxy completed questionnaire, patient or proxy interview and performance based assessment. A proxy is a person in the patient's life, such as a relative or caregiver, who is in a position to answer questions on their behalf. A self or proxy completed questionnaire is a list of questions, which either the patient or a proxy will fill out using any of several possible responses. An interview consists of the clinician speaking to the patient or proxy directly. Finally, performance based

Assessment Tool		ADL			IADL			Global Health			Combination			Performance		
		Katz Index	Barthel Index	PSMS	Lawton IADL Scale	FAI	NEADL	HAQ	SIP	SMAF	SF-36	Spector	FIM	GARS	PPT	PPB	TUG
Reliability	Inter Rater	4	4	4	4	3	-	-	4	4	-	-	4	-	4	-	4
	Test - Retest	-	4	-	-	2	4	4	4	4	4	4	4	-	4	4	4
	Internal	4	-	4	-	4	4	3	4	-	4	2	3	4	4	-	-
Validity	Con - current	-	3	3	3	3	2	4	3	4	4	-	4	4	3	3	2
	Predictive	3	3	-	-	-	-	4	-	-	4	4	4	4	-	2	1
Responsiveness		-	2	-	-	1	1	3	2	2	4	-	2	2	-	3	2
Acceptability		2	4	-	4	3	4	4	1	1	2	-	2	4	1	1	2

Table 2.7: ***Instrument performance properties***

assessments consist of the patient performing certain tasks under direct observation. In all of these cases there can be two sub-sections: quantitative or subjective assessments. Quantitative assessments have a definite answer e.g. the Timed Up and Go test measures the amount of time taken to walk a certain distance and back from sitting. Subjective assessments, e.g. the barthel index, rely on the person administering the test's judgement of the patient's performance or answer e.g. "How do you dress in the morning?" or rating the person's ability to walk up stairs. The resources required for performance or interview-based tests are not always available. For instance, in an epidemiological study, it may not always be feasible to interview a large number of participants with a tool like the Health Assessment Questionnaire. In that case a self or proxy completed report administered through the mail such as the Short Form-36 may be a more suitable option. As for the accuracy of the different methodologies, there are differing opinions. Research has shown wide variations in the correlations between self report and performance based measures [45, 46, 17]. Proponents of the self-report or interview methods argue that performance based tests demonstrate capacity of the patient in the ideal "best scenario" rather than typical performance. Those whose prefer performance based tests argue that the accuracy of the self-report measures are effected by the cognitive status or depressed mood of the patient [17] as well as a bias towards appearing higher functioning so that they can remain independent. In reality, both methodologies provide strengths and weaknesses. For a detailed comparitive review of self report and performance measures see [17].

2.4.2 Validation of Assessment Instruments

Table 2.7 shows that concurrent validity is a widely used measure used to test the validitiy of a scale, with almost all of the tools in this review having had concurrent validity reported. The concurrent validity of an instrument is designed to check whether the scale is actually assessing what it intends to. By comparing it to an existing "valid" scale and achieving a high correlation, the new scale is considered concurrently valid. However, this concurrent validity should be treated with caution. Often the existing scale has only been shown to be concurrently valid against a previously validated instrument. Because this previously validated instrument may also have only been concurrently validated against another scale there is a risk of a propagation of significant error. It is likely that the correlation

shown between measures was not one hundred per cent. Though the error observed may have been small, it will grow as each new assessment is validated against it and both incorporates this error and adds to it. Concurrent validity can still be considered a useful and easy way to investigate an instrument's validity. However, the weaknesses of this method should not be overlooked and other methods of validation such as predictive validity should also be evaluated where possible. Table 2.7 shows that while predictive validity has been reported for several of the tools in this review, it has not been shown to the extent that concurrent validity has. This is possibly due to the much larger trials required to prove predictive validity than are necessary for concurrent validity.

2.4.3 Selection of Functional Assessment Tool

It is clear that selection of a functional assessment instrument should be based on several criteria. The properties outlined in Table 2.7 should be taken into consideration to decide whether the scale performs sufficiently. However, the specific scenario in which the tool is being applied must also be considered. The type of patient (e.g. healthy older adult, frail older adult, sick older adult, sick younger adult) and the evidence of use of this tool with this patient group should be taken into account. The setting in which the assessment is to be performed is also relevant. For example, a patient who is being assessed in a clinical setting may be better suited to a different assessment tool to one who is to be assessed in his or her own home. Finally, the aim of the assessment (planning of care, screening, epidemiology) should be considered when choosing a tool.

2.4.4 Trends in Functional Assessment: the Role of Technology

We have described the significant changes that have occurred in the field of functional assessment. The state of the art has ranged from using short, quick assessments of the most basic ADLs required to survive in society, to comprehensive "global health" assessments that incorporate functional assessment but which also assess several other areas of health. However none of the shifts reflect the massive improvements in the resources available to medical workers made possible by the advancement of information and communications technologies. In the past few decades, there have been instances of administering these tools over the phone and the Internet [47]. This saves on human resources, and allows for frequent assessments. However, the advancements in technology, both in com-

munications and in sensor technology, have yet to be fully integrated into the functional assessment methodology. Even the most rudimentary integration of technology may provide huge benefits for functional assessment, both in terms of cost to the physician or specialist who perform the assessment, and from a policy standpoint in terms of both cost and effectiveness of the assessment and subsequent intervention. As a starting point, simply providing a physician the option of using an electronic version of the questionnaire form opens up several data management possibilities. Maintaining and tracking patient records are made much more convenient and trends in functional ability can be flagged without the need for the physician to study the individual data from each assessment in depth. Wireless data collection devices, including smart phone technology, are also beginning to be utilised. Questionnaires can be filled out and saved all on a smart phone device. This allows for all the same data management advantages as simple electronic versions of the questionnaires, while adding the advantage of portability. Health care workers can travel to patient's homes with all of the material necessary to carry out a functional assessment in a phone as well as the patient's functional assessment records. A smart phone could also provide tools such as a stop-watch as used in the Physical Performance Test. This further simplifies the job of the assessor as all tools and data collection can be kept in a single tool and semi-automated. Alternatively, a patient could remotely fill out electronic versions of the forms. For example, a tool that currently is sent out in the mail such as the Short Form 36 could be sent electronically to a person's phone. The person could complete the form and send back the answers all in a very short space of time and with minimal cost. While these examples are currently the forefront of the integration of technology into functional assessment, the issue lies more with development of supporting systems rather than lack of technological capacity. And with technological capabilities rapidly expanding, and costs decreasing, the question of how new technology can be utilised in the future to aid in functional assessment must be asked.

2.4.5 Technologies with Possible Applications for Assessment

Each method of assessment discussed in Section 2.4.1 presents its own strengths and weaknesses from inaccuracy due to bias in answers or unrealistic performance scenario to acceptability issues. Technology may provide different levels and types of assistance depending the assessment methodology being imple-

mented. When integrated to quantitative self-report or interview assessments, technology may remove the bias involved by directly measuring parameters rather than depending solely on the patient's recollection. For example, rather than asking how often a person has undertaken travel outings or car rides in the last month as in the Frenchay Activities Index, the person could be asked to carry a small gps sensor or phone in their pocket. This sensor could detect and monitor travel outings or car rides directly. With regards to subjective interviews data from technological systems may provide an aid to the clinician, informing their opinion. For example in the Health Assessment Questionnaire, the person is asked if they can ascend five stairs. Data from a simple sensor in a shoe could report whether the person has walked up steps in the last six months. If the patient has not ascended stairs lately, but was able to the last time they tried, they may be inclined to say they can perform this activity. This phenomenon of patients reporting abilities that they possessed a relatively long time ago was mentioned in the development of the FAI [31]. Having a quantitative measure such as this could significantly affect a clinician's opinion. Likewise with performance-based assessments, technology may provide quantitative assessments, where as subjective assessments could be assisted by the measured data e.g. the person's balance when standing up from a chair may be measured with a kinematic sensor and may inform the clinician's opinion on how well a person transfers as is asked in the barthel index. In any of these cases, technology may have the potential to improve accuracy, repeatability and acceptability, either reducing or eliminating significant amounts of work involved in performing functional assessments. One current trend in technology that could be useful in the area of functional assessment is the area of gaming systems utilising motion input. These are off-the-shelf systems such as the Nintendo-Wii and Microsoft-Kinect. These systems allow for the precise measurement and tracking of detailed movements, giving the ability to encourage a wide range of both upper and lower body movements through visual games. Custom software designed for use by older adults could be used both to perform functional assessments and to encourage activities and movements in which the person has shown a weakness. For example, these assessments could occur in monthly visits to a medical center under the supervision of staff with minimal training requirements. The health assessment questionnaire asks whether a person can bend down and pick up clothes from the floor. Using these technologies, functional reach like this could be assessed accuratly and repeatedly measuring the person's ability and the difficulty in their range of

movement. Another area in which there is a large and rapidly increasing body of research is the use of sensor technology for long-term monitoring of a person's energy expenditure and activity levels. These systems come in several forms with a wide range of designs. Some require the user to wear body sensor networks on their person [48]; others involve installing ambient intelligence in the home that monitors the inhabitants autonomously [49]. These systems vary in success but there are several reliable and affordable systems available. In practice, patients could be asked to keep a sensor device in their pocket. During their next visit to a doctor, the clinician could review the person's functional assessment data through an online interface informing their interview with the patient. Yet another commonly available technology is a balance board like the commercial Nintendo Wii balance board that could be used to perform detailed balance tests. Utilising technologies such as those mentioned in this section could allow for functional assessments to contain new and different technological inputs. This type of functional assessment could allow for the build up of detailed models of functional health for individual people. These models could be used to detect a degradation of function long before it may be caught with the systems that are currently in place.

2.4.6 Challenges involved in Developing Functional Assessment Technology

Though significant advancements in technology have led to the point where technology could be integrated to the considerable advantage of the field of functional assessment, the task of assessing functional ability through technology should not be underestimated.

Patient acceptance: The acceptability of technology to older adults must be taken into account. Technological interfaces must be designed in a simple and easy to use manner. The advantages of using the technology must also be made clear so that the person is motivated to comply. Providing feedback to the person may also increase motivation.

Assessor issues: The advantages to the careworker must also be clear. If the use of the technology is a more valid or accurate tool than existing solutions, this should be clearly proven. Likewise if the tool provides an assessment of equal

worth but with fewer resources required, this should be shown clearly.

Validation: Any new tool for use in functional assessment must be extensively validated. Parameters that were not possible to assess using questionnaires, such as gait characteristics or detailed data about balance, may lead to new types of assessment that may be more valid and more responsive to change than those available today. For these tools to be accepted into widespread clinical practice, the use of technology must be validated thoroughly. While concurrent validity can be tested as a useful and easily carried out initial validation, measures should also be validated against more definite criteria such as clinician's diagnosis and the validity of the measure as a predictor of functional decline. The advantages of the addition of this tool to the field of functional assessment should be clearly outlined. Where possible, the data generated by a piece of technology should be input into an existing functional assessment framework rather than creating a completely new scale. This will allow for comparability between results as well as encouraging widespread use of scales, which, hopefully could result in the development of gold standard scales.

2.5 Conclusion

A significant problem in the adaption of effective methods of functional assessment has been the saturation of the area with different instruments. The multitude of instruments available has led to few of their performance properties being extensively evaluated to the point where they can be considered a gold standard. A weakness of the field which was uncovered during this review was the method in which some instruments are tested. Instruments should be tested against some criteria other than existing tools, such as clinical evaluation or predictive validity before they are accepted and used with the general public. Significant points in the evolution of the field have been outlined: the introduction of BADL scales, IADL scales, Global Health scales, Combination scales and Performance Based Tools for functional assessment. With the current expansion in technology suitable for use in functional assessment, the authors feel that another significant point in this evolution is upon us. With this in mind, this review has sought to give some clarity to the development of the field so that the development of new tools are informed by the extensive work that has been carried out in the last fifty years. Going forward it is important that as technology is inte-

grated into the system, new measures are comprehensivly evaluated and put into widespread use, and that new systems are not introduced without clearly proving their contribution to the field.

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Chapter 3

Monitoring Human Health Behaviour in One's Living Environment: A Technological Review

Submitted as:

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3.1 Introduction

It has been found that low to moderate home and leisure based physical activity reduces the risk of coronary artery disease, congestive heart failure, peripheral vascular disease and chronic obstructive pulmonary disease [79]. Higher levels of daily physical activity are associated with less disability in older adults [80] and have been shown to prevent functional decline in old age [79]. It has also been reported that people with better physical function and who reported higher levels of physical activity perceived higher feelings of well being [81, 82]. Physical activity positively effects other aspects of mental health such as positive mood and lower levels of anxiety and depression [82]. Physical activity also has significant beneficial effects on obesity [83]. In fact, Warburton et al. reported a linear relationship between physical activity and health [83].

With the vast range of evidence in support of the benefits of physical activity, it is unsurprising that the measuring of physical activity has become an active research area. In fact even outside of the research domain, "activity monitors" have gained widespread traction with the general public as part of the "Quantified Self" movement. Quantified self describes the process of an individual participating in the collection of detailed data about a certain aspect of a their life in order to help them engage with that aspect. By collecting and presenting detailed data regarding the person's physical activity patterns, a person can act on these data to increase their activity levels. For example, if a person sees that they are far less active in the evenings they may be more likely to try to change this behaviour.

While presenting physical activity data to the user can help them to engage with their physical activity levels, it does present quite an incomplete picture of the behaviours that act as the source of their physical inactivity. With the introduction of minaturised and inexpensive sensing technologies the possibility has emerged to design activity monitoring systems with the ability to obtain far more data regarding a person's performance of activities of daily living. This richer, more in depth data has opened the possibility of expanding on data relating to physical activity and presenting data regarding the person's behaviour. This represents a significant paradigm shift in the field. These enhanced "behaviour monitors" have the ability to not only present quantified physical activity data, but to contextualise these data and to provide the user with detailed indicators as to the source of physical activity or inactivity.

The behaviour monitored by these enhanced devices can contain several different parameters that alone may not expand on physical activity data significantly but when combined provide a useful picture of the person's behaviour. These different aspects of behaviour can be seen in Figure 3.1. It can be seen in this block diagram that physical activity data forms one aspect of behaviour as monitored by behaviour monitors but it is not the main focus. The context in which the activity is performed, the activity of daily living which is the source of the activity (e.g. housework or walking to work) and even direct measurements of physical exertion can also form aspects of behaviour in these monitors.

A wide range of technologies have been used to detect and monitor events related to these aspects of behaviour. These varied approaches to behaviour monitoring using different technologies can make it difficult to decide on the optimal approach for a given application. Sections 3.2. and 3.3. of this paper will review these technologies and their use in performing behaviour monitoring in each aspect of behaviour shown in Figure 3.1. The aim of this review is to provide a resource to help in the decision of which approach should be used for a given application.

3.2 Technologies used in Behaviour Monitoring

In order for behaviour monitors to expand on the data generated by activity monitors, wider and more in depth data must be collected regarding the activities of daily living a person performs. In recent years, with the widespread introduction of MEMS technology, sensors have become miniaturised and inexpensive enough that it is feasible for a behaviour monitor to contain a range of sensing technologies. This section will review several of these technologies and the relevant parameters that must be considered if they are to be integrated into a system.

3.2.1 Inertial Sensors

3.2.1.1 Accelerometers

Accelerometers are used to measure acceleration. They were first developed in the early twentieth century as a method of measuring vibration on large structures such as bridges and buildings [84]. Their inclusion in airbag deployment systems is widely credited for their reduction in cost and ease of use leading to

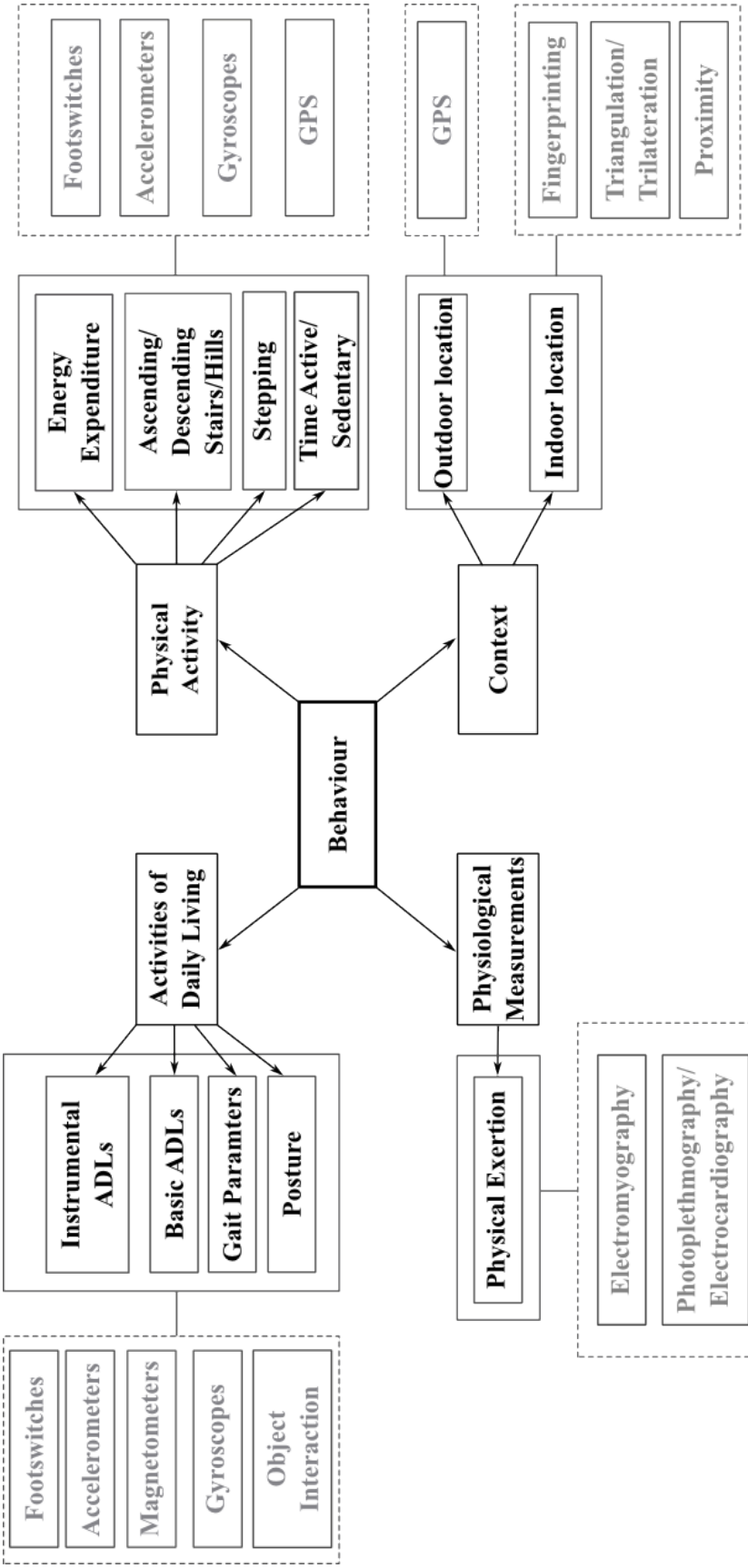
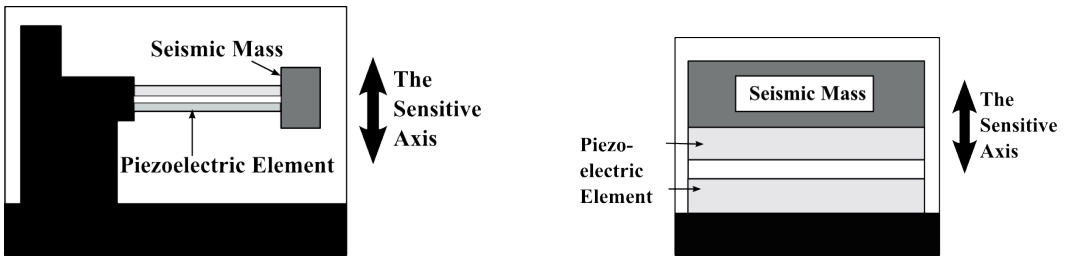


Figure 3.1: ***Block diagram showing aspects of behaviour as monitored by "behaviour monitors" and the technologies used to monitor each aspect.***



(a) ***Cantilever beam accelerometer*** **(b)** ***IC chip accelerometer***

Figure 3.2: ***Piezoelectric accelerometers***

the rapid expansion in their use. Modern accelerometers suitable for use in human activity monitoring can broadly be divided into two categories of technology each of which is described in this section.

Piezoelectric accelerometers are made in two different configurations: Cantilever beam accelerometers, also known as piezoresistive or strain gauge accelerometers (shown in Figure 3.2a.), contain a seismic mass suspended at the end of a piezoelectric element. As acceleration is experienced in the direction of the sensitive axis, the element experiences a deformation in the form of bending. This causes a charge to build up at the end of the piezoelectric element. The compression based piezoelectric accelerometer, shown in Figure 3.2b., relies on a similar principle. However, in this case the seismic mass is positioned on top of the piezoelectric element. This causes the element to be compressed when acceleration is experienced in the relevant direction, again causing the build up of charge at the end of the piezoelectric material.

Capacitive accelerometers have in recent years become the most widely used type of accelerometer due to their ease of use, reliability and lack of temperature calibration requirements. With the advent of MicroElectroMechanical Systems (MEMS) technology, capacitive accelerometers have become miniature and inexpensive enough to be integrated into a huge range of electronic devices such as smart phones, cameras and gaming systems. MEMS technology revolutionised the use of accelerometry in electronic devices. Capacitive accelerometers again contain a seismic mass that is suspended between fixed anchor "arms" as shown in Figure 3.3.

While in equalibrium,the floating arms of the seismic mass are separated from the fixed arms by a distance d as shown in Figure 3.4a. As the sensor experiences

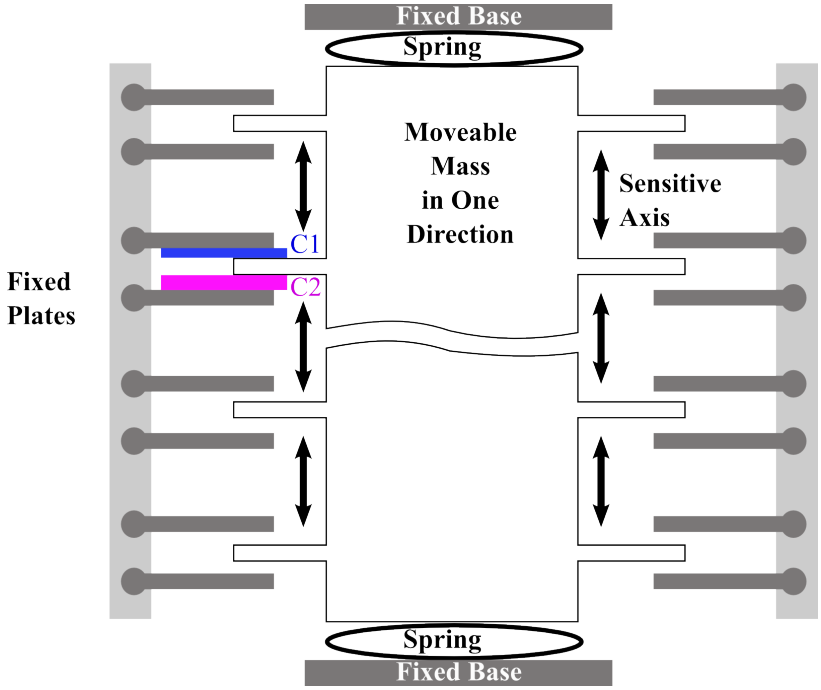


Figure 3.3: ***Structure of MEMS capacitive accelerometer showing floating mass and fixed arms***

acceleration, the floating mass changes position causing the distance between the floating and fixed arms to change (3.4b.). This change is distance results in a corresponding change in capacitance that when measured can give a measurement for acceleration. The relationship between the capacitance at the plates and the displacement of the sensor can be demonstrated as follows. The general equation for capacitance is:

$$Co = \epsilon_0 \epsilon \frac{A}{d} = \epsilon_A \frac{1}{d} \tag{3.1}$$

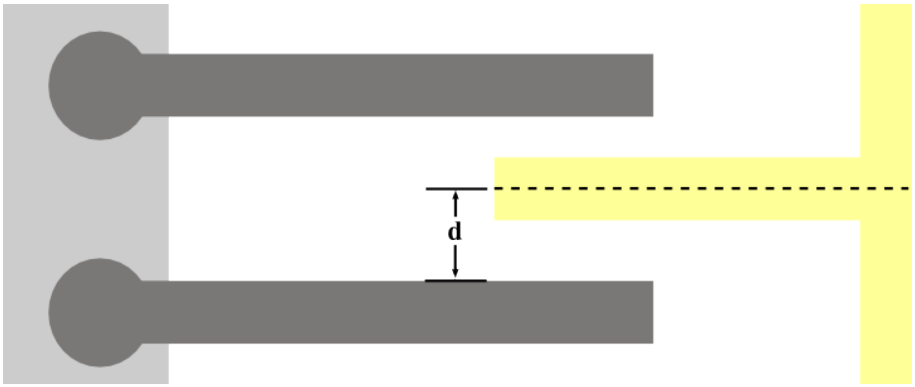
where A is the area of the electrodes, d is the distance between them, ϵ_0 is the permittivity of the material separating them and $\epsilon_A = \epsilon_0 \epsilon A$. Separating the equations to C_1 and C_2 i.e the capacitances of the plates above and below the floating arm we get the following equations:

$$C_1 = \epsilon_A \frac{1}{x_1} = \epsilon_A \frac{1}{d+x} = C_0 - \Delta C \tag{3.2}$$

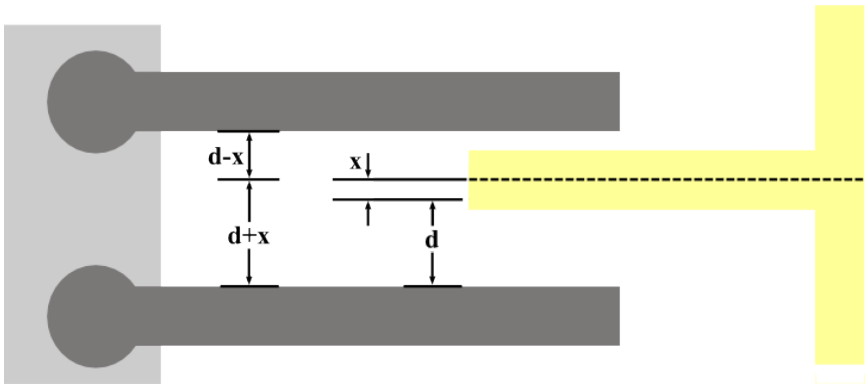
,

$$C_2 = \epsilon_A \frac{1}{x_2} = \epsilon_A \frac{1}{d-x} = C_0 + \Delta C \tag{3.3}$$

where x is the mass displacement, x_1 and x_2 are the corresponding displace-



(a) ***Equalibrium***



(b) ***Under acceleration***

Figure 3.4: ***Capacitive accelerometer in equalibrium and under acceleration. Shows displacement of floating arm caused by acceleration.***

ments to C_1 and C_2. If the acceleration is zero, then C_1 and C_2 are equal as x_1=x_2. If $x \neq 0$ the difference is capacitance is found to be:

$$C_2 - C_1 = 2\Delta C = 2\epsilon_A \frac{x}{d^2 - x^2} \tag{3.4}$$

The displacement x can be found by measuring ΔC and using the following formula:

$$\Delta C x^2 + \epsilon_A x - \Delta C d^2 = 0 \tag{3.5}$$

Simplifying this equation by eliminating the negligible $\Delta C x^2$ we are left with:

$$x \approx \frac{d^2}{\epsilon_A} \Delta C = d \frac{\Delta C}{C_0} \tag{3.6}$$

Therefore, the displacement x is approximately proportional to the capacitance difference ΔC.

Properties of accelerometers: Accelerometers are available in several different configurations. Depending on the application the following characteristics must be considered:

- *Range:* The full scale range of the accelerometer, usually expressed in g's, is a very important characteristic of an accelerometer. For example, in vibration monitoring applications a range of 2g is likely to be sufficient. However, in an exercise monitoring system a range of 2g is not likely to meet requirements. For example maximum acceleration experienced at the lower leg during running has been shown to be between 8g and 12g [85, 86]. The sensor could not provide any detailed information about the acceleration once it goes above 2g. Many sensors will allow the user a choice of ranges.

- *Sensitivity:* The sensitivity of an accelerometer is a measure of the ratio of change in the output signal to change in acceleration (input) often expressed in mV/g for analog sensors or Least Significant Bit g/(LSB) for digital sensors. The sensitivity of the sensor is often linked to the range with lower range accelerometers often providing a more sensitive measure than higher g rated sensors. An application for measuring vibration in a manufacturing line may require a very sensitive measure where as an impact detection system in a hard drive may not need this sensitivity.

- *Interface:* Accelerometers are available with analog and digital interfaces. Digital accelerometers are less susceptible to noise than their analog counterparts. Digital sensors can also be more power efficient than analog devices. This digital interface is usually implemented over SPI or I^2C.

- *Sensitive axes:* Accelerometers as shown in Figure 3.3. measure acceleration in a single plane. However, it is common for packages to contain two (bi-axial) or three (tri-axial) separate accelerometers installed orthogonally on a single die allowing sensing of acceleration in three planes.

- *Calibration:* Older accelerometers are susceptible to time related drift and temperature drift. These sensors require the implementation of complex calibration techniques and temperature compensation algorithms. However, the introduction of MEMS technology largely removed these requirements in modern accelerometers. These more modern sensors are reliable and do not experience significant drift over time [87]. Initial calibration is

Manufacturer	**STMicroelectronics**	**Freescale Semiconductor**	**Freescale Semiconductor**
Model	LIS331HH	MMA8452Q	MMA7361L
Interface	Digital	Digital	Analog
Range	+/-24g	+/-8g	+/-6g
Sensitivity	12mg/LSB	0.98mg/LSB	206mV/g
Bandwidth	500Hz	400Hz	400Hz
Noise Rating	$650\mu g/\sqrt{Hz}$	$99\mu g/\sqrt{Hz}$	$350\mu g/\sqrt{Hz}$
Package	3X3X1mm	3X3X1mm	3X5X1mm

*LSB = Least Significant Bit

Table 3.1: ***Typical accelerometer parameters***

still required to deal with the constant bias of the accelerometer however this calibration is comparably trivial.

- *Bandwith:* The maximum frequency at which the accelerometer can output data is an important consideration in many applications. Many common accelerometers will output data up to a rate of around 500 Hz as shown in Table 3.1. Higher bandwidths are available, however for the vast majority of applications including the monitoring of human movement this rate is more than adequate.

- *Noise rating:* Accelerometers will have a maximum noise rating often expressed as $\mu g/\sqrt{Hz}$. A common level of noise for a modern digital accelerometer is about $500\mu g/\sqrt{Hz}$ (Table 3.1) which is excellent for most applications.

- *Static/dynamic acceleration:* Several older accelerometers did not require an external power supply. These sensors relied on the accelerometer to generate its own current. A drawback of most of these sensors was their inability to detect static acceleration. Dynamic acceleration was required to generate the current necessary to measure acceleration meaning inclination could not be obtained from these sensors. However, the majority of modern accelerometers require an external power supply and can measure static acceleration.

Table 3.1. shows the operation parameters for some commonly used available accelerometers.

Set	Feature	Obtained by	
Direct features	**Raw axis output**	Direct output from accelerometer (V)	
	Axis acceleration	$g = \frac{V_x - Vo}{Vs}$	where: g is acceleration in g's, V_x is the raw output from the accelerometer, V_o is the voltage offset caused by the constant bias, Vs is the raw output from the accelerometer under gravity.
	Inclination	$\theta = \frac{180}{\pi} \cos^{-1}\left(\frac{a}{g}\right)$ [88]	where: a is acceleration from the sensor (m/s^2 or g*9.81), g is 9.81, θ is angle from the vertical for that axis
	Root Sum Square	$RSS = \sqrt{x^2 + y^2 + z^2}$	where: x, y, z are the accelerations on the xyz axes.
	Area under the curve	$A = \frac{1}{t} \times \left(\int \lvert x(t)\rvert + \int \lvert y(t)\rvert + \int \lvert z(t)\rvert\right)$ [89]	where: A is the integral of the magnitude of the signal from the three axes
Time domain features	**Mean**	$\bar{x} = \frac{\sum x_i}{N}$	where: N is the number of samples, x_i is the sample acceleration
	Median	The value separating the higher half of the values from the lower half	
	Variance	$\sigma^2 = \frac{\sum (x_i - \bar{x})^2}{N-1}$	
	Skewness	$Skewness = \frac{\sum (x_i - \bar{x})^3}{N\sigma^3}$	
	Kurtosis	$Kurtosis = \frac{\sum (x_i - \bar{x})^4}{N\sigma^4}$	
	Interquartile range	The range of accelerations when the top and bottom 25% are disregarded	
Frequency domain features	**Median frequency**	Using Fourier Functional Transform	
	Spectral energy	$\sum_1^n a_1^2 + a_2^2 + .. + a_{n^2}$	where: a is a co-efficient of the FFT
	Frequency domain entropy	$Entropy = -\sum p(X_i) \times log_2(p(X_i))$	where: X_i are the frequency components of the windowed time-domain signal for a given frequency band, p(X_i)are the probability of X_i [90]

Table 3.2: ***Accelerometer feature extraction shows some of the most commonly used accelerometer features for behaviour monitoring***

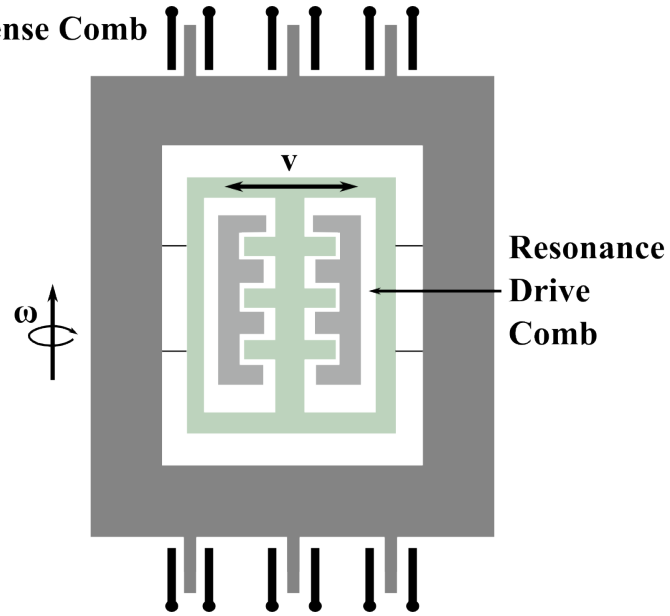


Figure 3.5: ***Layout of MEMS gyroscope showing resonance drive and coriolis sensing mechanism. The tines of the outer frame and the sense comb act as the "tuning fork"***

Feature Extraction: A large range of features have been extracted from accelerometers for use in behaviour classification algorithms. Preece et al provided an exhaustive description of these features [91]. A subset of the more commonly used features of accelerometer signals are described in Table 3.2.

3.2.1.2 Gyroscopes

Gyroscopes measure angular velocity and are often used in addition to accelerometers in applications where accurate monitoring of rotation is required. The vast majority of modern gyroscopes use vibrating mechanical elements to sense rotation. Modern gyroscopes can come in several different forms: 1) Vibrating Fork, 2)Vibrating Ring, 3) Piezoelectric Plate, 4)Laser Ring. Regardless of the technology, the measurement of rotation performed by gyroscopes relies on the Coriolos effect. Here, the operation of the most common MEMS gyroscope, the vibrating fork, will be used to demonstrate the operating principle. The layout of a common MEMs gyroscope is shown in Figure 3.5[92].

The Coriolis effect describes the apparent deflection of a moving object when viewed from a moving reference point. In a vibrating fork gyroscope, the two tines of the fork are vibrating at a high frequency in a given direction as shown in Figure 3.6. When the tines rotate, the Coriolis effect means that a force is expe-

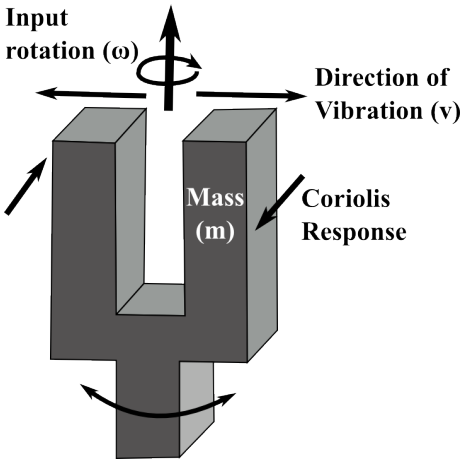


Figure 3.6: ***Gyroscope Coriolis Effect***

rienced on the tines in opposite directions. These forces are proportional to the angular velocity of the rotation. Equation 3.7. shows this relationship where F_c is the Coriolis force, ω is the angular velocity, m is the mass of the moving object and v is the linear velocity of that movement.

$$F_c = -2m(\omega \times \mathrm{v}) \tag{3.7}$$

Capacitive, piezoresistive or piezoelectric mechanisms can be used to quantify the movement of the opposing prongs relative to the plane of vibration and therefore the force involved (F_c) can be measured. Using this force, the angular velocity can be calculated as:

$$\omega = \frac{-F_c}{2 \times m} \times \frac{1}{V} \tag{3.8}$$

Properties of gyroscopes:

- *Range:* The range of angular velocities for which the gyroscope will correctly measure is important in the choice of a gyroscope. The maximum angular velocity is normally in the range of hundreds of $^o/s$. This range is usually sufficient for monitoring human movement. For example maximum angular velocity at the shank during walking is typically less than $200^o/s$[93]. However, the sensitivity of the gyroscope is closely related to the range, therefore the range should be chosen to best fit the application.
- *Sensitivity:* The sensitivity of a gyroscope is usually presented in LSB/$^o/s$ or

mV/$^o/s$ for digital and analog sensors respectively. For example a 15mV/$^o/s$ sensitivity means that for each change in angular velocity of $1^o/s$ the sensor output will change by 15mV. As with accelerometers the sensitivity of a gyroscope is inversely proportional to the range. This relationship is more pronounced with a gyroscope making the choice of the range particularly important. The range of the gyroscope should be chosen to be not much wider than the maximum required range for the application. The cross axis sensitivity, i.e. the measure of output seen on one axis when angular velocity is imposed on a different axis, of a typical modern digital gyroscope is generally < 2%.

- *Interface:* Digital gyroscopes are less common than analog sensors. However, they provide significantly decreased power consumption. Older analog gyroscopes used in the order of hundreds of mA current consumption. Modern digital sensors can require less than 10mA.

- *Sensitive axes:* Tri-axial gyroscopes have only recently become easily available at a reasonable cost with most newly introduced sensors now measuring three axes of angular velocity.

- *Calibration:* Temperature drift is a significant issue even with modern gyroscopes. For this reason, many gyroscopes will be shipped with on board temperature sensors. With these readings, temperature compensation algorithms can be implemented that largely overcome temperature drift. Calibration error is also a problem with gyroscopes meaning careful initial calibration is essential.

- *Bandwith:* The maximum frequency with which gyroscopes can generally be sampled at is much higher than that of accelerometers. Typical bandwidth for a gyroscope is in the range of several kHz. This bandwidth is more than sufficient for measuring the angular velocity of human movement.

Gyroscope error: Though accelerometers will contain many of the same sources of error as gyroscopes, these errors are much more pronounced when using gyroscopes due to their larger levels as well as the fact that integration of gyroscope signals is a very common method of feature extraction. With this integration any errors grow over time.

The simplest source of error from a gyroscope is the *Constant Bias*. This is the offset from zero when the gyroscope is not undergoing any rotation. This error grows linearly with time when integrated to calculate orientation, however, it is very easy to compensate for. The constant error is simply measured by taking a long reading from the gyroscope at rest and using the average of this reading as the constant bias. This constant ϵ can be simply subtracted from readings from the gyroscope.

Thermo-Mechanical Noise is a significant issue with MEMS sensors. Because MEMS gyroscopes contain such small moving parts, these small parts are susceptible to mechanical noise resulting from molecular agitation. It is common for manufacturers of gyroscopes to express the effects of this noise in Angle Random Walk (ARW) which shows how the noise effects the integrated signal. ARW is expressed in units of $^o/\sqrt{hr}$. For example if a gyroscope had thermo-mechanical noise of 0.2 $^o/\sqrt{hr}$, after one hour the standard deviation of the orientation error due to thermo-mechanical noise will be 0.2^o. After 2 hours the measurement of the orientation of the sensor through integration of the signal will be off by 0.28^o.

Bias drift describes the error introduced due to change in constant bias. This drift is expressed in terms of ARW and $^o/hr$ and is another source of error over time.

Temperature effects can also effect the constant bias level. These changes in bias can be compensated for with the installation of on board temperature sensors.

Calibration errors are accumulated in the integrated signal. For this reason correct initial calibration is of extreme importance. For a more comprehensive overview of error sources in gyroscopes see [94].

Table 3.3. shows the operation parameters for some commonly used available gyroscopes.

3.2.1.3 Magnetometers

Magnetometers are designed to measure magnetic fields. One of the most common applications of magnetometers is the use as a digital compass by measuring the earths magnetic field. Magnetometers are often based on the Lorentz force, which describes the force felt by a current conducting wire when in the presence of a magnetic field. The structure of a MEMS resonance based magnetometer is shown in Figure 3.7 [95].

Manufacturer	**Invensense**	**Invensense**	**Invensense**
Model	ITG-3200	IDG-500	IDG-1215
Axes	3	2	2
Interface	Digital	Analog	Analog
Range	+/- 2000^o/s	+/- 500^o/s	+/- 67^o/s
Sensitivity	14.375LSB/^{o}/s	2.0mV/°/s	15.0mV/°/s
Cross axis sensitivity	2%	1%	1%
Bandwidth	30kHz	24kHz	24kHz
Temperature sensor	Yes	Yes	Yes
Noise Rating	0.38 º/srms	0.8 mVrms	3 mVrms
Package	4X4X0.9mm	4X5X1.2mm	4X5X1.2mm

*LSB = Least Significant Bit

Table 3.3: ***Typical gyroscope parameters***

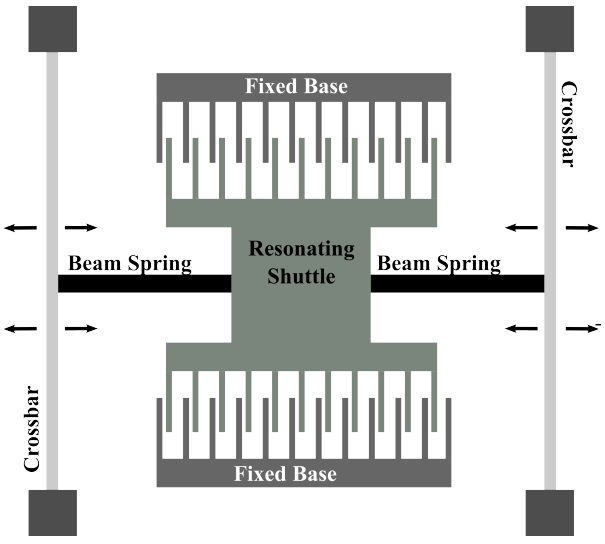


Figure 3.7: ***Resonance Magnetometer***

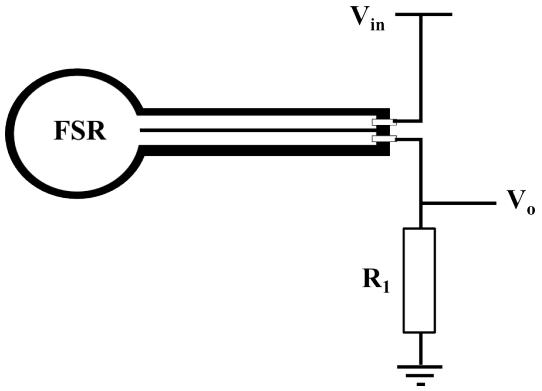


Figure 3.8: ***FSR voltage divider circuit***

The central mass called the shuttle is resonating. The crossbars connected to fixed points are conducting a DC current. In the presence of a magnetic field, a Lorentz force is felt on the crossbars which is then transferred to the shuttle through the beam springs. This force is proportional to the magnetic field experienced and alters the resonance of the shuttle. This change in resonance is detected by measuring the change in capacitance at the arms of the comb structure of the fixed base. This measured change can be used to measure the magnetic field which, when caused by the earth's magnetic field, can then be used to calculate direction.

3.2.2 Footswitches

Footswitches involve the installation of force sensors below the foot. By detecting changes in force at the sole of the foot during ambulation, several parameters related to gait including stance time, swing time and stride time can be monitored. The most common implementation of footswitches use Force Sensitive Resistors (FSR). FSRs act like variable resistors. Increased pressure on the surface of the FSR lowers the resistance as shown in Figure 3.9.

Footswitches take advantage of this resistance vs. force relationship by inserting FSRs into voltage divider circuits. When FSRs are used as part of a voltage divider circuit as shown in Figure 3.8., a measurement for the force exerted on the sensor can be generated at V_o described by the equation:

$$V_o = V_{in} \times \frac{R_1}{R_{FSR} + R_1} \tag{3.9}$$

The resistance R_1 is used to set the sensitivity and force sensing range of the FSR

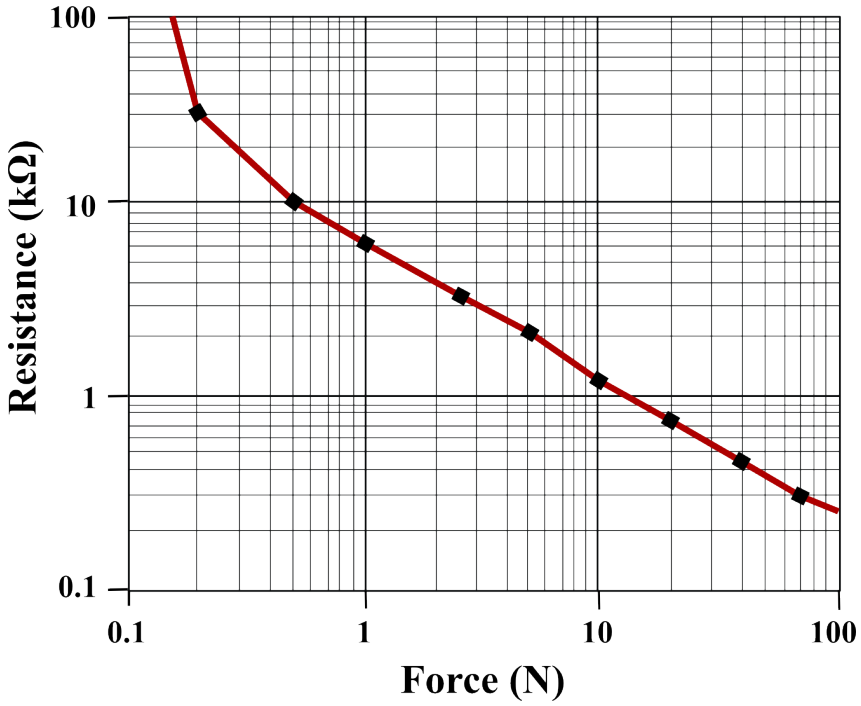


Figure 3.9: ***Resistance vs force exerted on FSR surface for an Interlink 400 series FSR. The resistance of the FSR reduces with increased force***

circuit as well as limit the current drawn by the circuit to reduce the power consumption of the circuit. This value can be anything from $1k\Omega$ to $100k\Omega$ depending on the sensitivity desired. For example if an FSR is intended to measure the force exerted by a persons grip in fine motor skill rehabilitation, the FSR circuit would be required to be very sensitive to small changes in force and may not require a large range of force measurement. However, when the circuit is used to implement a footswitch, these fine changes in force exerted are not important. In this application large changes in force are of interest and the circuit should be calibrated to have a larger range. Lower values for R_1 lead to a higher force sensing range for the circuit and a lower sensitivity. When calibrated correctly, this circuit can give an estimate of the force applied to the FSR, however this is subject to drift and should not be used as an accurate measure without calibration before each use. In an activity monitoring context footswitches are more often used as an on/off measure and so FSRs are a suitable technology when used in a correctly calibrated circuit.

By positioning FSRs at the heel and ball of the foot, heel strike, heel off, toe strike and toe off events can be detected by detecting when the output of the FSR circuit crosses a threshold. This threshold should be set at a level that best

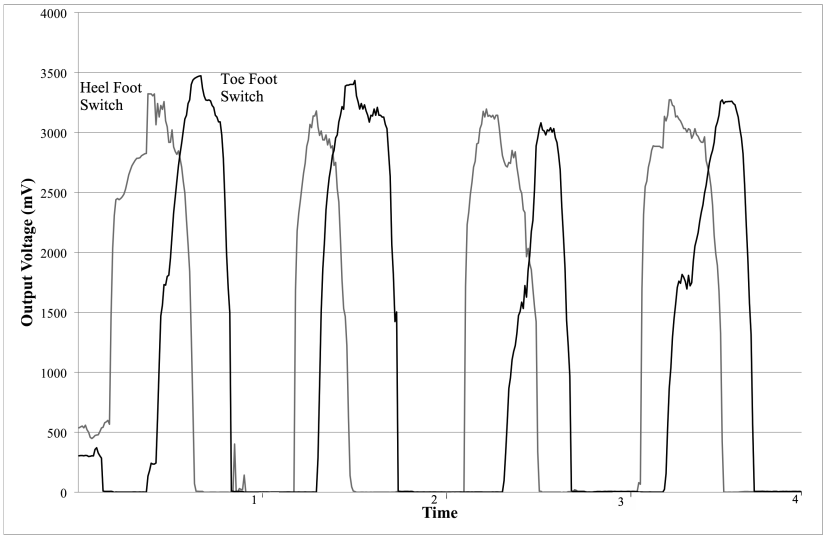


Figure 3.10: ***Graph of FSR circuit output during walking with 5$k\Omega$ calibration resistor and 5V supply voltage. FSRs placed at heel and ball of foot. Data can be used with threshold technique to determine gait events***

represents the forces during walking. Figure 3.10. shows the output of two FSR circuits placed under the heel and ball of the foot during walking.

FSRs tend to be relatively delicate sensors and will often be protected by dampening the forces they are subjected to. This can be done by housing them in a textile enclosure or using an epoxy coating. However, if this protective dampening is implemented it should be noted that the FSR circuit should be recalibrated as the outputs for different inputs will have changed due to the dampened forces.

FSRs are very thin sensors (~1mm) and so can easily be integrated under the foot without any discomfort. The resistance of the sensor when not under any force is generally around $1M\Omega$. The minimum resistance of the FSR under force is in the range of $k\Omega$.

The resistance of FSR sensors tend to drift over time under constant load. For example both the Interlink 400 series FSR and the Tekscan FlexiForce sensor claim a 5% drift per logarithmic time. This drift is a significant consideration in some force sensing applications. However, in a footswitch application where the FSR is operating in an on/off context, this drift is less important.

3.2.3 Barometric Pressure Sensors

Barometric pressure sensors are available in a wide range of configurations. In the context of activity monitoring, micro-machined sensors are the most appli-

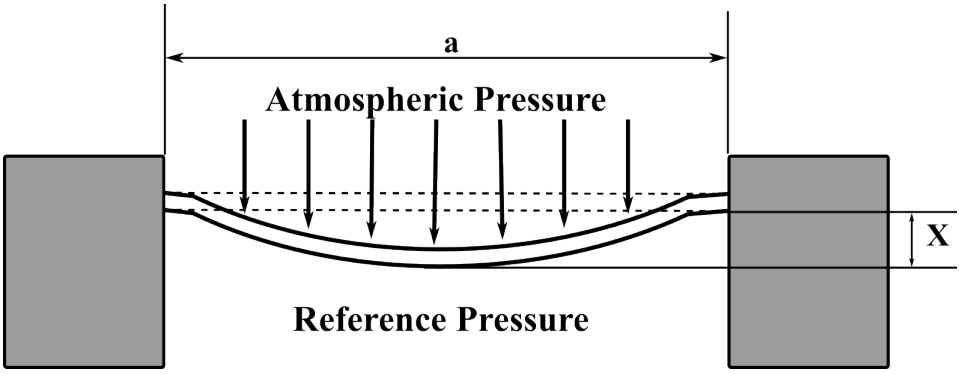


Figure 3.11: ***Barometric pressure sensor diaphragm: a is the area of the diaphragm, x is the displacement of the diaphragm due to the pressure differential***

cable. The most common form of barometric pressure sensor uses a diaphragm to obtain a measurement of pressure. Figure 3.11. illustrates the concept of such a diaphragm.

The deflection of the diaphragm caused by the difference between atmospheric pressure and the reference pressure is directly proportional to the atmospheric pressure. In the case of a circular diaphragm set up as shown in Figure 3.11., this relationship is as follows [96]:

$$X(r) = \frac{Pa^4}{64D}\left[1 - \left(\frac{r}{a}\right)^2\right]^2 \tag{3.10}$$

where ω is the deflection of the device, r is the radial distance from the center of the diaphragm, a is the diaphragm radius and P is the atmospheric pressure. D is the diaphragm flexural rigidity given by:

$$D = \frac{Eh^3}{12(1-v^2)} \tag{3.11}$$

where E,h and v are Young's modulus, thickness of the diaphragm and Poisson's ratio respectively.

All micro-machined barometric pressure sensors are loosely based on this principle. The two most common forms of MEMS pressure sensors are discussed in brief here.

Piezoresistive sensors: Figure 3.12. shows an example of a piezoresistive pressure sensor. Piezoresistive strain gauges are diffused into the diaphragm to measure the stress caused by the deflection due to the pressure difference between the reference and atmospheric pressures. This strain is proportional to

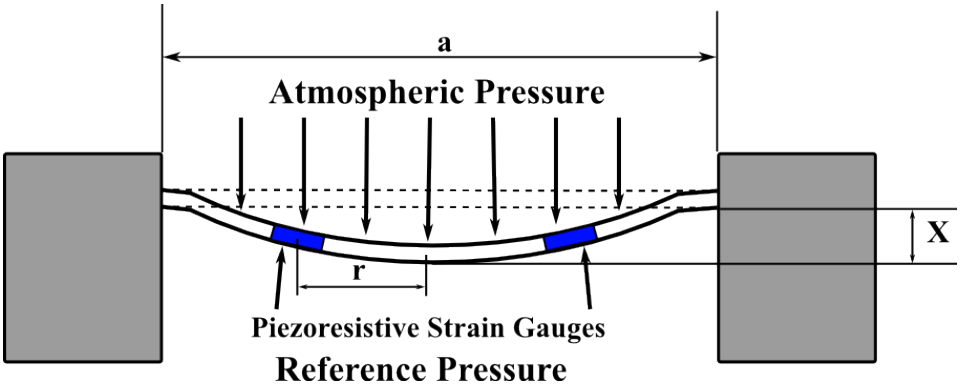


Figure 3.12: ***Piezoresistive barometric pressure sensor: r is the radial distance from the center of the diaphragm to the piezoresistive strain gauges***

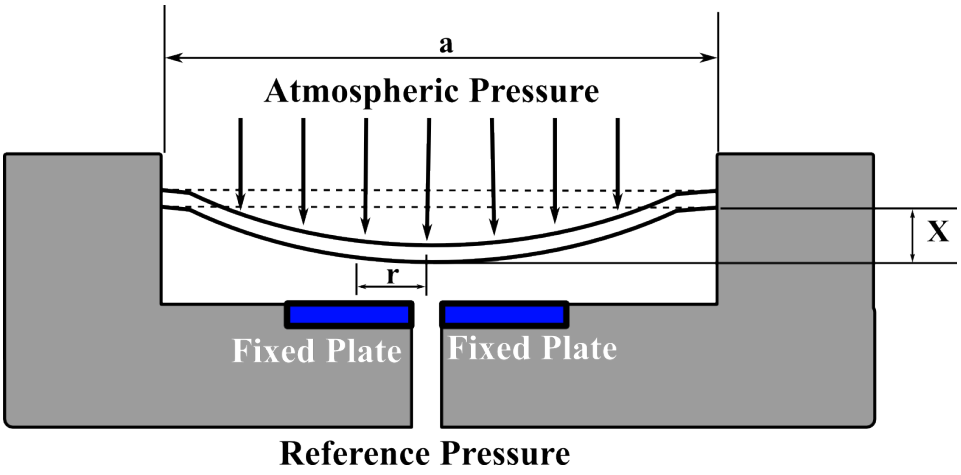


Figure 3.13: ***Capacitive barometric pressure sensor: r is the radial distance from the center of the diaphragm to the capacitor plates***

the difference in pressure.

Capacitive sensors are again based on a diaphragm. In this case, the deflection of the diaphragm causes a change in capacitance between the diaphragm and a fixed plate, shown in Figure 3.13.

Capacitance in a standard parallel plate capacitor can be expressed as:

$$C = \frac{\varepsilon A}{d} \tag{3.12}$$

where ε is the permittivity of the gap, A is the area of the plates and d is the distance between the plates. For a capacitive barometric pressure sensor, the capacitance between the diaphragm and the fixed plate is:

$$C = \int \int \frac{\varepsilon}{d - X(r)} r\,dr\,d\theta \tag{3.13}$$

where $X(r)$ is the deflection of the diaphragm given by Equation 3.10[96].

Altitude from barometric pressure: Barometric pressure has a known relationship with altitude allowing barometric pressure sensors to be used as altimeters. A simple equation can be used to determine altitude from barometric pressure:

$$altitude = 44330 \times \left(1 - \left(\frac{p}{p_0}\right)^{\frac{1}{5.255}}\right) \tag{3.14}$$

where p is the measure of barometric pressure and p_0 is the average pressure at sea level.

Properties of barometric sensors:

- Range: The range of barometric pressure sensors varies widely. However, a typical sensor suitable for use in activity monitoring may have a range of 300 to 1500 hPa. Atmospheric pressure at sea level is on average 1013 hPa and it is 600 hPa at 4000m above sea level. Therefore, this range is more than sufficient for altitude sensing in this area.

- Resolution: Typical resolution is in the order of 0.01 - 0.2 hPa. For example, a resolution of 0.03 hPa would result in a 0.25 m resolution in altitude at sea level.

- Noise: Atmospheric noise is typically in the order of between 0.1 and 1 meter. Therefore, measurements of anything less than 1m may be prone to errors when using a standard piezoresistive or capacitive pressure sensor.

Table 3.4. shows the operation parameters for some commonly used available barometric pressure sensors.

3.2.4 Physiological Measurements

3.2.4.1 Electromyography (EMG)

Muscle activation is caused by electrical activity carried by long axons in nerves that travel through the spine and end in the muscle. These axons branch out in

Manufacturer	**BOSCH**	**MEAS Switzerland**	**MEAS Switzerland**
Model	BMP085	MS5611-01BA01	MS5607-02BA03
Interface	Digital	Digital	Digital
Range	300-1100hPa	10 - 1200hPa	10 - 1200hPa
Resolution	0.01hPa	0.012hPa	0.024hPa
Noise	0.03hPa	-	-
Package	5X5X1.2 mm	5X3X1.7 mm	5X3X1 mm

*LSB = Least Significant Bit

Table 3.4: ***Typical barometric pressure sensor parameters***

the muscle and connect to several muscle fibers. Using this structure, the motor neuron can activate several muscle fibers simultaneously. The combination of this motor neuron and its connected muscle fibers are known as a motor unit. When the central nervous system activates a motor unit, neurotransmitters are released causing depolarisation waves to be sent through the muscle fibers towards each end. These waves cause a mechanical contraction as well as a noticeable electrical effect called the Motor Unit Action Potential (MUAP). Electromyography is the measurement of this action potential.

The first instance of the use of electromyography to measure electrical activity in muscles during voluntary contraction occurred in 1890. However, it was not until the nineteen forties that surface EMG was first put to clinical use [97]. The measurement consists of both the number of motor units recruited as well as the frequency with which these motor units are fired. This combination gives an indication of the level of muscle activation and an estimation of the force exerted by the muscle. Figure 3.14. shows an example of an EMG signal during muscle contraction.

Noise: Because of the very low voltage amplitudes involved with EMG signal noise is a significant issue. There are several factors related to noise in EMG, some of which are outlined here:

- *Electrode impedance*: a high electrode-skin impedance can lead to reduced signal amplitude, waveform distortion and power line interference in the EMG signal [98]. Electrode impedance can be reduced through careful preparation of the skin by removing hair and cleaning with alcohol. A high input impedance amplifier should also be used to reduce the effect of elec-

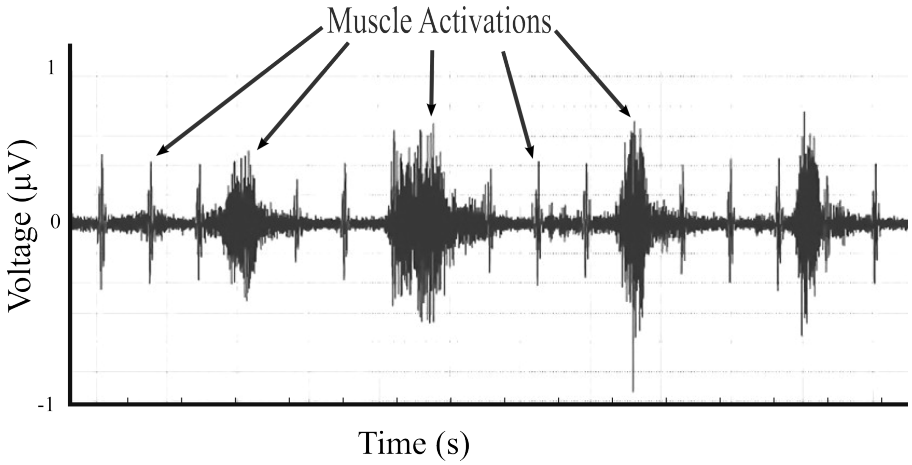


Figure 3.14: ***Electromyogram Signal showing muscle activations by measuring electrical activity***

trode impedance. For comprehensive recommendations on the placement and preparation of EMG electrodes see [99].

- *Motion artifact:* Motion between the electrode and the skin can introduce noise into the signal. This effect is greatly reduced by the use of conductive gel either coated on the electrodes or applied to the skin. Motion artifact can also be reduced through low pass filtering of the signal below 10Hz [98].

- *Cable motion artifact:* Noise can also be introduced through movement of the cables connected to the electrodes. This can be reduced through the use of shielded cables, limiting the length of cables and unity gain op amp buffers at the electrodes.

- *Mains power interference:* Interference from the mains power lines can also affect EMG data collection. Notch filtering at the mains frequency can help to eliminate this interference, however this is at the cost of losing some relevant EMG signal. Shortening EMG leads reduces interference from the mains as well as using shielded cables.

Amplification and signal processing: The electrical activity in the muscle caused by the motor unit activation is in the order of micro to milli Volts. Therefore, amplification is an important aspect of EMG. Placement of the amplifier close to or on the electrodes helps to reduce the effects of noise. Amplification is normally in the order of 500 times the raw EMG signal. The input impedance of the amplifier should be at least ten times larger than the electrodes impedance.

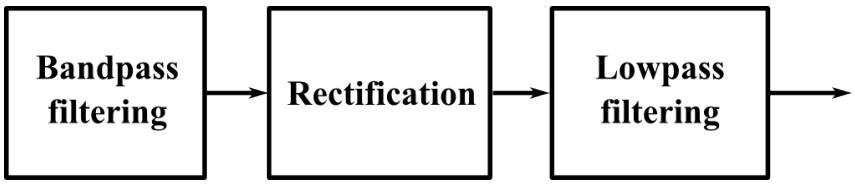


Figure 3.15: ***EMG signal processing of the linear envelope. First irrelevant signals are filtered out with band-pass filter. Signal is then rectified. Finally high frequencies are filtered out with a low pass filter.***

Amplifiers normally implement a band pass filter of between 10Hz and 500Hz to reduce noise. The vast majority of the EMG signal power is between 10-250Hz, therefore sampling frequency is recommended to be in the range of 1-2kHz [98]. A high Common Mode Rejection Ratio (CMRR) in the amplifier circuitry is also desirable to suppress signal components common to other electrodes. The signal processing of EMG is a complex area and a detailed analysis is outside of the scope of this brief outline of the technology. Figure 3.15. shows a brief overview of the general process of one approach to EMG processing i.e. the linear envelope. For a more in depth look at this area the reader is directed to [100].

Features: A large range of features can be extracted from EMG signals, however the majority of these are outside of the scope for an activity monitoring review. Zero crossing rate and frequency domain features have been introduced in the past, however the amplitude of the signal is by far the most commonly used feature. Two separate approaches are often used to measure the amplitude [100]. The Mean Absolute Value (MAV) is calculated using the following equation:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{3.15}$$

The Root Mean Square (RMS) is also commonly used as a measure of EMG amplitude:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{3.16}$$

where N is the number of samples, x_i is a sample from the EMG signal.

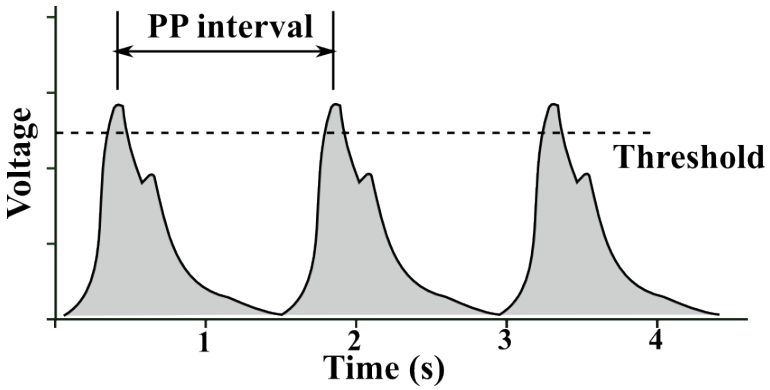


Figure 3.16: ***PPG signal showing peaks due to heart beats and threshold for detection of heart beat***

3.2.4.2 Heart Rate Monitoring

The two major approaches to monitoring heart rate that are widely used in the literature are discussed here;

Photoplethysmography (PPG) is an optical measurement technique that can be used to detect blood volume changes in the microvascular (smallest vessels of the circulatory system - capillaries, venules etc) bed of tissue [101]. These blood volume changes can be used to detect heart beats as well as several other cardiovascular features such as blood oxygen saturation, blood pressure, cardiac output and respiration [102]. For a behaviour monitoring application heart rate is the most applicable parameter monitored. This brief outline will focus on PPG for heart rate monitoring. The technique is based on the change in light absorption, reflection, transmission and fluorescence properties of the tissue with changes in blood volume.

PPG devices contain a light source, photodetector, amplification and filtering circuitry. Figure 3.16. shows an example of a PPG wave. This wave represents the amount of light received at the photodetector with each peak representing a pulsing of the heart. Some of the most important properties of PPG are discussed here:

– *Signal processing:* The signal processing of the PPG raw signal is a combination of band pass filtering and amplification. High pass filtering is used to reduce the DC component of the signal to generate a clearer representation of pulse. The fundamental frequency of the pulse is quite low (usually between ~1-3Hz), therefore high frequency noise such as movement artifact and power line interference can be easily removed with a low pass

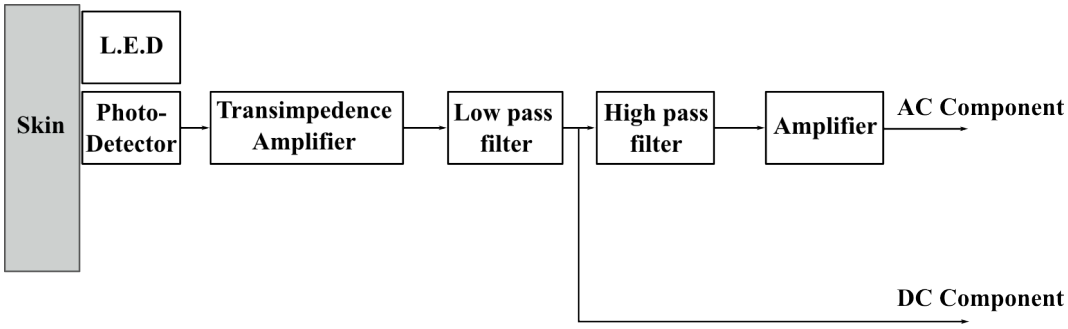


Figure 3.17: ***Reflective PPG signal processing showing generation of AC (used for heart beat detection) and DC (used for SPO2 measurement etc) components from raw signal. Transimpedence amplifier stage converts current from photodiode to voltage.***

filter. Figure 3.17. shows the process of signal processing of a PPG signal [102]. The choice of high pass filter cut off frequency is particularly important because of the trade off between DC component allowed through and signal distortion from too little or too much filtering respectively. However, for the detection of heart rate the DC component is not important.

– *Transmissive vs Reflective:* PPG can be performed with the light source transmitting light through the tissue to the photodetector or with the photodetector situated next to the light source and measuring the reflected light from the tissue.

– *Measurement site:* The use of reflective or transmissive PPG will largely dictate the options for measurement site. Using transmissive PPG, possible sites are more restricted with the most commonly used sites being the fingertip, toe or ear. Reflective PPG is more flexible. In both cases the pressure of the probe against the tissue is important. Too much pressure will restrict the blood flow in the tissue.

– Motion artifact: PPG measurement is very sensitive to motion artifact. Though some of this artifact may be reduced through filtering, significant movement of the sensors cannot be compensated for. Due to the nature of PPG movement of the photodetector will significantly affect the intensity of the light received. Therefore, care must be taken to limit movement through choice of measurement site. This makes the ear an attractive site for measurement. Other sites, especially with reflective PPG may not be suitable during movement e.g. ambulation.

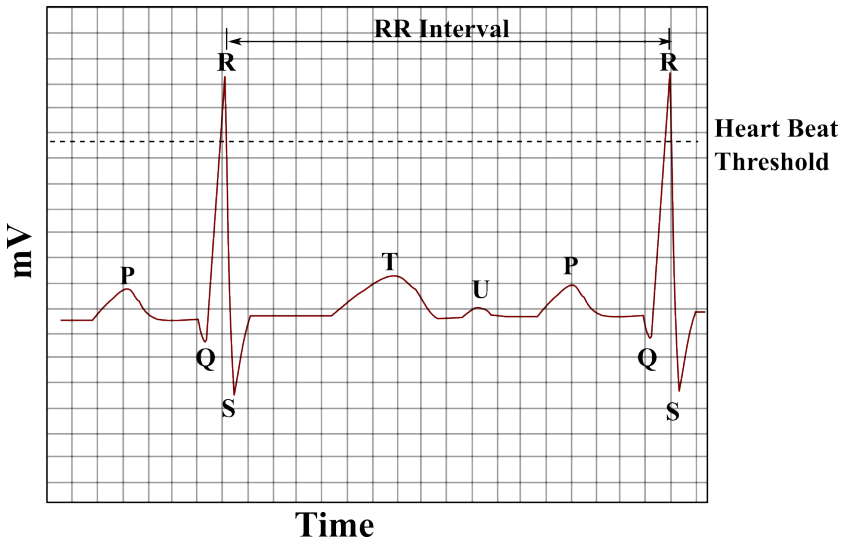


Figure 3.18: ***Electrocardiogram Signal showing different features of ECG. R peaks used to detect heart beats by detecting signal crossing threshold. RR Interval gives a measure of heart rate***

Electrocardiography An electrocardiogram is a test that records the electrical activity of the heart. The beating of the heart is caused by an action potential causing the heart muscle to contract similar to other muscle activations as described in Section 3.2.4.1. Heart rate can be determined from ECG signals through the detection of the QRS complex (shown in Figure 3.18). As the ECG relies on the detection of the electrical activity of the heart, many of the principals relevant to EMG also apply to ECG.

- *Noise:* Movement artifact, power line interference and cable artifact as well as interference from other muscle activity must all be minimised through filtering and cable shielding.
- *Filtering:* Filter cut off frequencies have been recommended as 0.67Hz and 150Hz for low and high cut off respectively [103].
- *Sampling frequency:* Sampling frequency has been recommended to be 500Hz [104].

3.2.5 Global Positioning System (GPS)

GPS has become by far the most widespread outdoor location system since the first satellite launch in 1978 and the network's completion in 1995. Though it is

not the only outdoor positioning system, the Russian GLONASS system and upcoming european Galileo location system provide similar services, the principles of operation are similar and so the more widely available GPS will be discussed in this paper. GPS is based on the concept of trilateration. A receiver uses a signal from at least four of the twenty four active GPS satellites in the network, to trilaterate its position based on the time taken for the signal to travel from the satellite to the receiver. Since the signal travels at the speed of light, any minute errors in timing could result in very large errors in positioning. Therefore, the receiver recruits a fourth satellite's signal to make sure that the clocks on the satellites and receivers are synchronised. If the satellite signal is blocked by buildings or mountains, or if the signal bounces off buildings before reaching the receiver, signal accuracy can be degraded.

The accuracy of locations provided by GPS varies widely depending on the number of satellites available for use and the signal strength available in a given location. Best case scenario accuracies of GPS are in the order of a couple of meters.

GPS consists of three operating segments: the space segment, the control segment and the user segment. The space segment is made up of the network of twenty four active GPS satellites. Each satellite is constantly transmitting a signal made up of several components including two digital codes and a navigation message. The digital codes are used to determine the distance from the satellite to the receiver. The navigation message contains information such as the location of the satellite in orbit.

The control segment of GPS consists of a worldwide network of tracking stations who's function is to track the location of the GPS satellites among other parameters. These tracking stations upload this information to the GPS satellites for integration into the navigation message.

The user segment is made up of the end users of GPS receivers. This receiver uses the signal from a GPS satellite to determine the distance between the receiver and the satellite. The signal contains a long pattern of bits that are also being generated by the receiver at precisely the same time. When the receiver "sees" this pattern it compares the phase difference between the received pattern and its own generated pattern. This phase is the time taken for the satellite signal to travel to the receiver. As the signal travels at the known speed of light, distance can then easily be calculated. Using the known distance to and position of four satellites a,b,c and d, the receivers location can be calculated at the

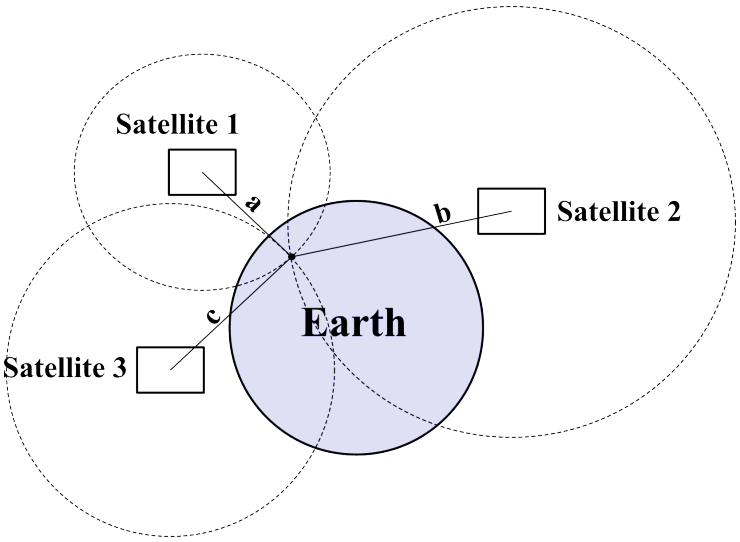


Figure 3.19: ***Two dimensional representation of the operation of GPS: shows three satellites used to triangulate position of receiver on earth by determining distances to receiver (a,b,c) and using intersection of three circles to determine location***

intersection of four spheres with radii of a,b,c and d with centers at the relevant satellites. Figure 3.19. demonstrates the operation principle in two dimensions.

3.2.6 Smart Homes

A smart home is a residence equipped with technology that observes the residents and provides proactive services [105]. The aim of the smart home varies widely from providing energy efficiency data [106], convenience and security [107] to health care applications. Smart homes can utilise a large range of technologies to detect and monitor a person's interaction with their home. In a behaviour monitoring context, there are two main types of smart home monitoring system. The first is based on indoor location and the second employs object interaction detection.

3.2.6.1 Indoor Localisation

Detecting indoor location is one of the most common implementations of the Smart Home in an activity monitoring context. There is a wide array of techniques available utilising indoor location as a method of monitoring older adults [108, 109, 110]. GPS has been used as the seminal outdoor localisation technology since 1998, however, GPS does not function indoors. No dominant technol-

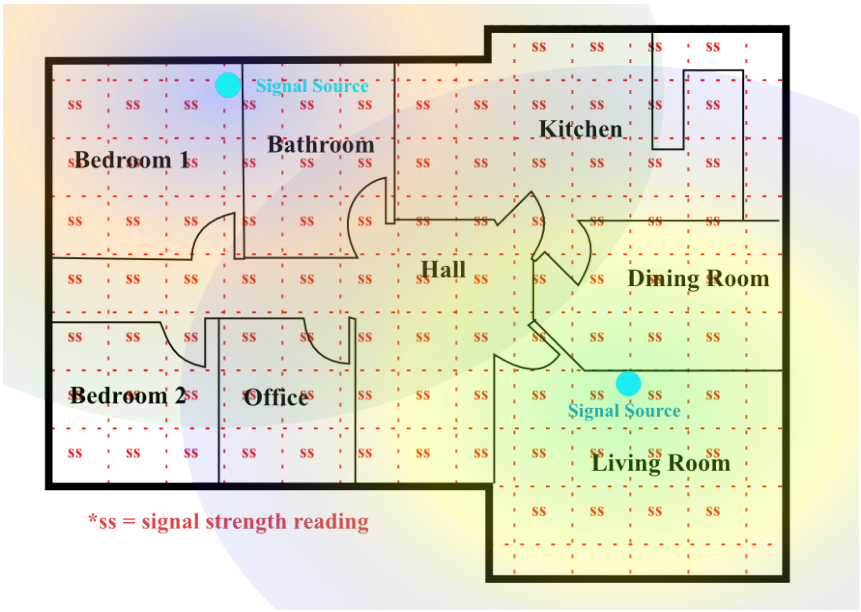


Figure 3.20: ***Fingerprinting signal map shows an example of a database of signal strengths used to train a fingerprinting based indoor localisation system. This database contains a separate entry for the signal strength at each position in a grid across a building***

ogy has emerged in the field of indoor localisation to rival GPS in the outdoor domain. Numerous different techniques and technologies have been implemented to detect indoor location, however there are significant trade-offs between cost of implementation, accuracy, precision and practicality.

Bluetooth [111], GSM [112], RFID [113], passive infrared [114], modulated infrared [115], ultra-wide band radio [109], WiFi [116], zigbee [117] and ultrasound [110] have all been used in indoor localisation systems. Regardless of the medium used, indoor location systems usually fit into one of four detection techniques: Proximity, fingerprinting, triangulation/trilateration and video analysis.

Fingerprinting systems rely on a training phase in which readings are taken for characteristics such as signal strength from any of several sources across a building. From this training phase, a signal strength "map" of the building is constructed as shown in Figure 3.20.

In operation, to obtain position information the system reads the current signal strength from the same sources and compares this signature to the training database. From this comparison, a likely position can be identified. An advantage to this type of system is that it can often be implemented using an existing network such as the GSM network [112] or a WiFi network [118]. However, drift in

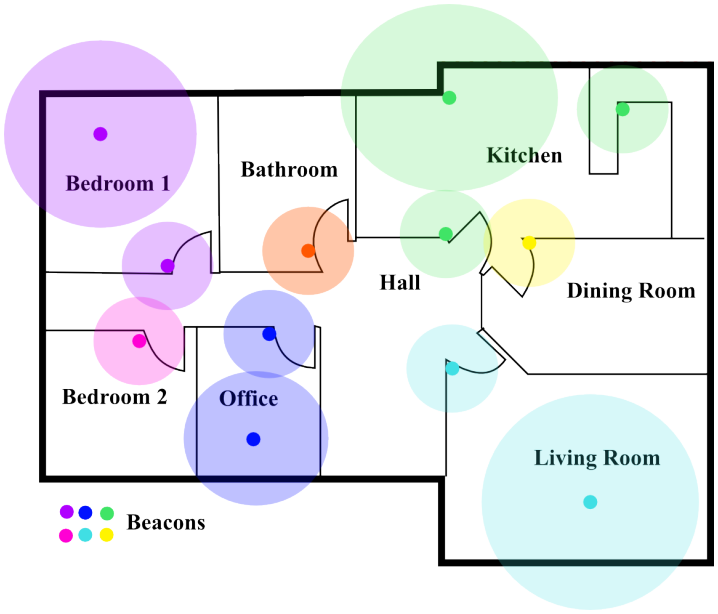


Figure 3.21: ***Proximity based indoor localisation shows an example layout of a house fitted with indoor localisation beacons. Problems with signal leakage into other rooms and overlap with other beacons can be seen***

signal readings is an issue and the network used to train the system may be subject to change. Accuracy is in the range of meters even in optimal circumstances.

Proximity based indoor location utilises one of two methods. Beacons can be carried by the person and receivers installed around the building (*transmissive localisation*) or the receiver can be carried and beacons installed in the building (*receptive localisation*). In either case, the operation of these systems rely on the detection of the person coming into range of a fixed point in the building. Beacon and receiver technology can be based on modulated infrared [115] or several other technologies. An issue with radio based beacon systems is leakage of beacon signal into other rooms as shown in Figure 3.21. Proximity based systems are inexpensive to implement, however resolution of position information is limited to proximity to a known point.

Indoor localisation using triangulation or trilateration uses any of three methods to determine distance from or angle relative to at least two points. Received signal strength methods rely on the degradation in signal to determine distance between a source and a receiver, one of which is fixed at a known location [119]. Time of Arrival based systems use the time taken for the signal to travel between points to determine distance [120] using Equation 3.17.

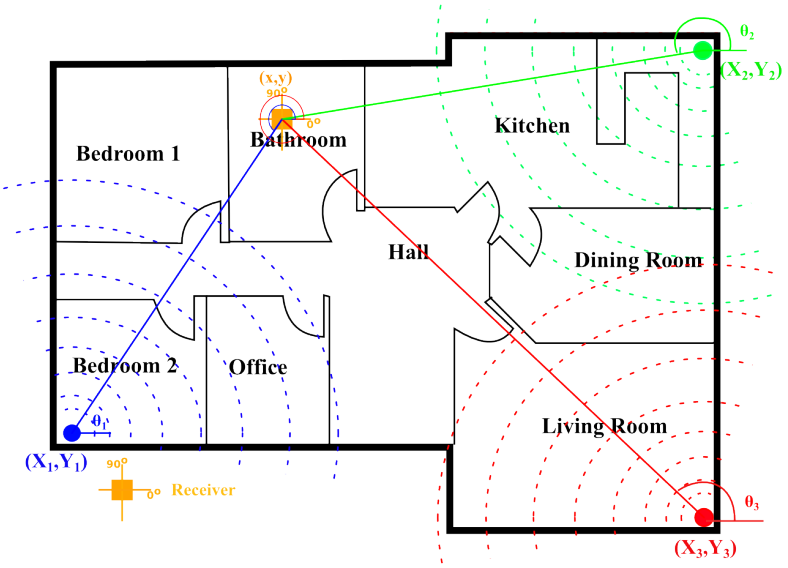


Figure 3.22: ***Triangulation based indoor localisation shows an example of a house fitted with a triangulation based indoor localisation system. The blue, green and red lines intercept at the users current location. Solving for the intercept point of the three lines allows detection of the current location.***

$$distance = c \times timeToArrive \tag{3.17}$$

where c is the speed of light $(3 \times 10^8 m/s)$and timeToArrive is the time it took for the signal to reach the receiver from the transmitter in seconds.

Angle of Arrival based systems use the direction that the received signal approaches from to determine the relative angle from the known location [116].

Using the angle of arrival as well as the known co-ordinates of the fixed transmitters, the equations of the lines between each of the transmitters and the receiver can be determined using Equations 3.18,3.19 and 3.20 [116]. where θ, X_n, Y_n, x and y are shown in Figure 3.22. The intercept point of the three lines then gives the co-ordinates of the receiver. When any of these variables are known, a simple triangulation or trilateration algorithm can calculate position. Triangulation based indoor location systems can be designed to be extremely accurate to the order of centimeters, however they tend to be expensive to implement.

$$L_1 : y = -tan\theta_1 \times x + X_1 \times tan\theta_1 + Y_1 \tag{3.18}$$

	Blue-tooth	**RFID**	**UWB radio**	**WiFi**	**Zigbee**	**Ultra-sound**	**IR**
Can penetrate walls?	Y	Y	Y	Y	Y	N	N

Table 3.5: ***Ability of signals used for indoor localisation to pass through walls***

$$L_2 : y = -tan\theta_2 \times x + X_2 \times tan\theta_2 + Y_2 \tag{3.19}$$

$$L_3 : y = -tan\theta_3 \times x + X_3 \times tan\theta_3 + Y_3 \tag{3.20}$$

Video analysis requires the installation of one or more video cameras. Image recognition techniques are used to determine the location of the person [121]. These systems are accurate and not overly expensive to implement. However there are privacy concerns associated with installing video cameras in some settings. It is also difficult to differentiate between people so this technique may only be suitable for single user applications.

Required accuracy: The accuracy required by an indoor localisation system will of course depend on the application. In a behaviour monitoring application, room level localisation will often be sufficient. However, in co-ordinate based localisation systems, the accuracy must be closely examined. For example, if a triangulation system is used with an accuracy of 2m, this could be considered a very accurate system for room level localisation. However, if a person is seated in a chair against a wall, it is possible that the system will classify them as being in the room on the opposite side of the wall with significantly different behaviour implications. In co-ordinate based localisation systems that use signals capable of passing through walls, very high accuracy is required to avoid this. For this reason, signals that cannot pass through walls are attractive for room level localisation and behaviour monitoring applications.

3.2.6.2 Object Interaction

Another form of technology used in Smart Homes involves the detection and monitoring of a person's interaction with objects around the home. The complexity of this type of system can range from simple door sensors that detect

when cabinets are opened to RFID tags on objects to detect when items are taken from the fridge, or when a toothbrush is used. Another technique that has been introduced to detect interaction with appliances is to monitor the power usage in the house [122].

For an in depth review of the sensors utilized in smart homes see [105].

3.3 Use of Sensing Technologies in Behaviour Monitoring Systems

Regardless of the technologies used to collect data in a behaviour monitor, the process of classifying sensor data into a behaviour classification remains similar. Figure 3.23. shows a flow chart of this process. Raw data from a single or combination of sensors are processed to extract relevant features from that data. For example, data from a wearable accelerometer could be processed to obtain the RSS of the output signal as a feature. The next step is to classify the data into a behaviour based on this feature. A multitude of approaches have been used to both extract features and classify behaviours however, the overall approach typically follows that in Figure 3.23.

This section will review the different approaches to monitoring each aspect of behaviour as set out in Figure 3.1. using the technologies reviewed in Section 3.2.

3.3.1 Physical Activity Monitoring

As the field of behaviour monitoring stems from work on activity monitoring devices, this is perhaps the most developed of the aspects of behaviour discussed in this paper. Typically, activity monitors can be divided into those that purely quantify activity without any regard for the source of activity e.g. measuring energy expenditure in kcalories, and those that perform some level of classification e.g. counting the number of steps a user performs.

Figure 3.24. shows the different aspects of physical activity as monitored in behaviour monitoring. Energy expenditure is one of the most common outputs of the physical activity systems in a behaviour monitor. This energy expenditure can be expressed in several different ways. Activity counts are one of the most common energy expenditure metrics. Activity counts are a difficult concept to

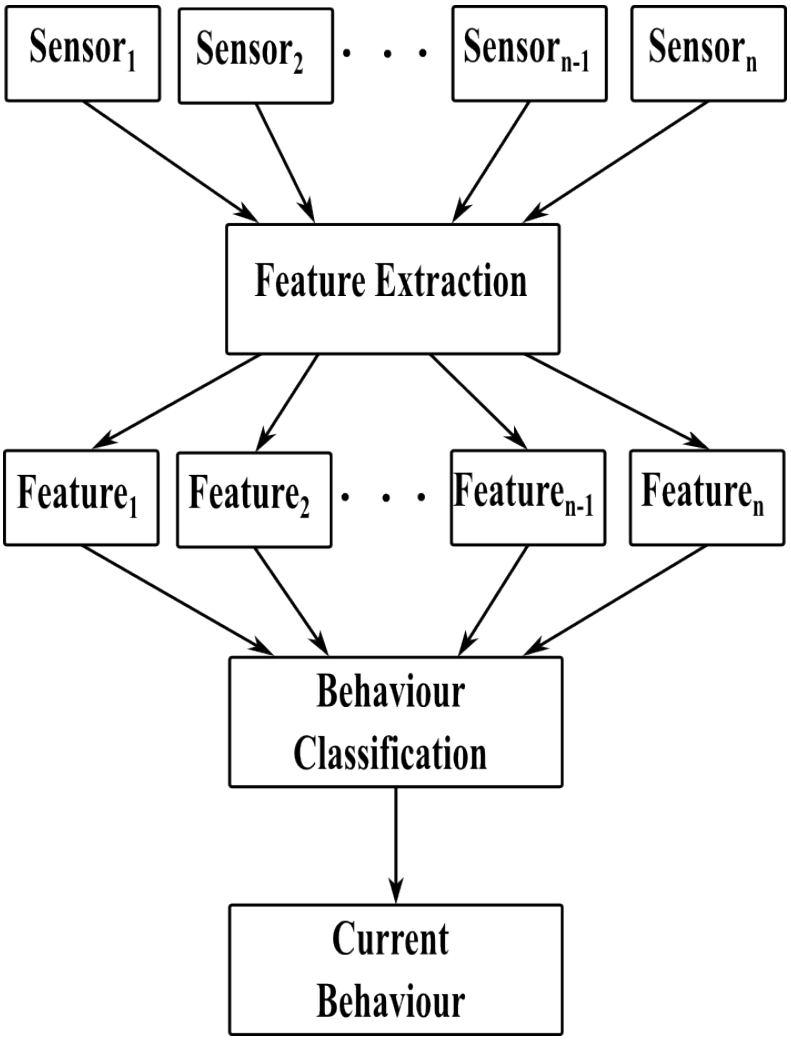


Figure 3.23: ***Behaviour classification process: shows the general flowchart of a behaviour monitoring system. Features are extracted from several different sources and input into behaviour classification algorithms to be classified as a specific behaviour.***

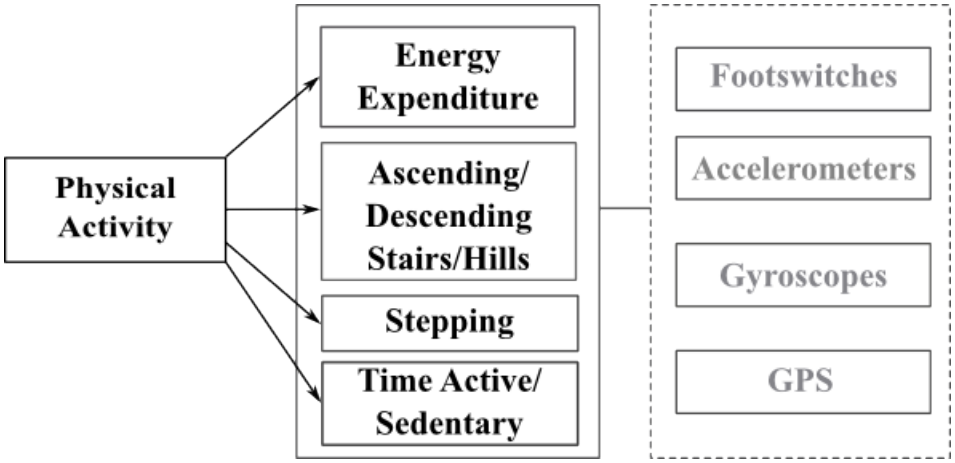


Figure 3.24: ***Block diagram of physical activity monitoring shows the different types of quantitative (energy expenditure) and classification (stairs/steps) physical activity parameters monitored in this aspect of behaviour monitoring.***

define succinctly due to the fact that they can be generated in significantly different ways. One of the clearest definitions of activity counts is that they are the raw outputs of an accelerometer in physical activity monitors [123]. One method of generating counts is to determine the number of times a raw accelerometer signal crosses a pre-set threshold sometimes, though not necessarily, set at 0 [124]. Another approach is to use a windowing technique and determine counts as the maximum level of the accelerometer signal during each window [125]. A fourth method is to use the area under the curve, or the integral of the accelerometer signal for each window [126]. A disadvantage of the activity counts method is the limited ability to compare results across different activity monitors due to different analog to digital converter settings or the use of different windowing lengths and techniques. Therefore, comparability of results is a significant disadvantage to using counts in their raw form. A large number of activity monitors use these counts as an input to an algorithm for representing energy expended in kcalories or kJoules.

The algorithms used to convert activity counts to energy expenditure also vary widely. One of the most accurate methods is to design a custom algorithm for each activity monitor using regression analysis. This involves using some gold standard for energy expenditure such as indirect calorimetry or doubly labelled water. An example of this technique was demonstrated by Freedson et al. [127] when they used linear regression to generate a predictive algorithm for energy

expenditure from activity counts during treadmill running. Fifty adults wore an activity monitor and an indirect calorimeter mask while running on a treadmill at three different speeds. Data from the activity monitor were correlated with the gold standard energy expenditure data and a predictive algorithm designed using linear regression. The advantage of using this approach to predicting energy expenditure is the accuracy of the resulting predictive formula. However, the task of developing this formula requires a research study involving a large number of participants. The gold standards of calorimetry and doubly labelled water are very expensive to perform. An alternative to regression analysis for predicting energy expenditure is to use published equations based on a persons Resting Metabolic Rate (RMR) and their activity level. Examples of these equations are the Scholfield [128] or the Harris and Benedict [129] equations shown in Equations 3.1 and 3.2.

$$(MenAged18-30)RMR = 15.0 * Weight(kg) + 690 \tag{3.1}$$

$$RMR = 88.363 + (13.397 * Weight(kg)) + (4.799 * Height(cm)) - (5.677 * age(years)) \tag{3.2}$$

These equations provide a method of calculating the energy a person expends at rest based on inputs such as their height, age and weight. This value for RMR can then be multiplied by a correction factor based on the person's activity levels creating an estimate for actual energy expenditure. A wide body of research is available in the literature relating to the accuracy of these equations [130, 131]. The obvious advantage to the use of these equations is that they eliminate the need for the expensive process of creating a proprietary algorithm for estimating energy expenditure. The disadvantage of using these predictive equations is that they are often less valid for populations other than those used in their development [131]. Therefore, it may be necessary to use different equations for different users.

Time spent active and inactive has also been used as a metric to measure physical activity. The method used to determine activity and inactivity can vary. Tudor-Locke et al. used counts per minute and a threshold to differentiate activity from inactivity [132]. Calories per minute or other accelerometer features such as RSS could also be used along with thresholds to determine time active.

Granat commented on the problems of comparison of results when using different methods to classify active time [133].

Physical activity has also been measured using classified activities such as the number of steps a user takes. Step counting has been performed using footswitches [134], accelerometers[135, 136], gyroscopes[93, 137] and magnetometers [134]. Footswitch based systems monitor the pressure at the sole of the foot to detect foot contact with the ground representing a step. Accelerometers have been used to detect steps in several ways including counting the number of zero crossings of the output [135] or the number of peaks over a set threshold [136]. Tong et al. used gyroscopes at the shank and thigh and the inclination or angular velocity to detect gait events including foot strike which allowed them to count steps [93]. Raffin et al. used a magnetometer based at the shank to determine angular velocity and from this detected heel strike and other gait events. From heel strike, a step count was generated.

Due to the significantly different energy expenditure requirements of ascending an incline [138], physical activity monitoring in behaviour monitors have also detected stair climbing and hill climbing. Coley et al. used the angular velocity at the shank obtained from a gyroscope to detect stair climbing [139]. The angular velocity peak during the stance period of gait was positive contrary to level walking. They detected stair ascent with 100% sensitivity and specificity.

3.3.2 Context

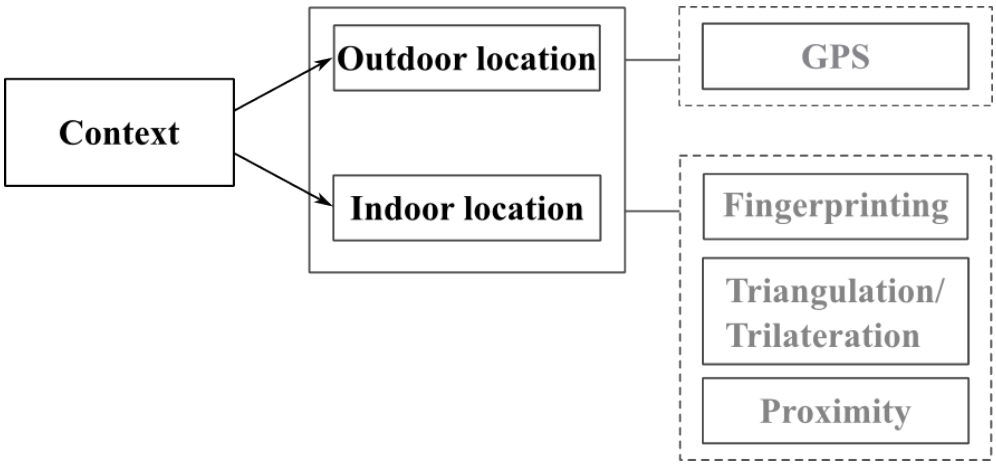


Figure 3.25: ***Block diagram of context information collection showing types of contextual information and technologies used to collect it.***

The measurement of physical activity is a very useful metric and can generate a significant amount of information regarding a person's behaviour. However, without any contextual information about the performance of this activity, little information is available regarding source of this activity. In order to increase the available information, behavioural monitors can incorporate both indoor and outdoor location.

Smart homes using indoor location can build a detailed behavioural model of a person's everyday life. A person's movement in their home relates to their activity behaviours and performance of activities of daily living. For example, if a person does not enter the kitchen until the afternoon, it is a reasonable assumption that they have not prepared breakfast. If the person enters the bathroom several times at night, it is reasonable to assume they may be experiencing nocturia. Le et al. used passive infrared sensors to determine location of an older adult and inferred activities of daily living from this location [49]. Using the time of day and the current location the following ADLs were classified: sleeping, breakfast, lunch, dinner, going out, toileting, taking a shower and grooming. Hanser et al. used a Ultra-Wideband location system to monitor patients in a nursing home suffering from dementia [140]. Helal et al. developed an ultrasound based triangulation localisation system for the monitoring of the elderly [110].

A person's mobility and behaviour outside of the home is also of importance. Walking outdoors has significant benefits towards improving overall daily activity patterns [141]. Community ambulation, i.e. mobility outside of the home, has been associated with the preservation of life skills for independent living, community participation and quality of life [142]. Shoval et al. [143] used GPS to monitor the activity patterns of forty nine older adults. The time they spent walking outdoors as well as their average speed and the distance walked were calculated from GPS data. This information could be used as a useful indicator of the person's mobility and activity levels. GPS has also been used to measure the maximum walking capabilities of people with multiple sclerosis [144] and peripheral arterial disease [145].

3.3.3 Physical Exertion

Physical activity and context measurement discussed thus far in this section provide a measurement of an event caused by the movement of the body. However, physiological measurements provides a measure of the action that causes that

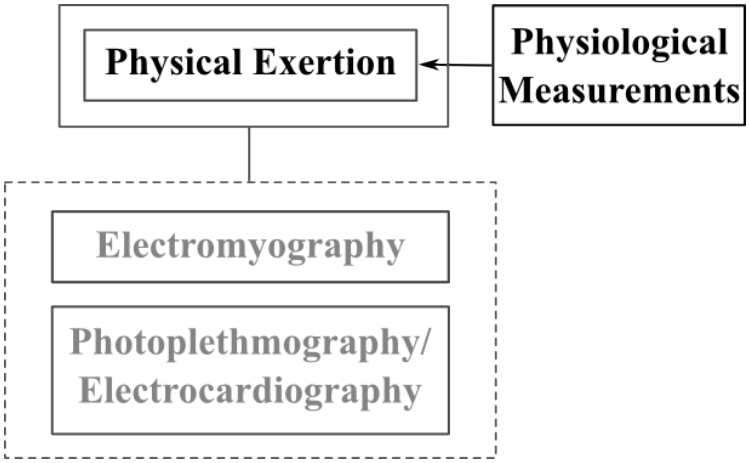


Figure 3.26: ***Block diagram of physical exertion information collection showing technologies used to collect physiological information relevant to behaviour montioring***

movement or its effect on the body. This more direct measurement allows a much more detailed picture of the behaviour to be generated.

Detection of which muscles are recruited for an action can be used to generate information about the activity as well as the effort required in performing that activity. In a behaviour monitoring context this ability has significant advantages for classifying a behaviour. The usability of EMG sensors is a concern as electrodes may not be suitable for longterm use.

Heart rate is one of the most direct methods of measuring physical exertion. However, several other parameters can also affect heart rate such as physical fitness, stress or caffeine intake which should also be taken into account. Heart rate has been used in combination with GPS as a measure of physical activity of children during school recess [146].

Measuring heart rate allows activity monitors to generate more personal data. For example, if a physically fit and an obese person go for a walk, a system based on inertial sensors will generate similar information about that activity for each person. However, the obese person will likely have experienced a much larger exertion. Integration of a heart monitor into an activity monitor allows for this difference to be detected.

3.3.4 Activities of Daily Living (ADLs)

Activities of daily living are those activities that are required to live in the home and the community. ADLs are divided into two main categories: Basic ADL and

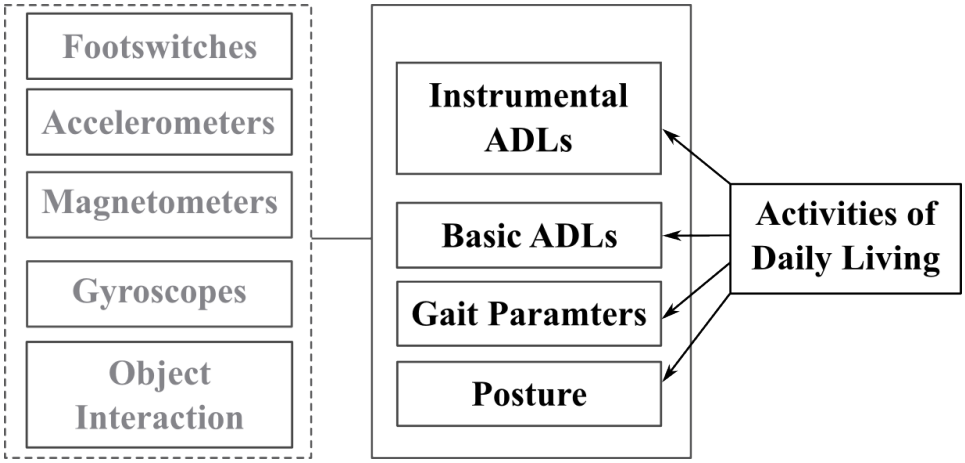


Figure 3.27: ***Block diagram of activities of daily living information collection showing types of ADL information and technologies used to collect it.***

Instrumental ADL. Basic ADLs are vital activities for life in the home such as feeding, bathing, grooming and toileting. Instrumental ADLs are higher level activities that are required to live in society such as handling finances, shopping and public transport. This category is probably the most difficult to classify and monitor of the four aspects of behaviour discussed in this paper. In fact, in order to detect ADLs, the other aspects of behaviour are often used as inputs to classification algorithms. For instance, Le et al. used passive infrared sensors to determine indoor location of an older adult and inferred activities of daily living from this location [49]. Using the time of day and the current location the following ADLs were classified: sleeping, breakfast, lunch, dinner, going out, toileting, taking a shower and grooming.

Roy et al. [147] used a combination of accelerometers and sEMG to detect several very specific activities of daily living including food cutting, shirt buttoning and postural transitions. This system can provide significantly more detailed information about behaviours being performed. This depth of information could be of particular benefit in monitoring older adults. Using sEMG Roy et al generated four variables related to muscle activation i.e. overall muscle activity (root mean square of window), the modulation of the muscle activity, the periodicity of the activation and the co-contraction of different muscles. A neural network was then trained to detect activities using test data from participants performing that activity. Using the combination of accelerometers and sEMG, the system achieved a sensitivity of $94.9\% \pm 1.4\%$ and a specificity of $99.1\% \pm 0.5\%$ across all activities tested. While these results are impressive, particularly considering the

specific nature of the activities tested, the system required sensors at five sites on the body all requiring electrode attachment. This may not be acceptable in a home monitoring application.

Posture can also be considered an activity of daily living. Differentiating between sitting, standing and lying has been performed with a wide range of approaches. Accelerometers are probably the most commonly used sensing technology for this purpose.

Posture classification using inertial sensors involves the monitoring of human movement and the subsequent attempt to classify this movement into a posture. Within the field of posture classification, there are again several different approaches. A significant deciding factor in the approach used is the number and placement of sensors. One of the most straight forward methods of posture classification using accelerometer sensors is a threshold based method.

Threshold based posture detection is normally based on the inclination of a sensor device. For multi-sensor systems, this makes the detection of different postures a straight forward process. For example, by placing a sensor at the thigh and the trunk, sitting, lying and standing can be detected based solely on the inclination of the sensors. If the thigh and the trunk are both close to horizontal, then the person is lying down, if the trunk is vertical and the thigh horizontal, the person is likely sitting down and if both the trunk and thigh are vertical the person is standing up [148, 149]. Threshold based posture detection has the advantage of simplicity. Therefore, algorithms can be run without significant computing power making systems using this technique less expensive and with lower computational and power consumption requirements. A weakness in threshold based posture detection is that to detect all static postures, two sensor locations are typically required. By using a single sensor at either the trunk or thigh, it is still possible to detect two of the three static postures based on a threshold algorithm.

Transition based posture detection is based on the detection of transitions between static postures, rather than on detection of the postures themselves. Within this field there are several possible methods for detecting transitions. Godfrey et al. used vertical velocity estimates derived from accelerometer data to differentiate between sit to stand and stand to sit transitions and evaluated the accuracy of their algorithms with older adults [150]. Sit to stand and stand to sit transitions were detected with a sensitivity and specificity of 89±9, 83±9 and 83±11, 89±8 per cent respectively. Gyroscopes have also been used to detect

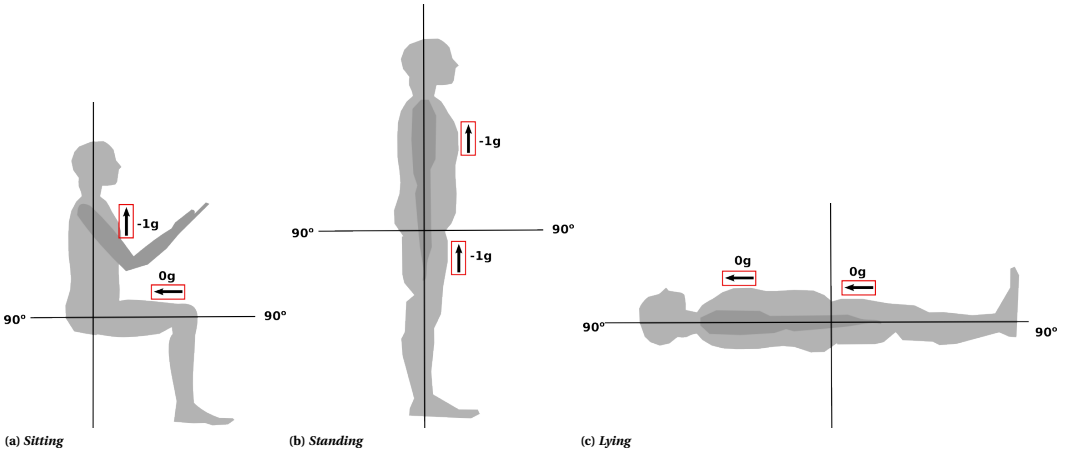


Figure 3.28: ***Threshold based posture detection: shows the operating principles behind two-accelerometer threshold based posture detection. The different static accelerations at the thigh and trunk during standing, sitting and lying can clearly be seen.***

postural transitions with similar results [136]. While these results are impressive for single sensor systems, because of the nature of transition detection systems, they may not be adequate for long term monitoring. If a postural transition is missed or incorrectly detected in a transition detection based system, the behaviour monitor will be wrong until another transition occurs. This may be a short period of error, however, if the person does not make a postural change for an extended period of time there could be significant error introduced.

A range of complex classification techniques have been used to determine activities from inertial sensors. Thresholds, neural networks, decision trees, fuzzy logic, markov models, support vector machines and several other techniques have been used. A complete analysis of the classification techniques used to classify activities from inertial sensor data is outside of the scope of this paper. For excellent in depth reviews of accelerometers used in human activity monitoring see [91] and [87].

Similarly, a person's interaction with household objects can generate useful information relating to their performance of activities of daily living. When a person turns on the oven, cooking can be assumed. If they interact with the vacuum cleaner, housework can be assumed to be taking place. These are useful inputs in monitoring an older person's ability to live independently. Philipose et al. used passive RFID tags and a glove mounted reader to detect interactions with objects [151]. From these interactions, they inferred fourteen different activities of daily

living. The majority of these ADLs were detected with high accuracy. Franco et al. [152] attempted to detect the performance of activities of daily living by monitoring the power usage of certain appliances in the home. Fleury et al. used a combination of infrared presence sensors, door contact sensors, microphones, a wearable inertial sensor and video cameras to detect several activities of daily living [153].

Virone et al. [154] developed a behavioural pattern recognition algorithm based on inputs from a theoretical smart home. The algorithm develops models for regular behaviour and generates alerts when a person deviates from their regular routine.

3.4 Multi-sensor Based Behaviour Monitoring Systems

Complex classification techniques have been used to detect the four aspects of behaviour discussed in this paper based on a combination of multiple sensors. Parkka et al. used a neural network and a multitude of sensors including ECG, accelerometers, GPS, galvanic skin response, magnetometers and altimeters to classify several complex activities of daily living [155]. Support vector machines have been used with accelerometer, video, audio, infrared presence detectors and temperature sensors as the inputs for classifying activities [153]. Similar examples using fuzzy logic and markov models are available [156, 157].

Several large projects have been carried out to develop complete telemedicine behaviour monitoring solutions. These projects typically contain sensors both ambient and body worn, feedback interfaces, carer interfaces, remote servers for data storage and processing, and all relevant communications infrastructure. Figure 3.29. shows a broad representation of a typical architecture for these telemedicine systems.

Table 3.6. represents four such monitoring systems. The Caalyx project and its follow on eCaalyx project are the most comprehensive systems containing a multitude of sensor technologies. These sensors generate a vast array of data relating to activity and behaviour. The Caalyx system generated alarms when physiological measurements were found to be outside of the norm. Other "health observations" were also generated when a health event involving a non vital measurement that did not require an alarm occurred. The architecture of the Caalyx system is shown in Figure 3.30.

The eCaalyx project (shown in Figure 3.31.) added a wearable vest containing

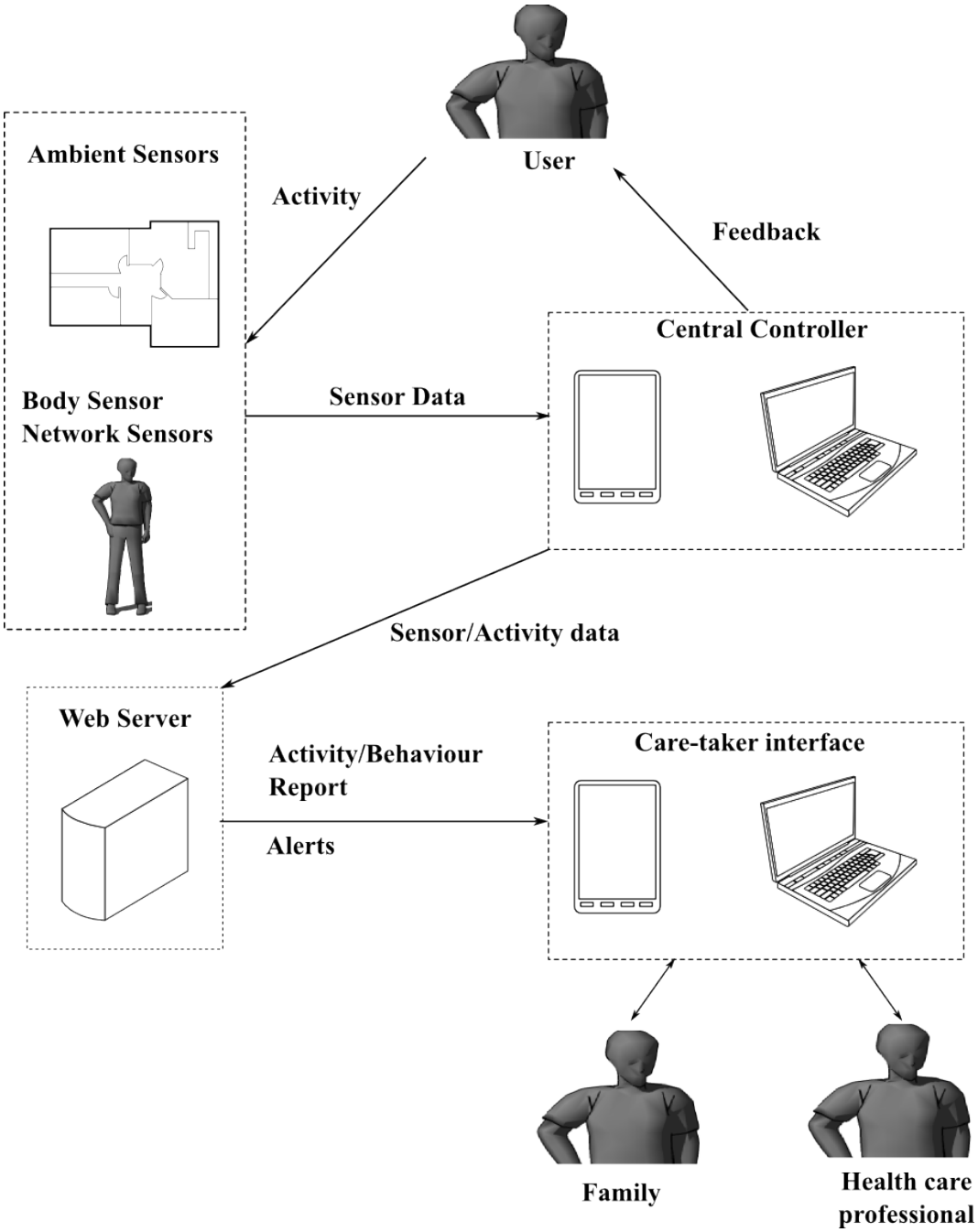


Figure 3.29: ***Telemedicine systems typical architecture. The four main components are behaviour sensing infrastructure, home based central controller, remote server and data presentation interface.***

Project	Sensor technologies	Parameters monitored	Platforms	Reports
Caalyx [158]	Body temperature, ECG, weighing scales, GPS, blood pressure meter, accelerometer, pulse oximeter (photoplethys-mograph)	Falls, posture, body temperature, mobility, heart rate, respiration rate, blood pressure, blood oxygen saturation,	Caretaker system, mobile system (waist belt with sensor, mobile phone), Home system	eHealth Records, health alteration alarms, "health observation" event. physiological parameters outside of norm alerts, location in emergency
eCaalyx[1]	ECG, pulse oximeter (photoplethys-mograph), galvanic skin response, skin temperature, GPS, RFID, passive infrared, weather station	Falls, posture, gait variability, energy expenditure, posture/activity detection, object interaction, weather, blood oxygen saturation, respiration rate	"Tricorder" device, T.V set top box, wearable vest, mobile phone, caretaker server	
CogKnow[2]	GPS, door contact sensors	Appliance use, location	Home based central controller (touch screen computer device), smart phone, web server	Patient records, user alerts (e.g. directions home if user forgets)
Liverpool Project [159]	Passive infrared, bed occupancy, toilet flushing sensor, door contact sensor, temperature sensor	Indoor location, time in bed, time outside home, application use	"Residential Monitoring Unit (RMU)", remote server	Behavioural profile graphic, appliance alerts (e.g. fridge door left open)

[1] http://www.ecaalyx.org/

[2] http://www.cogknow.eu/1/FP6_COGKNOW/

Table 3.6: ***Multi-sensor based telemedicine systems***

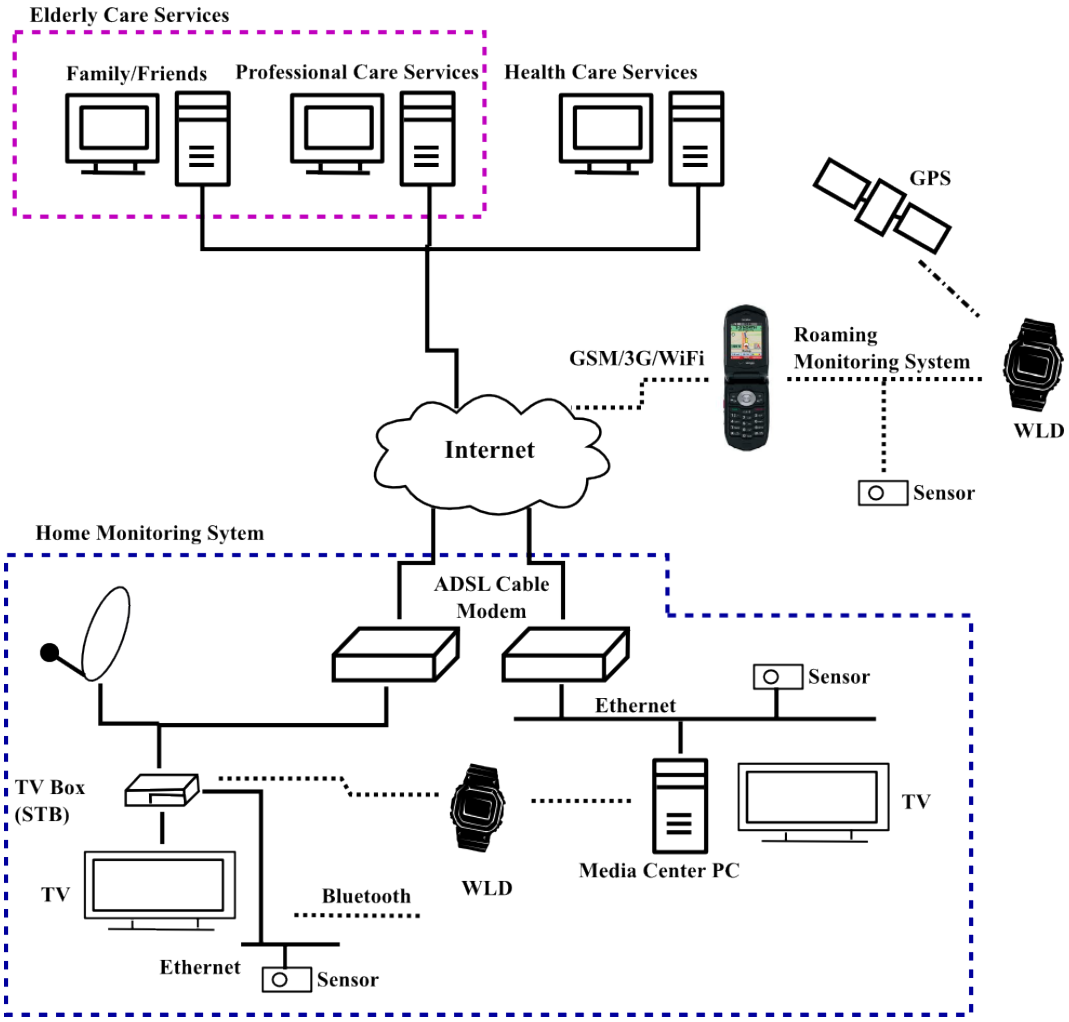


Figure 3.30: ***Architecture of Caalyx system showing platforms involved and communications infrastructure***

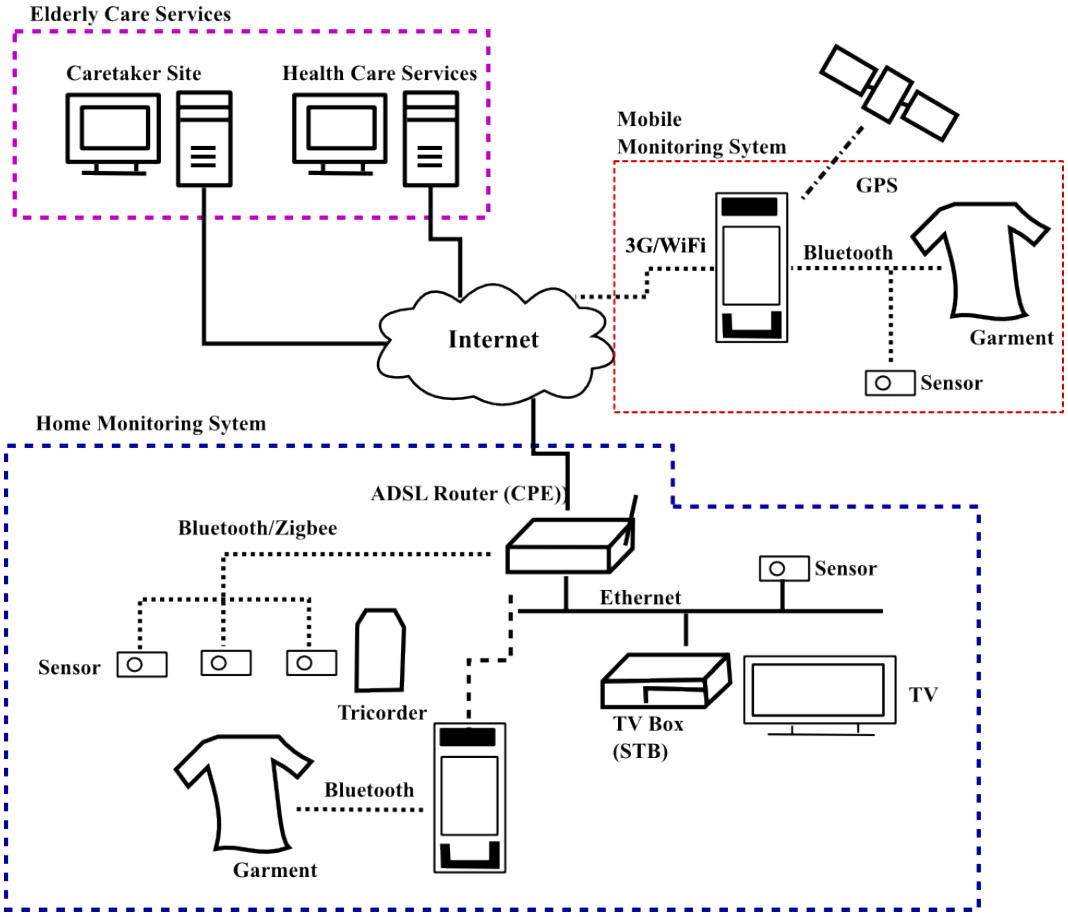


Figure 3.31: ***Architecture of Caalyx system showing platforms involved and communications infrastructure***

several sensors and also incorporated data mining algorithms to interpret these data and provided electronic health records for users. The figure also shows the significant infrastructure provided by the eCaalyx system with several communication technologies being used including Ethernet, GSM, Bluetooth, WiFi and Zigbee.

The CogKnow project was designed to assist older adults with mild dementia and is shown in Figure 3.32.

Application use is monitored by the system using contact sensors and a smart phone was used to provide reminders if for example the fridge door was left open. The Liverpool project's system uses its sensors to generate a graphic of user behaviour. This graphic is generated at a central server once per day and can be emailed as a pdf document to relevant carers. This behavioural profile graphic contains information such as time spent in bed and number of trips to the bathroom.

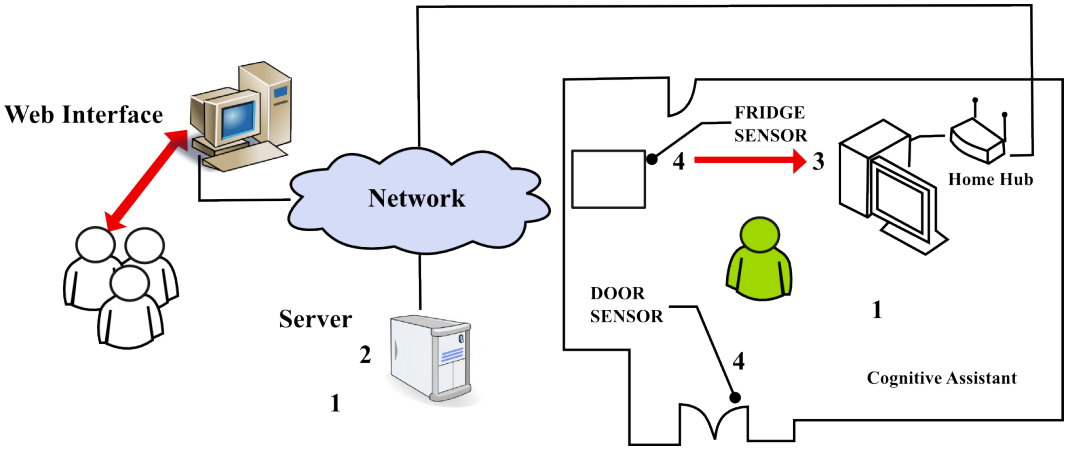


Figure 3.32: ***Architecture of CogKnow system showing platforms involved and communications infrastructure***

3.5 Behaviour Monitoring Commercial Devices.

Due to the complexity and number of sensors required to fully monitor behaviour, these monitors have not yet fully emerged into the commercial domain. However, In the past decade, the number of commercially available activity monitoring devices has expanded rapidly. This may be due to the decreasing cost of sensor components, the increase in the older population, the increasing obesity epidemic or the emergence of the "quantified self" movement. Despite the fact that these devices do not monitor the four aspects of behaviour, the authors feel that these devices are indicative of future commercial behaviour monitors and therefore should not be omitted from a review of behaviour monitoring technology. Table 3.7. shows a summary of several of the activity monitors currently available.

These devices are discussed in further detail in the following sections.

3.5.1 Research Targeted Activity Monitors

ActivPAL (PAL Technologies) The activPAL detects sitting/lying, standing, walking, step count and cadence. Data are collected and saved to the device and retrieved for post hoc analysis through a USB docking station and a proprietary software. The activPAL is one of the most widely validated devices available[160, 161, 162, 163] and has been used in several populations including preschool children [161], chronic lower back pain [164], chronic fatigue syndrome [164] and chronic obstructive pulmonary disease [165]. The popularity of the activPAL can

Device	activPAL	IDEEA	wGT3X+	Sensewear	Fitbit	Fuelband	Jawbone Up	BodyMedia FIT	MOTOACTV	BASIS
Technologies	Tri-axial accelerometer	Tri-axial accelerometer * 5	Bi-axial accelerometer	Bi-axial accelerometer, skin conductance, temperature	Tri-axial accelerometer, barometric pressure sensor	Tri-axial accelerometer	Tri-axial accelerometer	Bi-axial accelerometer, skin conductance, temperature	GPS, Tri-axial accelerometer	Accelerometer, photoplethysmograph, temperature sensor, moisture sensor
Battery life	> 8 days	3 days	30 days	5-7 days	> 5 days	4 days	10 days	5-7 days	20 hours	4 days
Memory capacity	4 MB	200 MB	512 MB (40 days)	28 days	7 days full data + 23 days summarised data	-	-	28 days	16 GB	-
Method of data transmission	Docking station	USB or RS232	USB or wireless	Wireless	USB or wireless	USB or Bluetooth	Phono	Wireless	USB	USB and Bluetooth
Parameters monitored	Posture, step count, cadence	Posture, gait details (walking, running, stairs, cycling, stride length, cadence), picking up object, individual limb position	Activity levels (METs, counts, kcalories), sleep activity, step count	Activity levels (METs, kcalories), step count, sleep activity, time lying down, skin temperature	Activity levels (kcalories), step count, number of floors of stairs climbed, sleep activity, time active, distance walked	Activity levels (kcalories, "Fuel (proprietry)), step count, time active, distance walked	Activity levels (kcalories), step count, time active, sleep activity	Activity levels (METs, kcalories), step count, sleep activity, time lying down, skin temperature	Activity levels (kcalories), step count, time active, distance walked	Activity levels (kcalories), step count, time active, sleep activity, heart rate, skin temperature, perspiration rate
Cost	€900 w/software	€3,052	€1045 w/software	€800 + €2000 advanced software	€99	€149	€129	€86 + €5.30/mo	€114	€152
Attachment	1 sensor, attached to thigh using PAL stickies	5 sensors, five locations (chest, thighs and feet), connected using wires	1 sensor, wrist worn	1 sensor, worn on upper arm	1 sensor, worn on waist, at chest or around neck	1 sensor, wrist worn	1 sensor, wrist worn	1 sensor, worn on upper arm	1 sensor, wrist worn	1 sensor, wrist worn
Size	13 cm^3	7x6.5x1.7 cm; 1.8x1.5x3 cm*5	4.6x3.3x1.9 cm	5.5x6.2x1.3 cm	4.8x1.9x0.97	ϕ14.7 cm	6.6x5.0 cm	5.5x6.2x1.3 cm	4.6x4.6x0.9 cm	3.6x3.6x2.7 cm
Weight	20g	59g; 2g*5	19g	45.4g	8g	27g	19g	45.4g	35g	44g
Research references *	52	65	34	205	12	0	0	0	0	0

* prices from direct quotes, website or named suppliers, currency conversions on 04/12/12

* Research references taken from search of ScienceDirect database

Table 3.7: ***Commercially available activity monitoring devices***

be explained in part by its unobtrusive nature and wide range of validation data.

Figure 3.33: ***activPAL***

IDEEA (MiniSun) The intelligent device for energy expenditure and physical activity (IDEEA) detects a large range of activities including very detailed descriptions of gait using fifteen different gait related parameters (listed in Table 3.7.). It detects the widest range of activities of any of the devices discussed in this section using five accelerometer sensors. However, this level of detailed monitoring comes at a cost of usability. The IDEEA requires sensors to be worn at five different locations on the body, all of which are connected by wires. Therefore, it may not be suitable for long-term monitoring of older adults. The system has been validated for use in gait analysis[166, 167] and for energy expenditure estimation [168].

Figure 3.34: ***IDEEA***

wGT3X+ (Actigraph) The wGT3X+ is the newest activity monitor available from Actigraph. This monitor uses an accelerometer to detect activity levels in METs (metabolic equivalent of tasks), activity counts, kcalories and parameters relating to sleep. The device also communicates with a smart phone application which can combine data with other compatible sensors including weighing scales, heart rate sensors and blood pressure sensors. Though this device is relatively new, the previous Actigraph systems are some of the most widely used activity

monitors in the research. Therefore, the wGT3X+ can draw on an extremely large base of validation data [169, 170, 171, 172]. Data are available for the use of Actigraph activity monitors for a wide range of populations including children [169], adolescents [173], older adults [174], diabetes [175], cardiovascular disease [176], and COPD [177] .

Figure 3.35: ***Actigraph wGT3+X***

Sensewear (BodyMedia) The Sensewear uses a kinematic sensor, temperature sensor and conductance sensor to monitor activity levels (including step count), body temperature, heat flux and galvanic skin response. The physical activity measure consists of step count, energy expenditure (kcalories and METs) and time spent lying down. The inclusion of biometric sensors as well as a kinematic sensor allows the Sensewear to collect additional parameters to those measured by the devices based on accelerometers alone. The Sensewear has been widely validated with several populations including obese adults [178, 179], chronic obstructive pulmonary disease (COPD) [177], depression [180], pregnant women [181] and hyperthyroidism [182].

Figure 3.36: ***Sensewear***

This is by no means an exhaustive list of the commercially available research targeted activity monitors. For a more complete review see [48, 183]

3.5.2 Consumer Targeted Activity Monitors

Recently, activity monitoring devices have become popular with the general public. This can possibly be attributed to the emergence of the "quantified self" movement. This movement is particularly relevant in the domain of activity because of the increase in sedentary lifestyles of the general public. This section will describe four of the mostly widely used consumer activity monitors for daily activity rather than targeted exercise. For a review of targeted exercise monitors see [184].

Fitbit The Fitbit line of daily activity monitors were one of the first to gain widespread traction with the general public. The device accelerometer is used to determine step count, energy expenditure and distance travelled. The altimeter is used to detect when the user ascends stairs. This is a particularly useful feature when the significant energy requirements of stair climbing are taken into account [185]. Sleep activity is also monitored by the device. The device's button is used to tell the Fitbit when the user is going to sleep. The device then monitors activity throughout the night to determine the quality of the person's sleep as well as the length and time taken to fall asleep. User feedback is provided through the onboard screen, an online interface and smart phone applications. These applications also allow the logging of the user's diet to complement activity data. The accuracy of the Fitbit's energy expenditure estimates have been examined and found to moderately underestimate calories burned in most cases [186, 187, 188]. However, in a consumer application, this moderate inaccuracy may not be a significant issue.

Figure 3.37: ***Fitbit***

Nike+ Fuelband This device tracks steps, distance walked and estimates energy expenditure. The Fuelband also presents a proprietary metric called "Fuel". Using this metric, the device generates goals for activity. Similar to the Fitbit, the

Fuelband provides an online and smart phone feedback interface in addition to the display on the device itself. No research is available regarding the validity of the Fuelband.

Figure 3.38: ***Nike+ Fuelband***

Jawbone Up The Jawbone Up is another wrist-worn activity monitor based on an accelerometer. The device monitors movement and vibrates to encourage activity after long periods of sedentarism. The device reports time spent in vigorous, moderate and light activity as well as step count, distance, energy expenditure and walking pace. A smart phone and web application provide feedback. These interfaces again allow the logging of food intake. Sleep quality is also monitored by the device through time taken to fall asleep, time in light and deep sleep and sleep activity.

Figure 3.39: ***Jawbone Up***

BodyMedia FIT (BodyMedia) The BodyMedia FIT is from the same company as the Sensewear activity monitor described in Section 3.5.1. Therefore, the device is based on an extremely well validated design. The FIT contains the same biometric and inertial sensors to the Sensewear and monitors similar parameters. However, the FIT is limited to a single user where as the Sensewear is designed to be used by several people with new profiles for each person possible.

Figure 3.40: ***BodyMedia FIT***

MOTOACTV (Motorola) The MOTOACTV is a wrist worn device containing a GPS sensor and accelerometer. The device also communicates with a heart rate sensor. While the device targets the monitoring of exercise performance, it also monitors garden work, walking and other daily activities. Reports include distance travelled both outside using GPS and inside using the accelerometer, energy expenditure, step count and walking pace. Feedback is provided through the device display and a smart phone application.

Figure 3.41: ***MOTOACTV***

BASIS The BASIS is a wrist worn device containing a richer suite of sensors than any other device discussed in this paper. Reports include activity, sleep quality and a graphical representation of behavioural patterns. Feedback is provided through the device display and a web application.

Figure 3.42: ***Basis***

3.6 Discussion

The field of behaviour monitoring is extremely wide, both in terms of technologies used and parameters monitored. For this reason, it is difficult to perform a detailed literature review of the entire field. There have however been several review papers into different areas within behaviour monitoring **(author?)** [189, 190, 191, 183, 48, 192, 193, 194, 195, 105, 91, 87]. For this reason, this paper has sought to give a more broad overview of the field of behaviour monitoring. After reviewing the range of approaches to behaviour monitoring, the importance of considering the application before choosing a particular approach is clear.

3.6.1 Usability vs Functionality

Regardless of the technological approach to behaviour monitoring, a trade off exists between the invasiveness of the system and the depth of the data that are generated. Inertial sensor based systems can provide detailed data about activities performed as shown by the IDEEA system discussed in Section 3.5.1, however for this depth of data, multiple sensor locations are required. This may not be a realistic option in longterm monitoring. Single inertial sensor based systems that rely on a thresholding method cannot provide the same depth of information, and transition detection algorithms are subject to error. Cost of implementation is another issue in the usability of a system. Smart homes that monitor a person's position to an accurate level require costly triangulation/trilateration indoor localisation. Less expensive forms of indoor localisation do not provide the same resolution. Therefore, the cost of the monitor must be taken into consideration when deciding on an activity monitoring solution. In the case of a residential

care facility, where several users can benefit from the same infrastructure, a triangulation/trilateration based smart home may be suitable. However, for single users in their own home, it may not be a cost effective solution.

3.6.2 Target Population

The population that the system is intended to be used by is another consideration when choosing an activity monitoring approach. Not only is it important that the particular approach has been validated with the relevant population, but certain approaches may be more suited to certain populations. For example, smart homes are a suitable activity monitor for older adults who have lost some of their independence because they may spend a large majority of their time in their home. However, smart home systems may not be a suitable choice for people who spend a large portion of their time outside of the home. In this case a system that integrates GPS may provide advantages. Similarly, several smart home systems will not be effective if there is more than one resident in the home as they may not be able to differentiate between people. In that case, an inertial sensor based system may be a better choice.

3.6.3 Differences Between Research and Consumer Devices

As can be expected, consumer devices contain a smaller range of technologies than those presented in the research. Therefore, they tend to monitor a smaller set of activity parameters usually focusing on activity quantification rather than classification. It is clear from Table 3.7. that there is a smaller range of sensors integrated into current commercial devices compared to those in research based systems.

However, a significant advantage of the consumer targeted devices discussed in Section 3.5.2 is the real-time interfaces that they provide. By giving feedback to a person in real-time, in addition to monitoring physical activity levels, increased physical activity can be encouraged. This has been shown to have a significant effect towards increasing levels [196, 197, 198]. However, some research shows this effect to be temporary [199]. Setting of goals for physical activity levels is suggested. This feature is implemented in several of the devices in Section 3.5.2 as well as the socialisation of physical activity levels. Physical activity levels of friends can be displayed to users providing an additional motivation through a

competitive mechanism. These motivational tools may be useful in activity intervention studies.

3.6.4 Data Presentation and Interpretation

The comparison of results from different activity monitoring devices can be an issue due to different methodologies and conventions used. Work has been introduced to try to equate results from accelerometers using different activity thresholds [200]. Another way to overcome the difference in output is by comparing classified activities or behaviours such as step count or time spent sitting. However, even with similar behaviours it is possible that different monitors cannot be compared. For example the Fitbit and Nike Fuelband devices both report inactive time. However, no definition is provided as to what "inactive" means for each device.

Granat proposed a framework for the presentation of activity data [133]. This framework puts an emphasis on an event based approach in which the activity, the time the activity started and the duration of the activity are all important. By reporting the duration of activities or "events" far more behavioural information can be deduced. For example if a person spends X% of their day being active, it is significant from a behavioural standpoint whether the majority of that activity occurred in one single bout or several short instances throughout the day.

Regardless of the comparability of results, the task of interpreting these data can be significant. For this reason, methods for the generation of a single metric to represent activity data have also been used. These metrics can combine several activity/behaviour inputs and represent overall activity in a single score for example "Nike Fuel". However, the methods used to generate this score are not published. For these scores to be useful in comparison across results, the logic behind their generation must be shown. This logic should be developed based on similar concepts across devices if results are to be compared. Because no method for this score generation has yet been widely adapted, research based activity monitors do not typically present these single score metrics.

3.6.5 Future Trends

The emergence of smart phone technologies as ubiquitous in the general population provides a significant opportunity for the monitoring of daily activity. These smart phones provide a platform for rich user interfaces for feedback provision

as well as an advanced suite of sensors including accelerometers, gyroscopes, magnetometers, ambient light as well as near field communication, bluetooth and internet connectivity. Realtime feedback will become a more widespread feature of activity monitors . The possibility of performing the monitoring using the smart phone's sensor suite may also have dramatic usability consequences by eliminating the cost and other issues related to extra specialised devices.

Wearable electronics is another field that may have significant effects on activity monitoring devices. While several of the devices discussed in this paper could technically be defined as wearable, the integration of sensors into clothing rather than simply strapping a sensor to a limb could vastly improve usability. Clothes could be manufactured to contain EMG sensors at the chest or inertial sensors within the fabric itself. Printed circuitry and flexible electronics are exciting technologies that may accommodate this.

Currently, systems that perform activity monitoring in a contextual way such as indoor or outdoor location systems are separate to activity detection systems such as inertial sensor based systems. Significant value could be added by combining the contextual information with activity data. For example, by adding outdoor location data, a system could not only display the number of calories burned in a day, but also break up this data into saying the person burned a certain amount of calories this week walking to work, or that their sleep quality was better on days that they have visited the gym.

Behaviour monitors could also be designed to fit into current clinical practice more efficiently. A significant barrier to the uptake of activity monitors to clinical situations is the inability of the medical system to adapt to this new input. A possible way of encouraging uptake would be to design the output of the monitors to mimic current clinical metrics. In this way, the implementation of activity monitoring programs would not require a significant change in the practices of clinical staff. In the area of functional assessment, the vast majority of assessments examine parameters that overlap significantly with the capabilities of activity monitor devices e.g. gait parameters. It is conceivable that assessments that target similar domains such as functional ability could be designed to be carried out using the outputs of technological activity monitors.

3.7 Conclusion

The field of behaviour monitoring is extremely active with a very large range of approaches currently being investigated. No single approach has emerged as the best method of monitoring behaviour, however, due to the diversity of human behaviour and the range of populations for which behaviour monitoring is useful, it is likely that all of the approaches discussed in this paper have a use. Behaviour monitoring devices have recently gained traction with the general public in a "quantified self" and weight management context, however they have yet to integrate fully into clinical practice. As well as maintaining usability and functionality, facilitating this integration will be one of the major challenges facing the field of behaviour monitor design in the future.

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Competing interests: None declared

Ethical approval: Not required

Chapter 4

The Development of a Wearable Behaviour Monitor

4.1 Introduction

4.1.1 Behaviour vs Activity Monitoring

Activity monitoring technology has been an active research area for over a decade. A wide range of activity monitoring devices have been introduced as reviewed in Chapter 3 of this thesis as well as in several other published literature review papers [48, 193, 201]. These devices can provide detailed reports regarding the amount of physical activity a person performs. More advanced activity monitors can classify this activity into different postures [150]. Other systems can provide a contextual report regarding a person's performance of activities of daily living. For example, Le et al. introduced a smart home based system that could report the amount of time a user spends in each room of the home as well as generate a visual report of their location throughout the day [49]. However, systems that combine the activity a person performs with contextual information such as indoor location are not common. These contextualised activity data may prove to be more useful than activity or location data when presented individually. These data could describe behaviour rather than activity alone. This may represent a paradigm shift in the monitoring of human activity from activity data alone to more detailed data regarding behaviour that may explain the cause of inactivity more effectively and give a better indication of quality of life. The development of a wearable device capable of performing this contextualised activity monitoring or "behaviour monitoring" both inside and outside the home is described in this chapter.

4.2 Proof of Concept

As the concept of combining activity data with contextual data has not been widely reported, it was deemed suitable to perform a preliminary proof of concept study using off the shelf hardware. The technology used in this study was chosen on the basis of ease of implementation. Therefore, the system used off the shelf devices and did not take into account the usability of the system.

Activity classification was performed using a two accelerometer, threshold based detection algorithm similar to that presented in [148]. Accelerometers were attached to the chest and thigh using elasticated velcro straps and tubifast bandaging. Posture was classified based on the inclination of the thigh and

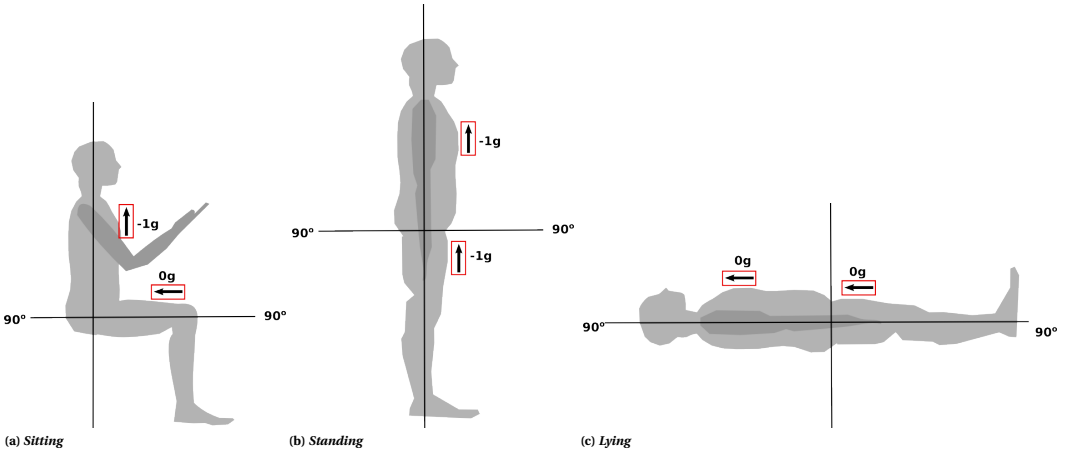


Figure 4.1: ***Threshold based posture detection: shows the operation principle of the two accelerometer threshold based posture classification method used. The static acceleration at the thigh and trunk are used to differentiate between the three postures.***

trunk as shown in Figure 4.1. The accelerometer platform used was the SHIMMER wireless sensor from Shimmer Research.

Radio Frequency Identification (RFID) based indoor localisation: An i-Card3 PCMCIA 868MHz RFID reader and iD2 semi-active RFID tags were used for the study. The reader was interfaced with a PDA device through an external PCMCIA adapter for control and data logging. The output power of the reader was configured to 11dBm for a tag read range of ~1.5m. The apparatus is shown in Figure 4.2. The RFID reader was configured with a sampling frequency of 1Hz. This frequent transmission from the reader meant that power consumption of the RFID reader was significant. This severely affected the battery life of the PDA. Maximum battery life was around 3 hours.

Indoor location detection was performed using an RFID proximity based technique. RFID tags were installed in each doorway of the home and users carried an RFID reader on their person. When the user came into proximity of an RFID tag, the system classified the user as entering the associated room. False detection of entries to rooms caused by users passing a doorway without entering the room were corrected when the user entered another room passing another RFID tag in the process.

Figure 4.2: ***Pilot study apparatus showing from left to right: the external PCMCIA slot for interfacing the RFID reader to the PDA, the PDA, the RFID reader and the SHIMMER accelerometer platform used in the study***

4.2.1 Testing

4.2.1.1 Protocol

Eight healthy young adults (4 male, 4 female, mean age: 28, SD ±10 years) were recruited to take part in this study. Figure 4.3. shows a participant wearing the apparatus for the study. The study was carried out in five different homes. Efforts were made to incorporate several different types of housing as the ambient sensor based RFID localisation system may be affected by different layouts of home causing RFID tags to be within differing proximities to each other. As the decision of transmit power and range was decided based on preliminary testing, this varying test environment was deemed important. The houses used include two rural bungalows (172m^2 & 370m^2), a two-storey suburban house (209m^2) and two city-centre apartments (51m^2 & 104m^2). Each participant was monitored by the system for an 8 hour period between the hours of 9am and 6pm. These hours were picked to incorporate the most active parts of the day. Informed consent was obtained from all subjects and ethical approval was granted by the National University of Ireland Galway Research Ethics Committee. Each participant was shadowed by a researcher for the entire duration of their participation in the study. Due to the short battery life of the PDA, participants were asked to place the PDA in a charging dock at times that they planned to be stationary for an extended period of time (over 30 mins). The researcher carried the charging dock with them as they followed the participant. The researcher kept a manual log of every time the person moved to a different room or changed their posture. This log was then used to verify the accuracy of the report generated by the system.

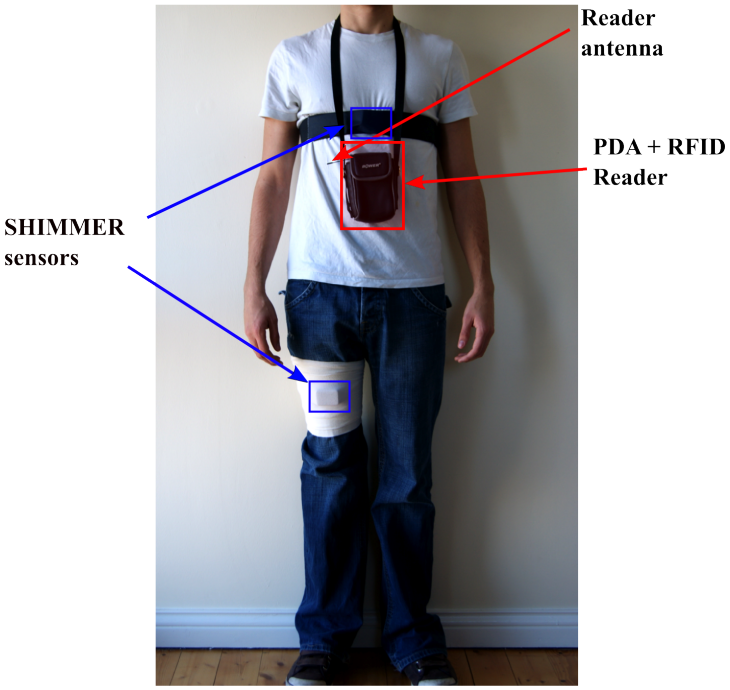


Figure 4.3: ***Participant wearing apparatus***

This log consisted of a time stamp, current activity (sitting, standing, lying or walking) and current indoor location.

4.2.1.2 Results

A total of 64 hours of monitoring was performed in which there were 294 location changes, 283 of which were successfully detected. Table 4.1. shows the accuracy of the RFID based location system. The system correctly identified the location of participants 92.4% of the total time monitored on average.

Figure 4.4. shows the data collected using activity data and Figure 4.5. shows activity data combined with indoor location data. In Figure 4.4. each subplot represents an hour of the day. The colour of the graph at any given point shows the users posture at that time. Figure 4.5. represents the same principal. In this graph, plots for each hour are split horizontally. The top half of the plots represents the user's posture at that time, the bottom half of the plot shows their location at the time.

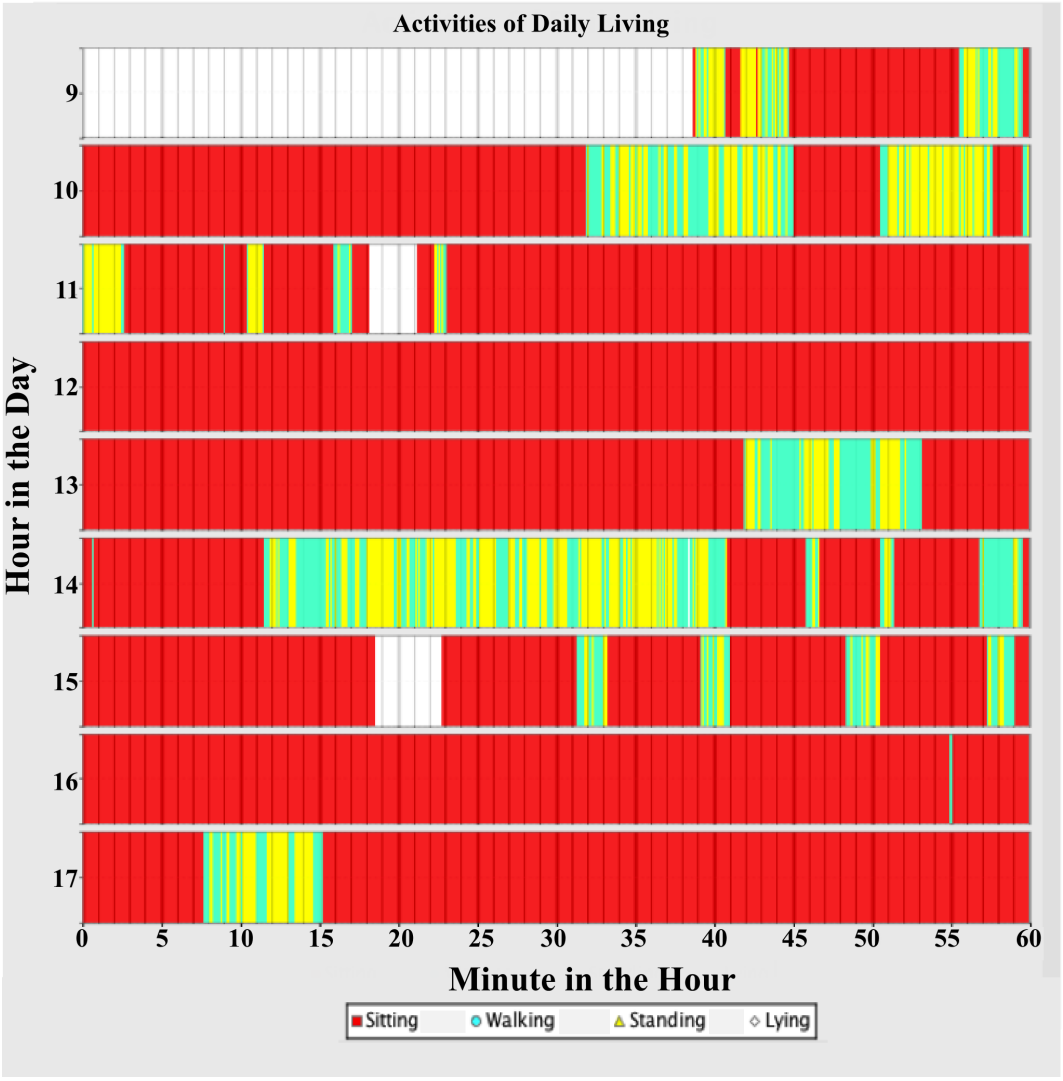


Figure 4.4: ***Activity only: shows the output from the pilot activity monitoring system alone. Periods of activity and inactivity are easily identified through relevant colour codes. Each subplot in the graph represents an hour of the day. Each vertical gridline represents a minute in the relevant hour.***

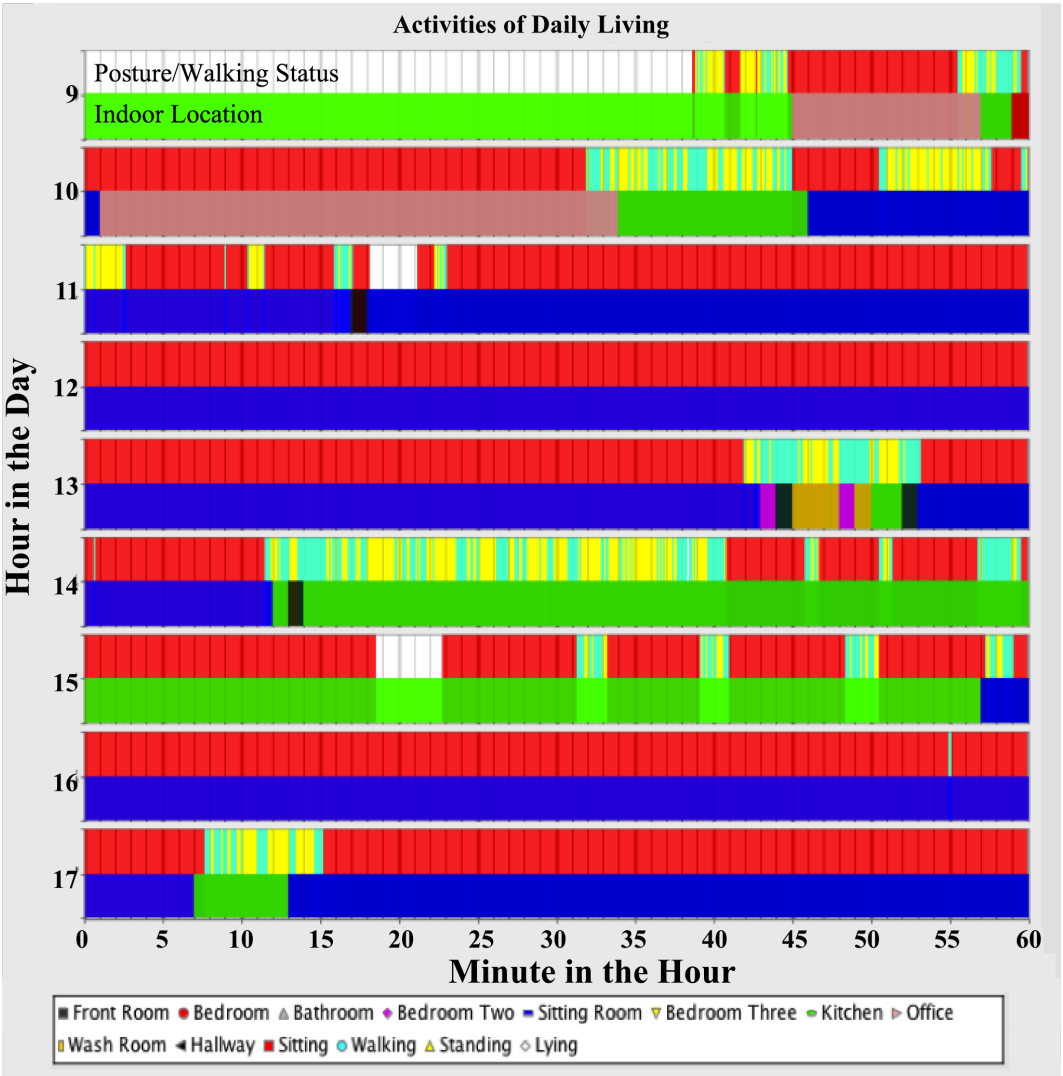


Figure 4.5: ***Contextualised activity: shows output from activity monitoring and localisation systems. Periods of activity are easily identifiable on the top half of each hour subplot as well as the context of the activity on the bottom half.***

Participant	Location Accuracy
1	91.9 %
2	96.0 %
3	97.9 %
4	94.3 %
5	99.8 %
6	94.5 %
7	76.0 %
8	91.3 %
Mean	92.4 %
S.Dev	7.9 %

Table 4.1: ***RFID location accuracy for each participant during pilot trial***

4.2.1.3 Discussion

Figure 4.4. gives a useful picture of the person's activity pattern for the day, showing several periods of activity throughout the day. The person is shown to be active when they first get up in the morning for about 5 minutes followed by almost an hour of sitting. There is then some intermittent periods of activity followed by over 2 hours of uninterrupted sitting. There is a 30 minute period of activity around 2 o clock and relatively little activity for the rest of the evening.

However, Figure 4.5. generates much more information than activity alone data. Not only can activity periods be identified, but the context of these periods is also available. For example, a long period of activity in the morning occurred in the kitchen, suggesting the user may have prepared breakfast. Again at midday, there was a long period of activity followed by a long phase of inactivity with intermittent periods of activity. This may suggest the user prepared lunch and cleared up afterwards. The long period of sitting just after the person got up can be seen to have occured in the office room suggesting the person used the computer or performed other desk work. These examples demonstrate the expanded data analysis capabilities provided when activity data is contextualised by providing location data also.

These results demonstrated the advantages of contextualising activity/posture data. The next step was to develop a new more usable system that not only contextualised posture/activity data with indoor location but also expanding the activity monitoring functionality drastically and added outdoor contextualisation too.

4.3 Design Considerations

4.3.1 Usability vs Functionality

The development of this device was heavily influenced by the findings of the literature review presented in Chapter 3 of this thesis. The trade off between functionality and usability is described in detail in that chapter. Wearable technology has been suggested as a way of improving the acceptability of the device without sacrificing functionality. Integrating the electronics into a piece of clothing, which the user then wears, provides usability advantages over other methods of attachment such as straps or double sided tape. With this in mind, the system described in this chapter was designed as a wearable device.

4.3.2 Integration into Clinical Practice

Another finding from the review in Chapter 3 is that the acceptance of the device into clinical practice should be a major consideration in behaviour monitor design. This goal was the core design principle of the device presented in this chapter. The current gold standard for functional activity assessment of older adults in a clinical context was reviewed in Chapter 2. Several of the activities examined in conventional assessment scales widely overlap with those monitored by behaviour monitoring devices or systems. One of the major advantages of conventional assessment tools is their straight forward outputs. The majority of those tools generate a single score, meaning changes in results are easily tracked and quickly interpreted. For behaviour monitors to be integrated into clinical practice in a meaningful way, it is our view that they need to mimic this simplicity in their design.

4.3.3 Design Requirements

With these design considerations in mind, the following set of requirements were defined for the system developed:

1. The system should be in the form of a wearable device
2. The system should be based at a single body location
3. The system should detect posture

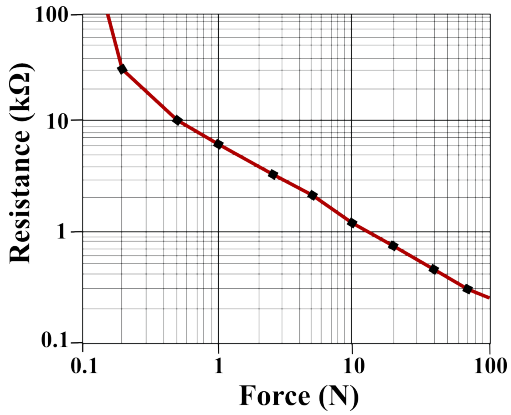
4. The system should detect indoor location
5. The system should detect outdoor location
6. The system should detect parameters related to gait
7. The parameters monitored by the system should overlap conventional assessment tools as closely as possible
8. The system should output a result in a single score that is meaningful to clinicians in addition to more detailed data
9. The system should be inexpensive
10. The system should provide feedback to the user

4.4 Technology Design

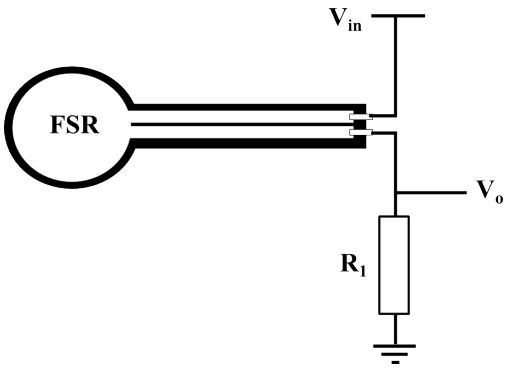
The proof of concept study described in Section 4.2 has shown the advantages of contextualising activity data. However, the technology used in this study is not practical for real world use. This section will describe the development of a more acceptable system with expanded activity and localisation functionality and with far superior usability characteristics over that used in the proof of concept study.

4.4.1 Posture/Activity Monitoring

The threshold based posture/activity detection technique used in the proof of concept system is an accurate and simple method of detecting posture. However, the requirement of two sensor locations on the body (at the thigh and trunk) means that it does not meet the usability criteria for the system. Therefore, other activity detection methods were considered. As the device was designed to be used by different populations including healthy adults, an activity monitoring solution based on accelerometer sensors was deemed the most suitable. Accelerometer sensor based systems can be worn outside of the home whereas smart home systems are limited to home use. The available accelerometer sensor based detection approaches are discussed in detail in Chapter 3. Approaches requiring two locations on the body were ruled out due to usability requirements and single body location transition based systems were ruled out due to possible significant error introduced by false positives and false negatives. Therefore, it



(a) ***Relationship between force exerted on an Interlink FSR and the sensors resistance***



(b) ***FSR circuit used in posture detection algorithm. Circuit places FSR sensor in a voltage divider circuit which generates a measurement of the force exerted on the FSR at V_o***

Figure 4.6: ***FSR properties and circuitry used in posture detection algorithm***

was decided that a new posture classification behaviour monitoring technique would be developed. This new method would be designed to fit into a wearable solution while using a single sensor location on the body and would not rely on transition detection to monitor posture.

The posture detection algorithms that were designed for use in the system rely on an accelerometer and a Force Sensitive Resistor (FSR). Differentiating between sitting and standing postures is done using the force sensitive resistor in a voltage divider circuit as shown in Figure 4.6b. placed under the user's heel. This circuit takes advantage of the force vs. resistance properties of FSR sensors shown in Figure 4.6a. and discussed in detail in Chapter 3. During standing, the force exerted on this sensor is much larger than that exerted during sitting due to the distribution of weight. During standing, the person's entire weight is exerted across their two feet. Therefore, the force exerted on the sole of the heel is approximately half of the users total weight. During sitting, only a fraction of the person's weight is exerted on the soles of their heels. Harrison et al. reported 25% of a users body weight to be exerted on the feet during upright sitting in a firm upright chair [202]. This is likely to be less when sitting in a chair that supports the thighs more such as a couch. This weight is distributed approximately equally during sitting on each foot. For example, a user who weighs 700N (~70kg mass) will exert approximately 350N on the FSR sensor during standing and only 87N during sitting (when disregarding the dampening effects of the FSRs protective

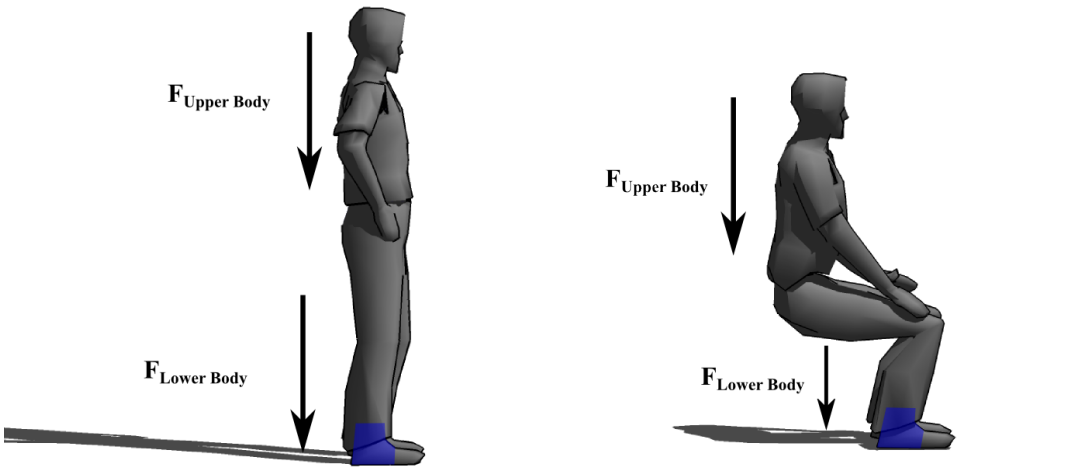


Figure 4.7: ***Forces exerted on heel sensor during standing and sitting. Force during standing is much larger.***

enclosure as discussed in Chapter 3). During standing, the majority of this force is exerted at the heel [203]. Where as during sitting this weight is more evenly distributed across the foot. Even within the heel, the FSR will only cover a fraction of the heel further reducing the force exerted on it. Meaning only a fraction of this 87N is exerted on the FSR during sitting, where as most is exerted on the FSR during standing. To illustrate this, if the weight distributed on the heel is taken to be 50% of the weight exerted on the entire foot, Figure 4.7. demonstrates the forces involved.

The measurement of this force is implemented using an FSR sensor in a voltage divider circuit as shown in Figure 4.6b. Equation 4.1. shows the relationship between the FSR resistance (set by the force exerted) and the output voltage of the circuit.

$$V_o = V_{in} \times \frac{R_1}{R_{FSR} + R_1} \tag{4.1}$$

where V_o, V_{in}, R_{FSR} and R_1 are shown in Figure 4.6b. The resistor R_1 sets the sensitivity and force sensing range of the circuit. Larger values for R_1 reduce the significance of R_{FSR} in the formula. Therefore, if a large resistor value is used, then a small increase in the force exerted on the FSR will result in output V_o approaching V_{in} as the resistor divider approaches 1. This increases the effect that reductions in FSR resistance have on the output voltage and decreases the range of forces that can be exerted on the FSR before V_o reaches its maximum value

equal to V_{in}. For example, a value of $100k\Omega$ for R_1 leads the equation to:

$$Vo = V_{in} \times \frac{100,000}{R_{FSR} + 100,000} \tag{4.2}$$

If a 10N force is exerted on the FSR decreasing its resistance from $1M\Omega$ to around $1k\Omega$ the equation becomes:

$$V_0 = V_{in} \times \frac{100,000}{101,000} = V_{in} \times 0.99 \tag{4.3}$$

Conversely, a small value for R_1 means that the FSR resistance has a larger effect on the resistor divided in the equation. Large drops in FSR resistance are required to affect the circuit output voltage. For example, a $1k\Omega$ value and the same 10N force on the FSR leads the formula to:

$$V_o = V_{in} \times \frac{1000}{2000} = V_{in} \times 0.5 \tag{4.4}$$

Because of the large variation in force between different users due to body weight, the choice of the configuration resistor R_1 in the FSR circuit was very important. Higher values for R_1 result in a more sensitive circuit with a lower force sensing range. Therefore, if the calibration resistance was chosen as too high a value, heavier users could cause the FSR readings to cross the standing threshold while sitting as the circuit would be too sensitive. If the value was too low, the FSR output may not cross the standing threshold for lighter users while standing as the circuit would not be sensitive enough. Laboratory tests were performed to find the best value for R_1. An FSR circuit was created with a potentiometer in place of the calibration resistor. Several colleagues were asked to stand on an FSR while the potentiometer was adjusted in $1k\Omega$ steps. Readings were taking of the output voltage at each step. A value for the calibration was chosen from this data based on the resulting graph. The most appropriate value was chosen as $5k\Omega$. This value generated an output that was not so sensitive as to give the maximum output when a person sat with their foot resting on the FSR but sensitive enough to respond to the additional weight of standing on the FSR. The output curve also allowed for the threshold to be set low enough so that a lightweight person would still exceed the threshold when standing on the FSR without being too sensitive to lesser forces that are exerted such as when sitting. The dampening effects of the protective enclosure used with the FSR resulted in a higher suitable value for R_1 than may have been expected. In this configuration the FSR acts as an effec-

tive on/off switch for standing detection.

Sitting and standing are differentiated from lying using the accelerometer. The accelerometer is used to determine the inclination (as discussed in Chapter 3) of the lower leg and is based at the ankle. During lying, the lower leg will be inclined closer to horizontal than during sitting and standing allowing for lying to be classified.These classification rules for the detection of posture using inclination at the ankle and force under the heel are shown in Equations 4.5. - 4.7.

$$Lying = (135^o < \theta < 45^o) AND (160^o < \phi < 70^o) AND (\text{FSR reading } < 2.3V) \quad (4.5)$$

$$Sitting = (135^o > \theta > 45^o) AND (160^o > \phi > 70^o) AND (\text{FSR reading } < 2.3V) \quad (4.6)$$

$$Standing = (135^o > \theta > 45^o) AND (160^o > \phi > 70^o) AND (\text{FSR reading } > 2.3V) \quad (4.7)$$

where θ is the inclination in the z plane (shown in Figure 4.9.), ϕ is the inclination in the y plane (Figure 4.9.), and FSR reading is the voltage from the output of the FSR circuit shown in Figure 4.6b. This novel technique for classifying posture is outlined in Figure 4.8.

Thresholds used to differentiate between sitting/standing and lying are also shown in Figure 4.8. The relevant planes for these thresholds are shown in Figure 4.9. Inclination thresholds for differentiating between upright postures and lying were chosen by taking measurements in several types of seat. Readings for inclination were taken while sitting in an office chair, two different couches, a stool and a kitchen chair. Thresholds were chosen to ensure that sitting in these different types of seating would be correctly classified.

To avoid misclassifications of posture due to accelerometer noise or a person's movements (e.g. stretching their legs out when sitting), new postures are not classified based on a single case of meeting relevant thresholds. A new posture must be detected a certain number of times before it is registered as a change in posture. Though this repeat detection requirement introduces a small delay in recognising new postures, this delay is in the order of 2-3 seconds and is considered acceptable.

Figure 4.10. shows a flowchart of the algorithm described for the detection of posture.

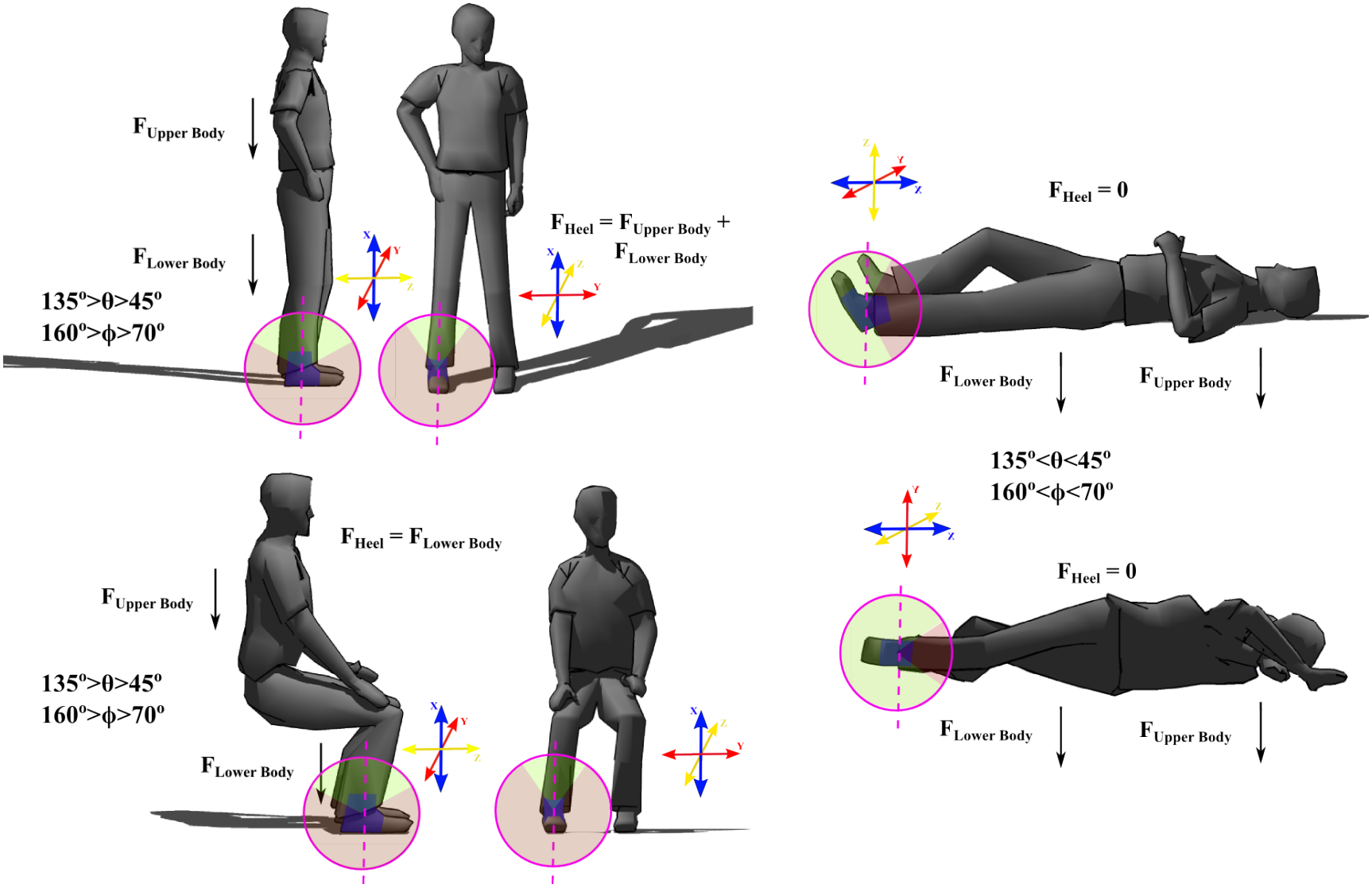


Figure 4.8: ***Smart Sock activity detection operation shows the logic used to determine posture. The thresholds used on the accelerometer readings to determine posture are shown where θ is the angle of the accelerometer in the z plane and ϕ is the angle in the y plane.***

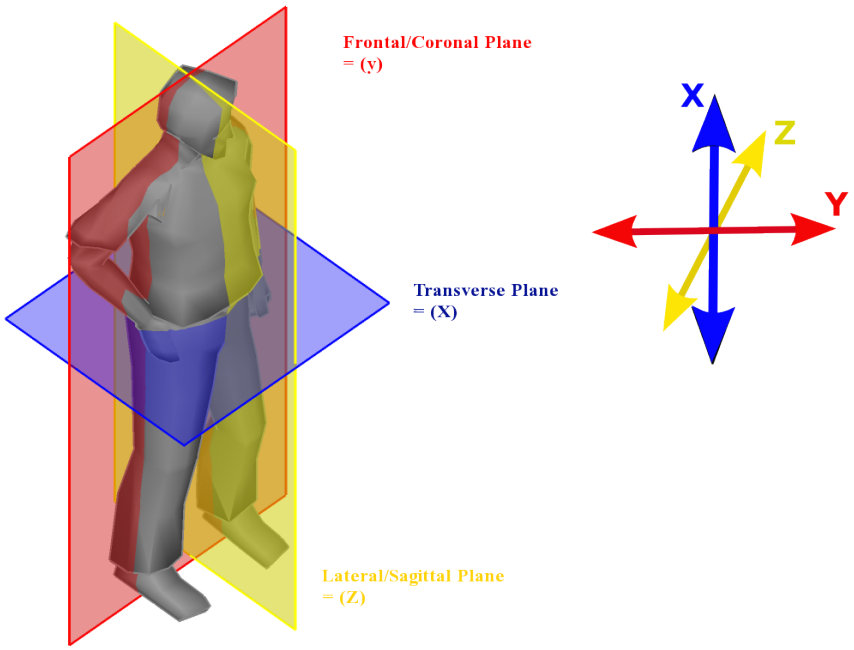


Figure 4.9: ***Planes used in setting thresholds for posture detection. Thresholds are implemented in both the coronal and sagittal planes.***

Walking detection is performed using a previously reported algorithm introduced by Lyons et al [148]. This algorithm has been validated for older adults [88]. The algorithm is based on the standard deviation of the magnitude of the three accelerometer axes over a window of n samples i.e.

$$DynamicActivity = \sigma \begin{bmatrix} \sqrt{x_1^2 + y_1^2 + z_1^2} \\ \sqrt{x_2^2 + y_2^2 + z_2^2} \\ \vdots \\ \sqrt{x_{n-1}^2 + y_{n-1}^2 + z_{n-1}^2} \\ \sqrt{x_n^2 + y_n^2 + z_n^2} \end{bmatrix} \tag{4.8}$$

This standard deviation is a measure of dynamic activity. If the standard deviation is greater than a set threshold then the activity taking place is classified as a dynamic activity. With the correct threshold and the accelerometer based in the wearable device at the ankle just above the shoe line, this dynamic activity is likely to be due to ambulation.

Thresholds were chosen by recording accelerometer output while walking on a treadmill at three different speeds: 2km/hr, 3.5km/hr and 5km/hr. The dy-

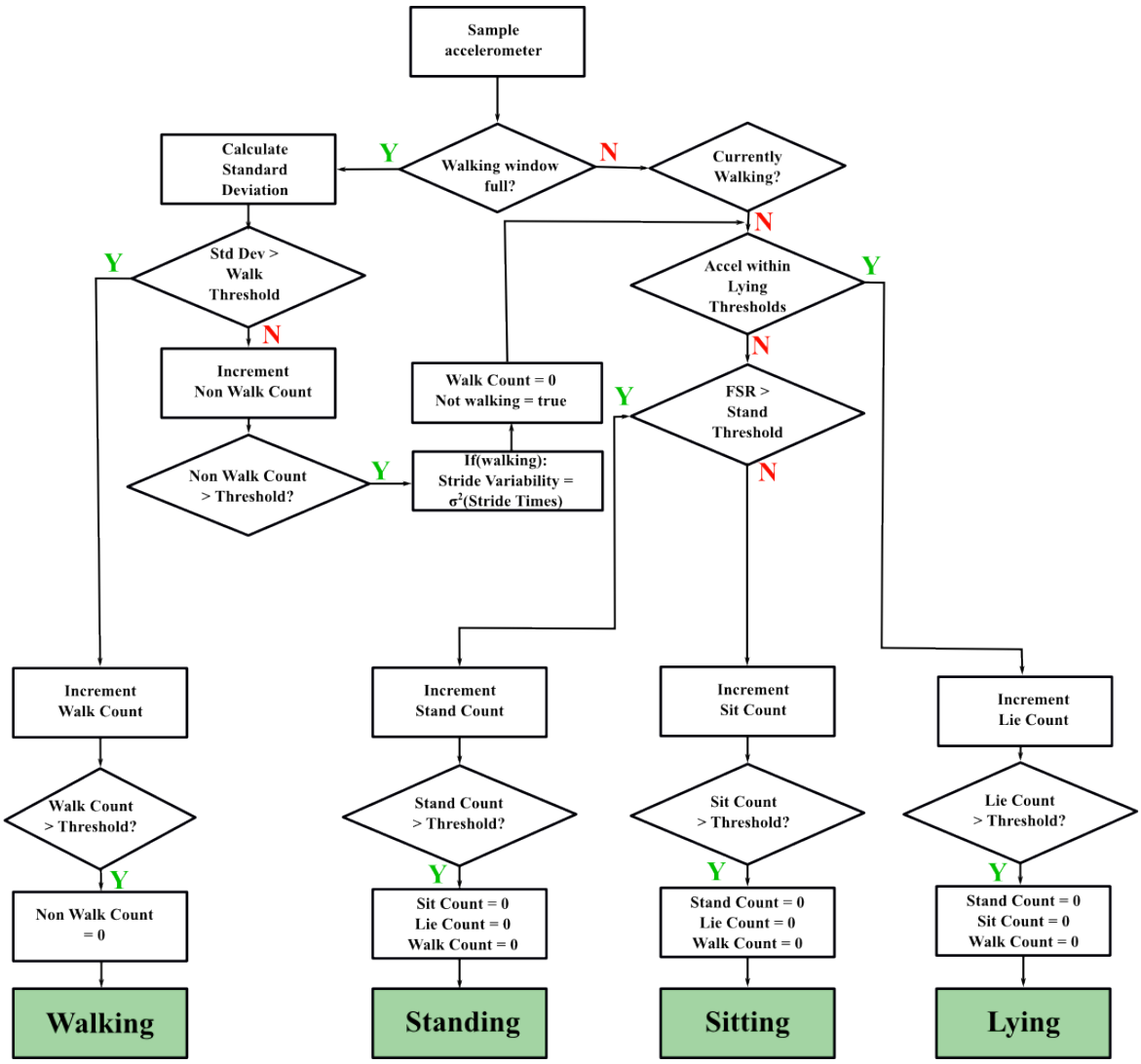


Figure 4.10: ***Posture/Activity detection flowchart: shows the logic used to determine sitting, standing, lying and walking***

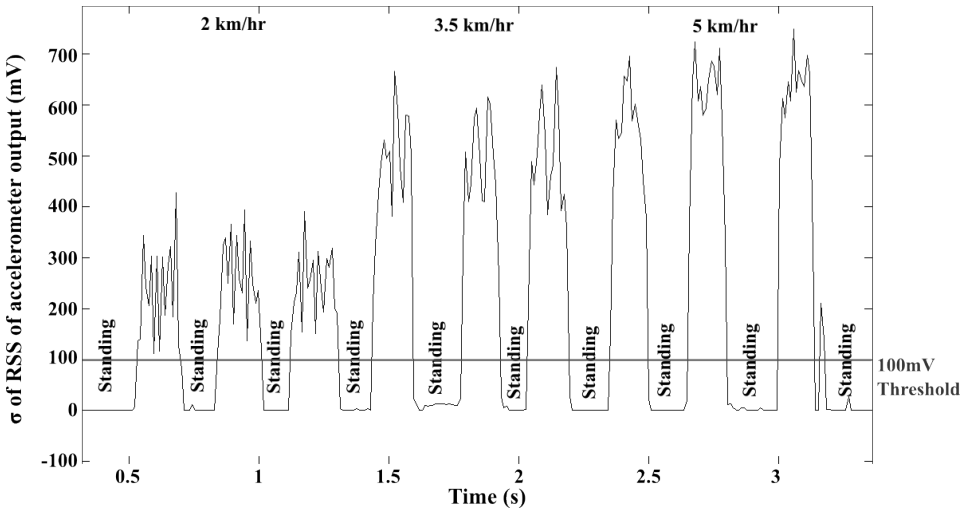


Figure 4.11: ***Dynamic activity during treadmill walking at 2km//hr, 3.5km/hr and 5km/hr. Threshold for standard deviation of the Root Sum Square of accelerometer signal for detection of walking set at 100mV.***

namic activity according to the equation above was calculated with a sampling frequency of 20Hz and a window of 1 second and graphed in Figure 4.11. The threshold chosen for the standard deviation of the magnitude of the three axes was 100mV based on this graph. This algorithm is shown graphically in Figure 4.10.

Gait parameters are also monitored by the device. A person's gait is often examined in performance based conventional activity assessments. These assessments usually rely on metrics such as time taken to walk a set distance or cadence and stride time variability (as may be judged based on observation). More in depth gait analyses are possible, however they are not feasible to perform in these every day assessments. The device described in this chapter was designed to emulate these assessment metrics. The force sensitive resistor is used for this purpose. Heel strike and heel off events are detected by monitoring the force exerted on the FSR. During ambulation, when the output of the FSR exceeds a threshold (the same threshold used to detect standing), the event is classified as heel strike. After this event, the Smart Sock waits for the FSR output to return below the threshold and this event is classified as heel off. These events are relevant to gait parameters as shown in Figure 4.12. The process consists of four main parts:

1. Begin process when person is classified as walking

2. Check whether the person's heel is on the ground

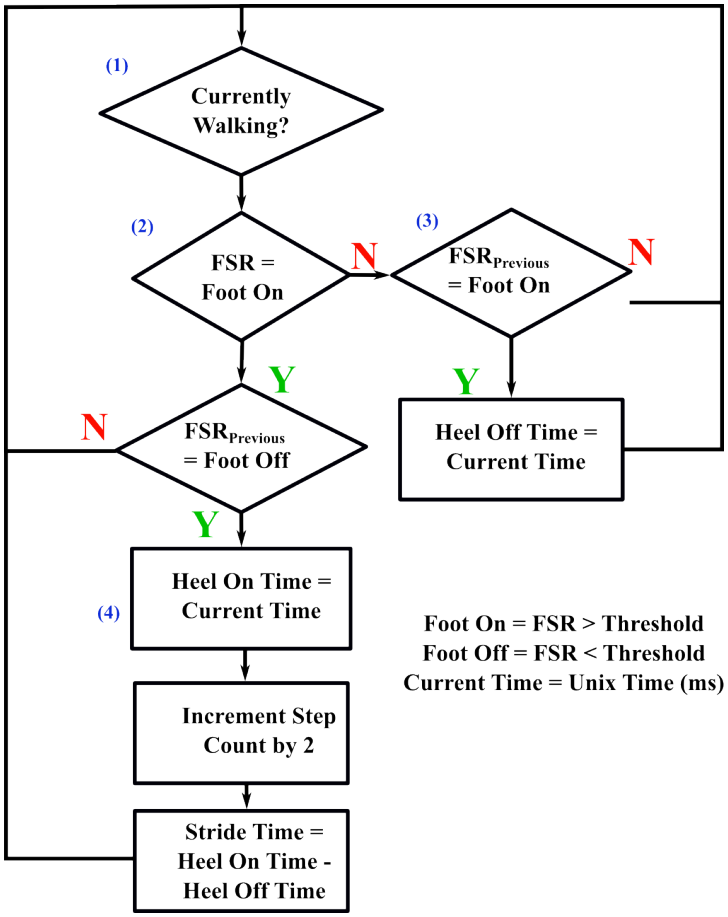


Figure 4.12: ***Gait parameters flow chart***

3. If it is not on the ground but was in the last iteration, heel off has occurred. The time of this occurrence is saved.

4. If it is on the ground but was not in the last iteration, heel strike has occurred. This time of occurrence is saved, the stride time calculated and the step count incremented by two (to account for step with other foot too)

Both cadence and stride time measurements are only integrated into daily average and variability calculations if they occurred during a walking instance that contained more than five steps. This is to ensure small or inconsistent stepping during short instances of stepping or shuffling (as opposed to walking) do not effect results. Stride variability is calculated for each instance of walking. The mean of these individual stride variability measures is then taken as the measurement for the day.

Energy expenditure: The device generates an estimate for energy expenditure in kcalories. The possibility of developing proprietary energy expenditure

Age	Males	Females
15-18	$EE = CF \times (17.6 \times weight + 656)$	$EE = CF \times (13.3 \times weight + 690)$
19-30	$EE = CF \times (15.0 \times weight + 690)$	$EE = CF \times (14.8 \times weight + 485)$
31-60	$EE = CF \times (11.4 \times weight + 870)$	$EE = CF \times (8.1 \times weight + 842)$
>60	$EE = CF \times (11.7 \times weight + 585)$	$EE = CF \times (9.0 \times weight + 656)$

*CF = Activity correction factor
*EE = Energy Expenditure

Table 4.2: ***Schofield equations***

algorithms for the system was investigated. However, due to the cost involved in gold standard testing (indirect calorimetry and doubly labelled water) as well as the repeated testing required for validity with different populations, this approach was not feasible. Therefore, energy expenditure estimation equations were investigated. The Schofield equation [128] was chosen for implementation in the device due to it's validation with different populations including older adults [130, 204]. It should be noted that none of the energy prediction formulae available have shown validity in all examinations [205, 206], however, as an estimate figure they were sufficient for use in this system. The Schofield equations for different aged men and women are shown in Table 4.2. The Schofield equation generates an estimate for the person's Resting Metabolic Rate (RMR). This RMR value represents the energy a person would expend while sitting still for 24 hours. For an estimate of actual energy expenditure, the RMR must be multiplied by a correction factor based on their activity level.

The correction factor for the Schofield equations depend on the current activity being performed. The correction factors used are as follows:

- Sedentary (Lying, sitting) = 1.2
- Lightly active (Standing) = 1.375
- Moderately active (Walking (cadence < 100)) = 1.55
- Very active (Running (cadence > 100)) = 1.725

To calculate the number of calories burned in a given period, the Schofield calculation is performed for the relevant activity level and divided by the time the activity was performed for. For example, if a thirty year old person who weighed 70 kg stood up for a five minute period. The calorific expenditure for that period would be calculated as follows:

$$EnergyExpenditure = (1.375 \times (15.0 \times 70 + 690)) \times \left(\frac{5}{60 \times 24}\right) = 8.307 kcalories \quad (4.9)$$

On the Smart Sock, each time a change in activity is detected, the energy expenditure for the previous period of activity is calculated and added to the total expenditure for that day.

4.4.2 Contextualisation - Indoor Location Monitoring

4.4.2.1 RFID Proximity Based Indoor Location

The RFID proximity based indoor localisation system used in the proof of concept study described in Section 4.2 performed with encouraging accuracy for such a prototype. However, as with the activity detection in that system, the localisation system is not usable in its current form. This system used active RFID tags in the doorways of each room in the home. After researching available active RFID readers, it was decided than none were compact enough for longterm usability. The most compact suitable readers available were > 60 mm long. This was considered much too large to be worn at the ankle in addition to other components in the wearable device. It would be possible to hold the reader at another location (e.g. in the person's pocket), however this would violate the single location requirement for the system set out in Section 4.3.3. Passive RFID readers were also investigated. The use of passive tags would significantly reduce the cost of the entire RFID system. Passive tags are also much smaller and easier to install than their active counterparts. Passive tags are available as stickers that can be attached to any non-metal surface. However, passive tags contain no power source and derive all of their power from the signal transmitted from the reader. Because of this, to achieve the necessary range (>1.5m), the transmit power and antenna size required for passive tags were too large to be acceptable in this system.

Aside from usability issues and despite the encouraging results obtained in the proof of concept testing, there are accuracy concerns with an RFID based localisation system. Similar to the error introduced in transition based activity detection systems, false positives and false negatives can cause significant inaccuracy in this type of system. Because radio signals can penetrate through walls, the RFID system must be calibrated so that the range of discovery for beacons only covers a small radius around the doorway. If this calibration was not per-

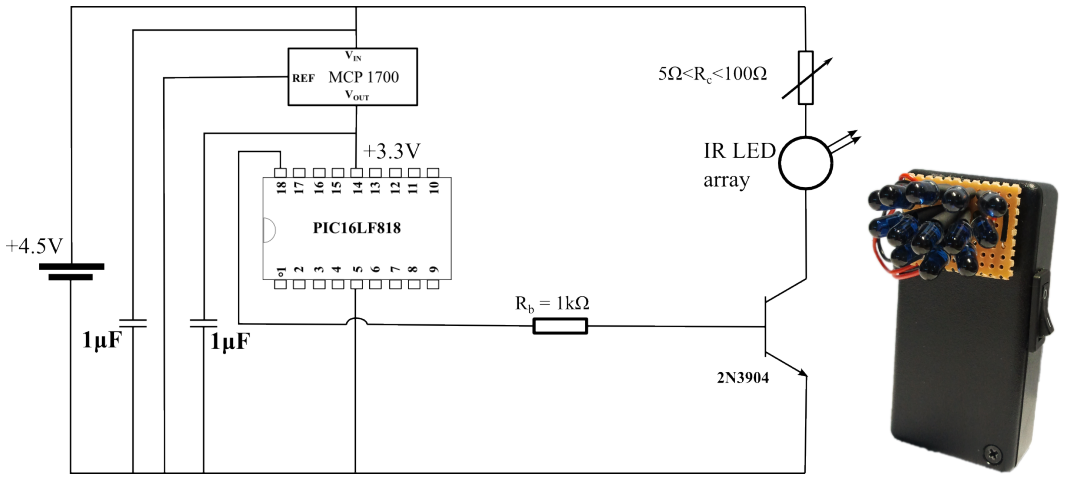
formed, RFID tags from the next room could be picked up when a person is near a wall inside another room. This would cause significant error. However, due to this calibration, the window of opportunity for the system to detect a person entering a room is quite small. If this window is missed, the system will classify an inaccurate location until the person changes location again, which could be a significant period of time later. This is an unacceptable source of error.

For the reasons outlined here, an RFID proximity based indoor localisation method was ruled out for use in the system.

4.4.2.2 Infrared Based Indoor Location

Though proximity based localisation using RFID was deemed to be unsuitable for inclusion in this system, proximity based localisation was still the most suitable technique of localisation due to cost of implementation and location resolution requirements. Therefore, other technologies were examined for use in the system. Infrared light does not have the same penetration properties as radio signals. Therefore, systems based on infrared do not need to be calibrated to the same small range as radio systems because there is no risk of signals leaking through walls. This means that the signal can be made to be powerful enough to cover a large area of a room. This larger area of coverage extends the window for beacon detection significantly, therefore the risks of false positives and false negatives are significantly reduced. Even if the beacon is missed as the person enters the room, it is likely that the signal will be picked up when the person is elsewhere in the room. The window for detection may be continuous if the beacon can cover the entire room.

Raw infrared light alone can only function as a presence detector as signals cannot be differentiated between each other. To differentiate between rooms, this light must be encoded and modulated to overcome ambient sources of infrared such as sun light. The first example of using modulated infrared light as a localisation medium was the Active Badge system [207][208] developed by Olivetti Research and Cambridge University. However, the Active Badge system is a form of *transmissive localisation* which means that the device carried by the user outputs a signal that is picked up by fixed receivers. These receivers must be networked and report back the users location to the central controller. This is in contrast to *receptive localisation* where the user carries the receiver, and the fixed points act as beacons. Receptive localisation removes the need for networked



(a) *Circuitry showing voltage regulator (MCP1700), PIC µController, IR LED array and transistor components*

(b) *Beacon Enclosure*

Figure 4.13: ***IR beacon design***

fixed points around the home making it easier and less expensive to set up.

The advantages provided by the lack of infrared penetration as well as the compact and inexpensive nature of infrared emitters and receivers made it a suitable technology for integration into the behaviour monitoring system being developed. The circuitry involved in the infrared beacons and an example of an enclosed beacon are shown in Figures 4.13a and 4.13b. The resistor R_c controls the current to the LEDs. This allows the range of each beacon to be configured between ~3m and ~10m. A potentiometer can be used to allow for easily reconfigurable beacon range.

The IR beacons transmit at a frequency of 20Hz in bursts of 1 second with 500ms between bursts. This 500ms delay between transmission bursts is designed to conserve power as the main source of power consumption in the beacon is the IR LEDs. Codes transmitted by the beacons consist of two binary encoded ASCII characters. There are 127 characters in the standard ASCII character set meaning there are 8001 possible code combinations. Therefore this convention of code generation is more than adequate to ensure no room codes overlap in a building. Figure 4.14. shows an example of the output of a beacon and the input of an infra red receiver housed in the wearable device. The output of the beacon contains a start bit to tell the device to expect a code transmission. The wearable device then examines the following 16 bits to determine the code sent. The first signal shown in this image is binary code for the number 5. The IR receiver's output is normally high and is driven low when an IR signal modulated at

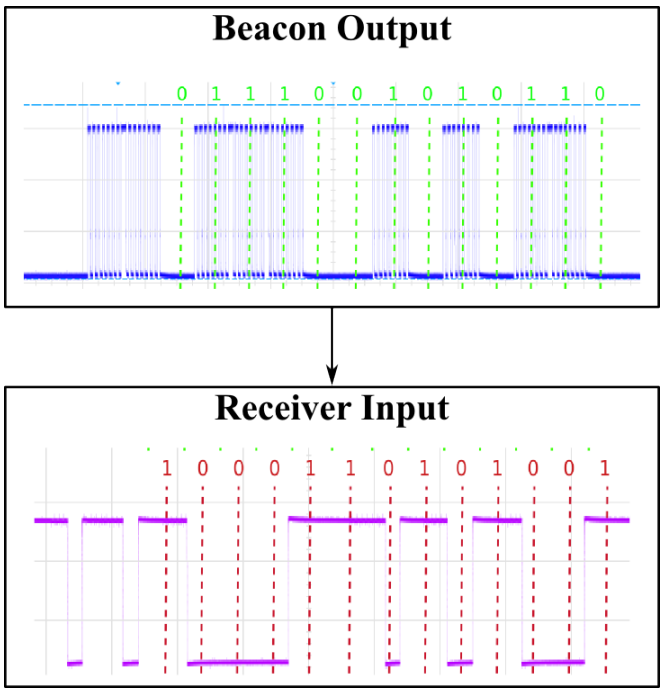


Figure 4.14: ***Indoor localisation signal at beacon and receiver. Beacon outputs inverted two ASCII character signal which is inverted again and input through the UART port on the wearable device from the receiver.***

36kHz is detected. Therefore, the receiver inverts the signal as seen in the image. The output of the IR beacons was formatted so that it would transmit a message over UART configured at a baud rate of 2400 bits per second. This means that the output of the IR receiver could be connected straight into a UART port on a micro-controller and be easily decoded. A user would note the code on each beacon in the house and input the room that it corresponded to on set up of the system. When the code was detected, the wearable device could look the code up in this database and classify the person as being in the corresponding room.

4.4.3 Contextualisation - Outdoor Location Monitoring

The defined requirements for the system, based on a thorough literature review of current activity assessment practice, state that the system should monitor outdoor location. The locations a person visits outside of their home is of significant interest. For example, if a person visits a medical center or hospital, this is relevant behavioural information and it is important that it is noted. Similarly, if a person stops visiting a location that they regularly frequent such as a public park, this is a significant change in their behaviour.

As described in Chapter 3 of this thesis, GPS is the seminal technology currently used for outdoor localisation. Embedded GPS modules are widely available, however the power requirements of this potential addition were a concern. GPS requires a relatively large amount of power to function. With the limited area available for a battery in the wearable device, these power requirements would have been difficult to accommodate. Therefore, the GPS sensor on a smart phone was chosen as the most suitable solution. Use of a smart phone opens up the possibility of using internet connectivity to expand on the GPS co-ordinates to obtaining addresses and other information. GPS technology alone can only provide position co-ordinates. When used alone, these co-ordinates generate limited information. However, when used in conjunction with a location database the address of given co-ordinates can be obtained. In addition to these address data, businesses and services are often marked in these databases. So it is possible to determine the function of a current location (e.g. a public park or a hospital). These databases are very large and are not suitable for hosting on an embedded device. However, with an internet connection, databases can be accessed in the cloud. The capabilities of a smart phone would also be useful in user feedback and remote reporting of activity data.

4.4.3.1 Proximity

While it is possible to constantly log a person's location outdoors using the GPS on a smart phone device, this approach is power hungry. Constant monitoring of location also introduces privacy concerns for users. Rather than constantly logging a person's outdoor location, a proximity based system was decided on. On set up of the system, several locations of interest are entered to the smart phone. These locations included the local medical centers, places of worship, grocery shops, shopping centers, leisure centers and the homes of any friends or family living in the area. Locations are divided into categories of functional locations (e.g. supermarket, petrol station, bank), religious locations, medical locations and social locations (bar, restaurant, friends/family home). The device enables the GPS sensor to check the outdoor location of the user every seven minutes. The GPS sensor is enabled for a maximum of fifteen seconds every seven minutes, and is disabled immediately when an accurate location is obtained. If the user is found to be within a given radius of a certain location for two location samples in a row, the visits for the relevant category are incremented. Therefore,

visits to a location are only incremented if the person is at that location for at least fourteen minutes.

This system maintains the functionality of monitoring a person's outdoor location while preserving privacy and power consumption.

4.4.4 Contextualised Activities

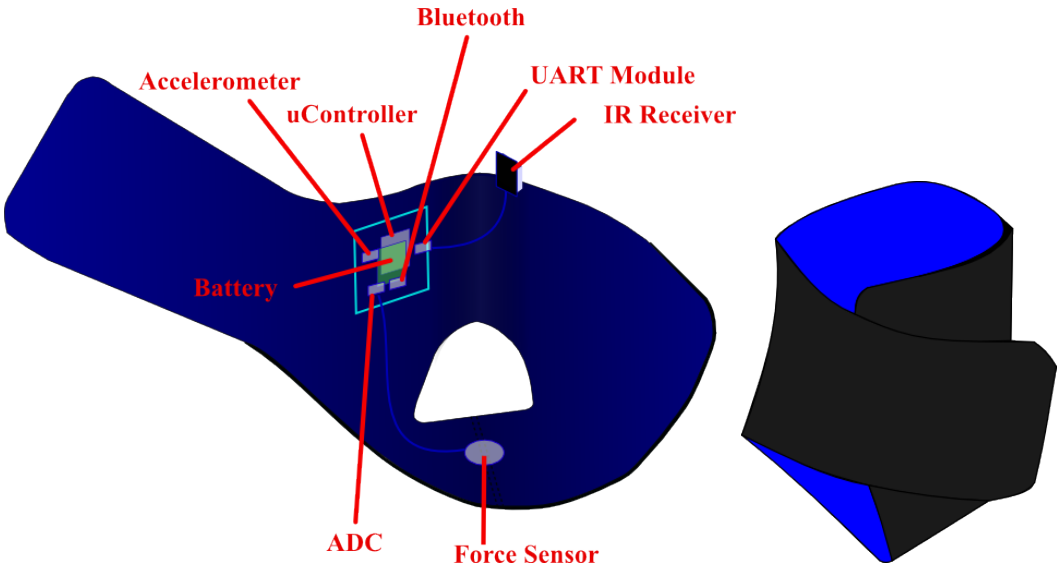
Using the combination of activity and location data, contextualised activities are inferred. If the user is located in the bathroom and is sitting, toileting is inferred. If the user is in the bedroom and is lying down, this time is logged as "time in bed day" between the hours of 10am and 9pm and "time in bed night" at all other times. If the user is lying in the bedroom at night and then goes to the bathroom, this is logged as "toileting night visit". Finally, if the user is walking in the kitchen, this is logged as "time active in kitchen" implying food preparation or other kitchen work.

4.5 Overall System Implementation

4.5.1 The Smart Sock

The behaviour monitoring solution designed to implement the algorithms described in Section 4.4. is called the Smart Sock. The device is worn in the form of a strap on sock at the ankle. This form, as well as the components contained in the sock can be seen in Figure 4.15. The sock was created in a nylon covered neoprene rubber material. This material provides the sock with sufficient structure to support the electronics while cushioning the user from hard components thus maintaining comfort. The material has non absorbent properties improving the hygiene considerations of wearing the sock for multiple days between washes. All electronic components housed in the sock were designed to be easily removable to facilitate washing.

The combination of the techniques described above mean that the Smart Sock is one of the most complete activity monitoring solutions available even before the localisation algorithms are implemented to contextualise the information. The complete operation of the system is outlined in Figure 4.16. Figure 4.17. shows the components that make up the overall system.



(a) *Open sock*

(b) *Closed Sock*

(c) *Donned Sock*

Figure 4.15: ***Smart Sock***

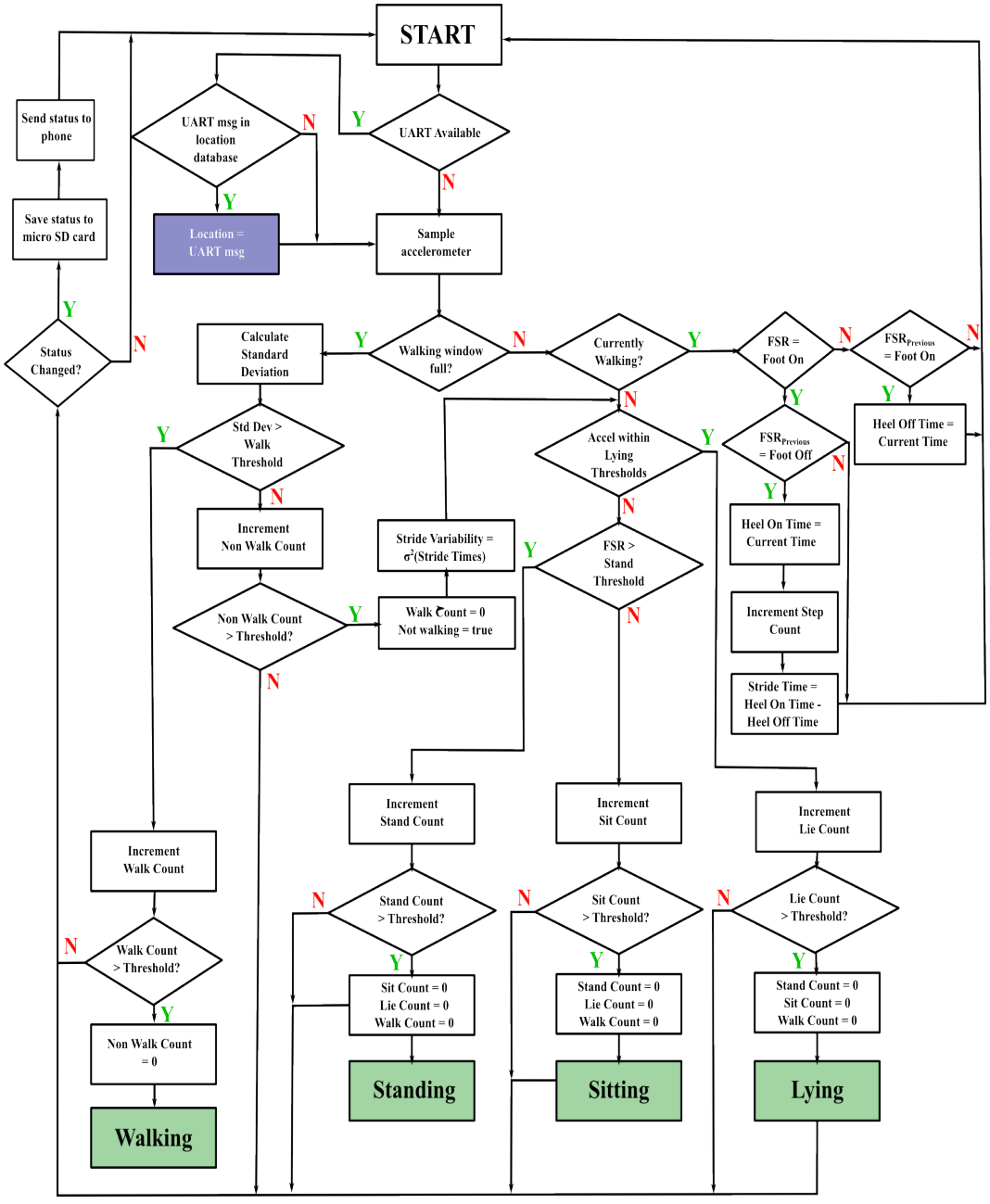


Figure 4.16: ***System flow chart showing posture, activity, indoor location and gait monitoring algorithms***

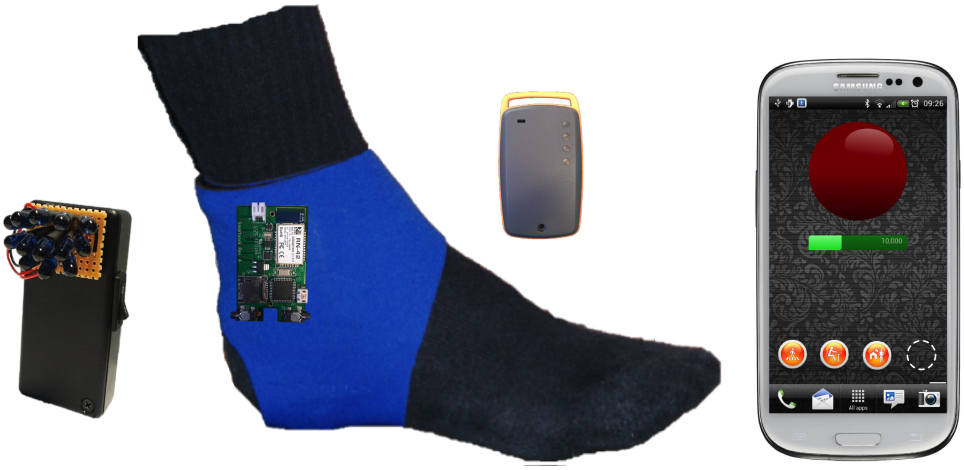


Figure 4.17: ***System components***

4.5.2 Hardware Development

A custom hardware platform was developed to be housed in the Smart Sock. The block diagram in Figure 4.18. shows the main components contained in the device. The device is enclosed in an ABS plastic enclosure with a 400 mAhr lithium polymer rechargeable battery. This enclosure facilitates easy removal of the electronic components of the sock, while shielding the user from any possible safety concerns linked to close contact with batteries or electronics. The manufactured version of this platform is shown in Figure 4.19.

4.5.3 Software Development

Figure 4.20. shows the architecture of the Smart Sock system and the software design and communication infrastructure involved in the system. The firmware for the beacon runs on a PIC16lf818 micro controller and is written in C. The Smart Sock firmware runs on the platform's ATMEL ATMEGA32U4 microcontroller. The firmware is also written in the C language. The smart phone application runs on any Google Android based device with an Android version greater than 1.5. Previous versions did not allow for custom Bluetooth applications. Finally the server is configured to accept incoming FTP connections for data upload. The communication technologies implemented by the system are a custom IR protocol, Bluetooth, GSM and WiFi.

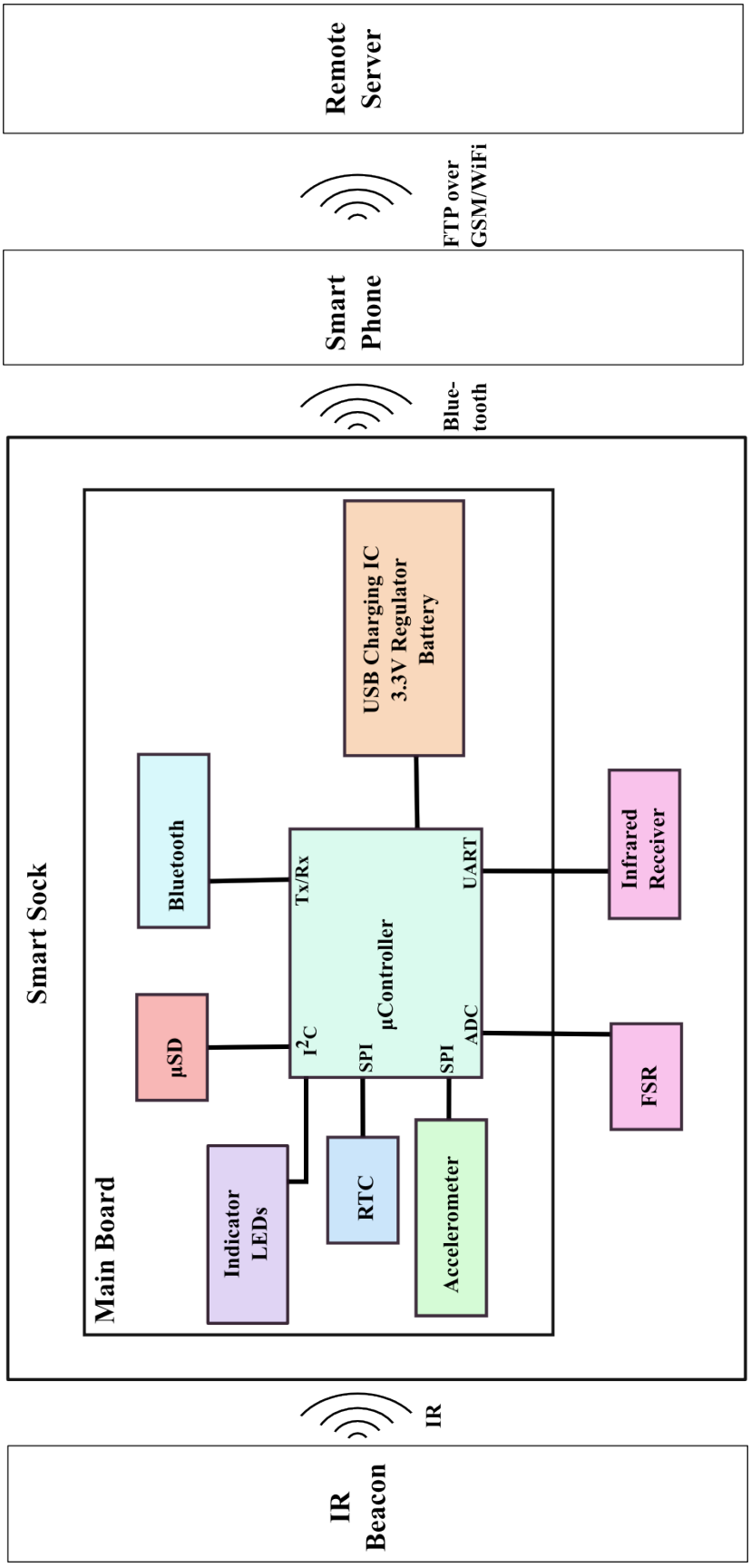


Figure 4.18: ***Smart sock block diagram***

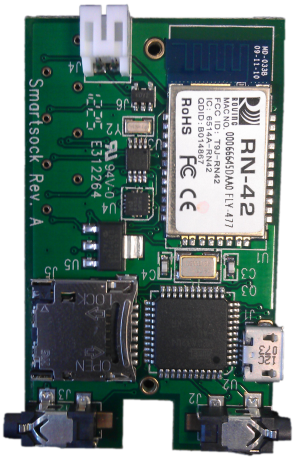


Figure 4.19: ***Manufactured board***

4.5.4 Data Reporting

Two approaches for data collection were integrated into the Smart Sock. The first method saves a log of activity to an on board micro SD card on the sock hardware. This method allows a user to wear a sock over a set number of days, then upload data by plugging the micro SD card from the sock into a laptop. The advantage of this approach is the lack of any requirement for network infrastructure and it's associated costs.

The second method of data collection is over the cellular network. In this configuration, all changes in activity status are sent over Bluetooth from the Smart Sock to the smart phone. The data are interpreted and analysed on the smart phone and a report is generated to be uploaded once a day to a remote server. This method allows carers to access the user's activity data in near real-time. This communication capability also allows for certain events to generate alerts. For example, if a person is detected as lying in the kitchen for an extended period of time, there is the possibility of a fall. The system can generate an alert in this situation after giving the user the option to cancel it.

User feedback: Smart phone data collection also creates the possibility of rich user feedback. Because a large margin of the target users of the Smart Sock are older adults, who may not be proficient in the use of technology, the design of an appropriate feedback interface was very important.

Figure 4.21. shows the interface for the feedback provided by the Smart Sock. The main "sphere" (shown in red) is the main feedback mechanism for the user.

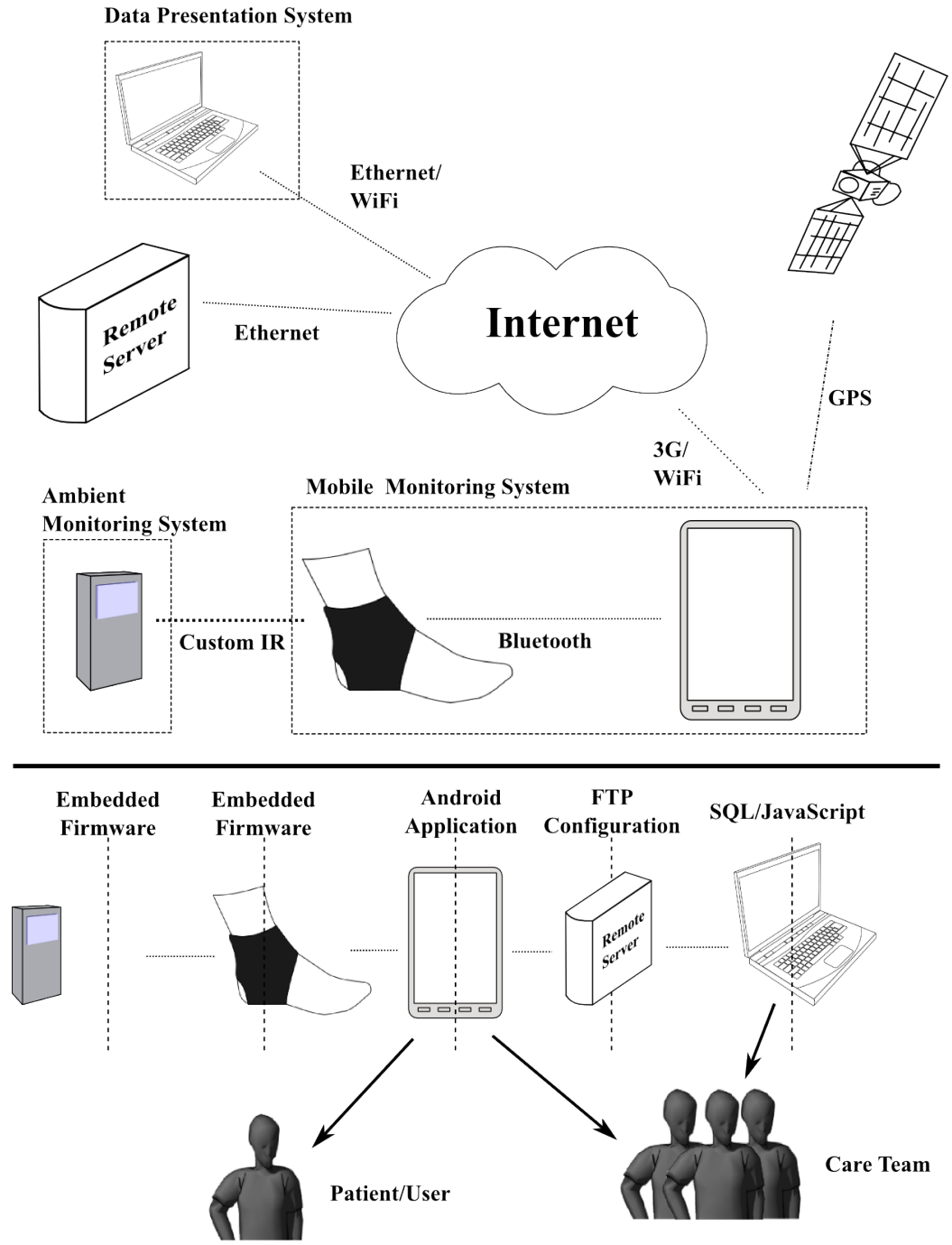


Figure 4.20: ***Software block diagram***

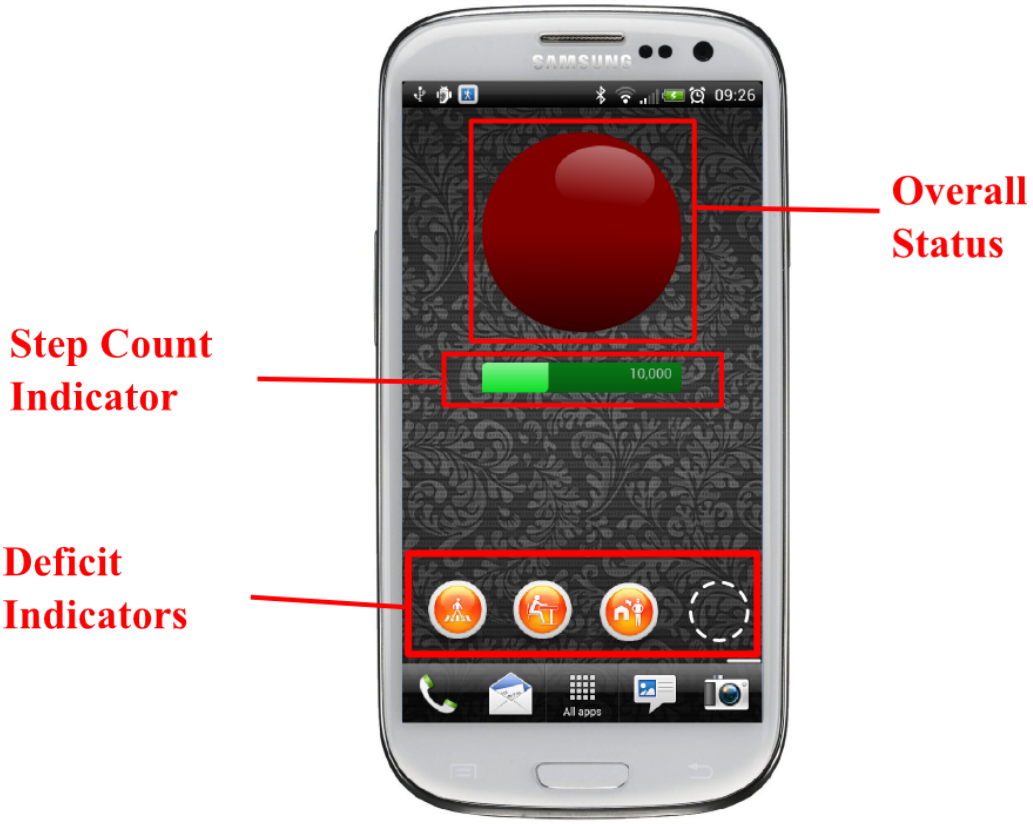


Figure 4.21: ***User feedback***

The colour of this sphere ranges from red to green depending on the activity and behaviour patterns a user has followed that day. Behavioural targets such as targeted time walking or number of outings from the home can be set for each individual user. The number of targets achieved is then used to set the color of the sphere as shown in Figure 4.22.

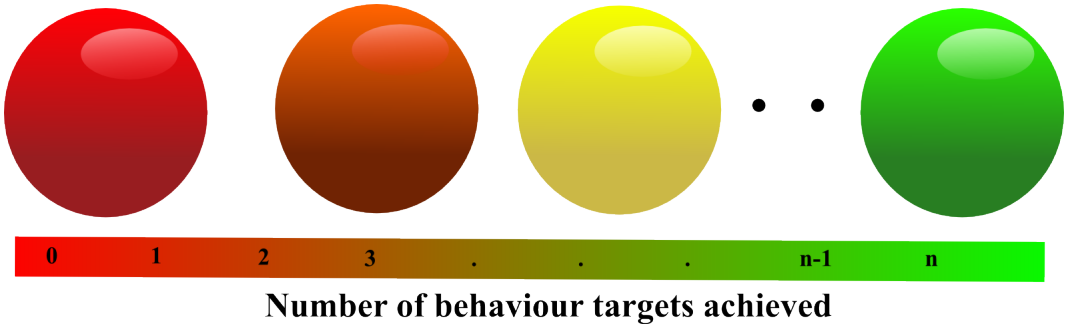


Figure 4.22: ***Sphere interface***

If the person's activity levels have been poor, an alert is presented as to how they should improve this. For example, in the image shown in Figure 4.21., the user's activity patterns have been poor. Alerts are shown in the form of orange circles at the bottom of the screen. The alerts shown in this example are walking, sitting and outdoor activity meaning that the user has not met targets for these activities so far today.

Figure 4.23: ***Behaviour alerts***

Touching these indicators generates an audio explanation. If the user was to go for a walk outdoors, these alerts would disappear and the colour of the sphere would be altered to reflect the improved activity. Audio and tactile cues are also given when a person's activity levels drop to a lower level encouraging the person to be more active.

This interface is presented on the home screen of the smart phone, meaning interaction with the phone to obtain this feedback is minimal.

4.6 Functional Assessment Engine

The design requirements set out in Section 4.3.3 state that the system should generate a single score that summarises behaviour data in a manner that is meaningful to clinicians. Though the device does generate a score based on the number of behaviour targets met, this score may not be meaningful to clinicians. Chapter two of this thesis reviewed the most widely used method of examining functional behaviour by clinicians. The parameters examined by these functional assessment tools widely relate to the parameters monitored by the device described in this chapter. Therefore, these assessment tools are a suitable metric on which to model the system's clinically meaningful output.

By modelling the behaviour monitor's single score output on conventional functional assessments, the methodologies used by the clinician do not require significant change. Rather than administering conventional assessment instruments periodically at medical check ups etc, the patient is asked to wear the behaviour monitor. From the clinicians point of view, data interpretation does not change. However, there is a vast improvement in the resolution of assessment data and assessments can be carried out much more frequently using autonomous methods. Figure 4.24. demonstrates a hypothetical care situation for an older adult over a 15 month period. This patient experiences an adverse health event (e.g. a fall) at the beginning of April and a resulting decline in functional health. The top graph in the figure shows the conventional care model where the patient is assessed every 3 months. This is an optimistic assessment schedule using conventional means. Significant functional decline is detected 3 months after the event that caused the decline. An intervention is put in place after this detection however the patient has already lost a significant part of their function meaning the clinicians options for planning an intervention are reduced as their patient may not have the functional ability to carry out many of the intervention options. This intervention does stabilise the patients function but only after a significant decline.

The bottom graph shows the hypothetical care situation for the same patient who has been given the Smart Sock behaviour monitor for autonomous functional assessments. Outputs from the device are used to perform weekly functional assessments. This allows the decline in function to be detected much sooner and before function has declined significantly. The decline is flagged after three successive weeks of moderate decline. This allows the clinician to put

an intervention in place much earlier and because no significant function has been lost before detection, this intervention is able to stop decline much sooner. Therefore functional health outcome is much better for the care situation incorporating autonomous functional assessment.

A functional assessment engine was designed to be implemented by the system. This engine takes the available inputs from the behaviour monitoring device and uses them to generate a predictive score for different conventional functional health assessment outcomes.

The device implements algorithms for several different conventional assessment tools discussed in Chapter 2 of this thesis (e.g. the Barthel Index). These algorithms use the available behaviour inputs in equations that follow the general form:

$$FAO_a = m_1 * (behaviour_1) + m_2 * (behaviour_2) + ... + m_n * (behaviour_n) + \epsilon \tag{4.1}$$

where FAO is a Functional Assessment Outcome that is predictive of the relevant conventional assessment tool outcome, m_n is a parameter multiplier that will generate an output that correlates to the output generated if the conventional assessment tool were to be administered, behaviour$_n$ is a behaviour output from the behaviour monitor and ϵ is a constant. The algorithms must be trained using the relevant conventional assessment tool to choose which behaviours from the device to input to the algorithms as well as to create valid values for m and ϵ as shown in Figure 4.25.

This training is performed using Multiple Regression. Multiple regression predicts an outcome based on a linear combination of two or more predictor variables. It is a very versatile method and can be applied across a vast number of fields. For example, in the literature multiple linear regression has been used to predict such diverse outcomes as one repitition maximum weight lifting strength using predictor variables such as age, height, percentage body fat, arm girth and others [209], liver volume for transplantation using height, weight, sex, CT estimated volume and other predictor variables [210] and amount of vicseral adipose tissue using height, weight, skinfold measurements, waist circumference and others [211]. Regardless of the outcome and income variables, the principles behind multiple linear regression are similar.

There are several ways to input predictor variables into a multiple regression equation. Some methods, including hierarchical and blockwise entry, rely on the

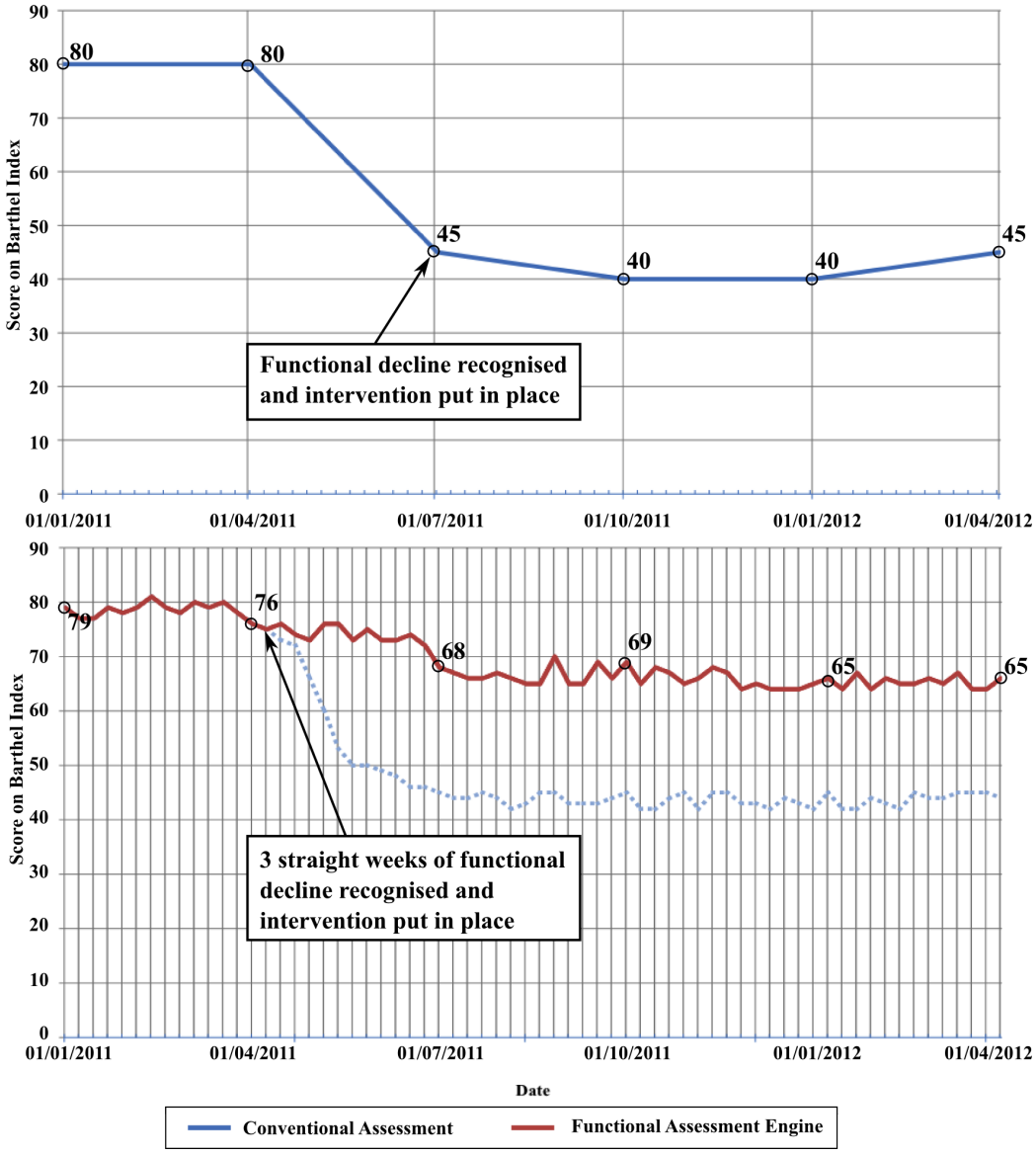


Figure 4.24: ***Hypothetical care situation for older adult over 15 month period. Top graph shows conventional method where questionnaires are administered every 3 months (best case scenario). Decline is not detected until significant decline has occured. Bottom graph shows autonomous functional assessment once per week. Decline is detected earlier and intervention put in place. Further decline is avoided. The dotted line shows the functional assessment trend that would have continued if this early detection had not occurred.***

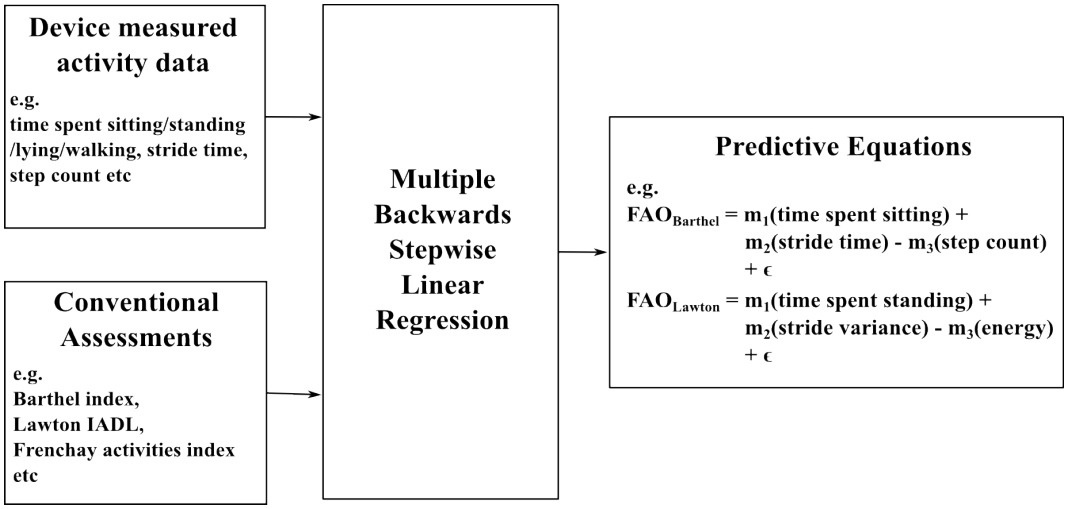


Figure 4.25: ***Process for training of functional assessment engine using conventional assessment tools and multiple linear regression***

user to input the predictors in the desired order. However, to use these methods, there must be some existing evidence as to which predictor variables should be included and in what order. If this evidence is not available, then methods such as backward and forward stepwise entry can be used. These entry methods use mathematical formulae and statistical significance to generate the behaviours (predictor variables) used in the model.

Backward regression is preferable to forward due to the problems of suppressor effects linked to forward regression **(author?)** [212]. Suppressor effects can cause predictors to be included in a model that may only be significant when other variables are controlled for. Backwards linear regression avoids this phenomenon. To choose predictors and their order using backwards stepwise linear regression all available predictor variables are inserted into the model. The contribution of each variable to the predictive ability of the model is investigated by examining the significance of the t-test for each predictor. If a predictor is not making a statistically significant contribution to how well the model predicts, the predictor is removed from the model and the model is generated using the remaining predictors. This is repeated until all predictors in the model contribute to the prediction of the outcome.

Because evidence in the literature for the autonomous assessment of functional health using a behaviour monitor is not yet available, no previous evidence as to which behaviour parameters should be input into the algorithm is available. Therefore a backwards stepwise linear regression is used to to train the

Functional Assessment Engine.

Due to the daily changes in behaviour, an average of behaviour data over two or more days is used as the input to the functional assessment engine. For example, on a single day a person may walk to the shop to do grocery shopping. This will have a significant effect on both their time spent walking and outdoor location data. It may be unlikely that they will do grocery shopping again the following day and so their behaviour data is affected. For this reason, input to the engine consists of two days averaged data.

The output equation of a multiple linear regression follows that of Equation 4.1. with a constant and coefficients for each included predictor variable along with several parameters relating to the fit and validity of the model. These parameters are discussed further here.

Validation of the Functional Assessment Engine: Because the output of the Functional Assessment Engine is intended for clinical use, the validation of the models used by the engine is of particularly high importance. Several statistical methods are available to examine the validity of a model generated through multiple linear regression.

One of most important tests of the model is the R^2 value which shows the amount of variation in the output variable that can be explained by the model. For example, an R^2 value of 0.6 would suggest that the model can account for 60% of the variation in the functional assessment outcome as measured by a conventional assessment tool.

Another test of the model is the adjusted R^2 value. Where the R^2 value represents the amount of variation explained in the data from the study sample, the adjusted R^2 value attempts to show the amount of variation explained if the model were to be generated from the entire population from which the sample was taken. In this way, the adjusted R^2 value represents the generalisation ability of the model. This value is calculated using Wherry's formula:

$$AdjustedR^2 = \left[1 - (1 - R^2)\left(\frac{(n-1)}{(n-v)}\right)\right] \tag{4.2}$$

where n is the number of participants and v is the number of predictors used in the model.

The F-ratio shows whether the model is an improvement in predictive ability over the mean as a best guess [212]. Is it the ratio of the variability in the data

that is explained by the model to the variability that is unexplained by the same model.

Beyond statistical methods, the validity of the model can also be tested by applying the Functional Assessment Engine to subjects that were not involved in the generation of the engine's models known as cross validation. The match between Functional Assessment Engine and conventional instrument generated scores is a good measure of validity.

The combination of all of these methods in the validation of the Functional Assessment Engine provide a comprehensive evaluation of the validity of the outputs of the engine. These tests were all implemented on the trained Functional Assessment Engine in the study described in Chapter 6 of this thesis.

4.7 Discussion

This paper has described the design and development of a new wearable contextualised activity monitor. Firstly, a pilot study was carried out with off the shelf hardware to investigate the advantages of contextualising activity/posture data. It is the author's view that the results of this preliminary investigation demonstrated significant behavioural monitoring advantages from contextualised activity over activity data alone.

Following this demonstration, a system with expanded functionality and far superior usability was developed. The system contains three components in the Smart Sock, infrared location beacons and a smart phone device. Using these components the device not only monitors a person's activity levels, but also detects the context in which these activities occur using indoor localisation. Using this contextualised activity the device generates a picture of the person's daily behaviour.

Section 4.3.3. set out a list of design requirements for the device. These requirements have been met in full by the device described in this chapter. The device is in the form of a wearable piece of clothing (a sock) and is worn at a single location on the body. The device can detect all of the parameters set out in the requirements and has been designed with conventional assessments in mind. The system provides rich user feedback and can generate a single metric to represent activity behaviours based on targets achieved.

4.8 Conclusions

The Smart Sock behaviour monitoring system has been developed to monitor a significant number of behaviours. The device is usable in that it is a wearable device based at a single location on the body. Novel posture detection algorithms have been designed and implemented. The realtime nature of these algorithms allow for rich user feedback through a smart phone device. The device can contextualise activity data with both indoor and outdoor location allowing for behaviour patterns to be detected. Finally, a Functional Assessment Engine has been introduced as a novel method of generating a clinically meaningful single score output. This engine is another novel contribution to the field of behaviour monitoring. Significant work remains in the validation of the device. The following chapters will describe this validation. Initial validation was performed with young healthy adults in a laboratory setting. The Functional Assessment Engine described in Section 4.6. requires training to generate a valid predictive score for functional assessment outcome. Training of this engine with an older adult population in their own homes is described in Chapter 6. As well as training the engine, the validity of the outputs of this engine are examined.

Chapter 5

Primary Validation of a Wearable Behaviour Monitor in a Laboratory Setting

5.1 Introduction

The monitoring of physical activity using electronic sensor technology is a rapidly expanding area. This expansion can be attributed in part to the increased focus on the severe lack of physical activity and obesity problems currently engulfing much of the western world. 59% of adult males and 47.5% of adult females are currently overweight or obese in the E.U. [213]. Considering the wide range of chronic health problems attributed to inactivity and obesity such as type 2 diabetes, cardiovascular disease, hypertension and certain types of cancer [214] this is a very disturbing trend and one that Eurostat statistics show is rapidly increasing. More disquieting still are the obesity figures for children in the E.U. Between 13.1% and 32.9% of boys and 12.4% and 37% of girls across the E.U. countries are overweight or obese [215]. This trend can be linked to several causes including the increasingly sedentary lifestyle of the population [216, 217]. The realisation of the severity of this situation has led to an increase in the awareness of the need to measure physical activity levels.

Sensors have been developed to monitor physical activity levels and, in doing so, help to raise a person's awareness of and engagement with how active they are in daily life. Commercial examples of these sensors have become ubiquitous in society. The Nike+ sensor suite and Adidas miCoach system are designed to monitor exercise performance and have become a common sight in fitness centres. The FitBit^{TM} and the Phillips direct life^{TM} sensors focus more on activity levels during activities of daily living rather than exercise. These sensors have evolved to such a state that they are affordable enough to be a viable consumer product. Physical activity monitors are also widely used in research. Several kinematic sensor based mobility monitoring systems such as the activPAL^{TM}, report time spent sitting, standing, lying and walking. A significant body of research is available in this area in the literature [48, 91, 193] . The evidence base for the advantages of physical activity is significant and due to the intensity of research in the area, is rapidly growing. Traditional means of assessing physical activity such as questionnaires have issues with accuracy and acceptability [218]. Therefore, sensor based physical activity monitors have become widespread in the literature as a means of quantitative measurement of physical activity. Both of the applications mentioned, especially research applications, require the activity monitor used to be proven as a valid measure. Therefore, it is necessary for any device that is intended for use in either research trials or consumer applications to be

comprehensively validated in human trials.

The device tested in the study described in this paper expands on many of the activity monitors that have been described in the literature. The device monitors similar activities to other systems however it also contextualises these activities with indoor and outdoor location. In doing this, the intention is to perform the functions of an activity monitor, but to also add elements towards a behaviour monitor. These expanded data may be of more use in attempting to change activity patterns or to gain a deeper understanding of behaviour patterns during daily life. The Smart Sock is a wearable real-time behaviour monitor that detects several parameters related to the performance of activities of daily living as described in Chapter 4. The device measures posture, indoor location and several parameters relating to gait. It does this using a device located at a single site at the ankle which is interfaced with a smart phone for data processing and display. One of the main advantages of the Smart Sock behaviour monitor over some of the commercial and research devices introduced to date is that it measures a wider range of parameters than existing single location devices and it does so in real time. The study described in this paper was designed to validate the Smart Sock and to establish the evidence base for its use in research and consumer applications.

5.2 Study Design

15 healthy young adults (10 male, 5 female, mean age: 27) were recruited to take part in this study. The study consisted of three separate sections: Prescribed Activities of Daily Living (ADLs), Simulated Free-Living and Treadmill Walking. Participants were asked to perform each of these sections in a random order. Participants wore the Smart Sock at the ankle while taking part in this study. A mock apartment was set up in four adjoining rooms in the Engineering Building on the NUI Galway campus.

The mock apartment shown in Figure 5.1. was divided into a “kitchen”, “bathroom”, “bedroom area”, “sitting room area” and “hallway”. Each area contained a networked camera whose feed was recorded at a central computer. The network of cameras covered the entire area of the mock apartment as well as the output of the Smart Sock on a smart phone device. The video footage from this camera network was used to determine the accuracy of the Smart Sock output in comparison with the real activity being performed. Figure 5.2. shows an example of

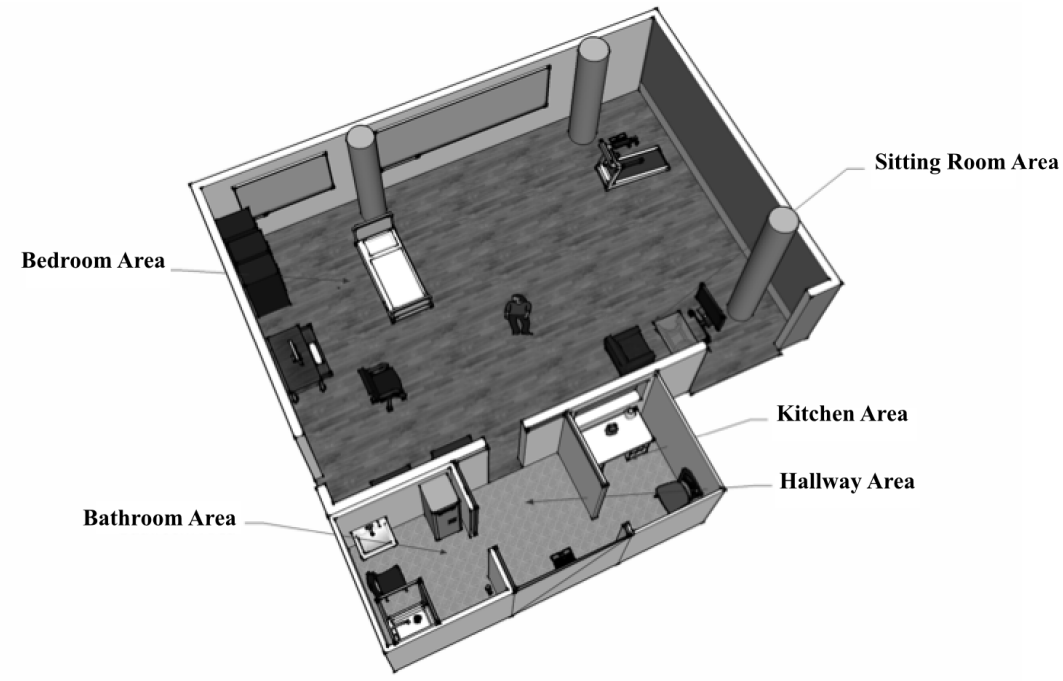


Figure 5.1: ***Mock apartment used to run study protocol***

the camera output. Each of the rooms was also fitted with an IR location beacon used in the Smart Sock's indoor location system as described in Chapter 4 of this thesis.

5.2.1 Prescribed ADLs:

The prescribed activities were designed in such a way that the participant would be required to enter different rooms several times as well as incorporating a wide range of ADLs. The prescribed ADL protocol asked the participant to stand up from and sit in different types of chair, lay on a bed and required the participant to engage in several instances of walking of various distances. The full list of prescribed ADLs can be seen in Table 5.1. This period of the study was used to validate the posture detection and indoor localisation features of the Smart Sock.

5.2.2 "Free-Living" Period:

A morning routine was chosen as a suitable "free-living" period as it was likely to incorporate various different activities in several different locations. The mock apartment also provided the facilities to complete this routine well. The desig-

Figure 5.2: ***Camera output used to validate device output vs actual location and activity performed***

	Activity	**Room**	**Duration/Distance**
1	Stand	Bedroom	~10 seconds
2	Walk to armchair	Sitting Room	~12 meters
3	Stand in front of armchair	Sitting Room	~10 seconds
4	Sit on armchair	Sitting Room	~20 seconds
5	Stand	Sitting Room	-
6	Walk to shower chair	Bathroom	~10 meters
7	Stand in front of chair	Bathroom	~5 seconds
8	Sit on shower chair	Bathroom	~20 seconds
9	Stand	Bathroom	~10 seconds
10	Walk to bed	Bedroom	~10 meters
11	Sit on Bed	Bedroom	~10 seconds
12	Lay down on bed	Bedroom	~30 seconds
13	Sit on bed	Bedroom	~5 seconds
14	Stand	Bedroom	~5 seconds
15	Walk to kitchen chair	Kitchen	~10 meters
16	Sit on kitchen chair	Kitchen	~20 seconds
17	Stand	Kitchen	~5 seconds
18	Walk to office chair	Bedroom	~10 meters
19	Sit on office chair	Bedroom	~

Table 5.1: ***List of prescribed ADLs performed by participants in prescribed ADL section of the protocol***

nated bedroom area contained a bed, the designated kitchen area contained tea and coffee making facilities, the designated sitting room area contained a television and newspapers and the bathroom designated area contained a sink, face cloth and towel. The participant was not given any further instruction other than to simulate their regular morning routine in any way they wished using the facilities provided. This period was designed to encourage the participants to perform several different ADLs in a random, uncontrolled fashion. Similar to the "Prescribed ADL" period, this section of the study was used to examine the accuracy of the Smart Sock in detecting posture and indoor location.

5.2.3 Treadmill Walking Section:

The third stage of the study design involved walking on a treadmill. Participants were asked to walk on a treadmill at three different speeds for 30 seconds each. The speeds used were 2 km/hr, 3.5 km/hr and 5 km/hr to represent slow, average and fast walking paces. Two cameras were set up at the treadmill, one at the level of the feet of the participant as shown in Figure 5.3a and the other pointing at a smart phone that displayed the output of the Smart Sock, shown in Figure 5.3b. The number of steps taken was counted from direct observation of the video. From the number of steps taken and the time spent walking, cadence was calculated as $Cadence = \frac{NumberOfStepsTaken}{Time(s)}$. Stride time measurement accuracy is also assessed using this part of the study protocol.

5.2.4 Parameters Monitored

The three stages described in Sections 5.2.1, 5.2.2 and 5.2.3. were used to test the devices abilities in detecting parameters in the following ways:

Posture/Activity detection: The accuracy of the device in detecting and monitoring posture and indoor location was tested in the prescribed ADL and free-living periods described above. The list of prescribed ADLs was designed to include several instances of all three postures and walking (sitting, standing, lying and walking). It incorporated sitting on various different types of chair and included numerous different transitions from different postures. The posture detection capabilities were also tested in the free-living period to ensure accuracy during a random combination of ADLs. The video footage of the mock apartment and the Smart Sock output was used to mark every time the participant's posture changed in reality and to check whether the Smart Sock detected this change and

(a) ***Treadmill camera output*** **(b)** ***Smart Sock output camera***

Figure 5.3: ***Camera output for gait parameters accuracy assessment protocol***

the time taken for this detection. The video was also used to determine whether there were false positives of changing posture in the Smart Sock's output.

Indoor location accuracy: The accuracy of the Smart Sock's indoor location algorithm was tested in a similar way to the posture detection assessment. The prescribed ADL list required the participant to enter different rooms several times. The free-living period was also likely to include entering different rooms. Again, the video footage of the mock apartment was used to mark instances when the person entered a different room. This was compared to the Smart Sock's output.

Gait parameters accuracy: The Smart Sock measures the number of steps taken, cadence, heel strike and heel off. The number of steps detected by the Smart Sock was compared to a manual count taken from the video footage as the person walked on a treadmill at a each of the three pre-determined speeds.

The device does not have the ability to fully monitor stance time and swing time as it cannot detect toe strike or toe off. However, the device does detect heel strike and heel off. From this, the device gives a measure of stride time. The validity of this estimate was examined by comparing it to the actual values obtained from the video footage and by testing if the the device could distinguish between different walking speeds. Three samples of steps were taken from the video footage for each of the participants walking during the treadmill section of the study. Sock detected heel strike and heel off events were measured using a "virtual LED" on the smart phone display. This "LED" lit up when the sock

detected the heel as being in contact with the ground and turned off when the contact ended representing heel strike and heel off events.

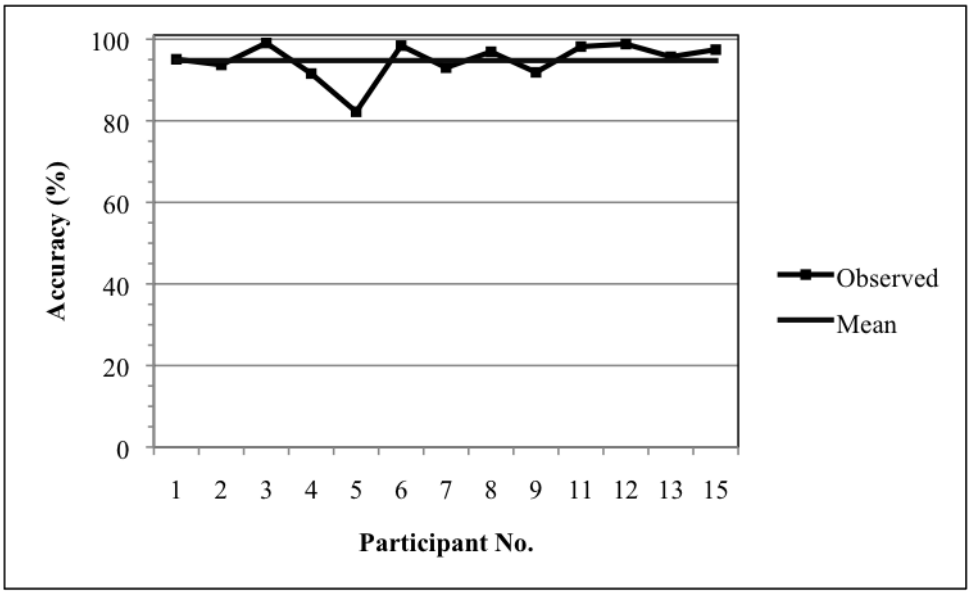
5.3 Results

There were a total of 3 hours and 12 minutes of monitoring prescribed ADLs, 2 hours and 40 minutes monitoring "free-living" activity and 1.4 km of treadmill walking for the monitoring of gait parameters. This section will present the Smart Sock's performance in each of the 3 periods for posture detection, indoor localisation and gait parameters.

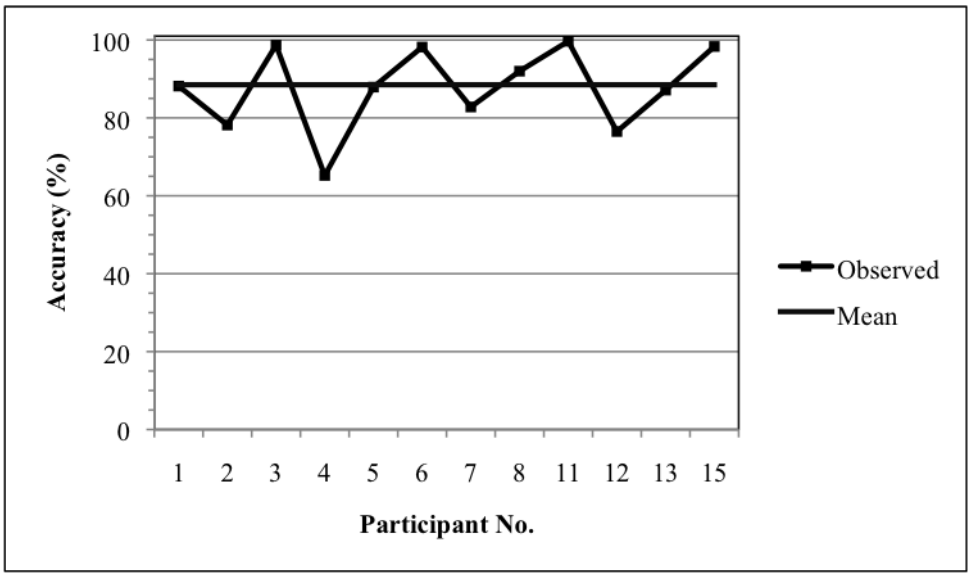
5.3.1 Posture/Activity Detection

Tables 5.2a. and 5.2b. show results for Smart Sock detected postures vs. actual postures for each participant in the prescribed ADL and free living sections of the study respectively. Video data for Participant 10 in the free living section were corrupted, therefore no free living accuracy data was available for this participant. Tables 5.3b. and 5.3a. show the sensitivity and specificity results for detecting posture for the Smart Sock during each section of the study. The sensitivity is a measure of the proportion of posture/activity changes that were correctly detected ($\frac{TruePositives}{TruePositives+FalseNegatives}$). Specificity is a measure of the proportion of posture/activity changes that did not occur and went correctly undetected ($\frac{TrueNegatives}{TrueNegatives+FalsePositives}$). Table 5.4. shows the mean length of time taken to detect each posture for each section of the study. Figure 5.4. shows the overall posture detection accuracy of the Smart Sock during each section of the study. The results are generated directly from the video footage from the study. "Percentage time correct" is taken as the time the Smart Sock showed the correct posture in relation to the total time of the study. This accuracy metric is presented in addition to sensitivity and specificity results to account for any delays in posture/activity detection. For example, if a person sits down from standing and there was a two minute delay before the device detected this change the sensitivity and specificity results would not be affected as the change was still detected. However, "Percentage time correct" results would take this delay into account.

The mean percentage time correct for the prescribed ADL and free-living sections of the study were 94.8% and 88.5% (SD ±4.59 and ±10.58) respectively.



(a) ***Prescribed activities***



(b) ***Free-Living activities***

Figure 5.4: ***Posture/activity detection percentage time correct***

Subject No.	Sit-Sta		Sta-Wal		Wal-Sta		Sta-Sit		Wal-Sit		Sit-Lie		Lie-Sit		Sit-Wal	
	A	D	A	D	A	D	A	D	A	D	A	D	A	D	A	D
1	14	14	16	16	8	8	5	5	8	8	3	3	3	3	0	0
2	12	12	13	13	7	7	6	6	8	8	3	3	3	3	1	1
3	14	14	15	15	6	6	6	3	9	9	3	3	3	3	0	0
4	14	14	14	14	7	7	7	7	8	8	3	3	3	3	1	1
5	13	13	18	18	11	11	7	4	8	8	3	3	3	3	0	0
6	14	10	18	18	6	3	3	3	12	12	3	3	3	3	0	0
7	13	13	13	13	7	7	7	7	8	8	3	3	3	3	2	2
8	14	13	16	15	7	7	3	3	9	9	3	3	3	3	2	2
9	15	15	14	14	5	5	5	5	10	10	3	3	3	3	0	0
10	16	14	15	15	8	7	7	7	8	8	3	3	3	3	0	0
11	14	13	13	13	6	6	6	6	9	9	3	3	3	3	2	2
12	14	14	15	15	8	8	7	7	8	8	3	3	3	3	1	1
13	15	15	17	17	8	8	6	6	9	9	3	3	3	3	0	0
14	13	12	12	12	6	6	7	7	7	7	3	3	3	3	2	2
15	13	13	16	16	7	7	5	5	10	10	3	3	3	3	1	1
Total	208	199	225	224	107	103	87	81	131	131	45	45	45	45	12	12

(a) ***Posture/Activity detection: Actual vs Sock detected - prescribed ADLs***

Subject No.	Sit-Sta		Sta-Wal		Wal-Sta		Sta-Sit		Wal-Sit		Sit-Lie		Lie-Sit		Sit-Wal	
	A	D	A	D	A	D	A	D	A	D	A	D	A	D	A	D
1	4	4	9	8	6	6	2	2	2	2	0	0	1	1	0	0
2	3	3	6	6	4	4	2	2	0	0	0	0	0	0	0	0
3	4	4	12	12	9	9	1	1	2	2	0	0	1	1	1	1
4	1	1	10	10	10	10	1	1	1	1	1	1	1	1	0	0
5	3	3	6	5	3	3	2	1	3	2	0	0	0	0	0	0
6	1	1	7	7	5	5	0	0	4	4	0	0	1	1	3	3
7	0	0	4	4	3	3	0	0	3	3	0	0	1	1	2	2
8	1	1	8	8	7	7	0	0	2	2	0	0	1	1	1	1
9	1	1	4	4	3	3	0	0	2	2	0	0	1	1	2	2
11	4	4	9	9	8	8	1	1	2	2	0	0	1	1	1	1
12	2	2	7	7	6	6	0	0	3	3	0	0	0	0	1	1
13	1	1	7	7	6	6	0	0	3	3	0	0	1	1	2	2
14	0	0	7	7	6	6	0	0	4	4	0	0	0	0	2	2
15	4	4	7	7	5	5	2	2	4	4	0	0	1	0	3	3
Total	29	29	103	101	81	81	11	10	35	34	1	1	10	9	18	18

(b) ***Posture/Activity detection: Actual vs Sock detected - free living***

* A: Actual

* D: Detected

Table 5.2: ***Posture/Activity detection: Actual vs Sock detected***

	Sit - Stand		Stand - Walk		Walk - Stand		Stand - Sit		Walk - Sit		Sit - Ly		Ly - Sit		Sit - Walk	
	Spec	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**
Mean	1.00	0.95	0.99	1.00	0.99	0.96	0.99	0.93	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SD	0.00	0.08	0.01	0.02	0.02	0.13	0.03	0.16	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00

(a) ***Sensitivity & Specificity - Prescribed ADLs***

	Sit - Stand		Stand - Walk		Walk - Stand		Stand - Sit		Walk - Sit		Sit - Ly		Ly - Sit		Sit - Walk	
	Spec	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**
Mean	0.99	1.00	1.00	0.99	0.99	1.00	0.92	0.92	1.00	0.97	1.00	1.00	1.00	1.00	0.99	1.00
SD	0.03	0.00	0.00	0.04	0.02	0.00	0.10	0.19	0.02	0.09	0.00	0.00	0.00	0.00	0.02	0.00

(b) ***Sensitivity & Specificity - free living***

Table 5.3: ***Posture/activity detection accuracy***

	Sit - Stand	Stand - Walk	Walk - Stand	Stand - Sit	Walk - Sit	Sit - Lie	Lie - Sit	Sit - Walk
Mean (s)	1.5	2.0	1.6	1.5	2.6	1.0	2.1	2.6
SD (s)	0.75	0.67	0.48	0.50	0.72	0.00	1.17	0.81

(a) ***Time taken to detect (s) - Prescribed ADLs***

	Sit - Stand	Stand - Walk	Walk - Stand	Stand - Sit	Walk - Sit	Sit - Lie	Lie - Sit	Sit - Walk
Mean (s)	1.4	2.1	2.2	2.1	2.1	1.2	2.9	1.7
SD (s)	0.48	0.23	0.83	0.82	0.48	0.32	1.09	0.99

(b) ***Time taken to detect (s) - Free-Living***

Table 5.4: ***Time taken to detect new postures/activities***

5.3.2 Indoor Location Detection

The Smart Sock's ability to detect indoor location was tested during the prescribed ADL and free-living periods of the study. There were six different location transitions possible in the setting shown in Figure 5.1.; bedroom to hallway, hallway to bedroom, hallway to bathroom, bathroom to hallway, hallway to kitchen and kitchen to hallway. Tables 5.5a. and 5.5b show the detected cases of location change vs. actual location changes for each participant. Table 5.6. shows the overall mean accuracy of the indoor location system for these transitions.

5.3.3 Gait Parameters

Step count and cadence

Figure 5.5. shows the relationship between the Smart Sock estimate of steps taken and the actual steps counted from the video footage during walking at 2km/hr, 3.5km/hr and 5km/hr. The mean correlation between manual step count using video footage and Smart Sock detected step count across all participants and walking speeds was 0.957.

Stride time

The Smart Sock measures heel strike and heel off times. From these events, an estimate for stride time is generated. Table 5.7. shows the device measured stride times compared to the actual values observed in the video footage for each participant. Participants 1, 8 and 13 were unable to perform the treadmill section of the study due to technical issues with the treadmill equipment. These issues also

Subject No.	Bed-Sit		Sit-Bath		Bath-Sit		Sit-Kitch		Kitch-Sit		Sit-Bed	
	A	D	A	D	A	D	A	D	A	D	A	D
1	6	6	3	3	3	0	3	3	3	0	6	6
2	6	6	3	3	3	3	3	2	3	2	6	6
3	6	6	3	3	3	0	3	3	3	0	6	6
4	6	6	3	3	3	0	3	3	3	1	6	6
5	6	6	3	3	3	0	3	3	3	2	6	6
6	6	6	3	3	3	2	3	3	3	2	6	6
7	6	6	0	0	0	0	3	3	3	3	6	6
8	6	6	0	0	0	0	3	3	3	1	6	6
9	6	6	0	0	0	0	3	3	3	1	6	6
10	6	6	3	3	3	0	3	3	3	0	6	5
11	6	6	3	3	3	1	3	3	3	1	6	6
12	6	6	3	3	3	0	3	3	3	0	6	6
13	6	6	3	3	2	0	0	0	0	0	6	6
14	0	0	0	0	0	0	0	0	0	0	0	0
15	6	6	3	3	3	0	3	2	3	0	6	6
Total	84	84	33	33	32	6	39	37	39	13	84	83

(a) ***Location detection: Actual vs Sock detected - prescribed ADLs***

Subject No.	Bed-Sit		Sit-Bath		Bath-Sit		Sit-Kitch		Kitch-Sit		Sit-Bed	
	A	D	A	D	A	D	A	D	A	D	A	D
1	2	2	2	2	2	1	1	1	1	0	2	2
2	2	1	2	2	2	2	2	2	2	1	2	2
3	2	2	2	2	2	1	2	2	2	0	2	2
4	2	2	1	1	1	0	2	2	2	0	2	2
5	2	2	3	3	3	0	3	3	3	1	2	2
6	2	2	1	1	1	1	1	1	1	0	2	2
7	2	2	0	0	0	0	2	2	3	2	2	2
8	2	2	0	0	0	0	2	2	2	2	2	2
9	0	0	0	0	0	0	0	0	0	0	0	0
10	3	3	2	2	1	0	2	2	2	0	2	2
11	2	2	1	1	1	0	3	3	3	1	2	2
12	1	1	2	2	2	0	2	2	2	0	1	1
13	2	2	2	2	2	0	2	2	2	2	2	2
14	2	2	3	3	3	2	3	3	3	1	2	2
15	2	2	2	2	2	1	2	2	2	1	2	2
Total	28	27	23	23	22	8	29	29	30	11	27	27

(b) ***Location detection: Actual vs Sock detected - free living***

* A: Actual

* D: Detected

Table 5.5: ***Location detection: Actual vs Sock detected***

	Bed - Hall		Hall – Bath		Bath - Hall		Hall - Kitchen		Kitchen - Hall		Hall - Bed	
	A	**D**	**A**	**D**	**A**	**D**	**A**	**D**	**A**	**D**	**A**	**D**
Occurrences	112	111	56	56	54	14	68	66	69	24	111	110
Accuracy	99.11%		100.00%		25.93%		97.06%		34.78%		99.10%	

Table 5.6: ***Indoor location accuracy (A:Actual, D:Detected)***

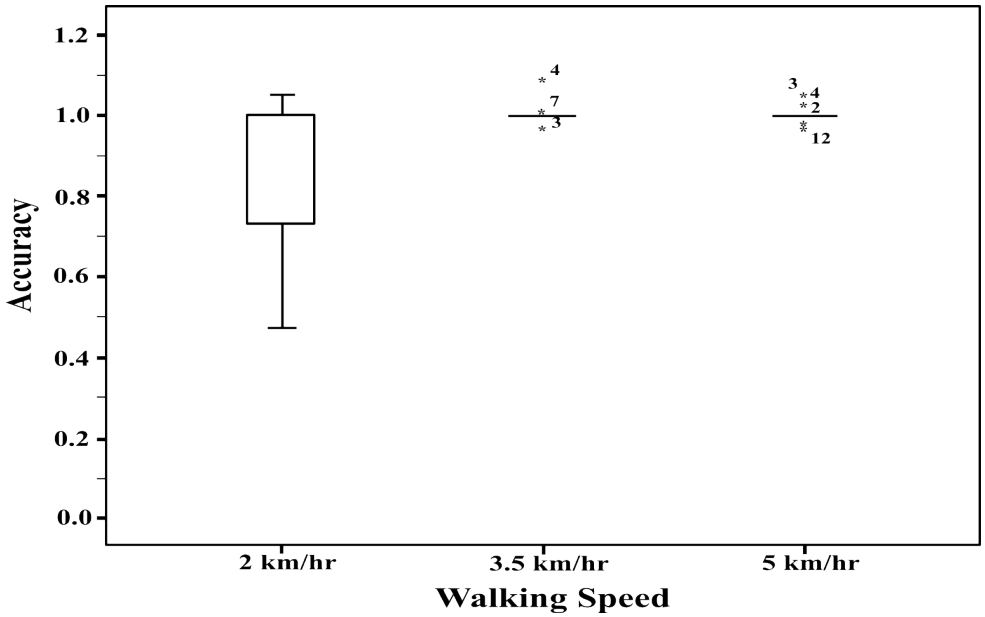


Figure 5.5: ***Step count accuracy box plot showing interquartile range of step count accuracy results and outliers (*)***

Subject No.	2 km/hr		3.5 km/hr		5 km/hr	
	Actual (s)	Sock Measured (s)	Actual (s)	Sock Measured (s)	Actual (s)	Sock Measured (s)
2	1.5	1.47	0.95	1.25	0.89	0.95
3	1.58	1.61	1.23	1.17	1	0.96
5	1.48	1.35	1.19	1.11	-	-
6	1.42	1.28	1.1	1.01	0.96	0.78
7	2.15	1.87	1.76	1.83	1.25	1.3
9	1.46	1.48	1.09	1.02	0.89	0.97
10	1.41	1.7	1.13	1.25	0.89	1.09
11	1.84	1.91	1.22	1.27	1.12	1.12
12	1.85	1.63	1.09	1.14	0.97	1.02
14	1.76	1.69	1.35	1.26	-	-
15	1.56	1.58	1.17	1.1	1.09	1.08
Mean	1.64	1.60	1.21	1.22	1.01	1.03
SD	0.23	0.20	0.21	0.22	0.12	0.14

Table 5.7: ***Stride time comparison: Actual vs Smart Sock measured***

Walking speed	t	Sig.
2 km/hr - 3.5 km/hr	7.496	0
3.5 km/hr - 5 km/hr	3.878	0.005
5 km/hr - 2 km/hr	18.479	0

Table 5.8: ***Stride time t-test results***

affected the 5km/hr measurement for participants 5 and 14. Stride time data for Participant 4 were unavailable due to the timing clock not being enabled on the recording computer. A stopwatch with millisecond resolution was displayed and recorded along with the two camera outputs shown in Figure 5.3. This stopwatch was used for timing of stride events. Therefore, if this stopwatch was not enabled, stride time events cannot be timed. A dependent t-test was also performed to investigate whether the estimates can differentiate between the different walking speeds – 2 km/hr, 3.5 km/hr and 5 km/hr. The results of this t-test are shown in Table 5.8.

5.4 Discussion

Sensitivity and specificity results across all of the different postural changes are very high with a mean of 0.98 and 0.99 respectively. However, for some participants sensitivity and specificity are lower for postural changes that are classified by the device using the pressure sensor under the heel. This is possibly due to the

fact that these participants were wearing different types of footwear or had significantly larger ankle diameters. This causedthe sensor to be poorly positioned under the person's heel. This source of error could be greatly reduced with a more structured placement of the FSR in the material of the sock as well as different size options for the sock. This outcome was integrated into the design of the next version of the Smart Sock. This addition is also expected to increase the overall accuracy of the monitor as this issue significantly impacted the mean accuracy in both the prescribed ADL and free-living sections of the results. The time taken to detect postural transitions is broadly in line with other devices in the research. Algorithms used to detect postural and activity changes typically require a certain window of data to perform this detection. The collection of this window can lead to a short latency in classifying new postures and activities. Few of the examples in the literature classify posture in real time without post-hoc analysis as the Smart Sock does. Therefore, it is significant that the device does not introduce a larger latency in detecting changes in posture or activity.

The indoor location system integrated into the monitor was thoroughly tested in both the prescribed ADL and free-living sections of the study. Of the six transitions between rooms, four performed with near perfect results. The two remaining transitions performed poorly due to the person walking out of the relevant room very quickly. These cases always involved passing through the "hallway" room. This room is 2.8m long and 1.5m wide. Therefore, to pass through this room typically takes less than 3 seconds. In this time, the beacon is transmitting however due to the way in which the beacon transmits code pulses with a 500ms delay between bursts as described in Chapter 4, a limited number of pulses are transmitted before the person has passed through the room. This limited number of pulses means that the probability of the Smart Sock successfully receiving a code is reduced. If the person were to pause in the room, or if the room were larger and took longer to pass through, the probability would be greatly increased.

These false negatives in instances of the person "passing through" the hallway would not significantly affect the overall accuracy of the system throughout the day as the time spent in the hallway is almost negligible in a 24 hour context. However, this problem may be solved with improved positioning of the beacon or alternatively by placing an extra beacon at the opposite end of the room. In the case of the four correctly placed beacons, the mean accuracy for detection of room transitions was 98.9 % of room transitions detected. Though the system did

not achieve 100% accuracy, it did perform very well, especially considering the inexpensive nature of the system as well as the lack of any significant infrastructural or networking requirements. It is the authors' conclusion that the location system, when set up correctly, is a viable solution for behaviour monitoring.

The monitor's step detection algorithms were tested while walking at three different speeds. Accuracy of step counts varied across the different speeds with extremely accurate results for walking at 3.5km/hr and 5km/hr. The monitor also gave an accurate count of steps during the slower walking speed, though this accuracy was affected by a longer delay in walking detection, which caused steps to be slightly underestimated. Cadence estimates are based on the number of steps taken and the time spent walking ($Cadence = \frac{StepCount}{time}$). Since the step count has been shown to be accurate, this implies that the monitor's estimate of cadence is also accurate to the same degree.

The mean stride times measured by the device were within 3% of the observed values at all walking speeds. The dependent t-tests show that the device can differentiate stride times between the different walking speeds with $p<0.01$ at all three walking speeds. This results suggest that the device can give a valid estimate for stride time and detect changes over time.

5.4.1 Limitations of the Study

One population likely to use the Smart Sock activity monitor is older adults. A possible limitation of the trial is that only healthy young adults were recruited to take part. However, it is likely that testing results will generalise to older populations. Though gait speed may differ significantly with older populations, testing was performed at very slow walking speeds. The algorithms used to detect walking have also been tested previously with an older population [88]. The postural algorithms used by the Smart Sock are expected to work with an older population similarly to a younger sample as they do not rely on dynamic movement or transition detection. Therefore, differences in movement should not affect accuracy. Indoor location algorithms also work independently to user movement and should not be affected by the user's gait or other behaviours. As a result, the authors' feel the results presented in this study should generalise very well across populations.

The design of the trial in a clinical laboratory setting may be considered a limitation of the study. However, the protocol was designed to test the device in the

most comprehensive way possible in a laboratory setting. The design of a mock apartment and inclusion of a free-living protocol were designed to compensate for the study not being carried out in a home setting.

5.5 Conclusions

This study was designed to validate the Smart Sock activity monitor. The results show that the device can accurately measure a person's posture, indoor location and several gait parameters. A significant finding from this study is that the detection of some postures could be significantly improved by redesigning the FSR placement in the sock. In the case of indoor location, accuracy in cases where the person enters and exits a room in quick succession could be improved through careful positioning of beacons or, if necessary, the addition of an extra beacon. As these beacons are compact and inexpensive, this is a viable option.

Results from this study suggest that the Smart Sock is a valid measure of activity levels in daily life and is suitable for use in research trials.

The next chapter in this thesis will describe a study involving older adults using the Smart Sock.

Chapter 6

Predicting Functional Health Using a Wearable Behaviour Monitor Incorporating a Functional Assessment Engine: A Proof of Concept Study

6.1 Introduction

Conventional functional assessment (reviewed in Chapter 2) suffers from error introduced through biased answers, misrecollection or differences in interviewer technique [219]. Conducting these types of assessment is also a large drain on resources with personnel hours being required to administer, observe and score these tests. This leads to the assessments being carried out less frequently than may be desirable.

Behavioural monitoring technology, as reviewed in Chapter 3 of this thesis, has the potential to monitor behaviour patterns relevant to functional health. However, the presentation and interpretation of the data generated by these monitors does not easily fit into current clinical practice. For behaviour monitors to be accepted into widespread practice, it is our view that the output from behaviour monitoring systems should mimic the current methods. This would allow clinicians to integrate these systems, with all of their associated advantages, into their current practice with minimal changes to how decisions are made re-

quired.

Chapter 4 of this thesis describes the design of a wearable behaviour monitor incorporating a "Functional Assessment Engine". The purpose of this engine is to generate a score for functional health. This score is designed to be predictive of the result that would be generated if the corresponding conventional assessment tool were administered. As described in Chapter 4, this engine must be trained to generate valid predictive scores for different conventional assessment tools. This training is performed using multiple backwards stepwise linear regression.

The objective of the study described in this chapter was to carry out this training on a sample from a population of older adults and to validate the resulting prediction models for six different widely used conventional functional health assessment tools.

6.2 Study Design

A wide range of functional health assessment tools are available and were reviewed in depth in Chapter 2. Due to the sheer number of different functional assessment tools available, it was impractical to include every assessment scale in the protocol for this study. Therefore, six different functional assessment metrics were chosen for inclusion including some of the most widely used tools across several areas of functional health. The tools chosen for inclusion are listed in Table 6.1. Tools were chosen in order to represent a wide range of functional health domains including:

- basic functional ability
- instrumental functional ability
- frailty
- mobility
- risk of hospitalisation

The behaviour monitor used in the study is the Smart Sock behaviour monitor that is described in Chapter 4 of this thesis. The behaviours monitored by the Smart Sock relate to different domains of mobility and physical activity. Because the device also uses indoor and outdoor location to contextualise activity, the parameters generate a more complete picture of the person's behaviour rather than

Assessment Metric	Function
Barthel Index [5]	Test of assistance needed for basic activities of daily living
Lawton IADL scale[6]	Test of ability for instrumental activities of daily living
Elderly Mobility Scale [220]	Test of person's mobility capabilities
HAQ (DI) [34]	Test of person's level of disability
Edmonton Frailty test [221]	Test of person's level of frailty
HARP [222]	Estimate of chances of hospitalisation in the near future

Table 6.1: ***Conventional assessment tools used in training of Functional Assessment Engine***

their activity levels alone. The following parameters measured by the Smart Sock were included for analysis in this study:

1. Percentage time spent sitting
2. Percentage time spent standing
3. Percentage time spent lying
4. Percentage time spent walking
5. Step count
6. Energy expenditure
7. Stride time
8. Stride time variance
9. Cadence
10. Social outings from the home
11. Religious outings from the home
12. Medical outings from the home
13. Functional outings from the home
14. Time between last activity at night, and first activity in morning

Participant	Barthel	Lawton	Elderly Mobility Scale	HAQ - DI	Edmonton Frailty	HARP	Falls this year	Age
1	90	7	12	8	2	0	0	68
2	100	8	16	2	3	0	2	73
4	80	4	10	39	4	4	1	72
5	100	8	13	1	2	1	0	79
6	100	6	13	2	3	1	1	80
7	80	3	13	27	6	4	5	74
8	90	7	13	13	4	2	1	73
9	90	7	11	9	4	1	0	56
10	90	6	13	4	4	1	0	63
11	100	4	16	16	6	3	0	58
12	100	7	16	1	2	0	0	68
13	100	7	16	0	4	1	0	59
14	100	8	11	7	1	0	0	61
15	90	8	20	26	2	2	0	87
16	95	8	20	20	5	3	0	84

Table 6.2: ***Participant characteristics***

Sixteen older adults (6 male, 10 female, mean age: 73 ±6.7 years) who were living in an assisted living community were recruited to take part in this study. Details regarding each participant can be seen in Table 6.2. Ethical approval was granted by the National University of Ireland Galway Research Ethics Committee. Participants were recruited through the local general practitioner with the only inclusion criteria that they were capable of providing informed consent and that they were independently mobile. Participants were asked to wear a Smart Sock and carry a smart phone either in their pockets or around their neck in a supplied pouch. Participants were trained in the donning and doffing of the sock as well as the charging of the smart phone on the first day of participation. A researcher first showed the participant how to don and doff the sock by demonstrating on themselves, then they put the sock on the participants ankles, finally the participant was asked to don and doff the sock while the researcher was present to ensure the participant properly understood the procedure. An instruction card was also given to the participant with photos showing how to don/doff the sock and how to charge the phone.

The sock was worn for a two week period in order to thoroughly test the usability and durability of the device. However, the battery life of the device is only

~26 hours. Due to participant dexterity and cognitive deficits it was not deemed feasible to have the participants charge the Smart Sock device every day. Therefore, data were collected from the Smart Sock on the first day, and one week later when the participants were provided with a new sock. The repeat measure was performed to overcome unusual activity levels due to sickness or the effects of being involved in the study as described in the development of the Functional Assessment Engine in Chapter 4. As outings from the home are much less repeatable than activity levels, outings were recorded everyday throughout the two week participation and averaged as number of outings per day.

Functional health data were collected using conventional questionnaire based assessments on the first day of the participants involvement in the study. Usability questionnaires were administered at the end of participation.

Before beginning data collection, participants were asked about locations they often frequent such as family/friends homes, hair dressers, bars, golf clubs etc. The GPS co-ordinates for these addresses were added to the co-ordinates for several common locations such as the supermarket, medical center and churches. This list was used to detect functional, social, religious and medical outings.

6.2.1 Data Analysis and Statistics

All statistical analyses were carried out with the statistical package "SPSS". Spearman correlation coefficients for the individual parameters monitored by the Smart Sock and the conventional assessment scores were examined.

Generation of models for training of the functional assesment engine: Chapter 4 of this thesis describes the technique used to train the Smart Sock's Functional Assessment Engine algorithms. Multiple linear regression was used with each of the conventional assessments and the inputs from the Smart Sock to generate predictive equations for functional health domains. Multiple linear regression is a statistical technique that can predict an outcome based on a linear combination of two or more predictor variables. In this case, the outcome variable is the output from a conventional functional health assessment instrument reviewed in Chapter 2. The predictor variables are the outputs from a wearable behaviour monitor described in Chapter 4 of this thesis.

Validity of the models: In order for the outputs of the trained Functional Assessment Engine to be accepted into clinical practice, the validity of the predictive scores generated by the engine must be investigated. There are several statistical methods available for examining the validity of the results of a predictive model generated through multiple linear regression. These methods were implemented to validate the results from the trained Functional Assessment Engine.

Firstly, the R^2 value generated by the model is used to show the amount of variation in the outcome variable that can be accounted for by the model. For example, an R^2 value of 0.74 would mean that the model can account for 74% of the variation in functional health as measured by the relevant conventional assessment instrument.

The adjusted R^2 value gives a measure of the variance that would be accounted for if the model were to be derived from the population from which the sample data were collected. Therefore, the adjusted R^2 values shows how well the model generalises i.e. the cross validity of the model. Ideally, the adjusted R^2 values for each model used in the Functional Assessment Engine would be close to the R^2 values.

The F-ratio is generated by running an ANOVA on the model to test if the model is significantly better at predicting the outcome than using the mean as a best guess [212]. This F-ratio is the ratio of the variability in the data that can be explained by the model to the variability unexplained by the same model. An F-ratio value of greater than 1 suggests that the improvement due to fitting the model is much greater than the inaccuracy within the model. The significance of the F-ratio determines whether the model can claim to significantly improve the ability to predict the outcome variable.

In addition to the statistical methods implemented to test the validity of the models used to train the Functional Assessment Engine, the outputs of these models were validated using a training and testing group. Data from the participants were randomly split into two groups with a ratio of 4:1. The models generated by the larger group were then also applied to the smaller group as "testing" participants whose data were not used in the linear regression to generate the models. Results estimated by the model were then compared to actual conventional assessment outputs.

As some of the fourteen independent variables may overlap, the multicolinearity of the variables was also investigated using a correlation matrix.

6.3 Results

In total, sixteen participants were monitored for a total of between forty-nine and fifty-two hours. For the sake of analysis, data were shortened to two twenty-four hour periods and parameters were averaged across the two days as described in the development of the Functional Assessment Engine in Chapter 4. These data were used to generate fourteen variables for each participant. Conventional assessment outputs made up six dependent variables. The individual correlations for each of the device generated variables vs the conventional variables are presented in Table 6.3.

Of the sixteen participants recruited, fifteen datasets were used in the analysis. This was due to loss of data for a single participant possibly as a result of water damage to the Smart Sock.

6.3.1 Individual Correlations

Table 6.3. presents the Spearman correlation co-efficientsfor each of the fourteen parameters monitored by the device against the total scores for the six dependent variables.

6.3.2 Multiple Linear Regression

A backwards stepwise multiple linear regression was performed using each of the conventional assessments as the dependent variable and the device generated variables as the independent variables (predictors). The results of each of these tests as well as statistics relating to their validity are presented here in Tables 6.4 and 6.5.

Tables 6.4 and 6.5 show adjusted R^2 values for each of the models which can be used as a test of generalisation. In addition to these scores, models were applied to two "testing" participants data that was not used in the generation of the models. The comparison between model generated assessments and conventional assessments is shown in table Table 6.6.

	Sitting	Stand-ing	Lying	Walk-ing	Step Count	Stride Time	Stride Varia-nce	Cade-nce	Time Lying Bed	Social Out-ings	Functi-onal Out-ings	Religi-ous Out-ings
Barthel	0.088	.588*	-0.456	.609*	0.223	-0.141	-0.151	0.217	-0.369	0.103	.593*	0.311
Lawton	0.395	0.344	-0.45	0.393	0.376	-0.274	0.45	-0.177	-0.189	0.327	0.466	0.313
EMS	0.082	0.082	-.634*	.677*	-0.138	-0.297	0.04	-0.118	-0.494	0.101	0.301	0.15
HAQ	-0.359	-0.483	.588*	-.566*	-0.4	0.333	-0.373	-0.046	0.158	-0.117	-.734**	-0.47
Edmonton Frailty	-0.538	-0.521	0.227	-0.23	-0.583	-0.135	-0.005	-0.019	-0.147	-0.399	-0.498	-0.372
HARP	-.562*	-0.275	.617*	-.562*	-0.224	0.241	-0.397	0.183	-0.04	-.611*	-.575*	-0.205

* p<0.05
** p<0.01

Table 6.3: ***Individual correlations between predictor variables from Smart Sock and conventional functional assessment instruments***

Variables Entered	B	Significance	Model R^2	Model Adj. R^2	Model F-ratio	F-ratio Sig
Constant	671.117	0.024	0.931	0.77	5.782	0.089
Sitting	11.371	0.039				
Lying	-1.637	0.113				
Walking	-6.467	0.044				
Stride Time	-0.262	0.035				
Stride Variance	-0.71	0.028				
Social Outings	-25.267	0.029				
Functional Outings	-29.357	0.054				

(a) ***Barthel Index***

Variables Entered	B	Significance	Model R^2	Model Adj. R^2	Model F-ratio	F-ratio Sig
Constant	59.773	0.027	0.874	0.684	4.605	0.081
Sitting	0.413	0.181				
Lying	-0.303	0.15				
Walking	-0.819	0.023				
Stride Time	-0.015	0.017				
Stride Variance	-0.018	0.133				
Cadence	-0.157	0.025				

(b) ***Lawton IADL Scale***

Variables Entered	B	Significance	Model R^2	Model Adj. R^2	Model F-ratio	F-ratio Sig
Constant	54.261	0.003	0.916	0.84	5.231	0.0047
Lying	-0.314	0.005				
Walking	-0.006	0.123				
StrideTime	-0.031	0.024				
StrideVariance	-2.185	0.111				
Social Outings	-0.786	0.457				
FunctionalOutings	-1.759	0.168				

(c) ***Elderly Mobility Scale***

Table 6.4: ***Results from multiple linear regressions including variables describing the model and its validity as discussed in Section 6.2.1.***

Variables Entered	B	Significance	Model R^2	Model Adj. R^2	Model F-ratio	F-ratio Sig
Constant	-216.705	0.011	0.81	0.62	4.628	0.069
Sitting	-5.445	0.03				
Walking	3.336	0.031				
StrideTime	0.138	0.008				
StrideVariance	0.271	0.02				
Cadence	0.923	0.045				

(a) ***Health Assessment Questionnaire (DI)***

Variables Entered	B	Significance	Model R^2	Model Adj. R^2	Model F-ratio	F-ratio Sig
Constant	-14.532	0.015	0.824	0.707	7.037	0.019
Sitting	-1	0.003				
Walking	0.58	0.002				
StrideTime	0.014	0.004				
StrideVariance	0.032	0.012				

(b) ***Edmonton Frailty Scale***

Variables Entered	B	Significance	Model R^2	Model Adj. R^2	Model F-ratio	F-ratio Sig
Constant	-23.573	0.002	0.924	0.847	12.095	0.008
Sitting	-0.797	0.002				
Walking	0.467	0.002				
StrideTime	0.017	0.001				
StrideVariance	0.03	0.004				
Cadence	0.092	0.015				

(c) ***Hospital Risk Admission Profile***

Table 6.5: ***Results from multiple linear regressions continued***

	Test Subject 1					Test Subject 2				
	Actual	**Model Day 1**	**Model Day 2**	**Model Average**	**Average Agree-ment**	**Actual**	**Model Day 1**	**Model Day 2**	**Model Average**	**Average Agree-ment**
Barthel (/100)	90	443.2	556.6	499.9	*5.55*	95	113.15	110.1	111.625	*1.175*
Lawton (/8)	8*	25.92	29.84	27.88	*3.45**	8*	6.785	6.158	6.42	*0.80**
EMS (/20)	16*	20.6	24.8	22.7	*1.41**	16*	19.22	18.41	18.82	*1.17**
Edmonton (/22)	2	-21.95	-28.86	-25.41	*-12.75*	5	5.4	5.073	5.23	*1.05*
HAQ (/60)	26	-130.6	-169.4	-150.0	*-5.76*	20	25.26	28.08	26.67	*1.33*
HARP (/3)	2	-18.54	-23.78	21.14	*-10.57*	3*	3.88	3.967	3.92	*1.31**

* *Assessment ceiling hit*

Table 6.6: ***Conventional scores vs model predicted scores for two test subjects using data from day 1, day 2 and an average of the two days. Assessment ceilings represent cases where the participant reached the maximum score on the conventional assessment and no further information was available regarding their actual functional status from the conventional instrument.***

6.4 Discussion

6.4.1 Individual Correlations

The correlations in Table 6.3 show that the most widely correlated variables measured by the activity monitor across all dependent variables are Functional Outings, Cadence, Percentage time spent walking and Percentage time spent lying though they are not the only correlated variables. The only variable with no correlations to any of the conventional assessment variables is religious outings. This may be because some of the participants were not religious, and some who may not be able to go on outings ordinarily are still brought to church by a friend or family member often. Therefore, across the range of functional health a person may or may not go on religious outings. The conventional assessment variables that are correlated with the most device measured variables are the Hospital Admission Risk Profile, the Barthel Index and the Health Assessment Questionnaire.

6.4.2 Multiple Linear Regression Models

Tables 6.4 and 6.5 show the models generated by the linear regressions using each of the conventional assessments as dependent variables. Models have been generated for all of the conventional assessment variables used in the study. All six of the models presented can explain a variance of over 80% when using R^2 as the identifier. However, adjusted R^2 values are also given due to the small sample size. The adjusted R^2 values generated for the six models range from 0.62 to 0.85 again suggesting that the model can account for a large portion of the variance in the data from the wider population. The F-ratio is a measure of how much the model improves the prediction of the outcome over the average difference between the observed values and those predicted by the model. If the improvement due to the model is much greater than the models inaccuracies, then the F-ratio will be greater than 1.

$$F = \frac{MeanSquare_{Model}}{MeanSquare_{Residual}} \tag{6.1}$$

In all six models presented in this paper, the F-ratio is much greater than 1. However, the change is only significant in three of the models. Each of the models are presented and discussed in this section. The equations presented are generated using the coefficients from the output of the multiple linear regression.

6.4.2.1 Barthel Index

The model generated for the Barthel index includes seven separate device generated variables. Using these variables, the model can account for 93.1% of the variance in the observed data and an estimated 77% of variance in the population data. The F-ratio suggests that this is a large improvement in predictive power, however the p value for the F-ratio does not reach significance. The model for predicting score on the Barthel index is:

$$\begin{aligned} &671.117 + 11.3711(timeSpentSitting) - 1.637(timeSpentLying) \\ &- 6.467(timeSpentWalking) - 0.262(strideTime) - 0.71(strideVariance) \\ &- 25.267(socialOutings) - 29.357(functionalOutings) \end{aligned} \quad (6.2)$$

A possible reason for the poor fit of the Barthel model is that the observed data is badly skewed towards the top of the scale. Figure 6.1. shows a graph of the model predicted values vs the observed data for each participant involved in the study. Figure 6.7. shows the model predicted vs the conventionally collected data for the testing participant group more closely. The graph clearly shows close agreement between the model and conventional data for testing participant 2, however it overestimates function ability for testing participant 1.

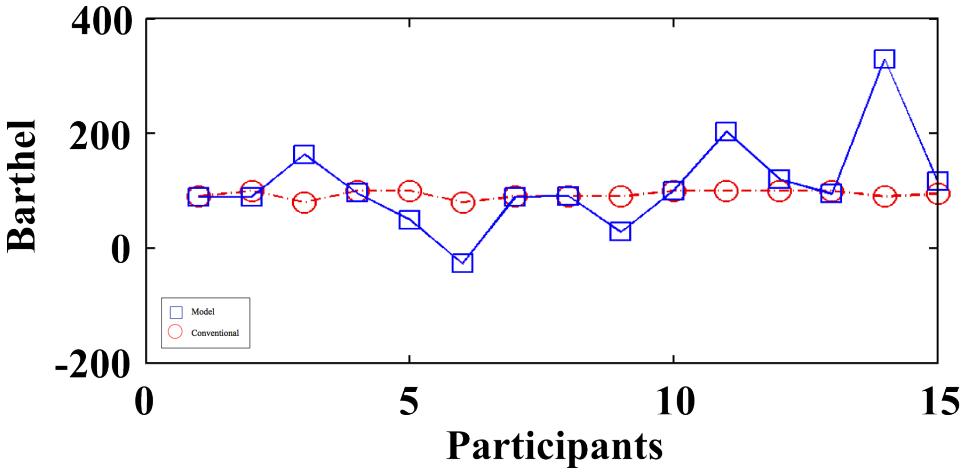


Figure 6.1: ***Model predicted vs. conventionally collected functional assessment data for the Barthel index. The last two data points in the graph represent the testing participant group***

6.4.2.2 Lawton IADL Scale

The model generated for the Lawton IADL scale uses six of the total device generated variables. Using these six variables, the model can account for 87.4% and 68.4% of the variance of the observed and population data respectively. Again, the F-ratio shows that this is a large improvement in predictability, however it is not quite a significant effect.

$$59.773 + 0.413(timeSpentSitting) - 0.303(timeSpentLying) - 0.819(timeSpentWalking) - 0.015(strideTime) - 0.018(strideVariance) - 0.157(cadence) \quad (6.3)$$

Figure 6.2. shows that the model predicted values are again close to the conventional assessments for almost all of the participants. The model score is significantly lower for participant 6. However, on closer examination of the raw behaviour data it was discovered that participant 6 spent an average of over 95% of their time lying down. Therefore it is possible that the conventional IADL scale overestimated this participants functional health, and the model in fact provided an improved measure. This is discussed further in Section 6.4.5. Figure 6.3. shows close agreement between the model and conventional data for testing participant 2 however there is an overshoot in comparison to testing participant

1. This participant scored the maximum score in the conventional Lawton index experiencing the "ceiling effect" discussed in Chapter 2. Therefore this overshoot may be due to the model not being subject to this ceiling effect and again providing an improved measure. This effect is seen in participant 11 in Figure 6.2. also.

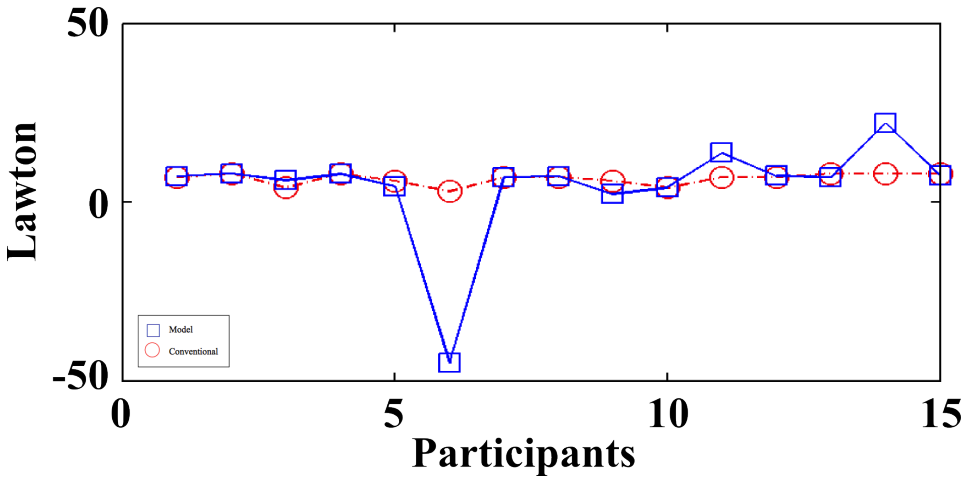


Figure 6.2: ***Model predicted vs. conventionally collected functional assessment data for the Lawton IADL scale. The last two data points in the graph represent the testing participant group***

6.4.2.3 Elderly Mobility Scale

The model relating to the Elderly Mobility Scale is a significant improvement in our ability to predict the outcome score on the scale using six independent variables. The F-ratio of this model is 6.14 with a p value of $p < 0.05$. The model can account for 90.2% of variance in the observed data and 75.5% in the overall population data.

$$\begin{aligned} 54.261 - 0.314(timeSpentLying) - 0.006(timeSpentWalking) \\ - 0.006(strideTime) - 0.031(strideVariance) \\ - 2.185(socialOutings) - 0.786(functionalOutings) \end{aligned} \quad (6.4)$$

Figure 6.3. again shows an agreement between the model and conventional data. Participant 6 is again predicted to be much lower by the model than conventional assessment. However this is due to the same behaviour data as discussed for the Lawton model. Testing participant 1 shows almost perfect agree-

ment in Table 6.6. and Figure 6.7. Testing participant 2 is slightly overestimated, however this participant again experienced the ceiling effect in the Elderly Mobility Scale and this overshoot may be accurate.

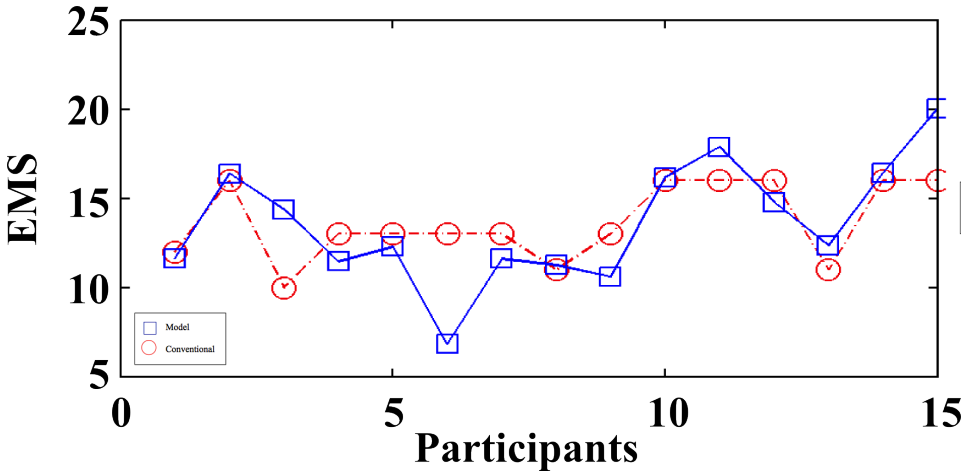


Figure 6.3: ***Model predicted vs. conventionally collected functional assessment data for the Elderly Mobility Scale. The last two data points in the graph represent the testing participant group***

6.4.2.4 The Health Assessment Questionnaire Disability Index

The HAQ's model can account for 98% and 90% of the variance in each population using eight independent variables. The F-ratio again suggests an improved prediction, with a p value of 0.077.

$$-216.705 - 5.445(timeSpentSitting) + 3.336(timeSpentWalking) + 0.138(strideTime) + 0.271(strideVariance) + 0.923(cadence) \quad (6.5)$$

Figure 6.4. shows close agreement for almost all participants. Participant 6 is significantly overestimated by the model compared to the conventional data. Higher scores on the HAQ suggest the person experiences higher levels of disability. This overshoot is in keeping with the predicted data from the other assessment tools and is again due to extremely sedentary behaviour data. Figure 6.7. shows close agreement for testing participant 2, however the predicted HAQ significantly underestimates the conventional assessment for testing participant 1. This could be a possible weakness in the HAQ model or it may suggest that the person's behaviour does not agree with the answers given in the conventional

assessment.

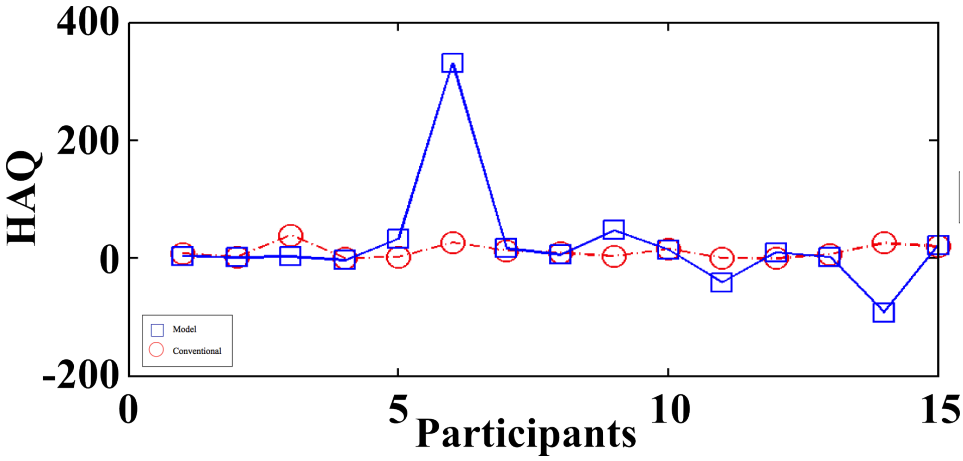


Figure 6.4: ***Model predicted vs. conventionally collected functional assessment data for the Health Assessment Questionnaire. The last two data points in the graph represent the testing participant group***

6.4.2.5 The Edmonton Frailty Test

This model accounts for 82.4% of the observed data variance and 70.7% of population variance while using four independent variables. The F-ratio is 7.037 suggesting an improvement and this improvement is significant with $p < 0.05$.

$$-14.532 - 1(timeSpentSitting) + 0.58(timeSpentWalking) + 0.014(strideTime) + 0.032(strideVariance) \quad (6.6)$$

Figure 6.5. shows close agreement for the majority of participants. Figure 6.7. shows that the model for the Edmonton Frailty test underestimates frailty for testing participant 1 but closely agrees for testing participant 2.

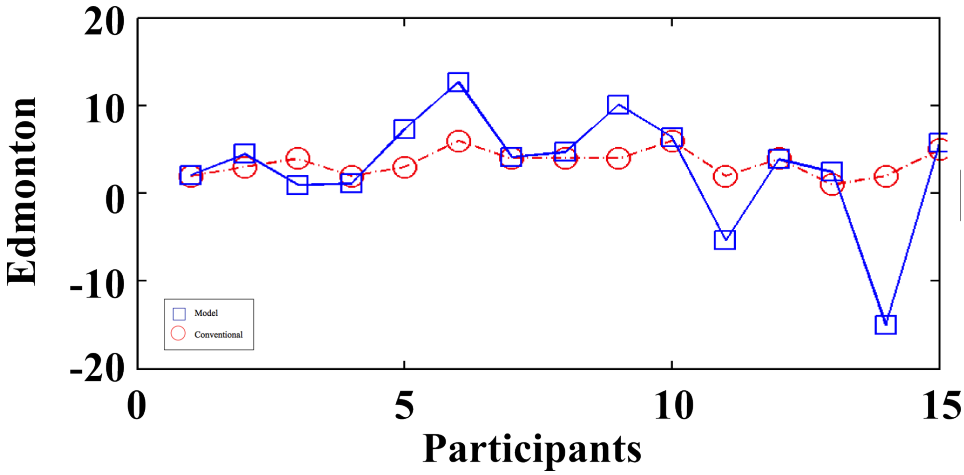


Figure 6.5: ***Model predicted vs. conventionally collected functional assessment data for the Edmonton Frailty test. The last two data points in the graph represent the testing participant group***

6.4.2.6 The Hospital Risk Admission Profile

The HARP model accounts for 92.4% and 84.7% in the observed and population data respectively. The F-ratio suggests a significant improvement with $p < 0.01$.

$$-23.573 + -0.797(timeSpentSitting) + 0.467(timeSpentWalking) + 0.017(strideTime) + 0.03(strideVariance) + 0.092(cadence) \quad (6.7)$$

The predicted values for the HARP closely agree with the conventional assessments for almost all participants. The overestimation for participant 6 is again apparent in Figure 6.6. The model again underestimates hospital admission risk compared to the conventional HARP for testing participant 1, but is in agreement for testing participant 2 (Figure 6.7.).

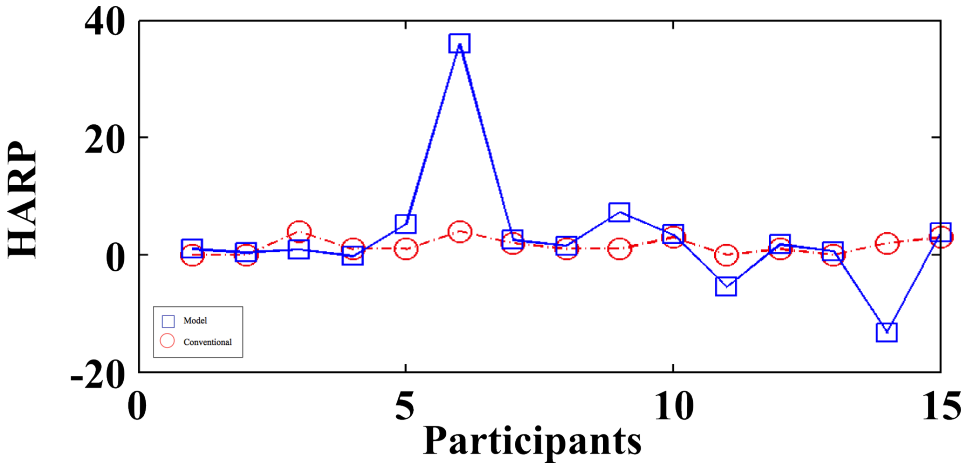


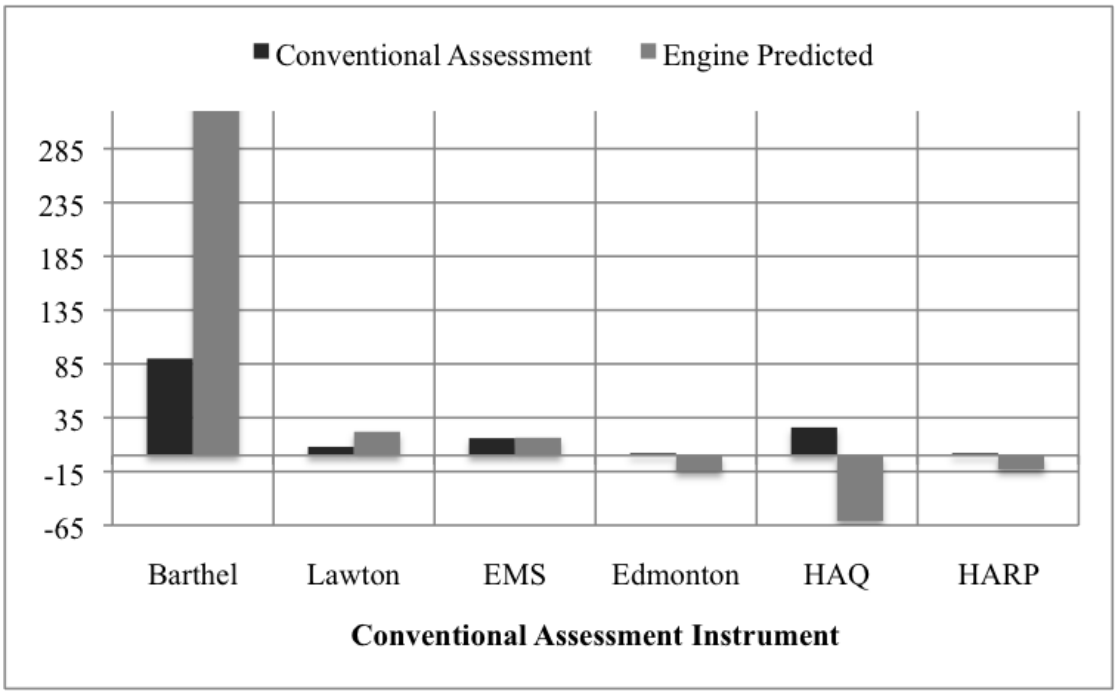
Figure 6.6: ***Model predicted vs. conventionally collected functional assessment data for the Hospital Admission Risk Profile. The last two data points in the graph represent the testing participant group***

All six models suggest an improved ability to predict outcome and all explain a large percentage of the variance in the observed data and the estimated population data. However, only three of the models have F-ratios that are significant. These three models are the Edmonton Frailty Scale model, the Elderly Mobility Scale model and the Hospital Risk Admission Profile model. Therefore, we can conclude that the models presented for these three dependent variables can significantly improve our ability to predict functional health in these three domains.

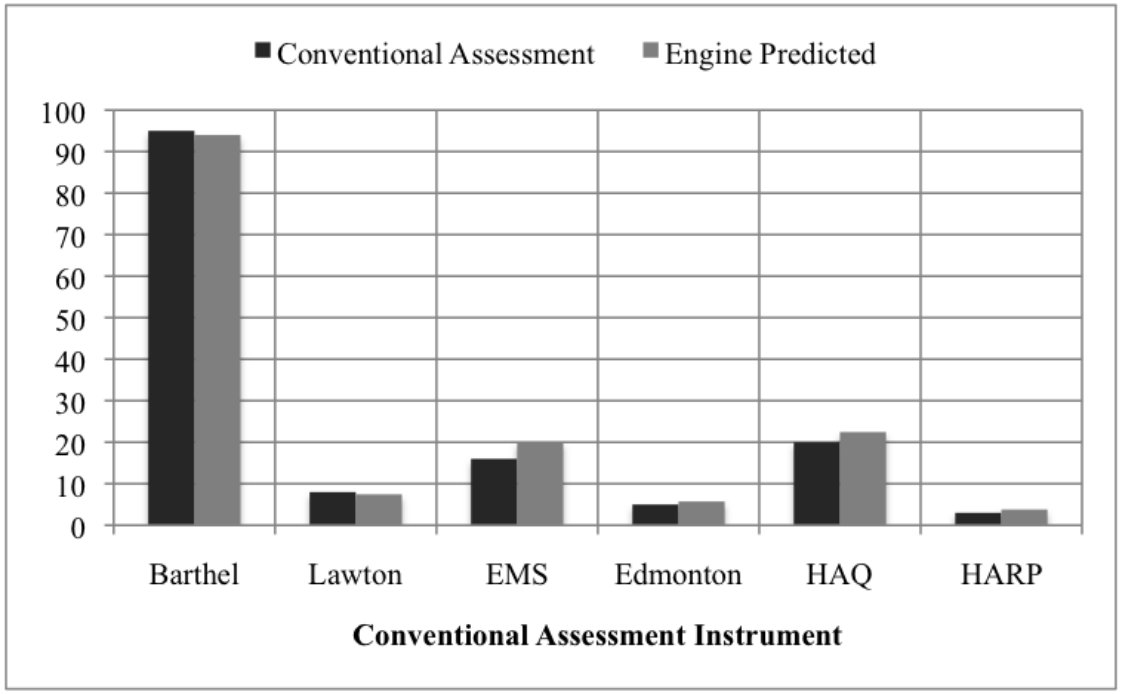
6.4.3 Validation of Models

As explained in Section 2, the small sample size used in this regression as well as the use of backwards stepwise multiple linear regression, mean that the generalisation of the models is of particular importance. The Adjusted R^2 values presented in Tables 3 & 4 are a useful initial indicator of the generalisation of the models. Testing of the models on two participants whose data were not used in the generation of the models was also carried out. The results of this testing can be seen in Table 6.6 as well as the last two participants shown in Figures 6.1. to 6.6.. These data are presented in more detail in Figure 6.7.

There is widespread agreement between the model generated assessment and the conventional assessment scores. In cases where the testing participant scored the maximum score on a conventional assessment, the model tended to generate higher scores. This suggests the models may overcome ceiling effects in the conventional assessment. In the case of the first testing participant, scores



(a) ***Testing participant 1. Functional Assessment Engine consistently overestimates this participants functional health compared to conventional methods for all six instruments suggesting the person's behaviour may not match the answers given in the conventional assessment.***



(b) ***Testing participant 2. Functional Assessment Engine predicted values closely match conventional assessments for all six instruments***

Figure 6.7: ***Model predicted vs. conventionally collected functional assessment data (average of two days data) for testing participant group***

were drastically underestimated for the Edmonton Frailty test, the HAQ and the HARP and overestimated for the Barthel index. Therefore, the models consistently predicted testing participant 1's functional health as higher than the conventional assessment. Therefore it is plausible that the behavioural patterns testing participant 1 follows may suggest that the conventional assessments could be underestimating their functional health. This testing participant was by far the oldest participant (88 years old). A larger sample size with improved distribution of age could help to determine why the models predict a higher level of function than the conventional tools and whether this is an accurate prediction. Overall, these results show a close level of agreement between the models and the conventional assessments, suggesting that the main models generalise very well.

All six models performed very well in predicting these outcomes for functional health. However, due to sample size, this training group is very small and should be taken as an indicator of validity rather than proof.

6.4.4 Predictor Variables in Models

6.4.4.1 Multi-coliniarity

The multi-colinearity of the models was also examined. This involved ensuring that none of the independent variables included in the models are too similar to each other. To test for co-linearity a correlation matrix was generated. Correlations between predictor variables of $p > 0.8$ were considered to represent a possible coliniarity problem [212]. A small minority of variables show correlations over this threshold i.e. Sitting vs Lying, Lying vs Walking and Step Count vs Religious outings. Therefore, multi-colinearity is not a significant problem in the models.

6.4.4.2 Most Widely Included Independent Variables

The resulting models from the Linear regressions for each dependent variable show the most important device generated variables. Though each model uses a different set of independent variables, some are common across all of the models. In any future implementation of autonomous geriatric assessment using behaviour monitoring technology, these variables should be strongly considered for inclusion.

– Percentage Time Spent Sitting - 6 models

- Percentage Time Spent Walking - 6 models
- Stride Time (ms) - 6 models
- Stride Variance (ms) - 6 models
- Percentage Time Spent Lying - 4 models
- Social Outings (/day) - 3 models
- Functional Outings (/day) - 3 models

6.4.4.3 Indoor localisation data

Initially, it was intended for indoor location data to be included in the generation of the functional assessment models. Collection of these data was integrated into the study protocol and implemented in the running of the study. However, indoor location data were not successfully collected for the majority of participants due to a design issue with the hardware in the Smart Sock wearable device. The IR receiver was designed to be positioned at the heel of the foot to maximise the line of sight between IR beacons and the receiver as a person entered a room. This placement ensured the maximum localisation accuracy in laboratory testing. However, during real world use this placement proved problematic. In donning the Smart Sock, participants caught the receiver or the cable connecting it to the main board between their heels and their shoes. This force caused the receiver to either unplug from its connector or often to break this connector meaning the board was no longer receiving beacon signals.

This issue became apparent after data collection was well under way with half of participants completed. Possible solutions were investigated however it was concluded that the hardware in the sock would require significant re-design . Therefore it was finally decided to initially exclude indoor location from the data analysis and training of the Functional Assessment Engine. An evaluation of the performance of the Functional Assessment Engine without these data was undertaken. Should the evaluation show that the trained Functional Assessment Engine could not predict functional assessment outcome without indoor localisation data then the hardware would have been re-manufactured and the data collected again.

However, following training and analysis using the data available, a high level of predictive power was established for the Functional Assessment Engine using

the data available. While it is possible that the addition of indoor localisation data could further enhance this predictive power, we were satisfied that sufficient predictive ability had been achieved and therefore it was not deemed necessary to re-test all of the subjects to obtain indoor localisation data.

6.4.5 Possible Reasons for Poor Fit

Though three of the models can significantly predict outcome in their respective dependent variables, there are still some notable differences between model predicted and observed values as shown in Figures 6.1. to 6.6. However, it may be premature to consider these differences as weaknesses of the models with regards functional health assessment. As mentioned earlier in this paper, conventional assessments are not without their problems [218]. It is possible that the models created using behavioural data may provide an improved estimate of functional health over conventional assessment tools. For example, the model for the Health Assessment Questionnaire shows a large overestimation for participant number 6. This may seem like a large error on the part of the model, however, when the data are examined in detail they show that participant 6 spends over 95% of their time lying down. Though the participants answers in the HAQ assessment suggest a higher level of functional health, the participant's actual behaviour does not agree with this assessment. This "overestimation" for participant six is apparent in all six of the models . In this way, there is the possibility that autonomously performed assessments using behaviour monitors and functional health models may provide a more factual picture of functional health than the conventional assessment.

6.4.6 Advantages of Models over Conventional Tools

In addition to this more accurate representation of a person's actual performed function, assessment based on models may also avoid the floor and ceiling effects seen with conventional assessment. For example, the model for the Lawton scale shows participants who are estimated to score above the minimum and maximum score on the conventional test. In practice, conventional assessments can often show participants at the minimum or maximum score, and in these cases the conventional assessment can provide no extra information. This may not be a problem with the model based assessment as suggested in Figures 6.1 to 6.6. The resolution of the conventional assessments can also be quite poor. For

example, the HARP has only a four step resolution. The model generated estimate for HARP has a much higher resolution. This improved resolution may also make the model generated assessment more sensitive to change in outcome.

6.4.7 Smart Sock Design Recommendations

6.4.7.1 Usability

At the end of each person's participation a usability questionnaire was administered. This usability questionnaire examined the participants' opinions regarding the Smart Sock in several areas and can be seen in the Appendices. Participants were asked to rate each area between 0 and 10. For example, between 0 and 10 rate the wearable device between lightweight and heavy where 0 is very lightweight and 10 is very heavy. The full results of this usability questionnaire for all participants can be seen in Figure 6.8.

Figure 6.8. shows that there were concerns that the sock was conspicuous. However, when usability assessment results are examined separately for male and female participants as shows in Figures 6.10. and 6.9. it can be seen that this worry did not effect males as it did females. The six male participants rated the conspicuousness of the sock at 1.7/10 suggesting the sock is acceptable for males in this regard. However, the average rating for conspicuousness when rated by female participants was 7.8/10. This high rating may suggest a possible issue with compliance in future use of the Smart Sock. When asked for suggestions to improve on this issue, several participants said that a choice of colours to match stocking colours would significantly reduce the noticeability of the sock. This suggestion should be implemented in future use of the Smart Sock.

Similarly female participants rated the sock as less aesthetic and beautiful than their male counterparts. However, male participants commented that this did not bother them, as the sock is not seen when worn with trousers.

Both male and female participants considered the sock to be lightweight, hygienic, flexible, soft and comfortable with males giving better ratings for all of these characteristics.

Participants rated the sock as easy to don and doff though there were some participants who rated the sock as moderately difficult to don and doff.

Overall, participants rated the usability of the device as excellent in almost all categories, and with slight colour changes aesthetic and conspicuous ratings would improve significantly.

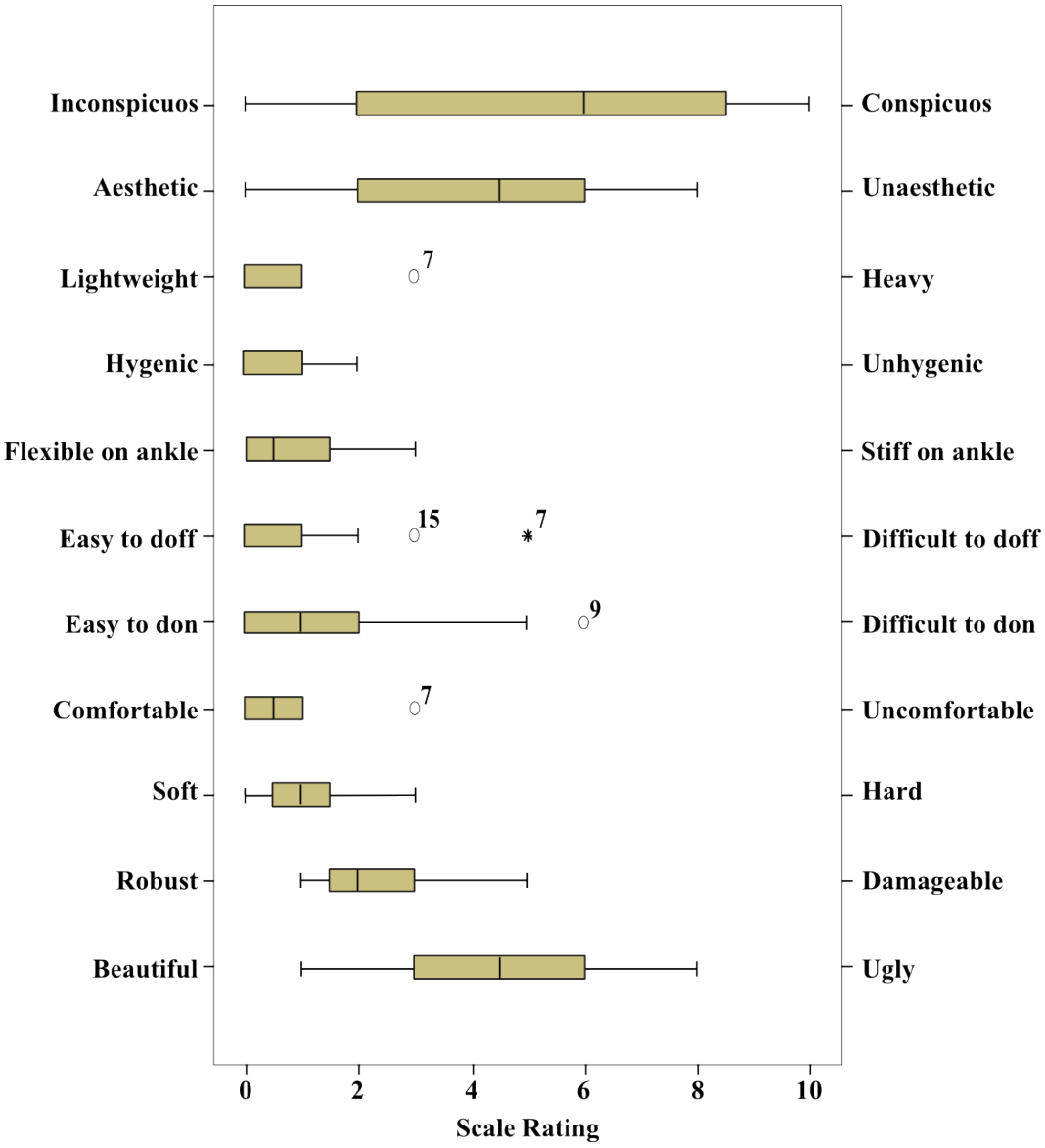


Figure 6.8: ***Boxplot of the results for usability assessment of Smart Sock. Participants were asked to rate the wearable device between 0 and 10 for each category with 0 corresponding with the description on the left and 10 corresponding to the description on the right.***

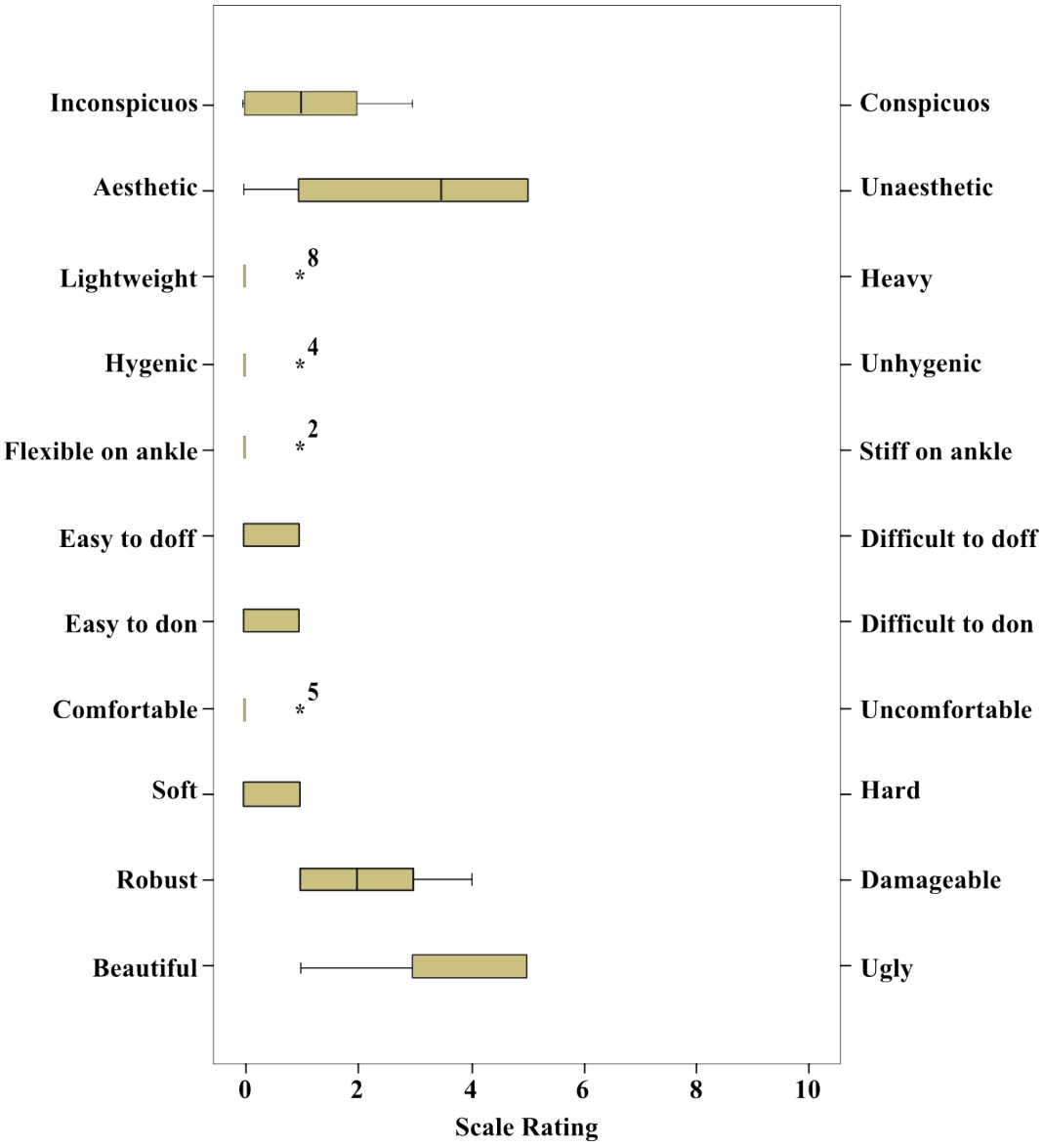


Figure 6.9: ***Usability results from male participants show favourable results across all categories with slightly wide ranges for beauty and aesthetics.***

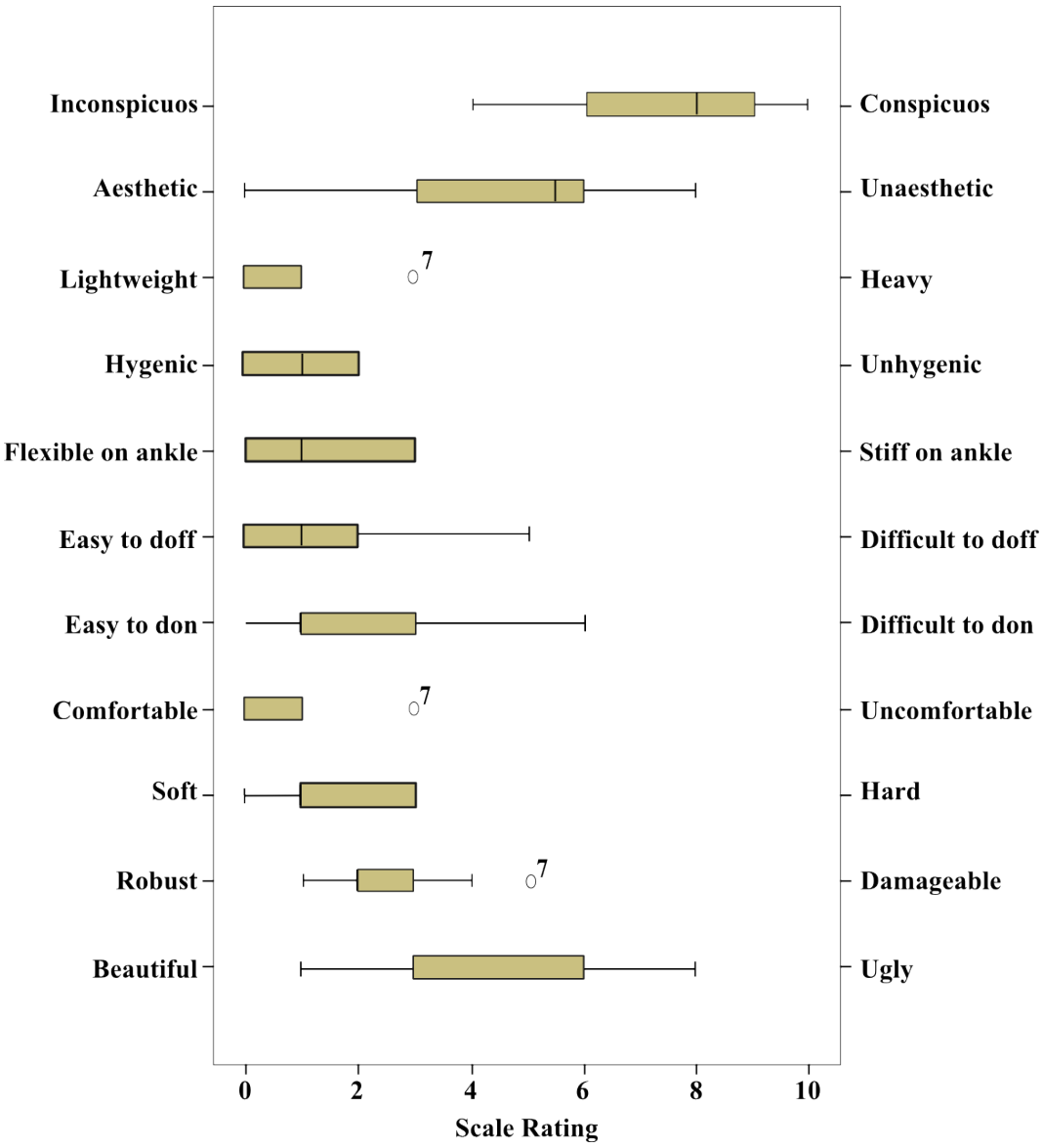


Figure 6.10: ***Usability results from female participants show favourable results across most areas except conspicuousness and with wide ranges for aesthetics and beauty.***

6.4.7.2 Hardware Design

Most aspects of the hardware contained in the Smart Sock performed very well. However, Section 6.4.4.3. discusses a significant issue with one aspect of the indoor localisation hardware. This issue stemmed from two different causes, the first being the placement of this connection at the heel. The connection is based at the point where the heel makes contact with the back of the shoe. This placement was designed to allow the best line of sight between infrared beacons and the receiver. However, participants often caught the connection between the shoe and the foot when putting on shoes. This pressure caused the receiver to either unplug or break. The solution to this issue is to reposition the connector on the main circuit board to the opposite end of the board. The cable used to connect to the IR receiver should also be replaced with an elasticated option or at least integrate a loop in the wire to facilitate significant "tugging" on the cable. The second cause of the broken connection was the connector chosen. The connectors are 2.5mm audio jack connectors and they were chosen to faciliate easy removal of the electronics from the Smart Sock to allow washing. However, these small connectors may be too fragile for repeated strains. This may not be an issue when the connector is relocated to avoid strain, however, these connectors should be replaced with a more robust option.

6.4.7.3 Beacon Placement

Beacons were placed inside the doorways of each room in participants homes. In the majority of cases, this placement did not cause an issue. However, in two cases where participants owned a pet or had young grandchildren, beacons were interfered with. In future implementations beacons should be fixed to the wall or floor.

6.4.8 Limitations of Study

The largest limitation of this study is the small sample size involved **(author?)** [223]. A rule of thumb for linear regression studies is that there should be ten participants per predictor variable [212], meaning ideally that this study would have one hundred and forty participants. However, that is far outside of the scope of this pilot study. Efforts were made to make up for the small sample size through cross-validation using adjusted R^2 values and data splitting into training

and testing participant groups.

Another limitation is the development of functional assessment models against conventional assessment tools. The weaknesses of concurrent validity testing are discussed in Chapter 2 of this thesis. These tools have been shown to contain significant sources of error often caused by biased answers and misrecollection. A future, larger trial, should use other metrics with which to develop models. A longterm trial tracking more direct functional health metrics such as illness, hospitalisation and falls should be carried out.

Due to a design weakness in the connector for the IR receiver on the Smart Sock as outlined in Section 6.4.7.2, a large majority of indoor location data were lost. Therefore, these data could not be included in the linear regression models. This connector has been redesigned and devices should be manufactured to reflect this before future trials.

6.5 Conclusions

This chapter has described a study designed to investigate the performance functional health assessments using data generated by a wearable behaviour monitoring device. Data from the device have been used to train the Functional Assessment Engine models presented in Chapter 4 for six widely used conventional assessment tools across different domains of functional health. All six models strongly suggest an improved ability to predict functional health assessment outcome, with three of the models showing statistically significant predictive ability (i.e. the Elderly Mobility Scale, the Edmonton Frailty Scale and the Hospital Admission Risk Profile).

These results and the models generated are a very exciting and novel contribution to the fields of both behaviour monitoring and functional health assessment. The results suggest that the Functional Assessment Engine incorporated into the Smart Sock behaviour monitoring device could be used to perform screening for functional health.

Not only can the trained engine developed give an accurate approximation of functional health as generated by conventional methods, there is strong evidence to suggest that these models could possibly provide an improved measure of functional health over the conventional methods of assessment. Sensitivity, resolution, repeatability and validity of the models may prove to be an improvement on some of the assessment methodologies currently widespread in med-

ical practice. The results of this study suggest that the Functional Assessment Engine overcomes problems with ceiling and floor effects seen in conventional assessments. Participants whose behaviour suggests a much lower level of function than their answers to questionnaires are flagged as lower functioning by the Functional Assessment Engine. Similarly, participants who report a lower level of functional health than their behaviour patterns suggest are also flagged as higher functioning than conventional assessments classify them.

These advantages add to the case for the incorporation of behaviour monitoring technology into functional health assessment beyond the reduced resource requirements and ability to perform far more frequent assessment. They suggest that the reduced resource, more frequent measure may even be a better measure of functional health.

This proof of concept study is the first to demonstrate the potential of a behaviour monitor and Functional Assessment Engine to perform valid functional health assessments that easily fit into current clinical practice. This demonstration may signify a significant point in the development of behaviour monitors for clinical applications and may help to solve significant acceptability issues that have acted as barriers to the integration of technology into functional health assessment.

Further trials are required to ensure the validity of these results in a larger long-term trial and to integrate more conventional assessment tools into the Functional Assessment Engine, however the initial results found in this study and presented here show a very exciting development in the field of functional health assessment.

Chapter 7

Conclusions and Discussion

Activity monitoring devices have been used extensively in the research in the last fifteen years. Recently, with the decreasing cost and miniturisation of sensor technologies, the ability to integrate several different sensor technologies into activity monitoring systems has emerged. This has allowed activity monitoring systems to significantly expand the range of data they can collect about a person's performance of activities of daily living. This expansion means that activity monitoring devices can evolve to a point that they are monitoring "behaviour" with activity acting as a single aspect rather than activity alone. These "behaviour monitors" may have significantly improved value in a health behaviour monitoring context. Despite this, and the considerable advances in the area of behaviour monitoring using technology, the concept has yet to gain significant traction in widespread clinical practice. Assessment of a person's performance of activities of daily living can be used to predict oncoming degradations in functional ability, morbidity, mortality, falls and need for institutionalisation. Assessment of a person's ability to perform these activities, known as functional assessment, is currently performed using questionnaires or by observing the person as they perform activities. In a clinical practice sense, these methods have significant flaws:

- They require significant resources to implement
- They contain significant inaccuracies
- They suffer from floor and ceiling effects
- They are unresponsive to change and have poor scoring resolution
- They can only be performed periodically for practical reasons

These weaknesses result in infrequent assessment and late diagnosis of functional decline. It has been shown that functional decline follows a hierarchical path, with some activities of daily living showing decline before other core abilities. Delayed diagnosis of decline means that interventions that could have been put in place at an early stage to preserve remaining function are not implemented. This can result in a loss of independence with severe social and economic consequences. Remaining in their own home is both the preferred outcome for the person and by far the most cost effective solution. The quality of life of older adults living in their own homes is also higher than that of those living in residential care facilities. 7% of people over the age of 65 in Ireland currently live

in nursing homes or hospitals [224]. This relatively small proportion of people account for ~60% of the health care budget for care of older people [225].

If it were possible to perform functional assessments autonomously using data collected by behaviour monitoring technology, assessments could be performed much more often. More frequent assessment would mean degradations in function could be flagged at a much earlier stage allowing for earlier intervention. The outcome of this early intervention could be the preserving of independence to the benefit of both the person and the health system.

The aim of this thesis was to investigate the possibility of performing functional assessment using data generated from a behaviour monitoring device. In order to achieve this aim, methods of conventional assessment were researched to best inform the development of a new behaviour monitor specifically designed for this purpose. The introduction of conventional assessments from the first in 1963 to the most recent in 2012 were investigated. The strengths and weaknesses of each tool were determined, and the parameters assessed across all tools were examined. The main findings of this review were that the field of functional assessment has been saturated with new instruments, sometimes without any significant justification for new tools. This has lead to a situation where no gold standard assessment of functional ability can be identified. The review also found that integration of information and communications technology has begun in the field of functional assessment but has yet to take full advantage of the level of technology available. This review was used to determine the desirable characteristics and relevant parameters that the behaviour monitor device should be designed to cater for.

A review of the technologies used in behaviour monitoring systems is presented in Chapter 3. Because of the broad nature of behaviour, the technologies used to monitor people as they live out their daily lives varies widely. This chapter was intended as a background for the design of a new behaviour monitoring system. The core technologies, classification techniques and commercial devices available are all discussed. The importance of the trade off between usability and functionality is highlighted as one of the main findings of this review. The data presentation and interpretation are also discussed as important in behaviour monitor design. Acceptance into clinical practice is highlighted as one of the biggest challenges facing the field of behaviour monitoring. This review was used to inform the development of a new behaviour monitor described in Chapter 4.

Chapter 4 of the thesis presents the development of a new behaviour monitoring device based on the requirements set out in the reviews of both conventional assessment and behaviour monitoring technology. The functionality of the device is significantly improved through the combination of behaviour data and contextual data in the form of indoor and outdoor location. Novel algorithms were designed to monitor posture with sensors based at a single location. These algorithms as well as location algorithms were all implemented to function in real time. A custom printed circuit board was developed to implement the system. This platform is designed to be integrated into a wearable "sock" to best preserve usability. The parameters monitored by this sock are:

- Time spent sitting, standing, lying and walking
- Time spent in different rooms of the home
- Step count
- Energy expenditure
- Stride time and stride variance
- Cadence
- Toileting trips
- Time spent in bedroom lying down during day and night
- Time active in kitchen
- Number of social, religious, functional and medical outings from the home

These capabilities make the device among the highest functioning behaviour monitors available, while maintaining good usability and realtime monitoring. A feedback interface for the user was also developed to take advantage of this real time capability. The device generates an output in the form of a single number. This figure is generated based on the number of preset behavioural goals that are met. While this is a useful metric for approximating behaviour in a single score, it may not be clinically acceptable. Therefore the design of a novel "Functional Assessment Engine" is also described. This unique "engine" contains newly developed algorithms for the prediction of functional health assessment outcome.

The algorithms are designed to be trained using a relevant population and conventional functional assessment instruments. In summary, the device developed uses novel algorithms to monitor a wide range of behaviours from a single body location and it does so in real time. This depth of data from a single body sensing location and incorporating realtime monitoring are not widely available in the literature. This training process of the device Functional Assessment Engine and its validation are described further in Chapter 6.

Validation testing of the device presented in Chapter 4 was performed in a mock apartment set up specifically for this trial. Participants were asked to perform a set list of prescribed activities followed by a period of free movement while wearing the device. The accuracy of the device output was assessed against video footage in real time. The device indoor location algorithms detected presence in a room with an accuracy of 98.82% except in those cases where a person passed through the room without stopping or spending any significant time in the room. The posture detection algorithms detected postures with an average sensitivity of 0.98 and specificity of 0.99. A protocol for testing the gait analysis algorithms in the sock was also implemented. Step count was accurately monitored while walking on a treadmill at 2 km/hr, 3.5 km/hr and 5 km/hr. Estimates for stride time generated by the sock are within 3% of those taken from video footage for all three walking speeds. Outcomes from this study suggested that the placement of the force sensitive resistor in the sock was extremely important and the sock design should be altered to ensure correct placement. The results also indicated that the sock was a valid measure for all parameters tested.

After developing and validating a behaviour monitor with a range of behaviours monitored , work turned to the training and validation of the Functional Assessment Engine described in Chapter 4. A protocol was designed to develop the algorithms used in the Functional Assessment Engine based on widely used conventional assessments of functional health and to investigate whether the trained Functional Assessment Engine could provide a valid prediction of functional health assessment outcome. It was plausible that the inputs from the behaviour monitoring device could provide a valid assessment for several different domains of functional health so the protocol was designed to incorporate a range of conventional assessments. Data were collected using both the behaviour monitoring device and the conventional assessments from a group of older adults living in an assisted living facility. An assisted living facility was deemed suitable as it provided access to participants with a wide range of func-

tional abilities. Multiple backwards stepwise linear regression was then used to generate predictive equations to relate behaviour data with conventional assessment data. These equations could then be used to predict a users score on a conventional functional assessment. The validity of these scores were investigated using statistical methods and a group of testing participants who's data were not used in the generating of the equation.

The results of the study described show that the trained Functional Assessment Engine is capable of significantly predicting functional health assessment outcome for three of the six instruments tested (Elderly Mobility Scale, the Health Assessment Questionnaire and the Hospital Admission Risk Profile). Statistical analysis including f-ratios also suggested positive predictive ability for the other three instruments tested, however these prediction models were not significant. It is possible that with a larger study sample, these models would also be significant.

The main outcome of this study was that the trained Functional Assessment Engine could generate a predictive scores for mobility, disability and risk of hospital admission based on the Elderly Mobility Scale, Health Assessment Questionnaire Disability Index and Hospital Admission Risk Profile respectively.

Usability of the device was assessed in this protocol also. Results of the usability assessment were that the device would be acceptable for long term use with minor aesthetic adjustments.

In summary, this thesis describes a body of work involving the design, development and validation of a wearable behaviour monitoring device for the performance of autonomous functional assessment. The aim was to demonstrate the feasibility of replacing conventional questionnaire based assessments in screening for functional decline. We have clearly shown the potential for this autonomous assessment. The demonstration of this potential is the first to be presented in the literature and paves the way for extremely exciting developments in the fields of both behaviour monitoring and functional health assessment.

It is envisioned that future work would expand on Chapter 6 of this thesis. The trial described in that chapter proves the potential of the use of technologically collected data for input to functional assessment, however, the sample size involved was far too small to definitively claim validity. An expanded trial with a significantly larger sample should be performed.

The feedback mechanisms available in the device should also be tested for use in intervention programs. Previous research has shown feedback to be an ef-

fective motivator in physical activity programs for weight management. The possibility of this effect generalising to functional health could be investigated. The device could be used to collect baseline functional ability data with no feedback provided. The effects of implementing a smart phone based feedback program on functional health over a long term program could then be examined.

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Appendix A

Ethical Approval Applications

OÉ Gaillimh
NUI Galway

RESEARCH ETHICS COMMITTEE APPLICATION FORM

For Applicant to complete:

Applicants' Name: Gearóid Ó Laighin

Title of Project: Mobility Monitoring Using RFID and Kinematic Sensors

For Ethics Committee use only:

Reference Number: _____ *Date received:* _____

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: **The Secretary**
NUI Galway Research Ethics Committee
Office of the Vice-President for Research
Science and Engineering Technology Building
NUI Galway

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	Not applicable
1	Electronic Copy of complete application. Filename: nuig_rec_appl_formv (single PDF document)	☑	☐	
1	Hard Copy of application form	☑	☐	

		Electronic Copy YES	Hard Copy YES	NO	Not applicable
1	Copy of protocol (No more than 4 A4 pages)	☑	☑	☐	
1	Participant consent form(s)	☑	☑	☐	☐
1	Participant information sheet(s)	☑	☑	☐	
1	Questionnaire(s)* ☐ Final version ☐ Draft Version	☐	☐	☐	☑
1	Sample letters (GP, Recruitment etc)	☐	☐	☐	☑
1	Copy of Risk Assessment Form**	☐	☐	☐	☑
1	Copy of Principal Investigators CV (2A4 pages max)	☐	☐	☐	☑
1	Annex 1**	☐	☐	☐	☑
1	Annex 2***	☐	☐	☐	☑
	Annex 3**** (1 copy per procedure for which risk identified)	☑	☑	☐	☐

* *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		Cross-over		Biological material	
Healthy volunteer	✓	Case-study		Foetal material	
Patient volunteer		Longitudinal		Hazardous materials	
'Incompetent' patients		Cross-sectional		Invasive procedures	
Children (under 16 yrs)		Placebo		Devices (in licence)	
Observational	✓	Therapeutic		Medicinal products	
Interview		Controlled		(in licence)	
Questionnaire		Double-blind		Devices	
Record-based		Single-blind		(outside licence)	
Randomised		Prospective		Medicinal products	
Non-randomised		Retrospective		(outside licence)	

SECTION 1 Applicant(s) Details

1. Title of project:

Mobility Monitoring Using RFID and Kinematic Sensors

2. Principal Investigator: *(All correspondence will be sent to this address unless indicated otherwise.)*

Family Name: Ó Laighin **Forename**: Gearóid **Title**: Professor

Contact address *(for correspondence regarding application)*:
Electrical & Electronic Engineering
NUI Galway
Galway

Tel: 091 492685 (Ext 2685) **Fax**: 091 494511 **Email**: gearoid.olaighin@nuigalway.ie

Mobile Number / Other Contact Number: 0876504801
Present appointment of PI: Professor of Electrical & Electronic Engineering
Qualifications of PI: B.E degree in Electrical Engineering from UCC,
M.Eng.Sc Degree from UCC,
Ph.D degree at National University of Ireland, Galway

3. Other Investigator(s):

Family Name: Lowe **Forename**: Shane **Title**: Mr.

Department: Electrical & Electronic Engineering

Institution: NUI Galway

Tel: 0876610315 **Fax**: 071 9621359 **Email**: s.lowe1@nuigalway.ie

Present appointment: IRCSET funded Ph.D student researcher with the Bioelectronics Research Cluster NUI Galway.

Qualifications: B.E degree in Electronic Engineering from NUI Galway

Family Name: Breslin **Forename**: John **Title**: Dr.

Department: Electrical & Electronic Engineering

Institution: NUI Galway

Tel: 353 91 492622 **Fax**: 353 91 494511 **Email**: john.breslin@nuigalway.ie

Present appointment: Lecturer in Electronic Engineering

Qualifications: B.E degree in Electronic Engineering from NUI Galway
Ph.D degree at NUI Galway

Family Name: **Forename**: **Title**:

Department:

Institution:

Tel: **Fax**: **Email**:

Present appointment:

Qualifications:

4. Other workers and departments/Institutions involved:

Name	Department/Institute	Appointment

5. Funding Sources:

(i) Has any funding been obtained/sought by the investigator in respect of this study?

Funding applied for: YES ☐ NO ☐ Not applicable ☑

Funding secured: YES ☐ NO ☐ Not applicable ☑

(ii) Name of sponsoring organisation from which funding has been obtained/sought?

N/A

(iii) Does the Investigator(s) have any direct involvement in the sponsoring organization?

e.g. financial, share-holding etc: YES ☐ NO ☐ Not applicable ☑

If YES, give details:

N/A

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:

Duration (months):

7. Signature of relevant personnel:

Principal Investigator 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: _____ **Date**: _____

Co-Signed by Supervisor where the P.I. 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: Prof. Gearóid Ó Laighin **Department**: Electrical & Electronic Engineering

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?)

To assess the accuracy of an RFID and kinematic sensor based mobility monitoring system over a period of 8 hours.

9. Scientific/theoretical background[1] to study (Approx. 250 words)

In 2001 17% of the European Union population was over the age of 65. It is estimated that by 2035 this figure will have reached 33%. With more people over the age of 65 requiring increased care and less people in the 18 – 65 tax paying workers bracket, this poses severe social and economic problems. Remote monitoring of the elderly, as a form of telemedicine, is therefore becoming more important as a means of managing the health of the elderly, without the need for expensive and socially isolating hospitalisation. Physical activity can be a useful indicator of a person's physical and mental health. Therefore the ability to monitor a person's mobility is an effective way of remotely monitoring that person's health status and quality of life. There are several remote monitoring systems in existence using kinematic sensors to measure the duration spent sitting, standing or lying down. While useful, this information gives a somewhat limited picture of the person's quality of life. If this information could be contextualised so that the system could say whether the person was sitting, standing or lying down as well as where the person is in the house, this could be used to give a much more complete report of the persons quality of life. Clearly if a person is found to be spending large portions of the day sitting down, it is significant to quality of life indication whether this is occurring in the sitting room or the bedroom. The proposed study uses RFID and kinematic sensors to give a complete report of the person's mobility.

10. Brief plan of investigation[2] (i.e. what do you intend to do?) (Approx. 250 words)

There will be ten participants recruited for this study. Each participant will be monitored in their own home for an eight hour period. The participant will wear a camera pouch around their neck containing a PDA (Personal Digital Assistand) and an RFID reader. Two accelerometers will be worn by the person. One on a velcro strap at the chest and the other strapped to the thigh using a velcro strap. Both accelerometers will be connected by wire to a data-logger in the person's pocket. The subject will be told to carry out their day as normal with the only constraint being that they must spend the duration of the study inside the house. The house will be set up by installing RFID tags in each doorway. They will be shadowed for the entire duration of the study by an investigator who will keep a log of movement round the house and duration spent sitting, standing or lying. Using a Matlab programme the data collected from the RFID and kinematic sensors will be compiled into a graphical report of mobility. This report will be compared with the investigators log and percentage accuracy will be calculated for the system.

11. List procedures or investigations involving risks to participants' well-being or safety (what, when, how often and risks associated with all procedures)

The participant will be told to carry out their day as normal. This means that they will not be asked to perform any activities that are not routine to them. There is no risk of electrical shock from the equipment used. All equipment is CE marked. The sensors at the waist and thigh are connected to the data logger in the pocket by wires. However these wires are cut to a length so that they are not loose or sticking out to avoid any risk of tripping.

[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.

Survey/Questionnaire		Interviews	
Case Study		• individual	
Observational	✓	• group	
Action research	✓	• person-to-person	
Record based		• telephone	
Cohort		• electronic	
Case control			
Other		Forms of Recording	
(please specify)		• Video	
		• Audio	
		• Photography	
		• Notes	✓
		• Electronic recording	✓

13. Size of the study (including controls):

(i) How was the size of the study determined?

This is a proof of concept study to assess the accuracy of a prototype mobility monitoring system. Sample size was chosen to account for statistical considerations and time taken to run each participant through the research protocol.

(ii) Was there formal statistical input into the overall study design? NO

(iii) What method of analysis will be used?

All analysis will involve recognised mathematical and statistical techniques.

14. Where[3] will the study take place and in what setting?

The study will take place inside the participant's homes

15. Does the study involve:

(i) distribution of a questionnaire? YES: ☐ NO: ✓

If YES, please append a copy of the questionnaire to this application. Please indicate whether the appended questionnaire is: Non-validated: ☐ Validated: ☐

(ii) the use of a existing medicinal product or medical device? YES ☐ NO ✓

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 ✓

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 ✓ If YES, please complete **Annex 2** of this application.

16. Peer Review/Critique[4]

[3] Geographical location; laboratory, hospital, general practice, home visits etc.

[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.*

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Has the protocol been subject to peer review? YES ☑ NO ☐

If the review formed part of the process of obtaining funding, please give the name and address of the funding organisation:

N/A

If the review took place as part of an internal process, please give brief details:

The protocol was reviewed by Shane Lowe (Electrical and Electronic Engineering), Prof. Gearóid Ó Laighin (Professor of Electrical & Electronic Engineering) and Alan Barrett (Ph.D student in the bioelectronics cluster in the NCBES)

If no review has taken place, please explain why and offer justification for this:

17. Does the study fall into any of the following categories?

Pilot:	YES ☑	NO ☐	Not applicable ☐
Multi-centre study	YES ☐	NO ☑	Not applicable ☐

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?

(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

Healthy young adults from the general public are being studied.

19. How will be the participants in the study be:

(i) Selected?

Participants will be selected from the general public for this study. Four healthy young adults will be used.

(ii) Recruited? (Please append advertisement materials to application)

Participants will be recruited from friends and family

20. What criteria will be used for inclusion and exclusion of participants?

(i) Inclusion criteria:

Young and Healthy Adults
Capable of giving informed consent
Independently mobile

(ii) Exclusion criteria:

Anything outside of the above

21. How many participants will be recruited and of what age groups?

Ten participants will be recruited.
All participants will be between the ages of 20 - 50

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:

N/A

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(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: ☑

If YES, please give details

26. Will participants receive any payment or other incentive to participate?

YES: ☐ NO: ☑

(i) If YES, give details of incentive per participant?

If YES, what is the source of the incentive?

SECTION 4 Consent

27. Is written consent for participation in the study to be obtained?
YES: ✓ 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

28. How long will the subject have to decide whether to take part in the study?
(If less than 24 hours, please justify)

The participants will have one week to decide whether or not to take part in the study. They will have the participants information sheets for one week before the decision is made.

29. Does the study include participants for whom English is not a first language?
YES: NO: ✓

If YES, give details of special arrangements made to assist these participants

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 16 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

(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?

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(iii) In what way, if any, can the proposed study be expected to benefit the individual who participates?

32. Are women of childbearing potential included in this study?
[please answer this question only where invasive or other interventions are planned which could be a risk to a pregnancy]
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: ☑

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	☑	YES	☐	NO
Self completion questionnaires	☐	YES	☑	NO
Interviews/interview administered questionnaires	☐	YES	☑	NO
Video/audio tape recording	☐	YES	☑	NO
Physical examination	☐	YES	☑	NO
Internal physical examination	☐	YES	☑	NO
Venepuncture*	☐	YES	☑	NO
Arterial puncture*	☐	YES	☑	NO
Biopsy material*	☐	YES	☑	NO
Other tissue/body sample*	☐	YES	☑	NO
Imaging investigation (not radiation)	☐	YES	☑	NO
Other investigations not part of normal care	☐	YES	☑	NO
Additional out patient attendance	☐	YES	☑	NO
Longer inpatient stays	☐	YES	☑	NO
Local anesthesia	☐	YES	☑	NO
General anesthesia	☐	YES	☑	NO

Other – please detail

Please indicate and justify where treatment is withheld as a result of taking part in the project.

35. Will any ionising or non-ionising radiation, or radioactive substances or X-Rays be administered to a participant?

YES: ☐ NO: ☑

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: ☑

* *Please see Guidance Notes*

If NO, please explain why not

SECTION 6 Risks and ethical problems

37. Are there any potential risks to participants?

YES: ☐ NO: ☑

If YES, please complete **Annex 3** for each procedure for which a potential risk occurs.

38. Is this study likely to cause any discomfort or distress, either physical or mental?

YES: ☑ NO: ☐

If YES, estimate the degree and likelihood of discomfort or distress entailed and the precautions to be taken to minimise them.

Participants may be concerned about the confidentiality of their test result data. To ensure confidentiality participants will be assigned participant numbers which will be used in place of their names on all documentation. A paper record linking the participant to their participant number will be kept in a locked drawer in the Electrical & Electronic Engineering department.

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?

The PDA and RFID reader hanging from the neck may cause some mild discomfort after pro longed periods of time. A camera pouch and strap designed for a camera of similar size and weight will be used to minimise this discomfort. Participants will be told to take off the pouch if any discomfort is felt and to only put it back on if and when they feel comfortable to do so.

.

(i) Will treatments provided during the study be available if needed at the end of the study?

YES: ☐ NO: ☐ Not applicable: ☑

(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.

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? Not applicable: ☐

This study has been submitted to Bernadette Costello for review to see whether it is covered by the NUIG indemnity policy.

(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? Not applicable: ☐

This study has been submitted to Bernadette Costello for review to see whether it is covered by the NUIG indemnity policy.

(ii) Will an undergraduate student be involved directly in conducting the project?

YES: ☐ NO: ☑

41. In cases of equipment or medical devices, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: ☐ NO: ☐ Not applicable: ☑

If YES, please give details and enclose a copy of the relevant correspondence with this application

42. In cases of medicinal products, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: ☐ NO: ☐ Not applicable: ☑

If YES, please give details and enclose a copy of the relevant correspondence with this application

[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: ☐ NO: ☑

Observation of participants: YES: ☑ NO: ☐

If YES to either:

(i) How are confidentiality and anonymity to be ensured?

Records taken will use the participant's "participant number" instead of their names. Only the researchers will have access to test data. All electronic copies of test data will be kept encrypted on a password protected computer and all hard copies will be kept in a locked drawer in the Electrical and Electronic Engineering Department

(ii) What arrangements have been made to obtain consent for these procedures?

(iii) What will happen to the tapes at the end of the study?

N/A

44. Will the study data be held on computer?

YES: ☑ 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: ☑ NO: ☐

If NO, please give reasons

45. Will records (preferably paper records) linking study participant ID with identifying features be stored confidentially?

YES: ☑ NO: ☐

Please give details of arrangements for confidential storage

Paper records linking participants to their participant numbers will be kept in a locked drawer in the Electrical and Electronic Engineering Department.

For how long will records be retained prior to destruction?

Records linking the participants with the test data will be kept for the duration of the study. Anonymous data from the study will be kept for a period of five years

46. Will the participants' medical records be examined by investigators in the study?

YES: ☐ NO: ☑

If YES, will information relevant **only** to this study be extracted: YES: ☐ NO: ☐ Not applicable: ☑

(i) If extra information is extracted, please justify

(ii) What, if any, additional steps have been taken to safeguard the confidentiality of personal medical records?

47. Will research workers outside the employment of NUI Galway examine medical or other personal records?

YES: ☐ NO: ☑

If YES, it is the responsibility of the Principal Investigator 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.

OÉ Gaillimh
NUI Galway

RESEARCH ETHICS COMMITTEE APPLICATION FORM

For Applicant to complete:

Applicants' Name: Gearóid Ó Laighin

Title of Project: Validation of the "Smart Sock" activity monitor

For Ethics Committee use only:

Reference Number: _____ *Date received:* _____

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: **The Secretary**
NUI Galway Research Ethics Committee
Office of the Vice-President for Research
Science and Engineering Technology Building
NUI Galway

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	Not applicable
1	Electronic Copy of complete application. Filename: nuig_rec_appl_formv (single PDF document)	☑	☐	
1	Hard Copy of application form	☑	☐	

		Electronic Copy YES	Hard Copy YES	NO	Not applicable
1	Copy of protocol (No more than 4 A4 pages)	☑	☑	☐	
1	Participant consent form(s)	☑	☑	☐	☐
1	Participant information sheet(s)	☑	☑	☐	
1	Questionnaire(s)* ☐ Final version ☐ Draft Version	☐	☐	☐	☑
1	Sample letters (GP, Recruitment etc)	☐	☐	☐	☑
1	Copy of Risk Assessment Form**	☐	☐	☐	☑
1	Copy of Principal Investigators CV (2A4 pages max)	☐	☐	☐	☑
1	Annex 1**	☐	☐	☐	☑
1	Annex 2***	☐	☐	☐	☑
	Annex 3**** (1 copy per procedure for which risk identified)	☑	☑	☐	☐

* *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		Cross-over		Biological material	
Healthy volunteer	✓	Case-study		Foetal material	
Patient volunteer		Longitudinal		Hazardous materials	
'Incompetent' patients		Cross-sectional		Invasive procedures	
Children (under 16 yrs)		Placebo		Devices (in licence)	
Observational	✓	Therapeutic		Medicinal products (in licence)	
Interview		Controlled			
Questionnaire		Double-blind		Devices (outside licence)	
Record-based		Single-blind			
Randomised		Prospective		Medicinal products (outside licence)	
Non-randomised		Retrospective			

SECTION 1 Applicant(s) Details

1. Title of project:

Validation of the Smart Sock activity monitor

2. Principal Investigator: *(All correspondence will be sent to this address unless indicated otherwise.)*

Family Name: Ó Laighin **Forename**: Gearóid **Title**: Professor

Contact address *(for correspondence regarding application)*:
Electrical & Electronic Engineering
NUI Galway
Galway

Tel: 091 492685 (Ext 2685) **Fax**: 091 494511 **Email**: gearoid.olaighin@nuigalway.ie

Mobile Number / Other Contact Number: 0876504801
Present appointment of PI: Professor of Electrical & Electronic Engineering
Qualifications of PI: B.E degree in Electrical Engineering from UCC,
M.Eng.Sc Degree from UCC,
Ph.D degree at National University of Ireland, Galway

3. Other Investigator(s):

Family Name: Lowe **Forename**: Shane **Title**: Mr.

Department: Electrical & Electronic Engineering

Institution: NUI Galway

Tel: 0876610315 **Fax**: 071 9621359 **Email**: s.lowe1@nuigalway.ie

Present appointment: IRCSET funded Ph.D student researcher with the Bioelectronics Research Cluster NUI Galway.

Qualifications: B.E degree in Electronic Engineering from NUI Galway

Family Name: Breen **Forename**: Paul **Title**: Dr.

Department: Electrical & Electronic Engineering

Institution: NUI Galway

Tel: 353 91 493126 **Fax**: 353 91 494511 **Email**: paul.breen@nuigalway.ie

Present appointment: Postdoctoral Researcher

Qualifications: B.E degree in Electronic Engineering from University of Limerick
Ph.D degree at NUI Galway

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4. Other workers and departments/Institutions involved:

Name	Department/Institute	Appointment

5. Funding Sources:

(i) Has any funding been obtained/sought by the investigator in respect of this study?

Funding applied for: YES ☐ NO ☐ Not applicable ☑

Funding secured: YES ☐ NO ☐ Not applicable ☑

(ii) Name of sponsoring organisation from which funding has been obtained/sought?

N/A

(iii) Does the Investigator(s) have any direct involvement in the sponsoring organization?

e.g. financial, share-holding etc: YES ☐ NO ☐ Not applicable ☑

If YES, give details:

N/A

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: 15/10/2011

Duration (months): 3 months

7. Signature of relevant personnel:

Principal Investigator 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: _____ **Date**: _____

Co-Signed by Supervisor where the P.I. 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: Prof. Gearóid Ó Laighin **Department**: Electrical & Electronic Engineering

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?)

To assess the accuracy of a wearable electronics activity monitor in detecting a range of activities of daily living.

9. Scientific/theoretical background[1] to study (Approx. 250 words)

In 2001 17% of the European Union population was over the age of 65. It is estimated that by 2035 this figure will have reached 33%. With more people over the age of 65 requiring increased care and less people in the 18 – 65 tax paying workers bracket, this poses severe social and economic problems. Remote monitoring of the elderly, as a form of telemedicine, is therefore becoming more important as a means of managing the health of the elderly, without the need for expensive and socially isolating hospitalisation. Physical activity can be a useful indicator of a person's physical and mental health. Therefore the ability to monitor a person's mobility is an effective way of remotely monitoring that person's health status and quality of life. There are several remote monitoring systems in existence using kinematic sensors to measure the duration spent sitting, standing or lying down. While useful, this information gives a somewhat limited picture of the person's quality of life. If this information could be contextualised so that the system could say whether the person was sitting, standing or lying down as well as where the person is in the house, this could be used to give a much more complete report of the persons quality of life. Clearly if a person is found to be spending large portions of the day sitting down, it is significant to quality of life indication whether this is occurring in the sitting room or the bedroom. Often the existing systems also require multiple sensors and cannot detect activity in real time. The proposed study uses Infrared beacons and a kinematic sensor to give a complete report of the person's mobility from a single sensor in real time.

10. Brief plan of investigation[2] (i.e. what do you intend to do?) (Approx. 250 words)

There will be thirty participants recruited for this study. Each participant will be be asked to perform a list of activities of daily living. The participant will wear a wearable activity monitor at their ankle while performing these activities. The activity monitor is designed as a sock. It attaches to the person by velcro around their ankle in a similar way to many commercial ankle support socks. While the person perform's these activities in four different adjoining rooms in the Engineering building NUI Galway, they will be recorded on video. This video will be used to validate the activity and location detected by the activity monitor. The accuracy of the monitor will be calculated from this video.

11. List procedures or investigations involving risks to participants' well-being or safety (what, when, how often and risks associated with all procedures)

The participant will only be asked to perform activites that will be familiar to them in everyday life such as lying down on a bed and sitting on a chair. There is no risk of electrical shock from the equipment used. All equipment is CE marked. There are no wires protruding from the sock. The sock is made of 1.5mm neoprene material and does not hamper balance.

[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.

Survey/Questionnaire	
Case Study	
Observational	✓
Action research	✓
Record based	
Cohort	
Case control	
Other	
(please specify)	

Interviews	
• individual	
• group	
• person-to-person	
• telephone	
• electronic	
Forms of Recording	
• Video	✓
• Audio	
• Photography	
• Notes	✓
• Electronic recording	✓

13. Size of the study (including controls):

(i) How was the size of the study determined?

This is a proof of concept study to assess the accuracy of a prototype mobility monitoring system. Sample size was chosen to account for statistical considerations and time taken to run each participant through the research protocol. Thirty participants will be recruited for this study.

(ii) Was there formal statistical input into the overall study design? NO

(iii) What method of analysis will be used?

All analysis will involve recognised mathematical and statistical techniques.

14. Where[3] will the study take place and in what setting?

The study will take place in ENG1001 in the Engineering Building, NUI Galway and the adjoining control room, changing room and internal hallway between them.

15. Does the study involve:

(i) distribution of a questionnaire? YES: ☐ NO: ✓

If YES, please append a copy of the questionnaire to this application. Please indicate whether the appended questionnaire is: Non-validated: ☐ Validated: ☐

(ii) the use of a existing medicinal product or medical device? YES ☐ NO ✓

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 ✓

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 ✓ If YES, please complete **Annex 2** of this application.

16. Peer Review/Critique[4]

[3] Geographical location; laboratory, hospital, general practice, home visits etc.

[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.*

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Has the protocol been subject to peer review? YES ☑ NO ☐

If the review formed part of the process of obtaining funding, please give the name and address of the funding organisation:

N/A

If the review took place as part of an internal process, please give brief details:

The protocol was reviewed by Shane Lowe (Electrical and Electronic Engineering), Prof. Gearóid Ó Laighin (Professor of Electrical & Electronic Engineering) and Paul Breen (Postdoctoral researcher in the bioelectronics cluster in the NCBES)

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 ☐
Multi-centre study	YES ☐	NO ☑	Not applicable ☐

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?

(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

30 Healthy young adults from the general public are being studied. All participants are between the ages of 18 and 60.

19. How will be the participants in the study be:

(i) Selected?

Participants will be selected from the general public for this study. Thirty healthy young adults will be used.

(ii) Recruited? (Please append advertisement materials to application)

Participants will be recruited from friends and colleagues

20. What criteria will be used for inclusion and exclusion of participants?

(i) Inclusion criteria:

Young and Healthy Adults between the ages of 18-60
Capable of giving informed consent
Independently mobile

(ii) Exclusion criteria:

Anything outside of the above

21. How many participants will be recruited and of what age groups?

Thirty participants will be recruited.
All participants will be between the ages of 18 - 60

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:

N/A

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(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: ☑

If YES, please give details

26. Will participants receive any payment or other incentive to participate?

YES: ☐ NO: ☑

(i) If YES, give details of incentive per participant?

If YES, what is the source of the incentive?

SECTION 4 Consent

27. Is written consent for participation in the study to be obtained?
YES: ✓ 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

28. How long will the subject have to decide whether to take part in the study?
(If less than 24 hours, please justify)

The participants will have one week to decide whether or not to take part in the study. They will have the participant information sheets for one week before the decision is made.

29. Does the study include participants for whom English is not a first language?
YES: ☐ NO: ✓

If YES, give details of special arrangements made to assist these participants

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 16 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

(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?

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(iii) In what way, if any, can the proposed study be expected to benefit the individual who participates?

32. Are women of childbearing potential included in this study?
[please answer this question only where invasive or other interventions are planned which could be a risk to a pregnancy]
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: ☑

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	☑	YES	☐	NO
Self completion questionnaires	☐	YES	☑	NO
Interviews/interview administered questionnaires	☐	YES	☑	NO
Video/audio tape recording	☑	YES	☐	NO
Physical examination	☐	YES	☑	NO
Internal physical examination	☐	YES	☑	NO
Venepuncture*	☐	YES	☑	NO
Arterial puncture*	☐	YES	☑	NO
Biopsy material*	☐	YES	☑	NO
Other tissue/body sample*	☐	YES	☑	NO
Imaging investigation (not radiation)	☐	YES	☑	NO
Other investigations not part of normal care	☐	YES	☑	NO
Additional out patient attendance	☐	YES	☑	NO
Longer inpatient stays	☐	YES	☑	NO
Local anesthesia	☐	YES	☑	NO
General anesthesia	☐	YES	☑	NO

Other – please detail

Please indicate and justify where treatment is withheld as a result of taking part in the project.

35. Will any ionising or non-ionising radiation, or radioactive substances or X-Rays be administered to a participant?

YES: ☐ NO: ☑

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: ☑

* *Please see Guidance Notes*

If NO, please explain why not

SECTION 6 Risks and ethical problems

37. Are there any potential risks to participants?

YES: ☐ NO: ☑

If YES, please complete **Annex 3** for each procedure for which a potential risk occurs.

38. Is this study likely to cause any discomfort or distress, either physical or mental?

YES: ☑ NO: ☐

If YES, estimate the degree and likelihood of discomfort or distress entailed and the precautions to be taken to minimise them.

Participants may be concerned about the confidentiality of their test result data and video recordings of the test. To ensure confidentiality participants will be assigned participant numbers which will be used in place of their names on all documentation. A paper record linking the participant to their participant number will be kept in a locked drawer in the Electrical and Electronic Engineering department. All video recordings will be kept on a password protected memory stick and locked in a drawer in the Electrical and Electronic Engineering Department.

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?

As the study is to be video taped, participants may be uncomfortable about the management of this footage. This video footage will be secured in a locked drawer, in the Electrical and Electronic Engineering department. The video footage will be destroyed when the study is complete.

(i) Will treatments provided during the study be available if needed at the end of the study?

YES: ☐ NO: ☐ Not applicable: ☑

(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.

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? Not applicable: ☐

This study is covered by the NUIG indemnity policy contact Bernadette Costello for further details.

(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? Not applicable: ☐

This study is covered by the NUIG indemnity policy contact Bernadette Costello for further details.

(ii) Will an undergraduate student be involved directly in conducting the project?

YES: ☐ NO: ☑

41. In cases of equipment or medical devices, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: ☐ NO: ☐ Not applicable: ☑

If YES, please give details and enclose a copy of the relevant correspondence with this application

42. In cases of medicinal products, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: ☐ NO: ☐ Not applicable: ☑

If YES, please give details and enclose a copy of the relevant correspondence with this application

[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: ☑ NO: ☐

Observation of participants: YES: ☑ NO: ☐

If YES to either:

(i) How are confidentiality and anonymity to be ensured?

Records taken will use the participant's "participant number" instead of their names. Only the researchers will have access to test data. All electronic copies of test data will be kept encrypted on a password protected computer and all hard copies will be kept in a locked drawer in the Electrical and Electronic Engineering Department

(ii) What arrangements have been made to obtain consent for these procedures?

N/A

(iii) What will happen to the tapes at the end of the study?

N/A

44. Will the study data be held on computer?

YES: ☑ 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: ☑ NO: ☐

If NO, please give reasons

45. Will records (preferably paper records) linking study participant ID with identifying features be stored confidentially?

YES: ☑ NO: ☐

Please give details of arrangements for confidential storage

Paper records linking participants to their participant numbers will be kept in a locked drawer in the Electrical and Electronic Engineering Department.

For how long will records be retained prior to destruction?

Records linking the participants with the test data will be kept for the duration of the study. Anonymous data from the study will be kept for a period of five years

46. Will the participants' medical records be examined by investigators in the study?

YES: ☐ NO: ☑

If YES, will information relevant **only** to this study be extracted: YES: ☐ NO: ☐ Not applicable: ☑

(i) If extra information is extracted, please justify

(ii) What, if any, additional steps have been taken to safeguard the confidentiality of personal medical records?

47. Will research workers outside the employment of NUI Galway examine medical or other personal records?

YES: ☐ NO: ☑

If YES, it is the responsibility of the Principal Investigator 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.

OÉ Gaillimh
NUI Galway

RESEARCH ETHICS COMMITTEE APPLICATION FORM

For Applicant to complete:

Applicants' Name: Gearóid ÓLaighin

Title of Project: Autonomous Geriatric Assessment

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	☐	☐	
1	Participant consent form(s)	X	☐	☐	☐
1	Participant information sheet(s)	X	☐	☐	
1	Questionnaire(s)* ☒ Final version ☐ Draft Version	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
1	Annex 1**	☐	☐	☐	X
1	Annex 2***	☐	☐	☐	X
1	Annex 3**** (1 copy per procedure for which risk identified)	☐	☐	☐	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	☐	Case-study	☐	Foetal material	☐
Patient volunteer	☐	Longitudinal	☐	Hazardous materials	☐
'Incompetent' patients	☐	Cross-sectional	☐	Invasive procedures	☐
Children (under 16 yrs)	☐	Placebo	☐	Devices (in licence)	☐
Observational	☐	Therapeutic	☐	Medicinal products	☐
Interview	X	Controlled	☐	(in licence)	
Questionnaire	X	Double-blind	☐	Devices	☐
Record-based	☐	Single-blind	☐	(outside licence)	
Randomised	☐	Prospective	☐	Medicinal products	☐
Non-randomised	☐	Retrospective	☐	(outside licence)	

SECTION 1 Applicant(s) Details

1. Title of project:

Autonomous geriatric assessment using and activity monitoring device

2. Principal Applicant: *(All correspondence will be sent to this address unless indicated otherwise.)*

Family Name: Ó Laighin **Forename**: Gearóid **Title**: Professor

Contact address *(for correspondence regarding application)*:
Electrical & Electronic Engineering,
NUI Galway,
University Road,
Galway.
Tel: 091 492685 (Ext 2685) **Fax**: 091 494511 **Email**: gearoid.olaighin@nuigalway.ie

Mobile Number / Other Contact Number: 0876504801
Present appointment of PA: Professor of Electrical & Electronic Engineering
Qualifications of PA: B.E degree in Electrical Engineering from UCC,
M.Eng.Sc Degree from UCC,
Ph.D degree at National University of Ireland, Galway

3. Other Investigator(s):

Family Name: Lowe **Forename**: Shane **Title**: Mr.

Department: Electrical & Electronic Engineering

Institution: NUI Galway

Tel: 0876610315 **Fax**: 071 9621359 **Email**: s.lowe1@nuigalway.ie

Present appointment: IRCSET funded Ph.D student researcher with the Bioelectronics Research Cluster NUI Galway.

Qualifications: B.E degree in Electronic Engineering from NUI Galway

Family Name: **Forename**: **Title**:

Department:

Institution:

Tel: **Fax**: **Email**:

Present appointment:

Qualifications:

Family Name: **Forename**: **Title**:

Department:

Institution:

Tel: **Fax**: **Email**:

Present appointment:

Qualifications:

4. Other workers and departments/Institutions involved:

Name	Department/Institute	Appointment

5. Funding Sources:

(i) Has any funding been obtained/sought by the investigator in respect of this study?

Funding applied for: YES ☐ NO ☐ Not applicable ☒

Funding secured: YES ☐ NO ☐ Not applicable ☒

(ii) Name of sponsoring organisation from which funding has been obtained/sought?

N/A

(iii) Does the Investigator(s) have any direct involvement in the sponsoring organization?

e.g. financial, share-holding etc: YES ☐ NO ☐ Not applicable ☒

If YES, give details:

N/A

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: 01/08/2012

Duration (months): 6

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: Prof. Gearóid ÓLaighin **Department**: Electrical & Electronic Engineering

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?)

Primary Objectives

- To test if the outputs of the Smart Sock activity monitor will correlate with existing widely used functional assessment tools.
- To test if the outputs of the Smart Sock activity monitoring device can detect frailty as detected by existing frailty assessment measures.

Secondary Objectives

- To test if the outputs of the Smart Sock activity monitoring device can detect or predict adverse health events
- To test if the outputs of the Smart Sock activity monitoring device detects social problems
- To test if the outputs of the Smart Sock activity monitoring device differentiates between people with recent adverse health events
- To test if the outputs of the Smart Sock activity monitoring device detects Insomnia or other sleep issues
- To test if the outputs of the Smart Sock activity monitoring device can predict hospitalisation risk.
- To test the Smart Sock activity monitoring device's usability

9. Scientific/theoretical background[1] to study (Approx. 250 words)

Conventional geriatric assessments, outside of pathological diagnoses, are often done using questionnaires or through interview with the patient or with a proxy. However, the results from these methods can suffer from error introduced through biased answers or mis-recollection.

Conducting these types of assessments is also a large drain on resources. Personnel hours are required to administer, observe and score these tests. To some extent, this drain has been improved with the use of information and communication technologies by digitising the test so that results can be managed more easily and some tests can be administered remotely. However, the burden of performing these assessments is only marginally reduced. This leads to the assessments being carried out less frequently than may be desirable.

If there were a method of performing these tests in an accurate and cost effective way, these assessments could be performed often and become a more integral part of geriatric care. This may allow for symptoms of illness to be detected and managed or treated before they present themselves in ways that have a more serious impact on quality of life such as a fall occurring.
One possibility for improving upon the conventional questionnaires could be to perform these assessments autonomously using activity-monitoring technology.

[1] A succinct background to be provided and to include reference to published work

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10. Brief plan of investigation[2] (i.e. what do you intend to do?) (Approx. 250 words)

Up to forty older adults will be recruited to take part in this study. Participants will be recruited through their GP. The study will involve participants wearing a small activity-monitoring device in the form of a sock throughout their waking day for a one-month period. Throughout their participation, there will be three scheduled visits by a researcher. On the first day of participation, several geriatric assessment tools will be administered. These assessments will be repeated in the middle of the month and on the last day of the study. Throughout the duration of the study, the device will monitor the participant's performance of activities of daily living and transmit data over the mobile network to a server in NUI Galway. These data, in combination with data from conventional assessments, will be used to determine whether the device is capable of performing accurate geriatric assessments.

11. List procedures or investigations involving risks to participants' well-being or safety
(what, when, how often and risks associated with all procedures)

Participants will not be asked to perform any specific activities. They will only be asked to carry on their life as normal while wearing the activity-monitoring device. There is no risk of electrical shock from the equipment used. There are no wires protruding from the sock. The sock is made of 1.5mm neoprene material and does not hamper balance.

12. Study design (tick as appropriate)

Survey/Questionnaire	X	Interviews	
Case Study		• individual	
Observational	X	• group	
Action research		• person-to-person	X
Record based		• telephone	
Cohort		• electronic	
Case control			
Other		Forms of Recording	
(please specify)		• Video	
		• Audio	
		• Photography	
		• Notes	
		• Electronic recording	X

13. Size of the study (including controls):

(i) How was the size of the study determined?

Sample size was chosen to account for statistical considerations and resources required to run this study. Forty participants will be recruited to take part.

(ii) Was there formal statistical input into the overall study design? YES NO

(iii) What method of analysis will be used?

All analysis will involve recognised mathematical and statistical techniques.

14. Where[3] will the study take place and in what setting?

The study will take place in the paticipant's own homes in an assisted living community.

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: [ ] Validated: [X]

(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.

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:

N/A

If the review took place as part of an internal process, please give brief details:

The protocol was reviewed by Shane Lowe (Electrical and Electronic Engineering) and Prof. Gearóid Ó Laighin (Professor of Electrical & Electronic Engineering).

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 [X] NO [ ] Not applicable [ ]

[ ] [X] [ ]

[3] Geographical location; laboratory, hospital, general practice, home visits etc.

[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.*

Multi-centre study YES NO Not applicable

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?

(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

Forty adults, older than 65, will be recruited for this study. People with forms of dementia will be excluded from participation.

19. How will be the participants in the study be:

(i) Selected?

Participants will be selected from the residents of assisted living communities.

(ii) Recruited? (Please append advertisement materials to application)

Participants will be approached through their GP.

20. What criteria will be used for inclusion and exclusion of participants?

(i) Inclusion criteria:

Older Adults over the age of 65,
Capable of giving informed consent,
Independently mobile,
Free from any form of dementia

(ii) Exclusion criteria:

Anything outside of the above.

21. How many participants will be recruited and of what age groups?

Forty participants will be recruited. All participants will be over the age of 65.

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:

N/A

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(ii) Exclusion criteria:

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

26. Will participants receive any payment or other incentive to participate?

YES: [ ] NO: [X]

(i) If YES, give details of incentive per participant?

If YES, what is the source of the incentive?

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

28. How long will the subject have to decide whether to take part in the study?
(If less than 24 hours, please justify)

The participants will have one week to decide whether or not to take part in the study. They will have the participant information sheets for one week before the decision is made.

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

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 16 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

(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?

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(iii) In what way, if any, can the proposed study be expected to benefit the individual who participates?

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	[X]	YES	[ ]	NO
Video/audio tape recording	[ ]	YES	[X]	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

Please indicate and justify where treatment is withheld as a result of taking part in the project.

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: [X] NO: [ ] Not applicable: [ ]

* *Please see Guidance Notes*

If NO, please explain why not

SECTION 6 Risks and ethical problems

37. Are there any potential risks to participants?

YES: ☐ NO: ☒

If YES, please complete **Annex 3** for each procedure for which a potential risk occurs.

38. Is this study likely to cause any discomfort or distress, either physical or mental?

YES: ☒ NO: ☐

If YES, estimate the degree and likelihood of discomfort or distress entailed and the precautions to be taken to minimise them.

Participants may be concerned about the confidentiality of their test result data. To ensure confidentiality participants will be assigned participant numbers which will be used in place of their names on all documentation. A paper record linking the participant to their participant number will be kept in a locked drawer in the Electrical and Electronic Engineering department. All data recording will be kept on a password protected memory stick and locked in a drawer in the Electrical and Electronic Engineering Department. Data will be anonomous and encrypted when transmitted over the phone network.

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?

(i) Will treatments provided during the study be available if needed at the end of the study?

YES: ☐ NO: ☐ Not applicable: ☒

(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?

This study is covered by the NUIG indemnity policy contact Bernadette Costello for further details.

(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?

This study is covered by the NUIG indemnity policy contact Bernadette Costello for further details.

(iii) Will an undergraduate student be involved directly in conducting the project?

YES: ☐ NO: ☒

41. In cases of equipment or medical devices, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: ☐ NO: ☐ Not applicable: ☒

If YES, please give details and enclose a copy of the relevant correspondence with this application

42. In cases of medicinal products, have appropriate arrangements been made with the manufacturer to provide indemnity?

YES: ☐ NO: ☐ Not applicable: ☒

If YES, please give details and enclose a copy of the relevant correspondence with this application

[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: [ ] NO: [X]

Observation of participants: YES: [X] NO: [ ]

If YES to either:

(i) How are confidentiality and anonymity to be ensured?

Records taken will use the participant's "participant number" instead of their names. Only the researchers will have access to test data. All electronic copies of test data will be kept encrypted on a password protected computer and all hard copies will be kept in a locked drawer in the Electrical and Electronic Engineering Department. Any data transmitted over the network will be anonymous and encrypted.

(ii) What arrangements have been made to obtain consent for these procedures?

N/A

(iii) What will happen to the tapes at the end of the study?

N/A

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

Paper records linking participants to their participant numbers will be kept in a locked drawer in the Electrical and Electronic Engineering Department.

For how long will records be retained prior to destruction?

Records linking the participants with the test data will be kept for the duration of the study. Anonymous data from the study will be kept for a period of five years

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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

(ii) What, if any, additional steps have been taken to safeguard the confidentiality of personal medical records?

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.

Appendix B

Conference Paper: The Age of the Virtual Trainer

Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 34 (2012) 242 – 247

Procedia Engineering

www.elsevier.com/locate/procedia

9th Conference of the International Sports Engineering Association (ISEA)

The age of the virtual trainer

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Abstract

Much of the developed world is currently affected by an overweight epidemic. A large population of people are undertaking a personal fitness regime in order to improve fitness, lose or maintain weight or for general health reasons. Conventionally, the best method to achieve the greatest results was often to obtain the services of a personal trainer. These fitness professionals are educated in physiology, exercise science and motivational methods, and use a combination of these expertise to design and assist in the performance of a tailored exercise program. With the advent of Smart Phones and affordable sensing technologies, the possibility to automate several of the functions of a personal trainer has emerged. These "Virtual Trainers" allow a person to manage their own personal fitness program while integrating close monitoring, sports science knowledge and motivational aspects - several of the same services a personal trainer will provide. This paper discusses several of the most widely used "Virtual Trainer" systems available today.

Keywords: Virtual trainer; exercise; fitness; activity monitor

1. Introduction

There are several reasons why the "Virtual Trainer" has recently become an active area, both in the research and consumer device domains. Obesity has become one of the most serious issues facing the health of the population in the western world. Several of the leading causes of death in the United States and the E.U can be contributed, at least in part, to obesity. Heart disease, liver disease, bowel cancer, breast cancer, kidney cancer and diabetes are all heavily linked to obesity [1]. Looking past the direct pathological effects of obesity, there are significant effects to a person's quality of life. The ability to perform activities of daily life can be affected by obesity. Some of the most effective methods of treating and avoiding obesity are a controlled diet and increased physical activity [2]. Personal trainers are knowledgeable with regards exercise performance and optimal, tailored exercise practices. However, a

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large proportion of overweight people who have a desire to lose weight will not consult a personal trainer. This may be due to financial cost, embarrassment or lack of knowledge. The virtual trainer may provide an effective method of combating these blocks.

2. The Virtual Trainer

The Virtual Trainer is a relatively new phenomenon in the fitness world made possible by the increase in mobile computers (Smart Phones) and more affordable sensing technologies. By integrating some of the monitoring, motivation and educational knowledge that a personal trainer provides into a personal device, a user can benefit significantly in their fitness routines.

2.1. Existing Technologies

There are several "Virtual Trainer" systems currently available in the consumer domain. A subset of some of the most widely used options is discussed in this paper. Though this group is far from exhaustive, for the purposes of this paper, the systems chosen show the wide range of abilities that a "Virtual Trainer" can provide. Figure 1 shows the systems to be discussed.

Fig. 1. Virtual Trainer Systems: (A) miCoach; (B) Nike+; (C) Endomondo; (D) Polar Heart Rate Monitor & Watch; (E) Runkeeper; (F) Kinect

The systems shown in Figure 1 are divided into three categories for the purposes of this paper, 1) Smart Phone Applications, 2) Sensor devices 3) Image Processing devices. Each category provides different advantages, which will be discussed in detail here. Table 1 shows an outline of the abilities provided by the six trainers.

Table 1. Virtual trainer system attributes

	Hardware	Technologies	Parameters Monitored	Exercise Feedback	Post Exercise Feedback	Training Programs	Users
Nike +	Smart Phone Foot pod Wristband	Smart Phone Application GPS Footswitch	Distance traveled Speed data Altitude data Energy Expenditure	Audio feedback Graphical feedback	Online dashboard	Running Different Distances Current Ability	> 4,000,000
miCoach	Smart Phone Foot pod Wristband Chest Strap Heart Rate Monitor	Smart Phone Application GPS Accelerometer Heart Rate Monitor	Distance traveled Speed data Altitude data Energy Expenditure Heart Rate data	Audio feedback Graphical feedback	Online dashboard	Various Sports Resistive + Aerobic Training Heart Rate Zones Current Ability	Unavailable
Polar	Wristwatch Chest Strap Heart Rate Monitor Foot pod GPS module	Wristwatch Heart Rate Monitor Accelerometer	Distance traveled Speed data Altitude data Energy Expenditure Heart Rate data	Wristwatch text feedback	Online dashboard, .csv, watch interface	Running Cycling Heart Rate Zones Resistive + Aerobic Training	Unavailable
Runkeeper	Smart Phone	Smart Phone Application GPS	Distance traveled Speed data Altitude data Energy Expenditure	Audio feedback Graphical feedback	Online dashboard	Running Different Distances Current Ability	6,425,000[3]
Endomondo	Smart Phone	Smart Phone Application GPS	Distance traveled Speed data Altitude data Energy Expenditure	Audio feedback Graphical feedback	Online dashboard		> 6,700,000
Microsoft Kinect	Kinect Xbox 360	IR Emitter IR Camera	Body orientation Body position	Audio feedback Visual form feedback	Television interface	Resistive + Aerobic Training	18,000,000 kinect users

It is evident from Table 1 that the technologies utilized in these “Virtual Trainers” do not vary widely. However the data generated are handled in different ways across the various trainers.

2.1.1. Category 1 – Smart Phone Applications

"Virtual Trainers" based on stand-alone smart phone applications usually use either GPS or the onboard kinematic sensors as the technologies of choice for monitoring exercise. The applications included in Table 1, Runkeeper and Endomondo, both utilize GPS for monitoring activities. Table 1 shows the multitude of parameters that can be determined using GPS. A drawback of using GPS is that it is confined to activities that involve moving from one location to another such as running, cycling, skiing etc. A significant advantage of this category of "Virtual Trainer" is that it allows use by anyone owning a Smart Phone. With smart phones becoming increasingly ubiquitous in the developed world, this allows the trainers to reach significant user bases. A second advantage of using a smart phone application is the wide range of related applications available for integration. For example any application like the ones listed in Table 1 would benefit from integration with a diet-tracking platform. In fact, Runkeeper recently released the Application Programming Interface for integration with their system as well as the Runkeeper developer program.

2.1.2. Category 2 – Sensor Devices

The Sensor Device category of "Virtual Trainer" comprises of any system that uses a central controller and an external sensor. The three systems from this category listed in Table 1 are Nike+, miCoach and Polar devices. In the case of Nike+ and miCoach, the central controller is a smart phone, wristband or stand-alone embedded controller. In the case of Polar systems, the central controller is usually a wristwatch. The external sensors include footswitches, accelerometers, heart rate sensors and external GPS sensors. The advantage of sensor device based trainers is increased functionality. These systems have the ability to monitor an increased number of parameters during exercise. In addition to this increased monitoring functionality, the sensor-based devices also avoid the drawback of only monitoring activities involving change in location. Using sensors such as accelerometers and footswitches, semi static activities such as running on a treadmill or using a stationary bike can still be monitored by detecting certain events such as steps. These detections can be performed in a number of different ways using neural networks, decision trees, support vector machines, Markov models etc. With the integration of these sophisticated detection algorithms, the number of events that can be detected can be significantly increased.

2.1.3. Category 3 – Image Processing

Image processing is not a recent concept. However, conventional image processing tends to be relatively complex and computationally intensive. This has lead to minimal integration to virtual training. The recent introduction of the Microsoft Kinect helps to solve both of these problems. Using an Infrared emitter and camera, the process is simplified significantly. The advantage of image processing is that it enables a "Virtual Trainer" to monitor the exact movement and position of the entire body during exercise. This allows the trainer to ensure optimal performance of the exercise, which leads to the best possible results. Figure 2 shows an example of the "Your Shape" Kinect virtual trainer monitoring the performance of a punch-squat exercise. The trainer on the left shows the proper form, the figure on the right shows the users current position and flags any deviation from proper form. The Kinect is limited to semi static activities such as squats or press-ups as the activity must take place within a relatively small area in the Kinect's view. Another advantage of "Virtual Trainers" based on the Kinect platform is that it is a very accessible form of exercise. It overcomes some of the mental blocks that people who are not used to exercise have to deal with. Exercise form can be explained and poor performance can be corrected with no embarrassment on the exercisers behalf.

Fig. 2. Kinect monitoring exercise performance

2.2. During Exercise Feedback

All of the "virtual training" systems discussed in this paper provide some type of feedback to the user during exercise. In the case of the category 1 and 2 systems, this feedback can include the time passed, distance traveled, energy expenditure estimate, average and current speed and average and current heart rate. The during exercise feedback provided by the Kinect differs significantly. In addition to the quantitative data relayed by the other systems, trainers on the Kinect platform can also provide qualitative feedback. As discussed in Section 2.1.3, the Kinect gives trainers the ability to critique form and performance of exercise in real-time and to grade that performance. Therefore, the optimal performance of the exercise is encouraged through the during exercise feedback.

2.2.1. During Exercise User Interface

User interface is of the upmost importance in the "Virtual Trainer's" feedback during exercise. While exercising, it is difficult to interact with technological platforms without disrupting exercise routine. Therefore, systems should be designed with the least obstructive user interface possible. In the case of Runkeeper, Endomondo, Nike+ and miCoach the majority of user interaction during exercise is done over an audio interface. Audio notifications are delivered at set intervals or at certain goals. Graphical feedback through the smart phone display is designed to be as clear as possible and to deliver the information at a glance. The miCoach system has gone further with the simplification of their interface. The miCoach wristband contains a LED display as well as a multicoloured LED. The display can show heart rate, calories burned and time by pressing a button, however, the multicolored LED is designed to provide and even more simple interface. The LED flashes at a rate to equal the current heart rate. The LED is colored to show the current heart rate zone the user is in. This allows the person to assess exercise intensity through the LED's colour with a very quick glance at the wrist strap.

2.3. Post Exercise Feedback

Post exercise feedback from the "Virtual Trainer" provides two main functions. The first function is to allow a user to interact with and learn from their previous exercise performance data. By studying performance over time, certain trends begin to emerge. For example, a person's increases in performance ability may plateau indicating a change in training program would be beneficial. The second function of

post exercise feedback is motivation to adhere to exercise. Polar, Runkeeper, Endomondo, Nike+ and miCoach all provide and online dashboard to display post exercise feedback. These dashboards contain all of the data generated by the systems. The data are displayed through graphs and figures in such a way as to simplify analysis. This allows for the first function of interacting with and planning future exercise. These online dashboards are also used for the second function of post exercise feedback discussed here. Motivation is delivered in several ways. Reinforcement of exercise is done through reward schemes. Users are given "badges" for completing certain tasks or reaching goals. These are presented through the dashboards. Social re-enforcement is also used. Runkeeper, Endomondo, Nike+ and miCoach all provide the functionality to connect to friends. These exercise social networks are used to motivate increased exercise through challenges and displaying friends exercise performance.

2.4. Training Programs

In addition to the monitoring and motivational capabilities provided by these trainers, several of the "Virtual Trainers" discussed here provide a platform to aid the planning of an exercise regime. Nike+ provides training plans to reach different distances for different abilities. Plans are made up of different length runs to incorporate training and rest days. Runkeeper provides similar plans. miCoach provides by far the most detailed training programs of any of the systems discussed in this paper. Based on the users end goal, miCoach will recommend a different program. This is not limited to running; different sports will target different areas for training based on current ability and specific goal. Programmes combine resistance and aerobic training to meet goals. All of these systems will also monitor and coach the user through their chosen training programme.

3. Conclusion

There is a wide range of technologies yet to be integrated into the world of sports and exercise and several technologies to be introduced in the near future that will make a significant difference to the virtual trainer. Wearable technologies may be one of the most important developments to be integrated into the "Virtual Trainer". The virtual trainer is a valuable addition to the world of fitness and exercise. When designed in consultation with personal trainers, sports scientists and behavioral scientists a virtual trainer can be an extremely effective tool for achieving optimal results from an exercise regime.

Acknowledgements

This project is supported by the Irish Research Council for Science, Engineering and Technology in partnership with Georgia Tech Ireland.

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[3] "Runkeeper Blog." [Online]. Available: http://blog.runkeeper.com/health-graph/health-data-infographic.
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Appendix C

Patent Application

Device for the Generation of Predictions for Functional Health Assessment Outcome Using Activity Monitoring Technology

December 13, 2012

1 Summary

This invention relates to a device capable of predicting a user's functional health as measured by questionnaire or performance based assessments of functional health. The device autonomously and continuously monitors the user's performance of a range of activities of daily living and uses data relating to these parameters to generate a predictive score for functional health assessment outcome. Activities monitored by the device include time spent sitting, standing, lying and walking, number of toileting trips, number and functional of trips outside the home, gait characteristics, step count and energy expenditure. The invention can be used in any case where an assessment of functional health status is desired.

2 Background to the Invention

The rapid demographic change in the age of the population in developed countries has led to the need to develop new approaches in how we can enhance the quality of life for an aging population. The health of older adults varies by degree and nature compared to that of the young, and can be further complicated by limitations in functional activities that may not be symptomatically apparent. Assessments of the health of older adults must go beyond pathological symptoms and focus on the person's ability to function in society.

Appendix D

Functional Health Questionnaire Pack

THE BARTHEL INDEX

Activity | **Score**

FEEDING
0 = unable
5 = needs help cutting, spreading butter, etc., or requires modified diet
10 = independent ____

BATHING
0 = dependent
5 = independent (or in shower) ____

GROOMING
0 = needs to help with personal care
5 = independent face/hair/teeth/shaving (implements provided) ____

DRESSING
0 = dependent
5 = needs help but can do about half unaided
10 = independent (including buttons, zips, laces, etc.) ____

BOWELS
0 = incontinent (or needs to be given enemas)
5 = occasional accident
10 = continent ____

BLADDER
0 = incontinent, or catheterized and unable to manage alone
5 = occasional accident
10 = continent ____

TOILET USE
0 = dependent
5 = needs some help, but can do something alone
10 = independent (on and off, dressing, wiping) ____

TRANSFERS (BED TO CHAIR AND BACK)
0 = unable, no sitting balance
5 = major help (one or two people, physical), can sit
10 = minor help (verbal or physical)
15 = independent ____

MOBILITY (ON LEVEL SURFACES)
0 = immobile or < 50 yards
5 = wheelchair independent, including corners, > 50 yards
10 = walks with help of one person (verbal or physical) > 50 yards
15= independent (but may use any aid; for example, stick) > 50 yards ____

STAIRS
0 = unable
5 = needs help (verbal, physical, carrying aid)
10 = independent ____

TOTAL (0–100):

_____

THE LAWTON INSTRUMENTAL ACTIVITIES OF DAILY LIVING SCALE

Ability to Use Telephone

1. Operates telephone on own initiative; looks up and dials numbers	1
2. Dials a few well-known numbers	1
3. Answers telephone, but does not dial	1
4. Does not use telephone at al	0

Shopping

1. Takes care of all shopping needs independently	1
2. Shops independently for small purchases	0
3. Needs to be accompanied on any shopping trip	0
4. Completely unable to shop	0

Food Preparation

1. Plans, prepares, and serves adequate meals independently	1
2. Prepares adequate meals if supplied with ingredients	0
3. Heats and serves prepared meals or prepares meals but does not maintain adequate diet	0
4. Needs to have meals prepared and served	0

Housekeeping

1. Maintains house alone with occasion assistance (heavy work)	1
2. Performs light daily tasks such as dishwashing, bed making	1
3. Performs light daily tasks, but cannot maintain acceptable level of cleanliness	1
4. Needs help with all home maintenance tasks	1
5. Does not participate in any housekeeping tasks	0

Laundry

1. Does personal laundry completely	1
2. Launders small items, rinses socks, stockings, etc	1
3. All laundry must be done by others	0

Mode of Transportation

1. Travels independently on public transportation or drives own car	1
2. Arranges own travel via taxi, but does not otherwise use public transportation	1
3. Travels on public transportation when assisted or accompanied by another	1
4. Travel limited to taxi or automobile with assistance of another	0
5. Does not travel at all	0

Responsibility for Own Medications

1. Is responsible for taking medication in correct	

dosages at correct time 1

2. Takes responsibility if medication is prepared in advance in separate dosages 0
3. Is not capable of dispensing own medication 0

Ability to Handle Finances

1. Manages financial matters independently (budgets, writes checks, pays rent and bills, goes to bank); collects and keeps track of income. 1
2. Manages day-to-day purchases, but needs help with banking, major purchases, etc 1
3. Incapable of handling money 0

ELDERLY MOBILITY SCALE

Lying to sitting
2 Independent
1 Needs help of 1 person
0 Needs help of 2+ people

Sitting to lying
2 Independent
1 Needs help of 1 person
0 Needs help of 2+ people

Sit to stand
3 Independent in under 3 seconds
2 Independent in over 3 seconds
1 Needs help of 1 person (verbal or physical) **0** Needs help of 2 + people

Standing
3 Stands without support & reaches within arms length
2 Stands without support but needs help to reach
1 Stands, but requires support
0 Stands, only with physical support (1 person)
Support = uses upper limbs to steady self

Gait
3 Independent (incl. use of sticks)
2 Independent with frame
1 Mobile with walking aid but erratic/ unsafe turning
0 Requires physical assistance or constant supervision

Timed walk
3 Under 15 seconds
2 16-30 seconds
1 over 30 seconds

Functional Reach
4 Over 20cm
2 10-20cm
0 Under 10cm or unable

Total: _____

Interpretation of scores*

14 – 20
Manoeuvres alone and safely. Independent in basic ADLs. These patients are generally safe to go home but may need home help

10 – 13
Borderline in terms of safe mobility and independence in ADLs. These patients will require some help with mobility manoeuvres.

< 10
Dependent in mobility manoeuvres & requiring help with basic ADLs (transfers, toileting, dressing etc.). May require Home Care Package/Long Term Care depending on patients' wishes and circumstances.

HEALTH ASSESSMENT QUESTIONNAIRE (HAQ-DI)©

	Without any difficulty	With some difficulty	With much difficulty	Unable to do
DRESSING & GROOMING				
Are you able to:				
Dress yourself, including shoelaces and buttons?				
Shampoo your hair?				
ARISING				
Are you able to:				
Stand up from a straight chair?				
Get in and out of bed?				
EATING				
Are you able to:				
Cut your own meat?				
Lift a full cup or glass to your mouth?				
Open a new milk carton?				
WALKING				
Are you able to:				
Walk outdoors on flat ground?				
Climb up five steps?				

Please check any AIDS OR DEVICES that you usually use for any of the above activities:

- ☐ Devices used for Dressing (button hook, zipper pull, etc.)
- ☐ Built up or special utensils
- ☐ Special or built up chair
- ☐ Cane
- ☐ Walker
- ☐ Crutches
- ☐ Wheelchair

Please check any categories for which you usually need HELP FROM ANOTHER PERSON:

- ☐ Dressing and grooming
- ☐ Arising

☐ Eating ☐ Walking

	Without any difficulty	With some difficulty	With much difficulty	Unable to do
HYGIENE				
Are you able to:				
Wash and dry your body?				
Take a tub bath?				
Get on and off the toilet?				
REACH				
Are you able to:				
Reach and get down a 5 pound object (such as a bag of sugar) from above your head?				
Bend down to pick up clothing from the floor?				
GRIP				
Are you able to:				
Open car doors?				
Open previously opened jars?				
Turn faucets on and off?				
ACTIVITIES				
Are you able to:				
Run errands and shop?				
Get in and out of a car?				
Do chores such as vacuuming or yard work?				

Please check any AIDS OR DEVICES that you usually use for any of the above activities:

☐ Raised toilet seat ☐ Bathtub bar

☐ Long-handled appliances for reach ☐ Bathtub seat

☐ Long-handled appliances in bathroom ☐ Jar opener (for jars previously opened)

Please check any categories for which you usually need HELP FROM ANOTHER PERSON:

☐ Hygiene ☐ Reach

☐ Grip ☐ Activities

Your ACTIVITIES: To what extent are you able to carry out your everyday physical activities such as walking, climbing stairs, carrying groceries, or moving a chair?

Completely	Mostly	Moderately	A little	Not at all

Your PAIN: How much pain have you had IN THE PAST WEEK?
On a scale of 0 to 100 (where zero represents "no pain" and 100 represents "severe pain"), please record the number below.

_____

Your HEALTH: Please rate how well you are doing on a scale of 0 to 100 (0 represents "very well" and 100 represents "very poor" health), please record the number below.

_____

-

Edmonton Frailty Scale

Frailty domain	Item	0 points	1 point	2 points
Cognition	Please imagine that this pre-drawn circle is a clock. I would like you to place the numbers in the correct positions then place the hands to indicate a time of 'ten after eleven'	No errors	Minor spacing errors	Other errors
General health status	In the past year, how many times have you been admitted to a hospital?	0	1 or 2	> 2
	In general, how would you describe your health?	Excellent	Fair	Good
Functional Independence	With how many of the following activities do you require help? (meal preparation, shopping,transportation, telephone, housekeeping, laundry,managing money, taking medications)	0 or 1	2 to 4	5 to 8
Social Support	When you need help, can you count on someone who is willing and able to meet your needs?	Always	Sometimes	Never
Medication Use	Do you use five or more different prescription medications on a regular basis?	No	Yes	
	At times, do you forget to take your prescription medications?	No	Yes	
Nutrition	Have you recently lost weight such that your clothing has become looser?	No	Yes	
Mood	Do you often feel sad or depressed?	No	Yes	
Continence	Do you have a problem with losing control of urine when you don't want to?	No	Yes	
Functional Performance	I would like you to sit in this chair with your back and arms resting. Then, when I say 'GO', please stand up and walk at a safe and comfortable pace to the mark on the floor (approximately 3 m away), return to the chair and sit down'	0 - 10s	11 - 20s	>20 or unwilling
Totals				

Hospital Risk Admission Profile

A. Age

Age	Risk Score	
<75	0	
75-84	1	
>84	2	Score: _____

B. Cognitive Function

MMSE Score	Risk Score	
15 - 25	0	
0 – 14	1	Score: _____

C. IADL Function

IADLs	Risk Score	
6 – 7	0	
0 – 5	2	Score: _____

Risk Categories

Total Score	Risk of decline in function	
4 or 5	High Risk	
2 or 3	Intermediate Risk	
0 or 1	Low Risk	Total Score: _____

Appendix E

Wearable Device Usability Questionnaire

Usability Questionnaire

In your opinion from your experience using this device, please rate each of the following categories on a scale of 1 – 10.

Ugly	0	1	2	3	4	5	6	7	8	9	10	Beautiful
Damageable	0	1	2	3	4	5	6	7	8	9	10	Robust
Hard	0	1	2	3	4	5	6	7	8	9	10	Soft
Comfortable	0	1	2	3	4	5	6	7	8	9	10	Uncomfortable
Easy	0	1	2	3	4	5	6	7	8	9	10	Difficult
Flexible	0	1	2	3	4	5	6	7	8	9	10	Stiff
Hygeni	0	1	2	3	4	5	6	7	8	9	10	Unhygenic
Lightweight	0	1	2	3	4	5	6	7	8	9	10	Heavy
Low-Quality	0	1	2	3	4	5	6	7	8	9	10	High Quality
Aesthetic	0	1	2	3	4	5	6	7	8	9	10	Un-Aesthetic
Solid	0	1	2	3	4	5	6	7	8	9	10	Weak
Simple to use	0	1	2	3	4	5	6	7	8	9	10	Complicated to Use
Conspicuous	0	1	2	3	4	5	6	7	8	9	10	In-conspicuous