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Publication Date	2018-06-11
Publication Information	McDermott, Barry, O'Halloran, Martin, Santorelli, Adam, McGinley, Brian, & Porter, Emily. (2018). Classification applied to brain haemorrhage detection: Initial phantom studies using electrical impedance measurements. Paper presented at the 19th International Conference on Biomedical Applications of Electrical Impedance Tomography, Edinburgh, Scotland, 11-13 June.
Publisher	EIT2018
Link to publisher's version	https://zenodo.org/record/1210247#.W3Rmf5NKigA
Item record	http://hdl.handle.net/10379/7553
DOI	http://dx.doi.org/10.5281/zenodo.1210247

Classification Applied to Brain Haemorrhage Detection: Initial Phantom Studies using Electrical Impedance Measurements

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Abstract: Machine learning and classification algorithms are applied to data collected from an EIT system. The system is used with an anatomically accurate head phantom setup in a variety of situations modelling normal and haemorrhagic brain. This initial study demonstrates the promise of classification, but also indicates challenges.

1 Introduction

EIT has traditionally shown most success when applied to situations featuring changes in time such as lung function monitoring [1]. Static or quasi-static lesions such as established brain haemorrhage have conversely proved challenging to detect using EIT [2]. Machine learning approaches have shown potential in tackling such cases with related diagnostic modalities such as microwave imaging [3] but have not to date been studied in depth in the EIT sphere.

In this study an anatomically accurate two layer head phantom was developed along with a range of phantom bleeds, varying in size and shape. A 16 electrode ring was placed around the head and connected to a Swisstom Pioneer EIT system. EIT data measurement frames were recorded for a wide variety of test scenarios differing in ring orientation, bleed size and bleed location. These frames were labelled as 'normal' or 'bleed'. This data was then divided and used to train and test classifiers to differentiate between the two cases. Linear support vector machines (SVMs) in particular showed good performance, thus sample results from this classifier are presented here.

2 Methods

A two layer head phantom was developed with an outer layer modelling aggregate scalp, skull and cerebrospinal fluid, constructed from a graphite, carbon black and polyurethane composite. This composite emulated the conductivity of this layer. Another composite based on these materials was used to produce phantom bleeds, modelled as spheres and rectangular cuboids of volume 6 ml to 36 ml. The conductivity of the brain compartment of the head phantom was modelled using saline. A ring of 16 EEG electrodes was placed around the head and connected to the Swisstom Pioneer. In total 216 different abnormal test scenarios were captured as EIT measurement sets differing in bleed size (4 sizes), location (9 locations) and ring position (6 ring orientations). A sample setup is shown in Fig. 1. An equal number of corresponding normal (healthy) scenarios were captured. These frames were divided in a variety of ways and used to train and test a range of classifiers. Linear SVMs appeared to perform best with some sample results shown from this classifier type shown in Table 1. A True Positive (TP) is where a bleed is detected and is truly present. A True Negative (TN) is where normal is detected and is truly the case.

Figure 1: This example of a typical test setup shows a rectangular cuboid bleed suspended into the saline brain layer of the head phantom.

	TP %	TN %
Train on all Rings (1-6)	84 %	95 %
Half Ring 3 Withheld	72 %	100 %
Half Ring 1 Withheld	75 %	100 %
Ring 1 Withheld	75 %	86 %
Ring 2 Withheld	0 %	100 %

Table 1: True Positive & True Negative % for linear SVM Classifier. Sample results are those from testing on withheld data (and training on all the rest); except for the first row which is the performance when trained with cross validation on all of the data (none withheld).

3 Conclusions

The results of this initial phantom study show that classification may help in applying EIT techniques to static or quasi-static situations such as detection of an established bleed. The classifier works well when the ring layout(s) used in test data match those in training data. However, introducing test data from an unseen ring can result in significantly poorer performance. Improved data processing as well as training on a significantly higher number of test cases (i.e. differing heads) should improve performance and help make the technology valuable clinically.

4 Acknowledgements

The research leading to these results has received funding from the European Research Council under the European Union's Horizon 2020 Programme/ ERC Grant Agreement BioElecPro n.637780, and from the Hardiman Research Scholarship, NUIG.

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