

**DETECTION OF FREEZING OF GAIT
AND GAIT INITIATION FAILURE IN
PEOPLE WITH PARKINSON'S DISEASE
USING ELECTROENCEPHALOGRAPH
SIGNALS**

By

Quynh Tran LY

Submitted to Faculty of Engineering and Information Technology

in partial fulfillment of the requirement for the degree of

Doctor of Philosophy

at the University of Technology Sydney



Sydney, December 2017

CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I, Quynh Tran Ly, certify that the work in the thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the content of this thesis is my own work. Any help that I have received in my research work and the preparation of the thesis itself has been duly acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Candidate

Production Note:
Signature removed prior to publication.

Quynh Tran Ly

Acknowledgement

First and foremost, I would like to thank Buddhism for the spiritual guidance, protection and so many blessings, which made me who I am today.

I would like to express my deepest gratitude to my Principal Supervisor, Professor Hung Tan Nguyen for providing intellectual guidance, constant support and sympathizing during my PhD journey. His invaluable knowledge in Electroencephalography and computational intelligence has enabled me to deeply understand the concept, keep me on the correct path and has contributed enormously to my research. I am very grateful to have had the chance to study and learn under his superb guidance and mentorship.

I would like to express my heartfelt thanks and memorize my research member and teacher Dr Ardi Handojoseno for providing valuable knowledge, support and friendship throughout my PhD journey. His insightful contribution and great assistance enabled me to go through and complete this research. I am very fortunate to have worked with and learned from him in his last three years. His intellect, kindness and compassion will always remain deeply in my heart.

I would like to express my extreme thanks my Co-supervisors, Dr Rifai Chai, Dr Nghia Nguyen for providing knowledge in computational intelligence, support in improving my research and encouragement during my PhD journey. I would like to truly extend my thanks to my key research colleague Dr Moran Gilat for helping in data collection, providing valuable science knowledge and great assistance in writing as well as editing all my published papers. I would like to thanks all my colleagues in Centre for Health Technology, my family and friends who supported and shared with me during my PhD journey.

Finally, and most importantly, my constant love and appreciation deeply goes out to my parents, my husband Tri Nguyen and my daughters Tran Nguyen, Hanh Nguyen. They are always an endless source of encouragement, strength and love in my life.

“This thesis is especially dedicated to my dearest parents Dich Cam Ly, Thi Tinh Tran, my husband Van Minh Tri Nguyen, my daughters Thien Nha Tran Nguyen and An Dieu Hanh Nguyen for their endless love, care and encouragement ...”

Contents

Contents

List of Figures	viii
List of Tables	x
Abbreviations	xii
Abstract	xiv
1 INTRODUCTION	1
1.1 MOTIVATION	1
1.2 PROBLEM STATEMENT	4
1.3 THESIS OBJECTIVES	6
1.4 THESIS CONTRIBUTIONS	7
1.5 THESIS OUTLINE	8
1.6 THESIS PUBLICATIONS	11
2 LITERATURE REVIEW	13
2.1 PARKINSON’S DISEASE (PD)	13
2.2 FREEZING OF GAIT (FOG)	16
2.2.1 Characterizing of Freezing of Gait in PD	16
2.2.2 Sub-types of FOG	18
2.2.3 Brain location associated with FOG and GIF in PD.....	19
2.3 TREATMENT OF FOG.....	20
2.3.1 Dopaminergic medication.....	23
2.3.2 Cueing techniques.....	23
2.3.3 Exercise training	24
2.3.4 Assistive devices.....	24
2.4 CURRENT STRATEGIES FOR FOG DETECTION	25
2.4.1 Measure leg/knee oscillations for FOG detection	28

2.4.2	Measure ECG signal for FOG detection.....	29
2.4.3	Measure EEG signals for FOG Detection	30
2.4.4	Review on current Computational Intelligence for FOG Detection.....	32
2.5	DISCUSSION AND PROPOSED STRATEGY	34
3	DETECTION OF FREEZING OF GAIT USING EEG AND ARTIFICIAL NEURAL NETWORKS	40
3.1	INTRODUCTION.....	40
3.2	SYSTEM OVERVIEW	41
3.3	STUDY, DATA COLLECTION	43
3.3.1	Study.....	43
3.3.2	Data Collection	44
3.4	COMPUTATIONAL INTELLIGENCE FOR FOG DETECTION.....	46
3.4.1	Signal Pre-Processing	46
3.4.2	Feature Extraction Algorithm based on Fast Fourier Transform (FFT)..	46
3.4.3	Feature Selection	51
3.4.4	Classification Algorithm using Artificial Neural Networks (ANN)	52
3.5	EXPERIMENTAL RESULTS	55
3.5.1	Feature Extraction Results.....	55
3.5.2	Affected EEG Montages Systems underlying FOG	61
3.5.3	Classification Results.....	62
3.6	DISCUSSION	63
4	DETECTION OF GAIT INITIATION FAILURE USING EEG AND SUPPORT VECTOR MACHINE	66
4.1	INTRODUCTION.....	66
4.2	SYSTEM OVERVIEW	68
4.3	STUDY, DATA COLLECTION	68
4.3.1	Study.....	68
4.3.2	Data Collection	69
4.4	COMPUTATIONAL INTELLIGENCE FOR GIF DETECTION	70
4.4.1	Signal Pre-Processing	70

4.4.2	Source separation: Independent Component Analysis Entropy Boundary Minimization (ICA-EBM)	72
4.4.3	Feature Extraction using Wavelet Transform (WT).....	74
4.4.4	Feature Extraction using Fast Fourier Transform (FFT).....	77
4.4.5	Classification Algorithm using Support Vector Machine (SVM).....	77
4.4.6	Classification Algorithm using ANN	79
4.5	EXPERIMENTAL RESULTS	79
4.5.1	Feature Extraction Results.....	79
4.5.2	Classification Results.....	85
4.6	DISCUSSION	88
5	ADVANCED DETECTION OF TURNING FOG AND GAIT INITIATION FAILURE USING EEG AND BAYESIAN NEURAL NETWORKS	90
5.1	INTRODUCTION: TURNING FOG AND GAIT INITIATION FAILURE.....	90
5.2	SYSTEM OVERVIEW	91
5.3	DATA COLLECTION.....	92
5.4	COMPUTATIONAL INTELLIGENCE.....	94
5.4.1	Data Pre-processing: Source separation ICA-EBM	94
5.4.2	Feature Extraction using S-Transform Decomposition	94
5.4.3	Feature Extraction using FFT and WT	96
5.4.4	Classification using Bayesian Neural Networks.....	96
5.4.5	Classification Algorithms using ANN and SVM	99
5.5	DETECTION OF TURNING FOG USING ICA-EBM (SOURCE SEPARATOR), S-TRANSFORM (FEATURE EXTRACTOR) AND BAYESIAN NEURAL NETWORKS (CLASSIFIER)	99
5.6	DETECTION OF GAIT INITIATION FAILURE USING ICA-EBM (SOURCE SEPARATOR), S-TRANSFORM (FEATURE EXTRACTOR) AND BAYESIAN NEURAL NETWORKS (CLASSIFIER).....	108
	Further comparison Classifier and Feature Extractors for Detecting GIF	113
5.7	DISCUSSION	114
6	CONCLUSION AND FUTURE WORK	117

6.1	CONCLUSION	117
6.2	FUTURE WORK	122
Appendix A	Research Ethics Clearance	124
Appendix B	Publications	127
References	150

List of Figures

Figure 2.1: The Relative proportion of five sub-types FOG observed during the TUG trials. (Shine et al. 2012; Snijders et al. 2012)	17
Figure 2.2: Comparison of BOLD activation and deactivation patterns during the contrast of the motor arrests and ‘walking’ using fMRI (Shine, Matar, et al. 2013)	22
Figure 2.3: The regional analysis reveals an increase of information flow to occipital underlying Turning Freezing using EEG signals (Handojoseno, Gilat, et al. 2015)	22
Figure 2.4: A Model of custom-made smart glasses allowing augmented reality visual cues when FOG happened (Janssen et al. 2017)	25
Figure 2.5: Three tri-axial accelerometers were attached to the shank, the thigh, and the lower back (Pham et al. 2017).	29
Figure 2.6: FOG detection system with a focus on the ECG and EC sensor systems (Mazilu et al. 2015)	30
Figure 2.7: Four electrodes related to cortical control of movement in FOG detection system (Handojoseno et al. 2012; Handojoseno, Shine, et al. 2015)	31
Figure 2.8: Overall EEG-based FOG detection in this thesis	39
Figure 3.1: Components of EEG-based FOG detection system	42
Figure 3.2: The international ten-twenty (10-20) system for electrode placement	44
Figure 3.3: Experiment to provoke FOG episode in PD patients	45
Figure 3.4: Raw, filtered and removed artifacts EEG data	47
Figure 3.5: FFT for feature extraction	48
Figure 3.6: Power Spectral Density of Effective Walking and Freezing of Gait	50
Figure 3.7: Comparison of PSD between Effective Walking and Freezing of Gait	50

Figure 3.8: Neural Networks Structure.....	52
Figure 3.9: Significant PSD pattern between EW and FOG in theta alpha, low beta and high beta.....	57
Figure 3.10: Boxplot of Centroid Frequency of EEG signals between EW and FOG.....	60
Figure 3.11: Scalp topography of EEG power activity underlying FOG.....	61
Figure 4.1: Components of EEG-based GIF detection system.....	69
Figure 4.2: Experiment 2 to provoke GIF episode in PD patients.....	70
Figure 4.3: Amplitude spectra of representative raw EEG data of one patient.....	71
Figure 4.4: EEG Data and ICA-EEG data	74
Figure 4.5: Wavelet decomposition of EEG signal with frequency at 512 Hz.....	75
Figure 4.6: EEG signal during GS and GIF episodes in time-frequency domain in C4.....	80
Figure 4.7: Wavelet Energy in Frontal and Central location underlying GS and GIF episodes	83
Figure 4.8: ROC plot.....	87
Figure 5.1: Components of EEG-based Turning FOG detection system.....	92
Figure 5.2: Experiment setup to provoke Turning FOG in PD patients	93
Figure 5.3: S-Transform Decomposition in Good Turn (1-5s), Turning FOG (6-10s) in F4 location	95
Figure 5.4: Time-frequency distributions of S-transform in Good Turn (1-5s), Turning FOG (6-10s) in F4 location.....	100
Figure 5.5: ROC plot.....	105
Figure 5.6: IC scalp maps underlying Good Start and Gait Initiation Failure....	110
Figure 5.7: The log evidence against the optimum number of hidden nodes	111
Figure 6.1: Fifteen affected channels underlying FOG based on our EEG data .	118
Figure 6.2: Best performances of proposed methods for detecting TF.....	121
Figure 6.3: Best performances of proposed methods for detecting GIF.....	121

List of Tables

Table 2.1: Motor and non-motor symptoms in PD (Magrinelli et al. 2016).....	15
Table 2.2: The affected brain locations underlying FOG in PD.....	21
Table 2.3: Overview of methods of selected FOG Detection studies (Rodríguez-Martín, Samà, Pérez-López, Català, Moreno Arostegui, et al. 2017)	26
Table 2.4: Overview of methods of selected FOG Detection studies (Rodríguez-Martín, Samà, Pérez-López, Català, Moreno Arostegui, et al. 2017).....	27
Table 2.5: Overview FOG detection methods, their advantages and disadvantages.....	35
Table 3.1: Features analysis of PSD between EW and FOG.....	58
Table 3.2: Features analysis of PSE between EW and FOG	58
Table 3.3: Features analysis of CF between EW and FOG	59
Table 3.4: Classification results of FFT based features using ANN in detecting FOG from EW.....	64
Table 3.5: Comparison of classification results in detecting FOG from EW.....	64
Table 4.1: Features analysis of WE between GS and GIF.....	82
Table 4.2: Features analysis of WEE between GS and GIF.....	84
Table 4.3: Features analysis of WCS between GS and GIF.....	85
Table 4.4: Classification results of WT based features using SVM in detecting GIF from GS.....	86

Table 4.5: Comparison of classification results in detecting GIF from GS using source separation ICA-EBM	88
Table 5.1: Feature analysis of ST (ST^{\max}) based feature between GT and TF in Frontal, Central and Parietal.....	101
Table 5.2: Feature analysis of ST (ST^{\max}) based feature between GT and TF in Occipital.....	102
Table 5.3: Feature analysis of ST (ST^{mean}) based features between GT and TF in Frontal and Central	103
Table 5.4: Feature analysis of ST (ST^{mean}) between GT and TF in Parietal and Occipital.....	104
Table 5.5: Classification Results of ST based features using BNN in detecting TF from GT.....	106
Table 5.6: Comparison of classification results in detecting TF using source separation ICA-EBM.....	107
Table 5.7: Feature analysis of ST (ST^{mean}) between GS and GIF in Frontal, Central and Parietal.....	109
Table 5.8: Feature analysis of ST (ST^{mean}) between GS and GIF in Occipital.....	110
Table 5.9: Classification Results of ST based features using BNN in detecting GIF from GS using ICA-EBM.....	112
Table 5.10: Comparison of classification results in detecting GIF using source separation ICA-EBM.....	113
Table 6.1: Significant results underlying Freezing events in this thesis.....	119

Abbreviations

3D: Three Dimensions

ANN: Artificial Neural Networks

BSS: Blind Source Separation

BNN: Bayesian Neural Networks

CF: Centroid Frequency

CWT: Continuous Wavelet Transform

DWT: Discrete Wavelet Transforms

ECG: Electrocardiography

EEG: Electroencephalography

EMG: Electromyography

EW: Effective Walking

FFT: Fast Fourier Transform

fMRI: function Magnetic Resonance Imaging

FOG: Freezing of Gait

FOGQ: Freezing of Gait Questionnaire

H&Y: Hoehn and Yahr stage

GIF: Gait Initiation Failure

GS: Good Start

GT: Good Turn

ICA: Independent Component Analysis

ICA-EBM: Independent Component Analysis Entropy Boundary Maximization

ICs: Independent Components

MMSE: Mini-Mental State Examination

PD: Parkinson's disease

PSD: Power Spectral Density

PSE: Power Spectral Entropy

pSMA: pre-Supplementary Motor Area

SVM: Support Vector Machine

ST: S-Transform

TF: Turning FOG

TUG: Timed Up and Go

UPDRS: Unified Parkinson's disease Rating Scale

WE: Wavelet Energy

WCS: Wavelet Centroid Scale

WEE: Wavelet Energy Entropy

Abstract

Parkinson's disease (PD) is the second most common age related neurodegenerative disorder, affecting approximately 1-2% of the elderly population. Freezing of Gait (FOG) is a very disabling feature of PD that causes frequent falls. During FOG, patients are suddenly unable to take a step despite the intention to walk or continue moving forward. The neural mechanisms of FOG are unclear and treatments have only limited effectiveness.

Based on contexts of behavioural measures in daily life, different types of FOG have been observed including: freezing when turning (TF); freezing when getting through narrow doorways; freezing when reaching a target; freezing when straight walking or freezing when initiating gait to start a movement (GIF). TF and GIF are recognized to be the most frequent triggers of FOG seen in PD patients.

To detect FOG, using parameters extracted from the Electroencephalogram (EEG) is one of the most promising methods. In the comparison of using "body-worn" sensors technique, EEG measures the activity of the brain where the root of FOG is occurring. Therefore, EEG will be quicker to detect FOG than "body-worn" sensors because of the time the neural signal has to travel all the way to the legs to be measured, thus offering the most optimal time window for intervention to overcome FOG.

The research in this thesis introduces advanced algorithms for FOG detection using EEG signals. These algorithms have been developed and applied successfully to detect FOG and its two common subtypes (GIF, TF) based on various features extractions and classifiers, providing high accuracy for detection. It was found that the combination of Independent Component Analysis Entropy Boundary Minimization (ICA-EBM), S-Transform (ST) and Bayesian Neural Networks (BNN) proved to be a very robust and effective method for freezing detection.

In the first study, abnormal changes of EEG signal to detect FOG were investigated. By using Fast Fourier Transform as the feature extraction and Artificial Neural Networks

(ANN) as a classifier, the EEG data of FOG could be detected effectively from seven PD patients with sensitivity, specificity and accuracy of 72.20%, 70.58% and 71.46%, respectively. Furthermore, FOG episodes were found to be associated with significant increases in the high beta band (21-38Hz) across the central, frontal, occipital and parietal EEG sites.

In the second study, the dynamic brain changes underlying a GIF episode and its detection were investigated in four PD patients. This research studied the brain activity underlying GIF by analyzing Wavelet Transform (WT) of EEG signals. Using ICA-EBM for EEG source separation, WT for feature extraction and Support Vector Machine (SVM) for classification, the correct identification of GIF episodes was improved with sensitivity, specificity, and accuracy of 83.94%, 89.39% and 86.67%, respectively.

The final classification results produced by this dissertation indicated that by applying source separation ICA-EBM for pre-processing EEG data, time-frequency ST techniques for feature extraction and BNN for classification, a freezing event can be successfully detected using EEG signals. The results for the TF detection were achieved with sensitivity, specificity, and accuracy of 83.00%, 87.60% and 85.40%, respectively. The results for the GIF detection were relatively similar with sensitivity, specificity, and accuracy of 88.96%, 90.26% and 89.50%, respectively.

With the final performance (ICA-EBM, ST, BNN) achieved by this thesis, future work will be carried out to pursue the eventual aim of the current research, which is developing an EEG-based system for detecting FOG that can be applied in real-time.