



**UNIVERSITI PUTRA MALAYSIA**

**AMPLITUDE INDEPENDENT MUSCLE ACTIVITY DETECTION  
ALGORITHM OF SOFT ROBOTIC GLOVE SYSTEM FOR HEMIPARESIS  
STROKE PATIENTS USING SINGLE sEMG CHANNEL**

**HUSAMULDEEN KHALID HAMEED**

**FK 2020 61**



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By

**HUSAMULDEEN KHALID HAMEED**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,  
in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

**August 2020**

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## **DEDICATION**

This thesis is especially dedicated to: My praiseworthy parents, my beloved wife, my son and my daughters, and my dearest brothers and sisters



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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**HUSAMULDEEN KHALID HAMEED**

**August 2020**

**Chairman : Associate Professor Wan Zuha Wan Hasan, PhD**  
**Faculty : Engineering**

Hand impairment is a consequence of many neurological diseases such as stroke, where the stroke affects about 15 million people worldwide annually and it is one of the main causes of hand disability. Therefore, hand robotic devices can be used to help stroke patients to perform activities of daily living and at home rehabilitation. Control of hand robotic devices by using Surface Electromyography (sEMG) signal is the most preferred control technique due to the advantages of this method like naturalness. However, robust controlling by using such method is still a challenging process because the amplitude of these signals is not constant over the recording time due to the variations in the electrode-skin interface characteristics; these involuntary amplitude variations deteriorate the detection performance of the amplitude-dependent methods and produce false alarms. Many algorithms have been developed in the literature to detect muscle activities; however, most of these algorithms depend on amplitude features in the detection process. The performance of the amplitude-dependent methods is highly deteriorated when the signal to noise ratio (SNR) is low, such as for signals obtained from the paretic muscles. To simplify soft robotic glove systems and make them more practical for use in daily basis, they should have minimum number of sEMG channels. In spite of some algorithms that have been developed in the literature to classify some hand motions by using single channel, the current implementation of soft robotic glove systems are still employing two channels for detecting the closing and opening movements of the hand, due to the intensive calculations required by these algorithms which impose difficulties on real time implementation. This thesis addresses the aforementioned problems, by innovating an amplitude-independent and computationally efficient muscle activity detection algorithm to control a soft robotic glove intended for hemiparesis stroke patients by using single channel. The algorithm employs the First Lag Autocorrelation and the Modified Sample Entropy methods to detect and classify weak hand closing and opening muscle activities by using signal obtained

from the Flexor Carpi Ulnaris forearm muscle. The detection performance of the proposed algorithm compared to three amplitude-dependent algorithms was verified on seven healthy subjects and on six hemiparesis stroke patients. The performance of the proposed algorithm has outperformed that of the amplitude-dependent algorithms regarding the detection of weak muscle activities and robustness against false alarms. High classification accuracies have been achieved for the seven healthy subjects (92%-100%) which are comparable to that obtained by applying sophisticated single channel classification algorithms in previous studies; moreover, good accuracies (70%-85%) have been obtained for the stroke patients. The computation efficiency of the proposed algorithm has enabled the implementation of the soft robotic glove system prototype by using simple hardware.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**ALGORITMA PENGESANAN AKTIVITI OTOT AMPLITUD BEBAS  
UNTUK MENGAWAL SISTEM SARUNG TANGAN ROBOTIK YANG  
LEMBUT UNTUK PESAKIT STROK HERIPAREISIS DENGAN  
MENGUNAKAN SALURAN sEMG TUNGGAL**

Oleh

**HUSAMULDEEN KHALID HAMEED**

**Ogos 2020**

**Pengerusi : Profesor Madya Wan Zuha Wan Hasan, PhD**  
**Fakulti : Kejuruteraan**

Kecacatan tangan adalah akibat daripada pelbagai penyakit neurologi seperti strok, di mana strok memberi kesan kepada kira-kira 15 juta orang di seluruh dunia setiap tahun, dan ia merupakan salah satu punca utama hilang upaya tangan. Oleh itu, peranti tangan robotik boleh digunakan untuk membantu pesakit strok untuk melakukan aktiviti kehidupan harian dan pemulihan di rumah. Kawalan peranti tangan robotik dengan menggunakan isyarat Permukaan Elektromiografi (sEMG) telah mendapat perhatian yang tinggi kerana kelebihan menggunakan kaedah kawalan yang mempunyai sifat menyerupai semula jadi. Walau bagaimanapun, kawalan kukuh dengan menggunakan isyarat sEMG masih merupakan proses yang mencabar kerana ciri amplitud isyarat berubah dari semasa ke semasa ketika proses rakaman disebabkan oleh variasi dalam ciri-ciri antaramuka elektrod-kulit; variasi amplitud luar kawalan ini mengakibatkan prestasi pengesanan kaedah yang bergantung pada amplitud merosot, dan menghasilkan amaran palsu. Pelbagai algoritma telah dibangunkan dalam literatur untuk mengesan aktiviti otot; namun, kebanyakan algoritma ini bergantung pada ciri amplitud dalam proses pengesanan. Prestasi kaedah yang bergantung kepada amplitud akan merosot apabila nisbah isyarat kepada bunyi (SNR) adalah lebih rendah daripada isyarat sEMG, seperti isyarat yang diperolehi dari otot-otot paretik. Untuk memudahkan peranti tangan robotik dan menjadikannya lebih praktikal untuk penggunaan harian, mereka memerlukan bilangan saluran sEMG minimum. Walaupun beberapa algoritma yang telah dibangunkan dalam literatur untuk mengklasifikasikan beberapa gerakan tangan dengan menggunakan saluran tunggal, implementasi sistem sarung tangan robotik lembut masih menggunakan dua saluran untuk mengesan aktiviti penutupan dan pembukaan tangan, disebabkan oleh pengiraan intensif yang diperlukan oleh algoritma-algoritma saluran tunggal, yang menjadikannya tidak praktikal untuk

pelaksanaan masa sebenar. Tesis ini membincangkan masalah yang disebutkan di atas, dengan menginovasi amplitud bebas dan pengiraan algoritma pengesanan aktiviti otot yang cekap untuk mengawal sarung tangan robot yang lembut untuk pesakit strok hemiparesis dengan menggunakan saluran sEMG tunggal. Algoritma ini menggunakan Autokolerasi Lag Pertama dan kaedah Entropi Sampel yang Diubahsuai untuk mengesan dan mengklasifikasikan aktiviti penutupan dan pembukaan otot tangan yang lemah, dengan menggunakan isyarat yang diperolehi daripada otot lengan Fleksor Carpi Ulnaris. Prestasi pengesanan algoritma yang dicadangkan berbanding dengan tiga algoritma yang bergantung kepada amplitud telah disahkan keatas tujuh subjek yang sihat, dan pada enam pesakit strok hemiparesis. Prestasi algoritma yang dicadangkan berhubung dengan pengesanan aktiviti otot lemah dan ketahanan terhadap amaran palsu telah mengatasi prestasi algoritma-algoritma yang bergantung kepada amplitud. Ketepatan klasifikasi yang tinggi telah dicapai diatas tujuh subjek yang sihat (92% -100%) yang mana setanding dengan ketepatan yang diperolehi dengan menggunakan algoritma klasifikasi saluran tunggal yang canggih dalam kajian terdahulu; selain itu, ketepatan yang bagus (70% -85%) telah diperolehi untuk pesakit strok. Kecekapan pengiraan algoritma yang dicadangkan telah membolehkan pelaksanaan prototaip sistem sarung tangan robotik lembut dengan menggunakan perkakasan mudah.



## ACKNOWLEDGEMENTS

*In the Name of Allah, Most Gracious, Most Merciful*

First and foremost, I would like to thank the Almighty God for the blessing of giving me strength and patience to complete my study.

And I would also like to thank:

-My wonderful parents, for their love and encouragement.

-My wife, for her precious love, steadfast support and patience throughout this journey.

I would like to take this opportunity to express my sincere gratitude and appreciation to my supervisor Assoc. Prof. Dr. Wan Zuha Wan Hasan for all his guidance, support and help during my study. Many thanks also due for the support given by my co-supervisors Assoc. Prof. Dr. Suhaidi Shafie, Assoc. Prof. Dr. Siti Anom Ahmad, Dr. Haslina Jaafar, and Dr. Liyana Najwa Inche Mat.

I also would like to thank the Universiti Putra Malaysia UPM for accepting my application to study at this prestigious Faculty of Engineering.

This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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## LIST OF ABBREVIATIONS

ADL	Activities of Daily Living
ANN	Artificial Neural Network
ATH	Adaptive Threshold
AWGN	Additive White Gaussian Noise
CWT	Continuous Wavelet Transform
DAQ	Data Acquisition Device
DC	Direct Current
DOF	Degree Of Freedom
EBPP	EMG Burst Presence Probability
EEG	Electroencephalogram
EMG	Electromyography
EOG	Electrooculography
FCR	Flexor Carpi Radialis
FCU	Flexor Carpi Ulnaris
FDS	Flexor Digitorum Superficialis
GLR	Generalized Likelihood Ratio
GMM	Gaussian Mixture Model
GUI	Graphical User Interface
IP	Integrated Profile
KNN	K-Nearest Neighbor
LBP	Local Binary Pattern
LBPAD	LBP EMG Activity Detection
MAV	Mean Absolute Value



MO	Morphological Operator
MREC	Medical Research and Ethics Committee
PA	Proposed Algorithm
PCA	Principal Component Analysis
PDF	Probability Density Function
R&F	Rectified and Filtered
RFID	Radio Frequency Identification
RMS	Root Mean Square
SampEn	Sample Entropy
SCI	Spinal Cord Injury
SD	Standard Deviation
sEMG	Surface Electromyography
SMO	Sequential Minimal Optimization
SNR	Signal to Noise Ratio
SSA	Singular Spectrum Analysis
SVM	Support Vector Machine
TKE	Teager Kaiser Energy
WT	Wavelet Transform

# CHAPTER 1

## INTRODUCTION

### 1.1 Overview and Motivation

Spinal cord injuries, traumas, natural aging, muscular dystrophy, cerebral palsy, Parkinson's disease, arthritis, and stroke are the main causes of arm impairment or even a chronic disability for an increasing part of the population [1]. For instance, about 78 million arthritis cases with grasping impairment are expected yearly in US by the year of 2040. Also, stroke affects about 15 million people worldwide annually [2] and it is one of the main reasons of upper limb disability, which limits the patient's autonomy to do activities of daily living (ADL) [3]. One of the most common conditions resulting from a stroke is hemiplegia or hemiparesis, as many as 88% of acute stroke patients have hemiparesis [51]. Hemiplegia means complete paralysis of one-half of the body, whilst hemiparesis means one-half of the body is only weakened [52]. Chronic hemiparesis afflicts about one-third of the stroke patients [53][54] and it is prevalent in the distal upper extremity especially for the fingers extension [55]. Therefore, hand robotic devices can be essential tools to help stroke patients afflicted with hand deficit to perform activities of daily living in addition to the possibility of restoring hand functions by home rehabilitation.

Rehabilitation is an indispensable solution that helps to revive the hand functions after a stroke by intensive and repetitive training. Studies have shown that 14% of stroke patients with no active upper limb motion at the beginning of the therapy can completely recover the paretic arm functions with rehabilitation, whilst about 30% of the patients can partially recover [57]. Rehabilitation is predominantly conducted in clinics under the therapist's supervision, but this process is costly, time-consuming, and needs special equipment only available in special places [4]. Therefore, an alternative solution is to utilize robotic gloves or hand exoskeletons to assist stroke patients in daily living activities or doing rehabilitation exercises at home.

In the last years, soft robotic gloves have emerged as an alternative to the traditional bulky and rigid exoskeletons due to their portability, efficacy, safety, less complex designs and light weight [1]. Among the three types of the soft robotic gloves, pneumatic actuated soft gloves are preferred over hydraulic actuated soft glove because it has less weight and over the cable actuated soft gloves because it has faster setup time and more safety [1][5][6].

Many studies on stroke patients [6][5][7][8] have proved that the use of the soft robotic gloves in home rehabilitation improves the grasping performance and grip strength of the impaired hand. Recently, controlling of the soft robotic gloves by using the surface electromyography (sEMG) signals has earned a lot of attention. This interest is motivated by the advantages of using the sEMG signal as a control signal, for instance, naturalness, direct correlation between the movement intention

and the sEMG signal [9], low time delay between human intention and movement of the device [10], and simple obtaining of sEMG signal by employing the surface electrodes. Many studies have proved that employing such control method for stroke rehabilitation led to enhance the levels of sEMG signals and improved the hand functions of the patients [36][39][115][116][122][127]. Therefore, nowadays the EMG based control is the most common method used to operate active orthotic devices [9].

## 1.2 Problem Statement

The sEMG signal amplitude is not constant over the recording time due to the changes in the person exerted force or due to the variation of electrode-skin interface characteristics as well as the changes in the ground reference level [13]. Moreover, it is found that motor unit over activity of paretic muscles in stroke subjects are sometimes producing Spurious Background Spikes that contaminate the voluntary sEMG signal, such spikes made it difficult to use the conventional amplitude-based methods for muscle activity detection [14][15]. Therefore, the muscle activity detection algorithms should be amplitude independent and insensitive to Spurious Background Spikes.

Many algorithms have been developed in the literature to detect the presence of muscle activities in sEMG signal [14-33]. However, most of these algorithms depend on amplitude features to report muscle activities or employing complex computation methods which impose difficulties on real time implementation. Moreover, the frequency domain analysis requires intensive calculations that would introduce constraints when implemented in real time. Therefore, the muscle activity detection algorithms intended to control robotic devices should have low computation efforts to enable real time implementation.

Until now, all the practical implemented soft robotic hand devices [34-42] have employed simple detection methods that use amplitude features to report muscle activities. Moreover, it is observed that sEMG signals with high signal to noise ratio have been used to control the gloves in the above endeavors, whilst the disabled people always have weak and low Signal to Noise Ratio (SNR) sEMG signals. In pathological muscles, the signals are characterized by a low activity level due to low firing rate, low number of motor units recruited, low activation threshold and very low signal to noise ratio [163]. Therefore, the muscle activity detection algorithm should be able to detect weak contraction levels and can deal with sEMG signals that have low signal to noise ratio.

To simplify the hand robotic system and make it more practical for use in daily basis with easy to wear and take off (don and doff), it should have minimum number of sEMG channels. All the practical implemented soft robotic gloves systems in the literature have employed two channels to detect the muscle activities for hand close and hand open. In spite of some studies that have tried to develop algorithms for

hand motions classification by using single sEMG channel [43-48], these algorithms have not been applied to control the practical implemented soft glove systems yet. This abstention is due to fact that most of these algorithms require high computation power and need time for training like neural networks which make them impractical for real time implementation on simple hardware. Moreover, these algorithms depend on amplitude features to classify hand movements and need controlled laboratory environments to get good classification accuracies. Additionally, previous experiments [49][50] have concluded that employing the traditional classification methods is inappropriate with the severely impaired stroke patients due to the weak sEMG signals and abnormal pattern of muscles activation. Therefore, it is necessary to develop a computationally efficient and amplitude independent classification method to distinguish at least between hand close and hand open activities by using sEMG signal obtained from a single channel.

### **1.3 Research Objectives**

This research aims to develop a pneumatic actuated soft robotic glove system for hemiparesis stroke patients that have hand impairment to help them in activities of daily living and at home rehabilitation. The system must be light weight, low cost, small size, has fast setup time, and controlled by a robust sEMG muscle activity detection algorithm. In order to realize this aim, it is necessary to fulfil the following objectives:

1. To propose an amplitude independent muscle activity detection algorithm that can distinguish between hand close and hand open muscle activities by using single sEMG channel. The algorithm must be computationally efficient and able to detect muscle activities that have low SNR (less than 3dB) as well as it should be insensitive to the spurious background spikes and can process the data in real time.
2. To introduce the best forearm muscle used to locate the single sEMG channel in order to get the best classification performance for the proposed algorithm.
3. To verify the performance of the proposed algorithm on healthy subjects and on hemiparesis stroke patients.
4. To propose a soft robotic glove system controlled by the proposed muscle activity detection algorithm and verifies its operation on a healthy subject.

### **1.4 Scope and Limitation of the Study**

The scope of this study is on the orthotic hand devices not prosthetic, where this research is focused on the development of an amplitude independent muscle activity detection algorithm used to control a soft robotic glove system intended for hemiparesis stroke patients by using sEMG signal to help them with the activity of daily living and at home rehabilitation. All the experiments that were conducted in this research have employed real sEMG signals and there is no use to simulated signals because of the stochastic nature of sEMG signals, where the modelling of

sEMG has been controversial and may lead to erroneous conclusions when compared to experimental data [33]. The sEMG signals from the medical point of view about how they are generated from the brain, how they are transferred through neurons, and the factors affect these signals are out of scope for this study. The research has managed to achieve its objectives by using real sEMG signals obtained from seven healthy subjects (six volunteers plus the researcher) and six hemiparesis stroke patients (as justified in section 3.4.2.1). The sEMG recording sessions for the healthy subjects were conducted at the Universiti Putra Malaysia and the clinical trials for the stroke patients were conducted at the Seberang Jaya Hospital, Penang. However, there are some limitations in conducting this research. Firstly, all the sEMG signals used to develop and verify the operation of the muscle activity detection algorithm were obtained by using the low cost MyoWare Muscle Sensor from Advancer Technologies, where a study by *Sophie et al.* [140] on ten healthy subjects has showed that using the low-cost MyoWare sEMG sensor is comparable to a commercial system for assessing muscle activation. Secondly, the approved ethics by the Medical Research and Ethics Committee (MREC) for this study has permitted to use only the sEMG sensor in the clinical trials without using the glove, therefore the tests that were conducted by using the glove were applied to only one healthy subject (the researcher). Whereas, all the sEMG signals obtained from the six healthy subjects and from the six stroke patients were used to verify the operation of the proposed algorithm without the use of the glove (bare hand).

## **1.5 Layout of the Thesis**

Chapter 1 presents the motivation of the study and the problem statement. It also introduces the aim, objectives, and gives a brief summary of the structure of the thesis.

Chapter 2 presents the literature survey about controlling by sEMG signals with the advantages and problems. It also gives a survey about muscle activity detection algorithms and sEMG controlled hand robotic devices.

Chapter 3 describes the research methodology carried out to achieve the objectives and discusses the steps that are taken to develop the proposed amplitude independent muscle activity detection algorithm, comparing it with the amplitude dependent algorithms and developing the prototype of the soft robotic glove system.

Subsequently, Chapter 4 presents the results with discussions and verifies the obtained results to rationally present the soft robotic glove system controlled by the proposed muscle activity detection algorithm.

Finally, Chapter 5 gives a summary and the conclusion according to the findings of this research. Suggestions and recommendations for future research in this area as well as the research contributions are also presented in this final chapter.

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## LIST OF PUBLICATIONS

- Hameed H. K., Zuha W. H, Shafie S., Ahmad S. A., Jaafar H., & Mat L. N. (2020). Investigating the performance of an amplitude-independent algorithm for detecting the hand muscle activity of stroke survivors, *Journal of Medical Engineering & Technology*
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- Hameed H. K., Zuha W. H, Shafie S., Ahmad S. A., Jaafar H., Mat L. N., Alkubaisi Y. (2020). Identifying the Best Forearm Muscle to Control Soft Robotic Glove System by Using a Single sEMG Channel. *IEEE ASET 2020 conference*



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