UNIVERSITI PUTRA MALAYSIA

ELECTROMYOGRAPHY SIGNAL PROCESSING BASED ON TIME AND TIME-FREQUENCY REPRESENTATIONS FOR PROSTHESIS APPLICATION

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ELECTROMYOGRAPHY SIGNAL PROCESSING BASED ON TIME AND TIME-FREQUENCY REPRESENTATIONS FOR PROSTHESIS APPLICATION

By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Master of Science

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January 2014

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Electromyography (EMG) is a technique to acquire and study the signal of skeletal muscles. Skeletal muscles are attached to the bone responsible for the movements of the human body. Regarding the vast variety of EMG signal applications such as rehabilitation of people suffering from some mobility limitations, scientists have done much research on the EMG Control System (ECS). Accordingly, using EMG signal for controlling a prosthetic hand has been developed remarkably in recent years. The ECS based on pattern recognition has been improved by using new techniques in the EMG signal processing. Some of the main concerns of the ECS are the accuracy and complexity of the system. Consequently, the development of the ECS in term of accuracy and speed is the main challenge in prosthetic control.

This thesis investigates the necessity of the ECS improvements by processing the EMG signal through a pattern recognition-based control system for prosthesis application. To reach this goal, different techniques in two domains of study, time and time-frequency, had been utilized to find the optimum features for EMG analysis. Mean Absolute Value (MAV), Root Mean Square (RMS), Zero Crossing (ZC) and Waveform Length (WL) were employed as feature extraction techniques in time domain and Wavelet Transform (WT) was used in time-frequency domain. Furthermore, an optimization in wavelet analysis had been investigated using twenty mother wavelets which improved the results of the EMG feature extraction. Afterwards, two discriminant analysis classifiers, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) had been utilized to differentiate the five hand movements. It is worth mentioning that eighteen healthy people had participated in EMG signal recording and different wrist motions (flexion, extension, abduction, adduction and rest) had been recorded.

As a result, the output of the proposed algorithm for EMG signal processing using various techniques presented an improvements in EMG signal classification in terms of accuracy. The highest classification accuracy obtained in this research was obtained by RMS feature in time domain as 98.06%. Also, the optimizing of wavelet features yielded 97.13% accuracy by applying WT+RMS (Root Mean Square of Wavelet coefficients) as the feature. On the other hand, an investigation on data segmentation before feature extraction had revealed the segment size of EMG

signal plays a significant role in EMG analysis. In this study, it was presented that the techniques of segmentation and segment size affect the classification accuracy. Based on the results of this thesis, the proposed algorithm for EMG signal processing can be applied to discriminate different hand grip postures efficiently. Overall, RMS feature was demonstrated as the optimum feature for EMG classification using QDA classifier.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah master sains.

SISTEM KAWALAN ELEKTROMIOGRAFI BERDASARKAN MASA DAN PERWAKILAN TIME-KEKERAPAN PERMOHONAN PROSTESIS

Oleh

FARZANEH AKHAVAN MAHDAVI

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Elektromiografi (EMG) juga dirujuk sebagai mioelektrik, adalah isyarat bioperubatan yang diambil dari rangka otot. Rangka otot yang bersambung kepada tulang bertanggungjawab untuk pergerakan badan. Oleh kerana penggunaan isyarat EMG sangat luas dan pelbagai sebagai contoh pemulihan pesakit yang menderita daripada pergerakan yang terhad, maka saintis telah membuat banyak kajian berkaitan sistem kawalan EMG (ECS). Disebabkan itu, beberapa tahun kebelakangan ini penggunaan isyarat EMG untuk mengawal tangan palsu telah dibangunkan. ECS berasaskan pengenalpastian bentuk atau paten telah dipertingkatkan dengan menggunakan teknik baru dalam analisis isyarat EMG. Terdapat beberapa perkara berbangkit dalam ECS seperti ketepatan dan kesukaran sistem tersebut. Disebabkan itu, pembangunan ECS dalam kata erti ketepatan dan kelajuan adalah cabaran utama dalam pengawalan tangan palsu.

Tesis ini bertujuan untuk menyiasat keperluan untuk meningkatkan ECS dengan memproses isyarat EMG melalui pengenalpastian paten berasakan sistem kawalan untuk aplikasi prostesis. Untuk mencapai objektif tersebut, teknik berbeza dalam dua domain kajian iaitu masa dan masa-frekuensi telah dikaji bagi mendapatan sifat optimum dalam analisis EMG. Mean Absolute Value (MAV), Root Mean Square (RMS), Zero Crossing (ZC) dan Waveform Length (WL) telah digunakan sebagai teknik pengektrakan ciri atau sifat dalam domain masa dan ‘Wavelet Transform’ (WT) dalam domain masa-frekuensi. Tambahan lagi, pengoptimuman dalam analisis wavelet telah dikenalpasti menggunakan dua puluh ibu wavelet yang mana ia menambahbaik keputusan pengekstrakan ciri EMG. Kemudian, dua pengelas pembezaan analisis, LDA and QDA telah direkrut untuk membezakan lima pergerakan tangan. Seramai lapan belas orang terlibat dalam rakaman isyarat EMG dengan pergerakan pergelangan tangan yang berbeza (membengkok, meregang,membengkok ke kanan, membengkok ke kiri, rehat) telah direkodkan.

Hasil dari kajian ini, terdapat peningkatan ketepatan pengkelasan isyarat EMG didalam ECS menggunakan pelbagai teknik yang diusulkan. Ketepatan pengkelas tertinggi yang didapati dari sistem ini telah dicapai melalui ciri RMS dalam domain masa sebanyak 98.06%. Pengoptimuman ciri wavelet mendapat 97.13% ketepatan dengan menggunakan WT+RMS sebagai ciri. Selain dari itu, satu kajian ke atas pembahagian data sebelum pengekstrakan ciri mendapati saiz pembahagian isyarat

EMG memainkan peranan penting dalam analisis EMG. Dalam kajian ini, ia membuktikan bahawa teknik pembahagian dan saiz bahagian mempengaruhi ketepatan pengkelasan dan kelajuan sistem. Berdasarkan keputusan dari kajian ini, algoritma yang dicadangkan untuk memproses isyarat EMG boleh diaplikasi untuk membezakan postur genggaman tangan dengan cekap. Keseluruhannya, sifat RMS yang telah terbukti sebagai sifat optimum dalam pengkelasan EMG menggunakan pengkelas QDA.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science.

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Declaration by Gradute Student

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LIST OF ABBREVIATIONS

AR	Autoregressive
bior	Biorthogonal
coif	Coiflet
CWT	Continous Wavelet Transform
db	Daubechies
DHWPT	Discrete Harmonic Wavelet Packet Transform
DWT	Discrete Wavelet Transform
ECS	Electromyography Control System
EMG	Electromyography
FCM	Fuzzy C-Mean
FL	Fuzzy Logic
FT	Fourier Transform
FWP	Fuzzy wavelet Packet
GA	Genetic Algorithm
IDWT	Inverse Discrete Wavelet Transform
LDA	Linear Discriminante Analysis
MAV	Mean Absolute Value
MAVS	Mean Absolute Value Slope
MLP	Multilayer Perceptron
MMDF	Median Frequency
MMNF	Mean Frequency
MUAP	Muscle Unit Action Potential
MV	Majority Voting
MW	Mother Wavelet
MWM	Mother Wavelet Matrix
NN	Neural Network
PCA	Principle Component Analysis

PSD	Power Spectrum Density
PWVD	Pseudo Wigner-ville Distribution
QDA	Quadratic Discriminant Analysis
RES	Ratio of Euclidean distance to Standard deviation
RMS	Root Mean Square
RWED	Running Windowed Exponential Distribution
RWPE	Relative Wavelet Packet Energy
SELDA	Self Enhancing Linear Discriminante Analysis
SEPCOR	Seprability and Correlation
SEQDA	Self Enhancing Quadratic Discriminante Analysis
SSC	Slope Sign Changes
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
sym	Symlet
TD	Time Domain
VAR	Varriance
WAMP	William Amplitude
WT	Wavelet Transform
ZC	Zero Crossing

CHAPTER 1

INTRODUCTION

1.1 Background

Nowadays, limb loss issue has fascinated researchers remarkably and the approach of prosthesis development has been considered in many countries. There are 1.7 million people with limb loss in the United States while it is predicted that this value will double by the year 2050 (Ziegler-Graham, MacKenzie, Ephraim, Travison, & Brookmeyer, 2008). Prosthetic hands have been designed as a replacement for upper limb amputees. Although the number of lower limb amputations is more than the upper limb amputations, the damage produced by upper limb loss is considerably more harmful (Baumgartner, 2001) because the proficiency of hand in accomplishing various activities in daily life is noticeable. Consequently, an appropriate designed of upper limb prosthetic device can improve the amputee's life physically and psychologically. There are two kinds of prosthetic hands, namely, passive prosthesis and active prosthesis. The passive form is a cosmetic type with excellent appearance provides a visual replacement of the amputation while the active prosthesis (also called a functional prosthesis) is used to imitate a natural hand to manipulate objects but its appearance is not attractive.

Electromyography (EMG) signal has been applied efficiently to control active prosthesis. One of the most significant advantages of EMG control is its property of hands-free control (Asghari Oskoei & Hu, 2007). The first clinically EMG prosthesis was presented by Russian expert in the 1960s (Plettenburg, 2006). In more than last 50 years, the EMG control system has been much improved. Overall, we can categorize all these improvements and achievements in three generations. First generation presents ON/OFF control system that uses a single rate of actuation. Second one comprises a state machine, large-scale threshold manipulation, signal amplification, the adjustment of the muscle contraction rate, and proportional control. Third generation includes programmable microprocessors allows an infinite range of adjustment of EMG characteristics (Asghari Oskoei & Hu, 2007).

On the other hand, applying microprocessor in the control system of EMG yields some proficiency such as using advanced signal processing techniques. In this way, it is probable to filter EMG signal by powerful techniques. Moreover, the robustness of EMG control system (ECS) can be improved by using pattern recognition control systems (Asghari Oskoei & Hu, 2007). In this Thesis, an improvement of EMG signal processing in the ECS based pattern recognition is investigated. ECS can be categorized into two groups: pattern recognition base control system and non-pattern recognition- based control system (B Hudgins, Parker, & Scott, 1994). Considering the various applications of ECS such as multifunction prosthesis (Kevin Englehart, Hudgin, & Parker, 2001; Kevin Englehart & Hudgins, 2003) wheelchairs (Han, Zenn Bien, Kim, Lee, & Kim, 2003), virtual keyboards and clinical application, the improvements of ECS shall provide outstanding services.

1.2 Related Work

Several techniques have been used to develop pattern recognition based ECS in recent years. Generally, EMG pattern recognition systems contain three major components, namely, preprocessing, feature extraction and classification. EMG feature extraction plays a critical role in improving the control system. Features characterize the raw EMG signal for classification, so even the strongest classifiers cannot perform well if they are not supported with good features. EMG features are categorized in three domains: time domain, frequency domain and time-frequency domain (Zecca, Micera, Carrozza, & Dario, 2002). A wide ranges of features (thirty seven features) in time and frequency domains had been presented and their properties on EMG signal processing had been studied in a research recently (Angkoon Phinyomark, Phukpattaranont, & Limsakul, 2012). Also, various time domain features were used to classify EMG signal by a support vector machine classifier (Oskoei & Hu, 2008). The most popular techniques in the EMG feature extraction are time domain features because of their computational simplicity (Asghari Oskoei & Hu, 2007). Mean Absolute Value (MAV) and Root Mean Square (RMS) are two famous time domain features (Clancy, Morin, & Merletti, 2002). Frequency domain features are generally applied to study muscle fatigue and Power Spectral Density (PSD) has been a main analysis in frequency domain (Asghari Oskoei & Hu, 2007).

Likewise, there are different techniques in time-frequency (also named time-scale) domain. The accuracy of some time-scale methods had been compared and it was concluded that continuous wavelet transform performed better than the other time-frequency analysis techniques (Karlsson, Yu, & Akay, 2000b). In another study different levels of wavelet functions were applied to find the best feature. Therefore, unwanted parts of the EMG signal were eliminated by selecting the suitable wavelet function (A. Phinyomark, Limsakul, & Phukpattaranont, 2011)

After feature extraction, features required to be classified into discriminant classes of hand movements. Some old and new techniques have been recruited as classifiers in EMG classification such as, Linear Discriminant Analysis (LDA), (Kevin Englehart, et al., 2001; Farrell & Weir, 2007; A Phinyomark, Hu, Phukpattaranont, & Limsakul, 2012; Zhang, 2013), Support Vector Machine (Kamavuako, et al., 2013; Oskoei & Hu, 2008; Shenoy, Miller, Crawford, & Rao, 2008), neural network (K. Englehart, Hudgins, Parker, & Stevenson, 1999; Kamavuako, et al., 2013), fuzzy logic (Ahmad & Chappell, 2008; Ajiboye & Weir, 2005; Park & Lee, 1998), and Neuro-fuzzy system (Chan, Yang, Lam, Zhang, & Parker, 2000; Karlik, Osman Tokhi, & Alci, 2003). Classifiers should be fast enough to recognize different muscle contraction patterns to actuate the prosthetic device in proper response time. Therefore, sometimes preprocessing and post-processing techniques may be required to speed up the control system too (Oskoei & Hu, 2008).

1.3 Problem Statement

EMG signal is a common input to control upper limb prostheses. Several research teams have recently tried to find the signal features with the best performance for optimizing the control system of the prosthesis (Asghari Oskoei & Hu, 2007; Angkoon Phinyomark, et al., 2012). To increase the accuracy of the EMG signal analysis in the first stage, it is essentially required to preprocess the signal before feature extraction. Normally, huge amount of data is produced after preprocessing which is a limitation of the ECS. As the processing of these data may cause time delay, recruiting efficient methods can compensate the delay and increase the accuracy simultaneously. In the aspect of the controbility in ECS, the accuracy of the system plays an important role. Accordingly, choosing proper techniques in feature extraction can improve the performance of the classifier in terms of accuracy. In this way, the characteristics of EMG pattern are distinguished remarkably in less classification error. Overall, the aim of this study is to improve the ECS through investigating various techniques in EMG signal processing to discriminate different hand postures. In this viewpoint, improving the classification accuracy has been regarded considerably.

1.4 Aims and Objectives

The aim of this thesis is to improve EMG signal processing through the ECS based on pattern recognition for prosthesis application. To achieve this goal, specific objectives are as follows:

- To study and analyse the EMG preprocessing technique based on data segmentation, time domain features and discriminant analysis classifiers.
- To investigate and compare the behaviour of some time and time-frequency techniques in the EMG feature extraction.
- To optimize the performance of the time-frequency features (wavelet coefficients).
- To increase the accuracy of EMG classification by finding proper feature and classifier.

1.5 Scopes of Work

As mentioned in the last sections, ECS is categorized into two types, pattern recognition control system and non-pattern recognition system. Figure 1.1 demonstrates the EMG control system based on pattern recognition.

As can be seen in the Figure 1.1, the data are collected by electrodes in the beginning and then signals are filtered. In the next stage, a controller process the EMG signal which includes four components, data segmentation, feature extraction, classification and digital controller. In this thesis, the analysis of EMG pattern recognition system has been investigated focusing on three modules of this system; data segmentation, feature extraction and classification. In data segmentation, the signal is preprocessed to be ready for feature extraction. This step helps to improve the accuracy and response time of the signal (Asghari Oskoei & Hu, 2007). Afterward, the pre-defined features are extracted for classification. The aim of this step is to find the most suitable features which can represent the characteristics of the EMG signal.

Since the best classifier cannot achieve acceptable results if they are not fed with suitable features, feature extraction plays an important role in the ECS improvement. Hence, some different features are utilized in this study to analyse their performance and find the most efficient one. Ultimately, a classifier recognizes the signal patterns in the last step and classifies it into a specific class.

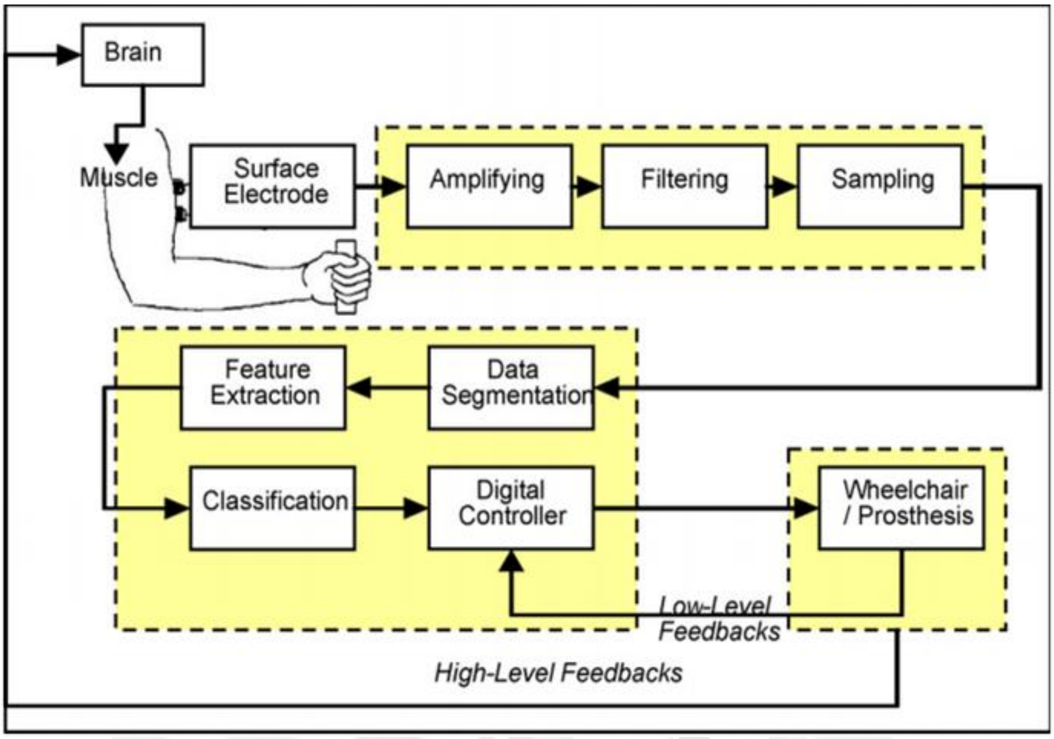

Figure 1.1. The EMG control system based on pattern recognition adopted from (Asghari Oskoei & Hu, 2007)

1.6 Thesis Contribution

The main contributions of this thesis in purpose of mentioned objectives are listed as follows:

- To find the optimum segment size for EMG signal processing.
- To calculate and extract EMG time domain features, namely, MAV, RMS, ZC, WL and use two classifiers to increase the accuracy.
- To calculate and extract EMG time-frequency domain features, (wavelet features) and optimize the wavelet analysis by finding the best mother wavelet and the depth of decomposition through applying 20 mother wavelets.
- To reduce the dimension of wavelet features by utilizing statistical information, MAV and RMS, of the wavelet coefficients as WT+MAV and WT+RMS.

1.7 Thesis Organization

The structure of this study reflects the sequence of improving the EMG signal processing in the pattern recognition based on ECS. The organization of this thesis is as follows:

Chapter 2 reviews some studies and publications on ECS for prosthesis application in the last years and highlights the significant achievements. Also, the theory of wavelet transform has been reviewed as one of the main technique of this research.

Chapter 3 introduces the methodology of this thesis and study the theories of different techniques applied in the proposed ECS. It is worth mentioning that in this chapter, the wavelet transform has been considered as a powerful technique for EMG analysis and multi-features are created from wavelet coefficients. Furthermore, an optimization of wavelet analysis has been done by finding the best mother wavelet between four families and 20 members of these families as wavelet functions. Ultimately, two evaluation criteria for defining the depth of wavelet decomposition are introduced in this chapter.

Chapter 4 describes the results of the proposed algorithm for EMG signal processing and analyses the achievements. The classification procedure of optimum features is evaluated in terms of accuracy and error and the performance of the various features are compared and discussed. In this chapter, the optimum features and classifier are revealed too.

Chapter 5 draws the conclusions from the results and the noteworthy points in each stage of the proposed EMG signal processing algorithm. Lastly, an outline of future work is presented to improve the ECS in other approaches.

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