UNIVERSITI PUTRA MALAYSIA

SURFACE ELECTROMYOGRAPHY CLASSIFICATION OF HAND MOTIONS USING TIME DOMAIN FEATURES FOR REAL TIME APPLICATION

AHMAD AKMAL BIN AHMAD NADZRI

SURFACE ELECTROMYOGRAPHY CLASSIFICATION OF HAND MOTIONS USING TIME DOMAIN FEATURES FOR REAL TIME APPLICATION

By

AHMAD AKMAL BIN AHMAD NADZRI

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

February 2016

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Master of Science

SURFACE ELECTROMYOGRAPHY CLASSIFICATION OF HAND MOTIONS USING TIME DOMAIN FEATURES FOR REAL TIME APPLICATION

By

AHMAD AKMAL BIN AHMAD NADZRI

February 2016

Chair: Siti Anom Ahmad, PhD

Faculty: Engineering

Surface electromyography is a technique of analyzing muscle functions through signals emanating from the physiological variations of muscles states. Through this technique, various applications such as prosthetic hands control have been made for purposes of giving basic functionality for people that are unable to do daily tasks. Many researches have been made over the years to develop the prosthetic hand control system by using the surface electromyography signals through pattern recognition. Recent researches have shown that various method have been able to achieve above 90% accuracy. However, the challenge of developing a control system that is both accurate while being suitable for real time application with less than 300 ms delay still remains. In addition, no literatures have been reported classifying hand motions with stages of contraction despite patterns being observed. The objective of this study is to investigate the accuracy and real time suitability of using time domain features and artificial neural network, to characterize and classify different hand motions and stages of the contraction. To achieve this goal, the signal is first segmented into windows of two sizes, which are 132.5ms and 165 ms, and then full wave rectified. Then the signal is separated into raw and normalized signal. Five time domain features, namely mean absolute value, variance, root mean square, integral absolute value and waveform length were extracted from the segmented windows to characterize three different hand motions of wrist flexion, wrist extension and co-contraction using raw signal and three different stages of contraction of start, middle and end using normalized signal. From the characterization obtained and t-test made, all raw features, waveform length normalized, and the 132.5 ms segmented window size were selected for classification. The features are then used by artificial neural network to be trained offline and evaluated for performance in terms of classification accuracy. Computational times have been recorded to determine real time suitability at all steps. It is determined that during feature extraction stage, the features were able to differentiate hand motions as the mean values were different. However, for stages of contraction, although patterns were

observed, only waveform length features could differentiate the different stages for all three motions. Overall, it is determined that an artificial neural network can be used with time domain features to achieve 98.5% accuracy when differentiating three different hand motions but not with stages of contraction achieving only 80.4% accuracy. Meanwhile, in terms of computational time, although artificial neural network is considered less suitable for real time application, when using time domain features, 245.8 ms delay is achieved which is below 300 ms, thus making it suitable for real time application.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

KLASIFIKASI PERGERAKAN TANGAN OLEH ELEKTROMIOGRAFI PERMUKAAN MENGGUNAKAN CIRI DOMAIN MASA UNTUK APLIKASI MASA NYATA

Oleh

AHMAD AKMAL BIN AHMAD NADZRI

Februari 2016

Pengerusi: Siti Anom Ahmad, PhD

Fakulti: Kejuruteraan

Elektromiografi permukaan adalah teknik menganalisis fungsi otot melalui isyarat dari variasi fisiologi otot. Melalui teknik ini, aplikasi seperti kawalan tangan palsu dibuat bagi memberikan fungsi asas untuk orang yang tidak dapat melakukan tugas harian. Kajian telah dibuat untuk membangunkan sistem kawalan tangan prostetik dengan menggunakan isyarat elektromiografi permukaan melalui pengecaman corak. Penyelidikan beberapa tahun kebelakangan ini menunjukkan beberapa kaedah mampu mencapai lebih 90% ketepatan. Namun, cabaran mencipta sistem kawalan yang tepat dan sesuai untuk aplikasi masa nyata dengan kelengahan kurang daripada 300 ms masih wujud. Tambahan pula, tiada penyelidikan telah dibuat bagi mengenal pasti ketepatan mengklasifikasi pergerakan dan tangan peringkat penguncupan walaupun ciri peringkat penguncupan telah dikenal pasti. Objecktif kajian ini ialah mengkaji ketepatan dan kesesuaian masa nyata dengan menggunakan ciri domain masa dan rangkaian neural buatan untuk mencirikan dan mengklasifikasi pergerakan tangan dan tiga peringkat pengucupan yang berbeza. Bagi mencapai matlamat, signal pada awalnya dibahagikan kepada tingkap yang mempunyai saiz 132.5 ms dan 165 ms dan gelombang penuh direktifikasi. Kemudian, signal dibahagikan kepada signal asal dan signal penormalan. Pada pengekstrakan ciri, lima ciri domain masa iaitu nilai min mutlak, varians , punca min kuasa dua, kamiran nilai mutlak dan panjang gelombang ini diekstrak untuk mencirikan tiga pergerakan tangan menggunakan signal asal dan tiga peringkat pengucupan yang berbeza menggunakan signal pernormalan. Ciri-ciri yang diekstrak kemudiannya digunakan untuk melatih rangkaian neural buatan secara luar talian dan menilai prestasi dari segi ketepatan. Masa pengiraan telah direkodkan untuk menentukan kesesuaian masa nyata pada setiap langkah. Ia ditentukan bahawa semasa peringkat pengekstrakan ciri, pergerakan tangan dapat dibezakan. Namun, bagi peringkat penguncupan, walaupun corak diperhatikan, hanya ciri panjang gelombang dapat membezakan dengan betul peringkat

pengucupan untuk ketiga-tiga pergerakan tangan. Secara keseluruhan, ia ditentukan bahawa rangkaian neural buatan dapat digunakan bersama ciri domain masa untuk mencapai ketepatan melebihi 98.5% apabila membezakan tiga pergerakan tangan namun bukan dengan peringkat pengucupan dengan 80.4% ketepatan. Dari segi masa pengiraan, walaupun rangkaian neural buatan dianggap kurang sesuai untuk kegunaan aplikasi masa nyata, apabila digunakan bersama ciri domain masa kelengahan masa 245.8 ms dicapai iaitu kurang daripada 300 ms maka membuatkan ia sesuai untuk aplikasi masa nyata.

ACKNOWLEDGEMENTS

In the name of Allah, Most Gracious, Most Merciful. First and foremost, I would like to convey my highest appreciation and thanks to Allah S.W.T for giving me the strength and *hidayah* to complete this thesis.

I am grateful to many people for assistance with the preparation of this study. I would like to convey my greatest gratitude to my supervisor, Dr. Siti Anom Ahmad and my co-supervisor Dr. Mohammad Hamiruce Marhaban for their patience, understanding, guidance and inspiration throughout the process of preparing in this thesis.

I would like to express my appreciation to Malaysia Ministry of Science, Technology and Innovation Research for the eScience Fund and also the University Grant Scheme (RUGS) funding.

I would like to thank my mother for her support and understanding.

Finally, thank you to those people who have helped with this thesis preparation but whose name was not mentioned here.

I certify that a Thesis Examination Committee has met on 5 February 2016 to conduct the final examination of Ahmad Akmal bin Ahmad Nadzri on his thesis entitled "Surface Electromyography Classification of Hand Motions using Time Domain Features for Real Time Application" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Master of Science.

Members of the Thesis Examination Committee were as follows:

Nashiren Farzilah Mailah, PhD
Senior Lecturer
Engineering
Universiti Putra Malaysia
(Chairman)

Syamsiah Mashohor, PhD
Lecturer
Engineering
Universiti Putra Malaysia
(Internal Examiner)

Umi Kalthum Ngah, PhD
Associate Professor
Engineering
Universiti Sains Malaysia
Malaysia
(External Examiner)

ZULKARNAIN ZAINAL, PhD
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

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. The members of the Supervisory Committee were as follows:

Siti Anom Ahmad, PhD
Senior Lecturer
Engineering
Universiti Putra Malaysia
(Chairman)

Mohammad Hamiruce Marhaban, PhD
Professor
Engineering
Universiti Putra Malaysia
(Member)

____
BUJANG KIM HUAT, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature: _________________________ Date: ___________________

Name and Matric No.: Ahmad Akmal Bin Ahmad Nadzri (GS35443)

Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

Signature: ______________________
Name of Chairman of Supervisory Committee: Siti Anom Ahmad

Signature: ______________________
Name of Member of Supervisory Committee: Mohammad Hamiruce Marhaban

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Acc	Accuracy
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
CC	Co-Contraction
CCE	Co-contraction End of Contraction
CCM	Co-contraction Middle of Contraction
CCS	Co-contraction Start of Contraction
CCSE	Co-contraction Start and End of Contraction
Class	Classifier
ECR	Extensor Carpi Radialis
EMG	Electromyography
FCU	Flexor Carpi Ulnaris
FD	Frequency Domain
FIS	Fuzzy Inference System
FL	Fuzzy Logic
GMM	Gaussian Mixture Models
GRNN	Generalized Regression Neural Network
I	Size of input layer
IEMG	Integral absolute value
LDA	Linear Discriminant Analysis
LVQ	Linear Vector Quantization
M	Middle
MAV	Mean Absolute Value
MF	Membership Function
MotAcc	Motion Accuracy
MVC	Maximum Voluntary Contraction
NN	Neural Network
Norm	Normalized
O	Size of output layer
RMS	Root Mean Square
SE	Start End
SEMG	Surface Electromyography
SOFM	Self Organizing Feature Map
STD	Standard Deviation
Subj	Subject
SubjAcc	Subject Accuracy
TD	Time Domain
TFR	Time Frequency Domain
TotCorr	Total Correctly Classified Windows
TotDelay	Total Delay time of SEMG system
TotSamp	Total Sample of Windows
VAR	Variance
WE	Wrist Extension
WEE	Wrist Extension End of Contraction
WEM	Wrist Extension Middle of Contraction
WES	Wrist Extension Start of Contraction
WESE	Wrist Extension Start and End of Contraction
WF	Wrist Flexion

WFE	Wrist Flexion End of Contraction
WFS	Wrist Flexion Start of Contraction
WFSE	Wrist Flexion Start and End of Contraction
WL	Waveform Length
WP	Wavelet Packet
WPT	Wavelet Packet Transform

CHAPTER 1

INTRODUCTION

1.1 Overview

The human hand is a complex system where about a quarter of the motor cortex in the human brain; the part of the brain which controls all movement in the body is devoted to the muscles of hand. The human hand and the brain are close partners in important and closely interconnected functions such as interacting with the physical world by touch and manipulation. These include activities such as making tools, writing and playing music. The highly versatile functions of the human hand depend on both its anatomical structure and the neural machinery that supports the hand [1].

Although the human hand is an important tool that allows the human brain to interact with the world, some people are unfortunate as to lose the functionality of the hand through injuries or natural defects that may lead to the amputation of the hand. This leads to people unable to do daily task properly that are considered simple such as to eat and drink and to wash one self. Prostheses aim to replace the missing functionality albeit a prosthetic hand is a pale comparison to the natural hand with its reduced capabilities. The human hand has a large number of degrees of freedom, sensor embedded in its structure and a complex hierarchical control for the prosthetic hand to try to emulate [2].

A prosthetic hand mainly consists of a mechanical system that actuates the movement of the prosthetic hand and a control system that send signals to control the type of motions to the mechanical system. A prosthetic hand controlled by electronic devices is considered externally powered and is where control methods are used. One of the methods to control externally powered prosthetic hand is through Electromyography (EMG) signals sent by electrical signals general when muscles contract during hand motions.

Numerous methods have been developed to control prosthetic hands through EMG. One of the more popular methods is Surface Electromyography (SEMG) due to its non-invasiveness. SEMG signal analysis has received wide interest especially in biomedical applications and clinical diagnosis in fields such as rehabilitation of motor disability. SEMG signals can provide important information for prosthetic hand control and possibly detect neuromuscular disorders for amputees [3].

A prosthetic basic function is to be able to output the correct hand motion intended by the user, using the SEMG signal generated. As classification accuracy is of importance, it plays a major role that will most probably decide whether users are happy with the SEMG system according to the classification rate with decent computational time. Thus extensive research has been done to find efficient methods.

To classify a hand motion, SEMG signal analysis normally goes through pre-processing, feature extraction and classification steps. Features need to be carefully selected in order to provide useful information for classification. Feature extraction can be divided into 4 major groups which are time domain (TD), frequency domain (FD), time frequency (TFR) and time scale representation [4]. Time domain features are generally easy to implement and calculate efficiently thus making it suitable for real time feature extraction. Feature extraction-based on TD methods show a good performance than feature extraction for SEMG pattern classification under various conditions [5-7].

In addition to classifying hand motions, there is a possibility to determine the stages of contraction during those hand motions using the features extracted. It was determined in [8] that when the subject's maximum voluntary contraction was controlled, actual motion do not occur during start and end of contraction where the same type of fluctuation occurs. Ideally, control of a prosthetic hand should occur during the middle of contraction and being able to determine stages of contraction will lead to optimal control of actual hand motion more accurate to the user's intent.

The features are used by a classifier to classify the different hand motions. Therefore, like selecting features to be used, selecting a suitable classifier is also of importance. In recent years, there were many literatures using ANN have reported an average classification accuracy of above 90%. Researches done in [9 - 21] were able to develop classifiers with above 90% accuracy. Some of the more popular classifiers were Fuzzy Logic (FL) systems and Artificial Neural Network (ANN).

1.2 Problem Statement

Based on recent studies, it is important for an SEMG control system to be able to achieve above 90% accuracy while being within the acceptable 300 ms delay [22]. Despite this, not many literatures mention the total time taken to classify the hand motion. This is especially true for studies involving widely used methods such as FD, TFR, and ANN, with more specific details at the steps of pre-processing, feature extraction and classification if it were to be implemented for real time application. Some methods sacrifice computational time for classification accuracy. There were no acceptable reported times for FD, TFR features [7]. An alternative to FD and TFR is TD features which are less computational have been reported to have comparable performance to FD features [5, 6]. Meanwhile, although ANN classifiers have produced rather good results in accuracy, the fastest ANN classifier was reported in [9], a grasp classifier using spectral moments with 97.5% accuracy at 378 ms for 4 grasps. Thus, in this study, classification accuracy and computational time are tested using time domain features and ANN to find whether the cause of the delay is the computational heavy features of FD, TFR used in other studies or the ANN itself.

At feature extraction step, time domain features were determined to be most efficient as mentioned in [4-6]. Characterization of time domain features is needed to differentiate different hand motions. However there were not many studies that use only time domain features for feature extraction. To achieve ideal control, stages of contraction should be recognized for classification. Despite the characteristics of stages of contraction determined in [8], there have been no literature reported studied in a non MVC controlled environment and that uses the characteristic for classification. MVC is where signal quality is controlled where that the signal from each subject is amplified in order to exceed a certain threshold criteria. In this type of study the focus is mainly on method comparison at the feature extraction and classification step. Meanwhile, in a non MVC controlled environment signal is not amplified and is analyzed as it is without the subjects SEMG signal having to meet a certain threshold criteria. As the objective of this study requires characterizing the different hand motion and stages of contraction, it focuses more on the signal analysis without any modification to the signal rather than method comparison at the feature extraction and classification step. Previous literature [8] only reported the characteristic of only one hand motion of CC. However, since the motion can be obtained by observing two SEMG channels, the minimum amount of motion that can be studied should be three as observed in [5]. The importance of identifying the different stages of contraction is the ability to identify when actual motion occurs or does not occur according to the stages of contraction. It is important to see whether a certain segmented size could differentiate the stages of contraction when it is modified using MVC. This will help improve user experience with more accurate classification of when the motion should occur.

1.3 Aim and Objectives

The aim of this study is to classify 3 different hand motions and stages of contraction from SEMG signal in order to achieve ideal control using time domain features and ANN while determining real time suitability. To obtain that aim, several objectives are to be attained:

(1) To study the characteristic of SEMG signal to differentiate hand motions and stages of contraction
(2) To design and implement a classifier for classifying both different hand motions and stages of contraction.

(3) To evaluate the performance in terms of classification accuracy and total time delay.

1.4 Scope of work

Although one of the objectives of this study is to research on the computational time of the proposed method, this research is done mainly by simulation and offline, as the SEMG data has already been acquired. The data set[23] used has three different hand motions and stages to contraction to concentrate on whether the stages of contraction can be differentiated for the different hand motions since in previous reported literature only 1 hand motion were studied for stages of contraction. Only two channels are used in this study as only the two channel of FCU and ECR are considered needed to be able to differentiate the 3 different hand motions. There are 3 hand motions studies in this study, and because the two SEMG are used it should at least be able to differentiate the 3 different hand motions chosen in this study. The time domain features were selected based on recommendations from other literatures.

The computational times were recorded at pre-processing, feature extraction and classification steps. For feature extraction, only time domain features were used as it is determined to be most efficient. At classification step, a fixed structure of the ANN is used so that a comparison can be made with other studies and to determine whether the number inputs will effect computation time when the amount of hidden neurons remain the same.

1.5 Thesis Layout

Chapter 1 describes some brief information of background and overview of research in the field that led to this project. It explains the aims and objectives of this study, where the main objective is to classify different hand motions and stages of contraction, as well as to evaluate the performance of the ANN in terms of classification accuracy and total delay time when using time domain features.

Chapter 2 reviews the types of prosthetic hand and the control system available for the prosthetic hand. It introduces basic concepts of SEMG signal and reviews the methods available for the SEMG signal analysis steps of pre-processing, feature extraction and classification of researches done, while discussing real time suitability.

Chapter 3 explains the methodology of this research for the SEMG signal analysis steps, in terms of the characterization of time domain features for hand motion and stages of contraction. Classification accuracy was tested by classifying only hand motions, and classifying both hand motions and stages of contraction. Computational times were recorded at each step of the pattern recognition based system.

Chapter 4 presents the result obtained from the methodology used. It shows the pattern observed for the different motions and stages of contraction. The classification accuracy and computational time were compared and the performances in this study were compared with other studies.

Chapter 5 will conclude the findings inferred from the results, with significant points at the steps of feature extraction and classification in terms of accuracy and total delay. Lastly, it discusses possible future works to find ways to improve classification accuracy while being suitable for real time application.

REFERENCES

[1] J. Randall Flanagan, and S. Roland Johansson, "Hand movements," *Encyclopedia of the human brain*, vol. 2, pp. 399-414, 2002.

[2] M. Zecca, S. Micera, M. C. Carroza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic Signal," Critical Review Biomedical Engineering, vol. 30, pp. 459-485, 2002.

[3] K. Peter," The ABC of EMG- A practical introduction to kinesiological electromyography," Noraxon Inc. USA, 2005.

[4] A. Phinyomark, P. Phukpattaranont and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications*, vol. 39, pp. 7420–7431, 2012.

[5] A. Phinyomark, P. Phukpattaranont and C. Limsakul, "Investigating long term effects of feature extraction methods for continuous EMG pattern classification," *Fluctuation and Noise Letters*, vol. 11, p. 1250028, 2012.

[6] D. Joshi, K. Kandpal and S. Anand, "Feature evaluation to reduce false triggering in threshold based EMG prosthetic hand," *Proceedings on Biomedical*, 2008, pp. 769–772.

[7] R. Boostani and M. H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand," Physiological Measurement, vol. 24, pp. 309-319, 2003.

[8] P. Romaiguere, J. Vedel, and S. Pagni, "Comparison of fluctuations of motor unit recruitment and de-recruitment thresholds in man," *Experimental Brain Research*, vol. 95, 517-522, 1993.

[9] J. Christopher Miller, "Real-Time feature extraction and classification of prehensile EMG signals," M.S. Thesis, San Diego State University, 2008.

[10] Z. Jingdong, "A five-fingered underactuated prosthetic hand control scheme," *International Conference on Biomedical Robotics and Biomechatronics*, 2006, pp. 995-1000.

[11] U. Baspinar, H. S. Varol and K. Yildiz, "Classification of hand movements by using artificial neural network," *International Symposium on Innovations in Intelligent Systems and Applications,* 2012, pp. 1-4.

[12] M. Leon, L. Leija and R. Munoz, "System for the identification of multiple movements of the hand," *International Conference on Electrical and Electronics Engineering*, 2006, pp.1-3.

[13] K. Ito, M. Tsukamoto and T. Kondo, "Discrimination of intended movements based on nonstationary EMG for a prosthetic hand control," *International Symposium on Communications*, 2008, pp. 14-19.

[14] Z. Liu and Z. Luo, "Hand motion pattern classifier based on EMG using wavelet packet transform and LVQ neural networks," *International Symposium on Information Technology in Medicine and Education*, 2008, 28–32.

[15] M. Arvetti, G. Gini, and M. Folgheraiter, "Classification of EMG signals through wavelet analysis and neural networks for controlling an active hand prosthesis," *IEEE International Conference on Rehabilitation Robotics*, 2007, pp. 531–536.

[16] J. Chu, I. Moon and M. Mun, “A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand,” *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 2232-2238, 2006.

[17] M. Khezri and M. Jahed, “A neuro-fuzzy inference system for SEMG based identification of hand motion commands,” *IEEE Transactions on Industrial Electronics*, vol. 58, pp. 1952-1960, 2011.

[18] W. Gabriela Favieiro and B. Alexandre, "Adaptive neuro-fuzzy logic analysis based on myoelectric signals for multifunction prosthesis control," *IEEE International Conference on Engineering in Medicine and Biology Society*, pp. 7888-7891, 2011.

[19] A. Ajiboye and R. Weir, "A heuristic fuzzy logic approach to EMG pattern recognition for multifunction prosthesis control," *IEEE Transactions on Biomedical Engineering*, vol. 52, pp. 280-291, 2005.

[20] L. Yang , T. Yantao and C. Wanzhong, "SEMG pattern recognition based on GRNN and adaboost," *International Conference on Electronics, Communications and Control*, 2011, pp. 1661-1664.

[21] H. Yonghong, K. Englehart, B. Hudgins and A. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Transactions on Biomedical Engineering*, vol. 52, pp. 1801-1811, 2005.

[22] T. R. Farrell and R. F. Weir, "The optimal controller delay for myoelectric prostheses," *IEEE Transactions Neural System Rehabilitation Engineering*, vol. 15, pp. 111–118, 2007.

[23] A. Siti Anom, "Moving approximate entropy and its application to the electromyographic control of an artifcial hand," Ph.D dissertation, University of Southampton, 2009.

[24] 10 rehabilitation options for patients with missing arm and/or hand. N.d. Retreived 21 April 2014 from http://researchonmedical.com/.

[25] Muzumdar and Ashok, “Powered Upper Limb Prostheses: Control, Implementation and Clinical Application,” Springer, 2004.

[26] N.d. (2014, 21 April). *Upper limb prosthetics; externally powered* [Online]. Available: http://www.upperlimbprosthetics.info/

[27] M. Asghari Oskoei and H. Hu, “ Myoelectric control systems - A survey,” *Biomedical Signal Processing and Control*, vol. 2, pp. 275-294, 2007.

[28] P. Kaufmann, K. Englehart and M. Platzner, "Fluctuating EMG signals: investigating long-term effects of pattern matching algorithms," *International Conference IEEE Engineering in Medicine and Biology Society*, 2010, pp. 6357–6360.

[29] J. V. Basmajian and C. J. De Luca, "Muscles alive: their function revealed by electromyography," William and Wilkins, 1985.

[30] K. Saladin, “Human Anatomy,” McGraw-Hill, 2007.

[31] D. G. Sale, “Neural adaptation to strength training,” *Strength and Power in Sport,* Second Edition, pp. 281-314, 2003.

[32] C. J. De Luca, “Physiology and mathematics of myoelectric signals,” *IEEE Transactions on Biomedical Engineering*(6), 1979, pp. 313-325.

[33] Z. Jingdong, X. Zongwu, J. Li, C. Hegao, L. Hong, and H. Gerd, “A five fingered underactuated prosthetic hand control scheme,” *IEEE International Conference on Biomedical Robotics and Biomechatronics*, 2006, pp. 995-1000.

[34] J. S. Ryan, T. Francesco, H. David, and E. Ralph, “Continuous decoding of finger position from surface EMG signals for the control of powered prostheses,” *IEEE EMBS Conference*, 2008, pp. 197-200.

[35] A. Siti Anom, J. I. Asnor, and A. Sawal, “Classification of surface electromyographic signal using fuzzy logic for prosthesis control application,” *IEEE Conference on Biomedical Engineering & Sciences*, 2010, pp. 471-474.

[36] V. L. Minas, K. A. Panagiotis, T. K. Pantelis, J. K. Kostas, “Learning task-specific models for reach to grasp movements: towards EMG-based teleoperation of robotic arm-hand systems,” *IEEE International Conference on Biomedical Robotics and Biomechatronics*, 2012, pp. 1287-1292.

[37] A. Md Rezanul, I. Muhammad Ibn, and O. K. Othman, “Electromygraphy (EMG) signal based hand gesture recognition using artificial neural network (ANN),” *International Conference on Mechatronics*, 2011, pp. 1-6.

[38] K. J. Kyung, W. K. Joo, K. L. Hyun, and B. C. Sung, “EMG pattern classification using spectral estimation and neural network,” *Conference SICE*, 2007, pp.1108-1111.

[39] Y. Bo, W. Huanling, and H. Ling, “The system of SEMG recognition for prosthetic hand control,” *International Forum on Strategic Technology Proceedings*, 2010, pp. 1-6.

[40] S. Friedhelm, L. Nicholas, “Motor unit recruitment in EMG definition of motor unit recruitment and overview,” *Medscape Reference, Diseases and Procedures*, pp. 1-6, 2014.

[41] J. L. Dideriksen, S. Muceli, S. Dosen, C. M. Laine, D. Farina, “Physiological recruitment of motor units by high-frequency electrical stimulation of afferent pathways,” *Journal of Applied Physiology(1985)*, vol. 118, pp 365-76, 2015.

[42] L. L. Pan, C. H. Yu, M. W. Tsai, S. H. Wei, L. W. Chou, “Estimating the tendency of motor unit recruitment during steady-hold and rapid contractions using surface EMG and Turns-amplitude analysis,” *European Journal of Applied Physiology,* vol. 115, pp. 2407-2414, 2015

[43] G. Boccia, D. Dardanello, V. Rosso, L. Pizzigalli, A. Rainoldi, “The application of SEMG in aging: a mini review,” *Journal of Gerontology*, vol. 61, pp. 477-484, 2015.

[44] C. J. D. Luca, S. S. Chang, S. H. Roy, J. C. Kline, S. H. Nawab, “Decomposition of surface EMG signals from cyclic dynamic contractions,” *Journal of Neurophysiology,* vol 113, pp. 1941–1951, 2015.

[45] K. Englehart and B. Hudgins, “A robust, real-time control scheme for multifunction myoelectric control,” *IEEE Transactions on Biomedical Engineering*, vol. 50, pp. 848-854, 2003.

[46] D. Farina and R. Merletti, “Comparison of algorithms for estimation of EMG variables during voluntary isometric contractions,” *Journal of Electromyography and Kinesiology*, vol. 10, pp. 337-349, 2000.

[47] D. A. Winter, "Biomechanics and motor control of human movement," John Wiley and Sons, 1990.

[48] *FFT window function* (n.d.) [Online]. Available: http://www.bores.com/

[49] M. Halaki, K. Ginn, “Computational Intelligence in Electromyography Analysis - A Perspective on Current Applications and Future Challenges,” INTECH publishing, October 2012.
[50] X. Chen, P. Xie , H. Liu , Y. Song, Y. Du, “Local band spectral entropy based on wavelet packet applied to surface EMG signals analysis,” *Journal of Entropy*, vol. 18, pp. 1-11, 2016.
[51] N. A. Kamaruddin, P. I. Khalid, A. Z. Shaameri, “The use of surface electromyography in muscle fatigue assessments–a review,” *Jurnal Teknologi*, vol. 74, pp. 1-5, 2015.
[52] M. Atzori, A. Gijsberts, I. Kuzborskij, S. Elsig, A. M. Hager, O. Deriaz, C. Castellini, H. Müller, B. Caputo, “Characterization of a Benchmark Database for Myoelectric Movement Classification,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, pp. 73-83, 2015.
[53] R. Raj and K. S. Sivanandan, “Estimation of elbow joint angle from time domain features of SEMG signals using Fuzzy Logic for prosthtic control,” *International Journal of Current Engineering and Technology*, vol. 5, pp. 2078-2081, 2015.
[54] M. Misiti, Y. Misiti, G. Oppenheim and J. Poggi,”Wavelet toolbox," *The MathWorks Inc.*,1996.
[55] R. Raul, “Neural network: a systematic introduction,” Springer, 1996.
[56] J. Timothy Ross, "Fuzzy logic with engineering applications," Wiley, 2004.
[57] S. N. Sivanandam, S. Sumathi and S. N. Deepa, "Introduction to fuzzy logic using MATLAB," Springer, 2007.
[58] M. Hakonena, H. Piitulainenb, A. Visalaa, “Current state of digital signal processing in myoelectric interfaces and related applications,” *Journal of Biomedical Signal Processing and Control*, vol. 18, pp. 334-359, 2015.
[59] S. Guo, M. Pang, B. Gao, H. Hirata, H. Ishihara, “Comparison of SEMG- based feature extraction and motion classification methods for upper-limb movement,” Journal of Sensors vol. 15, pp. 9022-9038, 2015.
[60] M. Khezri and M. Jahed, “A novel approach to recognize hand movements via SEMG patterns,” *IEEE International Conference in Engineering in Medicine and Biology Society*, 2007, pp. 4907-4910.
[61] N. S. Rekhi, H. Singh, A. S. Arora, A. K. Rekhi, “Analysis of EMG signal using wavelet coefficients for upper limb function,” *IEEE International Conference on Computer Science and Information Technology*, 2009, pp. 357-361.
[62] G. Shuang, Y. Yong, M. Carsten, L. Beisheng, and W. Chengdong, “Classification of multi-channels SEMG signals using wavelet and neural networks on assistive Robot,” *IEEE International Conference on Industrial Informatics*, 2012, pp. 1158-1163.
[63] S. Shuo, L. Jia, Y. Ming, X. Guixiang, “SEMG Signal Recognition Based on Wavelet Transform and SOFM Neural Network,” *International Conference on Intelligent Networks and Intelligent Systems*, 2009, pp. 312-315.
[64] J. M. Gutierrez, and R. Munoz “Wavelet neural network as EMG classifier,” *Pan America Health Care Exchanges*, 2011, pp. 67-71.

[65] Y. Rie, U. Junichi, T. Yutaka, and M. Yoshihisa, “Decomposition of electromyographic signal by principal component analysis of wavelet coeeficcients,” *IEEE Asian-Pacific Conference on Biomedical Engineering*, 2003, pp. 118-119.

[66] A. Phinyomark, A. Nuidod, P. Phukpattaranont and C. Limsakul, “Feature extraction and reduction of wavelet transform coefficients for EMG Pattern classification,” *Electronics and Electrical Engineering*, vol. 122, pp. 27-32, 2012.

[67] N. K. Rami, A. Adel, A. Ahmed, “Novel feature extraction method based on fuzzy entropy and wavelet packet transform for myoelectric control,” *International Symposium on Communications and Information Technologies*, 2007, pp. 352-357.

[68] D. F. Fernando, C. P. Julio, and J. F. Carmelo, “Evaluation of EMG processing techniques using information theory,” *Biomedical Engineering Online*, vol. 9, 2010.

[69] Snedecor, W. George, Cochran, G. William, “Statistical Methods,” Iowa State University Press, 1989.

[70] *Muscles of the forearm* (n.d.) [Online]. Available: http://profgannon.wikispaces.com/

[71] S. Karsoliya, “Approximating number of hidden layer neurons in multiple hidden layer BPNN architecture,” *International Journal of Engineering and Trends and Technology*, vol. 6, pp 714-717, 2012.

[72] M.T. Hagan, H. B. Demuth, M. H. Beale, “Neural Network Design,” PWS Publishing, 1996.

[73] I. Guyon, A. Elisseeff, “An introduction to variable and feature selection,” *Journal of Machine Learning Research*, vol. 3, pp. 1157-1182, 2003.

[74] P. Refaeilzadeh , L. Tang and H. Liu, “Cross-Validation,” Springer, 2009.

[75] M. B. I. Reaz, M. S. Hussain and F. Mohd-Yasin, "Techniques of EMG signal analysis: detection, processing, classification and applications," *Biological Procedures Online*, vol. 8, pp. 11-35, 2006

[76] L. Lukai, L. Pu, A. Edward Clancy, S. Erik and B. Englehart, "Signal whitening preprocessing for improved classification accuracies in myoelectric control," *IEEE Northeast Bioengineering Conference*, 2011, pp. 1-2.

[77] P. Punit, A. S. Christian, A. T. John, RB. Donald, and A. C. Edward, “Adaptive whitening in electromyogram amplitude estimation for epoch-based applications,” *IEEE Transactions on Biomedical Engineering*, vol. 52, pp. 331-334, 2005.