UNIVERSITI PUTRA MALAYSIA

CLASSIFICATION OF ANKLE JOINT MOVEMENTS BASED ON SURFACE ELECTROMYOGRAPHY SIGNALS

MAGED SALEH SAEED AL-QURAISHI

FK 2015 23

CLASSIFICATION OF ANKLE JOINT MOVEMENTS BASED ON SURFACE ELECTROMYOGRAPHY SIGNALS

By

MAGED SALEH SAEED AL-QURAISHI

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

August 2015

DEDICATION

I dedicate my dissertation work to my home (Yemen) and Thamar University for supporting me during this research.

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

CLASSIFICATION OF ANKLE JOINT MOVEMENTS BASED ON SURFACE ELECTROMYOGRAPHY SIGNALS

By

MAGED SALEH SAEED AL-QURAISHI

August 2015

Chairman : Asnor Juraiza Bt. Ishak, PhD
Faculty : Engineering

Electromyography (EMG) signal has valuable information about the force of the muscle contraction and the movement direction. This crucial information has been used for many years in exoskeleton, orthoses and prostheses robots. An essential part of those devices is EMG based control system that employs the EMG signal from different muscles to control prostheses and exoskeleton robot. However, using EMG signal as an input control signal for those devices is not easy due to the complexity nature of this signal that produces the different body movements. This difficulty can be overcome by using pattern recognition techniques to discriminant different limb movement's pattern then use the classified signal as input control signal to manipulate and drive the assistive robot devices. Though much research have been carried out to classify the upper and lower limbs movement based on the EMG signal, still there is a strong need to obtain an accurate pattern classification system in computationally efficient manner.

In this work two parts are primarily presented. The first partt was design and implements a multichannel EMG acquisition system to detect and acquire the leg muscles' signal. In this part four EMG channels were implemented using instrumentation amplifier (INA114) for pre-amplification stage then the amplified signal was filtered using band pass filter to eliminate the unwanted signals. Operational amplifier (OPA2604) was involved for the main amplification stage to get the output signal in volts. The EMG signals were detected during movement of the ankle joint of a healthy subjects. Then the signal sampled at rate of 2 kHz using NI 6009 DAQ card and LabVIEW software was employed to store and display the acquired signal. Fast Fourier Transform (FFT) and Signal to Noise Ratio (SNR) were applied to assess the recoded electromyography signal.

The second part is to classify four ankle joint movements which are dorsiflexion, plantar flexion, adduction and abduction. The data was collected from twenty healthy subjects using the custom multichannel EMG acquisition system designed in the first part of this project. In this section, new time domain feature set was evaluated and compared with well known time domain features. Three classifiers were employed to evaluate the two feature sets. These classifiers are linear discriminant Analysis (LDA), K

nearest neighbourhood (*k*-NN) and Naïve Bayes classifier (NB). The result showed the superiority of the new time domain feature set which are the logarithmic based time domain features upon the conventional time domain feature. In addition, the results show the outperformance of LDA classifier among the other two classifiers used in this study.

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

KELASIFIKASI PERGERAKAN BUKU LALI BERDASARKAN PERMUKAAN ISYARAT ELEKTROMIOGRAFI

Oleh

MAGED SALEH SAEED AL-QURAISHI

Ogos 2015

Pengerusi : Asnor Juraiza Bt. Ishak, PhD
Fakulti : Kejuruteraan

Isyarat Elektromiografi mengandungi maklumat-maklumat penting tentang daya pengecutan dan arah gerakan otot. Maklumat-maklumat penting ini telah digunakan selama bertahun-tahun pada eksorangka, ortosis lutut-buku lali-kaki dan prostesis robot. Salah satu bahagian penting dalam sistem kawalan berdasarkan isyarat Elektromiografi adalah penggunaan isyarat EMG dari otot yang berbeza untuk mengawal prostesis dan eksorangka robot. Walau bagaimanpun untuk mereka peranti dengan menggunakan isyarat Elektromiografi sebagai input adalah tidak mudah kerana sifat isyarat ini yang rumit hasil daripada kepelbagaian pergerakan badan. Masalah ini boleh diatasi dengan menggunakan teknik pengecaman corak untuk mengelaskan corak pergerakan anggota badan yang berbeza yang kemudiannya digunakan sebagai isyarat kawalan input untuk memanipulasi dan memacu peranti robot bantuan. Walaupun banyak kajian telah dijalankan untuk mengklasifikasikan pergerakan anggota badan atas dan bawah berdasarkan isyarat Elektromiografi, masih terdapat keperluan yang kuat untuk mendapatkan satu sistem pengkelasan corak tepat dengan pengiraan yang cekap.

Dalam hasil kerja ini dua bahagain utaman dibentangkan. Bahagain pertama adalah mereka bentuk dan melaksanakan sistem perolehan Elektromiografi pelbagai saluran untuk mengesan dan memperoleh isyarat otot kaki. Pada bahagian ini, empat saluran Elektromiografi telah diperolehi pada peringkat pra-penguatan menggunakan peralatan penguat (INA114). Isyarat yang dikuatkan akan ditapis menggunakan Penapis Lulus Jalur untuk menghapuskan isyarat yang tidak diingini. Penguat Kendalian (OPA2604) telah digunakan pada peringkat penguatan utama untuk mendapatkan isyarat keluaran dalam volt. Isyarat EMG telah dikesan semasa pergerakan sendi pergelangan kaki subjek yang sihat. Kemudian isyarat disampel pada kadar 2 kHz menggunakan kad DAQ (NI 6009) dan perisian LabVIEW telah digunakan untuk menyimpan dan memaparkan isyarat yang diperolehi. Jelmaan Fourier Pantas dan nisbah isyarat kepada hingar telah digunakan untuk menilai isyarat Elektromiografi yang direkodkan.

Bahagain kedua adalah untuk mengklasifikasikan empat pergerakan buku lali iaitu pendorsifleksan, flexi plantar, aduksi dan pemelarian. Data diperolehi daripada dua puluh orang subjek yang sihat menggunakan sistem pemerolehan EMG yang direka dalam bahagian pertama projek ini. Dalam seksyen ini, ciri baru domain masa dinilai

dan dibandingkan dengan ciri domain masa yang terserlah. Tiga Pengelas telah digunakan untuk menilai kedua-dua set ciri. Pengelas ini adalah Analisis Diskriminan Linear (LDA), K Kejiranan Terdekat (k-NN) dan Pengelas Naif Bayes (NB). Keputusan menunjukkan set ciri baru domain masa yang berasaskan logaritma, lebih unggul berbanding ciri domain masa yang konvensional. Tambahan pula, keputusan menunjukkan prestasi cemerlang pengelas LDA berbanding dua pengelas lain yang digunakan dalam kajian ini.

ACKNOWLEDGEMENTS

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

All praise and thanks are due to Allah, and peace and blessings be upon His Messenger. During the preparation of this thesis I have became indebted to many people for their patience, advice, and support. To all of them I owe very special thanks, and especially to my supervisor Dr. Asnor Juraiza Bt. Ishak would like to thank my co-supervisors: Dr. Siti Anom Bt. Ahmad and Dr. Mohd Khair Hasan, for their stimulating conversations, intriguing ideas and suggestions. I would like to thank Miss. Aini Fuzani for collecting EMG data from female participants.

I express my gratitude to my parents, wife, my daughters, my son, and to my family at my beloved city Thamar - Yemen for their patience and support.

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:

Asnor Juraiza Bt. Ishak, PhD
Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Siti Anom Bt. Ahmad, PhD
Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Member)

Moh Khair Hasan, PhD
Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Member)

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

Date:

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

WHO	World Health Organization
DoFs	Degree of Freedom
BLEEX	Brekeley Lower Extremity Exoskeleton
HAL	Hybrid Assistive Leg
FRF	Floor Reaction Force
sEMG	Surface Electromyography
CNS	Central Nervous System
PNS	Peripheral Nervous System
MU	Motor Unit
MUAP	Motor Unit Action Potential
iEMG	intramuscular Electromyography
ECG	Electrocardiogram
CMRR	Common Mode Rejection Ratio
TD	Time Domain
FD	Frequency Domain
TFD	Time-Frequency Domain
MAV	Mean Absolute Value
MAVS	Mean Absolute Value Slop
ZC	Zero Crossing
SSC	Slop Sign Change
WL	Waveform Length
VAR	Variance
CC	Cepstrum Coefficients
AR	Autoregressive
WAMP	Willison Amplitude
RMS	Root Mean Square
IEMG	Integrated EMG
LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
ANN	Artificial Neural Network
DASDV	Difference Absolute Standard Deviation Value
IAV	Integrated Absolute value
SSI	Simple Square Integral
MMAV	Modified Mean Absolute Value
DAMV	Difference Absolute Mean Value
TM	Absolute Value of Temporal Moment
LOG	Log Detector
AAC	Average Amplitude Change

SDV	Standard Deviation Value
MFL	Maximum Fractal Length
MYOP	Myopulse percentage rate
M2	Second Order Moment
PSD	Power Spectral Density
FFT	Fast Fourier Transform
STFT	Short Time Fourier Transform
WT	Wavelet Transform
DWT	Discreet Wavelet Transform
WPT	Wavelet Packet Transform
CWT	Continuous Wavelet Transformation
ED	Euclidean Distance
RES	Ratio of Euclidean distance to Standard deviation
SFS	Subset Forward Selection
ACO	ant colony optimization
PSO	particle swarm optimization
mRMR	Minimum Redundancy Maximum Relevance criterion
BPSO	Binary PSO
MI	Mutual Information
PCA	Principal Component Analysis
SOFM	self-organizing feature map
MCA	Mutual Component Analysis
FLD	Fuzzy Linear Discriminant
OFNDA	Orthogonal Fuzzy Neighborhood Discriminant Analysis
k-NN	k Nearest Neighborhood
MLP	Multilayer Perceptron
BP	Backpropagation
RBF	Radial basis function
NBC	Naive-Bayes Classifier
QDA	Quadratic Discriminant Analysis
MKL	Multiple Kernels Learning
LS_SVM	Least Squares Support Vector Machine
LIBSVM	Library of SVM
DF	Dorsiflexion
PF	Plantar Flexion
AD	Adduction
AB	Abduction
DAQ	Data Acquisition
DRL	Driven Right Leg
HPF	High Pass Filter
LPF	Low Pass Filter

GUI	Graphic User Interface
PCB	Printed Circuit Board
AI	Analog Input
labVIEW	laboratory Virtual Instrument Engineering Workbench
TA	Tebailis Anterior muscle
PL	Peroneus Longus muscle
GL	Gastrocnemius Lateralis muscle
GM	Gastrocnemius Medailis
SNR	Signal to Noise Ratio
SENIAM	Surface Electromyography for the Non-Invasive Assessment of Mus-
TTD	Traditional Time Domain features
LTD	Logarithmic based Time Domain features

CHAPTER 1

INTRODUCTION

According to the World Health Organization (WHO), elderly people at the least 65 years of age will raise in number by 88% in the next few years. Since there is an increasing population of senior citizen, there is also a rise in the incident of age-related diseases and disorders. These age relevant diseases and disorders include cerebral vascular accident (stroke), spinal cord injury, cerebral palsy, Parkinson's disease and multiple sclerosis [1]. As a result, theses chronic diseases and accident affect the senior people's aptitude to carry out their activities of daily living. For instance, skeletal muscles of stroke patient become weak, not used and tend to shorten as a result the joint become stiff [2].Consequently, the patient may lose their abilities to move and interact. Therefore, as the number of the population of the people suffering from these diseases and disorders increase, the demand for providing solutions for recovery and therapy also increase.

It has been shown that the rehabilitation training has a great impact on neurological recovery of limb function [1]. Traditionally, this job can be performed by the therapist manually in rehabilitation centres or hospitals. Recently, researchers put a lot of efforts to develop assistance devices to assist in rehabilitation process of the defected part of the body in both upper and lower limb. The realm of rehabilitation robotics involves the using of robotic technology and mechatronics to assist disabled people with the tools required to provide a better quality of life [1]. In addition, those devices provide an assistance to minimize the therapist repetitive, work restore mobility and reduce the recovery time [2].

In the last decade, exoskeleton robotics (wearable robots) devices have been developed as practical complementary systems to therapists to handle the defect joint or limb. The term exoskeleton is refer to a mechanical wearable device designed to mimics the body parts such as ankle joint part when it worn it transfers the torque produced by the actuators to the body [3]. Exoskeleton robot can efficiently incorporate the cognitive ability of human being and the benefit of robotic techniques to assist the users to carry out their needed activities. These devices were developed in full-limb exoskeleton i.e. for upper and lower limbs exoskeleton, upper limb exoskeleton and the other exoskeletons robots have been designed to support the shoulder, elbow, wrist and ankle joint.

Ankle joint exoskeleton robot is one of these devices used in different aspects such as power assist, rehabilitations and motion assist purposes. Choosing of the ankle joint in the research is due to the significant mechanical work that the ankle joint carried out during the stance of human walking [4].

Exoskeleton robot can be controlled by different control strategies. Those techniques can be classified according to the human-robot interaction method; the signals measured from the exoskeleton, the interaction force signal measured between the human and the exoskeleton and the signal measured from the human body [5]. First technique the control algorithm is able to predict or follow the user's intention according to the information obtained from the exoskeletons [6]. The second control strategy, the control algorithm designed according to the interaction force measured through the deformation of an elastic transmission element or structure placed at the exoskeleton robot link [7]. The third type of human-robot interaction is developed according to the biosignals measured from the human body that indicate the user motion intention. Thus, the motion intention can be completely estimated without data lose and delay, in compare to other approaches [8]. The biosignal that usually used in this field is the surface electromyography (sEMG) [9-12]. Based on this signal, corresponding control strategies have also been developed to assist the users to ensure daily living activities and rehabilitation exercises.

EMG based control becomes the core of the prostheses, orthoses and exoskeleton devices in the recent research. However, utilizing EMG as a control input signal to derive those devices is difficult due to several reasons; getting the same EMG signal for the same motion is not easy even with the same person, each person has own muscle activity level and different pattern for using their muscle for specific motion, and more than one muscle are involved in one joint's movement such as ankle joint movements. In addition, there is no one muscle responsible for certain motion [3]. Most of the aforementioned difficulties can be overcome by using pattern recognition techniques to classify different movement's pattern then use the classified signal as input control signal to manipulate and drive the rehabilitation or exoskeleton devices. Therefore, key point of EMG based control system is a pattern classification process.

1.1 Problem Statement

The most significant part in the pattern classification is the features extraction process [13]. An extensive amount of research has been done in this field resulting in a wide range of features for representing the EMG signal for the myoelectric control. Although patterns were successfully classified on intact subjects, these methods lack in the term of the complexity and processing time. Consequently, implement this methods in real time will be more complicated. Therefore, the need to determine an accurate pattern-recognition system that is easy to implement and operates under low computational load remains. Thus, many factors should take in consideration during these processes; maximum class separability, robustness and the computational complexity. A good feature space is one that outcomes in clusters which have maximum class separability or lowest overlap. Furthermore, the computational complexity should be kept low in a way that the relevant process can be applied with affordable hardware and in real time [13].

1.2 Thesis objectives:

The main goal of this project is to develop an accurate, ease to implement and low computational load pattern recognition based on multichannel sEMG signal to classify four ankle joint movements. The specific goals of this work are:

- To develop a low noise, affordable multichannel sEMG acquisition system

- To employ appropriate feature extraction algorithms that provides maximum class separabilty and low computational load.
- To classify the ankle joint movements using multichannel EMG signal channels.

1.3 Research scope

This research focuses on develop of EMG based pattern recognition system to classify ankle joint movements. This system starts with implementation of multichannel EMG signal acquisition system. This system is designed for laboratory student works and is limited to four channels. Modified time domain features were proposed and these features were evaluated using three different classifiers; linear discriminant analysis (LDA), k nearest neighbourhood (k-NN) and naïve Bayes classifier (NBC). The validation of the proposed pattern recognition method was carried out by evaluation of the classification accuracy of the different ankle joint movements and the experimental process is limited to offline testing.

The selection of the ankle joint movements is limited to four movements; dorsiflexion, plantar flexion, adduction and abduction. Dorsiflexion and plantar flexion have a significant impact stance of human walking, while adduction and abduction play an important role on human balancing during standing and walking as well.

1.4 Thesis Outlines

Chapter 1 of this thesis describes the problem statement, objectives and scope of this research. Chapter 2 covers the background of this work such as physiological nature of the EMG signal, EMG signal detection and processing, EMG control system, different feature extraction algorithm including the proposed feature set, dimensionality reduction techniques and the variety of classification methods. Multichannel EMG acquisition system implementation and testing were described in details in chapter 3. Chapter 4 illustrates the data collection protocol, data preparation and proposed research methodology. Details of the Results and discussion are provided in chapter 5 while the conclusion of the current work and potential future investigations are presented in chapter6.

REFERENCES

[1] A. B. Ortega, E. M'rmol, G. V. Valdés, G. L. López and H. A. Rivera, "Control of a virtual prototype for ankle rehabilitation," in *Intelligent Environments (IE), 2012 8th International Conference on*, 2012, pp. 80-86.

[2] N. Hogan, H. I. Krebs, J. Charnnarong, P. Srikrishna and A. Sharon, "MIT-MANUS: A workstation for manual therapy and training. I," in *Robot and Human Communication, 1992. Proceedings., IEEE International Workshop on*, 1992, pp. 161-165.

[3] H. He and K. Kiguchi, "A study on emg-based control of exoskeleton robots for human lower-limb motion assist," in *Information Technology Applications in Biomedicine, 2007. ITAB 2007. 6th International Special Topic Conference on*, 2007, pp. 292-295.

[4] A. Gitter, J. M. Czerniecki and D. M. DeGroot, "Biomechanical analysis of the influence of prosthetic feet on below-knee amputee walking." *American Journal of Physical Medicine & Rehabilitation*, vol. 70, pp. 142-148, 1991.

[5] W. Huo, S. Mohammed, J. C. Moreno and Y. Amirat, "Lower Limb Wearable Robots for Assistance and Rehabilitation: A State of the Art," .

[6] H. Kazerooni and R. Steger, "The Berkeley lower extremity exoskeleton," *Journal of Dynamic Systems, Measurement, and Control*, vol. 128, pp. 14-25, 2006.

[7] H. Kawamoto and Y. Sankai, "Power assist method based on phase sequence and muscle force condition for HAL," *Adv. Rob.*, vol. 19, pp. 717-734, 2005.

[8] J. L. Pons, "Rehabilitation exoskeletal robotics," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 29, pp. 57-63, 2010.

[9] H. Kawamoto, S. Lee, S. Kanbe and Y. Sankai, "Power assist method for HAL-3 using EMG-based feedback controller," in *Systems, Man and Cybernetics, 2003. IEEE International Conference on*, 2003, pp. 1648-1653.

[10] C. Fleischer, C. Reinicke and G. Hommel, "Predicting the intended motion with emg signals for an exoskeleton orthosis controller," in *Intelligent Robots and Systems, 2005.(IROS 2005). 2005 IEEE/RSJ International Conference on*, 2005, pp. 2029-2034.

[11] C. Fleischer and G. Hommel, "Embedded control system for a powered leg exoskeleton," in *Embedded Systems–Modeling, Technology, and Applications*Anonymous Springer, 2006, pp. 177-185.

[12] C. Fleischer, A. Wege, K. Kondak and G. Hommel, "Application of EMG signals for controlling exoskeleton robots," *Biomed. Tech.*, vol. 51, pp. 314-319, 2006.

[13] M. Zardoshti-Kermani, B. C. Wheeler, K. Badie and R. M. Hashemi, "EMG feature evaluation for movement control of upper extremity prostheses," *Rehabilitation Engineering, IEEE Transactions on*, vol. 3, pp. 324-333, 1995.

[14] R. Merletti and P. A. Parker, *Electromyography: Physiology, Engineering, and Non-Invasive Applications.* John Wiley & Sons, 2004.

[15] E. Henneman and L. M. Mendell, "Functional organization of motoneuron pool and its inputs," *Comprehensive Physiology*, 2011.

[16] G. Kamen and D. Gabriel, *Essentials of Electromyography.* Human Kinetics, 2010.

[17] S. Day, "Important factors in surface EMG measurement," *Bortec Biomedical Ltd Publishers*, pp. 1-17, 2002.

[18] J. R. Cram and J. C. Steger, "EMG scanning in the diagnosis of chronic pain," *Biofeedback Self.*, vol. 8, pp. 229-241, 1983.

[19] P. Konrad, "The abc of emg," *A Practical Introduction to Kinesiological Electromyography*, vol. 1, 2005.

[20] P. Hodges, "Applications in rehabilitation medicine and related fields," *Electromyography: Physiology, Engineering, and Non-Invasive Applications,* vol. 11, pp. 403, 2004.

[21] G. De Luca, "Fundamental concepts in EMG signal acquisition," *Copyright Delsys Inc*, 2003.

[22] G. E. Loeb, *Electromyography for Experimentalists.* University of Chicago Press, 1986.

[23] E. Guizzo and H. Goldstein, "The rise of the body bots," *IEEE Spectrum,* vol. 42, pp. 42, 2005.

[24] H. Kawamoto and Y. Sankai, "Power assist system HAL-3 for gait disorder person," in *Computers Helping People with Special Needs*Anonymous Springer, 2002, pp. 196-203.

[25] D. Graupe, J. Salahi and K. H. Kohn, "Multifunctional prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals," *J. Biomed. Eng.,* vol. 4, pp. 17-22, 1982.

[26] P. Parker, K. Englehart and B. Hudgins, "Control of powered upper limb prostheses," *Electromyography: Physiology, Engineering, and Noninvasive Applications,* pp. 453-475, 2004.

[27] R. Scott and P. Parker, "Myoelectric prostheses: state of the art," *J. Med. Eng. Technol.,* vol. 12, pp. 143-151, 1988.

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

[29] B. Hudgins, P. Parker and R. N. Scott, "A new strategy for multifunction myoelectric control," *Biomedical Engineering, IEEE Transactions on,* vol. 40, pp. 82-94, 1993.

[30] L. J. Hargrove, G. Li, K. B. Englehart and B. S. Hudgins, "Principal components analysis preprocessing for improved classification accuracies in pattern-recognition-based myoelectric control," *Biomedical Engineering, IEEE Transactions on,* vol. 56, pp. 1407-1414, 2009.

[31] G. Hefftner, W. Zucchini and G. G. Jaros, "The electromyogram (EMG) as a control signal for functional neuromuscular stimulation. I. Autoregressive modeling as a means of EMG signature discrimination," *Biomedical Engineering, IEEE Transactions on,* vol. 35, pp. 230-237, 1988.

[32] L. H. Smith, L. J. Hargrove, B. A. Lock and T. A. Kuiken, "Determining the optimal window length for pattern recognition-based myoelectric control: balancing the competing effects of classification error and controller delay," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 19, pp. 186-192, 2011.

[33] M. A. Oskoei and H. Hu, "Myoelectric control systems—A survey," *Biomedical Signal Processing and Control,* vol. 2, pp. 275-294, 2007.

[34] M. Zecca, S. Micera, M. Carrozza and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews™ in Biomedical Engineering,* vol. 30, 2002.

[35] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard and Y. Laurillau, "EMG feature evaluation for improving myoelectric pattern recognition robustness," *Expert Syst. Appl.,* vol. 40, pp. 4832-4840, 2013.

[36] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard and Y. Laurillau, "Feature extraction of the first difference of EMG time series for EMG pattern recognition," *Comput. Methods Programs Biomed.,* vol. 117, pp. 247-256, 2014.
[37] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield and K. B. Englehart, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *JAMA,* vol. 301, pp. 619-628, 2009.
[38] J. W. Sensinger, B. A. Lock and T. A. Kuiken, "Adaptive pattern recognition of myoelectric signals: exploration of conceptual framework and practical algorithms," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 17, pp. 270-278, 2009.
[39] M. Khezri and M. Jahed, "Real-time intelligent pattern recognition algorithm for surface EMG signals," *Biomed Eng Online,* vol. 6, pp. 45, 2007.
[40] D. Graupe, J. Salahi and D. Zhang, "Stochastic analysis of myoelectric temporal signatures for multifunctional single-site activation of prostheses and orthoses," *J. Biomed. Eng.,* vol. 7, pp. 18-29, 1985.
[41] A. Phinyomark, C. Limsakul and P. Phukpattaranont, "A novel feature extraction for robust EMG pattern recognition," *ArXiv Preprint arXiv:0912.3973,* 2009.
[42] A. Phinyomark, S. Hirunviriya, C. Limsakul and P. Phukpattaranont, "Evaluation of EMG feature extraction for hand movement recognition based on euclidean distance and standard deviation," in *Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010 International Conference on,* 2010, pp. 856-860.
[43] A. Phinyomark, S. Hirunviriya, A. Nuidod, P. Phukpattaranont and C. Limsakul, "Evaluation of EMG feature extraction for movement control of upper limb prostheses based on class separation index," in *5th Kuala Lumpur International Conference on Biomedical Engineering 2011,* 2011, pp. 750-754.
[44] D. Yang, J. Zhao, L. Jiang and H. Liu, "Dynamic hand motion recognition based on transient and steady-state EMG signals," *International Journal of Humanoid Robotics,* vol. 9, 2012.
[45] T. Lorrain, N. Jiang and D. Farina, "Influence of the training set on the accuracy of surface EMG classification in dynamic contractions for the control of multifunction prostheses," *J. Neuroeng Rehabil.,* vol. 8, pp. 25-0003-8-25, May 9, 2011.
[46] T. Chau, D. Chau, M. Casas, G. Berall and D. J. Kenny, "Investigating the stationarity of paediatric aspiration signals," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 13, pp. 99-105, 2005.
[47] Y. J. Cho and J. Y. Kim, "The effects of load, flexion, twisting and window size on the stationarity of trunk muscle EMG signals," *Int. J. Ind. Ergonomics,* vol. 42, pp. 287-292, 2012.
[48] C. Chatfield, *The Analysis of Time Series: An Introduction.* CRC press, 2013.
[49] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *Biomedical Engineering, IEEE Transactions on,* vol. 55, pp. 1956-1965, 2008.
[50] A. Phinyomark, P. Phukpattaranont and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Syst. Appl.,* vol. 39, pp. 7420-7431, 2012.
[51] A. Phinyomark, F. Quaine, Y. Laurillau, S. Thongpanja, C. Limsakul and P. Phukpattaranont, "EMG amplitude estimators based on probability distribution for muscle–computer interface," *Fluctuation and Noise Letters,* vol. 12, 2013.

[52] K. S. Kim, H. H. Choi, C. S. Moon and C. W. Mun, "Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions," *Current Applied Physics,* vol. 11, pp. 740-745, 2011.
[53] S. Karlsson, J. Yu and M. Akay, "Enhancement of spectral analysis of myoelectric signals during static contractions using wavelet methods," *Biomedical Engineering, IEEE Transactions on,* vol. 46, pp. 670-684, 1999.
[54] R. Merletti and L. R. L. Conte, "Surface EMG signal processing during isometric contractions," *Journal of Electromyography and Kinesiology,* vol. 7, pp. 241-250, 1997.
[55] O. Paiss and G. F. Inbar, "Autoregressive modeling of surface EMG and its spectrum with application to fatigue," *Biomedical Engineering, IEEE Transactions on,* pp. 761-770, 1987.
[56] K. A. Farry, I. D. Walker and R. G. Baraniuk, "Myoelectric teleoperation of a complex robotic hand," *Robotics and Automation, IEEE Transactions on,* vol. 12, pp. 775-788, 1996.
[57] P. Gallant, E. Morin and L. Peppard, "Feature-based classification of myoelectric signals using artificial neural networks," *Medical and Biological Engineering and Computing,* vol. 36, pp. 485-489, 1998.
[58] S. Du and M. Vuskovic, "Temporal vs. spectral approach to feature extraction from prehensile EMG signals," in *Information Reuse and Integration, 2004. IRI 2004. Proceedings of the 2004 IEEE International Conference on,* 2004, pp. 344-350.
[59] K. Englehart, B. Hudgins, P. Parker and M. Stevenson, "Time-frequency representation for classification of the transient myoelectric signal," in *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE,* 1998, pp. 2627-2630.
[60] K. Englehart, B. Hudgin and P. A. Parker, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *Biomedical Engineering, IEEE Transactions on,* vol. 48, pp. 302-311, 2001.
[61] R. Battiti, "Using mutual information for selecting features in supervised neural net learning," *Neural Networks, IEEE Transactions on,* vol. 5, pp. 537-550, 1994.
[62] G. H. John, R. Kohavi and K. Pfleger, "Irrelevant features and the subset selection problem," in *Machine Learning: Proceedings of the Eleventh International Conference,* 1994, pp. 121-129.
[63] R. Kohavi and G. H. John, "Wrappers for feature subset selection," *Artif. Intell.,* vol. 97, pp. 273-324, 1997.
[64] I. H. Witten and E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques.* Morgan Kaufmann, 2005.
[65] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *The Journal of Machine Learning Research,* vol. 3, pp. 1157-1182, 2003.
[66] M. Dash and H. Liu, "Feature selection for classification," *Intelligent Data Analysis,* vol. 1, pp. 131-156, 1997.
[67] S. Guan, J. Liu and Y. Qi, "An incremental approach to contribution-based feature selection," *J. Intell. Syst.,* vol. 13, pp. 15-42, 2004.
[68] J. Reunanen, "Overfitting in making comparisons between variable selection methods," *The Journal of Machine Learning Research,* vol. 3, pp. 1371-1382, 2003.

[69] E. Gasca, J. S. Sánchez and R. Alonso, "Eliminating redundancy and irrelevance using a new MLP-based feature selection method," *Pattern Recognit*, vol. 39, pp. 313-315, 2006.
[70] C. Hsu, H. Huang and S. Dietrich, "The ANNIGMA-wrapper approach to fast feature selection for neural nets," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on,* vol. 32, pp. 207-212, 2002.
[71] R. Caruana and D. Freitag, "Greedy attribute selection." in *ICML,* 1994, pp. 28-36.
[72] P. Pudil, J. Novovičová and J. Kittler, "Floating search methods in feature selection," *Pattern Recog. Lett.,* vol. 15, pp. 1119-1125, 1994.
[73] M. M. Kabir, M. Shahjahan and K. Murase, "A new hybrid ant colony optimization algorithm for feature selection," *Expert Syst. Appl.,* vol. 39, pp. 3747-3763, 2012.
[74] A. Ahmed, "Feature subset selection using ant colony optimization," 2005.
[75] C. Huang and J. Dun, "A distributed PSO–SVM hybrid system with feature selection and parameter optimization," *Applied Soft Computing,* vol. 8, pp. 1381-1391, 2008.
[76] H. Huang, H. Xie, J. Guo and H. Chen, "Ant colony optimization-based feature selection method for surface electromyography signals classification," *Comput. Biol. Med.,* vol. 42, pp. 30-38, 2012.
[77] R. N. Khushaba, A. AlSukker, A. Al-Ani, A. Al-Jumaily and A. Y. Zomaya, "A novel swarm based feature selection algorithm in multifunction myoelectric control," *Journal of Intelligent and Fuzzy Systems,* vol. 20, pp. 175-185, 2009.
[78] K. Englehart, B. Hudgins, P. A. Parker and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys.,* vol. 21, pp. 431-438, 1999.
[79] K. Englehart, B. Hudgins and A. D. Chan, "Continuous multifunction myoelectric control using pattern recognition," *Technology and Disability,* vol. 15, pp. 95-103, 2003.
[80] Y. Huang, K. B. Englehart, B. Hudgins and A. D. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *Biomedical Engineering, IEEE Transactions on,* vol. 52, pp. 1801-1811, 2005.
[81] P. Parker, K. Englehart and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *Journal of Electromyography and Kinesiology,* vol. 16, pp. 541-548, 2006.
[82] R. N. Khushaba and S. Kodagoda, "Electromyogram (EMG) feature reduction using mutual components analysis for multifunction prosthetic fingers control," in *Control Automation Robotics & Vision (ICARCV), 2012 12th International Conference on,* 2012, pp. 1534-1539.
[83] K. B. Englehart, *Signal Representation for Classification of the Transient Myoelectric Signal,* 1998.
[84] 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," *Biomedical Engineering, IEEE Transactions on,* vol. 53, pp. 2232-2239, 2006.
[85] A. D. Chan and G. C. Green, "Myoelectric control development toolbox," in *Proceedings of 30th Conference of the Canadian Medical & Biological Engineering Society,* 2007, pp. M0100-1.
[86] J. Han, M. Kamber and J. Pei, *Data Mining, Southeast Asia Edition: Concepts and Techniques.* Morgan kaufmann, 2006.

[87] S. A. Ahmad, A. J. Ishak, S. H. Ali and P. H. Chappell, "Review of Electromyography Control Systems Based on Pattern Recognition for Prosthesis Control Application." *Journal of Applied Sciences Research,* vol. 7, 2011.

[88] J. C. Gonzalez-Ibarra, C. Soubervielle-Montalvo, O. Vital-Ochoa and H. G. Perez-Gonzalez, "EMG pattern recognition system based on neural networks," in *Artificial Intelligence (MICAI), 2012 11th Mexican International Conference on,* 2012, pp. 71-74.

[89] S. Pati, "Classification using EM," .

[90] D. Zhang, Y. Wang, X. Chen and F. Xu, "EMG classification for application in hierarchical FES system for lower limb movement control," in *Intelligent Robotics and Applications*Anonymous Springer, 2011, pp. 162-171.

[91] Q. She, Z. Luo, M. Meng and P. Xu, "Multiple kernel learning SVM-based EMG pattern classification for lower limb control," in *Control Automation Robotics & Vision (ICARCV), 2010 11th International Conference on*, 2010, pp. 2109-2113.

[92] C. Ling, A. Qingsong, H. Yan, L. Quan and M. Wei, "A real-time leg motion recognition system by using mahalanobis distance and LS_SVM," in *Audio, Language and Image Processing (ICALIP), 2012 International Conference on,* 2012, pp. 668-673.

[93] R. N. Khushaba, A. Al-Ani and A. Al-Jumaily, "Orthogonal fuzzy neighborhood discriminant analysis for multifunction myoelectric hand control," *Biomedical Engineering, IEEE Transactions on,* vol. 57, pp. 1410-1419, 2010.

[94] A. H. Al-Timemy, G. Bugmann, J. Escudero and N. Outram, "Classification of finger movements for the dexterous hand prosthesis control with surface electromyography," *Biomedical and Health Informatics, IEEE Journal of,* vol. 17, pp. 608-618, 2013.

[95] D. Tkach, R. Lipschutz, S. Finucane and L. Hargrove, "Myoelectric neural interface enables accurate control of a virtual multiple degree-of-freedom foot-ankle prosthesis," in *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*, 2013, pp. 1-4.

[96] S. Siriprayoonsak, *Real-Time Measurement of Prehensile EMG Signals*, 2005.

[97] I. P. I. Amplifier, "Burr–Brown Corporation," *USA, March,* 1998.

[98] R. Merletti, A. Botter, A. Troiano, E. Merlo and M. A. Minetto, "Technology and instrumentation for detection and conditioning of the surface electromyographic signal: state of the art," *Clin. Biomech.,* vol. 24, pp. 122-134, 2009.

[99] C. Sinderby, L. Lindstrom and A. E. Grassino, "Automatic assessment of electromyogram quality," *J. Appl. Physiol. (1985),* vol. 79, pp. 1803-1815, Nov, 1995.

[100] B. Freriks and H. Hermens, *European Recommendations for Surface Electromyography: Results of the SENIAM Project.* Roessingh Research and Development, 2000.

[101] I. C. Sacco, A. A. Gomes, M. E. Otuzi, D. Pripas and A. N. Onodera, "A method for better positioning bipolar electrodes for lower limb EMG recordings during dynamic contractions," *J. Neurosci. Methods,* vol. 180, pp. 133-137, 2009.

[102] R. O. Duda and P. E. Hart, *Pattern Classification and Scene Analysis.* Wiley New York, 1973.

[103] G. H. John and P. Langley, "Estimating continuous distributions in bayesian classifiers," in *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence*, 1995, pp. 338-345.

[104] J. Machado and A. Balbinot, "Executed Movement Using EEG Signals through a Naive Bayes Classifier," *Micromachines,* vol. 5, pp. 1082-1105, 2014.

[105] J. Valls-Solé, J. C. Rothwell, F. Goulart, G. Cossu and E. Muñoz, "Patterned ballistic movements triggered by a startle in healthy humans," *J. Physiol. (Lond.),* vol. 516, pp. 931-938, 1999.
[106] L. Stark, "Neurological control systems; studies in bioengineering," 1968.
[107] H. L. Teodorescu and L. C. Jain, *Intelligent Systems and Technologies in Rehabilitation Engineering.* CRC Press, 2010.