UNIVERSITI PUTRA MALAYSIA

CLASSIFICATION OF ANKLE JOINT MOVEMENTS BASED ON SURFACE ELECTROMYOGRAPHY SIGNALS

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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

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August 2015

Chairman : Asnor Juraiza Bt. Ishak, PhD
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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

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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.

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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.

I certify that a Thesis Examination Committee has met on 18 August 2015 to conduct the final examination of Maged Saleh Saeed Al-Quraishi on his thesis entitled "Classification of Ankle Joint Movements Based on Surface Electromyography Signals" 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.

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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.

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