HAND AND ELBOW GESTURE RECOGNITION BASED ON ELECTROMYOGRAPHY SIGNAL

ALA ABOBAKR ABDULHAFIDH AL-DUBAI

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Special dedicated to

my beloved father, mother, brothers, sisters and friends

who have encouraged, guide and inspired me

throughtout my journey of education.

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ABSTRACT

This project intends to analyze and classify the Electromyography (EMG) signal of muscles that is involved in certain hand and elbow gestures. The Electromyography (EMG) data acquisition protocol is then outlined and performed where the recorded Electromyography (EMG) signal corresponds with certain hand and elbow gestures. Therefore, four hand gestures were targeted, "hand contraction, forearm rotation, wrist extension and wrist flexion". Thus, the EMG data that have been collected from 6 subjects are compared at a small demographic scale which is age and gender. Whereas, the EMG signals are collected using the software Lab-Chart 7 with 2 channel and 5 electrodes. The pre-processing of the EMG raw signals is presented using a 6th order Butterworth band pass filter, low and high pass filter with normalization. Furthermore, the features are evaluated using Variance (VAR), Standard Deviation (SD) and Root Mean Square (RMS) to test the significance of the features. Nevertheless, the K-Nearest Neighbour (KNN) classifier is used in order to classify the EMG signals for hand gestures. Lastly, the results from this project showed that the classifier has classified the gestures with a low performance due to the fewer amounts of the subjects and some other reasons.

ABSTRAK

Projek ini bertujuan untuk menganalisis dan mengelaskan isyarat elektomiografi (EMG) pada otot yang terlibat dalam isyarat tangan yang tertentu. Data yang diperoleh dari signal Elektromiografi (EMG), kemudiannya signal yang dinyatakan akan dilaksanakan di mana isyarat direkodkan oleh Elektomiografi (EMG) sepadan dengan isyarat tangan tertentu. Oleh itu, empat isyarat tangan menjadi sasaran iaitu "penguncupan tangan, putaran lengan, lanjutan pergelangan tangan dan pergelangan tangan akhiran". Oleh itu, data EMG yang telah dikumpulkan dari 6 subjek dibandingkan pada skala demografi kecil iaitu umur dan jantina. Manakala, isyarat EMG dikumpul menggunakan perisian Lab-Carta 7 dengan 2 saluran dan 5 elektrod. Pra-pemprosesan isyarat mentah EMG yang dibentangkanselepas menggunakan perintah 6th Butterworth band penapis lulus, penapis laluan rendah dan tinggi dengan normal. Tambahan pula, ciri-ciri yang dinilai dengan menggunakan *Variance* (VAR), sisihan piawai (SD) dan *Root Mean Square* (RMS) untuk menguji kepentingan ciri-ciri. Walau bagaimanapun, pengelas *K-Nearest Neighbour* (KNN) digunakan untuk mengelaskan isyarat EMG dari isyarat tangan. Akhir sekali, hasil daripada projek ini menunjukkan bahawa pengelas telah mengklasifikasikan gerak isyarat pada prestasi yang rendah berdasarkan jumlah subjek yang kurang dan beberapa sebab yang lain.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Electromyography signal signifies the bioelectrical activity of muscle that allows movement of body parts. For example, elbow flexion and extension are the effect of contraction and relaxation of biceps and triceps brachii. These are the two muscles situated at the upper arm. Likewise, hand gesture is connected to the work of muscles situated on the forearm. For example, hand flexion and adduction is the act of flexor carpi ulnaris. Knowing that movement of human limb is the outcome of muscles action, electromyography; that is the recording of muscle's bioelectrical activity; can be used to define the limb gesture. This is conceivable with the progression in signal processing methods and numerous machine learning algorithms.

Gestures are a method of nonverbal communication in which observable by bodily actions are used to communicate important messages, either in place of speech or together and in parallel with spoken words. Gestures include movement of the hands or elbow, face, or other parts of the body. Physical non-verbal communications such as purely expressive displays, proxemics, or demonstration of joint attention differ from gestures, which communicate specific messages. Gestures are culture-specific and can relay very different meanings in different social or cultural settings. Gesture is distinctive from sign language. Although some gestures, such as the ubiquitous act of pointing, differ little from one place to another, most gestures do not have unchanging or universal meanings but mean specific meanings in certain cultures. A single emblematic gesture can have very different connotation in different cultural contexts, stretching from complimentary to highly offensive (Nguyen, 2008).

Electromyography (EMG) signal is a degree of muscles' electrical activity and usually signified as a function of time, defined in terms of amplitude, frequency and phase. This bio signal can be used in various applications together with diagnoses of neuromuscular diseases, controlling assistive devices like prosthetic/orthotic devices, controlling machines, robots, and computer. EMG signal based dependable and effective hand gesture identification can help to improve good human computer interface which in turn will increase the quality of life of the disabled or aged people. The purpose of this studey is to define the process of distinguishing different predefined hand gestures (left, right, up and down) using K Nearest Neighbour (KNN). KNNs are mainly useful for complex pattern recognition and classification tasks. The ability of learning from examples, the ability to reproduce arbitrary non-linear functions of input, and the highly parallel and regular structure of KNNs make them particularly suitable for pattern recognition tasks. The EMG pattern signatures are taken out from the signals for each movement and then KNN utilized to classify the EMG signals based on features. A back-propagation (BP) network with Levenberg-Marquardt training algorithm has been used for the detection of gesture. The conventional and most effective time and time-frequency based features (namely mean absolute value (MAV), root mean square (RMS), variance (VAR), standard deviation (SD), zero crossing (ZC), slope sign change (SSC) and waveform length (WL)) have been chosen to train the neural network (Ahsan, Ibrahimy & Khalifa, 2011) .

1.2 Problem Statement

Electromyography signal corresponds to human limbs, movement. Thus, for hand gestures, there would be EMG signals that can be required from certain muscles that can represent the related quipsters. To obtain the EMG pattern of the related hand and elbow gestures, a feature of EMG need to be extracted as simplification from the original EMG. Since there are many methods and techniques for EMG feature extraction, each technique need to be evaluated to search for the best technique that could classify and recognize the correct hand and elbow gestures based on the EMG signal.

1.3 Objective

i. To record and perform electromyography data acquisition protocol that record of certain hand and elbow gestures.

ii. To perform features extraction using time-domain features and to classify the EMG signals using K-Nearest Neighbour (KNN) classifier.

iii. To determine the best feature extraction with best classification accuracy.

1.4 Scope

This project involves various stages of signal processing method which are:

i. Experiment

To prove the project's objectives, an experiment will be carried out to analyse electromyography (EMG) signal out with the corresponding hand and elbow gesture.

ii. Signal Analysis

EMG signals are classified as electrode noise, motion artifacts, power line noise, ambient noise, and inherent noise in electrical & electronic equipment's. The first three types of noise can be eliminated by using typical filtering procedures such as Butterworth band pass filter, low and high pass filter or the use of a good quality of equipment with a proper electrode placement.

iii. Classification

Simple classifiers such as Linear Discriminate Analysis (LDA), K Nearest Neighbour (KNN), Support Vector Machine (SVM), and Artificial Neural Network (ANN) have been used widely in so many previous studies in order to make decisions on the signal for the emotion recognized (Yuvaraj et al., 2014). Training and testing of the data set were required to accurately classify the signals into each emotion; the performances of the classifiers were validated through 5-fold cross validation method (Merzagora, Bunce, Izzetoglu & Onaral, 2006) & (Murugappan, Ramachandran & Sazali, 2010). So in this project will use the K Nearest Neighbour (KNN) to classify the signals.

Therefore, the scope of this project will be focused on the development of feature extraction and the classification algorithm of the surface EMG signal.

1.5 Background of the study

In the previous studies, EMG signals have been used in so many fields in order to diagnose the hand gesture recognition in a different application. It has been used in feasibility of building robust surface electromyography-based hand and elbow gesture interfaces. The study explored the feasibility of building robust surface electromyography (EMG)-based gesture interfaces starting from the definition of input command gestures. As a first step, an offline experimental scheme was carried out for extracting user-independent input command sets with high class reparability, reliability and low individual variations from 23 classes of hand and elbow gestures (Xiang et al., 2009).

Also, EMG signals have been used in Electromyography (EMG) signal based hand and elbow gesture recognition using K Nearest Neighbour (KNN).EMG signal based reliable and efficient hand gesture identification can help to develop good human computer interface which in turn will increase the quality of life of the disabled or aged people. The purpose of this project is to describe the process of detecting different predefined hand gestures (left, right, up and down) using K Nearest Neighbour (KNN). KNNs are particularly useful for complex pattern recognition and classification tasks (Ahsan, Ibrahimy & Khalifa, 2011).

EMG signals have been used in such application as controlling active prosthesis, wheelchairs, exoskeleton robots, rehabilitation, silent speech recognition, and controlling video games as it can be measured on a human skin surface with non-invasive electrodes. In commercially available prosthetic devices EMG signals have been exploited for a proportional control strategy. To improve its usability, a control strategy based on the classification of EMG signals has been widely studied, in such a strategy, a classifier is constructed for the surface EMG signals to recognize the intended human movements using classified movements to generate the corresponding behaviour of the device. The EMG signal is also used to help to detect neuromuscular abnormalities (Balbinot, Júnior & Favieiro, 2013).

1.6 Project Outline

The overall idea of this thesis is about classify and identify the EMG signals with hand and elbow gesture:

i. Chapter 1: Provides an overview on the history of the project. It also views some other points such as the problem statement of the study, objectives, scope and the outline of the paper.

ii. Chapter 2: Provides the literature review that gives deep theoretical background for the important parameters and concepts making up the title of the study or the project.

iii. Chapter 3: Mainly discusses on the methodology and how the flow of the project will be, it also provides the reader with information of what mechanisms will be used to drive the project to an end.

iv. Chapter 4: It shows the results gotten and to provide a discussion on them.

v. Chapter 5: Is about the conclusion; this is dedicated to end up the report of the project, it basically states the difficulties and obstacles faced during the progress of the project as well as giving recommendations for a better future work if possible.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter will bring to highlight the literature review on the different components that contributed to this study. The themes revised are identified as Electromyography (EMG), Hand and Elbow Gesture Recognition and Digital Signal Processing Methods.

2.1 Gesture Recognition

The pattern recognition processing is necessary to identify the different gestures using EMG signal, and many algorithms have been applied. The essential aim of building hand gesture recognition system is to create a natural interaction between human and computer where the recognized gestures can be used for controlling a robot or conveying meaningful information (Ahsan, Ibrahimy & Khalifa, 2011).

2.2 The concept of Hand Gesture Recognition

Many hand gestures require simultaneous contraction of multiple overlapping muscles and this makes it difficult to directly map the surface electromyography (sEMG) to different hand and finger gestures. Thus, systems that have been reported in literature estimate the hand and finger commands by training the system for the user with a limited number of commands such as individual finger gestures or some functional hand gestures (N & I.r, 2016). Previous studies along these lines of investigation have used neural network architecture and a classification scheme employing multiple pixel-based features or the full set of joint angles for a robust system of recognition. Number of studies have analysed the recordings to obtain the most suitable signal features and classification techniques (Stanescu, 2013).

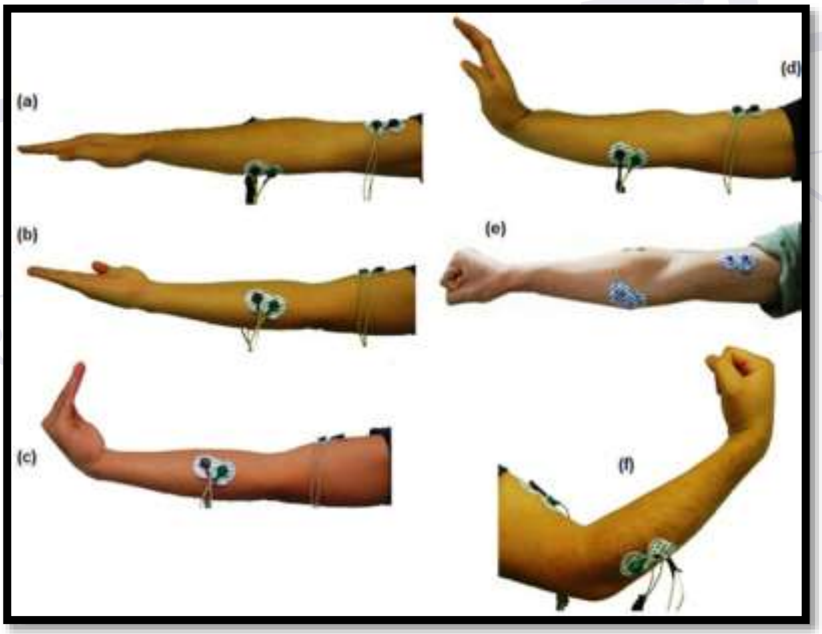

Figure 2.1: The movements characterized by the developed system: (a) Relaxed; (b) Forearm rotation; (c) Wrist flexion; (d) Wrist extension; (e) Hand contraction and (f) Forearm flexion (Li & Li, 2013).

2.3 Electromyography (EMG)

As stated before, electromyography is an instrument used to measure the muscle responses or electrical activity in response to a nerve's stimulation of the muscle by means of placing an electrode into the muscle or placed on the skin (Sadikoglu, Kavalcioglu & Dagman, 2017). The main focus of this study is towards a brief analysis as regards to the sources of the signal, bands of the signal and the recording of the signal is in all certainty vital.

In the previous studies, EMG signals have been used in a variety of fields in order to analyse muscle cells all throughout the human body. EMG signals are also used as a diagnostics tool for identifying neuromuscular diseases, or as a research tool for studying kinesiology, and disorders of motor control. EMG signals are sometimes used to guide botulinum toxin or phenol injections into muscles (Ahsan, Ibrahimy & Khalifa, 2011). EMG signals are also used as a control signal for prosthetic devices such as prosthetic hands, arms, and lower limbs (Dewhurst, 2014).

EMG signals have been used in such application as controlling active prosthesis, wheelchairs, exoskeleton robots, rehabilitation, silent speech recognition, and controlling video games as it can be measured on a human skin surface with non-invasive electrodes. In commercially available prosthetic devices EMG signals have been exploited for a proportional control strategy. To improve its usability, a control strategy based on the classification of EMG signals has been widely studied, in such a strategy, a classifier is constructed for the surface EMG signals to recognize the intended human movements using classified movements to generate the corresponding behaviour of the device. The EMG signal is also used to help to detect neuromuscular abnormalities (N & I.R, 2016).

In another study, EMG signals have been used in Electromyography (EMG) signal based hand gesture recognition using artificial neural network (ANN).EMG signals based on reliable and efficient hand gesture identification can help to develop good human computer interface which in turn will increase the quality of life of the disabled or aged people (Rafiee, Rafiee, Yavari & Schoen, 2011). The gesture recognition is to create a system that recognizes the gestures and use them for controlling the device (Balbinot, Júnior & Favieiro, 2013). The gestures can be from any bodily motion but importantly from face and hand. There are many common modalities include mechanical sensors, vision based system etc. The surface Electromyogram has the advantage of easy recording and non-invasive. The hand gestures are captured by sensors through EMG signals (STANESCU, 2013). Therefore, the methods that were used are signal acquisition, pre-processing surface electromyography (sEMG), feature extraction and classification of gestures.

2.3.1 The Source of EMG

Muscle account for about 40% of the human mass, ranging from the small extra-ocular muscles that turn the eyeball in its socket to the large limb muscles that produce locomotion and control posture (Bronzino & Peterson, 2014).

There are several types of nerves but generally speaking, the two major types are motor and sensory nerves. Motor nerves carry signals from the brain to the muscle to enable contraction and movement, and sensory nerves relay information to the brain. When the nerve is stimulated with metal electrodes (metallic patches that can conduct signals), a response can be measured by surface (on the skin) electrodes some distance away in sensory nerves overlying the nerve itself. For the motor nerves, the response is usually detected over the muscle that is activated by that nerve. In this fashion, results can reveal information about the size and speed of the electrically conducted impulse. The size usually reveals the number of nerve fibres present and the speed, the integrity of the myelin (insulating membrane around the nerve ‘axon’ or cable).

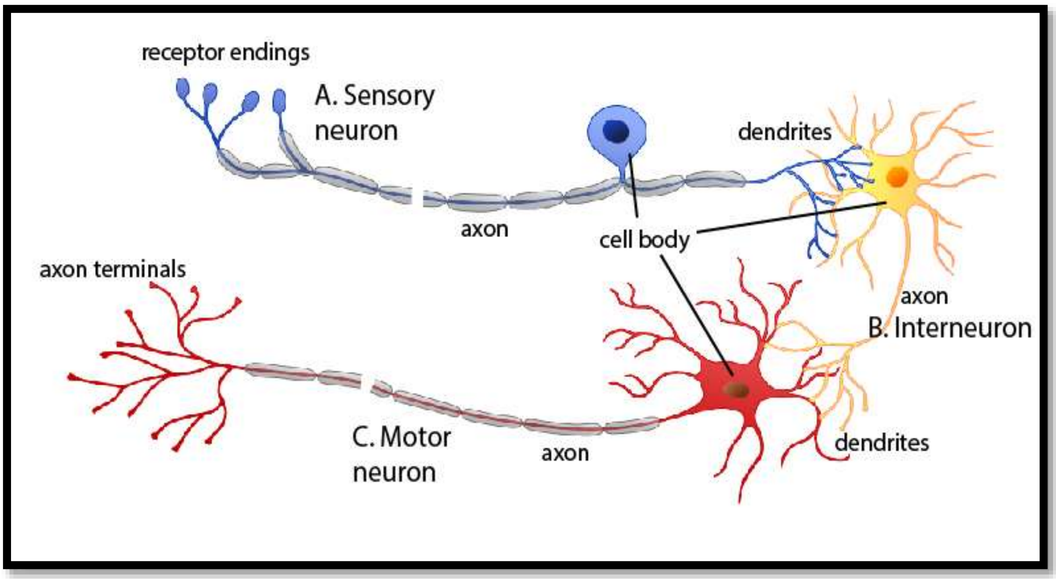

Figure 2.2: The architecture of a motor nerve and (A) is the architecture of a sensory nerve (Reaz, Hussain & Mohd-Yasin, 2006).

The main nerves that are needed to know for the wrist and hand come from the median, ulnar, and radial nerves. These nerves supply the skin, muscles, joints, and other tissues. The nerves allow you to feel what your hands and fingers are touching and help you move those muscles around. Electromyography (EMG) is a non-invasive technique for measuring muscle electrical activity that occurs during muscle contraction and relaxation cycles. The silver-silver chloride electrodes are the part of the instrument that is in contact with the skin. They make electrical contact between the skin and the sensor. The electrodes are either directly connected to (or "snapped on") the sensor, or indirectly connected via an extender cable.

2.3.2 EMG Signal Patterns

Muscular fibres which create the motor unit are not collected in one branch, yet they are located on a big area between branches of other units. It has a decisive significance for the regulation of the contraction strength through increasing the frequency of discharge in single motor unit and though engagement of other motor units.

Therefore, during relaxation, a muscle shows no electric relevant activity so that the electric line is straight. This is called an isometric contraction. However, during contraction, potential of motor units are deviating the EMG line. This line is a product of frequency and amplitude produced by registered potentials. Muscle contraction comes in two different types: isometric and isotonic contraction. Isometric contraction occurs when the muscle produces pressure without joint movement, such as when carrying or pushing objects. Although muscle fibers fire during isometric contraction, no changes occur in muscle length or joint motion. Nevertheless, isotonic contraction leads to changes in muscle length and consequently causes joint movement. This type of contraction is the most important in daily hand movements.

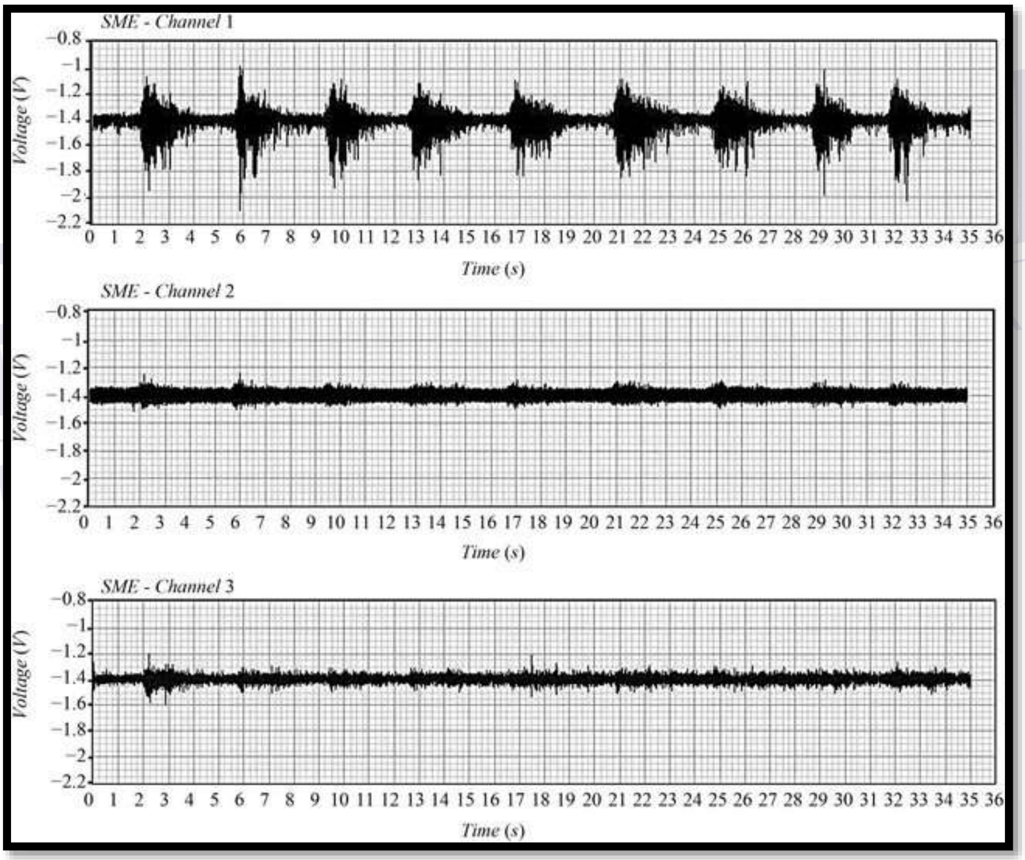

Figure 2.3: The signal acquisition during motion of wrist extension (Li & Li, 2013).

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