



**A classification of EMG Signal from Masseter and
Buccinators Muscles to Control the Directional
Movement of Power-assisted Wheelchair**

By

**HAYDER ABDULAZEEZ YOUSIF AL-YASARI
(1431311405)**

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LIST OF ABBREVIATIONS

ADC	Analog to Digital Converter
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ANOVA	Analysis of variance
AR	Autoregressive
ARC	Auto regressive coefficient
BPANN	Back-Propagation Artificial Neural Network
CJC	Continues Jaw Clenching
CMRR	Common Mode Rejection Ratio
CSFNN	Section Function Neural Network
DB	Double Blowing
DC	Double Clenching
DJC	Double Jaw Clenching
DRNN	Dynamic Recurrent Neural Networks
DSP	Digital Signal Processing
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
EPW	Electrical Power Wheelchair
FCM	Fuzzy C-Means

FDC	Forehead Double Click
FIR	Finite Impulse Response
FLS	Fuzzy Logic System
FMMNN	fuzzy min-max neural networks
FN	Fuzzy-Neuro
FR	Frequency Ration
FSM	Finite State Machines
GB	Go Backwards
GF	Go Forward
HMI	Human-Machine Interface
HMM	Hidden Markov Model
HOS	Higher-order Statistical
IAV	Integral Absolute Value
KNN	K-nearest neighbor
LDA	Linear Discriminant Analysis
LM	Levenberg-Marquardt
LPC	Linear Prediction Coefficients
MAV	Mean Absolute Value
MAX	Maximum amplitude
MCI	Muscles Computer Interface
MDF	Median Frequency
MES	Myoelectric Signals

MFMD	Modified Frequency Median
MNF	Mean Frequency
MNP	Mean Power
MPKF	Mean Peak Frequency
MUAP	Unit Action Potentials
PCA	Principal Component Analysis
PSR	Power Spectrum Ratio
RBF	Radial Basis Function
RMS	Root Mean Square
RS	Reduce Speed
SB	Single Blowing
SC	Single Clenching
SD	Standard Deviation
SJC	Single Jaw Clenching
SSC	Slope Sign Changes
ST	Stop
STFT	Short Time Fourier Transformation
SVM	Support Vector Machine
TDANN	Time-Delayed Artificial Neural Networks
TL	Turn Left
TR	Turn Right
VAR	Variance
WL	Waveform Lengths

WPT	Wavelet Packet Transform
WVD	Wigner-Ville Distribution
ZC	Zero Crossings

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Klasifikasi Isyarat EMG dari Masseter dan Buccinator Otot untuk Mengawal Pergerakan Arah Kerusi roda kuasa-dibantu

ABSTRAK

Terdapat ramai orang yang tidak boleh mengawal pergerakan anggota badan ke atas atau ke bawah. Juga, terdapat ramai orang yang terlibat dengan beberapa bentuk kecederaan antaranya ialah lumpuh, saraf tunjang, dan kebanyakan orang berusia tidak berupaya mengawal anggota badan ke atas dan ke bawah. Oleh itu, adalah perlu untuk menyediakan mereka dengan alat kawalan alternatif yang boleh membantu dan membolehkan mereka dalam pergerakan, di mana kerusi roda adalah sangat penting untuk membantu mereka dalam kehidupan seharian untuk bergerak dari satu tempat ke tempat lain dengan cara yang selesa. Objektif utama penyelidikan ini adalah untuk mengawal pergerakan kerusi roda dalam lima arah (ke hadapan, belakang, berhenti, kiri dan kanan), dengan menggunakan isyarat daripada masseter dan buccinator otot sebagai isyarat kawalan. Kemudian diekstrak ciri-ciri model yang autoregresif, panjang gelombang, bermakna nilai mutlak dan punca min kuasa dua, dan kemudian mengklasifikasikan mereka dengan menggunakan K-terdekat jiran pengelas dan analisis linear diskriminan untuk memilih keputusan yang lebih baik klasifikasi dan menggunakannya sebagai kawalan isyarat untuk pergerakan kerusi roda dalam kaedah offline. Hasil klasifikasi menunjukkan bahawa ketepatan pengelas jiran K-terdekat adalah sangat tinggi berbanding dengan pengelas analisis diskriminan linear, di mana kadar tertinggi ketepatan adalah 98.88% apabila menggunakan pengelas KNN dengan model AR 4-perintah.

A classification of EMG Signal from Masseter and Buccinators Muscles to Control the Directional Movement of Power-assisted Wheelchair

ABSTRACT

There are many people who cannot control the movement of their upper or lower limbs. Also, there are many people affected with some form of paralysis, suffering from a spinal cord injury, and many elderly people are unable to control their upper and lower limbs. Therefore, it is necessary to provide them with an alternative control device that can help them to achieve some mobility independence, where the wheelchair is very important for these people to help them in their daily lives for moving from one place to another in a comfortable manner. The main objective of this research work is to control the movements of the wheelchair in five directions (forward, reverse, stop, left and right), using signals from the masseter and buccinators muscles as control signals. Then extracted the features of the autoregressive model, waveform length, mean absolute value and root mean square, and then classify them by using a K-nearest neighbor classifier and linear discriminant analysis to choose the better result of the classification and utilize it as a control signals for the wheelchair movement in offline method. The result of classification shows that the accuracy of the K-nearest neighbor classifier is very higher compared with the linear discriminant analysis classifier, where the highest rate of accuracy was 98.88% when using the KNN classifier with the AR model 4-order.

CHAPTER 1

INTRODUCTION

1.1 Background

People who are affected by tetraplegia have difficulties in controlling their arm and leg movements. In a recent survey, it has been observed that nearly 1.2 million people have a spinal cord injury and over 5.6 million Americans live with some form of tetraplegia (Siegel, 2009). This may lead to difficulty or inability in moving their upper or lower limbs, and hence they are limited in walking around and interacting with the outside world. Therefore, it is necessary to provide an alternative control device that can help them to achieve some mobility independence. To provide a rehabilitative device in the form of locomotive assistance, this research work proposes to develop jaw and buccinator muscle controlled wheelchair locomotion for people who are suffering from an inability to control the movement of their upper or lower limbs.

There are different methods used in wheelchair movement control using Electromyograms (EMG). Where the EMG measures the muscle's electrical activity in response to a nerve's stimulation of that muscle (Reaz, Hussain, & Mohd-Yasin, 2006), since EMG signals contain a wealth of information about muscle functions, there are many approaches in analyzing the EMG signals. It is important to know the features that can be extracted from the EMG signals. The ideal feature is important for the achievement in EMG analysis (Daud, Yahya, Horng, Sulaima, & Sudirman, 2013).

The Electroencephalogram (EEG) is a test that is also used to detect abnormalities related to electrical activity of the brain (Rechy-ramirez & Hu, 2011). Additionally, the Electrooculogram (EOG) is a technique used for measuring the cornea-retinal standing potential that exists between the front and the back of the human eye (Nemade, 2005).

In this research work, EMG signals of masseter and buccinator muscles are employed to control the wheelchair's movements. After collecting the EMG signals extracted, some features then classify it with a simple classifier and use it as a control signal for the wheelchair's movements.

1.2 Problem Statement

A recent survey of the tetraplegia population (Siegel, 2009), shows that nearly 1.2 million Americans are either living with some form of Tetraplegia or suffering from multiple sclerosis, where this may lead to difficulty or inability in moving their upper or lower limbs. For this reason, they are limited in walking around and interacting with the outside world. Hence, it is necessary to provide a rehabilitative device for this community so that they can move freely in their homes and in public environments. The device that helps them to move freely from one place to another in a public environment is a wheelchair, the movement of the wheelchair is controlled by using the EMG device for recording the signals of muscles and using them as control signals. There are many different methods available for acquiring the signals from the muscles which are then used to control wheelchair locomotion, such as from the shoulders (Moon, Lee, Chu, & Mun, 2005), forehead muscles (Zhang, Dai, Luo, & Hu, 2011), and upper limbs (Chong & Hong, 2008).

1.3 Research Objectives

The main objective of this research work is to control the movements of the wheelchair in five directions (forward, reverse, stop, left and right), using signals from the masseter and buccinator muscles as control signals.

To achieve the main objective, the following sub-objectives are devised:

1. To design a method for acquiring the EMG signals based on masseter and buccinator muscle movements.
2. To develop techniques and algorithms for extracting features from the EMG signals.
3. To develop a classification algorithm using a K-nearest neighbor classifier and linear discriminant analysis.
4. To develop a simple system for controlling a wheelchair using the EMG signals.

1.4 Scope and Limitations

The scope of this research is confined to the design and the development of the wheelchair movement based on the masseter and buccinators muscles. The EMG signals of masseter muscle are used as a control signals for the wheelchair movements in three directions namely, forward, reverse (turn around in the other direction 180 degree) and stop. Meanwhile the signals of buccinators muscle are used as a control signals for the wheelchair movements in two directions (right and left).

1.5 Research Outlines

This thesis consists of a five chapters; chapter 1 introduces the reseach background and the people who suffer from the amputation of upper and lower limbs, and elderly people who are unable to control the movement of their upper or lower limbs. It also describes the problem statement of this study, the objectives of this research work, and the scope of the thesis.

Chapter 2 explains the characteristics of the EMG signals, the method of recording the EMG signals from the masseter and buccinator muscles. It also describes the domain of these signals, and explains the operation of analyzing these signals and how to extract their features, as well as describing the literature review on the method of classification of the EMG signals to use them as control signals for the wheelchair movements.

Chapter 3 explains the protocol of recording the signals of the lower jaw muscles (masseter muscles) and buccinator muscles, and how to normalize the EMG signals, and explains the ANOVA test, the test for validity the EMG signals. It also explains the operation of analyzing the signals and introduces the suitable features that are extracted from the AR model, WL, MAV and RMS. KNN and LDA classifier to be used inorder to control the wheelchair movement.

Chapter 4 shows all the results of features analysis and the result of ANOVA test, also shows the result of classification in this research work and its discussion.

In chapter 5 the findings of this study are summarized and concluded, and recommendations for future work are provided.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Recently, electric powered wheelchairs have become increasingly important as assistive technology and rehabilitation devices for elderly people and disabled people who lack full or partial control of their upper or lower limbs as a result of spinal cord injuries, hemiplegia, quadriplegia and amputation of upper or lower limbs (Angkoon Phinyomark, Limsakul, & Phukpattaranont, 2011).

The demand for providing support and assistance for disabled people in daily life is increasing. Users can control the movement of their wheelchair by using a conventional input device such as a keyboard, joystick or mouse. However, elderly people and people with severe physical disabilities like spinal cord injury or hemiplegia who lack the ability to control their upper or lower limbs, cannot use conventional input devices to control their wheelchair movement, therefore a controlled wheelchair based on an Electromyogram (EMG) is very important, where the EMG signal is more easily obtained and has less signal interference (Xu, Zhang, Luo, & Chen, 2013).

There are many methods for collecting the EMG signals from muscles which can be used in controlling wheelchair movements, such as from the shoulders (Moon et al., 2005), forehead muscles (Wei & Hu, 2009a; Zhang et al., 2011), upper limbs (Chong & Hong, 2008), bio potential signals interface (Wei, Hu, & Zhang, 2011; Maskeliunas & Simutis, 2011), and the wrist and ankle muscles (Ohkubo & Shimono, 2013). the

recording of electrical signals can be obtained during contraction of the muscles, then filtered and analyzed to use them as control signals for the wheelchair movement.

2.2 Human Muscles

The nervous system always controls muscle activity (contraction/relaxation) (Reaz et al., 2006), where the activities of the muscles differ from one person to another. The muscles are very important in the control of rehabilitation devices, where different types of muscles are used to control a wheelchair such as: shoulder muscles, forehead muscles, upper and lower limb muscles, and wrist and ankle muscles. But there are many people who are unable to control the movement of their upper or lower limbs (Paralysis - Simple English Wikipedia, 2015), and there are many people living with some form of tetraplegia, hemiplegia, quadriplegia and amputation of upper or lower limbs (Phinyomark et al., 2011). This means that these people cannot control their wheelchair movement by using the muscles that are mentioned above, however these people can control the movements of their masseter and buccinator muscles easily and can use these muscles in controlling their wheelchair movements (Wei et al., 2011). Therefore, for this reason, this research work will be based on using the masseter and buccinator muscles as a controlling method.

2.2.1 Lower Jaw Muscles (Masseter Muscles)

The masseter is the major muscle for the function of chewing by the human jaw, and it is very important for elevating the lower jaw as shown in Fig 2.1, while the deep tissue of this muscle helps to protract it forward. However, the lower jaw is the only bone of the

human skull that is actually moveable during this action, while the upper jaw is fixed all the time. In addition, the masseter works primarily because there is a lot of movement that must be done by the mandible.

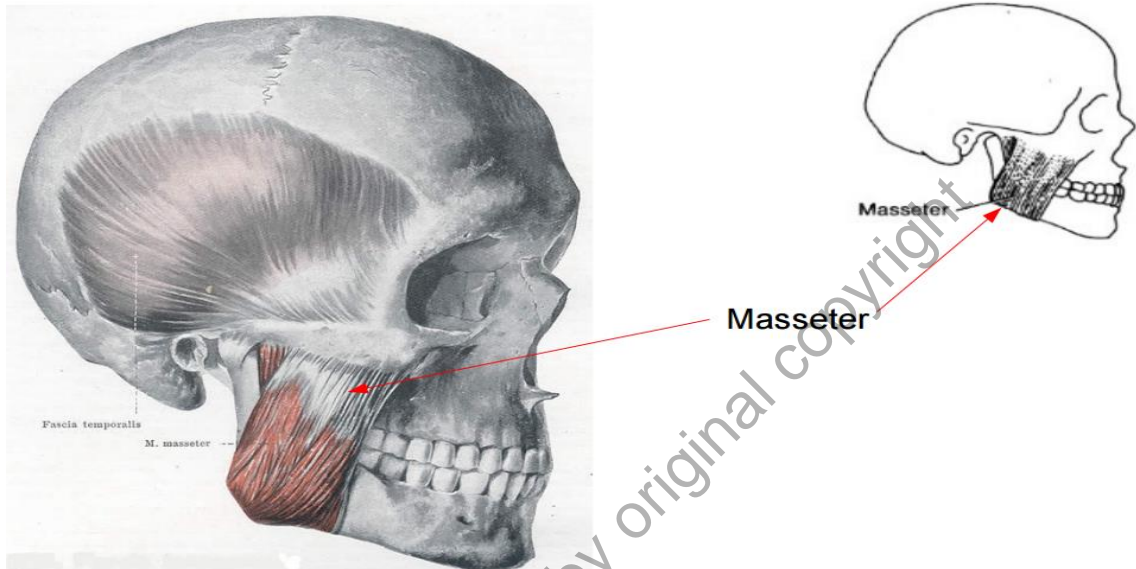


Figure 2.1: Jaw Muscles (Masseter Muscles) (Sae-Lee, Wanigaratne, Whittle, Peck, & Murray, 2006)

The masseter muscles are located on the right side and left side of the face in the region of the parotid (Sae-Lee et al., 2006), at the back of the human jaw. The masseter muscle is very visible during clenching of the jaw. Its contraction is very strong only in front of the lower ears (Pain & Disorder, 2014), and where the side of the jaw that is nearest the ear is covered by the masseter muscle.

2.2.2 Buccinator Muscle

The buccinator muscle is a square, plain-shaped bilateral mimic muscle, which is composed of the adaptable and mobile portion of the human cheek as shown in Fig 2.2 (Helena et al., 2008). It plays a major role in the chewing of food and compressing the

cheeks against the molars, therefore the buccinator muscle functions as an accessory muscle for mastication. This muscle is used for blowing, sucking and whistling. The contraction of the buccinator muscle is gradual when the mouth is closing, also during blowing. The maintaining of the required tension of the cheeks is very important, in order to avoid biting on the jugal mucosa (Tabe, Ueda, Kato, Nagaoka, & Nakashima, 2005).

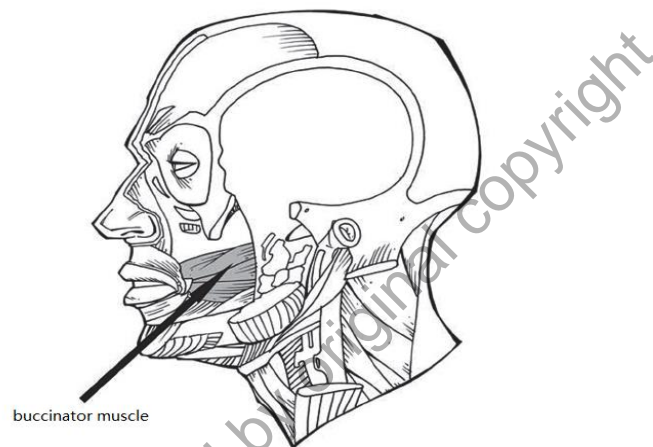


Figure 2.2: Buccinator Muscles of the Human (Helena et al., 2008).

2.3 Electromyogram (EMG)

The use of biomedical devices has become important within daily life, where the design of these devices involves specific software with integrated signals to the biomedical devices. These devices are designed as filtration system EMG transmission for prosthetic arms, jaw muscles, neck muscles and other muscles. EMG indication provides traits involving very low voltage amplitude with low-frequency common-mode industrial noise (Reaz et al., 2006).

The Electromyogram is a device that is used to measure the muscle's electrical activity in response to a nerve's stimulation of that muscle (Reaz et al., 2006), since the

EMG signals contain a wealth of information about muscle functions. The EMG device is very reliable and widely used in controlling rehabilitation devices, where there are many people who use the EMG in controlling their wheelchair movements based on signals from different muscles such as: the forehead muscles (Zhang et al., 2011), facial muscles (Silva, Morere, Naves, De Sa, & Soares, 2013), and hand muscles (Mahendran, 2014).

2.3.1 EMG Electrodes

Three types of electrodes that are used for collecting EMG signals include surface, wire and needle. Needle and wire electrodes are very useful for collecting the electrical signals from muscles that are in deeper layers. Additionally, they tend to be the most suitable electrodes with regard to evaluating the time-force relationship associated with EMG signals, in addition to interfacing with a human using a biomechanical device (Konrad, 2006).

The surface electrodes have different shapes, sizes, and materials. The configuration of mono-polars has two electrodes: one for collecting the signal from the muscle and another electrode being a reference electrode. These configurations lack the ability to remove the noise from the signals of the muscle around the target muscle (Konrad, 2006) while bipolar electrodes can overcome this problem by separating all noise from the surrounding muscles.

In fact, the use of bipolar electrodes is very important to reduce the noise ratio with the EMG signals (Wang, Tang, & E Bronlund, 2013), where the bipolar electrodes use differential amplification, and the differential amplification causes a 180 degree reversal phase with each input (Yungher, Craelius, & Threlkeld, 2010). The bipolar electrode is