



# **Biceps Brachii Surface EMG Classification Using Neural Networks**

by

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# List of Abbreviations

Abs	Absolute
ADC	Analog to Digital Converter
AI	Artificial Intelligence
AMD	Advanced Micro Devices
ANN	Artificial Neural Network
ATA	Analog Telephony Adapter
AUX	Auxiliary
BNC	Bayonet-Locking Coupling
BMI	Body Mass Index
BPN	Backpropagation Network
C	Celsius
CMRR	Common Mode Rejection Ratio
DAQ	Data Acquisition
dB	Decibel
DDR	Double Data Rate
Dev	Device
DLR	German Aerospace Center
D-Sub	D-Subminiature connector

DVD	Digital Versatile Disc or Digital Video Disc
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
F	Fahrenheit
FFT	Fast Fourier Transform
FIFO	First In First Out
FIR	Finite Impulse Response
ft	feet
GB	Gigabytes
GHz	Gigahertz
HIT	Harbin Institute of Technology
HMM	Hidden Markov Model
Hz	Hertz
IEMG	Intramuscular Electromyography
KB	Kilobytes
kg	Kilogram
LED	Light Emitting Diode
LM	Levenberg-Marquardt
m	Meter
mA	Milliampere
Max	Maximum

MIT	Massachusetts Institute of Technology
MLP	Multi-Layer Perceptron
mm	Millimeter
ms	Milliseconds
MSE	Mean Squared Error
MS/s	Millions of samples per second
MUAP	Motor Unit Action Potential
mV	Millivolt
mW	Milliwatt
NI	National Instrument
NN	Neural Network
No	Number
PNN	Probabilistic Neural Network
R	Read
RAM	Random Access Memory
RMS	Root Mean Square
ROM	Range of Motion
RP	Resilient-Propagation
RPM	Revolution Per Minute
RTI	Referred to Input
RW	Read and write
s	Second

SD	Standard Deviation
SDRAM	Synchronous Dynamic Random Access Memory
SEMG	Surface Electromyography
SVM	Support Vector Machine
T	Time
USB	Universal Serial Bus
V	Volts
Var	Variance
VC	Vapnik-Chervonenkis
Vs	Voltage second
w	With
Windows XP	XP means experience. Windows XP is a family of 32-bit and 64-bit operating system produced by Microsoft
WT	Wavelet Transform
WVD	Wigner-Ville Distribution
WXGA	Wide Extended Graphic Array

## ABSTRAK

# KLASIFIKASI EMG PERMUKAAN BICEPS BRACHII DENGAN MENGGUNAKAN RANGKAIAN SARAF

Disertasi ini membentangkan suatu pendekatan berdasarkan sistem MATLAB bagi aplikasi pemulihan pemantauan klinikal. Rasional utama bagi pembangunan sistem tersebut adalah kerana isyarat-isyarat EMG yang teransang mempunyai perbezaan bergantung kepada aktiviti pergerakan otot. Oleh yang demikian, penyelidikan ini bertujuan untuk mengaji isyarat-isyarat EMG yang teransang dari otot biceps brachii dan mengelaskan corak isyarat tersebut mengikut kelas aktiviti masing-masing. Sistem yang dicadangkan mengandungi dua bahagian utama. Bahagian pertama adalah berkenaan dengan pembangunan sebuah platform perolehan EMG. Platform ini mengandungi tiga modul iaitu; modul perolehan, modul prapemproses dan modul penyarian sifat. Modul perolehan digunakan untuk memperolehi isyarat-isyarat EMG dari subjek. Beberapa kaedah-kaedah meeproses dijalankan di dalam modul prapemproses, di mana isyarat EMG akan mengalami suatu siri proses-proses seperti penapisan, penerusan dan pengamiran. Selepas prapemproses, isyarat itu akan dihantar ke modul penyarian sifat. Dalam modul ini, ciri-ciri statistik seperti min, maksimum, varians dan sisihan piawai dihitung untuk mewakili corak isyarat tersebut. Bahagian kedua sistem ini adalah mengenai pengelasan corak EMG dengan menggunakan rangkaian saraf. Rangkaian 'feedforward BackPropagation' (BPN) dan 'Probabilistic Neural Network' (PNN) dipilih sebagai pengelas untuk mengelaskan aktiviti-aktiviti otot. Dalam fasa eksperimen-tasi, 30 orang subjek-subjek wanita mengambil bahagian dalam kajian ini. Mereka diminta melakukan beberapa siri pergerakan dengan menggunakan otot biceps brachii. Keputusan eksperimen menunjukkan bahawa isyarat EMG yang teransang berbeza mengikut kegiatan otot dan ciri-ciri statistik yang asas adalah mencukupi bagi mewakili corak EMG. BPN dengan Levenberg-Marquardt (LM) algoritma dan PNN yang tercadang telah mencapai kadar klasifikasi keseluruhan 88% manakala BPN dengan Resilient-Propagation (RP) algoritma mencapai satu klasifikasi keseluruhan 87.11%. Dengan keputusan yang memuaskan ini, keberkesanan pengelas tercadang menglasifikasi corak EMG terbukti.



## ABSTRACT

# BICEPS BRACHII SURFACE EMG CLASSIFICATION USING NEURAL NETWORK

*This thesis presents an approach of MATLAB-based system for clinical rehabilitation monitoring application. The main rationale for the development of such a system is that the pattern of the EMG signals elicited may differ depending on the activity of the muscle movement. Therefore, this research aims to study EMG signals elicited from biceps brachii muscle and classify the signal pattern to their respective class of activity. The proposed system consists of two main parts. The first part is about the development of an EMG acquisition platform. This platform consists of three modules; acquisition module, preprocessing module and feature extraction module. The acquisition module is used to acquire EMG signals from the subject. Several signal processing methods are carried out in the preprocessing module, where the EMG signal will undergo a series of processes like filtering, rectification and integration. After preprocessing, the signal is passed to the feature extraction module. In this module, statistical features such as mean, maximum, variance and standard deviation are computed to represent the signal pattern. The second part is regarding EMG pattern classification using neural networks. Feedforward BackPropagation Network (BPN) and Probabilistic Neural Network (PNN) are chosen as the classifiers to classify muscle activities. In the experimentation phase, 30 female subjects took part in this study. They were asked to perform several series of voluntary movement with respect to biceps brachii muscle. The experimental results show that EMG signals of different biceps activity is differed and simple statistical features are sufficient to represent the EMG pattern. The proposed BPN with Levenberg-Marquardt (LM) algorithm and PNN had achieved an overall classification rate of 88% while BPN with Resilient-Propagation (RP) algorithm achieved an overall classification of 87.11%. With these satisfactory results, the effectiveness of the proposed classifiers in EMG pattern classification problem is proven.*

# Chapter 1

## Introduction

### 1.1 Overview

Biosignal is a kind of signal that can be measured from biological beings. It is the electrical signal that is produced by the differences of electrical potential between specialized cells. Electroencephalogram (EEG), electrocardiogram (ECG) and electromyogram (EMG) are among the best known biosignals. Study on electromyography has begun for decades, however it has been in the recent 15 years that it has drawn much interest and passion from researchers to evolve it due to the present advanced electronic technology.

Based on the current state of the art, researchers are keen on integrating the expertise in biological components with the devices from electronics and mechanical engineering. This in turn for example can help the disabled to lead a way of life with dignity, peace and longer life. There are quite a numbers of successful products existing in the market, for instance the pacemaker for heart problems, intelligent prosthesis for arm amputees, camera based vision substitution for blind people, medical robots used in surgical rooms and emotion controlled machines for bed-ridden elders.

Since EMG has had a great contribution to various kind of applications, its benefits have become more apparent. Apart from the traditional use of EMG in physiological and biomedical field, EMG is also dedicated to medical research, rehabilitation, sports science and ergonomics. Our research is also along this line of applications, in particular, sensing EMG signals from a group of neurologically intact subjects. We are focusing on studying the pattern of the EMG response elicited through voluntary contraction of the biceps brachii muscle. The raw EMG signals will not be useful without further analysis. A series of signal processing steps will be carried out to extract information from the raw signals. With proper feature extraction, obtained information can be presented and interpreted in a more intelligent way. There are several methods of analysis which can fully utilize the information of the signal. Each method applies differently depending on its application.

Although many researches have been done in the past few decades, the mystification of EMG still remains and some of it still open to questions. However, with trial and error procedures and lots of experimental testing, sufficient experience in dealing with EMG signals can be obtained. This thesis will present the basic knowledge of EMG and the processing techniques applied towards the development of a real-time muscle activity classification system.

In this work, the overall biomedical components for upper limb classification comprised of a sensor placed on the surface of the muscle for detecting EMG signal, a DAQ to transform the analog signal to digital signal, a computer for data storage, software for signal processing and feature extraction and finally the development of neural network algorithms for classification. All these components form the basic construction units for this research.

## 1.2 Scope

Generally, the scope of this research is limited to the following:

- The human body has numerous muscles, however only the biceps brachii muscle is interested in this study. This muscle is chosen because of its easiness to be recognized and its accessibility for sensor placement.
- The biceps brachii muscle is located in the upper arm and it can be use to perform a variety of movements. It specifically plays a role to perform elbow flexion and forearm rotation. In this research, elbow flexion will be emphasized in which several activities concerning to biceps muscle will be carried out.
- There are several types of EMG sensors particularly meant for EMG analysis, for instance, needle and fine wire EMG. However, in this research, the surface EMG sensor is opted to be applied. This is because surface EMG is a non-invasive procedure and the subject will be free of discomfort when the electrode is placed onto the skin.
- Apart from that, a variety of algorithms have been used for the EMG classification. Each of the classification method has it own approach and advantages. In this research, feedforward backpropagation network with different learning algorithms and radial basis network are chosen for the pattern classification problem.
- In addition, this research will be served as a platform to study the feasibility and practicality of an automated rehabilitation physiotherapy monitoring system.

### 1.3 Motivation

The main rationale to carry out this research is to gain in-depth knowledge and experiences on EMG such that the signals can be extended to be used in an application. An EMG signal can be quite complicated. A nerve impulse could have triggered a reaction which then makes a muscle to contract. Although the confusions arise as to which muscle would respond, the benefits of determining this mystery from EMG signals become more perceptible. Therefore, there is a motivation to carry out a study to investigate and solve the problems pertaining to any EMG signals.

Moreover, for the disabled people, analysis of EMG signals can be very useful. EMG signals are easy to be generated and studies have shown that even paralyzed people can produce discernible EMG signals through self effort (Walker et al., 1998). Based on this hypothesis, the brain continues to generate signals to a muscle even though a human has lost a particular limb. Therefore, there is an inspiration of developing a classification system that can classify EMG pattern accordingly to specific muscle activity from a group of intact subjects. From there, the proposition of this study is evaluated and the feasibility to extend the system to amputees can be considered.

Furthermore, it is found that there are very few automated rehabilitation software for patients seeking physiotherapy. For this reason, there is a need to contribute to this area. Software developed for this purpose can have valuable economic value and high return in investment. Hence software development in this field is an area to be explored within the context of this research. In addition, as far as upper limb patients are concerned, most of the biceps injury and motor dysfunction cases must undergo training regimens in order to regain functional control. As such, there is a need to develop a specific system to assist them in their therapy in a more comfortable manner.

## 1.4 Problem Statements

EMG is very easy to use and consequently too easy to be abused. It is inherently problematic, with many shortcomings and thus has questionable values (Klasser and Okeson, 2006). Most of the biosignals such as ECG, EEG and EMG have very low amplitude levels. Therefore the delicate nature of EMG signals can be problematic in the acquisition stage.

The core problem related to EMG signals is how to preserve the fidelity of the signal from noise contaminations. Any irrelevant contribution of frequencies, for instance, ambient noise, motion artifacts and power line radiation may pollute the real EMG signals. Furthermore, unnecessary filtering will also distort the EMG signals. So, it is vital that the detecting and recording devices are capable of processing the signal properly.

Apart from noise, many other factors such as electrode types, electrode location, cabling and skin resistance will directly influence the reliability of the obtained EMG signals. For these reasons, many considerations need to be given extra attention in the process of developing the proposed system.

In addition to that, EMG signals vary from subject to subject. It is pretty challenging to classify muscle activities according to a specific movement. Even for the same muscle activity, EMG signals elicited by the subjects may differ. Some people may indicate higher signal amplitude while some others may give a lower signal amplitude. All these increases the variability and dependents of the EMG signals to external biological factors.

## 1.5 Objectives

The objectives of the research are indicated as follows:

- To investigate the effectiveness of using statistical features of the EMG signals as the discriminating factors for the different type of actions performed by the biceps brachii muscle.
- To design a system with neural networks to classify the type of actions performed by the biceps brachii muscle from the EMG signals recorded.

## 1.6 Research Methodology

The research has been carried out in the following stages:

- **First stage**

A thorough literature review was done to gather further information and knowledge regarding EMG signals analysis. Basic human anatomy and functional mechanism are studied. Besides that, EMG signals handling and acquisition theories were emphasized. Furthermore, various signal processing techniques and classification methods were studied and analyzed before a decision was made to apply a suitable method. In addition, existing applications of EMG are reviewed.

- **Second stage**

The data acquisition process was carried out. All the hardware and software were assembled and properly set up. An EMG acquisition platform which containing

several SIMULINK modules was built utilizing blocks units. Experiments were carried out using intact female subjects of varying body mass index. The subjects were requested to perform a series of activities concerning to biceps brachii muscle. The data obtained was then recorded and stored.

- **Third stage**

In this stage, work was carried out towards the development of a classification system. Several neural network algorithms were used to perform the classification task. The statistical feature vectors computed from the EMG data obtained was then used as an input to the neural network. In order for optimum results, some trials were done to fine tune the uncertain structural parameters of the network. Validation process was carried out to test the reliability of the trained network after completing the learning process. Lastly, the trained networks were applied to classify new cases. The performance rates of each respective algorithm were then compared.

The overall research methodology is shown in Figure 1.1.