"I hereby declare that I have read through this report entitle "Pattern Recognition Of EMG Signal During Load Lifting Using Artificial Neural Network (ANN)" and found that it has comply the partial fulfillment for awarding the degree of Bachelor of Electrical Engineering (Control, Instrumentation and Automation)"

Signature : ....

Supervisor name : ENCIK MOHD HAFIZ BIN JALI

Date : 1/6/2015

PATTERN RECOGNITION OF EMG SIGNAL DURING LOAD LIFTING USING ARTIFICIAL NEURAL NETWORK (ANN)

NOOR FAIZA BINTI KAMARUZAMAN

A report submitted in partial fulfilment of the requirements for the degree of Bachelor in Electrical Engineering (Control, Instrumentation & Automation)

Faculty of Electrical Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

To my beloved parents

Moh Minah Binti Abdullah and Kamaruzaman Bin Mat Ali

And

Fellow Friends

"I declare that this report entitle "Pattern Recognition of EMG Signal during Load Lifting Using Artificial Neural Network (ANN) is the result of my own research except as cited in references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature : ……………………………………….

Student name : NOOR FAIZA BINTI KAMARUZAMAN

Date : 1/6/2015

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ABSTRACT

This research describes pattern recognition of electromyography (EMG) signal during load lifting using Artificial Neural Network (ANN). EMG is a technique to quantify and record the muscle action when people perform certain operation and activities. This research will classify the EMG signal based on force apply to the arm due to the gravity act on it during load lifting. Recognizing pattern based on EMG signal is not an easy task because of the nonlinearities behavior of the signal. It required a good classifier to distinguish each pattern. The motivation of this project is to help the person suffer with hemiparesis to perform daily activities as well as to improve the lifestyle. It is important for patients to realize the hopes of hemiparesis after experiencing their inability to do activity as a normal human. Recognizing EMG pattern is crucially important for design the prosthesis arm that enables the patients to lift the heavy load despite of their muscle weaknesses. Therefore, a proper analysis of muscle behavior is necessary. The objectives of this research are to extract the important features of EMG signal using time domain analysis and to classify EMG signal based on load lifting using ANN. The analysis was performed to five subjects that were chosen for the most part in view of criteria determined. The EMG signal are gained at long head biceps brachii. At that point, the subjects were solicited to lift the heaps from 2kg, 5kg, and 7kg.It is expected an accurate classifier which can recognize the pattern precisely and could be further used for design the prosthesis arm.

ABSTRAK

Kajian ini menerangkan cara mengenalpasti corak isyarat Electromyography (EMG) semasa mengangkat beban dengan menggunakan Artificial Neural Network (ANN). EMG adalah teknik untuk mengukur dan merekodkan tindakan otot apabila manusia melakukan operasi dan aktiviti-aktiviti tertentu. Kajian ini akan mengelaskan isyarat EMG berdasarkan daya dikenakan kepada lengan akibat tindakan graviti di atasnya semasa mengangkat beban. Mengenalpasti corak berdasarkan isyarat EMG bukan satu tugas yang mudah kerana situasi parameter bagi isyarat adalah tidak sekata. Ia memerlukan pengelas yang baik untuk membezakan setiap corak. Motivasi projek ini adalah untuk membantu orang yang menderita dengan hemiparesis untuk melakukan aktiviti harian dan juga untuk meningkatkan gaya hidup mereka. Adalah penting untuk merealisasikan harapan pesakit hemiparesis selepas mereka mengalami ketidakmampuan untuk melakukan aktiviti sebagai manusia biasa. Menyedari corak EMG amat penting untuk mencipta lengan prostesis yang membolehkan pesakit untuk mengangkat berat walaupun mereka mengalami masalah lemah otot. Oleh itu, analisis yang betul untuk mengenalpasti tindakan otot diperlukan. Objektif kajian ini adalah untuk mendapatkan ciri-ciri penting isyarat EMG dengan menggunakan analisis domain masa dan untuk mengelaskan isyarat EMG berdasarkan mengangkat beban dengan menggunakan ANN. Analisis ini dilakukan ke atas lima orang yang telah dipilih berdasarkan kriteria yang telah ditetapkan. Isyarat EMG yang dibaca adalah di bisep brachii. Pada ketika itu, subjek telah diminta untuk mengangkat beban daripada 2kg, 5kg, dan 7kg. ANN dijangka satu pengelas yang tepat di mana ANN dapat mengenalpasti corak dengan tepat dan boleh digunakan untuk mencipta lengan prostesis.

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CHAPTER 1

INTRODUCTION

1.0 Project Background

Electromyography research started when Francesco Redi [1] found that muscle could create power in 1666 by reported that electrical ray fish produced electricity by utilizing a specific muscle [2]. Then, Alessandro Volta [2] had made a gadget which could create electricity and could be utilized to stimulate muscle. The next invention that was done by Luigi Galvani[1] has done a research to a frog in 1971 and has demonstrated that electrical incitement of muscular tissue produces contraction and force. The absence of constrained instrumentation has restricted Luigi Galvani[2] work and has held his labor for 40 years until a galvanometer is created in early 1800. In year 1838, Carlo Matteucci [1] has demonstrated that bioelectricity can be produced by muscular contraction and in 1842 he has shown that from the frog's muscle, action potential can be created from it. Guillaume Duchenne [3] has empowered electrically by reaching it to skeletal muscle and he is the one that initiated that medical electricity could be used for medical purposes. Guillaume Duchenne [2] also systematically mapped out function of about every facial muscle and established out that the muscles around the eye are just only active during genuine smile, meanwhile for a not genuine smile; it will just influence the muscle in the mouth[4]. Willem Einthoven[1] has built up a thin conductor wire that could be utilized for electromyography as a part of 1903 which has permitted Forbes to be the first individual to utilize floating electrode in a moving body which has permitted them to record electromyography signal of an elephant and Forbes [1] additionally utilized Cathode Ray Tube (CRT) to amplify the action potential. At that point, the improvement of concentric needle electrode was develop by Adrian and Bronk [3] in 1929 and has utilized it for researching motor control and muscle schemes. This has enabled the detection of electromyography signal in individual and small group of muscle fibers [1] and the development of concentric needle electrode has been changed to the hypodermic needle with protected wire in its barrel [2]. Then, Herbert Jasper [5] has built a first electromyography and made a unipolar needle electrode amid his exploration from year 1942-1944. In 1962, John Basmajian [5] has gathered all the information of electromyography furthermore made a fine-wire electrode which is more agreeable contrasted with needle electrode. Finally, the most vital individual in the surface electromyography history is Carlo J. De Luca [4] and has written a cited-paper on 'The Use of Surface Electromyography in Biomechanics.

The electromyography is the inquiry of the electrical signal when the muscles emanate.. Myoelectric sign is framed by a variety in the condition of muscle fiber membranes. There are numerous boundless utilization of electromyography that is in the rehabilitation part, medical research, ergonomic and sports science. This boundless utilization can help in the estimation of muscular performance through investigating muscle signal. There are two sorts of electrodes which can be utilized to distinguish electromyography signal that is surface and needle electrodes. . Feature extraction of electromyography signal can be done by using three basic methods that are in time domain analysis method, frequency domain analysis method and time-frequency analysis method. Other than that, there are two sorts of contraction which is finished by our muscle, which comprises of isometric and non-isometric (element) contraction.

The role of Electromyography inside biomechanics contemplated and setup can be measured by 4 major areas that is, a body part, forces, movement and muscle activation. The body parts will be controlled by bone and segment which will have the analysis in term of structure and 2 proportions. Next, the development will analyzed based on distance, angle, velocity or acceleration and force will be analyzed in term of linear force, moment and torque. Finally, the muscle initiation will be examined on the muscle action capability of the muscle. These four strategies can be classified as kinesiological investigation, which is utilized as a base to begin a research on new things. This research will be in view of EMG in term of force which can be utilized to help numerous applications, for example, prosthesis design, rehabilitation of muscle and designing a workout regime.

The purpose of this project is to develop a classification of electromyography (EMG) for load lifting using Artificial Neural Network (ANN). From movement of our body, electrode will detect and change impulse signal to electrical signal. After EMG signal acquisition, analysis the signals are proceed by selecting the feature extraction. Then the last part of EMG signal is selecting the classification for EMG signal. In this research, feature extraction is in time domain while for classification is Artificial Neural Network

1.1 Motivation Of Project

Hemiparesis or one-sided weakness affects about 8 out of 10 stroke survivors, causing weakness or the inability to move one side of the body. One-sided weakness can affect arms, hands, legs and facial muscles.. Hence, prosthesis arm will be expected to help the hemiparesis individual to procure a living without the assistance from others. Thusly, the improvement of upgrade of prosthesis equipment was expected to guarantee that the operation of prosthetic hand is the same as the operation of a typical human hand. This upgrade of prosthesis equipment needs an analysis which can be utilized as a guideline or data to build up the enhancement of prosthesis arm.

Therefore, a utilization of bio signal l is important in analyzing the reaction of the body that will be valuable to help in the process of outlining the prosthetic hand based on the reaction of an electrical signal or bio signal send toward the muscle. The electromyography is an electrical signal that will be acquired when the reaction of muscle happens and this data could help in the designing another prosthetic arm.

The prosthesis arm design ought to consider numerous factors that could influence the movement and the load that could be lifted by the arm. The design of the arm additionally relies on upon the experimental setup. Consequently, the following inspiration of this venture is to focus the pattern recognition of electromyography (EMG) signal during load lifting. Ultimately, the fundamental inspiration of this project is to describe pattern recognition of electromyography (EMG) signal during load lifting using Artificial Neural Network (ANN) that can be utilized as a part of the design of prosthetic arm.

1.2 Problem Statement

To identity the actual EMG signal that originates in the muscle is not easy due to the various noise signals or artifacts. The attributes of the EMG signal depend on the internal structure of the subject like individual skin formation, blood flow velocity and the measuring site. These attributes produce different types of noise signals that can be found in EMG signals. . This research is an important step for prosthetic arm design. Prosthetic arm could not emulate hundred percent human normal hands and limited their life capabilities but it can help them to live as a normal person.

Therefore, a proper analysis of muscle behavior is necessary. The force that is applied to the biceps brachii muscle will be focused in this research. The force will be varied by the weights of the loads. The surface electromyography (sEMG) signal will be extracted to obtain the characteristic of the muscle and will be evaluated to feed into the classifier. The classification of EMG signals is very important to categorize the intended action. There are many type of EMG classification, which can be differentiating based on the accuracy.

1.3 Project Objective

Below describes the objective on this project:

1. To extracted the EMG signal using time domain analysis.
2. To classify EMG signal for load lifting using Artificial Neural Network (ANN).
3. To analyze the ANN classification performance.

1.4 Project Scope

Project scope will be a guideline to achieve the objectives and of this project. The scope was shown as below:

1. Long head biceps brachii will be the muscle that used in this research.
2. This research will use surface electrode.
3. NI myRIO, Muscle V3 and LabVIEW will be used for data acquisition
4. The feature extraction that will be used in this research is the time domain.
5. The feature parameters will be used are root mean square (RMS) , mean absolute value (MAV), standard deviation(STD) and variance.
6. Artificial Neural Network (ANN) will be the classifier in this research.
7. There are 5 subjects based on the criteria in Table 1.1:

Table 1.0: The criteria of target subject

Specification	Age	Height (cm)	Weight (kg)	Load Applied To The Muscle (kg)	Health Condition
5 Male	20-30	160-180	60-90	2,5 and 7	Normal

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

Electromyography (EMG) is a record of external activity from the muscle (Z., Mohammed, and Abbas H, 2012) [6]. Nowadays, many research about detect, analysis, process and classify of EMG were done because application of EMG signal in biomedical and clinical is very important. This EMG signal can be study as muscle contraction activity based on behavior of body movement. Electric signal will be produce when contraction or tighten of muscle occurs in the body movement.

The understanding of EMG signal origin and character is necessary background to proceed to the study of pattern recognition [2]. The EMG origin related with the work of nervous system. The transmission of electromechanical is between starting nerves from the brain that produces action potential that propagates through nerve fibers. Action potential will move with nerve fiber and finally stimulate the prosthetic muscle.

2.1 Literature Review

2.1.1 EMG signal

EMG sensor is uses to measure the electrical activity of muscle. The electrical activity produces an electrical signal from the muscle by placing EMG sensor on the surface of the skin. This raw EMG signal consist of a series of spikes whose amplitudes depends on the amount of force delivered from load by muscle.

2.1.2 Type of Electrode

Surface electrode is an example of non-intrusive electrode that have been utilized for measuring muscle electrical activities amid muscle contraction. The surface electrodes are separated into two main groups which are inactive and active electrodes. Passive electrodes have no inbuilt circuitry including amplifiers and filter [7] other than these electrodes obliges gel to beat a high impedance amid muscle contraction. Meanwhile, for active electrode, it has constructed in amplifier and filter which are they decrease motion artifact and increase the signal to noise ratio [8].

Figure 2.0: Surface Electrode

The advantages of utilizing surface electrodes are these electrodes are easy to understand, simple to apply and without a doubt its exceptionally helpful while amid the exercises or moving application amid the muscle contraction [7]. Other than that, the individual who conducts the process of paste the surface electrodes do not oblige any certificated or medical supervision [9]. Other than that, by utilizing this non-invasive electrodes, there is minimal pain will cause minimal pain with the application [7] [8]. The weaknesses of non-invasive electrodes are the process of paste the surface electrodes are restricted just in a skin surface and this electrode only can measure the large muscle. Other than that, this electrode additionally has a large pick-up area and will have more potential for crosstalk form adjacent of muscles [10].

Gregory S Rash [10] expressed that the most of the researchers these days utilized surface electrode as a part of their approach and research to measure an electrical signal delivered by a muscle because of its advantages and features.

2.1.3 Feature Parameter, Feature Extraction and EMG Classification

EMG classification is one of the most difficult in EMG analysis due to large variations in EMG features. To extract useful features from the residual muscle is difficult. Nowadays, many researches proposed many kinds of EMG feature to classify posture. However, how to select a feature subset with the best discrimination ability from those features is still an issue for classifying EMG signals (Huang et al., 2003) [11]. Since it is very difficult to extract a feature parameter, the multiple feature parameters for EMG pattern classification is desirable to uses. But overall pattern recognition performance may degrade due to the inclusion of an additional feature parameter with a small reparability. Table 2 shows several example feature parameters [12]

Table 2.0 Feature Parameters

Feature Parameters (Phinyomark & Baraani ,2009)	
1. Integrated EMG	$IEMG = \sum_{n=1}^{N} \lvert h_n \rvert$
2. Mean Absolute Value	$MAV = \frac{1}{N}\sum_{n=1}^{N} \lvert h_n \rvert$
3. Modified Mean Absolute Value	$MMAV = \frac{1}{N}\sum_{n=1}^{N} \lvert h_n \rvert W_n \qquad W_x = \begin{cases} 1 & 0.25N \le n \le 0.75N \\ 0.5 & otherwise \end{cases}$
4. Variance of EMG	$VAR = \frac{1}{N-1}\sum_{n=1}^{N} h_n^2$
5. Waveform Length	$WL = \sum_{n=1}^{N-1} \lvert h_{n+1} - h_n \rvert$
6. Wilson Amplitude(WAMP)	$WAMP = \sum_{n=1}^{N-1} f(\lvert h_{n+1} - h_n \rvert),\ f(x) = \begin{cases} 1 & x \ge threshold \\ 0 & otherwise \end{cases}$

The total of features analysis in the electromyography (EMG) signal is three which are time domain, frequency domain and time, frequency domain [13]. The time domain features are simple and fast method to do features extractions of EMG signals because it already in time domain. So, it is unnecessary to transform the signal to another and the calculation of the time domain features can be calculated from raw EMG signal after preprocessing.

The classification of electromyography (EMG) signal patterns has been research by many researchers in this era. There are different types of classifiers, which are effectively used for different EMG applications, such as Artificial Neural Network (ANN), fuzzy classifier, Linear Discriminant Analysis (LDA), Self-Organizing Map (SOM) and Support Vector

Machines (SVM).[14] The raw EMG signal is represented as a feature vector in the feature extraction process, which is used as an input to the classifier. Because raw EMG signals directly feed to the classifier, they are not practical due to the randomness of the EMG signal.

2.1.4 Biceps Muscle

The biceps muscle that will select in this research is biceps brachii and the position of the muscle is shown in Figure 2.0. Biceps brachii is Latin phrase that meaning two headed muscle which are the long head biceps brachii and the short head biceps brachii. Long head biceps brachii is the more visible.

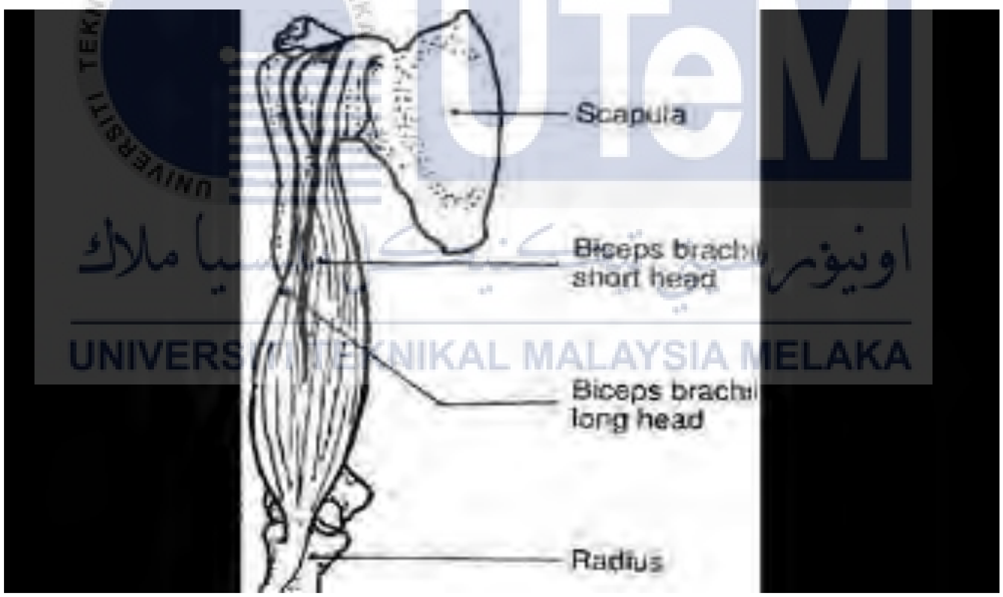


Figure 2.1: Bicep Branchii

2.1.5 Noise in EMG Signal

EMG signal comprise of unwanted noise that interface the signal. This occurrence noise make the signal become unstable and. Therefore, there are a few recognize noise that disturbs the output waveform of EMG:

1. Inherent noise in electric equipment
   - Generally by all electronics equipment
   - Frequency range from 0 to several thousand Hz
   - Cannot be eliminated
   - Reduced by using high quality components
2. Ambient noise
   - Electromagnetic radiation source are from radio transmission, electric wires and fluorescent lights
   - Essentially impossible to avoid
   - Dominant frequency is 60 Hz
   - Amplitude is 1-3x EMG signal
3. Motion Artifact
   - Two main sources that produced the noise came from electrode/ skin interface electrode cable
   - Reducible by proper circuitry and set up
   - Frequency range is 0-20 Hz

2.1.6 Filtration

Filter is one of the important stages for developing EMG bio-potential amplifier. This is because there is many unwanted noise that can disturb the output of EMG waveform. The frequencies that produced by EMG signal is in range of 50 Hz to 5000 Hz. However, a very useful data in EMG signals is dominant frequency which is in the range of 50 Hz to 150 Hz. The used of Low Pass Filter is because of the presence of electrical interference from the surroundings of the system are always present and the interference induced on the body common to the bio potential sensing electrodes is called the common mode interference.. This interference was suppressed conventionally by the use of Low Pass Filter. The use of High Pass Filter is because of occurrence DC drift. High Pass Filter is uses to suppress the DC drift but not totally eliminates them.

2.1.7 Artificial Neural Network

An artificial neural network (ANN) reflects a system that is based on operations of biological neural networks and hence can be defined as an emulation of biological neural systems. ANN's are at the forefront of computational systems designed to produce, or at least mimic, intelligent behaviour. Not at all like traditional Artificial Intelligence (AI) frameworks that are intended to specifically imitate balanced, coherent thinking, have neural systems gone for repeating the hidden preparing components that offer ascent to knowledge as a rising property of intricate, versatile frameworks. Neural system frameworks have effectively been produced and sent to settle design acknowledgment, scope organizing, business knowledge, mechanical technology, or instinctive issue related viewpoints. In software engineering, neural systems picked up a great deal of steam throughout the most recent couple of years in zones such determining, information examination, and in addition information mining.

It has to be pointed out that data analytics is normally defined as the science of examining raw data with the purpose of drawing conclusions about that information. Data analytics is utilized as a part of numerous businesses to permit organizations to either settle on better business choices, or in science, to confirm/invalidate existing models or speculations. Data analytics contrasts from data mining by scope, purpose, and focus of the analysis. Data Mining portrays the procedure of finding new patterns out of very large data sets and does as such by applying a vast set of methods that begin out of statics, artificial intelligence, or database management. The real data mining errand mirrors a programmed (or self-loader) investigation of vast amounts of information and the objective is to extract previously unknown patterns likes gatherings of data records (cluster analysis), unordinary records (anomaly detection), or dependencies (association rule mining). Thus, information mining fundamentally concentrates on sorting through large data sets (by using refined programming applications) to distinguish unfamiliar examples and build up concealed connections (otherwise known as extract value). Data analytic concentrates on deduction, the procedure of determining a conclusion that solely based on what is already known to the researcher. To compress, a neural network can be depicted as an exceptionally parallel framework that is fit for determining ideal models that straight processing cannot handle. Some more remarks sort of ANN's are:

1) Feed Forward Neural Network.

   Feed forward neural network is a basic neural network sort where synapses (connections) are produced using a data layer to zero or more concealed layers and eventually to an output layer. The feed forward neural network sort is a standout amongst the most widely recognized neural network being used. It is suitable for some sorts of utilizations. Feed forward neural network are frequently prepared through simulated annealing, genetic algorithms, or via one of the propagation techniques. More specifically, simulated annealing can be utilized to help a neural system to aid a neural network to avoid local minima scenarios in its energy function. Simulated annealing fundamentally includes perturbing the independent variables (the ANN weights) by an irregular value and keeping track of the value with the least error.

2) Self Organizing Map (SOM).

   SOM is neural networks that contains two layers and executes a winner take all strategy in the output layer. Instead of taking the output of individual neurons, the neuron with the highest output is viewed as the winner. SOM’s are regularly utilized for clustering related problems where the output neurons represent groups that the input neurons are to be classified into. SOM's may utilize an aggressive learning technique.

3) Hopfield Neural Network

   Hopfield neural network is a basic single layer that intermittent neural network. The Hopfield neural network is trained via an algorithm that teaches it to learn to recognize patterns. The Hopfield network will show that the pattern is perceived by resounding it back. Hopfield neural network are regularly utilized for pattern recognition.

ANN - Pros:

- A neural network can be utilized to comprehend linear as well as non-linear programming tasks
- As a part of an ANN fails, the net keeps on working (taking into account its exceptionally parallel nature)
- A neural network learns and does not need to be re-programmed
- An ANN can be utilized to comprehend classification, clustering, and regression related problems

ANN - Cons:

- Most ANN's oblige a preparation stage to work/function
- As an ANN's architecture varies from microprocessors, ANN's have to be emulated
- Large ANN's require rather powerful HW to keep running ((to accomplish reasonable execution times)

ANN - Processing Units

To emphasize, an ANN comprises of a pool of straightforward processing units that communicate by sending signal to one another over a large number of weighted connections. Every unit performs a moderately fundamental task; get data from neighbours or outer sources and use that data to register a output signal that is propagated to different units in the ANN. Beside the real information processing task, weights must be balanced.. ANN's recognize among 3 sorts of units;

- The Input Units that get data from outside the net.
- The Output Units that acts as the ANN endpoints.
- The Hidden Units where the input and output signal stay inside of the ANN structure. Amid operation, units can be redesigned either synchronously or asynchronously.

ANN - Topologies

In general, ANN solutions can be classified as:

- Feed-Forward ANN's.

  In such an ANN solution, the data moves from the input to the output units in an entirely bolster forward way. Data processing may produce numerous layers, but no feedback connections are implemented.

- Recurrent ANN's.

  These sorts of ANN's incorporate feedback connections. Contrasted with feed forward ANN's, the dynamic properties of the system are fundamental. In a few circumstances, the activation values of the units undergo a relaxation process so that the network advances into a steady state where these activation values stay unaltered.

ANN - Training

An ANN must be planned and actualized in a manner that the set of input data results into a desired output (either direct or by using a relaxation process). The weights can be set unequivocally (using from the earlier learning) or the net can be prepared by sustaining learning patterns into the solution and by letting the net change/modify the weights as indicated by some learning rule. Learning based solution can be categorized as:

- Supervised or associative learning, where the net is prepared by measuring input and matching output patterns (learning by example). These input/output sets might either be given by an outer teaching component or by the net itself (self-supervised approach).
- Unsupervised learning (self-sorting out ideal model), where the net (output) unit is prepared to react to groups of patterns within the input framework (just input however no output examples are given). In this paradigm, the system should discover statistically salient features in the input population. Contrasted with the supervised learning method, there is no there is no a priori set of categories into which the patterns are to be classified, rather the system needs to build up its own particular representation of the input stimuli.
- Reinforcement Learning, where the net applies a learning standard that is viewed as a transitional type of the over 2 sorts of learning. In this method, the learning machine executes some activity on environment and as a result, receives some feedback/response. The learning segment evaluations its activity (as either great or terrible) in light of the ecological reaction and changes its parameters appropriately. As a rule, the parameter change procedure is proceeded until a balance state surfaces where no further conformities are essential.

2.2 Related Research Work

2.2.1 EMG Signal Analysis: Detection, Processing, Classification and Applications [15]

This paper is about Techniques of EMG signal analysis: detection, processing, classification and applications. The purpose of this paper is to illustrate the various methodologies and algorithms for EMG signal analysis to provide efficient and effective ways of understanding the signal and its nature. EMG signals acquired from muscles require advanced methods for detection, decomposition, processing, and classification. This paper highlighting the up-to-date detection, decomposition, processing, and classification methods of EMG signal along with a comparison study.

Based on this project that is pattern recognition of electromyography (EMG) signal during load lifting using Artificial Neural Network (ANN), this journal really help in order to understand the flow of the project. This is because the mission of this journal and this project is exactly same that is signal analysis. The main difference both of them is how to classify the EMG signal. In this project will use ANN but in the journal it uses wavelet analysis. Based on this journal, the steps can be listed down. First, the signal needs to detect. Second, process the signal. Third, classify the signal. These three steps will help more in how to analysis the EMG signal.

2.2.2 Pattern Classification of Time-Series EMG Signals Using Neural Networks [16]

This journal describes Pattern Classification of Time-Series EMG Signals Using Neural Networks. This paper proposes a pattern classification method of time-series EMG signals using neural network for prosthetic control. This project will describe pattern recognition of electromyography (EMG) signal during load lifting using Artificial Neural Network (ANN). So, this journal actually gave more knowledge about neural network and how to classify using neural network.

2.2.3 Source Detection of Surface Electromyography Signal [17]

Next reference is the document by Thought Technology Ltd from "The Basic of Surface Electromyography Applied to Psychophysiology". The signal generated by the muscle fibers is captured using electrode, then amplified and filtered by the sensor. This project will use the surface electrode, so this document gave more knowledge in order to understand surface EMG signal.

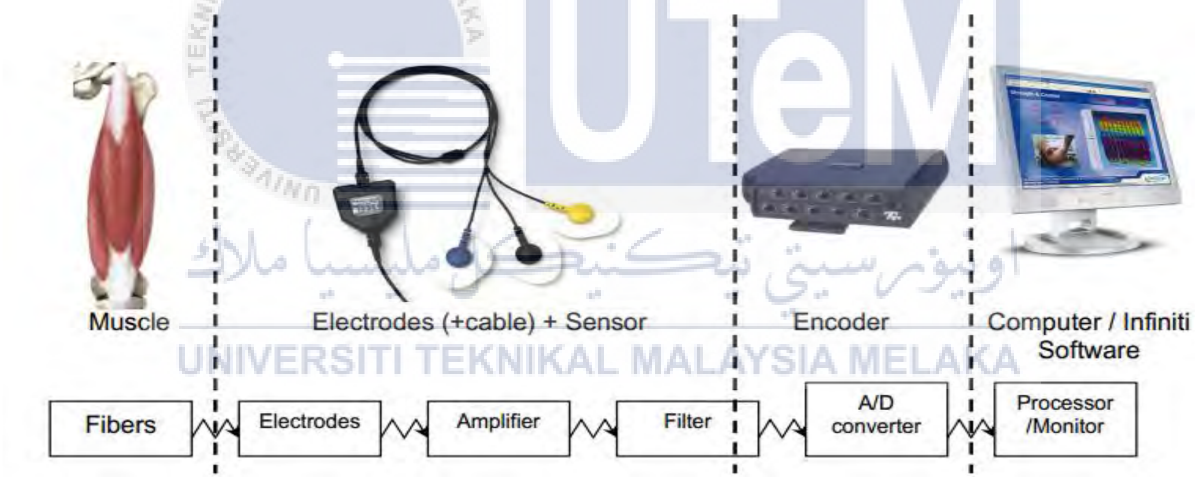


Figure 2.2: Source detection of EMG signal

2.2.4 Surface Electromyography Signal Processing and Classification Techniques [18]

This paper gave detailed information about clearing up commonly associated artifacts and noises from EMG signal, EMG features and the various methodologies for analyzing the signal. The paper also shows the summary of most important classification. Artificial Neural Network also include in that summary. This paper gave knowledge about the noises and artifacts from EMG signal. From this paper, the information of the noise and artifact can be listed down and try to reduce its. It also gave a bit detail about ANN which is related to this project.

CHAPTER 3

METHODOLOGY

3.0 Overview

In this chapter the methodology of the project is discussed in order to complete the project based on the requirement. Basically, methodology can be defined as the systematic, theoretical analysis of the methods applied to a field of study.

3.1 Introduction

In this project methodology, it will show the step by step that needed to do before, during and after experiment. This research methodology explains each phase briefly one by one. Experiment set up and experiment guideline also include in this project methodology. To make the project methodology more clearly, flowchart and Gantt Charts also include in the summary of the project methodology. Gantt Charts are utilized as a part of to demonstrate the schedule and track progress in completing tasks.

3.1.1 Experimental setup

First of all, the skin preparation is needed to reduce the resistivity of the skin. Conductivity of skin and cleaning of the skin and is the two different parts in the skin preparation. Cleaning of the skin will have the process of cleaning hair, dirt, shaving, and implementing the alcohol swab. Meanwhile, conductivity process will be the process of implementing the conductivity gel to the skin before placing the electrode.

The electrodes are used to detect or sense the existence of EMG signal at muscle. The electrodes are located at long head biceps brachii muscle which is the most suitable muscle to represent the flexion motion. Location of biceps muscle is measured each time EMG signals are acquired from the subjects to make sure the position of sensor is fix each time sensor is placed at the subject’s skin. This is crucial to ensure data consistency. In order to collect EMG signal, 5 male without any physical disorder will be the subject of this experiment as shown in Table 1. The subjects were asked to sit straight and lift a dumbbell from 0° to 90° as shown in Figure 2. The lifting load was conducted for duration of 10 seconds and the stop watch was used due to computer time and real time is not the same. There were 3 main tasks that will be divided into three different loads that are 2kg, 5kg and 7kg.

Figure 3.0: Position during load lifting

Table 3.0: Subject Details

Subject	1	2	3	4	5
Age	23	23	24	24	24
Weight (kg)	60	64	90	85	61
Height (cm)	179	161	165	176	163
Gender	Male	Male	Male	Male	Male

3.1.2 EMG Signal Acquisition

After the experimental setup, EMG signal can be acquired using signal acquisition device. NI myRIO will be the data acquisition and Muscle V3 as EMG signals preamplifier as shown in Figure 3. Electrode is connected to the NI myRIO and then is linked to LabVIEW to view and record the signal as shown in Figure 4. Muscle V3 will produce filtered signal therefore no preprocessing need to be conduct from the raw signal.

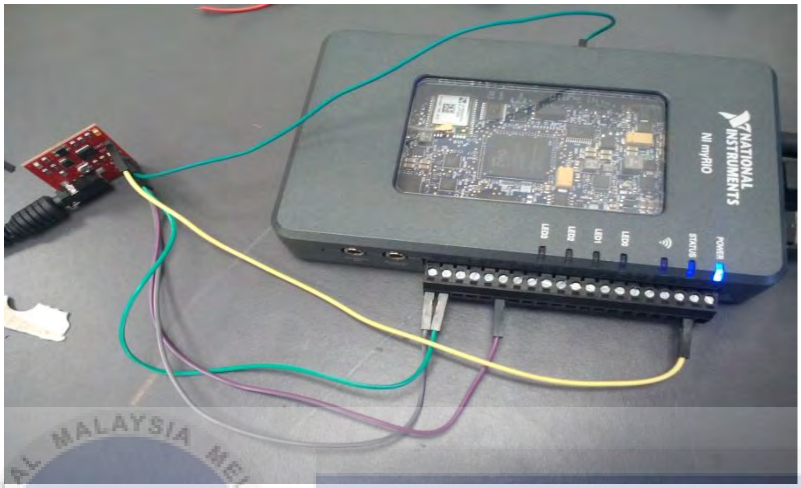


Figure 3.1: NI myRIO and Muscle V3

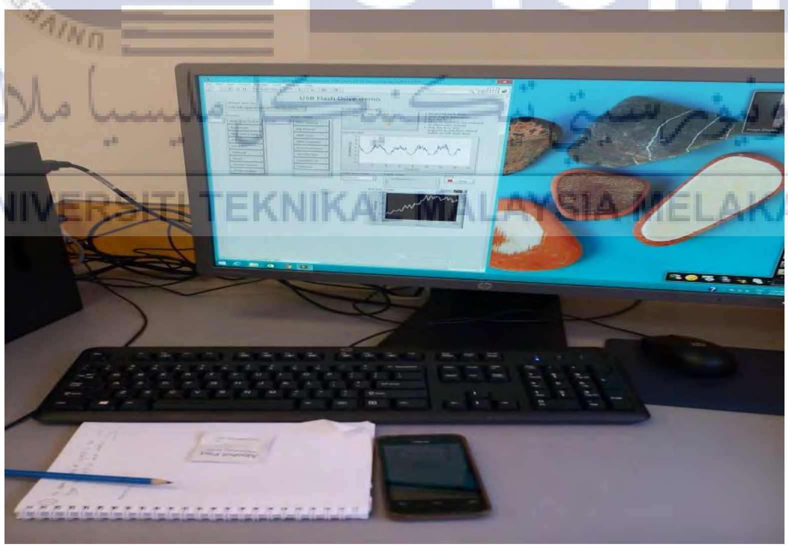


Figure 3.2: LabVIEW

3.1.3 Time-Domain Features Extraction

So as to accomplish an effective EMG pattern recognition, numerous features need to be utilized as input to the classifier. Each feature reflects a unique character individually. Therefore, a combination of several features capable to describe the classification system more accurately [19]. In order to transform the raw signal into reduced representation set of features, a feature extraction is needed. For classification process, these features are very useful. Five time domain feature extraction methods which are Root Mean Square (RMS), Mean Absolute Value (MAV), Standard Deviation (STD) and Variance (VAR) are decided for this research. The formulas for each of these features are demonstrated as:-

1. Root Mean Square (RMS)

   The RMS speaks to the square foundation of the normal force of the EMG signal for a given time of time. Because of the sufficiency of the sign is measured as an element of time, it is known as a period area variable

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} EMG(i)^2} \qquad (1)$$

2. Mean Absolute Value (MAV)

   The MAV is the computer calculated likeness the average rectified value (ARV). It is measured as an element of time. Along these lines, it is known as a period space variable. It speaks to the region under the EMG flag once it has been amended, it is characterized by the negative voltage qualities have been made positive. The mean total worth is figured utilizing a moving window. It is ascertained for every window of information as per the mathematical statement:

$$\mathrm{MAV} = \frac{1}{S}\sum_{1}^{S}|f(s)| \qquad (2)$$

3. Standard Deviation (STD)

The STD of an arrangement of information is the square base of the change, where $\bar{x}$ alludes to the mean of the specimen. The outcomes taken from information are oftentimes composed as the mean ± ST:

$$\mathrm{STD}_{n-1} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (3)$$

4. Variance (VAR)

Highlight that uses the EMG sign force is a VAR. It takes the mean estimation of the square of the deviation. Be that as it may, mean of EMG sign is near to zero. In outcome, difference of EMG can be ascertained by:

$$\mathrm{VAR} = \frac{1}{N-1}\sum_{n=1}^{N} X_n^2 \qquad (4)$$

3.1.4 Feature Selection

There are several repetitions of EMG data from the subjects in order to select the most appropriate signal. The EMG signal during rest position will act as reference. The features which have less percentage of error are chosen for the input of the classifier. This is to ensure the efficiency of the classification result. Therefore, ANOVA test is conducted to make sure the features are valid or less percentage of error. There are a few redundancies of EMG information from the subjects to choose the most suitable sign. The EMG sign amid rest position will go about as reference. The features which have less rate of slip are decided for the input of the classifier. This is to ensure the efficiency of the classification result. Accordingly, ANOVA test is directed to verify the features are legitimate or less rate of slip. On the off chance that the P-value is under 0.05, so the features are satisfactory or in other word legitimate. In this venture, the P-value is 0.0286. Figure 5 demonstrates features variation based on the lifting load while Figure 6 demonstrates the P-value.

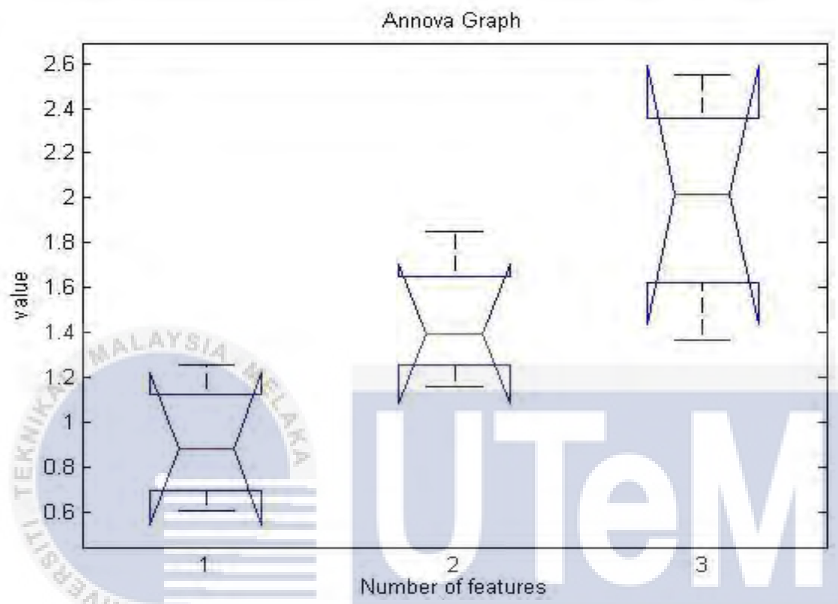


Figure 3.3: ANOVA Graph

Table 3.1: ANOVA Table

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	2.32014	2	1.16007	8.45	0.0086
Error	1.23556	9	0.13728		
Total	3.5557	11			

3.1.5 Classification

The last phase of this work is classification. The pattern of the EMG signal is prepared to be perceived after the selection of feature. EMG signal consists of numerous sorts of classifiers, however as for this research, the classifier that is being utilized is the Artificial Neural Network (ANN). The cortical structures of the brain have been taken as model to compute ANN which comprise networks of connections that work together to produce an output function. Using a set numeric outputs, it is able to map data. It has input layer, hidden layer and output layer, thus it is been applied widely in training networks. However, to produce high accuracy network, the neurons on each layer must be carefully considered. The performance of the network could be affected by the number of hidden neurons. If the hidden layer and its neurons is increased, the network performance would not improve so, to achieve an optimized network, the number of hidden neurons is tested. Unfortunately, there are some drawbacks in determining the number of neurons such as the network requires more memory and becomes even more complicated if the numbers of hidden neurons are too large. On the other hand, the network would face difficulty in adjusting the weight and may cause over fitting if the number of hidden neurons is too low. Even a slight change in input would cause difficulty in generalizing the network.

Using back propagation algorithm, the input signal is propagated forward through network layer. To compute the value of error function, an array of predetermined input is compared with the desired output response. Those errors are propagated in a retrograde manner via synaptic connections. The synaptic weight would be adjusted, to ensure that the actual response value of the network has actually moved closer to the desired response [20].

BPNN has hidden neurons and linear output neurons which are the feed-forward networks. Range of values from -1 to 1 is generated via sigmoid function in the hidden layer of network [21]. In between the input and output neurons, there are layers of hidden processing units. The weights and biases are updated in the connections to the output. The learned error between the input and target, the deltas, is propagated back through the network [22]. To minimize the error and increased the rate of network performance, the training process was all iteratively adjusted. BPNN network was constructed using MATLAB software. In order to determine the weights of each node and its uses, the network requires data for learning and testing. Before stopping the network, it will be trained to meet the conditions below:-[23]

i- maximum number of epochs reached

ii- the gradient performance drops lesser than the minimum gradient

iii- increasing validation performance more than the maximum number of times it failed since the last decreased one

The network's performance is evaluated based on the Mean Squared Error (MSE) of the training data which evaluates the target outputs and the network outputs, the characteristics of the training, validation, and testing errors. Lowest MSE while exhibiting similar error characteristics among the training, validation and testing indicates the network's best performance. MSE that shows very good result would be unsatisfactory if the validation and testing vary greatly during the training process. The network is said to be not generalized. Further tuning and training need to be conducted in order to improve the network's performance [24].

3.2 Flow Chart of Project Methodology

The flow chart of this project methodology is as shown below;

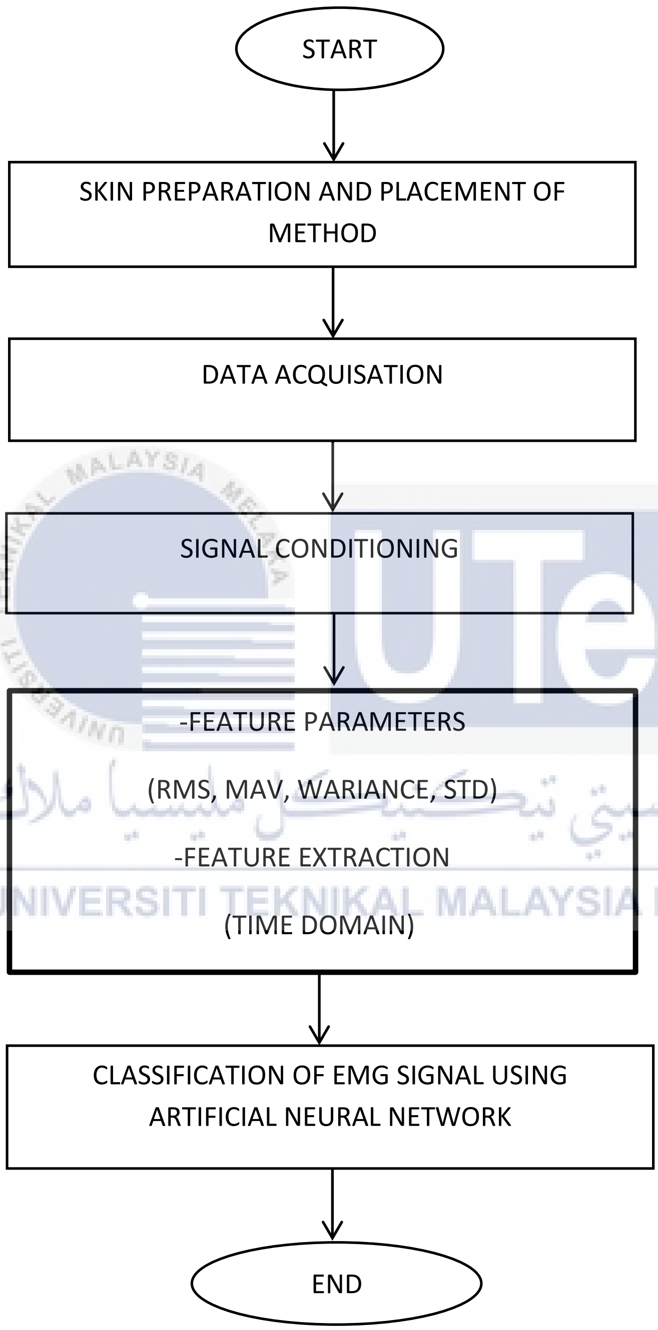


Figure 3.4: Flow chart

3.3 Gantt Chart

Table 3.2: Gantt chart of FYP 1

	Weeks									
Project Activities	1	2	3	4	5	6	7	8	9	10
Find supervisor and decide title										
Research about EMG signal										
Research about data acquisition, signal conditioning, signal processing and classification of EMG signal										
Research about classification of EMG using Swarm Intelligence Technique										
Find out the methodology and the preliminary result for progress report										
Writing the progress report										
Presentation										

Table 3.3: Gantt chart of FYP 2

	Week															
Project Activities	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Continues the project from FYP 1.																
Write the Draft of Final Report																
Submit Draft of Final Report to supervisor.																
Makes correction of the reviewed Draft of Final Report																
Submit Final Report to panel and supervisor.																
Presentation																

3.4 Summary

Based on this chapter, the method to apply from initialization of this project until the last part that is classification of EMG data have been go through one by one. The feature already selected for this project. The classification also have been specified which is Artificial Neural Network. Finally, this chapter is really helps in order to achieve the objective of this subject.

CHAPTER 4

RESULT AND DISCUSSION

4.0 Introduction

This section will furnish with describes pattern recognition of electromyography (EMG) signal during load lifting using Artificial Neural Network (ANN). The best training performance is at the lowest epoch, MSE and time elapsed.

4.1 Neural Network Analysis

By utilizing the feature extraction value, the data will be validated by utilizing Neural Network analysis. Neural network can evaluate its performance using mean square error and confusion matrices. The data gathered was prepared by utilizing a two-layer feed-forward network with scaled conjugate gradient backpropagation. There are others a few techniques accessible, however for this research, just scaled conjugate gradient backpropagation) was included. The training process based on training data, tester data and validation data. After it accomplishes the error goal, all the weight results can be utilized for testing purpose.

4.2 Scaled Conjugate Gradient Backpropagation

By using this method, the features extraction acts as input and the output is the target of this research.

Table 4.0: Features Extraction

	Pattern 1	Pattern 2	Pattern 3
MAV	1.26038001060905	1.85419650022013	2.55204162482846
RMS	0.989629999999999	1.44558600000000	2.15408399999999
STD	0.780617920841896	1.16134022752509	1.36871246997518
VAR	0.609364338339525	1.34871112406802	1.87337382546555

Next is fitting network. This network is feed forward neural network utilization to fit an input-output relationship. Set the shrouded neuron network as per wanted output in light of the fact that different numbers of hidden neuron will create different value of Mean Square Error (MSE). MSE is the average squared difference value of output and targets. Lower the value is better and zero means no error.

In order to optimize the network performance, different number of hidden neurons is simulated for several times until the satisfactory result is achieved. [10]. For Figure 4.0, it is 60% training and 10 hidden neurons number and the best training performance is 0.30066 at epoch 14. While for 60% training and 20 hidden neurons number as shown in Figure 4.1, the best training performance is 0.011022 at epoch 6. The best training performance is at the lowest MSE.

Based on Figure 4.2 and Figure 4.3, there are also same percentage of training but different number of hidden neurons. Error sizes are well distributed since most error approaching zero values that make the trained model perform better as shown in Figure 4.3. Noted that many authors advise that for real data sets histograms based on 5-20 bins usually suffice [11].

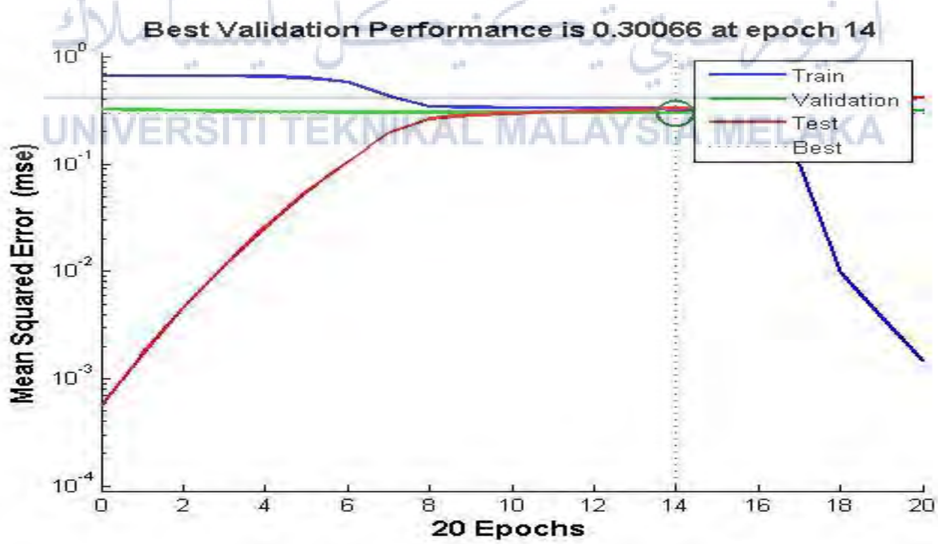


Figure 4.0: Training for 10 Numbers of Hidden Neurons

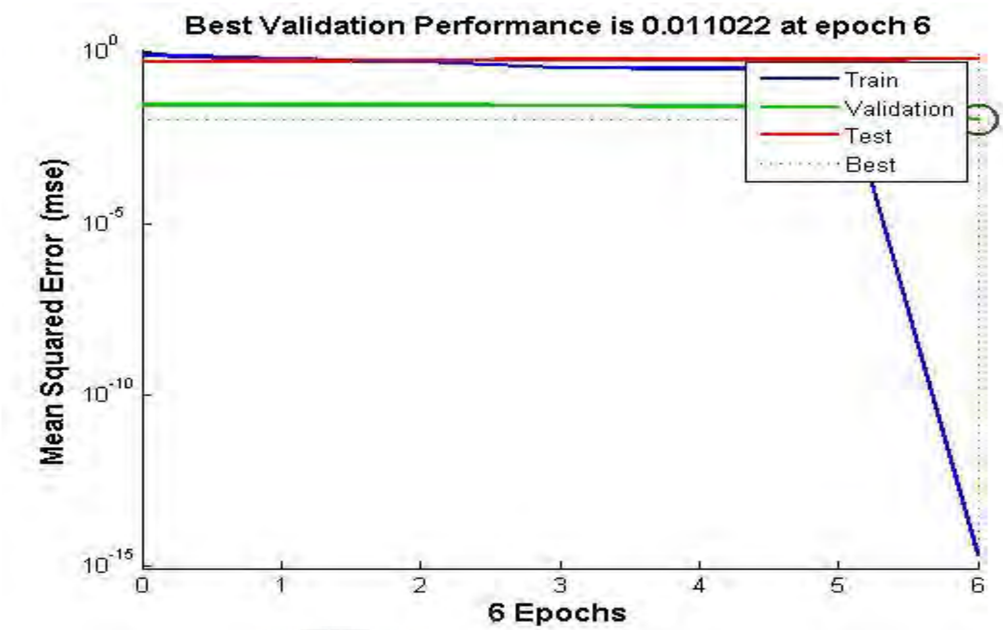


Figure 4.1: Training for 20 Numbers of Hidden Neurons

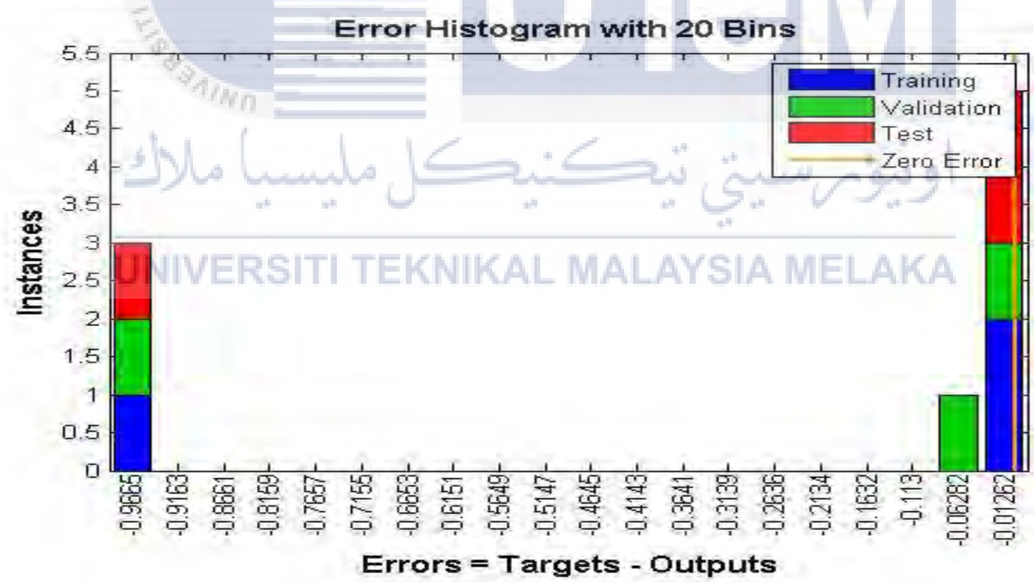


Figure 4.2: Training for 10 Numbers of Hidden Neurons

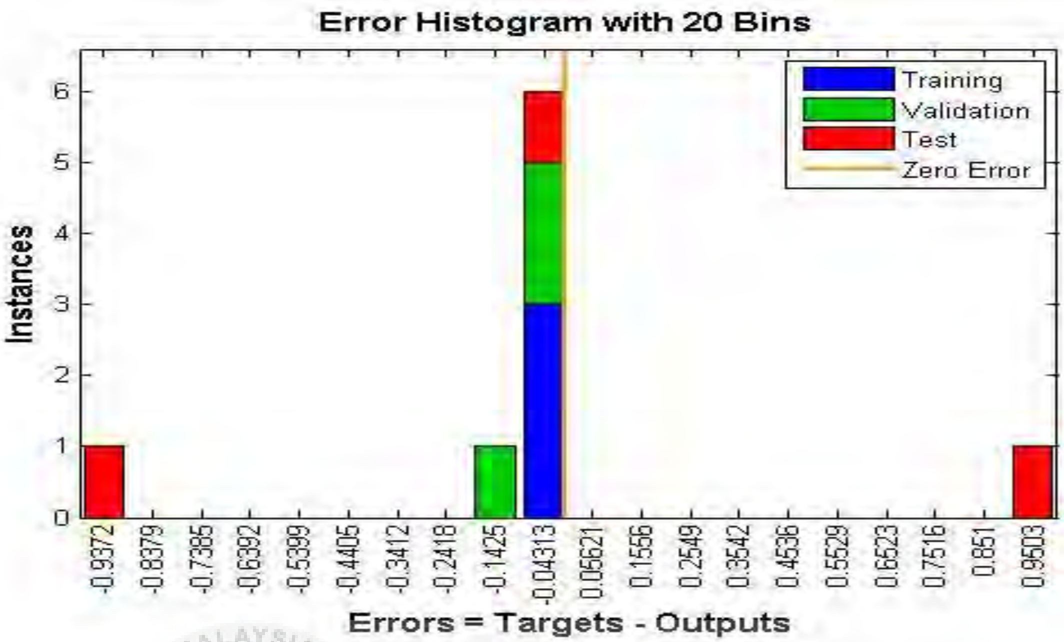


Figure 4.3: 60% Training for 20 Numbers of Hidden Neurons

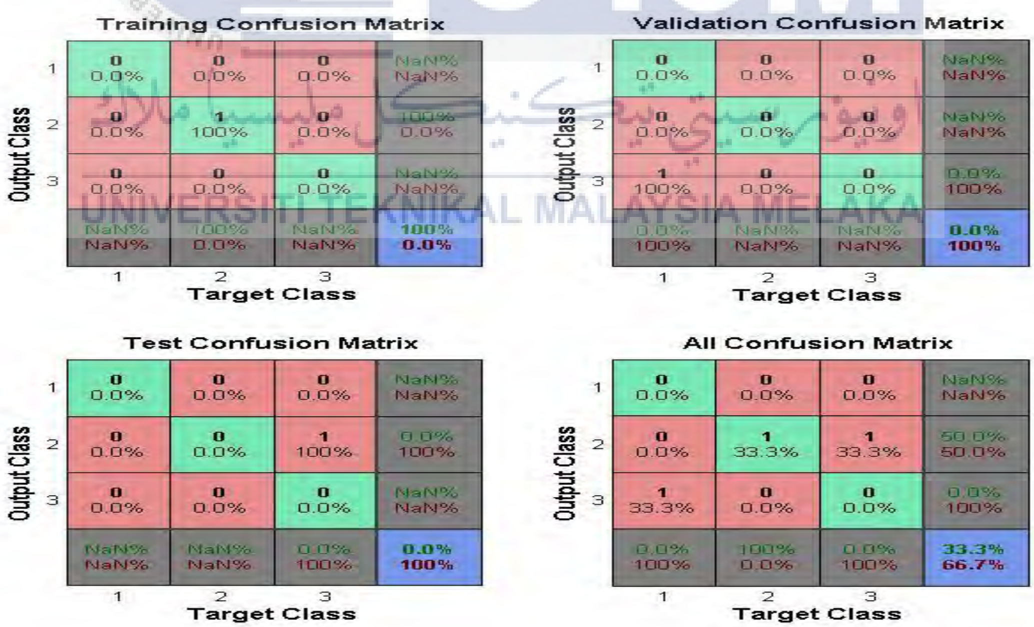


Figure 4.4: Training for 10 Numbers of Hidden Neurons

Figure 4.5: Training for 20 Numbers of Hidden Neurons

Refer to all confusion matrix. Firstly, look at Figure 4.4, at interior square percentages, there were 33.3% is correctly and 66.7 is incorrectly assigned. So, this is unacceptable because the percentage of incorrect is higher than correct.

After that, look at Figure 4.5. First, look at column one for class 1 targets. There were 3 class 1 targets. 1 was assigned correctly (GREEN) to output class 1. Then, ignore the colors for 0 entries. So, 100*1/1 = 100% (GREEN) of class 1 targets were correctly assigned. Second, look at column two for class 2 targets. There were 3 class 1 targets. 1 was assigned incorrectly (RED) to output class 3. Then, ignore the colors for 0 entries. So, 100*1/1 = 100% (RED) of class 3 targets were correctly assigned. Third, look at column three for class 3 targets. There were 3 class 1 targets. 1 was assigned correctly (GREEN) to output class 3. Then, ignore the colors for 0 entries. So, 100*1/1 = 100% (GREEN) of class 3 targets were correctly assigned. Fourth, look at row one for targets assigned to class 1. 1 target was assigned to output class 1. 1 target from class 1 were correctly (GREEN) assigned to class1. Then, ignore the colors for 0 entries. So, 100*1/1 = 100 %(GREEN) of assignments to class 1 were correct. Fifth, look at row three for targets assigned to class 3. 2 targets were assigned to output class 3. 1 target from class 2 were incorrectly (RED) assigned to class 3. 1 target from class 3 were correctly (GREEN) assigned to class 3. Then, ignore the colors for 0 entries. So, 100*1/2 = 50% (GREEN) of assignments to class 3 were correct and 100*1/2 =50% (RED) of assignments to class 3 were incorrect. Lastly, look at interior square percentages. There were 1+1+1 = 3 targets. So, 100*2/3 = 66.7% is correctly and 100*1/3 = 33.3% is incorrectly. Therefore, this is acceptable because the percentage of correct is more than incorrect.

Table 4.1: Summary of the Experiment Result

No of neurons	Percentage of training	Stop Epochs	Time Elapsed (Second)	MSE
10	60	14	0.35	0.30066
20	60	6	0.01	0.011022

4.2 Summary

Based on the result, it can be concluded that the ANN model produce the best training performance is 0.011022 at epoch 6. It is definitely a good performance result as it shows that this neural network can perform pattern recognition of the bicep brachii muscle signal. Hence this classifier can be used for designing an accurate prosthetic arm control.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

This section will close all the finding of the research, from the earliest starting point of the research until the analysis of the data gathered. EMG is a method for determining the electrical signal from the muscle to monitor the muscle condition. Hence, EMG signal conveys significant data in regards to the nerve system of bicep branchii. From the research, the raw EMG signals of ordinary subjects were effectively measured from the bicep branchii. At that point so as to get the raw EMG signals, the subjects must experience a few techniques like skin preparation, equipment set up and sensor placement procedure to avoid undesirable signal mixed. These methodologies are very essential so as to pick up a superior nature of EMG signal. In light of previous research, raw EMG signals also contain a noise occur from the internal noise which is tissue characteristic, skin impedance and muscle belly. While for the outer noise, it is brought on by the encompassing environment condition, and contraction between skin and electrodes. . Placement of electrodes also will contribute to the noise if it was pasted improper and not in the trunk muscle. Then, a raw EMG sign ought to filter to reduce or eliminate the unexpected signal and noise occurred during the EMG signal recording. For this research, the

EMG signal gathered by utilizing Muscle Sensor V3 was a normalized signal which implies the output were at that point being sifted and amended with full wave correction which will total all the signals. Henceforth it makes easier to extract features from the EMG signals.

Then, RMS, MAV, STD and VAR features was effectively being separated from the standardize EMG data. All the features are suggested as input for a classification purpose by utilizing neural network. Neural network classification is a supervise kind of classification that need a target to differ between the input and output. Based on the result, it can be concluded that the ANN model produce the best training performance is 0.011022 at epoch 6. It is definitely a good performance result as it shows that this neural network can perform pattern recognition of the bicep brachii muscle signal. Hence this classifier can be used for designing an accurate prosthetic arm control.

However even though the ANN produces almost good result, it can be further improved by applying other artificial intelligence algorithm such as genetic algorithm to shorten the training time and stop epochs.

Other than that, there are a few things need to be enhance for further explores. While dealing with muscles, EMG machine utilized ought to be high specification and sufficient to identify the muscle condition in light of the fact that the extent of muscle is distinctive between the area of the muscle. Ahead of time, this task still can enhance by classified the different muscles and different feature extraction of bicep branchii a two-layer feed-forward network with scaled conjugate gradient backpropagation.

REFFERENCE

[1] Medved V., Measurement of human locomotion, CRC Press, Boca Raton, 2001.

[2] Clarys, J. P. Electrology and localized electrization revisited, Journal of Electromyography and Kinesiology, Vol. 4, pp 5-14 1994.

[3] Basmajian JV and De Luca CJ, *Muscle Alive*,5th edition,William and Wilkins, Baltimore, 1985

[4] De Luca, C. J., The use of surface electromyography in biomechanics, *Journal of Applied Biomechanics*, Volume 13, Pages 135-163, 1997.

[5] Basmajian JV, Stecko GA., A new bipolar indwelling electrode for electromyography, *J Applied Physiology*, volume 17, page 849, 1961.

[6] Z., Mohammed, and Abbas H. "Artificial Human Arm Driven by EMG Signal", MATLAB – A Fundamental Tool for Scientific Computing and Engineering Applications - vol 1, 2012.

[7] Huang et al. "Automatic EMG Feature Evaluation for Controlling a Prosthetic Hand Using a Supervised Feature Mining Method: An Intelligent Approach" 2003 International Conference on Robotics and Aut0mation, 2003.

[8] Peter Konrad, A Prac Introduction to Kinesiological Electromyography,*The ABC of EMG*, Ver.1.0, 2005.

[9] Slim Yacoub, Kosai Raoof, "Noise Removal from Surface Respiratory EMG Signal, World Academy of Science, Engineering and Technology", 2008.

[10] Serge H. Roy, "The Use of Electromyography for the Indetification of Fatigue in Lower Back Pain".

[11] Gregory S. Rash, EdD, Electromyography Fundamentals, [online]. Available at: http://educ.ubc.ca/faculty/sanderson/courses/HKIN563/pdf/EMGfundamentals.pdf, [accessed 5 October 2013].

[12] Phinyomark et al, "Feature Extraction and Reduction of Wavelet Transform Coefficients for EMG pattern Classification", Electronics and Electrical Engineering, no.6, 2012.

[13] Phinyomark, Phukpattaranont, and Limsakul, "Feature Reduction and Selection for EMG Signal Classifications, vol 39, no.8, pp. 7420-7431; Jun 2012.

[14] Chowdhury et al, "Surface Electromyography Signal Processing and Classification Techniques", Sensors, 2013.

[15] M.B.I. Reaz, M.S. Hussain and F. Mohd-Yasssin. "Techniques of EMG signal analysis : detection, processing, classification and application", Biological Procedures Online, 2006, pp. 11-35.

[16] Toshio Tsuji. "Pattern classification of time-series EMG signals using neural networks", International Journal of Adaptive Control and Signal Processing, 12/2000.

[17] Thought Technology Ltd, “The Basic of Surface Electromyography Applied to Psychophysiology”, Document Number MAR908, 2008.

[18] Rubana H. Chowdhury, Mamun B.I Reaz and Mohd Alauddin Bin Mohd Ali, “Surface Electromyography Signal Processing and Classification Techniques", Sep. 2013.

[19] Ahsan, M.R., 2011. Electromygraphy (EMG) signal based hand gesture recognition using Artificial Neural Network (ANN). Proceeding of the International Conference on Mechatronics (ICOM), Vol.4

[20] B. Hudgins, P. Parker, and R. Scott.:A new strategy for multifunction myoelectric control. IEEE Trans. Biomed. Eng., vol. 40, no. 1, pp. 82– 94, Jan. 1993. Favieiro, G.W.

[21] Balbinot, A. Barreto, M.M.G. : Decodin Arm Movements by Myoeletric Signals and Artificial Neural Networks. Conference of Biosignals and Biorobotics(BRC). pp 1-6. 2011.

[22] Mars,P, Chen JR, Nambiar, R Learning Algorithms.: Theory and applications in signal processing, control and communications. CRC 1996

[23] Ahsan, M.R. ; Ibrahimy, M.I. ; Khalifa, O.O. EMG Motion Pattern Classification through Design and Optimization of Neural Network. International Conference on Biomedical Engineering (ICoBE), pp 175-179.2012.

[24] George R. Terrell and David W. Scott. Oversmooth nonparametric density estimates. J. of the Amer. Stat'l. Assn., 80:209{214, 1985.

[25] M.H. Jali, T.A. Izzuddin, Z.H. Bohari, M.F. Sulaima, H. Sarkawi, "Predicting EMG Based Elbow Joint Torque Model Using Multiple Input ANN Neurons for Arm Rehabilitation ",

Proceedings of the UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, pp 189-194, 2014.

[26] M.H. Jali, Z.H. Bohari, M.F. Sulaima, M.N.M. Nasir and H.I. Jaafar, "Classification of EMG Signal Based on Human Percentile using SOM", Research Journal of Applied Sciences, Engineering and Technology, 8(2): 235-242, 2014.

[27] M.H.Jali,'I.M.Ibrahim, Z.H.Bohari, M.F.Sulaima, M.N.M.Nasir Classification of Arm Movement Based on Upper Limb Muscle Signal for Rehabilitation Device", Journal of Theoretical and Applied Information Technology, 68(1):125-137, 2014.

APPENDICES

A. Feature Parameters

Feature Parameters (Phinyomark & Baraani ,2009)	
1. Integrated EMG	$IEMG = \sum_{n=1}^{N} \lvert h_n \rvert$
2. Mean Absolute Value	$MAV = \frac{1}{N} \sum_{n=1}^{N} \lvert h_n \rvert$
3. Modified Mean Absolute Value	$MMAV = \frac{1}{N} \sum_{n=1}^{N} \lvert h_n \rvert W_n \quad W_x = \begin{Bmatrix} 1 & 0.25N \leq n \leq 0.75N \\ 0.5 & otherwise \end{Bmatrix}$
4. Variance of EMG	$VAR = \frac{1}{N-1} \sum_{n=1}^{N} h_n^2$
5. Waveform Length	$WL = \sum_{n=1}^{N-1} \lvert h_{n+1} - h_n \rvert$
6. Wilson Amplitude(WAMP)	$WAMP = \sum_{n=1}^{N-1} f(\lvert h_{n+1} - h_n \rvert), \ f(x) = \begin{Bmatrix} 1 & x \geq threshold \\ 0 & otherwise \end{Bmatrix}$

B. Formula MAV,STD,VAR and RMS

1. Root Mean Square (RMS)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} EMG(i)^2} \quad (1)$$

2. Mean Absolute Value (MAV)

$$\mathrm{MAV} = \frac{1}{S}\sum_{1}^{S}|f(s)| \quad (2)$$

3. Standard Deviation (STD)

$$\mathrm{STD}_{n-1} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (3)$$

4. Variance (VAR)

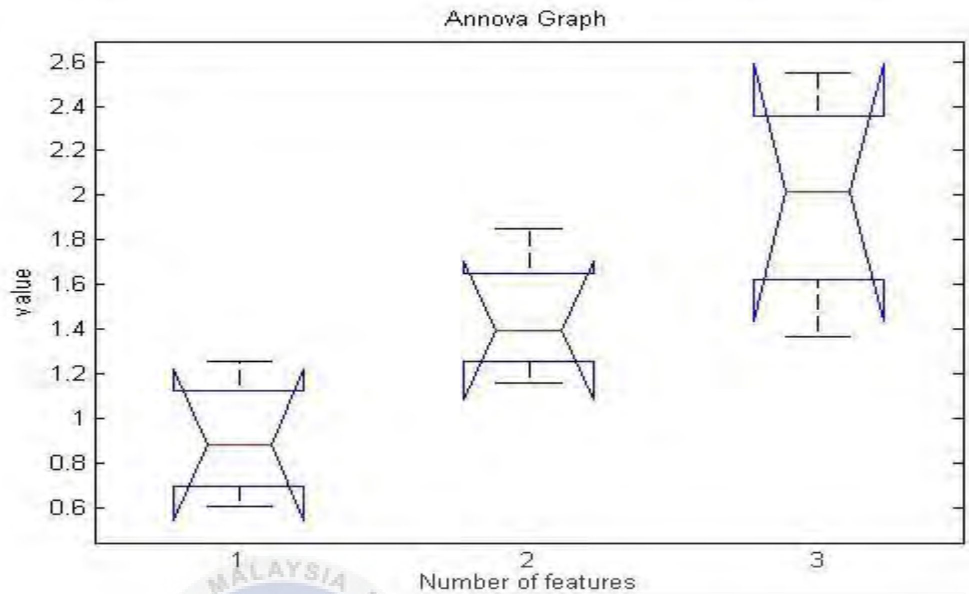
$$\mathrm{VAR} = \frac{1}{N-1}\sum_{n=1}^{N} X_n^2 \quad (4)$$

C. Position of Electrode

D. Skin Impedance Range

Impedance Range(KOhm)	Recommendation
1-5	Very good condition
5-10	Good and recommended if feasible
10-30	Acceptable for easy condition
30-50	Less Good(needed attention)
>50	Bad

E. Anova Graph



F. Anova Table

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	2.32014	2	1.16007	8.45	0.0086
Error	1.23556	9	0.13728		
Total	3.5557	11			

G. Coding Feature Extraction and ANOVA Test for MATLAB

```
data=xlsread('data.xlsm');

%Calculate Root Mean Square

data_squared = data.^2;  %squares each term in the vector

mean_data_squared = mean(data_squared );   %mean of the squared values

RMS = sqrt( mean_data_squared );  %square root of the mean of the squared values

%Calculate Mean Absolute Value

MAV=[meanabs(data(:,1)) meanabs(data(:,2)) meanabs(data(:,3))];

%Calculate Standard Deviation

STDE=[std(data(:,1)) std(data(:,2)) std(data(:,3))];

%Calculate Variance

VARI=[var(data(:,1)) var(data(:,2)) var(data(:,3))];

Features=[RMS;MAV;STDE;VARI];

%ANOVA test between Features

>> Pattern=Features';

>> p=anova1(Features);  % Type anova1 at help menu in matlab for description
```

H. Research Methodology

FACULTY of ELECTRICAL ENGINEERING

2014/2015

RESEARCH METHODOLOGY

EXPERIMENT ACQUISTION DATA FOR ELECTROMYOGRAPHY SIGNAL CLASSIFICATION FOR BICEP BRANCHII

OBJECTIVES:

At the end of this experiment, student should be able;

1. To collect the raw data of EMG signal in term of time domain features.
2. To recognize the behaviour of EMG signal.
3. Prepare the EMG signal in order to patterning and classification stage.

REFERENCES

1. The ABC of EMG- A practical introduction to Kinesiological Electromyography.
2. Techniques of EMG signal analysis: detection, processing, classification and applications
3. Investigation of optimum electrode locations by using an automatized surface electromyography analysis technique
4. Classification of Paraspinal Muscle Impairment by Surface Electromyography.
5. Electrode Placement Guide by Compex Performance US.

LIST OF EQUIPMENTS

1. 15 unit NIHON KOHDEN VITRODE *Disposable Electrodes* EMG surface electrode.
2. 2 unit Muscle Sensor v3 Kit with 2 analogue input channel.
3. 1 unit NI myRIO.
4. A load of 2 kg, 5kg and 7 kg.

5. A Stop watch.
6. 5 unit Razor shaver.
7. 1 box of Alcohol Swab
8. 3 unit Wet tissue boxes.
9. Multimeter.

PRE TASK PROCEDURE

1. Firstly, all the subject that selected randomly must be briefly explain on the experiment conducted.
2. The subject/participant consist of 5 person are normal without any health problem
3. After demonstrate the experiment conduct that is necessary in order for the subject get the rough fixture about the experiment.
4. Next, get ready for the entire respondent to undertake the skin preparation proceeding before start the experiment.

5. Experiment will be start after participant known about the experiment and the risk after the experiment.
6. Lastly, before start the experiment, check the skin impedance by using multimeter in order to make sure the resistance on the surface area low.

SKIN PREPARATION PROCEDURES

There are several way to done the skin preparation and the following procedures may be considered as steps to prepare the electrode application:

1) Removing the hair:

This step is needed and important to improve the adhesion of the electrodes, especially under humid conditions or for sweaty skin types and/or dynamic movement conditions. After removing the hair, clean up the surface with wet tissue before proceed to the next step.

2) Cleaning of the skin:

There are several method can be done to cleaning of the skin before start to paste the surface electrode. First, we can use cleaning paste, alcohol pred pad, alcohol swab and sand paper.

Method A:

First method is by using special abrasive and conductive cleaning pastes (Nuprep EEG & ECG skin preparation Gel) which is will remove dead skin cells that produce high impedance and clean the skin from dirt and sweat to prevent from external noise.

Method B:

Second method are using alcohol pred pad. This method are use alcohol as alternative way to remove the dead skin cells and this method may be sufficient for static muscle function tests in easy conditions.

Method C:

Last method can be classified to cleaning the skin surface is by using a very fine sand paper. A soft and controlled pressure in 3 or 4 sweeps usually is enough to get a good result. This method are less preferred because it can harmed the skin surface and also the participant.

Attention: Avoid any harm to the skin from rubbing too hard! The use of sandpaper should be combined skin with an alcohol pad.

Whichever skin preparation method and electrode application technique is used, when all the process done properly, the skin typically receives a light red colour. This indicates good skin impedance condition.

Table : Skin impedance range

Impedance Range(KOhm)	**Recommendation**
1-5	Very good condition
5-10	Good and recommended if feasible
10-30	Acceptable for easy condition
30-50	Less Good(needed attention)
>50	Bad

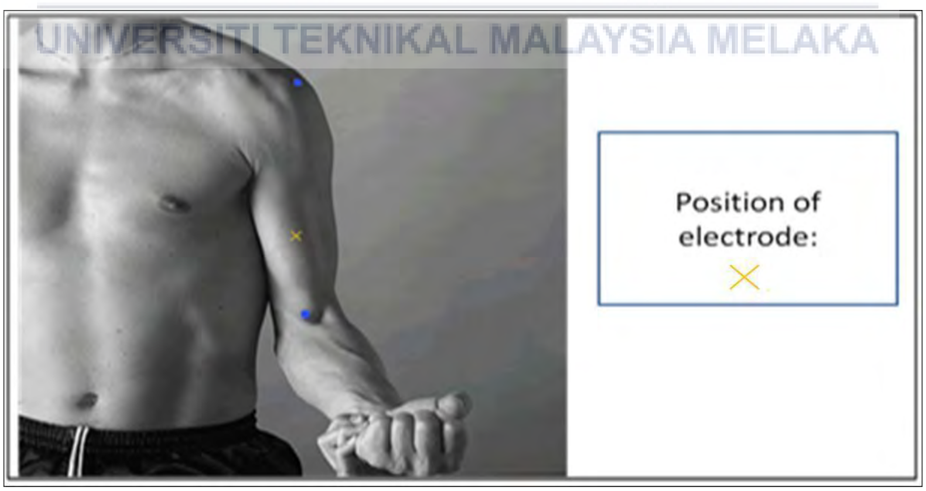


Figure 2: Placement of Electrode

EXPERIMENTAL PROTOCOL:

1. This experiment overall take about 15 minutes average for each subject during completed all the task.
2. The data will be collected for 3sets of session which is load lifting of 2 kg, 5kg and 7 kg.
3. Subject will undergo the load lifting during seat around 10 second for each lifting.
4. Every set will contain 3 times repetitive.

TASK 1: PROCEDURE

1. Firstly, put a little electrolyte gel at the surface electrode
2. Then placed accurately the surface electrode on long head bicep branchii and the nearest less muscle as the ground.(refer to figure 2)
3. Next, clip the cable correctly at the surface electrode. (red and blue are positive electrode, black are ground electrode).
4. Connect the electrode channel to the NI myRIO as interfere before connect it to the LabVIEW in PC.
5. At starting, subject will be test on static condition which is in rest condition.
6. Next, subject will lift the load of 2 kg from 0 positions to 90 degree position and repeat it about 10 seconds and data from the screen will be saved directly to the PC.
7. Then, subject will rest around 2 minutes before start run second trial and same like third trial, the subject also need a rest around 2 minutes before proceed it. Data from the screen will be saved directly to the PC.
8. Then, repeat procedure 5 -7 for load of 5 kg and 7 kg. Each load need to repeat the process for three times.

9. All the data from the screen will be save directly to the PC for next process.