"I hereby declare that I have read through this report entitle "*Features extraction of Surface Electromyography (sEMG) in term of force*" 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	:	Dr. Chong Shin Horng ……………………………………
Date	:	16/6/2014 ……………………………………

FEATURES EXTRACTION OF SURFACE ELECTROMYOGRPAHY IN TERM OF FORCE

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A report submitted in partial fulfillment of the requirements for the degree of Bachelor in Electrical Engineering (Control, Instrumentations and Instrumentations)

Faculty of Electrical Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2014

I declare that this report entitle "*Features extraction of Surface Electromyography (sEMG) in term of force*" 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.

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ABSTRACT

The research of feature extraction based on surface electromyography in term of force is done to help the people with upper limb amputation disabilities. Therefore, this research will focus on the relationship between the normalized electromyography (EMG) signal and force. This objective of this research is to do feature extraction of electromyography (EMG) in term of force in time domain. Then, the statistical analysis by using a simple linear regression technique on scatter plot was done to analyze the relationship between force and electromyography (EMG). 10 subjects are selected that mainly based on criteria of weight and the health condition of the person. The selected muscle is long head biceps brachii. The experiment is divided into three main tasks which consist of angles of 45^0,90^0 and 120^0. In addition, three tasks which consist of loads of 2kg, 4kg, and 6kg are done. The feature extractions with mean absolute value, root mean square (RMS), variance and standard deviation are analyzed by using simple linear regression analysis. The calculation of force formula from electromyography (EMG) signal is used to predict force. The average value is used to develop the equation of force because it has high value of correlation coefficient as compared to the value for all the subjects. Two methods to determine the reliability of the equation are based on the percentage of calculating force error and percentage of average predicted force error. The result has stated that mean shows the best feature extraction based on simple linear regression analysis characteristics. The result has shown that the performance for calculating force and average predicted force are inaccurate because the value of percentage of error is high. Hill-Based model and neural network are ways to improve the inaccuracy of simple linear regression technique to predict force.

ABSTRAK

Penyelidikan pengekstrakan ciri-ciri elektomiografi permukaan dari segi daya tenaga telah dilakukan untuk membantu rakyat yang cacat di bahagian tangan . Oleh itu, penyelidikan ini akan memberi tumpuan kepada hubungan antara isyarat elektomiografi (EMG) dengan daya tenaga. Objektif pertama kajian adalah untuk melakukan pengekstrakan ciri elektomiografi(EMG) dari segi daya tenaga di dalam domain masa . Kemudian , analisi statistik dengan menggunakan teknik regresi linear pada graf berselerak telah dilakukan untuk menganalisis hubungan di antara daya tenaga dan elektomiografi (EMG). Skop projek ini adalah dengan memilih 10 orang subjek berdasarkan kriteria berat badan dan keadaan kesihatan subjek. Kemudian, otot yang telah dipilih adalah bisep dan senaman yang telah dilakukan adalah senaman lengkungan bisep. Eksperimen itu dibahagikan kepada tiga tugasan utama yang terdiri daripada sudut 45^0,90^0 dan 120^0 .Kemudian, tugasan akan di bahagikan kepada tiga lagi tugasan di dalam satu tugasan utama yang terdiri daripada berat 2kg , 4kg , dan 6kg . Daya tenaga ini dikira dari formula model daya tenaga otot yang telah dikawal oleh beban dan sudut. Kemudian,teknik pengekstrakan yang mempunyai ciri yang terbaik di kalangan purata, RMS, varians dan sisihan piawai telah dianalisis dengan menggunakan analisis regresi linear. Teknik regresi linear telah digunakan dengan mengunakan graf berselerak yang mempunyai hubungan voltan dan daya kuasa. Pengiraan formula daya tenaga dari isyarat elektomiografi(EMG) adalah kaedah untuk meramalkan daya tenaga. Nilai purata telah digunakan untuk membangunkan persamaan daya tenaga kerana ia mempunyai nilai pekali korelasi yang tinggi berbanding dengan nilai untuk semua teknik pengekstrakan. Terdapat dua kaedah untuk menentukan kebolehpercayaan persamaan iaitu untuk mengira peratusan ralat bagi pengiraan daya kuasa dan purata ramalan daya kuasa. Hasilnya telah menyatakan bahawa purata mempunyai ciri pengekstrakan terbaik berdasarkan ciri-ciri analisis regresi linear. Hasil kajian menunjukkan bahawa prestasi buruk apabila pengiraan daya tenaga dan ramalan purata daya tenaga mempunyai nilai peratusan ralat yang besar.

This research of "Features Extraction of sEMG in Term of Force" (ID-51) has been accepted to be presented in IEEE EMBS INTERNATIONAL STUDENT CONFERENCE 2014 (ISC2014).

TABLE OF CONTENT

CHAPTER		TITLE	PAGE

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

This chapter will give a brief explanation of the theory and application of the EMG signal. Other than that, this chapter will show the purpose of this research and the problem that can be solved from this research. Lastly, the objective was set to ensure that this research will fulfill its target while the scope will ensure that this research will always be on track based on the criteria chosen.

1.1 Project Background

The electromyography (EMG) is the inquiry of the electrical signal when the muscles emanate. Myoelectric signal is formed by a variation in the state of muscle fiber membranes. There are many widespread use of electromyography that is in the rehabilitation part, medical research, ergonomic and sports science. This widespread use can help in the measurement of muscular performance through looking into the muscle signal. There are two types of electrodes which can be used to detect electromyography (EMG) 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 types of contraction which is done by our muscle, which consists of isometric and non-isometric (dynamic) contraction.

The role of Electromyography within biomechanics studied 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 segments which will have the analysis in term of structure and proportion. Next, the movement will be analyzed based on distance, angle, velocity or acceleration and force will be analyzed in term of linear force, moment and torque. Lastly, the muscle activation will be analyzed on the muscle action potential of the muscle. These four methods can be categorized as kinesiological analysis, which is used as a base to start a research on new things. This research will be based on EMG in term of force which can be used to aid many applications such as prosthesis design, rehabilitation of muscle and designing a workout regime.

1.2 Project Motivation

The upper limb amputation is an less fortunate individual which unable to live their normal life and will hold the progress of the individual to earn a living. Therefore, prosthesis arm is needed to aid the upper limb amputation individual to earn a living without the help from others. Therefore, the development of enhancement of prosthesis equipment is needed to ensure that the operation of prosthetic hand is the same as the operation of a normal human hand. This enhancement of prosthesis equipment needs an analysis which can be used as a guideline or data to develop the enchancement of prosthesis arm. Therefore, a use of bio signal is important in analyzing the reaction of the body that will be useful to aid in the processes of designing 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 is obtained when the reaction of muscle happens and this data could aid in the designing a new prosthetic arm.

The feature extraction technique is a method to ensure that the characteristic of the electromyography signal. Feature extraction of electromyography consists of time domain feature extraction, frequency domain feature extraction and time-frequency domain feature extraction. Every domain feature can analyze the muscle in different ways and in this project the suitable domain that will be used is the time domain. The time domain features normally are used for muscle contraction and muscle activity detection. The feature extraction from muscle contraction is important in determining the force that will be applied to the muscle through biceps curl exercise. The higher the value of force is applied to the muscle will make the value of feature extraction to increase. However, the problem that will occur in this project is to choose the best feature extraction. The best features extraction has to be selected for the purpose of designing prosthethic arm.

The prosthesis arm design should consider many factors that could affect the movement and the load that could be lifted by the arm. The design of the arm also depends on the experiment setup. Therefore, the next motivation of this project is to determine the force by determining the movement of the elbow angle and the load that will be lifted in the biceps curl exercise. Lastly, the force that is needed by the prosthehic hand must be the same with normal hand force to ensure that the human can control the movement of the prosthethic hand.

1.3 Problem Statement

Prosthetic arm capabilities is not the same as normal human hand. This has limited their life capabilities and may cause disadvantages to another person to help them to live as normal person. Therefore, a proper analysis of muscle behaviour was needed. The analysis of muscle has many criteria and this research will be focusing on the force that is apply to the biceps muscle. The force will be varied by the weights and angles that will be applied to the muscles for analysis to help in designing of prosthesis arm. This could help to enhance the prosthesis arm in term of lifting many variables of loads with different angles.

Therefore, by using surface electromyography (sEMG) to do the analysis on the behaviour of muscle when force is applied to muscles, it could assist in development of a prosthesis hand which could lift loads based on angles set. The surface electromyography (sEMG) signal will be extracted to obtain the characteristic of the muscle and will be evaluated by using statistical analysis on scatter plot to produce an information for the other researcher to develop a better prosthesis arm.

1.4 Objective

There are two objectives that will provide to achieve the target of this research:

1. To extract the feature of surface electromyography (sEMG) in term of force in time domain.
2. To analyze the feature of the extracted signal by using statistical analysis

1.5 Scope

This research scope will be a guideline to guide towards achieving the objectives and the scopes of this project was shown as below:

1. The muscle that involved in this research is biceps brachii.
2. The exercise that is conducted in this research is by using biceps curl method.
3. Electromyography sensor that will be used is a Muscle V3 sensor (appendix G) and the output of the sensor will be in normalized electromyography (EMG) signal.
4. A surface electrode will be used in this research.
5. The Arduino Mega 2560 will be used as the microcontroller that acts as a data acquisition
6. The feature extraction that will be used is in the time domain which is mean, root mean square (RMS), standard deviation and variance.
7. The analyze part of feature extraction electromyography (EMG) is by using a simple linear regression technique in the scatter plot.
8. There are 10 subjects based on criteria in Table 1.1:

Table 1.1: The criteria of target subject

Specifications	Age	Height	Weight	Load applied to the muscles	Health Condition
10 Male	18-35	160cm to180cm	50kg to 90kg	0kg to 6kg	Normal

CHAPTER 2

LITERATURE REVIEW

This chapter will give a brief explanation of the theory and the history of EMG. Other than that, this chapter will also describe on the study based on the featured extraction and relationship between force and electromyography signal. Lastly, this chapter will also provide the knowledge of force and electromyography (EMG) mathematical model based on the statistical analysis that will focus more on the scatter plot.

2.1 Electromyography (EMG) Background

Electromyography is a study of bio-signal that is produced from the movement of the muscle. The main contributor to this electromyography or bio-signal from body movement is related to motor unit which consists of motor neuron and muscle fibre [1]. Normally, during voluntary contraction a combination of motor unit recruitment and changes in motor unit activation frequency can be modulated to force [2]. The build-in low pass filter inside the human body which consist of connective tissue and skin layers has caused the surface electromyography (sEMG) to cause the firing frequency to produce non-originality to electromyography (EMG) signal firing and amplitude signal characteristic .

The bio-signal appears when muscle membrane movement or excitation allows the muscle to go through the process of depolarisation and repolarisation . This process is called an action potential where the muscle membrane potential is produced when sodium (Na+) influx exceed a certain threshold voltage and will cause a depolarisation process happen.

Figure 2.1 shows the process of depolarisation and repolarisation when there is a movement in muscle membrane.

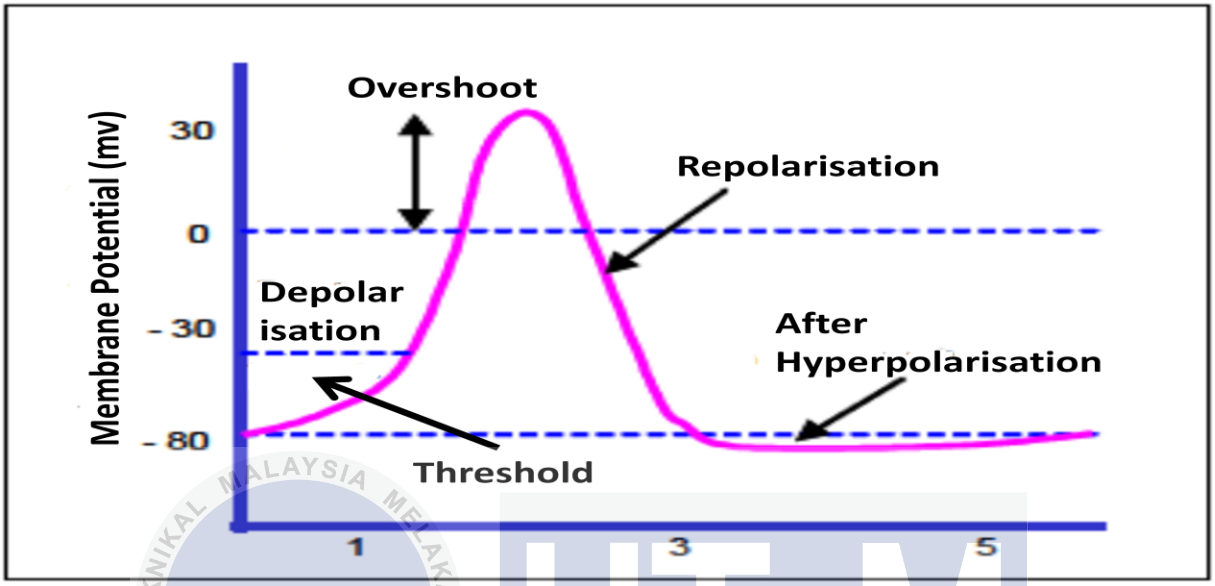


Figure 2.1: The action potential of electromyography (EMG) signal [1].

The raw surface electromyography (sEMG) has several noises that affect the purity of the signal. The noises that are present when obtaining the surface electromyography (sEMG) are tissue characteristic, cross talk, surrounding noise and the internal amplifier noise [1]. The tissue characteristics such as temperature of the skin, physiological changes and thickness of the skin will affect the electrical conductivity, thus affect the surface electromyography (sEMG) signal. Other than that, cross talk will also affect surface electromyography (sEMG) signal by the interferences of the Electrocardiography (ECG). Surrounding noise is another factor that could affect the surface electromyography (sEMG) which the noise in the surroundings will make the signal to be distorted. Therefore, the experiment of the electromyography should be run in the surrounding with less noise condition.

2.2 Electromyography (EMG) History

Electromyography research began when Francesco Redi [3] discovered that muscle could generate electricity in 1666 by documented that electrical ray fish generated electricity by using a specialized muscle. Then Alessandro Volta [4] had created a device which could generate electricity and could be used to stimulate muscle. The next invention that was done by Luigi Galvani has done a research to a frog in 1971 and has shown that electrical stimulation of muscular tissue produces contraction and force. The lack of limited instrumentation has limited Luigi Galvani work and has held his work for 40 years until a galvanometer is developed in early 1800. In year 1838, Carlo Matteucci has proved that bioelectricity can be developed or produced by muscular contraction and in 1842 he has demonstrated that from the frog's muscle, action potential can be produced from it. Guillaume Duchenne [5] has stimulated electrically by contacting it to skeletal muscle and he is the one that initiated that medical electricity could be used for medical purposes.

Guillaume Duchenne also systematically mapped out function of nearly every facial muscle and founded out that the muscles around the eye are only active during genuine smile, meanwhile for a not genuine smile; it will only affect the muscle in the mouth. Willem Einthoven has developed a thin conductor wire that could be used for electromyography in 1903 which has allowed Forbes to be the first person to use floating electrode in a moving body which has allowed them to record electromyography signal of an elephant and Forbes also used Cathode Ray Tube (CRT) to amplify the action potential. Then, the development of concentric needle electrode was developed by Adrian and Bronk in 1929 and has used it for researching motor control and muscle schemes. This has enabled the detection of electromyography signal in individual and small group of muscle fibers and the innovation of concentric needle electrode has been changed to the hypodermic needle with insulated wire in its barrel.

Then, Herbert Jasper [6] has constructed a first electromyography and created a unipolar needle electrode during his research from year 1942-1944. In 1962, John Basmajian has compiled all the information of electromyography and also created a fine-wire electrode which is more comfortable compared to needle electrode. Lastly, the most important person in the surface electromyography history is Carlo J. De Luca [7] and has written a cited-paper on 'The Use of Surface Electromyography in Biomechanics.

2.3 Time Domain Feature Extraction of EMG Signal

There are three types of features analysis in the electromyography (EMG) signal which are time domain, frequency domain and time, frequency domain or time scale representation [8-9]. The time domain features are normally a fast and simple method to do features extractions of electromyography (EMG) signal. This is because the features are because electromyography (EMG) signal is already in time domain, therefore, the transformation of the signal to another domain is not needed and the calculation of the electromyography (EMG) signal of time domain can be calculated from raw EMG signal time domain [10-12]. However, there is a disadvantage of time domain because of the non-stationary properties of the electromyography (EMG) signal which is not featured in time domain feature extraction which the data is assumed in stationary signal [13]. Variation in the features in the time domain will largely obtained because of usage of surface electromyography (sEMG) in recording the dynamic contraction and the interferences through recording has caused major disadvantages to the features that are extracted from energy property [14]. However, the time domain frequency is mainly used in many fields because of the classification in low noise environment and can just use raw electromyography (EMG) signal to extract the features. The electromyography (EMG) extracted features in time domain is mainly will be used in the force based research application. Kamal Kothiyal [15] has used root mean square (RMS) to compare the influence of experimental setup of experimental condition on muscle strain. Angkoon Phinyomark [16] has found out that mean absolute square (MAV) was an easy way for detection of muscle contraction level and a popular feature used in prosthesis control application. S. Thongpanja [17] has found out that time domain feature were frequently used as a muscle force detection tool and Variance, root mean square (RMS) and mean absolute square (MAV) as the feature extraction for the research.

2.4 Biceps Muscle.

The biceps muscle that will be chosen in this research was biceps brachii and the position of the muscle was as shown in Figure 2.2. Biceps brachii was taken from the Latin phrase meaning two headed muscle. The two headed muscle means that the biceps brachii was divided into two parts. The first part will be the long head biceps brachii and the second part will be short head biceps brachii. Normally, the most visible between these two muscles was long head biceps brachii [18].

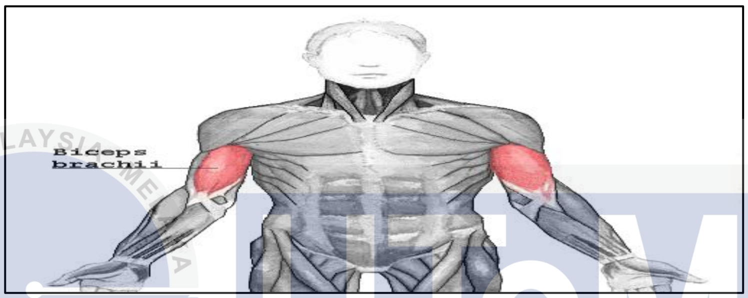


Figure 2.2: Position of Biceps Brachii

2.5 Types of Electrode

There were two types of electrode in electromyography (EMG) which were intramuscular electrode and surface electromyography (EMG). The intramuscular electrode needed a needle or fine wire to be inserted into the skin which will make the electrode to be invasive to the skin [1]. The intramuscular electrode procedure should be done by the medical expertise to avoid any injuries from happening to the subjects or samples. However, the intramuscular has advantages in the accuracy of the sensor because the intramuscular directly look into muscle because the fine wire or needle is inserted directly inserted inside the muscle. The procedure to apply the fine wire to the muscle was to insert the needle with fine wires and then removed the needle to allow the fine wire to be connected with the spring to be connected to pre amplifier [1]. Figure 2.3 will show the example of intramuscular electrode.

The surface electrode just needed to apply the electrode to the skin of the samples or subjects. Therefore, it will give the drawback to this electrode because it only could be done to the skin muscle [1]. This surface electrode was non-invasive because it will only be applied on the skin and not inserted in the skin as intramuscular electrode. The advantage of non-invasive electrode has made the surface electrode suitable for kinesiology study [1]. Lastly, the surface electrode procedure could be done by all people with the knowledge of skin, muscle because it is non-invasive. Figure 2.3 will show the example of surface electrode.

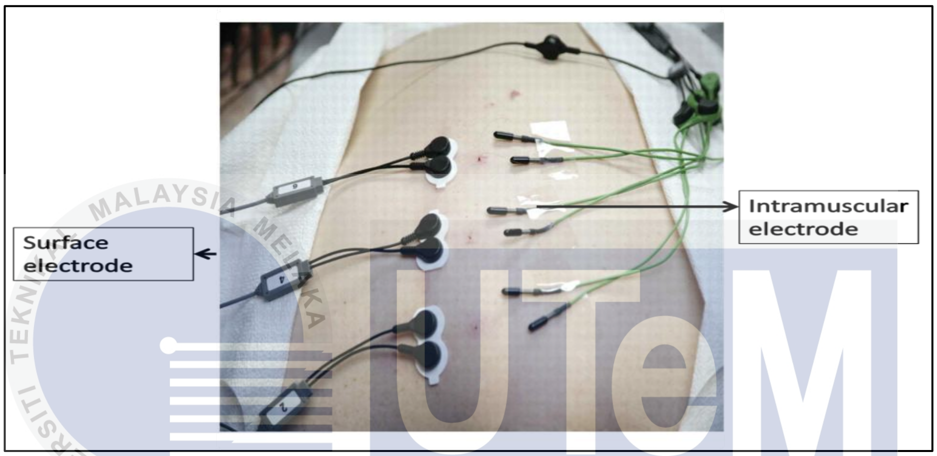


Figure 2.3: Surface electrode and intramuscular electrode that was applied to the subjects

2.6 Effect of Load in Electromyography (EMG) Signal.

The contraction of muscle voluntarily against a constant load, the electrical activity in the muscle will increase with time and maintains by recruitment of additional motor unit. Eason [19] has said that recruitment of additional motor unit is important to compensate for constantly decreasing force available per fiber. Muscle contract powerfully has caused the increase in electrical activity. This has provided a platform for Dempster [20] to study the capability of different muscles implicate in the movement at different joints. Azeem, M. A [21] has found out that relationship of load toward electromyography signal is that it is dependent on the optimal increase in motor unit potentials and change in recruitment pattern to increase in the initial length due to lift the load.

2.7 Force Mathematical Modelling for Biceps Curl Exercise

Biceps curls exercise will be the third class of lever which has fulcrum at the other end, force in the middle and the weight is on the opposite side of the fulcrum. This formula that was used by Larry V.D [22] was to find the force acting on the weight. The Willams. M [23] has found a way to calculate the force that was acting on the biceps muscle. There will be few elements that were needed to calculate the force. The first element was the distance of the elbow to the biceps muscle, the distance of the elbow to the middle part of the arm and the distance of the elbow to the centre of the weight. The next element was the weight of the load, and the weight of the arm. The free body diagram will be shown in Figure 2.4 [23]. The formula to gain force that was exerted to the biceps muscle will be explain in the methodology section.

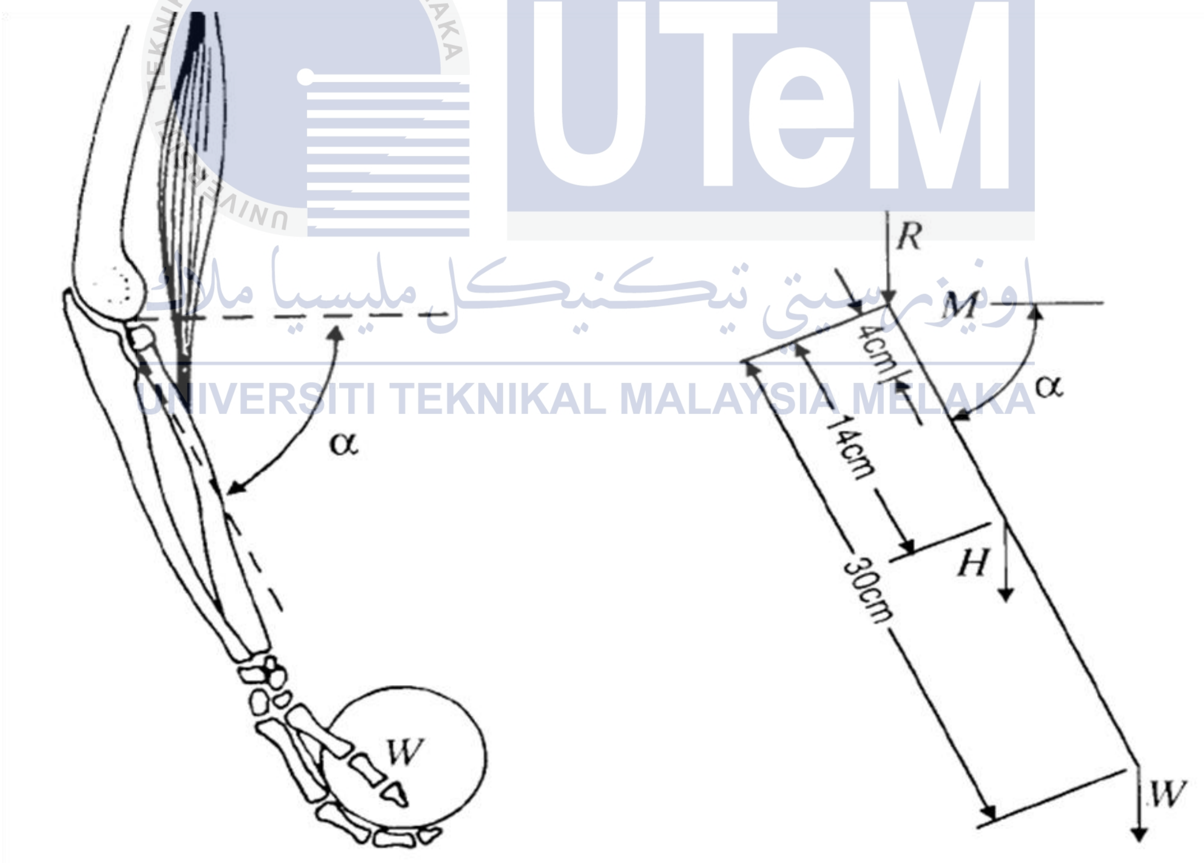


Figure 2.4: Free body diagram of biceps muscle [23]

2.8 Electromyography (EMG) Signal and Force Relationship.

Force prediction based on electromyography (EMG) signal could be done by using statistical analysis. There are few methods of statistical graph such as scatter plots and a histogram that could be used before statistical analysis is done. The easiest statistical analysis method that could be used to predict force is by using linear regression methods. Katherine Anne Wheeler [24] has used scatter plot graph and analyze it based on linear regression technique. The equation of the force and electromyography (EMG) signal was produced by Katherine Anne Wheeler [24] and the correlation coefficient was determined to check the accuracy of the linear fit.

Force prediction is important in the designing prosthetic arm and Jacob Rosen [25] has compared the performance of the two methods to predict the moment developed at human elbow joint based on kinematics and neuromuscular activity [25]. The method that was used to predict the force is by using Hill-Based model and neural network [25]. Winter J.M [26] has said that the Hill-based is using a direct modelling approach which it uses an input of myoelectric activity and joint kinematic and the output will produce the joint moment. Sepulveda [27] has said that neural network is a technique in solving ambiguous and complicated problems and it also allow recognizing a new pattern or shape. The result of the experiment has proved that the Hill-based model has a superior prediction compare to the neural network model [25].

CHAPTER 3

METHODOLOGY

This chapter will indicate the process of work to achieve the objective. The methodology will give a brief idea of the detail procedure that will be done in this research. The previous chapter on literature review has discusses on how the previous research has been done to achieve the target.

3.1 Experimental Protocol

The experimental protocol is set to ensure that the experiment is conducted as stated in the scope. This experimental protocol will set into two main things which are the subject criteria and experimental guideline.

3.1.1 Subject Criteria

There are a total of 10 subjects that will be selected to conduct this experiment and the subjects need to have a healthy upper limb condition. The further specification of samples can refer to Table 1.1 in Chapter 1. The subject with too much fat is not selected as the subject of this experiment because the fat will become a noise to the electromyography signal. The subjects is filtered out from the list of subject if the biceps muscle of the subject could not be detected. The subjects must have a healthy condition of the upper limb part of the body to ensure that the electromyography (EMG) signal is not disturbed.

3.1.2 Experimental Guideline

The experimental guideline is important to ensure that the data that will be gained from the experiment is valid and to ensure the experiment is always in the correct path. The single lifting load is conducted for duration of 11 seconds and the stop watch is the equipment to control the time because the computer time and real time is not the same. The exercise of biceps curl is done for 10 times to obtain 10 normalized EMG signal data per task set. There were 3 main tasks that are divided in term of angles. The angles are set to task 3(45^0), task 2 (90^0) and task 1(120^0) and each task of angle is divided into three more tasks which consist of three different loads. The load is varied from 2kg to 6kg.The subjects are given 10 minutes of rest per load experiment and 1 minute of rest per lift experiment. The total time for one subject to complete the whole experiment was around 4 hours

3.2 Experimental Setup

3.2.1 Data Acquisition Setup

The data acquisition equipment that is used in this research was Arduino Mega 2560, which is used as an interface between computer (MATLAB), Muscle V3 sensor and goniometer. The function of the goniometer is to collect the angle signal for the purpose of calculating force. The configuration of Arduino EMG shields is important to ensure that the raw signal of EMG in channel 1 is in the same configuration. The Simulink Matlab have an important role in interfacing the Arduino Mega 2560, Muscle V3 and goniometer sensor by using block diagram of EMG as shown in Figure 3.1. Therefore, this data acquisition setup is important to ensure that the interfacing between a computer and Arduino EMG shield exist for data displaying or saving purposes.

The sampling rate of the shield was set to 0.001s and is set in the Matlab run on target hardware configuration panel. The problem of different time between computer time and real time is solved by using a stop watch. However, the plotting of the electromyography signal and angle signal will be plotted by using simulation time or computer time. Lastly, the goniometer is calibrated as shown in Figure 3.1.

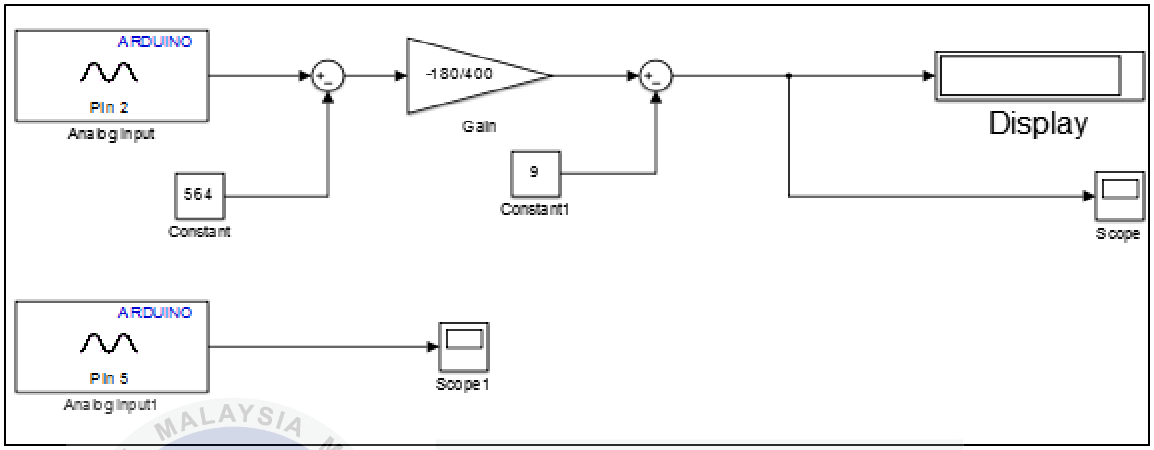


Figure 3.1: Simulink block diagram to interface the Arduino Mega 2560 with Arduino EMG shield and goniometer

3.2.2 Electrode Selection

There are two types of surface electrode that is available for this experiment which is dry electrode and disposable electrode. The dry electrode is preferred in this experiment because it was hard to dispose unless it was damaged. However, due to the attachment of the goniometer, the dry electrode is not selected because of limited space in the biceps muscle. Therefore, the disposable electrode is used in this experiment to compliment the problem of limited space due to the limited space in the biceps muscle.

3.2.3 Muscle Location

Muscle location is important in determining which part of muscle that is used in this research. The muscle that has been mentioned in the scope was biceps brachii. Biceps brachii muscle is divided into two types which are long head biceps brachii and short head biceps brachii. The most visible muscle of biceps brachii is long head. Therefore, this long head biceps brachii muscle of muscles is selected for this research.

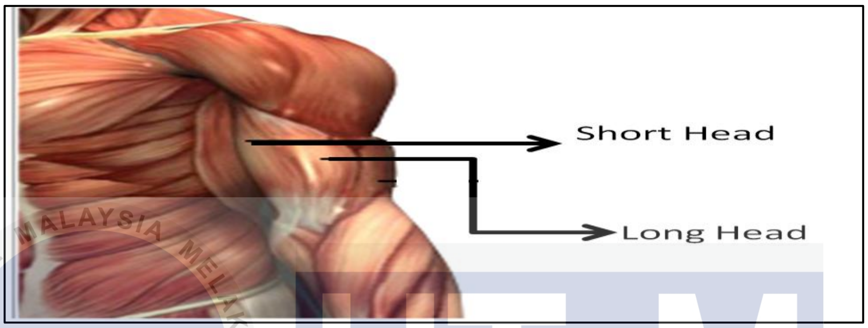


Figure 3.2: Composition of biceps brachii muscle

3.3 Noise Analysis

Noise analysis is important in determining the noise that is present in the electromyography (EMG) signal. The noise signal is detected from the frequency domain that is obtained from the fast Fourier transform (FFT). The lower frequency signal in electromyography (EMG) frequency domain is normally the dominant part of the signal.The dominant frequency of electromyography (EMG) signal is normally around 50Hz. This can be proven from the fast fourier transform of the muscle V3 normalized electromyography (EMG) signal. Figure 3.3 shows that signal to noise ratio is high and the data have low noise and high signal. The signals are checked to ensure that the signal will not be distorted by noise.

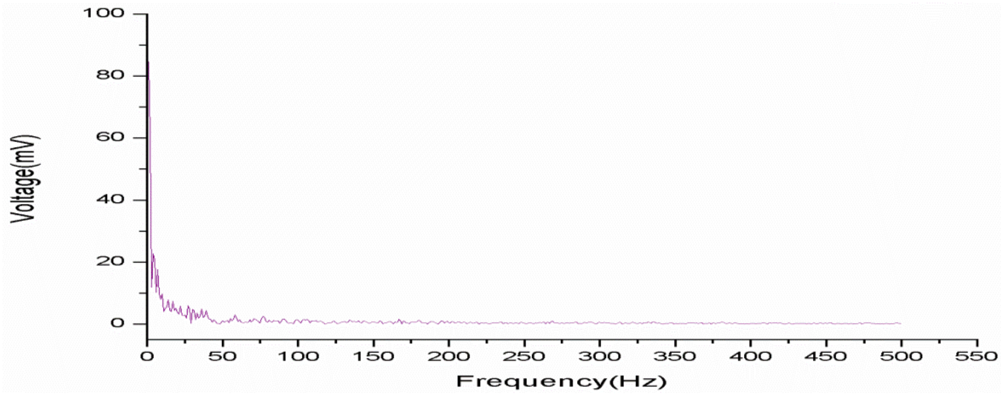


Figure 3.3: The frequency domain of electromyography (EMG) signal.

3.4 Skin Preparation and Placement of Electrode

3.4.1 Skin Preparation

The skin preparation is important to reduce the resistivity of the skin to obtain a good electromyography (EMG) signal. The recommendation for skin impedance range was as shown in Table 3.1. Other than that, skin preparation also helps to increase the conductivity of the skin, which will help in inquiring the electromyography (EMG) electrical signal. The skin preparation will be divided into 2 parts which is cleaning of the skin and conductivity of skin. Cleaning of the skin will have the process of shaving, cleaning hair and dirt, and implementing the alcohol swab. Meanwhile, conductivity process will be the process of implementing the conductivity gel to the skin before the electrode is placed.

Table 3.1: The recommendation for skin impedance range. [1]

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

3.4.2 Placement of Electrode

The placement of electrode is defined as the placement of the two bipolar sites of a muscle in relation to a line between two anatomy marks. The target of electrode placement is to obtain a suitable location to achieve a good and stable surface electromyography (EMG) signal. There are two ways for placement of electrode method. The surface electromyography (EMG) is arranged longitudinally with respect to the long axis. The distance between two electrodes at biceps brachii was 20mm. The sensor distance for biceps brachii muscle is shown in Figure 3.4. The position of placement of the electrode at biceps brachii is shown in Figure 3.5. The position of references is normally placed at the bone side, for example the position of reference electrode is placed at the elbow, wrist or shoulder.

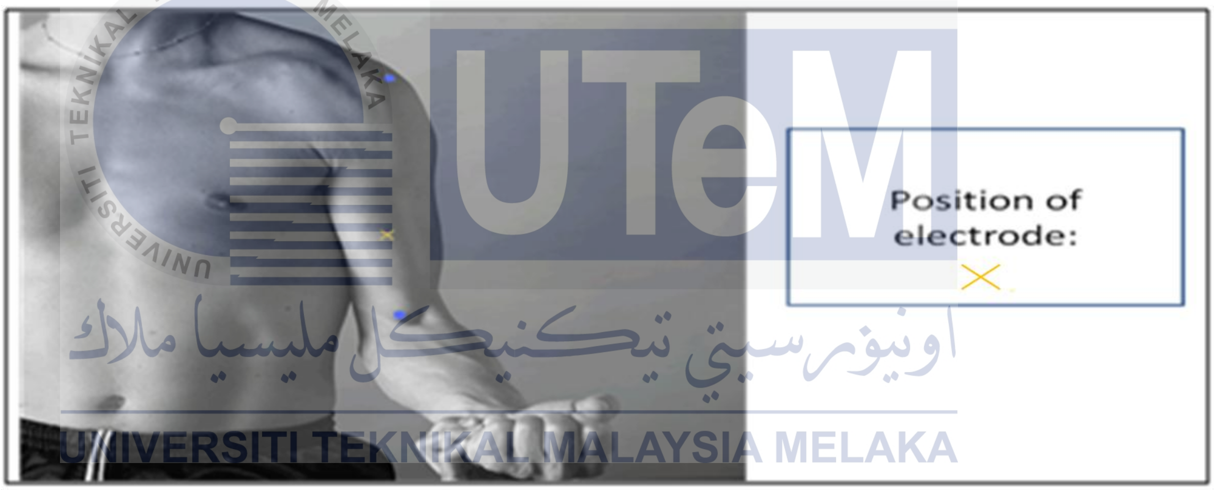


Figure 3.4: Position of electrode placement of biceps brachii muscle

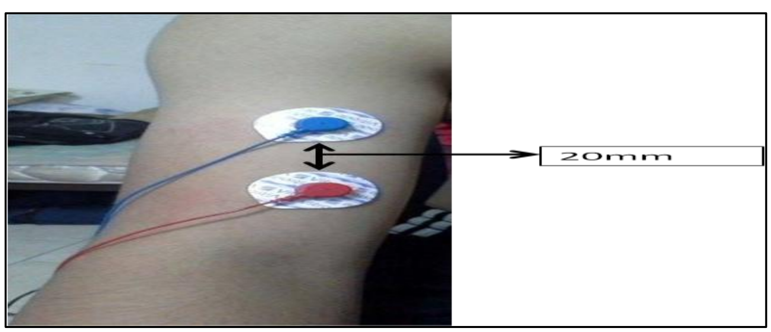


Figure 3.5: Distance of sensor for biceps brachii muscle

3.5 Experimental Procedure

3.5.1 Flow of the Experimental Procedure for Single Task

This experimental procedure is important to ensure the process of collecting the raw EMG data from the subjects to have the same configuration to ensure the validity of the data. Therefore, the flow chart below will show the flow of the experimental procedure for 1 task as set by experimental protocol.

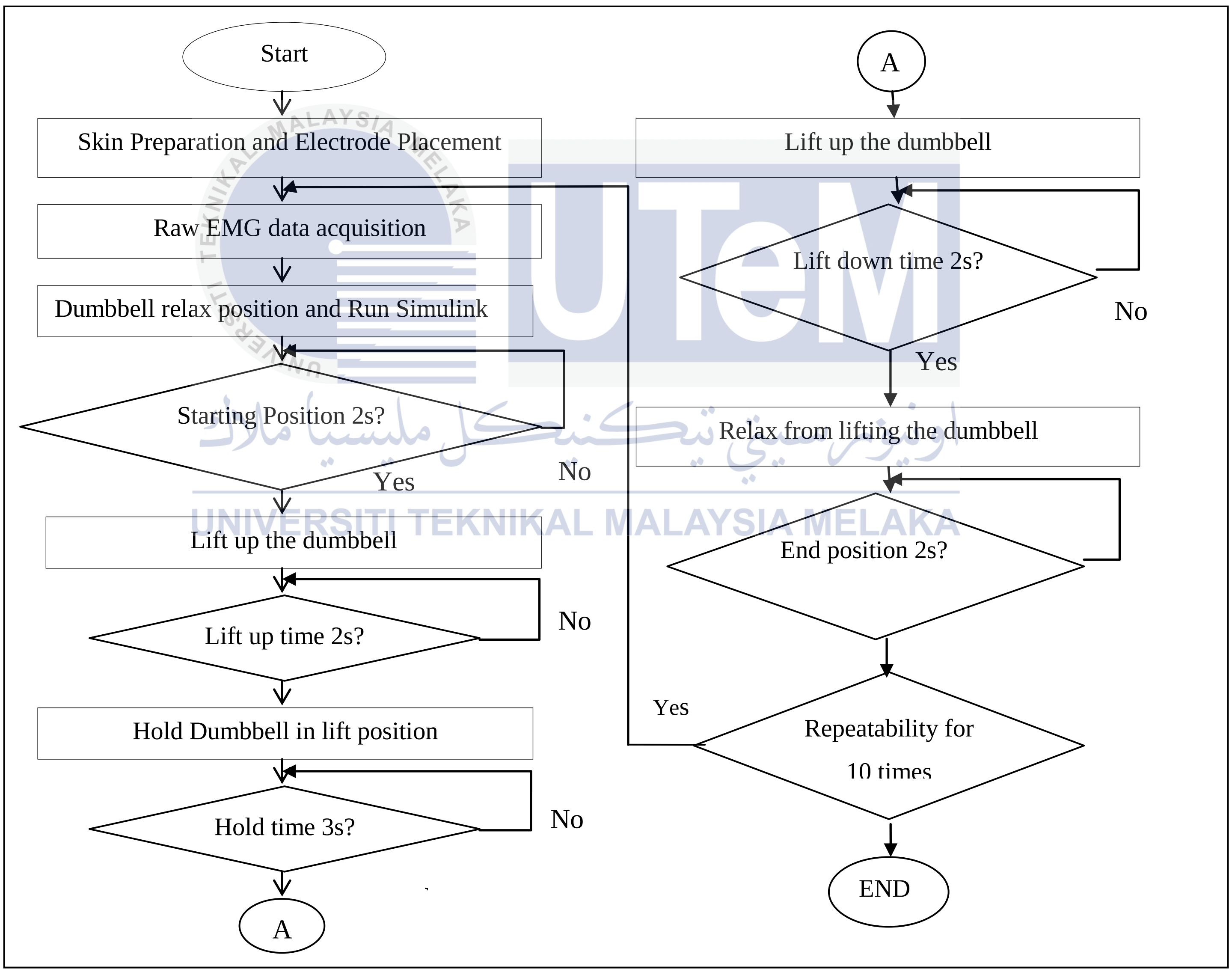


Figure 3.6: Flow Chart of Experimental procedure for 1 task

3.5.2 Exercise Procedure

The experiment is conducted in a standing position with the right posture to ensure that the subject is not using their body to support the weight. The total times of the single lifting process were 11 seconds and the distribution of time is stated in Figure 3.5. Subjects were needed to be in relaxed condition before lifting and need to do a warm up to prevent injuries. After the warm up, the subjects are needed to rest about 10 minutes. Therefore, the total time for one subject to complete the experiment is around 4 hours. The lifting process is done by biceps curl exercise and the subjects had to lift their arm based on angle and load set. The angle signal is obtained from the goniometer that is attached to the upper limb part of the body. The Figure 3.7 shows the picture of a subject that has a goniometer attached to their body. The load is set to 2kg, 4kg and 6kg and the subject must lift all three angles in every set of loads.

(a) (b)

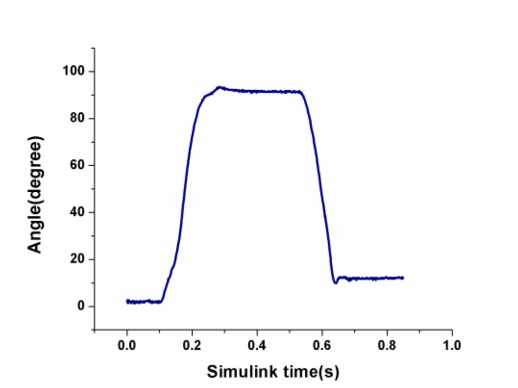
Figure 3.7: Goniometer setup on the subject. (a) Resting condition (b) Lifting up condition

3.6 Data Collection and Feature Extraction of Electromyography (EMG) Signal

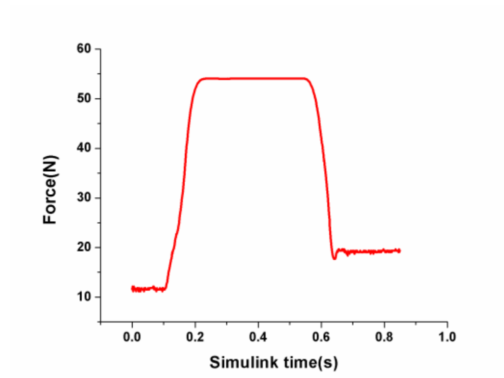
The exercise with single load is producing 10 electromyography signals, one subject is producing 90 electromyography signals. Therefore, the total numbers of electromyography signal that is collected from all the samples are 900 signals. The limitation of the sensor to obtained normalized electromyography (EMG) signal has caused the signal to have a non-linearity characteristic when compare with force signal. Then, feature extraction is done with the signal by using on two ways which is by using Matlab and Origin Lab. By using Matlab, the signal processing tool is used to extract the information of normalized EMG signal.. There are four types of time domain feature extraction of EMG signal that is used in this research. The feature extraction techniques are mean absolute value (MAV), root mean square (RMS), variance and standard deviation. The angle signal is recorded from goniometer signal. The goniometer is calibrated as shown in Figure 3.1. Statistical analysis in term of force is calculated from the angle signal and load.

3.7 Force Data Collection

The force data collections is mainly varied from the angle and load that is obtained in the data collection procedure. The force can be calculated from the muscle model that has been shown in the Chapter 2. Table 3.2 and Table 3.3 are the free body diagram of arm for the three main tasks and the formula for biceps force muscle model. Table B.1 in Appendix B shows the value component that is needed to be measured in all the subjects to achieve the calculated muscle force. Table 3.2 and Table 3.3 explain about three of the angles that are calculated to obtain the force. The zero loads and zero angles of elbow flexion will have a zero Newton(N) of force that make this load and angles to be neglected in this experiment. The example of force and angle graph shown in Figure 3.8.



(a)



(b)

Figure 3.8: Angle and force signal per lifting process. (a) angle signal (b) force signal

Table 3.2: Free body diagram for force equation with an elbow angle of 90^0 and 45^0

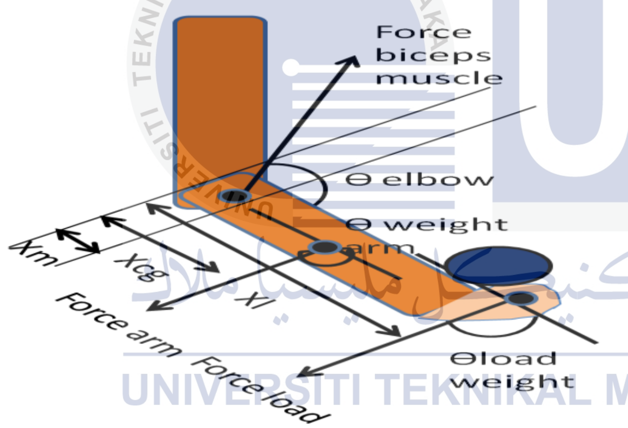
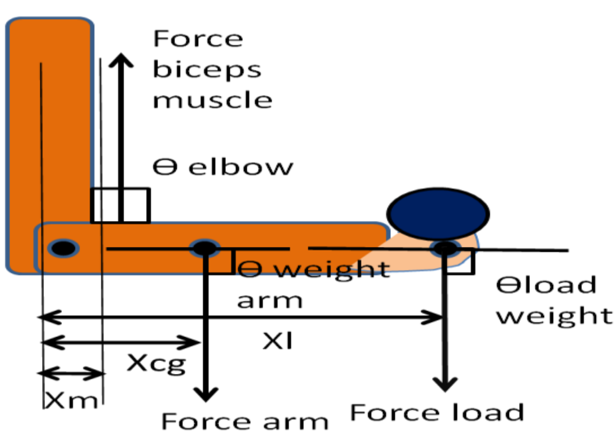
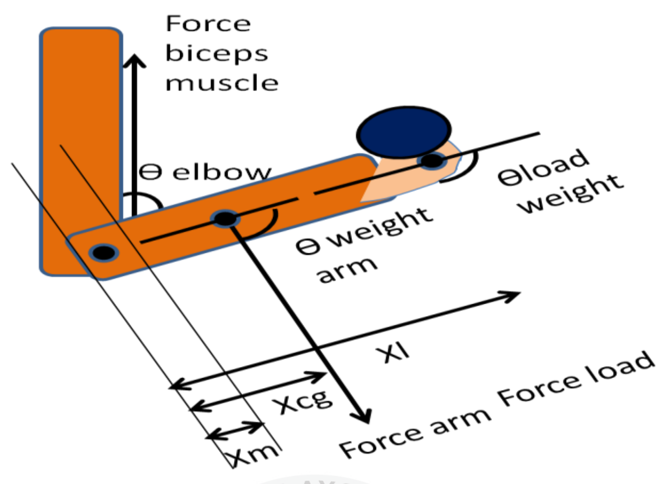
Free body diagram	Force formula
 Elbow angle= 45 .	$\theta_{load} = \theta_{arm} = 90 - \theta_{elbow}$ $\theta_{load} = \theta_{arm} = 45^0$ $F_{Load} = mass_{load} \times 9.81 \times \cos\theta_{load}$ $F_{Load} = mass_{load} \times 9.81 \times \cos 45^0$ $F_{arm} = mass_{arm} \times 9.81 \times \cos\theta_{arm}$ $F_{arm} = mass_{arm} \times 9.81 \times \cos 45^0$ $F_{biceps\_muscle} = \frac{F_{arm} \times X_{cg} + F_{load} \times X_l}{X_m}$
 Elbow angle= 90^o.	$\theta_{load} = \theta_{arm} = 90 - \theta_{elbow}$ $\theta_{load} = \theta_{arm} = 0^0$ $F_{Load} = mass_{load} \times 9.81 \times \cos\theta_{load}$ $F_{Load} = mass_{load} \times 9.81 \times \cos 0^0$ $F_{arm} = mass_{arm} \times 9.81 \times \cos\theta_{arm}$ $F_{arm} = mass_{arm} \times 9.81 \times \cos 0^0$ $F_{biceps\_muscle} = \frac{F_{arm} \times X_{cg} + F_{load} \times X_l}{X_m}$

Table 3.3: Free body diagram for force equation with elbow angle of 120^0.

Free body diagram	Force formula
 Elbow angle= 120°.	$\theta_{load} = \theta_{arm} = 90 - \theta_{elbow}$ $\theta_{load} = \theta_{arm} = 0^0$ $F_{Load} = mass_{load} \times 9.81 \times \cos\theta_{load}$ $F_{Load} = mass_{load} \times 9.81 \times \cos 0^0$ $F_{arm} = mass_{arm} \times 9.81 \times \cos\theta_{arm}$ $F_{arm} = mass_{arm} \times 9.81 \times \cos 0^0$ $F_{biceps\_muscle} = \dfrac{F_{arm} \times X_{cg} + F_{load} \times X_l}{X_m}$

3.8 Validation of Selection for Simple Linear Regression Technique as Statistical Analysis Method

The validation of simple linear regression technique is important to ensure that the right method is selected to detect the best feature extraction and to evaluate the relationship of force and electromyography signal. The signals from the normalized electromyography (EMG) signal must be extracted and the average value for calculated force must be collected. These two values are to determine the linear characteristic between the data. There are three different angles and three different loads that are selected in this experiment. Therefore, to check the linear characteristic of force and electromyography (EMG) signal, an experiment is divided into two experiments. The first experiment is to vary the force and constant the angles. The second experiments are to vary the angles and constant the force. From these two experiments, the linear characteristic of the two experiments was examined. The experiment that has a linear characteristic is selected to proceed with the next methodology. This linear characteristic in the experiment is also to prove that simple linear regression technique is valid to be used as the statistical analysis method to analyze the relationship of force and electromyography (EMG).

3.9 Evaluation of Features Extractions Data

The evaluations of data are based on statistical analysis, which is by using scatter plot refer to figures in Appendix C. This statistical analysis is done by using origin lab to evaluate the data. The scatter plot has an x axis of force and y axis of the amplitude of electromyography (EMG) signal. The best feature extraction is selected by using simple linear regression analysis. The best feature extraction technique is determined by the correlation coefficient, error of the gradient of linear fit and error of gradient of the slope. The correlation coefficient that is the highest between all the feature extractions will be selected as the best feature extraction technique. The error of gradient and the error of the slope of the linear fit with the scatter plot is an element to select the best feature extraction. The feature extraction technique with the lowest value of both errors is selected as the suitable feature extraction. Therefore, feature extraction technique with the highest correlation coefficient and lowest errors is selected to proceed with the next methodology

3.10 Force-Electromyography (EMG) Relationship

The force electromyography relationship is determined by using simple linear regression technique. This technique is to provide with the equation that is produced from the linear fit from scatter plot based on the average value of all of the subjects. The linear equation based on Figure 3.9 is shown in Equation 3.1. The voltage is selected as the y-axis and the force will be selected as the x-axis. The derivation of equations of voltage and force from Figure 3.10 are shown in Equation 3.2 to Equation 3.3. These equations are useful to predict force from electromyography (EMG) signal.

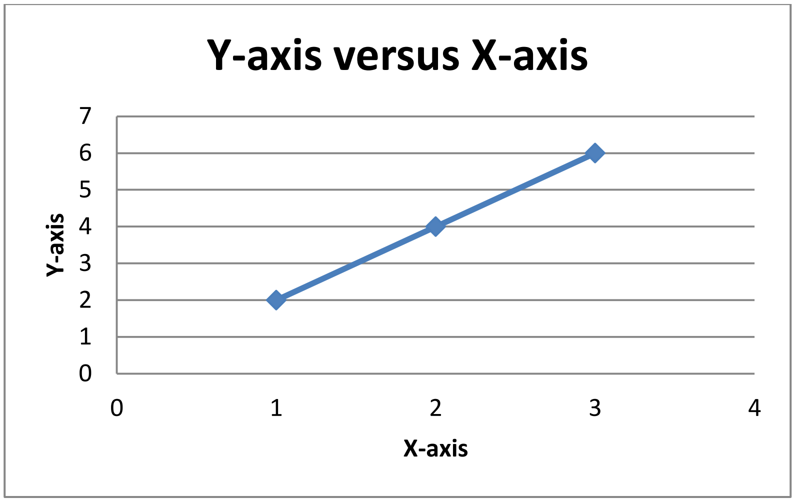


Figure 3.9: The linear graph based on x-axis and y-axis

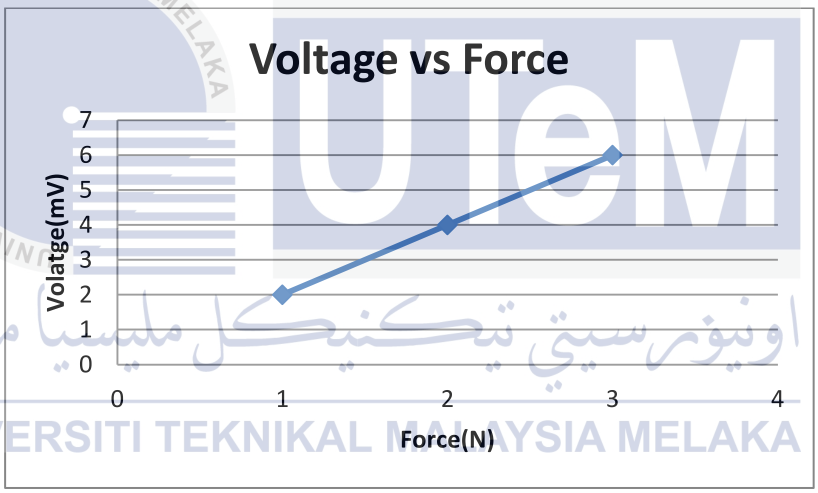


Figure 3.10: The linear graph based on voltage and force

$$Y = mX + C \tag{3.1}$$

$$\text{Voltage} = m\text{Force} + C \tag{3.2}$$

$$\text{Force} = \frac{\text{Voltage} - C}{m} \tag{3.3}$$

3.11 Reliability of the Data

The next step is to validate the data to know the reliability of the equation of force and electromyography (EMG). The force is compared between the experimental and the calculation force. This is to compare the performance of the equation of force with the calculation force. The percentage of error is to determine the performance of the equation which will be determined by the set point that is based on calculation force. The next reliability test will is determined by the determining the performance between the averages experimental predicted force with the experimental force of all 10 subjects. This is to compare with the set point of the predicted force that is needed by the subject to lift an arm. Then, the set point is compared with the experimental force of the 10 subjects. Then, the standard deviation is compared with the set point to know the percentage of error. This percentage of error will determine the reliability of the data for the second reliability test.

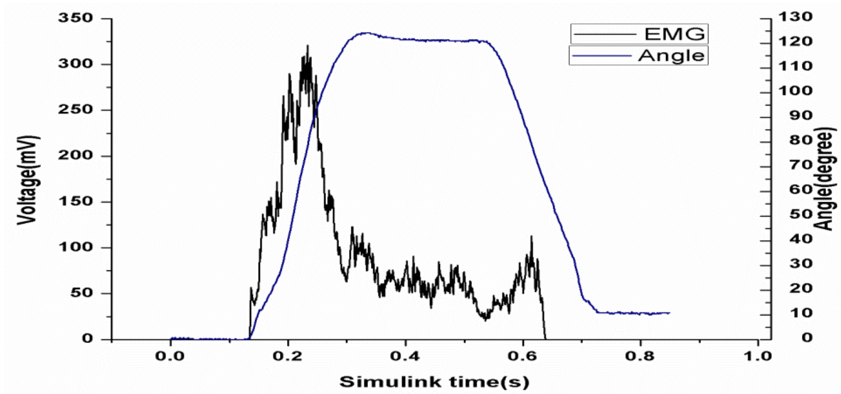
CHAPTER 4

RESULT AND DISCUSSION

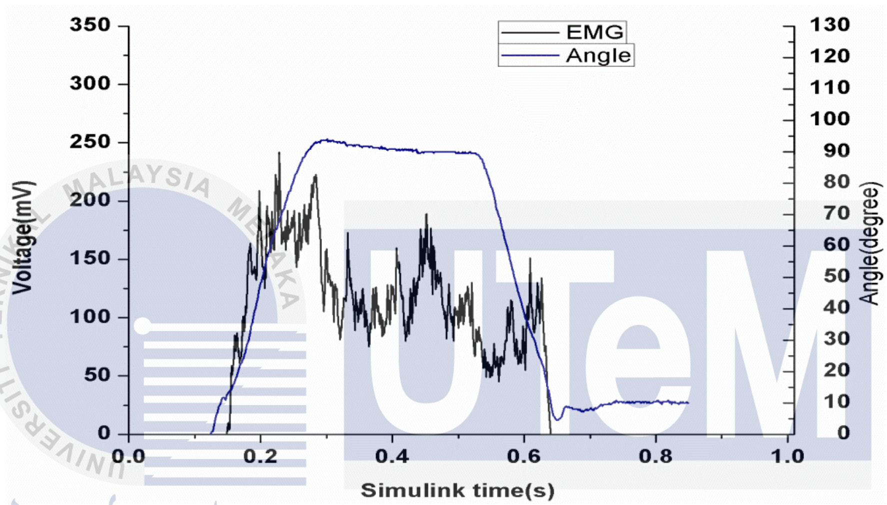
This chapter will provide with the signal relationship of the electromyography (EMG) with force and angle. Then, the best feature extraction is selected based on the simple regression technique analysis that is based on the error and correlation coefficient. The simple linear regression technique is used to develop a force equation based on the electromyography signal. The performance result is evaluated based on the error analysis of between the calculated and experimental muscle force. Lastly, the performance of result is evaluated based on the error analysis of between the predicted and experimental muscle force

4.1 Normalized Electromyography (EMG) Signal and Angle Signal.

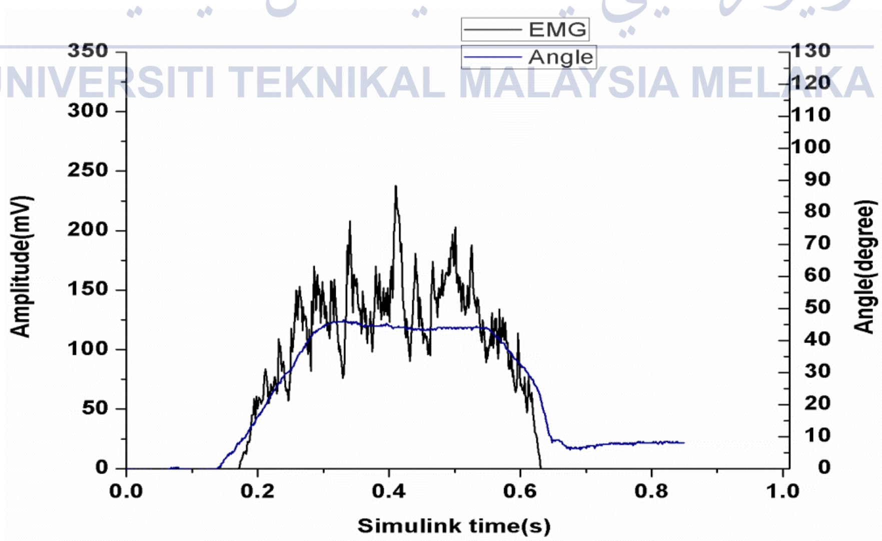
This subchapter will provide with the result of the electromyography (EMG) signal and the angular signal that are obtained from the goniometer. There are 3 angles selected based on the methodology. The graph of the electromyography (EMG) signal and angle signal are shown in Figure 4.1. The angle signal before the lift up signal is initially in 0^0. Then, the signal is lifted up to selected angle. Lastly, after the load is lifted down by the hand, the angle position should be 0^0. However, due to the human error that caused the inability of the hand to reach the position of 0^0 after the hand is lifted down. The reading of angles is not perfect because of the human action that has an error and could not be compared with a machine which has no or less error.



(a)



(b)



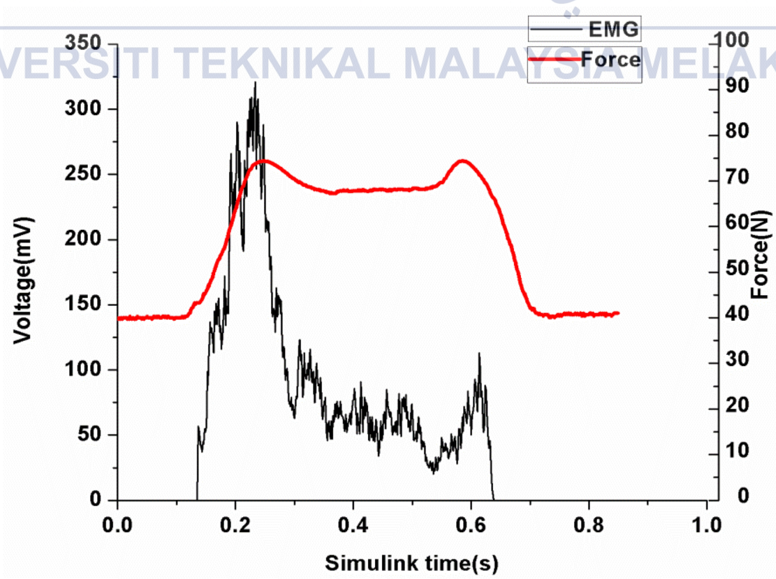
(c)

Figure 4.1: Combination of normalized EMG signal with angle signal (a)120^0 (b)90^0(c)45^0

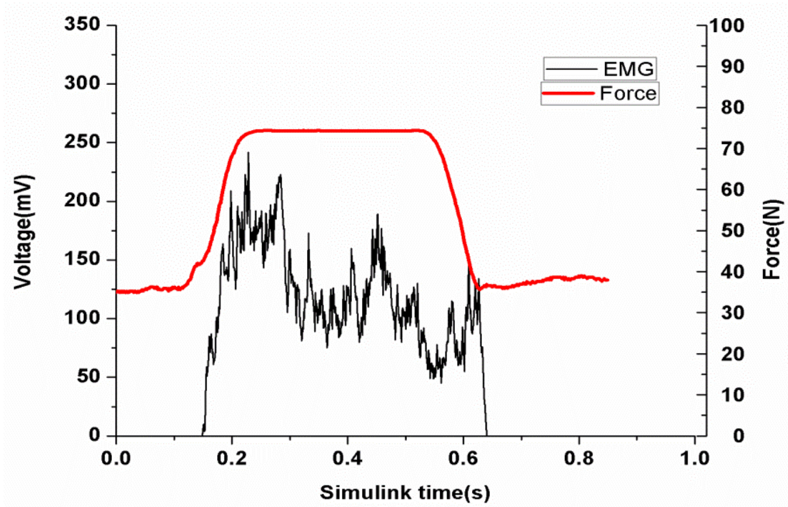
The effect of angles toward the electromyography (EMG) signal is the amplitude of the lift up process is increased due to the velocity of the movement of hand to lift the load to a certain angle for 2 seconds. The longer the distance of elbow angle to reach its position, the higher the amplitude of the lift up. The holding process has shown a significant drop in the amplitude of the electromyography (EMG) because the muscle is in relax condition and just need a little force to hold the load. This theory could be supported by the Chapter 4.2 that will be discussed on the relationship of force and normalized electromyography (EMG) signal.

4.2 Normalized Electromyography (EMG) Signal and Force Signal.

The force is calculated from the angle of elbow flexion and load as the main element for force muscle model formula. Then, the values in Table B.1 in appendix B, load and angle signal is inserted to Table 3.2 and Table 3.3. Figure 4.2 is the graph for the combination of electromyography (EMG) signal with muscle force signal of 120^0, 90^0 and 45^0. This calculated force is important to determine the mean muscle force for determining the experimental mean muscle force from the electromyography signal. This analysis to produce experimental muscle force will be discussed in Chapter 4.4.



(a)



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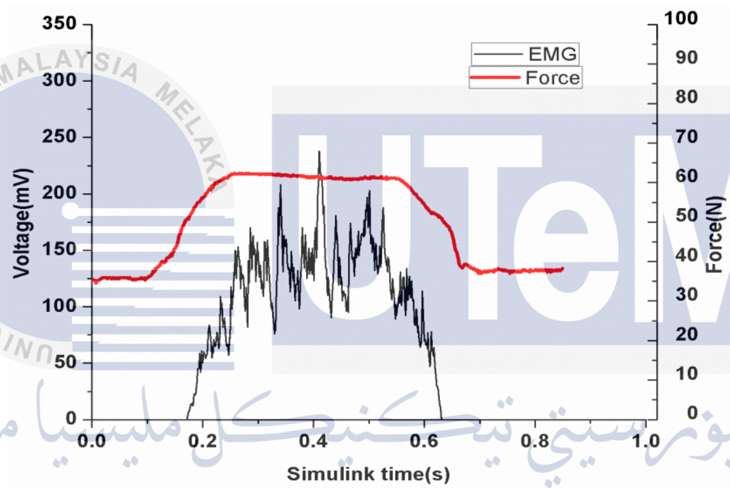


(c)

Figure 4.2: Combination of normalized EMG signal with muscle force signal (a) 120^0 (b) 90^0(c)45^0

Figure 4.2 shows that the force at angle 45^0 is the lowest because of the effect of the cosine rule that will affect the gravitational force. For cosine rule, the value is 7.07×10^{-1} from the value of full force at 45^0. Then, for the force at angle 90^0, the force is 1.00×10^0 from the value of full force. Figure 4.2 shows that the force at 90^0 is at the maximum force because of the effect of the cosine toward gravitational force. Lastly, for force at 120^0, the force is 8.66×10^{-1} from the value of full force. Force in 120^0 will show a significant drop of force in certain levels. This is because when the elbow angle reaches $90^{0,}$ the force will be maximized. Then, the force will start to reduce when then elbow angle reaches 120^0.

The problem with electromyography (EMG) sensor is that it dealing with human that will produce a variety of signal from the bicep muscle. This can be proven from the signal that produced linearity characteristic between force and electromyography (EMG) signal as shown in Figure 4.2 (c). Then, from Figure 4.2(a) and Figure 4.2 (b), the non-linearity happen between force and electromyography (EMG) signal. This happens due to the limitation of the sensor that is used and the technique of the completing the bicep curl exercise Therefore, when dealing with human, the perfect linear characteristic relationship between force and electromyography (EMG) is hard to obtained because of limitation of the sensor and the human error. Therefore, the signals of the ten subjects is extracted to analyze the relationship of force and electromyography (EMG) signals.

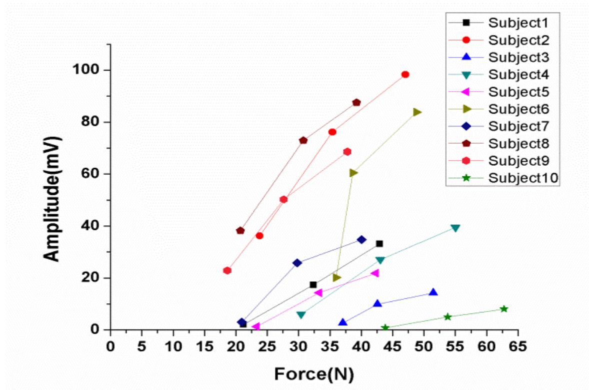
4.4 Validation of Selection for Simple Linear Regression Technique as Statistical Analysis Method

This validation of simple linear regression as the statistical analysis method is important for force and electromyography relationship. The linear characteristic in the experiment that is discussed in Chapter 3.8 analysis is important in determining the validity. The feature of the normalized electromyography (EMG) signal that is obtained in Chapter 4.2 is extracted and the average or mean force from the calculated force is obtained from the result in Chapter 4.2. Then, the value is plotted in scatter plot based on the experiments set.

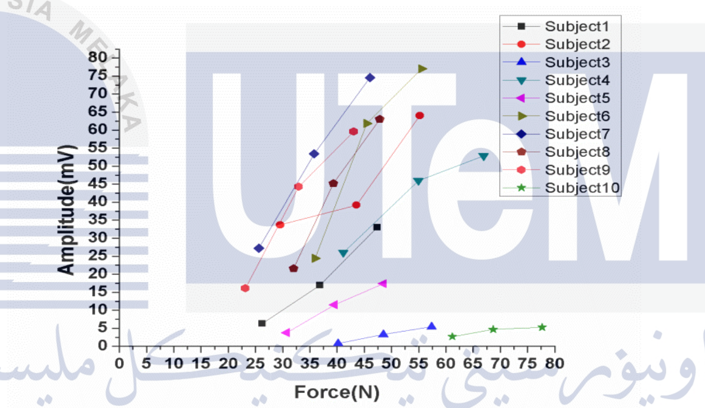
The first experiment which varies the value of load and constant the value of angle is to validate the linearity in the relationship for the use of simple linear regression technique analysis. The mean and standard deviation features are shown in Figure 4.3 and Figure 4.4. Then, the variance and root mean square (RMS) are shown in Figure F.1 and Figure F.2 in appendix F.

The second experiment which varies the value of angle and constant the value of load is to validate the linearity in the relationship for the use of simple linear regression technique analysis. The mean and standard deviation features are shown in Figure 4.5 and Figure 4.6.

Then, the variance and root mean square (RMS) are shown in Figure F.3 and Figure F.4 in appendix F.



(a)



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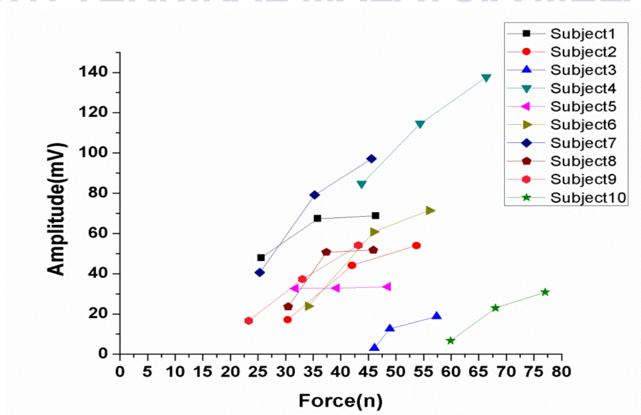
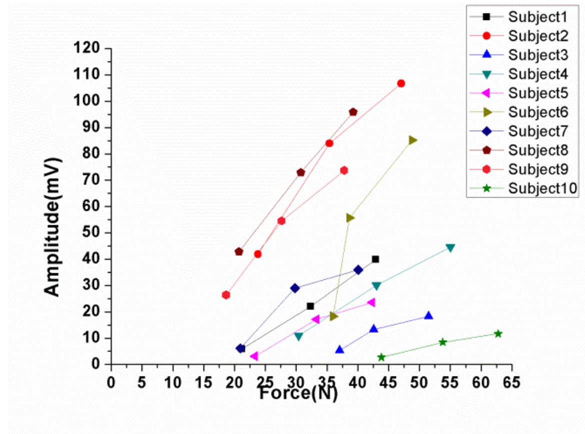
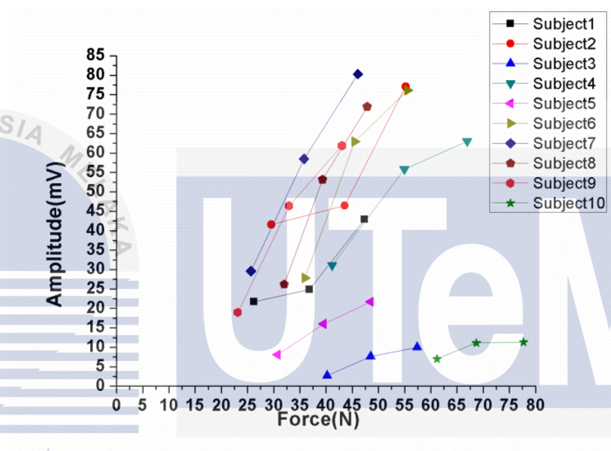


(C)

Figure 4.3: Experiment based on mean feature extraction with variation of loads from 2kg to 6kg and constant angles of (a) 120^0 (b) 90^0 (c) 45^0.



(a)



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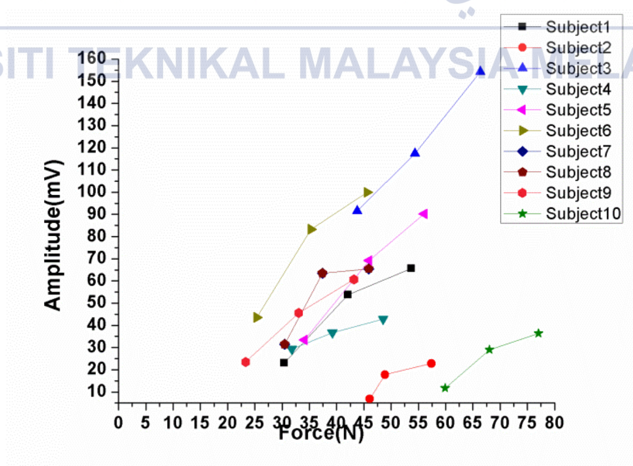
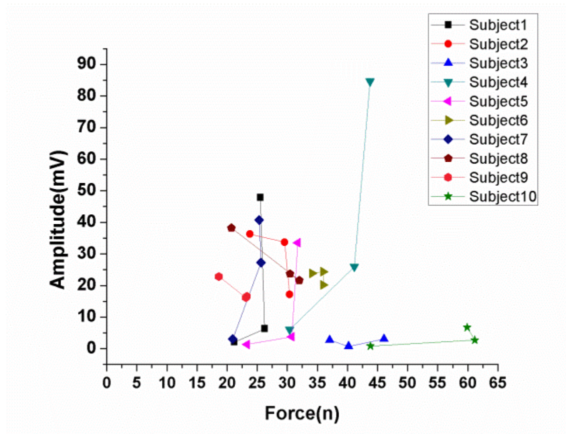
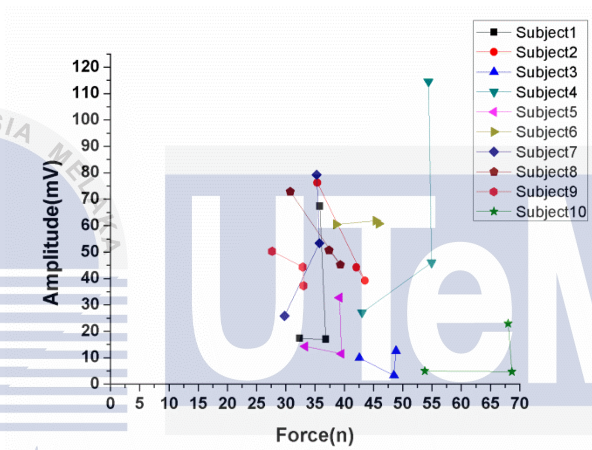


(C)

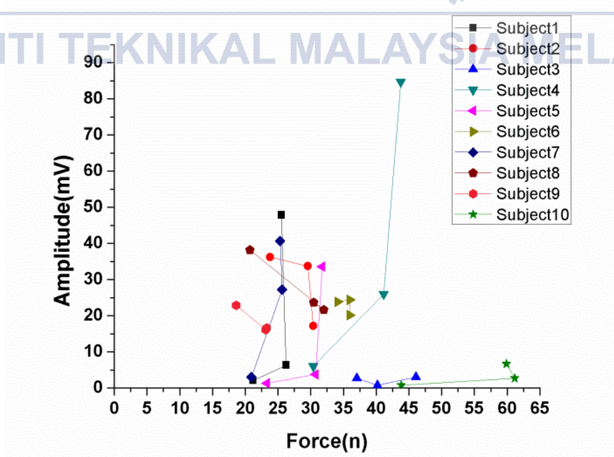
Figure 4.4: Experiment based on standard deviation (SD) feature extraction with variation of loads from 2kg to 6kg and constant angles of (a) 120^0 (b) 90^0 (c) 45^0.



(a)

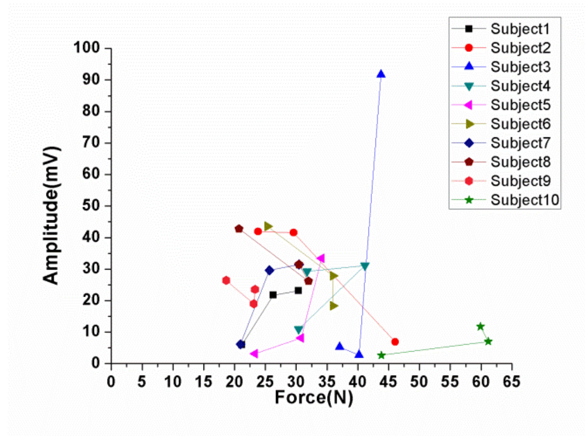


(b)

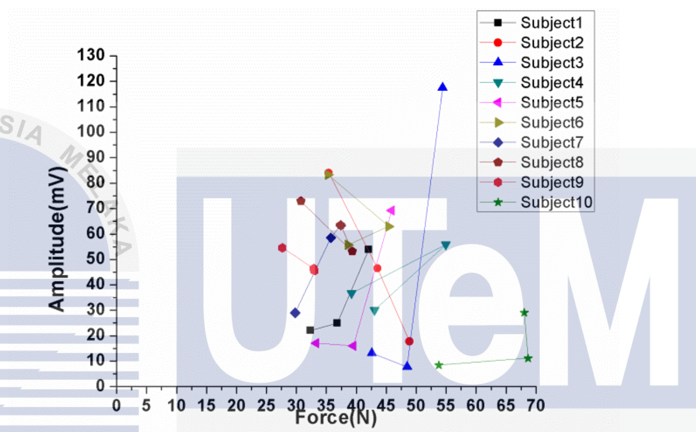


(C)

Figure 4.5: Experiment based on mean feature extraction with variation of angles from 45^0 to 120^0 and constant loads of (a) 2kg (b) 4kg (c) 6kg



(a)



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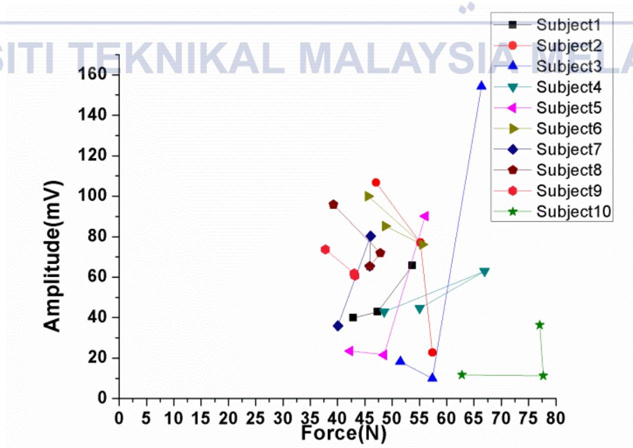

(C)

Figure 4.6: Experiment based on standard deviation (SD) feature extraction with variation of angles from 45^0 to 120^0 and constant loads of (a) 2kg (b) 4kg (c) 6kg

From Figure 4.3 and Figure 4.4, as the load increase the average force and the extracted features are increased. Therefore, there is linear characteristic in the first experiment. However, not all subjects show the perfect linear line. This is due to the limitation of the electromyography (EMG) sensor. However, the not perfect linear line is still following the rule of linear characteristic which is to increase the value of force and extracted features as the value of loads increased.

From Figure 4.5 and Figure 4.6, as the angle increase the average force and the extracted features are not increasing. The value of force is the highest at 90^0 but the extracted features value is increasing with the value of angles. Therefore, the shape of linear line is not possible. The second experiment is also hard to predict and to relate the electromyography (EMG) with force because of the non-linearity occurs in the data in the entire subject.

The conclusion of this chapter is that the first experiment is suitable to use for simple linear regression technique due to it the linearity characteristic that occurs in the data of the entire subjects, although not all is perfect linearly because of the limitation of the sensor. The second experiment is unsuitable for the use to proceed with the next methodology due to its non-linearity characteristic. Therefore, the validation of the simple linear regression as the technique of statistical analysis can only be obtained if the first experiment is selected to proceed with the next methodology. The second experiment will make the selection of simple linear regression technique is unsuitable because of the non-linearity. The conclusion is the simple linear regression is able to be use as statistical analysis by varying the load and constant the angle that is set as the task1(120^0), task 2(90^0) and task 3(45^0).

4.4 Evaluation of Feature Extraction.

There are four feature extractions that are being used in this experiment, which are root mean square (RMS), mean, standard deviation and variance. The simple linear regression technique is used to detect the standard error in the voltage intercept and error of the slope of the equation for voltage. Then, the strength of the linear relationship with scatter data is determined by the value of correlation coefficient, r. The simple linear regression technique is used as a method to analyze the scatter plot from the value of mean force and the extracted features for all ten subjects. Then, the three components obtain from the simple regression technique and are used to evaluate the performance of all the features extraction technique. The selection of the best feature extraction is based on the highest correlation coefficient, r, and lowest standard error for both of slope and voltage intercept.

4.3.1 Analysis of Best Feature Extraction Techniques by using Simple Linear Regression Technique Analysis.

The simple linear regression is important to determine the best feature extraction for determining the relationship between electromyography (EMG) signal and force. Three factors that will determine the best feature extraction is the correlation coefficient, r, standard error of voltage intercept and standard error of slope of voltage equation. The methodology has provided with three main tasks which was based on angles. The analysis of scatter plot is based on a single angle and in single task has 3 sets of load. All the figures in appendices C will show on how the linear regression technique has produced linear fit from the scatter plot of the extracted features.

The graph of scatter plot and linear fit in appendices C is a method to introduce the implementation of the linear regression technique to the scatter plot that has the data about the mean of the force and data of extracting features. Each one of the features extraction technique based on all the tasks are able to produce a voltage force equation, correlation coefficient, r, the standard error for the voltage intercept and standard error of the slope of the voltage force equation. Table 4.1 has provided the characteristics for simple linear regression analysis for four of the feature extraction techniques. These characteristics could analyze for the purpose of choosing the best feature extraction technique.

Table 4.1: Features extraction selection based on characteristics of linear regression analysis.

Angle(^{o})	**Feature Extraction**	**Voltage force equation**	**Correlation coefficient ,r**	**Standard error of voltage intercept(mV)**	**Standard Error of slope (mV)**
120	Root mean square(RMS)	V=0.67F+43.97	2.42×10^{-3}	3.00×10^{1}	6.49×10^{-1}
120	Mean	V=0.46F+27.52	1.923×10^{-3}	2.07×10^{1}	4.47×10^{-1}
120	Standard deviation	V=0.49F+34.02	2.83×10^{-3}	2.19×10^{1}	4.73×10^{-1}
120	Variance	V=112.80F-566.49	5.05×10^{-2}	3.27×10^{3}	7.08×10^{1}
90	Root mean square(RMS)	V=0.16F+41.90	3.18×10^{-2}	2.21×10^{1}	4.77×10^{-1}
90	Mean	V=0.09F+27.21	3.29×10^{-2}	1.57×10^{1}	3.38×10^{-1}
90	Standard deviation	V=0.12F+31.58	3.08×10^{-2}	1.59×10^{1}	3.42×10^{-1}
90	Variance	V=26.62+807.98	4.70×10^{-3}	1.33×10^{3}	2.87×10^{1}
45	Root mean square(RMS)	V=0.50F+32.04	1.578×10^{-2}	2.62×10^{1}	6.78×10^{-1}
45	Mean	V=0.30F+21.50	2.15×10^{-2}	1.88×10^{1}	4.87×10^{-1}
45	Standard deviation	V= 0.31F+24.66	2.16×10^{-2}	1.93×10^{1}	5.01×10^{-1}
45	Variance	V=41.15F+708.58	1.279×10^{-2}	1.99×10^{3}	5.16×10^{1}

4.3.2 Discussion of Linear Regression Technique Analysis to Select The Best Feature Extraction Technique.

Task 1(120^{o}) has shown that mean has the lowest correlation coefficient, r value of 1.92×10^{-3} and the variance has the highest correlation coefficient, r value of 5.05×10^{-2}. The higher the value of correlation coefficient, r will give an indication that the linear fit line will follow the scatter plot. Table 4.1 has showed that the lowest value for standard error of voltage intercept is mean by value of 2.07×10^{1}mV. The extracted feature of variance has the highest standard error of the voltage intercept with a value of an error of 3.27×10^{3}mV. Other than that, the standard error of slope has a lower value in the main feature with an error of 4.47×10^{-1}mV. The extracted feature of variance has the highest standard error of slope with an error of 7.08×10^{1}mV. The correlation coefficient, r is the best in the variance features because it has the highest value. However, the error for variance extracted features has the highest value. Therefore, the variance could not be selected as the best feature extraction technique because it did not meet the specification of the best feature extraction technique by using simple linear regression technique. Then, means extracted feature is evaluated and it has the smallest value of errors. However, the correlation of coefficient value for mean is the lowest compared to the other features extraction technique. The mean feature also could not follow the specification of the best features extraction technique. Therefore, for task 1, the selection of the best feature extraction technique could not be achieved.

The task 2 (90^{o}) has shown that the variance has the lowest correlation coefficient, r of 4.70×10^{-3} and mean has the highest correlation coefficient, r of 3.29×10^{-2}. Table 4.1 has showed that mean extracted feature has the lowest standard error of the voltage intercept with an error of 1.57×10^{1}mV. The extracted feature of variance has the highest standard error of the voltage intercept with an error of 1.33×10^{3}mV. Other than that, Table 4.1 has showed that mean feature has the lowest standard error of slope with an error of 3.38×10^{-1}mV. The extracted feature of variance has the highest standard error of the slope with a value of an error of 2.87×10^{1}mV. The correlation coefficient, r is best in the mean features because it has the highest value. The mean extracted feature is selected because it has the smallest value in term of error of voltage intercept and error of slope. Therefore, for task 2, mean is selected as the best feature extraction technique that is used in the next methodology.

The task 3 (45^o) has shown that the variance has the lowest correlation coefficient, r value of 1.27×10^{-2} and mean has the highest correlation coefficient, r value of 2.15×10^{-2}. Table 4.1 has showed that the standard error of voltage intercept has the lowest value at mean feature with an error of 1.88×10^{1} mV. The extracted feature of variance has the highest standard error of the voltage intercept with a value of an error of 1.99×10^{3}mV. Other than that, Table 4.1 has also shown that the standard error of slope has the lowest value at mean feature with an error of 4.87×10^{-1} mV. The extracted feature of variance has the highest standard error of the slope with a value of an error of 5.16×10^{1} mV. The correlation coefficient, r is best in the mean features because it has the highest value. The mean extracted features will also be selected because it has the smallest value in term of error of voltage intercept and error of slope. Therefore, for task 3, mean is selected as the best feature extraction technique that is used in the next methodology.

The average data of all the characteristic of simple linear regression analysis from features extraction technique based on all the tasks will be tabulated in Table 4.2. The average value for linear regression analysis has showed that the mean and standard deviation have the good characteristic in term of correlation coefficient, r, standard error of voltage intercept and standard error of slope. However, there is only one feature extraction technique that will be selected to proceed with the next methodology which is the mean feature. Therefore, the mean feature extraction technique was chosen as the best feature extraction technique based on simple linear regression technique and the mean feature will be used to develop a voltage and force relationship.

Table 4.2: Average characteristics value for linear regression analysis

Feature Extraction	**Correlation coefficient ,r**	**Standard error of voltage intercept(mV)**	**Standard Error of slope (mV)**
Root mean square (RMS)	1.66×10^{-2}	2.61×10^{1}	6.01×10^{-1}
Mean	1.88×10^{-2}	1.84×10^{1}	4.24×10^{-1}
Standard deviation	1.84×10^{-2}	1.90×10^{1}	4.39×10^{-1}
Variance	2.26×10^{-2}	2.20×10^{3}	5.03×10^{1}

4.4 Force-Electromyography (EMG) Relationship.

The force and electromyography technique is important in determining the mean force from the mean of electromyography (EMG) voltage. This simple linear regression method is to obtain the equation of force from a mean of electromyography (EMG) voltage. The mean is selected as the best feature extraction and the average mean extracted feature value of 10 people is used as the value to be plotted in the scatter graph. The previous result in Chapter 4.2 has proved that the low level of correlation coefficient from linear fit that has been produced from all 10 subjects data in one scatter graph. Therefore, the average method is selected in determining the force from a mean of electromyography (EMG) voltage because it will improve the correlation coefficient to be near to the value of one. The correlation coefficient value that is near to one will produce a linear line that is near to the data in the scatter plot. Then, linear line will produce a force equation from the mean of electromyography (EMG) voltage.

4.4.1 Force-Electromyography (EMG) Equation.

The force-electromyography (EMG) relationship is important in predicting the force from the mean electromyography (EMG) voltage. Table 4.3 show the average value of ten subjects for all the tasks. Then, Table 4.1 has provided with the data of calculated mean force and value for mean extracted feature.

Table 4.3: The average value of force and electromyography (EMG)

Task	Force 2kg (N)	Mean 2kg (mV)	Force 4kg (N)	Mean 4kg (mV)	Force 6kg (N)	Mean 6kg (mV)
1(120^0)	3.51×10^1	2.98×10^1	4.40×10^1	5.22×10^1	5.40×10^1	6.17×10^1
2(90^0)	3.46×10^1	1.63×10^1	4.45×10^1	3.26×10^1	5.46×10^1	4.52×10^1
3(45^0)	2.76×10^1	1.33×10^1	3.67×10^1	3.59×10^1	4.67×10^1	4.90×10^1

After the average value is tabulated, the data of the entire task is plotted in scatter graph for the simple linear regression technique to occur. Figure 4.3 show the scatter plot and linear fit line for task 1(120^0), Figure 4.4 show the scatter plot and linear fit line for task2 (90^0) and Figure 4.5 show the scatter plot and linear fit line for task3 (45^0).

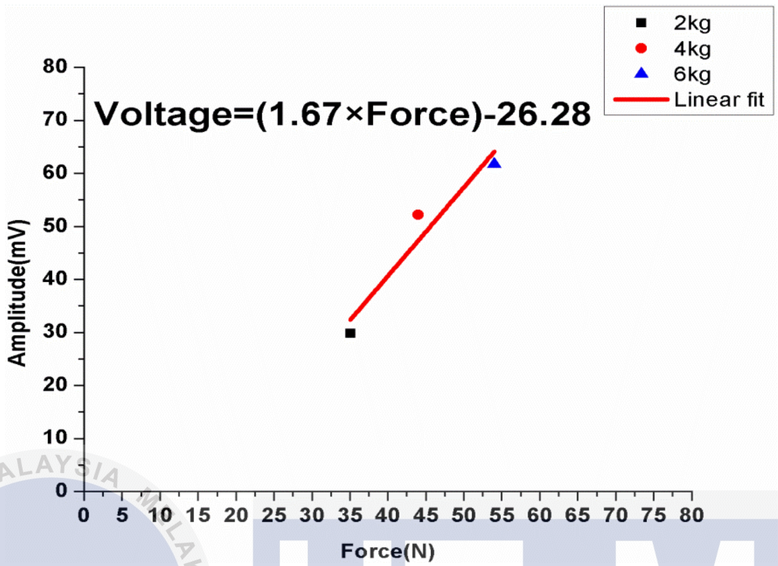

Figure 4.3: Scatter plot and linear fit line for task 1.

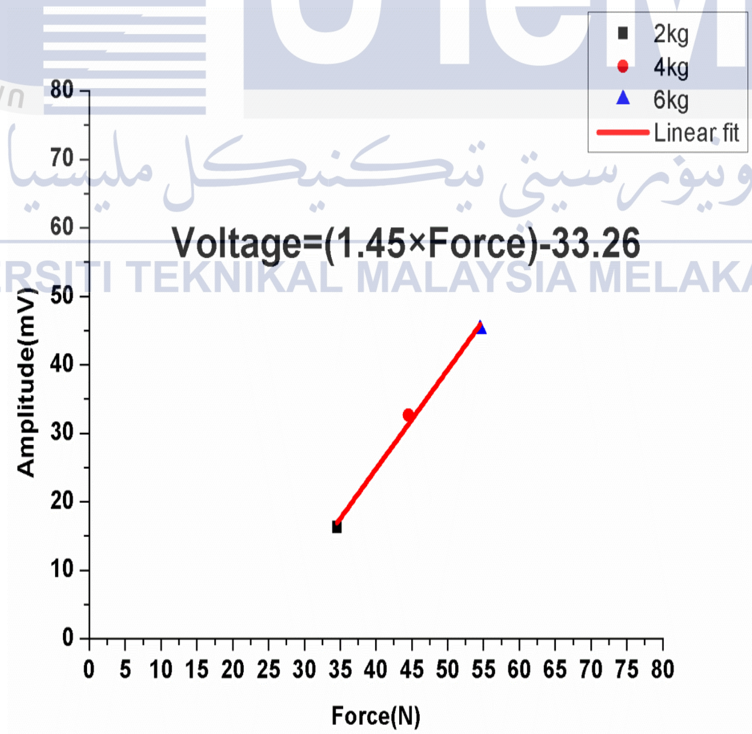

Figure 4.4: Scatter plot and linear fit line for task 2.

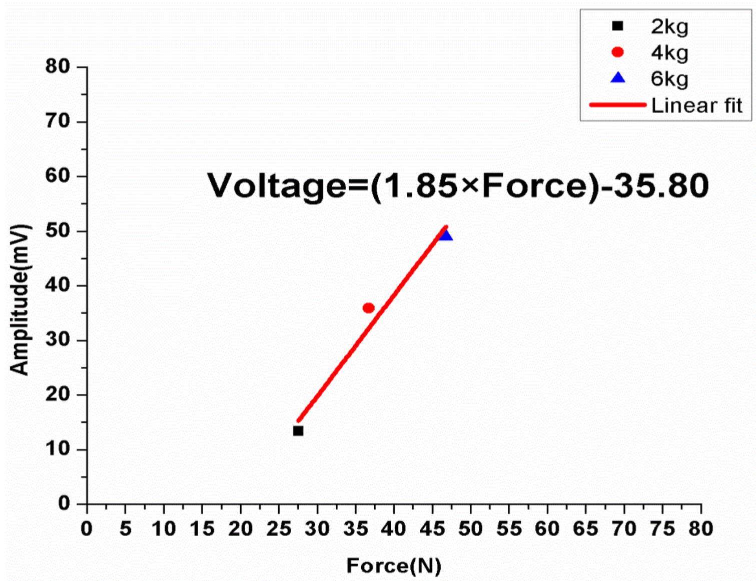

Figure 4.5: Scatter plot and linear fit line for task 3.

Then, the force and mean electromyography (EMG) voltage equation is produced from the linear fit line from simple linear regression technique. The characteristic value for simple linear regression technique analysis for the average value of 10 subjects in Table 4.4 is compared with the average characteristics value for simple linear regression technique analysis for all 10 subjects in Table 4.5.

Table 4.4: Characteristic value for linear regression technique for the average value of 10 subjects

Task	Voltage force equation	Correlation coefficient ,r	Standard error of voltage intercept(mV)	Standard error of slope (mV)
$1(120^0)$	V=1.67F-26.28	8.65×10^{-1}	2.02×10^{1}	4.49×10^{-1}
$2(90^0)$	V=1.45F-33.26	9.88×10^{-1}	5.07×10^{0}	1.125×10^{-1}
$3(45^0)$	V=1.85F-35.80	9.36×10^{-1}	1.27×10^{1}	3.36×10^{-1}

Table 4.5: Average characteristics value for linear regression technique for all 10 subjects

Task	Voltage force equation	Correlation coefficient ,r	Standard error of voltage intercept(mV)	Standard error of slope (mV)
$1(120^0)$	V=0.46F+27.52	1.92×10^{-3}	2.068×10^{1}	4.47×10^{-1}
$2(90^0)$	V=0.09F+27.21	3.29×10^{-2}	1.57×10^{1}	3.38×10^{-1}
$3(45^0)$	V=0.30F+21.50	2.153×10^{-2}	1.88×10^{1}	4.87×10^{-1}

The correlation coefficient value for average value of 10 subjects is near to one compared to the average correlation coefficient value for all 10 subjects, which is far away from the value of one. The value correlation coefficient of 8.65×10^{-1} for task1, 9.88×10^{-1} for task 2 and 9.36×10^{-1} for task 3 is to ensure that the average value of 10 subjects is selected to produce an equation of force from mean electromyography (EMG) voltage. The value of the standard error of voltage intercept and standard error of slope is also smaller in the average value of 10 subjects compared to the average value of the standard error of voltage intercept and standard error of slope for all 10 subjects. Therefore, the average value is selected as a technique to obtain the equation of force and mean electromyography (EMG) voltage.

There are three equations which will be determined based on the task set. Equation 4.1 is the equation for mean voltage of electromyography (EMG) for task 1, Equation 4.2 is equation for a mean voltage of electromyography (EMG) for task 2 and Equation 4.3 is an equation for mean voltage of electromyography (EMG) for task 3.

$$\text{Mean\_Voltage}_{\text{Task1}} = 1.67(\text{Mean\_Force}_{\text{Task1}}) - 26.28 \tag{4.1}$$

$$\text{Mean\_Voltage}_{\text{Task2}} = 1.45(\text{Mean\_Force}_{\text{Task2}}) - 33.26 \tag{4.2}$$

$$\text{Mean\_Voltage}_{\text{Task3}} = 1.85(\text{Mean\_Force}_{\text{Task3}}) - 35.80 \tag{4.3}$$

Then, the output that needs to be achieved in this research is to determine the mean force from the mean voltage of electromyography (EMG) signal. Therefore, the equation of mean force must be determined from Equation 4.1 to Equation 4.3. Equation 4.4 is the equation of mean force for task 1, Equation 4.5 is the equation of mean force for task 2 and Equation 4.6 is the equation of mean force for task 3. The reliability of the equation to relate the force and electromyography (EMG) will be evaluated in the next chapter.

$$\text{Mean\_Force}_{\text{Task1}} = \frac{(\text{Mean\_Voltage}_{\text{Task1}}) + 26.28}{1.67} \tag{4.4}$$

$$Mean\_Force_{Task2} = \frac{(Mean\_Voltage_{Task2}) + 33.26}{1.45} \quad (4.5)$$

$$Mean\_Force_{Task3} = \frac{(Mean\_Voltage_{Task3}) + 35.80}{1.85} \quad (4.6)$$

4.4.2 Prediction of Force.

The force is predicted from the Equation 4.5 to Equation 4.7 and the value of force is shown in Table 4.6. The average value of calculated and experimental is compared to evaluate the mean force needed to lift a single load with an angle. Therefore, the value of mean voltage and mean force will be decided for the prosthetic hand to lift the load based on load and angle.

Table 4.6: Comparison between averages calculated force and average experimental force

Task	**Mean Force 2kg(N)**		**Mean Force 4kg(N)**		**Mean Force 6kg(N)**	
Mean Force	Experimental	Calculated	Experimental	Calculated	Experimental	Calculated
1	3.35×10^1	3.47×10^1	4.69×10^1	4.37×10^1	5.26×10^1	5.37×10^1
2	3.42×10^1	3.46×10^1	4.55×10^1	4.45×10^1	5.41×10^1	5.46×10^1
3	2.67×10^1	2.68×10^1	3.83×10^1	3.67×10^1	4.60×10^1	4.67×10^1

Table 4.6 shows that the value of mean muscle force that will be needed to lift the load based on each task. For task 1, the subject will need 3.35×10^1 N for experimental mean muscle force and 3.47×10^1N for calculating mean muscle force to lift the load of 2kg for angle 120^0. Other than that, the subject will need 4.69×10^1 N for experimental mean muscle force and 4.37×10^1 N for calculating mean muscle force to lift the load of 4kg for angle 120^0. Lastly, the subject will need 5.26×10^1 N for experimental mean muscle force and 5.37×10^1 N for calculating mean muscle force to lift the load of 6kg for angle 120^0.

For task 2, the subject needed 3.42×10^1 N for experimental mean muscle force and 3.46×10^1 N for calculating mean muscle force to lift the load of 2kg for angle 90^0. Other than that, the subject needed 4.55×10^{1} N for experimental mean muscle force and 4.45×10^{1}N for calculating mean muscle force to lift the load of 4kg for angle 90^{0}. Lastly, the subject needed 5.41×10^{1} N for experimental mean muscle force and 5.46×10^{1} N for calculating mean muscle force to lift the load of 6kg for angle 90^{0}.

For task 3, the subject needed 2.67×10^{1} N for experimental mean muscle force and 2.68×10^{1} N for calculating mean muscle force to lift the load of 2kg for angle 45^{0}. Other than that, the subject needed 3.83×10^{1} N for experimental mean muscle force and 3.67×10^{1} N for calculating mean muscle force to lift the load of 4kg for angle 45^{0}. Lastly, the subject needed 4.60×10^{1} N for experimental mean muscle force and 4.67×10^{1} N for calculating mean muscle force to lift the load of 6kg for angle 45^{0}.

The theory of force is maximum at 90^{0} has been proven based on the result of muscle force in Table 4.6. Then, the theory has stated that the lowest muscle force was in angle 45^{0} and was also proven to result in Table 4.6. The calculated and experimental is almost the same. Therefore, the mean force equation has produced a reliable value of mean force for the entire tasks. The next task is to find the mean voltage from the calculated mean force. The mean voltage will be calculated by using the formula in Equation 4.1 to Equation 4.3 based on the value of the data in Table 4.6.

Table 4.7: Comparison between averages calculated mean voltage and average experimental mean voltage

Task	**Mean voltage 2kg(mV)**		**Mean voltage 4kg(mV)**		**Mean voltage 6kg(mV)**	
Mean voltage	Experimental	Calculated	Experimental	Calculated	Experimental	Calculated
1	3.169×10^{1}	2.98×10^{1}	4.68×10^{1}	5.22×10^{1}	6.35×10^{1}	6.17×10^{1}
2	1.691×10^{1}	1.628×10^{1}	3.13×10^{1}	3.27×10^{1}	4.59×10^{1}	4.52×10^{1}
3	2.678×10^{1}	2.67×10^{1}	3.67×10^{1}	3.89×10^{1}	4.68×10^{1}	4.61×10^{1}

The Table 4.7 has shows that, mean voltage that is needed to lift the load based on each task. For task 1, the subject needed to 3.16×10^{1} mV for experimental mean voltage and 2.97×10^{1} mV for calculating mean voltage to lift the load of 2kg for angle 120^{0}. Other than that, the subject needed to 4.68×10^{1} mV for experimental mean voltage and 5.22×10^{1}mV for calculating mean voltage to lift the load of 4kg for angle 120^{0}. Lastly, the subject needed 6.35×10^{1} mV for experimental mean voltage and 6.17×10^{1} mV for calculating mean voltage to lift the load of 6kg for angle 120^{0}.

For task 2, the subject needed 1.691×10^{1} mV for experimental mean voltage and 1.628×10^{1} mV for calculating mean voltage to lift the load of 2kg for angle 90^{0}. Other than that, the subject needed 3.13×10^{1} mV for experimental mean voltage and 3.27×10^{1} mV for calculating mean voltage to lift the load of 4kg for angle 90^{0}. Lastly, the subject needed 4.59×10^{1} mV for experimental mean voltage and 4.52×10^{1} mV for calculating mean voltage to lift the load of 6kg for angle 90^{0}.

For task 3, the subject needed $2.68\ \times10^{1}$ mV for experimental mean voltage and 2.67×10^{1} mV for calculating mean voltage to lift the load of 2kg for angle 45^{0}. Other than that, the subject needed 3.673×10^{1} mV for experimental mean voltage and 3.89×10^{1} mV for calculating mean voltage to lift the load of 4kg for angle 45^{0}. Lastly, the subject needed 4.68×10^{1} mV for experimental mean voltage and 4.61×10^{1} mV for calculating mean voltage to lift the load of 6kg for angle 45^{0}.

A mean voltage value for each task is important in determining the main force that is needed in each single task. This value of mean voltage is important in designing the prosthetic arm. This voltage could be used to control the ability of the prosthesis arm to lift a load with a certain value of angles. Then, the calculation of the mean force is needed for the prosthetic arm to lift the load with a certain value of angles. Therefore, the mean voltage will determine the mean force, which could be used to determine the weight and the angle that could be lifted by the subject. This force-electromyography (EMG) could help in designing the prosthetic arm by predicting force from electromyography (EMG) signal.

4.5 Reliability of Force-Electromyography (EMG) Equation.

This reliability of force-electromyography (EMG) equation is to determine the performance of the experimental mean force by finding the percentage of error from the calculated mean force. This percentage of error will determine the accuracy of the experimental mean force. Then, the value of the experimental mean force will be compared with the average value of predicted experimental mean force. This is important to determine the accuracy of the predicted mean force. Therefore, the accuracy of the linear fit that will produce the predicted data will be analyzed with the data that is produced from the mean electromyography (EMG) voltage.

4.5.1 Comparison between Experimental Muscle Force and Calculated Muscle Force.

The reliability of mean force electromyography (EMG) equation will be determined by comparing the experimental force with the calculated force. The experimental mean force is the mean force that was calculated from the Equation 4.4 to Equation 4.6 and calculated mean force is the mean force that is calculated from the muscle model. Appendix D and Appendix E will show the comparison between experiment and calculated results. The error will be calculated to evaluate the performance of the equation. Table 4.8 to Table 4.10 will show the error that will be produced by the equation. The equation of percentage of error is as shown in Equation 4.7. The calculated force was set as the theoretical value and the experimental force was set as the experimental value. The percentage of error based on the force was stated as shown in Equation 4.8.

$$\text{Percentage of error}(\%) = \frac{|\,\text{Theoretical Value - Experimental Value}\,|}{\text{Theoretical Value}} \times 100 \quad (4.7)$$

$$\text{Percentage of error}(\%) = \frac{|\,\text{Calculated Force - Experimental Force}\,|}{\text{Calculated Force}} \times 100 \quad (4.8)$$

Table 4.8: Error and percentage for calculation mean muscle force of error for task 1(120^{0})

Subject	Error 2kg (N)	Percentage of error 2kg (%)	Error 4kg(N)	Percentage of error 4kg (%)	Error 6kg(N)	Percentage of error 6kg (%)
1	1.884×10^{1}	7.35×10^{1}	1.764×10^{0}	4.78×10^{0}	1.053×10^{1}	2.27×10^{1}
2	4.44×10^{0}	1.463×10^{1}	6.39×10^{0}	1.476×10^{1}	5.74×10^{0}	1.076×10^{1}
3	2.85×10^{1}	6.19×10^{1}	2.33×10^{1}	4.81×10^{1}	3.08×10^{1}	5.33×10^{1}
4	2.25×10^{1}	5.15×10^{1}	3.06×10^{-1}	5.58×10^{-1}	3.16×10^{1}	4.77×10^{1}
5	4.04×10^{0}	1.275×10^{1}	8.65×10^{0}	2.19×10^{1}	1.287×10^{1}	2.66×10^{1}
6	4.16×10^{0}	1.228×10^{1}	2.02×10^{1}	4.44×10^{1}	2.33×10^{0}	4.16×10^{0}
7	1.475×10^{1}	5.81×10^{1}	2.40×10^{1}	6.72×10^{1}	2.82×10^{1}	6.19×10^{1}
8	5.84×10^{-1}	1.926×10^{0}	1.488×10^{1}	3.76×10^{1}	7.89×10^{-1}	1.728×10^{0}
9	2.31×10^{0}	9.92×10^{0}	2.06×10^{1}	6.24×10^{1}	4.87×10^{0}	1.133×10^{1}
10	3.61×10^{1}	6.47×10^{1}	4.25×10^{1}	6.19×10^{1}	3.96×10^{1}	5.37×10^{1}
Average	1.368×10^{1}	3.61×10^{1}	1.625×10^{1}	3.34×10^{1}	1.679×10^{1}	2.94×10^{1}

Table 4.9: Error and percentage for calculation mean muscle force of error for task 2(90^{0})

Subject	Error 2kg (N)	Percentage of error 2kg (%)	Error 4kg(N)	Percentage of error 4kg (%)	Error 6kg(N)	Percentage of error 6kg (%)
1	1.175×10^{0}	4.44×10^{0}	1.768×10^{0}	4.78×10^{0}	1.511×10^{0}	3.19×10^{0}
2	1.66×10^{1}	5.61×10^{1}	6.39×10^{0}	1.478×10^{1}	1.191×10^{1}	2.15×10^{1}
3	1.677×10^{1}	4.16×10^{1}	2.33×10^{1}	4.81×10^{1}	3.07×10^{1}	5.35×10^{1}
4	3.15×10^{-1}	7.66×10^{-1}	3.06×10^{-1}	5.58×10^{-1}	7.56×10^{0}	1.136×10^{1}
5	5.24×10^{0}	1.703×10^{1}	8.65×10^{0}	2.19×10^{1}	1.365×10^{1}	2.80×10^{1}
6	3.80×10^{0}	1.066×10^{1}	2.02×10^{1}	4.44×10^{1}	2.05×10^{1}	3.69×10^{1}
7	1.618×10^{1}	6.26×10^{1}	2.40×10^{1}	6.72×10^{1}	2.83×10^{1}	6.15×10^{1}
8	5.82×10^{0}	1.825×10^{1}	1.485×10^{1}	3.76×10^{1}	1.867×10^{1}	3.89×10^{1}
9	1.093×10^{1}	4.71×10^{1}	2.06×10^{1}	6.24×10^{1}	2.10×10^{1}	4.88×10^{1}
10	3.64×10^{1}	5.95×10^{1}	4.25×10^{1}	6.19×10^{1}	5.11×10^{1}	6.58×10^{1}
Average	1.133×10^{1}	3.18×10^{1}	1.627×10^{1}	3.64×10^{1}	2.05×10^{1}	3.69×10^{1}

Table 4.10: Error and percentage for calculation mean muscle force of error for task 3(45^0)

Subject	Error 2kg (N)	Percentage of error 2kg (%)	Error 4kg(N)	Percentage of error 4kg (%)	Error 6kg(N)	Percentage of error 6kg (%)
1	7.25×10^{-1}	3.42×10^{0}	3.66×10^{0}	1.135×10^{1}	5.68×10^{0}	1.328×10^{1}
2	1.513×10^{1}	6.35×10^{1}	2.51×10^{1}	7.09×10^{1}	2.54×10^{1}	5.40×10^{1}
3	1.635×10^{1}	4.39×10^{1}	1.798×10^{1}	4.20×10^{1}	2.44×10^{1}	4.75×10^{1}
4	7.82×10^{0}	2.57×10^{1}	9.06×10^{0}	2.11×10^{1}	1.441×10^{1}	2.61×10^{1}
5	3.24×10^{0}	1.394×10^{1}	6.26×10^{0}	1.885×10^{1}	1.122×10^{1}	2.64×10^{1}
6	2.43×10^{0}	8.76×10^{0}	1.347×10^{1}	3.46×10^{1}	1.593×10^{1}	3.25×10^{1}
7	1.089×10^{0}	5.15×10^{0}	5.40×10^{0}	1.813×10^{1}	4.5×10^{-1}	1.144×10^{0}
8	1.935×10^{1}	9.29×10^{1}	2.80×10^{1}	9.10×10^{1}	2.74×10^{1}	6.98×10^{1}
9	1.307×10^{1}	6.99×10^{1}	1.883×10^{1}	6.82×10^{1}	1.869×10^{1}	4.93×10^{1}
10	2.41×10^{1}	5.49×10^{1}	3.18×10^{1}	5.91×10^{1}	3.91×10^{1}	6.23×10^{1}
Average	1.035×10^{1}	3.82×10^{1}	1.595×10^{1}	4.35×10^{1}	1.824×10^{1}	3.82×10^{1}

The maximum percentage of error for task 1 with the load of 2kg is detected at subject 1 at 7.35×10^{1} %. This is because of the data that is obtained for the 10 subjects are not precise. This has caused the variable number of percentage of error for all 10 subjects. The point which is far away from the linear fit will provide with the large number of errors which is subject 1. Then, for task 1 with 4 kg load the maximum percentage error is detected at subject 7 at 6.72×10^{1}% and for task 1 with 6kg load the maximum percentage error is detected at subject 7 at 6.19×10^{1}%. This error also happens because of the point of these two forces is far away from the linear fit. The subject 7 has the worse accuracy compared to the other subject in task 1.

The maximum percentage of error for task 2 with the load of 2kg is detected at subject 7 at 6.26×10^{1}%. This is because of the value of the force is far away from the linear fit graph. Then, for task 2 with 4 kg load the maximum percentage error is detected at subject 7 at 6.72×10^{1}% and for task 2 with 6kg load the maximum percentage error is detected at subject 10 at 6.58×10^{1}%. This error also happens because of the point of these two forces is far away from the linear fit. The subject 7 has the worse accuracy compared to the other subject in task 2.

The maximum percentage of error for task 3 with the load of 2kg is detected at subject 8 at 9.29×10^{1}%. This is because of the value of the force is far away from the linear fit graph. Then, for task 3 with 4 kg load the maximum percentage error is detected at subject 8 at 9.10×10^{1} % and for task 3 with 6kg load the maximum percentage error is detected at subject 8 at 6.98×10^{1}%. This error also happens because of the point of these two forces is far away from the linear fit. The subject 8 has the worse accuracy compared to the other subject in task 3.

The performance equation of force and electromyography (EMG) voltage is decided by the total percentage of error of the entire load in a single task. The total percentage error for task 1 is 3.29×10^{1}% and has the lowest error for the entire task. Then, for task 2 the total percentage of error is 3.50×10^{1}% and for task 3 the total percentage of error is 3.99×10^{1}% which has the highest total percentage of error. The percentage of error is large that will reduce the accuracy to produce desired force. Therefore, this simple regression technique is unsuitable for classification of mean feature in term of force because of the percentage of error produce.

These percentages of errors are because of the large number of data for mean force and mean electromyography (EMG) voltage that is used to form the equation to obtain the experimental force data. Furthermore, the data of all 10 subjects is averaged for the simple linear regression technique to form the equation for predicting force. Therefore, the simple linear regression technique is the easiest and inaccurate way to predict force from a large number of data.

Table 4.11: Average error and average percentage for calculation mean muscle force of error

Task	**Percentage of error 2kg (%)**	**Percentage of error 4kg (%)**	**Percentage of error 6kg (%)**	**Total percentage of error (%)**
1(120^{0})	3.61×10^{1}	3.34×10^{1}	2.93×10^{1}	3.29×10^{1}
2(90^{0})	3.18×10^{1}	3.63×10^{1}	3.69×10^{1}	3.50×10^{1}
3(45^{0})	3.82×10^{1}	4.35×10^{1}	3.82×10^{1}	3.99×10^{1}

4.5.2 Comparison between Experimental Muscle Force and Average Predicted Muscle Force.

This chapter will do a comparison between the average predicted mean force and the experimental mean force. The value of average experimental predicted mean force muscle has been stated in Table 4.6 and is compared with the experimental data force for each subject. The percentage of error could be calculated as shown in Equation 4.7. The predicted force is set as the theoretical value and the experimental force is set as the experiment value. The percentage of error based on the force is stated as shown in Equation 4.9.

$$\text{Percentage of error}(\%) = \frac{|\text{Predicted Force} - \text{Experiment Force}|}{\text{Predicted Force}} \times 100 \qquad (4.9)$$

Table 4.12: Error and percentage of error of average experimental predicted mean muscle force for task 1(120^0)

Subject	**Error 2kg (N)**	**Percentage of error 2kg (%)**	**Error 4kg(N)**	**Percentage of error 4kg (%)**	**Error 6kg(N)**	**Percentage of error 6kg (%)**
1	9.66×10^0	2.79×10^1	1.235×10^1	2.82×10^1	3.14×10^0	5.85×10^0
2	8.70×10^0	2.51×10^1	1.544×10^0	3.52×10^0	5.68×10^0	1.063×10^1
3	1.711×10^1	4.94×10^1	2.04×10^1	4.68×10^1	2.67×10^1	4.98×10^1
4	3.17×10^1	9.14×10^1	4.05×10^1	9.28×10^1	4.43×10^1	8.26×10^1
5	1.135×10^0	3.25×10^0	8.37×10^0	1.928×10^1	1.833×10^1	3.41×10^1
6	4.67×10^0	1.354×10^1	8.39×10^0	1.923×10^1	4.73×10^0	8.81×10^0
7	5.39×10^0	1.553×10^1	1.934×10^1	4.43×10^1	2.01×10^1	3.74×10^1
8	4.78×10^0	1.381×10^1	2.37×10^0	5.44×10^0	7.01×10^0	1.313×10^1
9	9.01×10^0	2.60×10^1	5.68×10^0	1.301×10^1	5.63×10^0	1.051×10^1
10	1.493×10^1	4.31×10^1	1.425×10^1	3.26×10^1	1.955×10^1	3.64×10^1
Average	1.075×10^1	3.09×10^1	1.334×10^1	3.05×10^1	1.559×10^1	2.89×10^1

Table 4.13: Error and percentage of error of average experimental predicted mean muscle force for task 2(90^0)

Subject	Error 2kg (N)	Percentage of error 2kg (%)	Error 4kg(N)	Percentage of error 4kg (%)	Error 6kg(N)	Percentage of error 6kg (%)
1	$7.16v10^0$	2.07×10^1	9.47×10^0	2.13×10^1	8.73×10^0	1.60×10^1
2	1.16×10^1	3.35×10^1	5.40×10^0	1.21×10^1	1.25×10^1	2.30×10^1
3	1.11×10^1	3.22×10^1	1.94×10^1	4.35×10^1	2.79×10^1	5.11×10^1
4	6.26×10^0	1.81×10^1	1.01×10^1	2.26×10^1	4.81×10^0	8.82×10^0
5	9.04×10^0	2.61×10^1	1.37×10^1	3.07×10^1	1.96×10^1	3.60×10^1
6	5.18×10^0	1.50×10^1	2.10×10^1	4.72×10^1	2.15×10^1	3.94×10^1
7	7.14×10^0	2.06×10^1	1.52×10^1	3.42×10^1	1.98×10^1	3.63×10^1
8	3.25×10^0	9.41×10^0	9.58×10^0	2.15×10^1	1.19×10^1	2.18×10^1
9	5.33×10^{-1}	1.54×10^0	8.95×10^0	2.01×10^1	9.50×10^0	1.74×10^1
10	9.79×10^0	2.83×10^1	1.84×10^1	4.13×10^1	2.80×10^1	5.13×10^1
Average	7.11×10^0	2.06×10^1	1.31×10^1	2.95×10^1	1.64×10^1	3.01×10^1

Table 4.14: Error and percentage of error of average experimental predicted mean muscle force for task 2 task 3(45^0)

Subject	Error 2kg (N)	Percentage of error 2kg (%)	Error 4kg(N)	Percentage of error 4kg (%)	Error 6kg(N)	Percentage of error 6kg (%)
1	6.31×10^0	2.36×10^1	8.05×10^0	2.19×10^1	9.51×10^0	2.04×10^1
2	1.224×10^1	4.54×10^1	2.38×10^1	6.47×10^1	2.57×10^1	5.50×10^1
3	5.97×10^0	2.23×10^1	1.201×10^1	3.28×10^1	1.975×10^1	4.21×10^1
4	4.17×10^0	1.564×10^1	2.77×10^0	7.53×10^0	6.07×10^0	1.309×10^1
5	6.71×10^0	2.51×10^1	9.67×10^0	2.63×10^1	1.562×10^1	3.33×10^1
6	3.47×10^0	1.301×10^1	1.538×10^1	4.16×10^1	1.793×10^1	3.83×10^1
7	4.73×10^0	1.773×10^1	1.541×10^0	4.18×10^0	6.20×10^0	1.331×10^1
8	1.325×10^1	4.94×10^1	2.20×10^1	5.99×10^1	1.994×10^1	4.26×10^1
9	4.91×10^0	1.839×10^1	9.77×10^0	2.66×10^1	9.68×10^0	2.07×10^1
10	7.00×10^0	2.61×10^1	1.473×10^1	4.00×10^1	2.31×10^1	4.93×10^1
Average	6.86×10^0	2.56×10^1	1.208×10^1	3.26×10^1	1.531×10^1	3.28×10^1

The maximum percentage of error for task 1 with the load of 2kg is detected at subject 4 at 9.14×10^{1}%. This is because of the value of the predicted mean force point is far away from mean force for subject 4. Then, for task 1 with 4 kg load the maximum percentage error is detected at subject 4 at 9.28×10^{1}% and for task 1 with 6kg load the maximum percentage error is detected at subject 4 at 8.26×10^{1}%. This error also happens because of the predicted mean force of these two point is far away from the main forces for subject 4. Therefore, subject 4 has the worse accuracy compared to the other subject in task 1.

The maximum percentage of error for task 2 with the load of 2kg is detected at subject 3 at 3.22×10^{1}%. This is because of the value of the predicted mean force point is far away from mean force for subject 3. Then, for task 2 with 4 kg load the maximum percentage error is detected at subject 3 at 4.35×10^{1}% and for task 2 with 6kg load the maximum percentage error is detected at subject 3 at 5.11×10^{1}%. This error also happens because of the predicted mean force of these two point is far away from the mean forces for subject 3. Therefore, subject 3 has the worse accuracy compared to the other subject in task 2.

The maximum percentage of error for task 3 with the load of 2kg is detected at subject 10 at 2.61×10^{1}%. This is because of the value of the predicted mean force point is far away from mean force for subject 10. Then, for task 3 with 4 kg load the maximum percentage error is detected at subject 10 at 4.04×10^{1}% and for task 3 with 6kg load the maximum percentage error is detected at subject 10 at 4.93×10^{1}%. This error also happens because of the predicted mean force of these two point is far away from the mean forces for subject 10. Therefore, subject 10 has the worse accuracy compared to the other subject in task 3.

Table 4.15: Average error and average percentage for average experimental predicted mean muscle force of error

Task	**Percentage of error 2kg (%)**	**Percentage of error 4kg (%)**	**Percentage of error 6kg (%)**	**Total percentage of error (%)**
$1(120^{0})$	3.09×10^{1}	3.05×10^{1}	2.89×10^{1}	3.01×10^{1}
$2(90^{0})$	2.06×10^{1}	2.95×10^{1}	3.01×10^{1}	2.67×10^{1}
$3(45^{0})$	2.56×10^{1}	3.26×10^{1}	3.28×10^{1}	3.03×10^{1}

The performance of predicted of average mean force is decided by the total percentage of error of the entire load in a single task. The total percentage error for task 2 is 2.67×10^{1}% and has the lowest error for the entire main task. Then, for task 1 the total percentage of error is 3.01×10^{1}% and for task 3 the total percentage of error is 3.03×10^{1}% which has the highest total percentage of error. The percentage of error is large and this will reduce the accuracy of the predicted average mean force. The predicted average mean force is the desired mean force which is needed by the subject to lift a load based on a different weight and angle. Therefore, if the experimental mean force value is far away from the predicted mean force, the accuracy to classify force in term of angles and load is difficult.

These percentages of errors are because of the large number of data for mean force and mean electromyography (EMG) voltage that is used to form the equation to obtain the experimental force data. The linear fit line will determine the desired average predicted force. This linear fit line is formed from the simple linear regression technique. This technique will find the best linear fit based on the distribution of the data from 2kg to 6kg. The large number of data that has a low precision will cause the variation in error. Therefore, for a large number of data that is not precise, a simple linear regression technique is not suitable because the outcome of force will not be accurate because of the high value of percentage of error.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The objective to extract the feature of surface electromyography (sEMG) in term of force in time domain is achieved in this research. There are four feature extractions that are analyzed by using simple linear regression technique analysis. There are three characteristics which is analyzed to obtain the best feature extraction technique. The highest value of correlation coefficient, the lowest value of standard error for slope and lowest value of standard of error for voltage intercept. Mean feature is selected as the best feature extraction technique because the feature has satisfy the entire characteristic above. Therefore, the mean is the best feature extraction in term of force compares to root mean square (RMS), variance, and standard deviation.

The objective to analyze the extracted signal by using statistical analysis is achieved in this research. The first analysis is to compare the calculated force with experimental force. The calculated force is produced from the muscle model force formula and experimental force is produced from the equation that was produced from simple linear regression technique. The percentage of error is the method to compare the forces. Therefore, the result for percentage of error is in the range of 29% to 43%. This high value of percentage of error and variation of percentage of error has proved that this system is not suitable to predict force because it has a low accuracy and low precision. Therefore, the conclusion is that the accuracy and precision of experimental force that is gained from simple linear regression technique is not suitable for predicting force.

The second analysis was to compare the value of predicted force with the experimental force. This analysis is important to determine the suitable force and electromyography (EMG) voltage that is needed by the prosthesis arm to complete the biceps curl exercise. The percentage of error is the method to compare the forces. Therefore, the result for percentage of error is in the range of 25% to 32%. This high value of percentage of error and variation of percentage of error has proved that this system is not suitable to be used in the design of prosthetic arm because it has a low accuracy and low precision. Therefore, the conclusion is that the accuracy and precision of experimental force that was gained from simple linear regression technique is not suitable in designing prosthesis arm. This is because the prosthetic arm will need just a single value of force or electromyography (EMG) voltage to complete the biceps curl exercise. Lastly, the simple linear regression technique is the easiest way to analyze the signal and this simple linear regression technique is unsuitable for a large number of data which are not precise. Therefore, recommendation is needed for the next research.

5.2 Recommendation

The first recommendation is to change from simple linear regression technique in producing force to two recommended force prediction technique. Jacob Rosen [20] has stated that the Hill based and neural network is the most accurate method to predict force. These two techniques could be use for a large number of data set.

Then, the second recommendation is to change the muscle V3 electromyography (EMG) sensor. This is because muscle V3 electromyography (EMG) sensor is suitable for the application purpose because the signal is in normalized form. The new electromyography (EMG) sensor which will produce a raw signal, suitable for analysis and less noise will be needed in the future research,

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APPENDIX A

GANTT CHART

	2013 [FYP 1]				2014 [FYP 2]					
Activity / month	**SEP**	**OCT**	**NOV**	**DEC**	**JAN**	**FEB**	**MAC**	**APRIL**	**MEI**	**JUNE**
Understanding project										
Literature review										
Seminar journal preparation										
Experimental Setup										
Select a participant & design a methodology										
Progress report writing & FYP 1 presentation										
Collecting Data for EMG signal										
Feature Extraction of EMG signals										
Evaluation of extracted feature										
Final report writing										
Prepare for Presentation project FYP 2										

APPENDIX B

COMPONENTS OF FORCE MUSCLE MODEL FORMULA

Table B.1: List of components that has been measured for force muscle model calculation.

Subject	Distance of elbow with biceps muscle, Xm (cm)	Distance of elbow with point of force arm, Xcg (cm)	Distance of elbow with centre of the load, Xl (cm)	Weight of arm, Wa (Kg)
1	6.5	17	36.5	1.08
2	6	16	35	1.33
3	9	17	40	3.52
4	6	16	36	2.13
5	8	17	36	1.94
6	7.5	16	38	2.10
7	8	17	36	1.31
8	8	16	34	2.14
9	7.5	13	38	1.29
10	8	18	36	4.63

APPENDIX C

SCATTER PLOT AND LINEAR FIT LINE

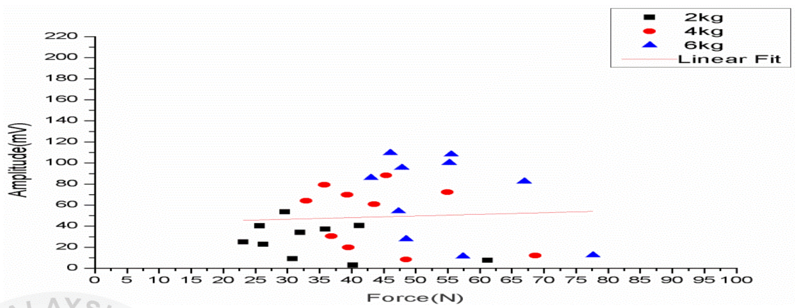


Figure C.1: Root mean square (RMS) scatter plot with linear regression technique for angle 120^0

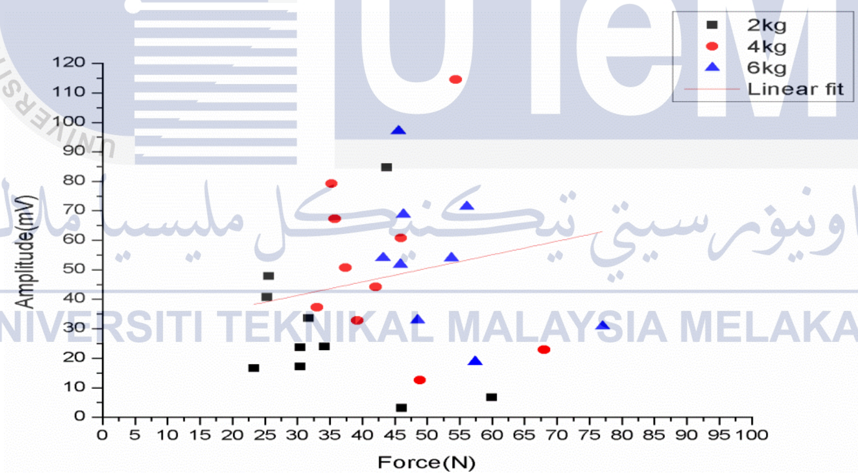


Figure C.2: Mean scatter plot with linear regression technique for angle 120^0

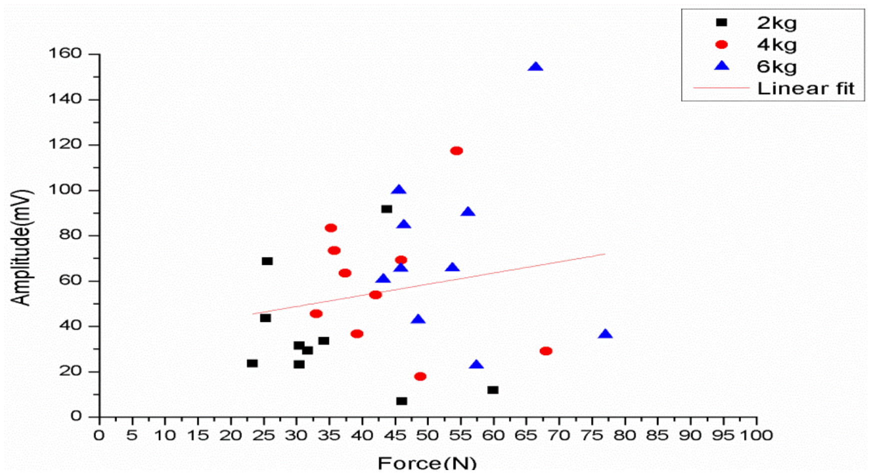


Figure C.3: Standard deviation scatter plot with linear regression technique for angle 120^0

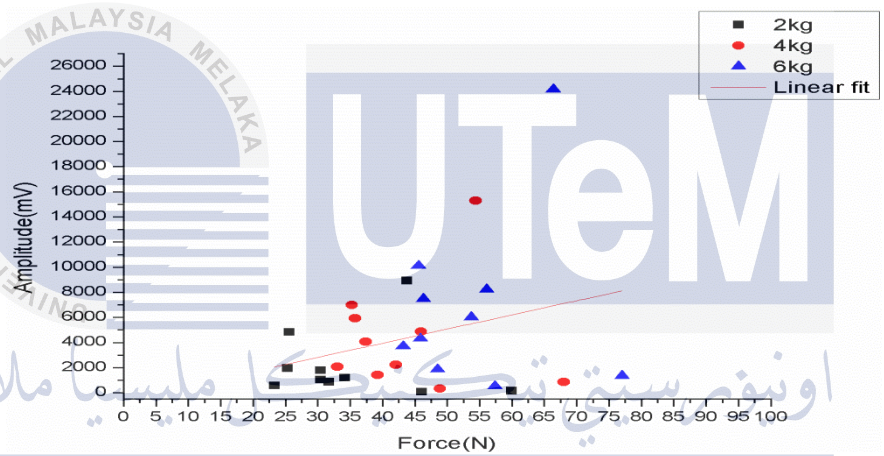


Figure C.4: Variance scatter plot with linear regression technique for angle 120^0

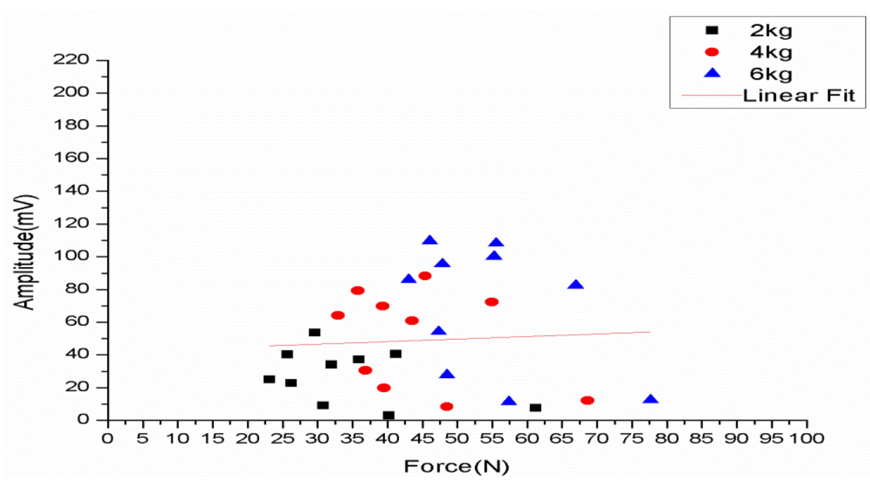


Figure C.5: Root mean square (RMS) scatter plot with linear regression technique for angle 90^0

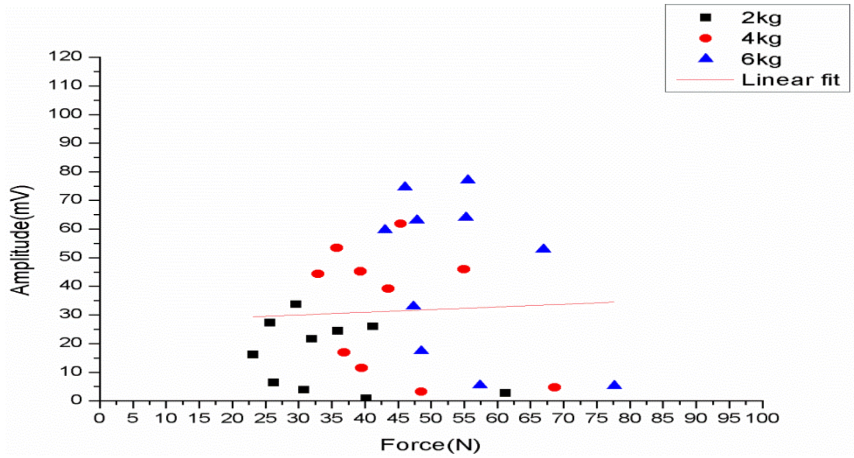


Figure C.6: Mean scatter plot with linear regression technique for angle 90^0

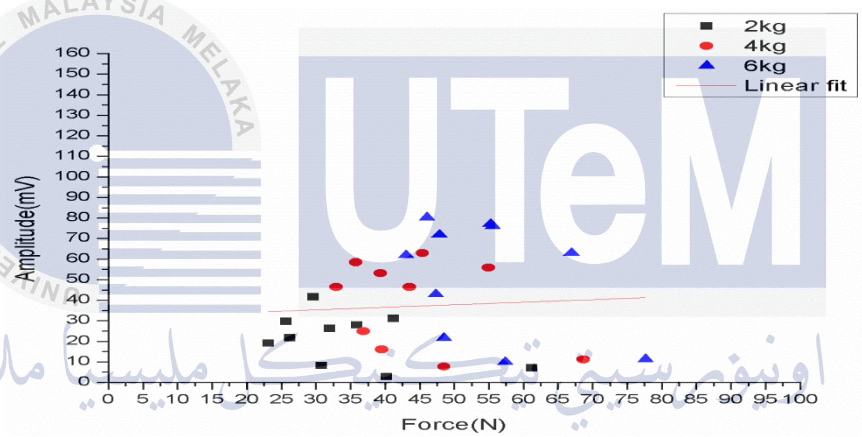


Figure C.7: Standard deviation scatter plot with linear regression technique for angle 90^0

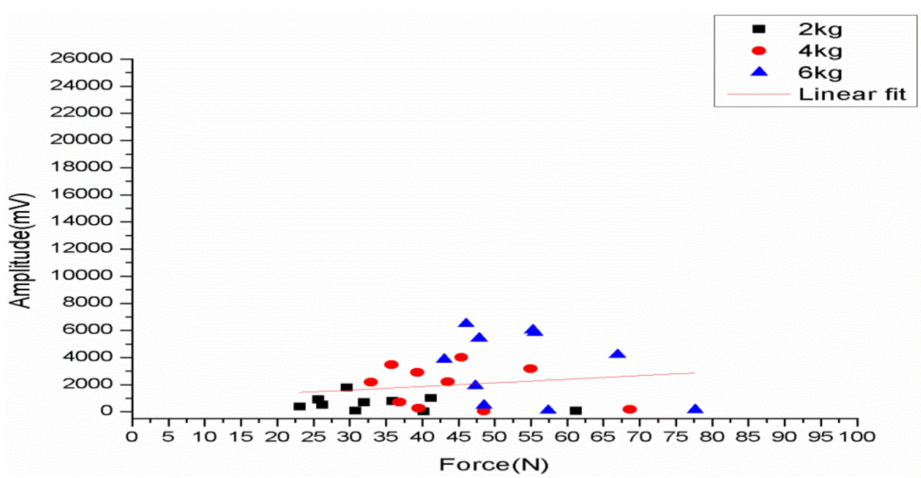


Figure C.8: Variance scatter plot with linear regression technique for angle 90^0

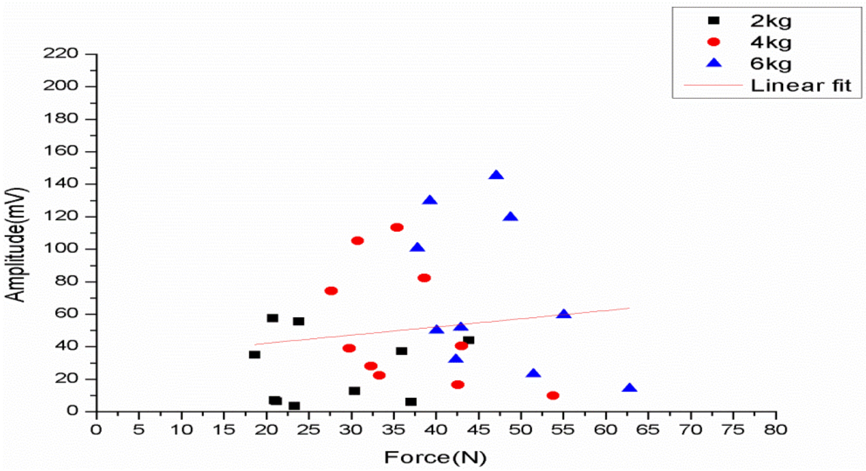


Figure C.9: Root mean square (RMS) scatter plot with linear regression technique for angle 45^0

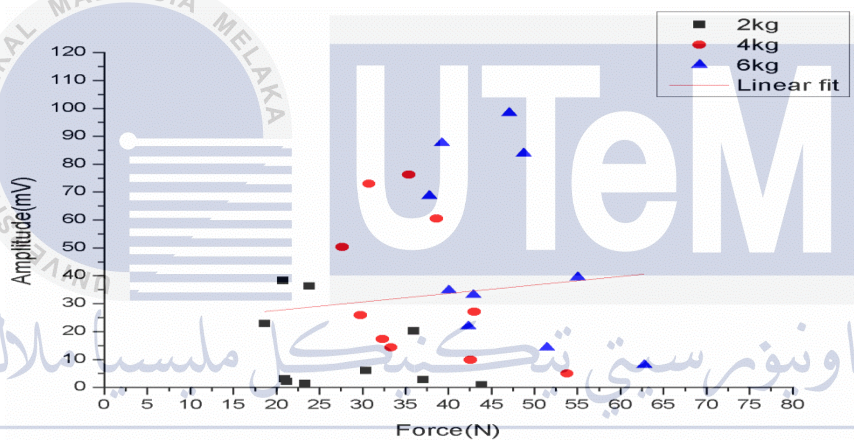


Figure C.10: Mean scatter plot with linear regression technique for angle 45^0

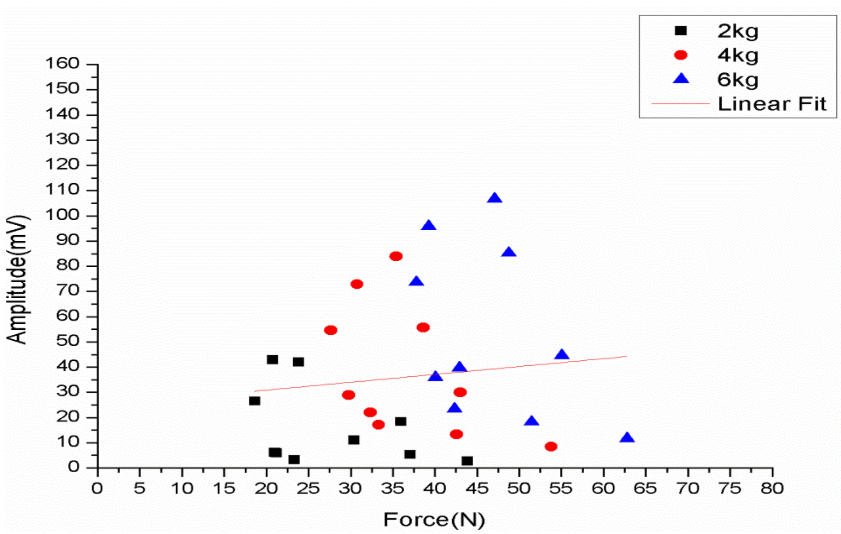


Figure C.11: Standard deviation scatter plot with linear regression technique for angle 45^0

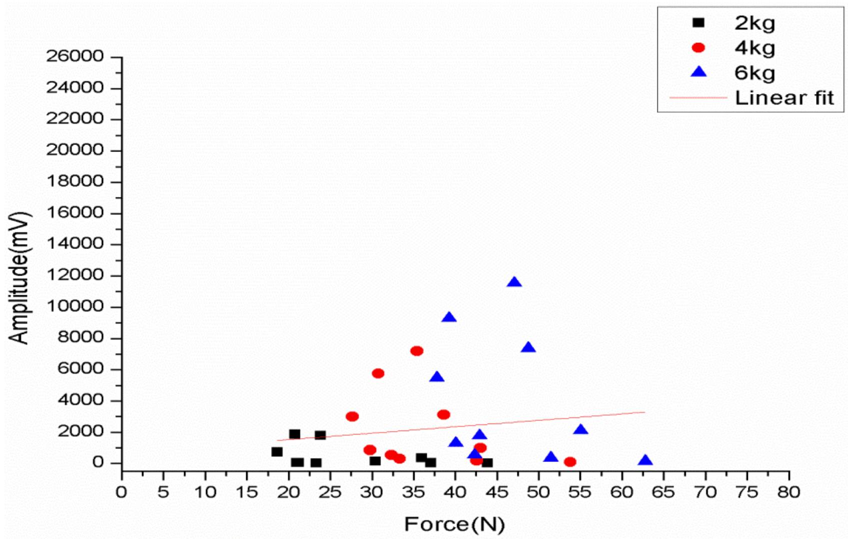


Figure C.12: Variance scatter plot with linear regression technique for angle 45^0

APPENDIX D

COMPARISON BETWEEN EXPERIMENTAL FORCE AND CALCULATED FORCE

Table C.1: Comparison between experimental force and calculated force result for task 1(120^0)

Subject	Experimental force 2kg (N)	Calculated force 2kg (N)	Experimental force 4kg (N)	Calculated force 4kg (N)	Experimental force 6kg (N)	Calculated force 6kg (N)
1	44.31105	25.54491	55.96321	35.79383	56.81796	46.3121
2	25.95991	30.39775	42.12122	42.0702	48.00097	53.73686
3	17.53984	46.07006	23.23882	48.86969	26.95941	57.75858
4	66.32208	43.77814	84.18177	54.3867	98.02678	66.3867
5	35.78378	31.74655	35.29029	39.21562	35.3716	48.21562
6	29.99027	34.14578	52.04814	45.94184	58.40724	56.07517
7	40.04478	25.32394	63.00016	35.27293	73.77008	45.55865
8	29.8754	30.45909	46.03418	37.37916	46.66779	45.87916
9	25.64444	23.33064	37.97874	33.04445	48.04578	43.17778
10	19.70863	55.77285	29.41729	64.67196	34.13992	73.7853

Table C.2: Comparison between experimental force and calculated force result for task 2(90^0)

Subject	Experimental force 2kg (N)	Calculated force 2kg (N)	Experimental force 4kg (N)	Calculated force 4kg (N)	Experimental force 6kg (N)	Calculated force 6kg (N)
1	27.42261	26.25719	35.07076	36.82956	45.82181	47.33214
2	46.17686	29.57342	49.93625	43.54798	67.07469	55.21465
3	23.45288	40.18029	25.18445	48.49767	26.67007	57.38656
4	40.83687	41.1522	54.61893	54.92516	59.36294	66.92516
5	25.5374	30.77512	30.86449	39.51223	34.92305	48.51223
6	39.75945	35.95844	65.58299	45.41498	76.05133	55.54831
7	41.72026	25.65153	59.78241	35.76452	74.34872	46.05023
8	37.83263	32.00795	54.12094	39.32918	66.41495	47.82918
9	34.04672	23.14468	53.48854	32.92653	64.05325	43.05987
10	24.78502	61.17913	26.14758	68.67206	26.5518	77.67206

Table D.3: Comparison between experimental force and calculated force result for task 3(45^0)

Subject	Experimental force 2kg (N)	Calculated force 2kg (N)	Experimental force 4kg (N)	Calculated force 4kg (N)	Experimental force 6kg (N)	Calculated force 6kg (N)
1	20.45866	21.1835	28.68245	32.33893	37.22524	42.90955
2	38.92632	23.80377	60.49965	35.39392	72.46578	47.06059
3	20.80137	37.06385	24.6991	42.59502	27.05071	51.4839
4	22.60052	30.4157	33.965	43.02304	40.66643	55.02304
5	20.06351	23.30614	27.06259	33.32603	31.15672	42.32603
6	30.23868	27.80387	52.02125	38.63982	64.62823	48.77316
7	22.04095	20.96182	35.1934	29.79434	40.53626	40.08005
8	39.98801	20.73137	58.73717	30.7494	66.63732	39.2494
9	31.6786	18.64317	46.5034	27.65422	56.41919	37.78756
10	19.76994	43.84172	22.02118	53.78539	23.68756	62.78539

APPENDIX E

COMPARISON BETWEEN EXPERIMENTAL VOLTAGE AND CALCULATED VOLTAGE

Table E.1: Comparison between experimental voltage and calculated voltage result for task 1(120^0)

Subject	Experimental voltage 2kg (N)	Calculated voltage 2kg (N)	Experimental voltage 4kg (N)	Calculated volatge 4kg (N)	Experimental volatge 6kg (N)	Calculated voltage 6kg (N)
1	16.4448	47.8330	33.5871	67.3224	51.1800	68.7521
2	24.5616	17.1389	44.0850	44.1703	63.5986	54.0048
3	50.7751	3.0555	55.4578	12.5876	70.3253	18.8107
4	46.9417	84.6487	64.6856	114.5208	84.7568	137.6780
5	26.8176	33.5703	39.3104	32.7449	54.3638	32.8809
6	30.8306	23.8801	50.5607	60.7741	67.5097	71.4103
7	16.0752	40.6972	32.7159	79.0924	49.9197	97.1062
8	24.6642	23.6879	36.2387	50.7151	50.4558	51.7749
9	12.7412	16.6112	28.9885	37.2416	45.9375	54.0797
10	67.0040	6.6830	81.8887	22.9217	97.1316	30.8208

Table E.2: Comparison between experimental voltage and calculated voltage result for task 2(90^0)

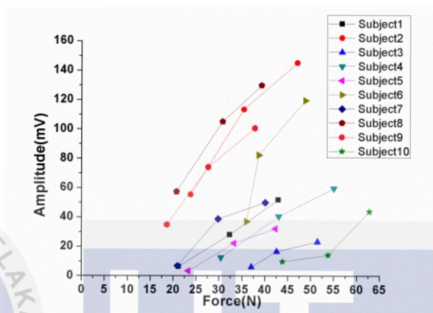
Subject	Experimental voltage 2kg (N)	Calculated voltage 2kg (N)	Experimental voltage 4kg (N)	Calculated volatge 4kg (N)	Experimental volatge 6kg (N)	Calculated voltage 6kg (N)
1	4.8232	6.51341	20.1563	17.6055	35.3881	33.1977
2	9.6327	33.7127	29.9000	39.1649	46.8202	64.0208
3	25.0158	0.7561	37.0785	3.26741	49.9701	5.4219
4	26.4254	25.9681	46.4003	45.9562	63.8039	52.8364
5	11.3755	3.7792	24.0469	11.5051	37.0996	17.3912
6	18.8929	24.4055	32.6077	61.8574	47.3041	77.0396
7	3.9448	27.2492	18.6116	53.4448	33.5290	74.5703
8	13.1635	21.6110	23.7815	45.2340	36.1090	63.0639
9	0.3091	16.1203	14.4957	44.3168	29.1921	59.6388
10	55.4704	2.6881	66.3374	4.6642	79.3901	5.2504

Table E.3: Comparison between experimental voltage and calculated voltage result for task 3(45^0)

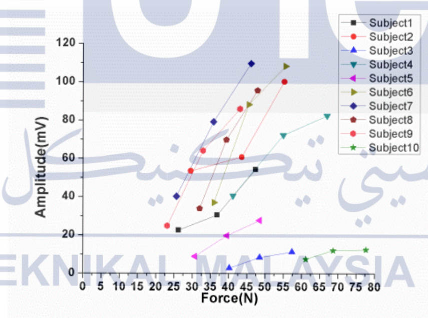
Subject	Experimental voltage 2kg (N)	Calculated voltage 2kg (N)	Experimental voltage 4kg (N)	Calculated volatge 4kg (N)	Experimental volatge 6kg (N)	Calculated voltage 6kg (N)
1	21.1835	20.4586	32.3389	28.6824	42.9095	37.2253
2	23.8037	38.9263	35.3939	60.4996	47.0605	72.465
3	37.0638	20.8013	42.5950	24.6991	51.4839	27.050
4	30.4156	22.6005	43.0230	33.9649	55.0230	40.6665
5	23.3061	20.0635	33.3260	27.0625	42.3260	31.15672
6	27.8038	30.2386	38.6398	52.0212	48.7731	64.6282
7	20.9618	22.0409	29.7943	35.1933	40.0800	40.5362
8	20.7313	39.9880	30.7493	58.7371	39.2493	66.6373
9	18.6431	31.6786	27.6542	46.5034	37.7875	56.4191
10	43.8417	19.7699	53.7853	22.0211	62.7853	23.6875

APPENDIX F

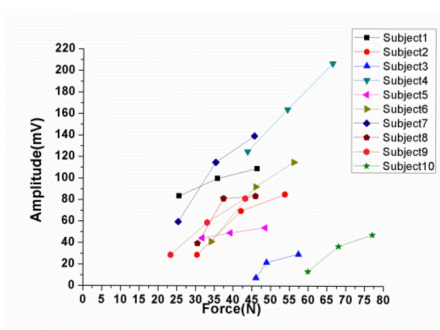
Validation of Selection for Simple Linear Regression Technique as Statistical Analysis Method



(a)

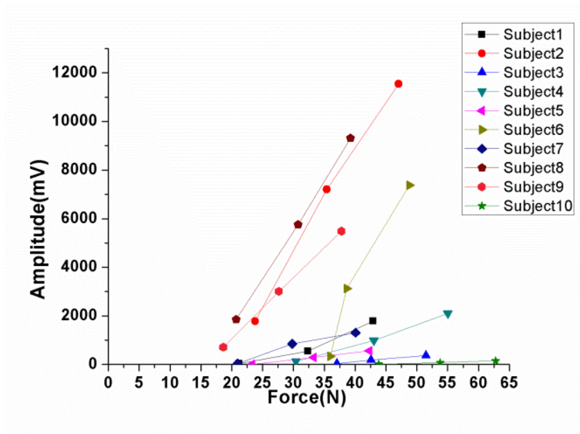


(b)

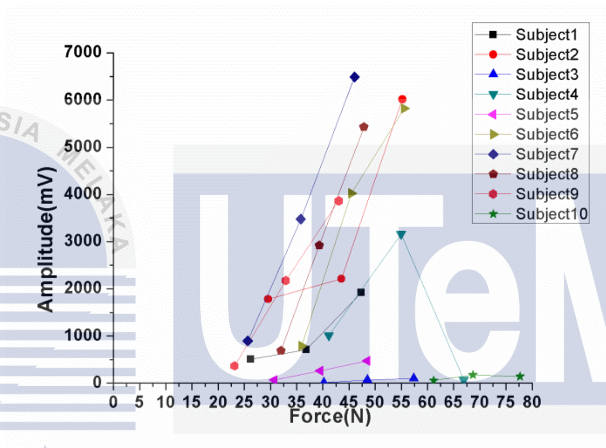


(C)

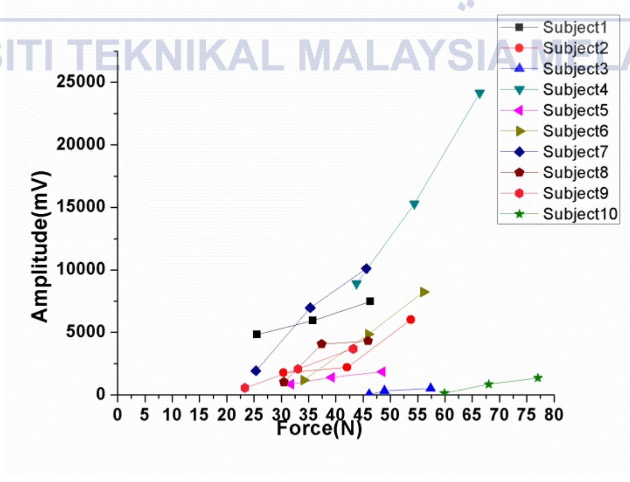
Figure F.1: Experiment based on root mean square (RMS) feature extraction with variation of loads from 2kg to 6kg and constant angles of (a) Angle120^0 (b) angle 90^0 (c) angle 45^0.



(a)

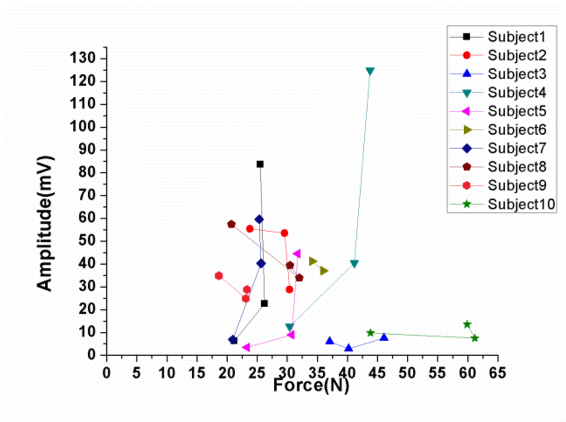


(b)

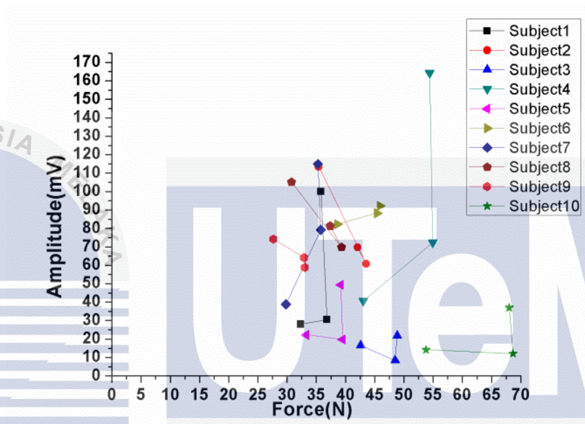


(C)

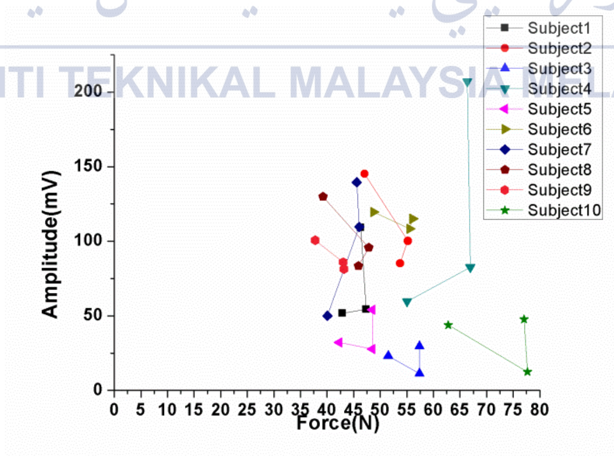
Figure F.2: Experiment based on variance feature extraction with variation of loads from 2kg to 6kg and constant angles of (a) Angle120^0 (b) angle 90^0 (c) angle 45^0.



(a)

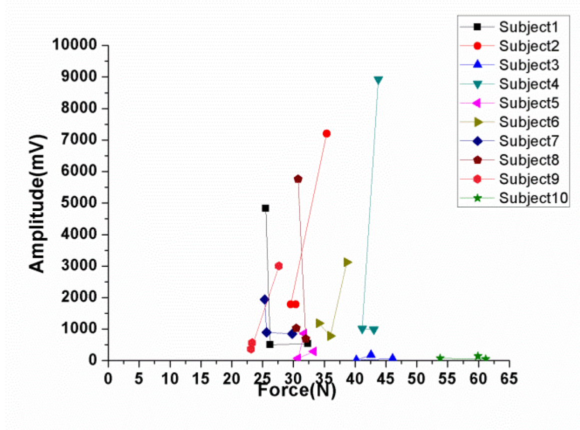


(b)

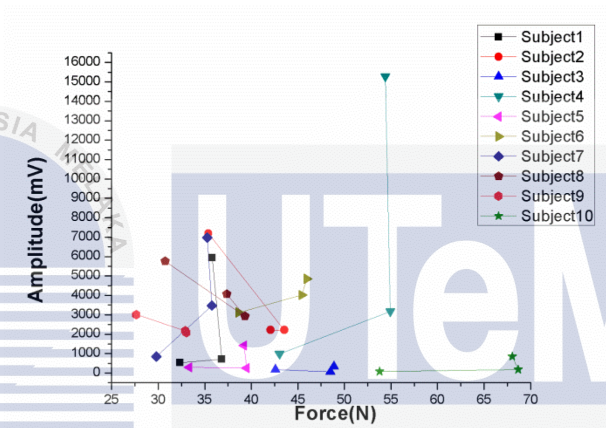


(C)

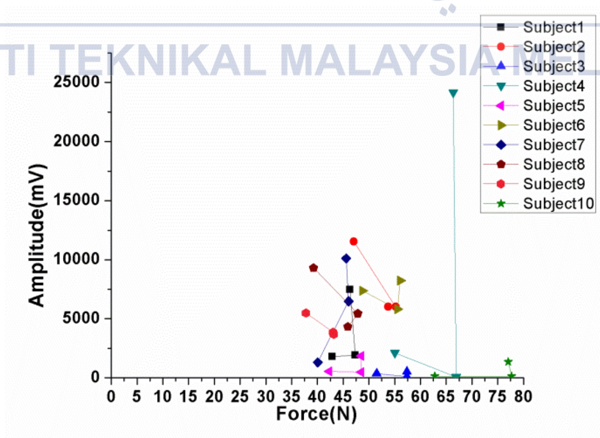
Figure F.3: Experiment based on root mean square (RMS) feature extraction with variation of angles from 45^0 to 120^0 and constant loads of (a) 2kg (b) 4kg (c) 6kg



(a)



(b)



(C)

Figure F.4: Experiment based on variance feature extraction with variation of angles from 45^0 to 120^0 and constant loads of (a) 2kg (b) 4kg (c) 6kg

APPENDIX F

MUSCLE V3 USER MANUAL