CLASSIFICATION OF NEUROMUSCULAR DISORDERS BASED ON ELECTROMYOGRAPHY (EMG) SIGNALS

By

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FINAL PROJECT REPORT

Submitted to the Electrical & Electronics Engineering Programme
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
(Electrical & Electronics Engineering)

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CERTIFICATION OF APPROVAL

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Approved by,

(Associate Professor Dr. Irraivan Elamvazuthi)

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK

Jan 2012

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

NGUYEN HOANG XUAN DUY

ABSTRACT

Electromyography (EMG) signals are the measure of activity in the muscles. The motion of the muscles will be generated and recorded using skin surface electrodes. EMG signals can be found from anywhere on the exterior of human's body such as biceps, triceps, shoulder, arm, hand, leg. The aim of this project is to identify the neuromuscular diseases based on EMG signals by means of classification. The neuromuscular diseases that have been identified are healthy, myopathy and neuropathy. The signals were taken and analyzed from EMG lab database to become datasets for classification system. The classification was carried out using Artificial Neural Network. In this project, there are two techniques that used to classify three different types of muscular disorders such as Multilayer Perceptron (MLP) and Wavelet Neural Network (WNN). And the input that applied to these systems using feature extraction from EMG signals. In time domain, five feature extraction techniques that used to extract the sample of signal such as Autoregressive (AR), Root mean square (RMS), Zero Crossing (ZC), Waveform length (WL) and Mean Absolute Value (MAV). The comparison between different techniques will be included based on the accuracy of the result. The input data has been used in Multilayer Perceptron (MLP) to train the classification system. Besides that, frequency domain was used for extracting the useful information from EMG signal for Wavelet neural network (WNN) such as Power Spectrum Density (PSD), both systems were trained and the test performances were examined after training to provide the best result.

ACKNOWLEDGEMENT

In order to accomplish this final year project, this is not only my work all along the way but also the help from my supervisor in lending me a hand to finally achieve success in this work.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
EMG	Electromyography
MLP	Multi-layer Perceptron
WNN	Wavelet Neural Network
RBF	Radial Basis Function
AR	Autoregressive
RMS	Root Mean Square
MAV	Mean Absolute Value
ZC	Zero Crossing
WL	Wave Length
FFT	Fast Fourier Transform
DFT	Discrete Fourier Transform
CWT	Continuous Wavelet Transform
AIC	Akaike Information Criterion
PSD	Power Spectrum Density
BP	Back-Propagation

CHAPTER 1
INTRODUCTION

1. 1 Background of the study

Automation and Control is one of the important field in Electrical & Electronic Engineering and this major covers all about the algorithms about controlling system that are being used in real industry such as robotics, oil and gas, medical and etc. Therefore, to understand and learn about this major, can help the engineers adapt easily during doing projects. There are millions of research papers about automation and control and it is increasing day by day.

As we are in the final year student in Electrical & Electronic Engineering department and get the major in Automation and Control, our task is try to study and understand all the knowledge that related to the modern control and automation so that we can get an opportunity to become a professional engineer and work into the real industry after graduating.

1.2 Problem Statement

Stroke is always a major cause for long term disability worldwide. In the last few decades, there are more than fifty percent of stroke survivors in the USA and fifteen million people worldwide suffer from stroke while one third of them are permanently disabled [1]. This is the main reason why all scientists all over the world try to do research for inventing a machine that can assist the stroke patients get more rehabilitation on their own.

The project is about classification of Neuromuscular Disorders based on Electromyography (EMG), Multi-Layer Perceptron (MLP) and Wavelet Neural network (WNN). The task is to search and find the algorithms to develop the classification system that can detect the Neuromuscular Disorders. This project requires of the basic knowledge about neural network, the human body, the biomedical field and the control algorithm. All this knowledge is not easy to understand because it is concerned with the medical field and human body; however that is really a challenge to get an opportunity to work with the new project about control system.

1.3 Objective

The main objective in this project is about the Electromyography (EMG) signal; this is a technique for evaluating and recording the electrical activity produced by skeletal muscles. To develop a classification system in order to classify three types of neuromuscular disorders by using two different techniques, Multi-layer Perceptron (MLP) and Wavelet Neural Network (WNN).

1.4 Scope of study

The main scope of this project consists of research, simulation, and analysis. The research in this final year project help student to understand about the new technology used in biomedical with control algorithm. Furthermore, the basic knowledge will be applied to improve the testing and analyzing, the simulation to be done by using MATLAB software.

CHAPTER 2
LITERATURE REVIEW

2.1 Electromyography signal

Electromyography (EMG) is one of the important techniques in clinical applications; EMG is a biomedical signal that is used to measure electrical currents generated in muscles during its activities. EMG signal is a complicated signal and is dependent on the anatomical and physiological properties of muscles.

There are many methods to detect EMG signal, and surface EMG is the most common method to get the input signal because it is non-invasive and can be managed by personnel. A number of factor and the amplitude are two important elements that affect to the surface EMG signal vary from the μV to the low mV range. The amplitude of the signal can range from 0 to 10 mV (peak-to-peak) or 0 to 1.5 mV (RMS). The usable energy of the signal is limited to the 0 to 500 Hz frequency range, with the dominant energy being in the 50-150 Hz range [1]. The raw of the EMG signal will be shown as Figure 1.

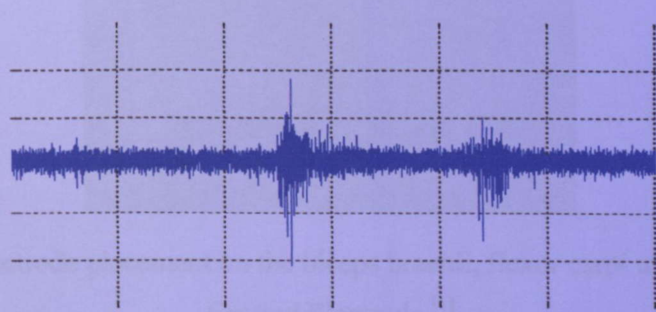


Figure 1: The figure showing a raw EMG signal

The surface EMG signals are measured by using surface electrodes. Silver chloride (AgCl) surface electrodes are placed on the biceps brachii which measures the myoelectric activities during the flexion and extension of the elbow and the flexor carpi ulnaris which assists in the flexion and extension of the wrist. A third electrode placed at the elbow joint serves as a ground reference for the system.

2.2 Recording and storing EMG data

Generally, the EMG signals are obtained from many subjects (healthy subjects, subjects suffering from neuropathy, subjects suffering from myopathy) with different of mean age (range 2 months to 60 years old). Before EMG measurements, the skin sites were abraded and cleaned with alcohol. Myolelectric control, which is used the surface EMG signals as a system input, Silver chloride (AgCl) surface electrodes are placed on the biceps brachii, the flexion and extension of the elbow and wrist will be captured and analyzed, a third electrode placed at the elbow joint serves as a ground reference for the system. The Figure 2 shows the step how to put the electrode placement on the biceps brachii, flexor carpi ulnaris and the Ground Electrode. The signal will be processed step by step before the output is stored on hard disk [1].

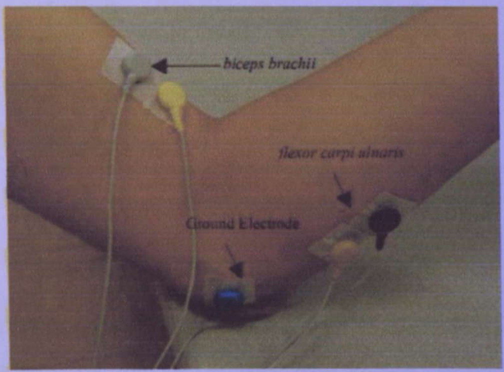


Figure 2: Electrode placement on the biceps brachii, flexor carpi ulnaris and the Ground Electrode [1]

A differential amplifier is being used with the arrangements of the bipolar electrode which function to suppress the signals common into both electrodes. The main task of this method is to subtract the potential between two electrodes and then amplifies the difference. At the moment the best Common-Mode Rejection Ratio (CMRR) that can be achieved is about 120 dB/Octave [2]. The signal is then filtered by using the many filters method such as high-pass, low-pass and notch filter. The typical band-pass frequency ranges are from 10 and 20 Hz for the high pass filtering to between 500 and 1000Hz for the low-pass filtering. The high pass filter is necessary in this case because the movement of artifacts will comprise of low frequency components (less than 10Hz) and low-pass filter is used to remove high-frequency components to avoid signal aliasing. However, see Figure 3 below, there are problems when the notch filtering is used to remove power-line (A/C) noise components because the EMG signal has large signal contributions at these and neighboring frequencies so that the result of notch filtering will be the loss of the important EMG signal information, therefore this filter should be avoid as a general rule [4].

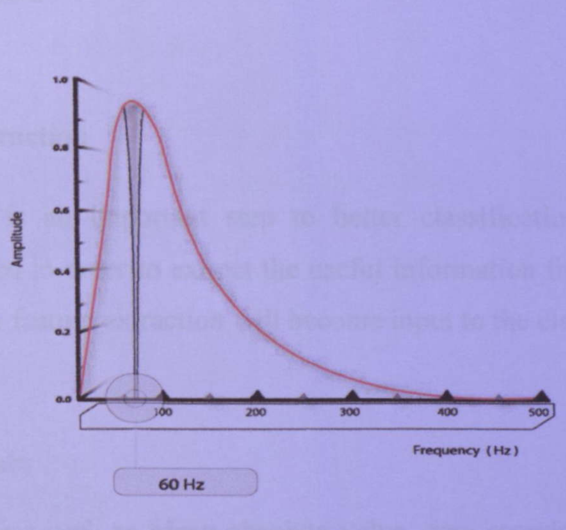


Figure 3: Schematic representation of a typical EMG power spectrum and the notch filtering caused loss of information as the shaped area [4]

A direct interface between the circuits and the computer is accomplished using the National Instruments DAQ board (PCI-MIO-16XE-10). Signals are digitized in A/D conversion with 16-bit resolution. The sampling rate set to 100 kHz may be chosen as required [2]. The data at the output of A/D converter is stored on hard disk of computer. The Figure 4 will show the block diagram of measuring system from step to step and store data into the computer.

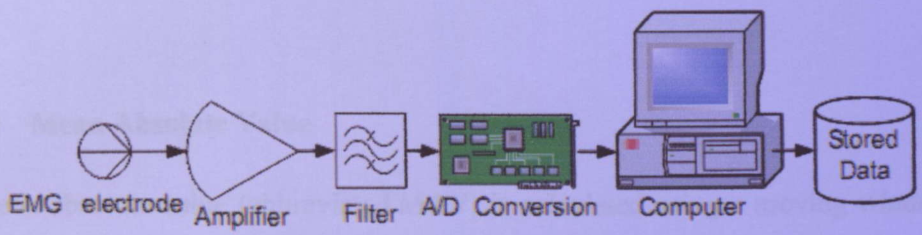


Figure 4: Block diagram of measuring system [2]

After the EMG signal is stored in the computer, the feature extraction using for development of classification system, the variety methods of spectral analysis such as Fast Fourier Transform (FFT), Auto Regressive (AR) are common method to apply in this extraction.

2.3 Feature extraction

Feature extraction is an important step to better classification results. Feature extraction are needed in order to extract the useful information from the signal , the data that taken from feature extraction will become input to the classification result.

2.3.1 Time domain

Time domain features such as Mean absolute value, zero crossings, and waveform length are commonly apply in EMG feature extraction:

2.3.1.1 Zero crossings

The frequency that provided from the signal is counted by the number of times the waveform crosses to zero [1] . A threshold (σ) is included to reduce noise induced zero crossings. Let's get the two consecutive samples x_k and x_{k+1}, the increase of the zero crossing count, if :

$$\{x_k > 0 \; and \; x_{k+1} < 0\} \; or \; \{x_k < 0 \; and \; x_{k+1} > 0\} \qquad (2.1)$$

$$\text{And} \quad |x_k - x_{k+1}| \geq \sigma$$

2.3.1.2 Mean Absolute Value

The mean absolute value (abbreviated MAV) is calculated using a moving window [1] . The MAV of the signal x in segment i that has N samples will be given by equation (2.2)

$$\overline{x_i} = \frac{1}{N} \sum_{k+1}^{N} |x_k| \qquad (2.2)$$

2.3.1.3 Mean Absolute Value Slope

Mean Absolute Value (MAV) is the difference between the mean absolute values of adjacent segments pass through the entire sampled signal [1]. The Mean Absolute Value can be described as equation (2.3)

$$\overline{\Delta x_i} = \overline{x_{i+1}} - \overline{x_i} \qquad (2.3)$$

2.3.1.4 Slope Sign Changes

A measure for the frequency content of the signal is provided by a change in the slope sign. Given three consecutive samples x_k and x_{k+1} the slope sign count is incremented [1], if

$$\{x_k > x_{k-1} \; and \; x_k > x_{k+1}\} \; or \; \{x_k < x_{k-1} \; and \; x_k < x_{k+1}\} \qquad (2.4)$$

$$\text{And} \quad |x_k - x_{k+1}| \geq \sigma \text{ or } |x_{k-1} - x_k| \geq \sigma$$

2.3.1.5 Waveform Length

Waveform Length is a feature which provides information on the waveform amplitude, frequency and duration. The length of the waveform is the accumulation of the over each analysis can be described as equation (2.5).

$$l_0 = \sum_{k-1}^{N}(x_k - x_{k-1}) \tag{2.5}$$

Feature extraction is a very interesting area of research. Many mathematical tools have been developed to extract the waveforms. And the common mathematical tools are Fast Fourier Transform (FFT) and Auto Regressive (AR).

2.3.2 Fast Fourier Transform based methods

The spectral analysis should be applied to create the meaningful of EMG signal. In this reason, Fast Fourier Transform can be used because this method is not complex. During taking FFT of a finite EMG signal, it must be framed with the power of 2 such as 64 or 128 [2]. And Windowing technique is used to evaluate the frequency spectrum for the corresponding frame. Fourier analysis is extremely useful for data analysis since it breaks down a signal into sinusoidal function of different frequencies. For another sample vector data, Fourier analysis is performed using the Discrete Fourier Transform (DFT). The formula of FFT can be described by equation (2.6) below:

$$X[m] = \sum_{n=0}^{N-1} x[n]e^{-j\omega n} \tag{2.6}$$

Since $\omega = \frac{2\pi f}{F_s}$ and $f = mF_s/N$, we have the equation (2.7) :

$$X[m] = \sum_{n=0}^{N-1} x[n]e^{\frac{j2\pi mn}{N}} \tag{2.7}$$

The inverse of DFT is defined as equation (2.8) :

$$x[n] = \frac{1}{N}\sum_{m=0}^{N-1} X[m]e^{\frac{j2\pi mn}{N}} \tag{2.8}$$

where x is a length N discrete signal sampled at times t with spacing.
By using Euler's relation in equation (2.9)

$$e^{jx} = \cos(x) + j\sin(x) \tag{2.9}$$

DFT can now be expressed as equation (2.10)

$$X[m] = \sum_{n=0}^{N-1} x[n]\cos\left(\frac{2\pi mn}{N}\right) - j\sum_{n=0}^{N-1} x[n]\sin\left(\frac{2\pi mn}{N}\right) \tag{2.10}$$

From the equation above, it can be seen that DFT now consist of a real part and an imaginary part for every frequency number m. Therefore, the magnitude and phase spectra can be expressed as equation (2.11)

$$|X[m]| = \sqrt{Re(X[m])^2 + Im(X[m])^2} \tag{2.11}$$

And

$$\theta(m) = arctan\frac{Im(X[m])}{Re(X[m])} \tag{2.12}$$

The equation (2.13) and (2.14) will show the characteristic of real and imaginary of signal m

$$Re[m] = \sum_{n=0}^{N-1} x[n]\cos\left(\frac{2\pi mn}{N}\right) \tag{2.13}$$

$$Im[m] = -\sum_{n=0}^{N-1} x[n] \sin\left(\frac{2\pi mn}{N}\right) \tag{2.14}$$

However, when the amplitude of EMG signal is very low, Artificial Neural Network (ANN) is used to test a dianosed spectral curve that estimated from the result of FFT analysis. That is the reason why the choice of frame length is an important factor in EMG spectral analysis. In this study the fram length will be choen is 128 and the FFT coefficient of EMG signal are required to generate ANN as training and testing inputs [2]. The next method will be explained in this study is about Auto Regressive (AR) that give the clearly information about feature extraction.

2.3.3 Auto Regressive model

An Auto Regressive (AR) model is a type of random process which is used to shape and predict different types of natural phenomena. The AR model of a signal is given by the equation (2.15) :

$$x(k) = \sum_{i=1}^{M} a_i x(k-i) + e(k) \tag{2.15}$$

where x(k) is the signal we wish to shape , a_i is the coefficient of the AR model of the signal, M is the number of order, and e(k) is white noise. We have chosen the Burg method since it offers good performance to spectral leakage by its recursive structure [2] . For some method, we can combine the AR and DFT together to improve the EMG signal modeling in which training and testing.

2.4 Artificial Neural Networks

Neural Network is the large number of interconnection nodes that perform summation and threshold. Most of neuron network connected into the brain, which consists of millions cell to transfer the signals to the whole human body [3]. The Figure 5 will show a group of neural network in human brain.

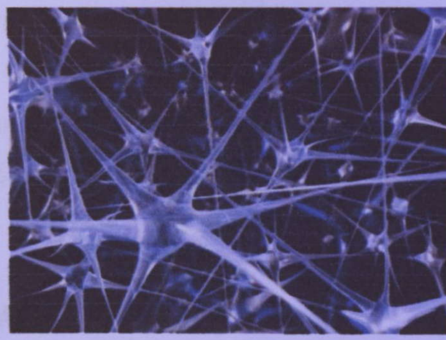


Figure 5: A group of neural network [10]

Artificial Neural Networks (ANN) is one branch of the field known as "Artificial Intelligent" (AI) which comprises Fuzzy logic and Genetic Algorithms. The ANNs structure is based on the function of the human brain with capability of generalization [3]. By using the training, ANNs can identify and learn correlated patterns between the input data sets and target output to get the prediction outcome of new independence input.

From the structure of the human brain, an ANN consists of interconnection processing unit (called nodes and units) that perform summation and threshold. Each unit is designed to copy its biological properties, the neuron. There are 10^{10} to 10^{12} neurons inside the human nervous system which can store numerous bits of information [3]. A neuron is composed of a nucleus, cell body, dendrites which provide input connection from other neurons and an axon trunk which carries the output actions to others neuron and terminal links.

ANNs have gained a lot of success over the previous years as a powerful technique to solve many problems from the real worlds. Furthermore, ANNs can be used in different field of science such as biomedical, medicine, chemistry and also in finance. The purposes of using ANNs in solving problems related to prediction, classification, control and identification.

The most widely used learning algorithm in ANNs is the Back-propagation algorithm. There are various types of ANNs like Multilayer Perceptron (MLP), Radial Basic Function (RBF) and Kohonen network [5]. There is the correlation between the majority of the network and traditional mathematical such as non-parametric pattern classifiers, clustering algorithm and non linear filter.

2.5 Application of Artificial Neural Networks

The application of ANNs can be divided into the following categories [3]:

- *Forecasting and prediction*: ANNs can be shown the high efficiency and powerful tool for prediction based on the database from previous information and predict what is going to happen in the future which mostly used in weather forecast.

- *Classification and diagnostic*: In many field of medical, ANNs have been applied as a useful tool in order to diagnostic and classify between the input pattern representing forms of abnormal type with the corresponding disease group.

- *Pattern recognition*: the recognition of complex pattern such as handwritten, speech recognition and also in the area of image processing can be successfully done with ANNs.

- *Estimation and Control*: the application of ANNs in this field can be applied in system identification, parameter estimation and optimization.

2.6 The architecture of ANNs

The architecture of ANNs can be defined as the number of layers and the number of nodes in each of the layer [6]. See as Figure 6, Neural network (NN) can be illustrated by using a graph G and ordered *(V,E)* consisting of E of edges and vertices $V = \{1,2,..n\}$ and arcs $A = \{i, j \mid i \geq 1, j \leq n\}$ with the following restrictions:

- V is divided into a set of input nodes V_I, the hidden node V_H and output node V_O.
- The vertices are also divided into various layers.
- Any arc *{i,j}* must have node i in layer *{h-1}* and node j in layer *{h}*.
- Arc *{i,j}* is named with the numeric value of w_{ij}.

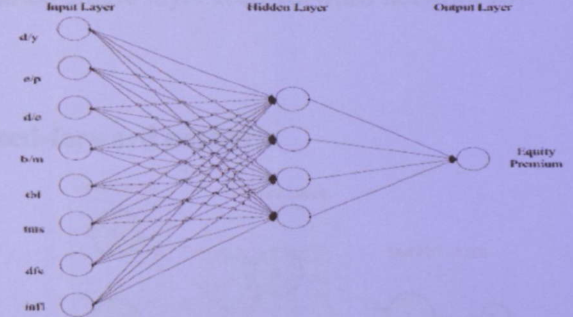


Figure 6: Architecture of neural network [9]

The graph of neural network is directed when each edge is allocated an orientation in the network which called directed graph. There is one way to transfer from input layer to hidden layer and from hidden layer to output layer that named feed forward network [6]. The vertices graph represented neurons between input and output and the edges is the synaptic links. There are various different classes of the network, they are single layer feed-forward network , multilayer feed-forward network and recurrent network… which will be deeply explained on the next part :

2.6.1 Single layer feed-forward network

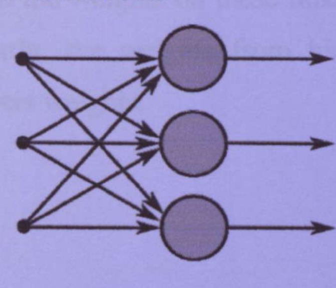


Figure 7: Single Layer Feed-forward network [9]

Based from the Figure 7, the single layer feed-forward network is the simplest network from neural network, it consists only input layer and output layer (no hidden layer). The input layer will receive the input signals and output layer will receive output signals. Each node from input layer can connect with all output layers in the one dimension but not vice-versa, that is the reason why this network has named as feed-forward. And the signal will be transmitted directly from input layer to output layer that called single layer feed-forward network [6].

2.6.2 Multilayer feed-forward network

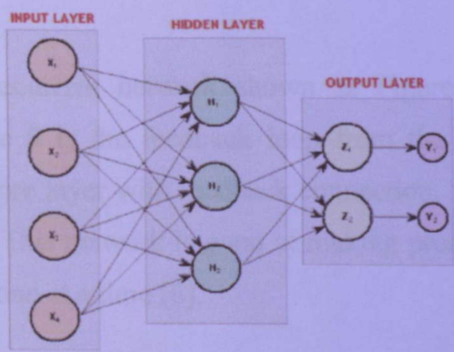


Figure 8: Multilayer feed-forward network [11]

As per the name of this network that has been shown in Figure 8, it is made of multi layers. The different between multilayer network and single network is about the hidden layers between the input layers and output layers. The computational units of hidden layer are known as hidden neurons. The hidden layers play important role of computations before directing the input to output layers. The signals will transmit from input to hidden layer and the weights on these links are preferred to as input-hidden layer weights. Similarly, the weights from hidden to output layers are preferred as hidden-output layers weights.

2.6.3 Recurrent networks

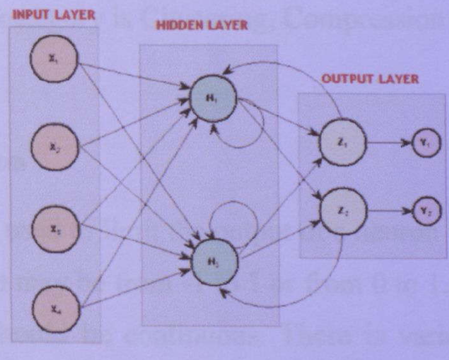


Figure 9: A recurrent neural network [11]

The different between recurrent network shown as Figure 9 and feed-forward network shown as Figure 8 is the feedback loop from the hidden input. In this network will have one more layer with feedback connection. There can be neurons with self-feedback links. This network is good at making predictions; a sequence is presented to the network one at a time [6].

2.6.4 The learning methods of ANNs

The learning methods of ANNs can be divided into two basic categories [6]:

- Supervised learning: In this method, the target or desired output pattern will be set at the beginning of training and every input pattern will be trained the network that associated with a desired output pattern. A teacher is assumed to present during the process of learning when a comparison is built between the computed output and correct expected output, the error is determined in each comparison .The Pattern Recognition and Regression are tasks in this category.

- Unsupervised learning: There is little bit different between this method and supervised learning as above, the target output is not presented to the network. The system need to learn of itself by discovering and adapting to the structure of features in the input patterns because no teacher is available in the desired patterns. Tasks that deeply related to this category is Clustering, Compression and Filtering.

2.6.5 Activation function

The activation function is used to limit the output of a neuron in network to a certain value. The range of output may be from -1 to 1 or from 0 to 1.An activation function for a back-propagation should be continuous. There is various type of activation function such as:

Linear :

$$f_i(S) = cS \tag{2.16}$$

Threshold or step :

$$f_i(S) = \begin{cases} 1\, if\; S > T \\ 0\; otherwise \end{cases} \tag{2.17}$$

Ramp :

$$f_i(S) = \begin{cases} 1\; if\;\; S > T_2 \\ \frac{S-T_1}{T_2-T_1} \quad if\; T_1 \leq S \leq T_2 \\ 0\; if\; S < T_1 \end{cases} \tag{2.18}$$

Sigmoid:

$$f_i(S) = \frac{1}{(1+e^{-cS})} \tag{2.19}$$

Hyperbolic Tangent:

$$f_i(S) = \frac{(1-e^{-S})}{(1+e^{-cS})} \tag{2.20}$$

Gaussian:

$$f_i(S) = e^{\frac{-S^2}{v}} \tag{2.21}$$

2.7 Back-propagation Algorithm

Back-propagation algorithm is one of the important methods of training multilayer neural network which based on the procedure of supervised learning. An error signal is generated during learning algorithms and compared with the obtained output. Based on the error signal, neural network will improve the system performance by modifying its synaptic connection weights [7].

The multilayer network will consist of 3 layers, the input layer have *'l'* nodes, hidden layer have *'m'* nodes, and output layer have *'n'* nodes. The activation function will be considered as *sigmoid function* for the hidden and output layers, the activation function for input layer will be *linear*.

The algorithm concerns with the following steps :

Step 1 : The inputs and outputs are column normalized regarding to the maximum values. So the range of input and output is between 0 and 1. For each training pair, the assumption that 'l' inputs will be given by $\{I\}_I=(l \times 1)$ and 'n' output will be given by $\{O\}_O=\{n \times 1\}$ in a normalized form [6].

Step 2 : The number of neuron from hidden layer are assumed to lie between $l < m < 2l$.

Step 3 : *[K]* represents the weights of synapse that connect between input neurons and hidden neurons and *[T]* is the weight of synapse that connect between hidden neurons and output neurons. The value of the weights will be random from -1 to 1. For the general problems, the values of threshold are taken as zero.

We have the equation (2.22):

$$[K]_0 = [random\ weights]$$

$$[T]_0 = [random\ weights]$$

$$[K]_0 = [T]_0 = [0] \tag{2.22}$$

Step 4 : The set of input and output will be presented for the training data. The patterns to the input layer $\{I\}_I$ is presented as inputs. The output of input layer may be measured by using linear activation function as equation (2.23)

$$\underset{1\times 1}{\{O\}_I} = \underset{1\times 1}{\{I\}_I} \tag{2.23}$$

Step 5 : The inputs to the hidden layer will be calculated by multiplying weights of synapse as the equation below

$$\underset{n\times 1}{\{I\}_H} = \underset{n\times m}{[K]_T} \times \underset{m\times 1}{\{O\}_I} \tag{2.24}$$

Step 6 : The activation function between hidden and output will be *sigmoid function* , so we have the equation

$$\{O\}_H = \left\{\frac{1}{(1+e_{Hi}^{-I})}\right\} \tag{2.25}$$

Step 7 : The inputs to the output layers are calculated by multiplying weights of synapse as the equation below

$$\underset{m\times 1}{\{I\}_O} = \underset{m\times 1}{[T]_T} \times \underset{1\times 1}{\{O\}_H} \tag{2.26}$$

Step 8 : Assume that the output layer units evaluate the output using sigmoid function, the equation will be shown as equation (2.27) below

$$\{O\}_O = \left\{\frac{1}{(1+e_{Oj}^{-I})}\right\} \tag{2.27}$$

Step 9 : The error between network output and expected output is calculated for the i^{th} training set as equation (2.28)

$$E^p = \frac{(\Sigma(V_j - O_{oj})^2)^{\frac{1}{2}}}{n} \qquad (2.28)$$

Step 10 : {d} is calculated as equation (2.29)

$$\{d\} = \{(V_k - O_{ok}) \times O_{ok} \times (1 - O_{ok})\} \qquad (2.29)$$

Step 11 : The matrix [Y] will be calculated as

$$\underset{m \times n}{[Y]} = \underset{m \times 1}{[O]_H} \times \underset{1 \times n}{\{d\}} \qquad (2.30)$$

Step 12 : We find

$$\underset{m \times n}{[\Delta T]^{t+1}} = \alpha \underset{m \times n}{[\Delta T]^t} + \delta \underset{m \times n}{[Y]} \qquad (2.31)$$

where $\alpha : momentum$

δ: $\boldsymbol{learning\ rate}$

Step 13 : We find

$$\underset{m \times 1}{\{e\}} = \underset{m \times n}{[T]} \times \underset{n \times 1}{\{d\}} \qquad (2.32)$$

$$\underset{m \times 1}{\{d^*\}} = \underset{m \times 1}{\{e_i(O_{Hi}) \times (1 - O_{Hi})\}} \qquad (2.33)$$

The [X] matrix will be calculated

$$[X] = \{O\}_I \times \langle d^* \rangle = \{I\}_I \times \langle d^* \rangle \qquad (2.34)$$

Step 14 : We find

$$[\Delta K]^{t+1} = [K]^t + \delta[X] \tag{2.35}$$

Step 15 : After we get the result for $[\Delta K]^{t+1}$ and $[\Delta T]^{t+1}$, The matrix of $[K]^{t+1}$ and $[T]^{t+1}$ will be calculated as two equations (2.36) and (2.37) below:

$$[K]^{t+1} = [K]^t + [\Delta K]^{t+1} \tag{2.36}$$

$$[T]^{t+1} = [T]^t + [\Delta T]^{t+1} \tag{2.37}$$

Step 16 : The error rate will be measured as the equation (2.38)

$$\text{Error rate} = \frac{\Sigma E_p}{\text{nset}} \tag{2.38}$$

Step 17: The repeat step 16 will be continued until the error rate convergence is less than the tolerance value.

2.7.1 Multilayer Perceptron

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for classification. The term neural network was traditionally used to refer to a network or circuit of biological neurons. Multilayer Perceptron (MLP) is a type of feed-forward network. The algorithm used in this method is back-propagation. The feed-forward network comprises three layers: the input layer, hidden layer and the last is output layer [8] . The hidden layer is between the input and the output layers.

A simple of feed-forward network is shown is Figure 10 , the system has an input layer , one hidden layer in the middle and one output layer on the right hand side. Weights are the unit that incorporated into the connections from input nodes to hidden nodes and from hidden nodes to the output node.

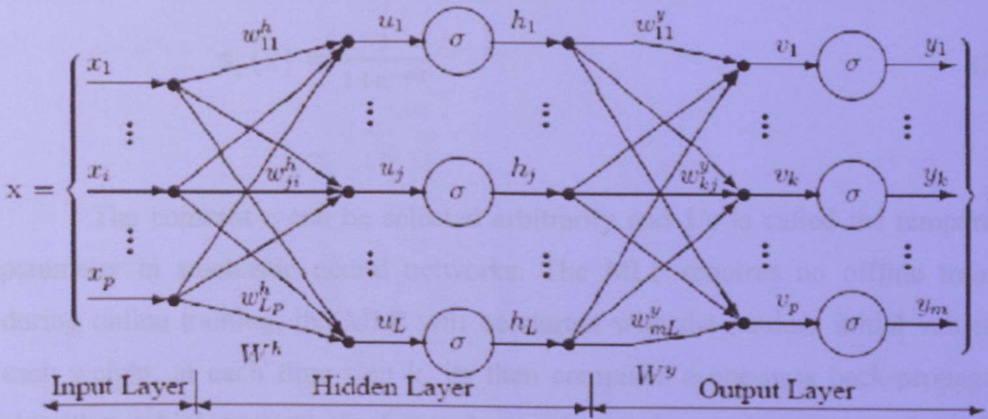


Figure 10: The three layers of a MLP [8]

- *Input layer*: A vector of predictor variable value (from x_1 to x_p) is represented as the input layer . The input layer standardizes these values so that the range from each value is from -1 to 1. There will be a constant input of 1.0 that called *bias*, the bias is fed to each of hidden layer in the middle side, which is multiplied by a weight and added to the sum going into the neuron [8].

- *Hidden layer*: The value from each input neuron is multiplied by a weight *(w_{ji})* and the resulting weighted values will be added together producing a combined value of u_j. This weighted sum u_j is fed into a transfer function, σ, which output a value h_j. The output from hidden layer are distributed to the output layer .

- Output layer : The value from each hidden layer neuron will be multiplied by a weight (w_{kj}) and the resulting weighted values are added together producing a combined value v_j. The weighted sum (v_j) is then fed into a transfer function σ, which outputs a value of y_k. The y values are the outputs of the network.

The weights of the MLP are trained by using the error back-propagation method .This method is one of the common method that use in many case related to the neural network [2]. One of the most popular activation function for this method is the sigmoid, a real function $s_c : IR \rightarrow (0, 1)$ defined by the expression :

$$s_c(x) = \frac{1}{1+e^{-cx}} \tag{2.39}$$

The constant c can be selected arbitrarily and 1/c is called the temperature parameter in stochastic neural networks. The MLP requires no offline training, during online training, the MLP will be started with the random initial values for each weight, at each time step k, its then computes a one-pass back-propagation algorithm, which consists of a forward-pass propagating the input vector through the network layer by layer, and then the backward-pass will be used to update the weights by the gradient descent rule.

2.7.2 Radial Basis Function

Like the MLP, the Radial Basis Function (RBF) also consists of three layers, the most different between MLP and RBF is about the input values of the RBF are each assigned to a node in the input layer and passed directly to the hidden layer without using weights. The hidden layer nodes that are called RBF units will be determined by a parameter vector called center and a scalar called *width*. In this network, the Gaussian density function is used in the hidden layer as an activation function same as sigmoid function using in MLP [8]. The linear weights w_{ij} between hidden layers and output layers are solved or trained by a linear least squares optimization algorithm. The overall input-output mapping $f: X \in R^n \rightarrow Y \in R^m$ is shown as equation (2.40).

$$y_i = w_0 + \sum_{j=1}^{h} w_{ij} e^{\frac{\|x-c_j\|^2}{\beta_j^2}} \tag{2.40}$$

Where X in the input vector, $C_j \in R^n$ is the j^{th} center of RBF unit in the hidden layer, h is the number of RBF units, w_0 and w_{ij} are the bias term and weight between the hidden and output layers, and y_i is the i^{th} output in the m-dimensional space. Once the center of RBF are proven, the width of the i^{th} center in the hidden layer is found by the equation (2.41).

$$\beta_i = \left[\frac{1}{h}\sum_{j=1}^{h}\sum_{k=1}^{n}\left\|c_{ki} - c_{kj}\right\|\right]^{\frac{1}{2}} \tag{2.41}$$

Where c_{ki} and c_{kj} are the k^{th} value of the center of i^{th} and j^{th} RBF units. There are four different ways of input and output mapping using the RBF, depending on the type of input data is fed to this network.

2.8 Wavelet neural network (WNN)

2.8.1 Wavelet neural network Architecture

Wavelet Neural Network (WNN) have been successfully used for tasks involving classification. During the training mode, the different between MLP and WNN is the replacement to wavelet from the global sigmoid activation units from classical feed-forward neural network [12].

The wavelet transform will be used as a preprocessor whereby the feature extraction are extracted from the input signal and fed to a classical ANN for nonlinear classification. Wavelet is used to replace the sigmoid hidden node of ANN that will be shown as Figure 11.

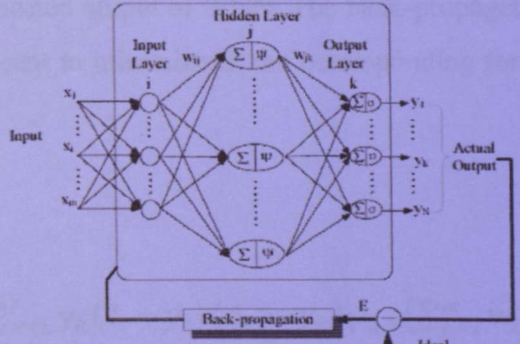


Figure 11: Structure of WNN architecture [11]

From the Figure 11, X will represent as input mode vector and Y will represent as output mode vector of the network. w_{ij} represents the connection weights between input mode and hidden mode, and w_{jk} represents the connection weights between hidden mode layer and output mode layer [9]. The output of the WNN will be shown as equation (2.42).

$$y_k(t) = \sigma\left[\sum_{j=1}^{n} w_{jk}\,\varphi_{a,b}\left(\sum_{i=1}^{m} w_{ij}\,x_i(t)\right)\right] \quad (k = 1,2,\ldots.n) \tag{2.42}$$

2.8.2 Wavelet neural network training algorithm

There will be many algorithms have been applied to wavelet neural network such as gradient descent, conjugate gradients… however, the advantages of wavelet neural network architecture is that it can be trained in stages using linear optimization algorithms, this will allow for improving convergence and the training faster compared with nonlinear alternatives.

Same as MLP, the back propagation algorithm is used in this training, in which the weights and bias will be modified so as the minimum error will be minimized with an average quadratic error function of the equation (2.43) :

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{N}\left[d_k^p - y_k^p\right]^2 \tag{2.43}$$

Where d_k^p is the expected output of WNN. The back-propagation algorithm actually adopts gradient descent to minimize E, the corresponding formula will be shown as follows :

$$\frac{\partial E}{\partial w_{jk}} = -\sum_{p=1}^{P} y_k(1-y_k)(d_k-y_k)\varphi_{a,b}\left(\sum_{j=1}^{m} w_{ij}\,x_i(t)\right) \tag{2.44}$$

$$\frac{\partial E}{\partial w_{jk}} = -\sum_{p=1}^{P}\sum_{k=1}^{N} y_k(1-y_k)(d_k-y_k)\varphi_{a,b}\left(\sum_{i=1}^{m} w_{ij}\,x_i(t)\right) \qquad (2.45)$$

$$\frac{\partial E}{\partial w_{jk}} = -\sum_{p=1}^{P}\frac{\sum_{k=1}^{N} y_k(1-y_k)(d_k-y_k)w_{jk}\,\varphi'_{a,b}\left(\sum_{i=1}^{m} w_{ij}\,x_i(t)\right)x_i^p}{a_j} \qquad (2.46)$$

$$\frac{\partial E}{\partial b_j} = -\sum_{p=1}^{P}\sum_{k=1}^{N} y_k(1-y_k)(d_k-y_k)w_{jk}\,\varphi'_{a,b}\left(\sum_{i=1}^{m} w_{ij}\,x_i(t)\right)/a_j \qquad (2.47)$$

$$\frac{\partial E}{\partial a_j} = -\sum_{p=1}^{P}\sum_{k=1}^{N} y_k(1-y_k)(d_k-y_k)w_{jk}\,\varphi'_{a,b}\left(\sum_{i=1}^{m} w_{ij}\,x_i(t)\right)\left(\frac{\left(\sum_{i=1}^{m} w_{ij}\,x_i(t)\right)-b_j}{a_j}\right)/a_j^2 \qquad (2.48)$$

$$w_{ij}(t+1) = w_{ij}(t) - n\frac{\partial E}{\partial w_{ij}} + \mu\Delta w_{ij}(t) \qquad (2.49)$$

$$w_{jk}(t+1) = w_{jk}(t) - n\frac{\partial E}{\partial w_{jk}} + \mu\Delta w_{jk}(t) \qquad (2.50)$$

$$a_j(t+1) = a_j(t) - n\frac{\partial E}{\partial a_j} + \mu\Delta a_j(t) \qquad (2.51)$$

$$b(t+1) = b_j(t) - n\frac{\partial E}{\partial b_j} + \mu\Delta b_j(t) \qquad (2.52)$$

Where n refers to w_{ij}, w_{jk}, a_j and b_j learning rate parameter, μ prefer to momentum their own factors.

2.9 Main characteristics of the muscular diseases

In this research, there are three types of muscular diseases can be classified separately in healthy, myopathy and neuropathy [13].

- Healthy: a person who is not affected by a disease nor damaged muscle so that he or she is able to move freely at anytime. Most of the people from the age 15 to 30 years old can get normal muscle and do not depend on any medical devices.

- Myopathy: is a muscular disease in which the muscle fibers do not function for any one of many reasons, resulting in muscular weakness. Other symptoms of myopathies can be included muscle cramps, stiffness, and spasm and different type of myopathies such as muscular dystrophies, mitochondrial myopathies, dermatomyositis, polymyositis.

- Neuropathy: is damage to a single nerve or nerve group, which results in loss of movement, sensation, or other function of that nerve. Nowadays, with the high technology in medical, more than 100 types of neuropathies have been found and identified into three categories: Mononeuropathy, multiple mononeuropathy and Polyneuropathy.

CHAPTER 3
METHODOLOGY

3.1 Procedure Identification

The objective of this research is to design the algorithm for classification method. The EMG input signal will be taken from the many subjects, the signal is then process and store into the computer, later the algorithm will be designed to analyze them and get the output signal to control the prototype.

Literature review is the initial thing in order to do in this project; all the important information will be evaluated carefully to get the correct direction to design the control algorithm. MATLAB software was used to do the simulation about control system.

Several main procedures have been identified towards accomplishing the project. Base on the Gantt chart from the Appendix A. The process for planning and selecting techniques from feature extraction and classification system will be summarized in the flowchart below followed by detailed explanation as Figure 12:

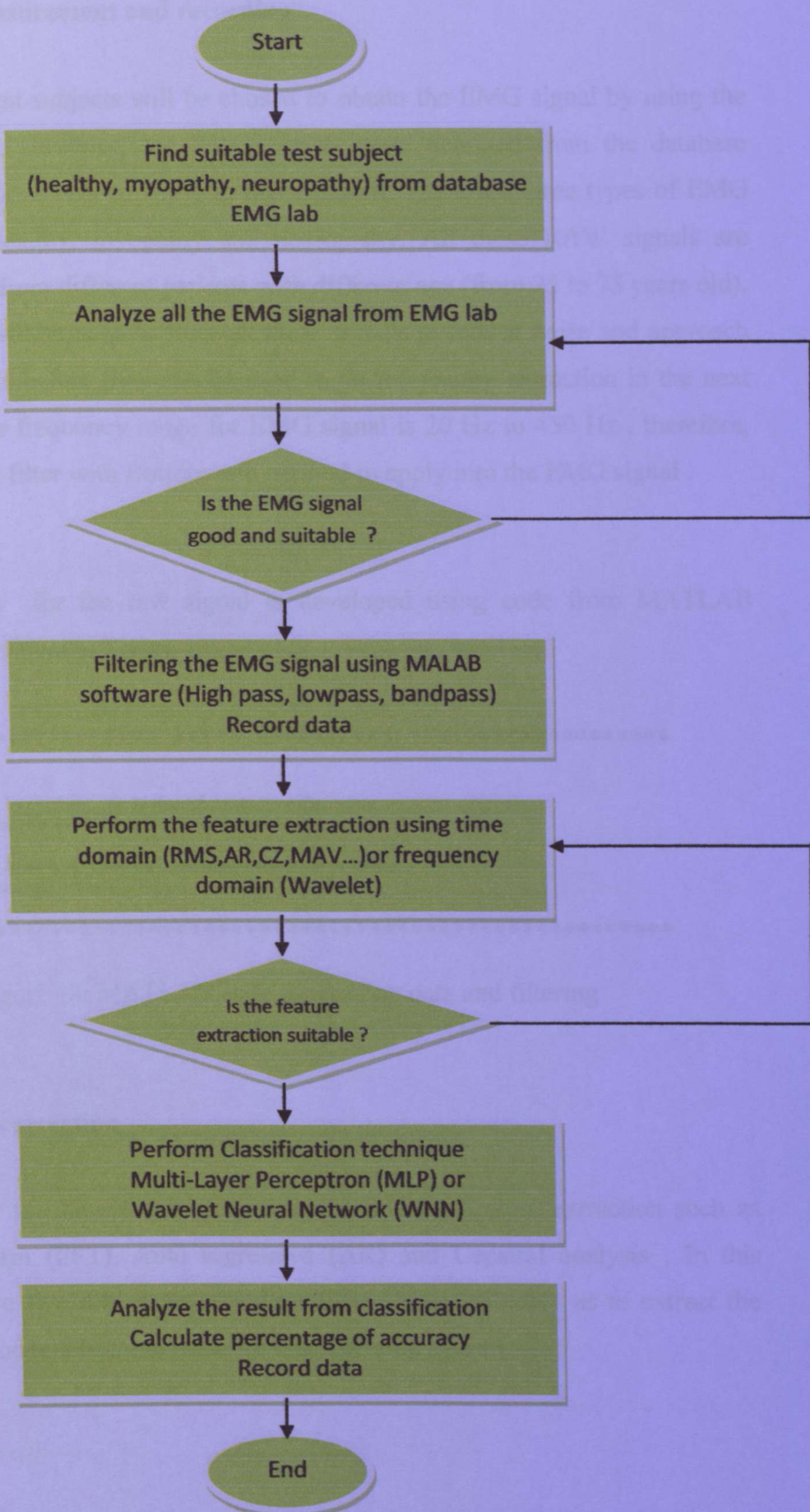


Figure 12: The flow chard of the design and implementation of process

3.2 EMG measurement and recording

Generally, different subjects will be chosen to obtain the EMG signal by using the medical machine. However, the EMG signals were obtained from the database source from *EMGlab* [14] to apply in this research. There are three types of EMG signal such as healthy, myopathy and neuropathy. All these RAW signals are already recorded from different patients with different age (from 25 to 75 years old). Then the filters will be used to filter all these signals to reduce noise and approach the clearly signals before they can be used to do the feature extraction in the next step. The suitable frequency range for EMG signal is 20 Hz to 450 Hz , therefore, we use band-pass filter with Butterworth method to apply into the EMG signal .

The code for the raw signal is developed using code from MATLAB software will be shown in Figure 13:

```
*********************************************************

clear;
fid = fopen('C:\normal.dat', 'r'); % Read the data from the source
EMGnor = fread(fid, [1,5000], 'int16', 'b'); % Choose the sample with 5 seconds
fclose(fid);
[b,a]=butter(4,[0.04 0.9], 'bandpass'); %Range from 20Hz to 450Hz
EMGout = filter(b,a,EMGnor);

*********************************************************
```

Figure 13: MATLAB code for reading data and filtering

3.3 Feature extraction

There are many techniques that can be used to do the feature extraction such as Fourier Transform (FFT), Auto regressive (AR) and Cepstral analysis . In this project, there are five different methods will be chosen to apply as to extract the useful information and become input for classification system.

3.3.1 Time domain

3.3.1.1 Auto regressive (AR)

Autoregressive (AR) model is another popular linear feature extraction method for biological signal. AR complex process, in a non-stationary context, is given by equation (3.1) below:

$$x(n) = \sum_{k=1}^{p} a_k x(k-i) + e(k) \tag{3.1}$$

Where

p : model order

x(n) : data of the signal at point n

a_k : the real valued AR coefficient

e(k) : the white noise error term independent of past sample.

Before the choice of Auto-regressive (AR) to perform feature extraction, the selecting model order of AR need to be done first [15,16]. A model order which is too high will over fit the data and present too much noise ,however, a model order which is too small will not sufficiently represent the signal. There are many methods to choose the model order, and the Akaike Information Criterion (AIC) is one of the most common will be explained at the equation below :

$$AIC(p) = \ln(\sigma_p^2) + \frac{2p}{N} \tag{3.2}$$

where p is the model order, N is the length of the signal and σ_p^2 is the variance of the error sequence at order p. by using MATLAB software, the diagram below will show the result in Figure 14 :

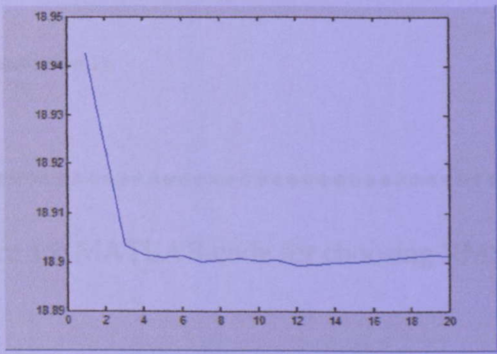


Figure 14: AIC of EMG signal from healthy patient

Based on the AIC above, it can be seen that AIC value do not change too much after model 6 , so order 6 can be chosen as the model order . However, the order 8 can get the best result in this case, so it will be chosen for the next step.

The second step after choosing the model order of AR is find the coefficient as feature to discriminate the different of three stages: normal, myopathy and neuropathy [16]. In this, the AR parameters are estimated using a constrained least squares minimization procedure.

3.3.1.2 Root mean square (RMS)

The root mean square (abbreviated RMS), also known as quadratic mean, is a statistical measure of the magnitude of a varying quantity . The RMS value of a set of values is the square root of the average of the square of the original values. The RMS for a set of n values such as $\{x_1, x_2 \dots x_n\}$ will be given by equation (3.3):

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \cdots + x_n^2)} \tag{3.3}$$

****

```
for i = 1:number_win
datainfor = x(start:en,:).*repmat(datawindow,1);
feature(i,:) = sqrt(mean(datainfor.^2));
start = start + window_inc;
en = en + window_inc;
end
```

****

Figure 15: MATLAB code for choosing RMS

3.3.1.3 Mean absolute value (MAV)

The mean absolute value (abbreviated MAV) is calculated using a moving window [1] . The MAV of the signal x in segment i that has N samples will be given by equation (3.4) and the code in Figure 16 :

$$\overline{x_i} = \frac{1}{N} \sum_{k+1}^{N} |x_k| \tag{3.4}$$

****

```
for i = 1:number_win
   datainfor = x(start:en,:).*repmat(datawin,1);
   feature(i,:) = mean(abs(datainfor));

   start = start + window_inc;
   en = en + window_inc;
end
```

****

Figure 16: MATLAB code for choosing Mean Absolute value

3.3.1.4 Zero crossing

The frequency that provided from the signal is counted by the number of times the waveform crosses to zero . A threshold (σ) is included to reduce noise induced zero crossings [1] . Let's get the two consecutive sample x_k and x_{k+1}, the increase of the zero crossing count, if :

$$\{x_k > 0 \; and \; x_{k+1} < 0\} \; or \; \{x_k < 0 \; and \; x_{k+1} > 0\} \tag{3.5}$$

and $$|x_k - x_{k+1}| \geq \sigma \qquad (7)$$

****

```
for i = 1:number_win
  y = x(start:en,:).*repmat(datawin,1);
  y = (y > 1) - (y < -1);
  a=1;
  b=exp(-(1:window_size/2))';
  fil = filter(b,a,y);
  fil = ( fil > 0) - ( fil < -0);
  datafil = diff( fil);
  feature(i,:) = (sum(abs(datafil)==2));
  start = start + window_inc;
  en = en + window_inc;
end
```

****

Figure 17: MATLAB code for choosing Zero crossing

3.3.1.5 Waveform length (WL)

A feature by using waveform length can approach the information on the waveform amplitude, frequency and duration [1]. The length of the waveform is the accumulation of the over each analysis that is given by equation (3.6) and MATLAB code in Figure 18:

$$l_0 = \sum_{k-1}^{N}(x_k - x_{k-1}) \tag{3.6}$$

****

```
for i = 1:number_win
  datainfor = x(start:en,:).*repmat(datawin,1);
  feature(i,:) = sum(abs(diff(datainfor,2)));

  start = start + window_inc;
  en = en + window_inc;
end
```

■■

Figure 18: MATLAB code for choosing Waveform Length

3.3.2 Frequency domain

Besides time domain, there will be another technique for feature extraction called frequency domain with include many methods based on frequency domain to extract the data from EMG signals.

3.3.2.1 Wavelet transform

Wavelet transform use two dimensional time-frequency representation. This is an important feature extraction technique for local analysis of non-stationary and fast transient response. The main reason of using this method is to generate the subset of the frequency components of the interested signals. The noise and unwanted parts will be reduced effectively through the selection of the valuable frequency components [17,18].

Wavelet are generated from a single basic wavelet $\psi(t)$, which is known as mother wavelet , the algorithms of this wavelet will be shown as equation (3.7) below :

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), a, b \in R; a \neq 0 \tag{3.7}$$

where a, b are the scale and translation factors, $\frac{1}{\sqrt{a}}$ represents the energy normalization across the different scales.

There are two different types of Wavelet transform, they are Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT) [17,18]. The continuous wavelet transform used to divide a continuous-time function into wavelet. And Discrete wavelet transform used to overcome the redundancy of continuous wavelet transform by scaling and translating in discrete steps which shown as equation (3.8):

$$d_{j,k} = \langle f, \psi_{j,k} \rangle, \psi_{j,k} = a_o^{-\frac{j}{2}} \psi\left(a_o^{-j} t - k b_o\right) \tag{3.8}$$

where j, k are integers, $a_o > 0$ is fixed dilation step ,b_o is the translation factor is dependent on a_o.

The discrete wavelet transform often used in real time engineering application. This is useful technique that interactively transform as signal into multi-resolution subset of coefficients.

3.4 Cross validation

Cross validation (CV) is the method that used to compare the number of learning ANN models to estimate the best performance. [17] The combination between training and validation dataset are divided into N non-overlapping subsets, the training will be repeated N times and after finish each time, one of the N subsets will be used as the validation set and the other N-1 subsets will become the training set. And the average of classification error will be computed when the training finish.

In this classification, the 60% of data will be selected randomly for the dataset of training the network and 20% of the data for validation after each training epoch. The best network from training session will be applied to the remaining 20% of the data as the test set, the Figure 19 will show the graphic of train, validation and test data.

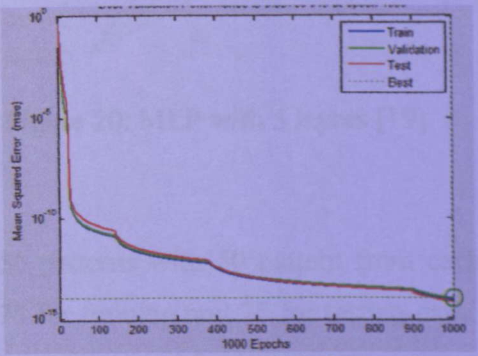


Figure 19: Graphic of train, validation and test data.

3.5 Classification using Artificial Neural Networks

3.5.1 Multilayer Perceptron

ANNs are widely used in the biomedical field for modeling, data analysis and diagnostic classification. The most frequently used training algorithm in classification problems is the back-propagation (BP) algorithm, and in this project, this algorithm will be used to train the data , and the EMG signal data will be employed for designing classifiers, namely Multilayer perception (MLP) [19].

We used MLP to classify the feature into three classes: Normal (NOR), Myopathy (MYO) and Neuropathy (NEU) that will be shown in Figure 20. The input will be ten and the output will be three, while the hidden unit can have ten or more than nodes, and we could only use a few values such as 10,20,30,40,50...

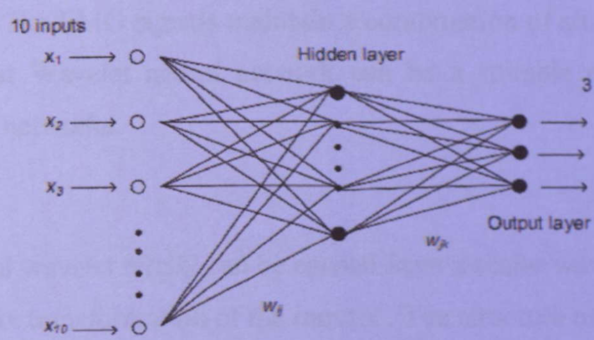


Figure 20: MLP with 3 layers [19]

Assume that we have 150 patterns with 50 pattern from each class. Dividing this data into two equal set, 75 for training and 75 for testing data. In order to make the neural network training more accuracy, the input feature vectors were normalized so that they fall in the range [0,1.0]. And the output of the training will be divided into 3 groups code as shown in Table 1.

Table 1: Group of three stages of Normal, Myopathy and Neuropathy

Group/Types	Normal (NOR)	Myopathy (MYO)	Neuropathy (NEU)
Group 1	0.9	0.1	0.1
Group 2	0.1	0.9	0.1
Group 3	0.1	0.1	0.9

After training, the testing data will be used again to test the classification, each pattern input is fed to the classifier and the resulting output are computed [19,20]. The maximum output is assumed to be the predicted class. We use the group of data to use for testing data after training. Each group represent to different data from normal, myopathy and neuropathy patient.

3.5.2 Wavelet neural network

Wavelet can offer many attractive features for the signal analysis and joint input-space localization. The EMG signals maintain a combination of slow variations over long period so that Wavelet neural network can be a suitable choice than other mainstream neural networks.

A multidimensional wavelet *Ψ(zjk)* can be caused from a scalar wavelet *Ψ(z)* via an affine vector–matrix transformation of the input x . The structure of wavelet neural network model can be shown as Figure 21 below:

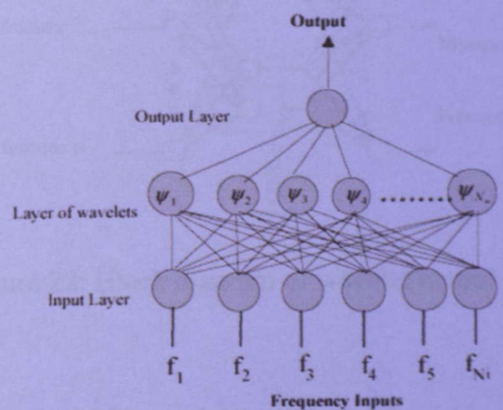


Figure 21: Wavelet neural network model

There are three layers from wavelet neural network, the input layer consists of the frequency inputs that taken from feature extraction in frequency domain. The next layer of wavelets include a multidimensional wavelet Ψ (zjk) and the output layer can become an output [17,18] . The structure of wavelet neural network is almost same with Multilayer Perceptron (MLP) with input layer, hidden layer and output layer.

Wavelet analysis now becomes a common method for analyzing variations of power with a time series. Time series is composed into time-frequency space; the determination can be caused in both the dominant modes of variability in time. Wavelets based on ANNs have been developed and used for function approximation and can be called WANNs. The used of WANNs can overcome the problem that conventional ANNs had.

In WANNs, a wavelet function in hidden layer was utilized to approach better performance with neural network. In this research, Morlet wavelet function was used in hidden layer. The training data set has been used to train in wavelet neural network [18]. Based on Figure 22, the Morlet wavelet function and sigmoid function were used as hidden layer and output layer activation function of WNN.

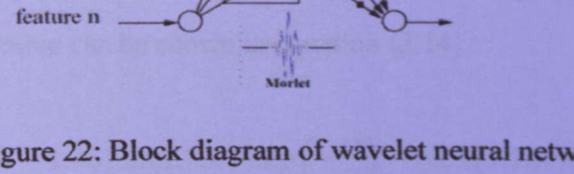


Figure 22: Block diagram of wavelet neural network

The different between ANNs and WANNs is that the replacement of sigmoid function in the MLP of ANNs with nonlinear wavelet basic function, $\varphi\left(\frac{t-b}{a}\right)$, where a and b are the scale factor and translation factor of the wavelet function. And the function of the nonlinear wavelet can be shown in equation (3.9).

$$y(t) = \sum_{i=1}^{h} w_i \varphi\left(\frac{t-b}{a}\right) \tag{3.9}$$

Unlike in the standard of Back-propagation algorithm, by using Newton's method it can be derived that the parameter updating equations in training can be followed as equation (3.10)

$$\Delta w_i = \sum_{t=1}^{h}[d(t) - y(t)]\, \varphi\left(\frac{t-b_i}{a_i}\right) \tag{3.10}$$

With the value of Δa_i and Δb_i will be shown as equation (3.11) and (3.12)

$$\Delta a_i = \sum_{t=1}^{N}[d(t) - y(t)]\frac{w_i}{a_i^2}(t - b_i)\varphi'\left(\frac{t-b_i}{a_i}\right) \tag{3.11}$$

$$\Delta b_i = -\sum_{t=1}^{N}[d(t) - y(t)]\frac{w_i}{a_i}\varphi'\left(\frac{t-b_i}{a_i}\right) \tag{3.12}$$

The form of $\varphi(t)$ and $\varphi'(t)$ depend on the selected wavelet function. In this research, the used of Morlet wavelet function can be derived as equation (3.13) :

$$\varphi(t) = \cos(1.75t)\exp\left(-\frac{t^2}{2}\right) \tag{3.13}$$

And the first derivative can be shown in equation (3.14) :

$$\varphi'(t) = -1.75\sin(1.75t)\exp\left(-\frac{t^2}{2}\right) - t\cos(1.75t)\exp\left(-\frac{t^2}{2}\right) \tag{3.14}$$

After training network, test data set were used to test the result. In classification of neural network, the optimum values for number of hidden node need to be done at first, and then to determine optimum learning rate

CHAPTER 4

RESULT & DISCUSSION

4.1 EMG signal

Figure 23, 24 and 25 show the EMG signals for Myopathy, Neuropathy and Healthy condition that was obtained from the *EMGlab* [14] . All the signals were taken from three types of EMG signals with the first 500 samples.

a. Myopathy

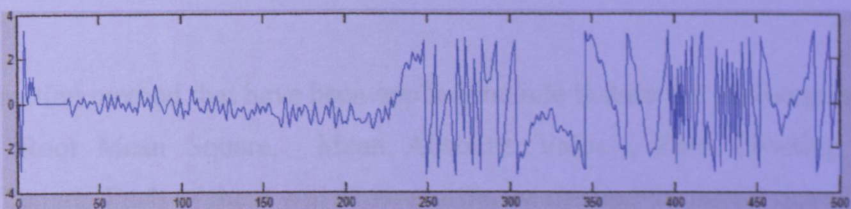


Figure 23: Myopathy EMG signals

b. Neuropathy

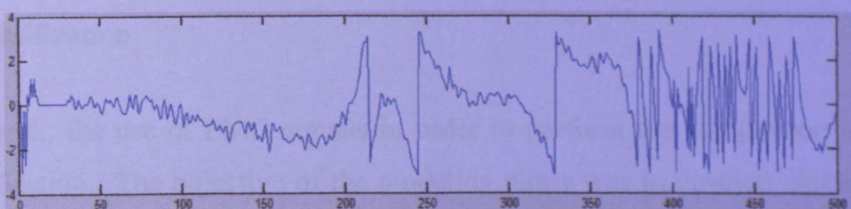


Figure 24: Neuropathy EMG signals

c. Healthy

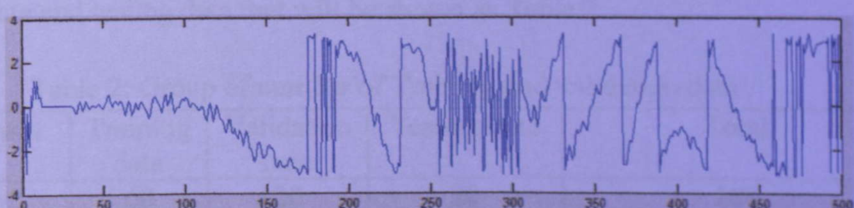


Figure 25: Healthy EMG signals

4.2 Feature extraction

For each channel EMG taken from different patients, the signals are processed in order to extract important features from them. By using a sliding analysis window, a window of 256ms in length with space in 32ms is used to produce a single feature vector. The Figure 26 will show the sliding analysis window from signal.

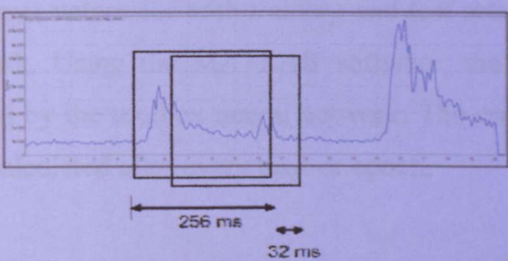


Figure 26: Sliding analysis window

Feature extraction method that have been applied include feature for: Autoregressive coefficient, Root Mean Square, Mean Absolute Value , Zero Crossing and Waveform Length. Each of them will show a different method to use for extract the signal into each column in the matrix of training and testing data.

4.3 Classification

In this research, the use of EMG signals in order to perform the comparison using MLP classification. The objective of the modeling phase was to develop classifiers that are identified as three different types. For developing neural network classifiers, 300 examples were randomly taken from the database to become training data, validation data and testing data that will be shown as Table 2.

Table 2: Group of number of Training and validation data

Group/Types	Training data	Validation data	Testing data	Total
Healthy	60	20	20	100
Myopathy	60	20	20	100
Neuropathy	60	20	20	100
Total	**180**	**60**	**60**	**300**

The MLP was designed with Auto regressive of EMG signal in the input layer, output layer consisted of three nodes representing three different types of classification. The number of hidden layer will be chosen in this training is one because it was found that only one hidden layer can solve the problem [21, 22, 23]. A training rate of 0.01 and momentum coefficient of 0.95 was found optimum for this training network by using modified error back-propagation algorithm training. The mean of square error (MSE) representing the mean square of deviation of MLP output from the target values for both training and test sets was used for estimating the optimal network. Using the MATLAB software, the develop of the training session can be used by the toolbox neural network. The error of the network on the validation data is calculated after every pass or epoch.

Table 3: Neural network training parameters

Sum square error (SSE)	0.00001
Total Epoch	10,000
Initial learning coefficient	0.01
Momentum coefficient	0.95

Table 3 shows all the procedure of training MLP, this included time, number of epoch, the performance and the gradient of mean square error. The training will stop once the mean square errors reach the target value (1e-5). This training used by MATLAB toolbox to reduce time and memory of the computer can be shown in Figure 27 (a) and (b).

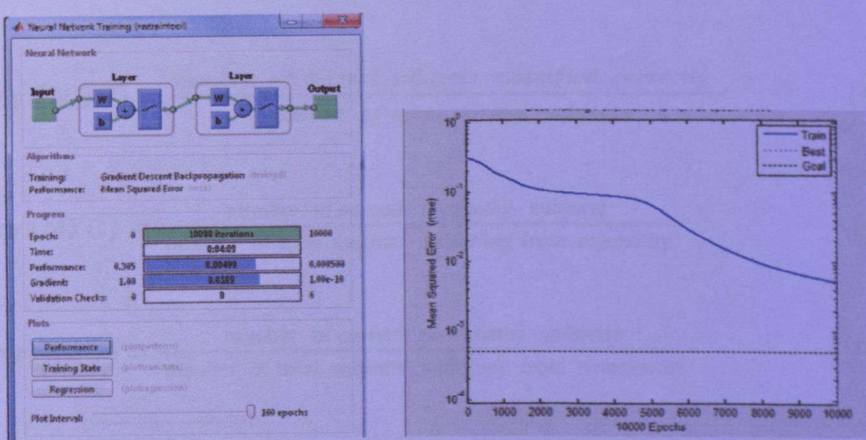


Figure 27: (a) Neural Network Training toolbox (b) Mean square Error

The computed of Auto-regressive (AR) [24] was used as the input of MLP and the classification results of MLP were displayed on the chart as Figure 28.

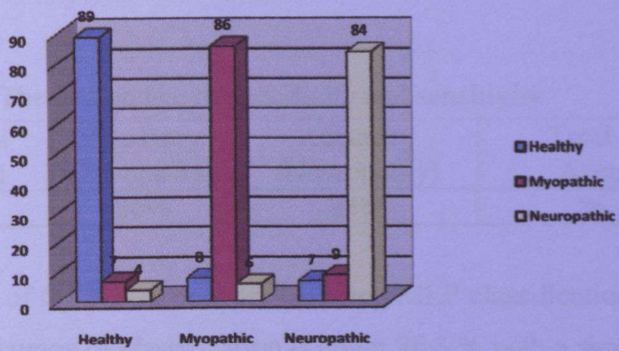


Figure 28: The classification result between three different groups

Based on the chart from Figure 28, 11 healthy subjects were classified incorrectly in the healthy class , they were classified as the suffering subjects (7 myopathy and 4 neuropathy subjects), 14 myopathy subjects were classified as healthy (8 subjects) and neuropathy (6 subjects), and 16 neuropathy subjects were classified as a healthy (7 subjects) and myopathy (9 subjects).

By using the computational of the following values, the percentage of accuracy were determined by following the equations from (4.1) to (4.4):

$$* \, Accuracy\,(NOR) = \frac{number\ \ of\ \ normal\ \ subjects\ \ classified\ \ correctly}{number\ \ of\ \ total\ \ normal\ \ subjects} \tag{4.1}$$

$$* \, Accuracy\,(MYO) = \frac{\text{number of correct myopathy subjects}}{\text{number of total subjects suffer ing from myopathy}} \tag{4.2}$$

$$* \, Accuracy\,(NEU) = \frac{\text{number of correct neuropathy subjects}}{\text{number of total subjects suffering from neuropathy}} \tag{4.3}$$

$$* \, Total\ classification\ accuracy = \frac{\text{number of correct classifi ed subjects}}{\text{number of total subjects}} \tag{4.4}$$

The statistical values are calculated by the equation above is shown in Table 4 , the accuracy between healthy , myopathy and neuropathy are 89% from healthy , 86% from myopathy and 84% from neuropathy.

Table 4: The percentage of specificity and sensitivity

Statistical	Accuracy (Healthy)	Accuracy (Myopathy)	Accuracy (Neuropathy)	Total Class Accuracy
MLP	89%	86%	84%	86.3%

The testing performance of the neural network by using MLP classification is found to be satisfactory; the accuracy of classification is about 86.3 % with a single hidden unit as a classifier. The classification using learning algorithm (MLP) could be trained faster to another classification method.

4.4 Classification by using another feature extraction

After using Auto-regressive, there will be four methods from feature extraction that can be applied into classification system, moreover, to increase the percentage of high accuracy, there will be five different datasets are created and labeled as Table 5

Table 5: Five different datasets divided into five groups

Group	Description
Group 1	healthy / unhealthy (abnormal)
Group 2	healthy / myopathy
Group 3	healthy / neuropathy
Group 4	myopathy / neuropathy
Group 5	healthy / myopathy / neuropathy

To obtain best classification, 5 different methods from feature extraction will be used as the input of the training [25]. They are:

- Autoregressive
- Root mean square
- Mean absolute value
- Zero crossing
- Waveform length.

The result of accuracy for each datasets based from each feature extraction is used to compare with other results is shown in Table 6.

Table 6: The classification result based on different techniques

Classifaction of group	Number of data per class	Classification accuracy (%)				
		Auto regressive (AR)	Root mean square (RMS)	Mean absolute value (MAV)	Zero Crossing (ZC)	Waveform length (WL)
healthy / unhealthy	100/100	81.75%	**82.5%**	80.5%	81.75%	**82.5%**
healthy / myopathy	100/100	**83%**	77.5%	82%	79.5%	81%
healthy / neuropathy	100/100	**83.5%**	**83.5%**	75%	82.5%	80.5%
myopathy / neuropathy	100/100	**82.5%**	78.5%	77.5%	77%	77%
healthy / myopathy / neuropathy	100/100/100	**86.3%**	78.7%	82%	76.3%	75.7%

All the data above will be shown as the bar chart on Figure 29 to show up the result of classification accuracy.

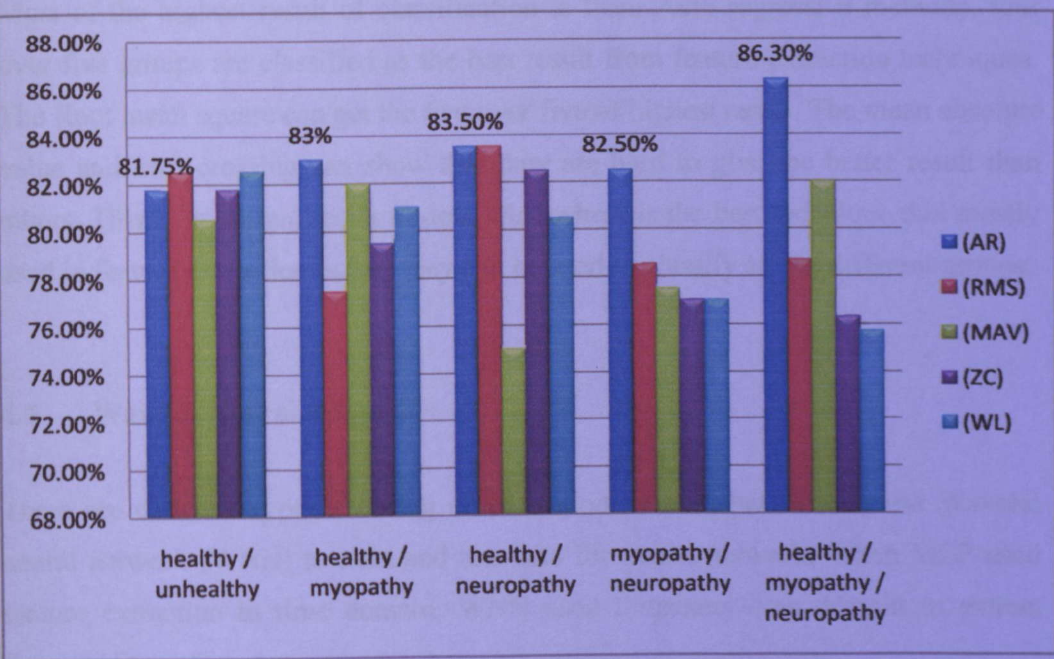


Figure 29: The chart on classification result from different techniques

Based on the Table 6 , the classification accuracy result between each different groups using different feature extraction are shown clearly with the percentage and the best feature extraction will be highlight to demonstrate the highest accuracy in each group. From the group 1 with healthy subjects and unhealthy subject , we can realize that the Root mean square (RMS) and Waveform length (WL) can get the highest result of classification accuracy (82.5%), group 2 with healthy and myopathy subjects, the Auto regressive from feature extraction give the top result in this case with 83% , similarly, from group 3 with healthy and neuropathy subjects, there are two techniques from feature extraction can get the highest result from classification, they are Auto regressive (AR) and root mean square (RMS) with the same result 83.5% . And from group 4 and group 5, the highest result comes from Auto regressive also with the percentage is 82.5% (myopathy and neuropathy) from group 4 and 86.3% from group 5 (healthy , myopathy and neuropathy). The highest success from two classes are from healthy and neuropathy with 83.5% , this shows that healthy and neuropathy groups are the most distinguishable when comparing with the other group such as healthy and myopathy, myopathy and neuropathy. The other groups are difficult to get the good result in classification.

Most of the highest result of classification is from Auto regressive methods, four over five groups are classified as the best result from feature extraction techniques. The Root mean square can get the two over five of highest result. The mean absolute value and zero crossing can show that they are hard to give the better result than others. This is important result to determine where is the best technique that mostly used in feature extraction before they can be used to classify all the different groups.

4.5 Wavelet Neural network

There are different types of using classification system that we can use Wavelet neural network (WNN) to train and test data for neural network. When MLP used feature extraction in time domain, WNN used frequency-time domain to extract feature of neural.

4.5.1 Feature extraction using frequency domain

Based on the MLP feature extraction, Autoregressive coefficient can be used to become an input to MLP training system, and also with WNN, the use of Power spectrum density (PSD) can become an input to WNN training system.

Power Spectrum Density (PSD) values are also used as feature for EMG signal. There are many methods to obtain PSD such as Welch and Burg functions. In this research, Burg method can be used to obtain the value of Auto regressive (AR). It is also to use AR to obtain Power Spectrum Density (PSD). After obtaining the a_k coefficient and σ_p^2 using *arburg* function and with some suitable model order chosen by AIC, we can compute the PSD using the formula (4.5)

$$P(f) = \frac{\sigma p^2 \Delta t}{\left|1+\sum_i^p a_{pi} e^{-j2\pi fi\,\Delta t}\right|^2} \tag{4.5}$$

Where $a_{p0}=1$. By using MATLAB, we can compute the PSD and sketch the diagram as Figure 30.

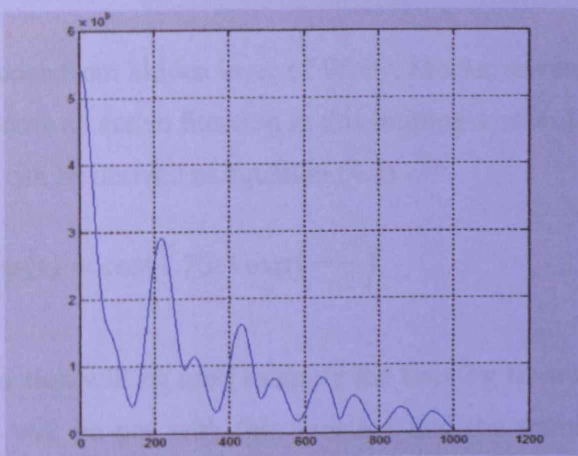


Figure 30: AR burg of PSD for healthy subjects

We have chosen the Burg method since it offers good performance to spectral leakage by its recursive structure. Burg algorithm is one possible method to estimate the autoregressive coefficients from equidistant data. The Burg algorithm is a recursive algorithm. Specifically, the *p*th step of the algorithm reflection coefficient is estimated while the previous coefficients $k_1 ... k_{p-1}$ remain fixed. This algorithm can get easily adapted to evaluate the reflection coefficients from multiple segments of data. Spectrum estimation of AR method does not suffer from frequency problem, and it is very useful for signals to have a narrow bandwidth.

4.5.2 Classification of Wavelet neural network

The computed of PSD from feature extraction becomes an input to the WNN training system, there are 20 signals taken from database will be divided into 900 samples to perform training and 300 samples to perform testing data, the dataset from the input will be shown as the Table 7.

Table 7: Number of training and testing data from three different groups

Group/Types	Training data	Testing data	Total
Healthy	300	100	400
Myopathy	300	100	400
Neuropathy	300	100	400
Total	**900**	**300**	**1200**

There will be 40 nodes from hidden layer of WNN, Morlet wavelet neural network will be used to become an active function in this training system [26]. The equation of Morlet function can be derived as equation (4.6)

$$\varphi(t) = \cos(1.75t)\exp\left(-\frac{t^2}{2}\right) \quad (4.6)$$

Morlet wavelet function will be used to apply the training from the hidden layer of WNN, each input will be put with this function and the training will be started immediately until the last input ended.

Sigmoid function will become the activation function from the output, there are 3 nodes of output layer to show the result of Normal, Myopathy and Neuropathy. In order to make the wavelet neural network training more accurate, the input feature vectors are normalized so that they fall in the range [0,1.0]. And the output of the training can be divided into 3 groups code in Table 8.

Table 8: The three output result based from three different groups

Group/Types	Normal (NOR)	Myopathy (MYO)	Neuropathy (NEU)
Group 1	0.9	0.1	0.1
Group 2	0.1	0.9	0.1
Group 3	0.1	0.1	0.9

After training all the data, the test data will be performed to test the result. Same as MLP, there are five different groups from table 8, and the result of the percentage of accuracy will be shown as Table 9.

Table 9: The percentage of accuracy from WNN

Classifaction of group	Number of class	Number of data per class	Classification accuracy (%)	
			Number of samples corrected classified	Power spectrum Density (PSD)
healthy / unhealthy	2	100/100	92/89	90.5%
healthy / myopathy	2	100/100	91/90	90.5%
healthy / neuropathy	2	100/100	92/86	89%
myopathy / neuropathy	2	100/100	91/92	91.5%
healthy / myopathy / neuropathy	3	100/100/100	92/89/87	89.3%

Based on the result from test data, all the percentage of accuracy is around 90% , this can be considered that Wavelet neural network can produce better results than MLP based from the feature extraction Power Spectrum Density (PSD). The highest result from table 9 is from the group 4 with myopathy and neuropathy, the accuracy is 91.5% , the lowest result is come from group 5 with three different classes is 89.5% .

When compared all these result from WNN to MLP, the Figure 31 will represents all the result of accuracy from two different classification system, MLP used Auto regressive (AR) as the feature extraction in time domain, and WNN used Power

Spectrum Density (PSD) as feature extraction in frequency domain. The comparison will come from five different groups of healthy, myopathy and neuropathy also.

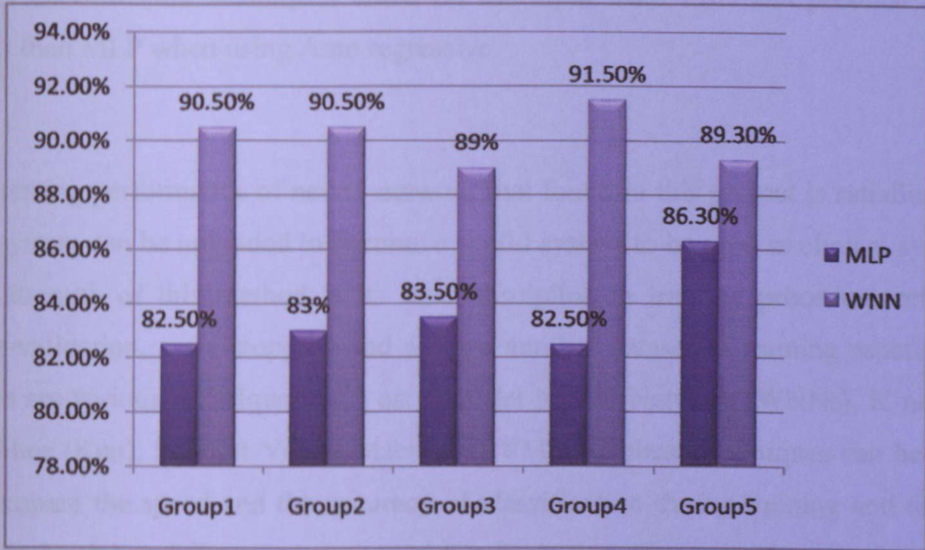


Figure 31: The comparison between MLP and WNN accuracy

The result from the Figure 31 shows that the accuracy when using WNN can get higher percentage than MLP classification system. It can be clearly checked that the test data from WNN can approach high accuracy. Based on group 1 (healthy and unhealthy), each class got 100 data sample for testing, and 92 samples were correctly classified as healthy subjects and 89 samples as correct as unhealthy subjects. The 90.5% from group 1 is come from the total of corrected subject divided by number of total samples using for testing and can be shown on equation (4.7):

$$\frac{92+89}{100+100} \times 100\% = 90.5\% \tag{4.7}$$

Same as with the result for the other groups, especially in group 5 with three class of healthy, myopathy and neuropathy, 92 samples of healthy, 89 samples of myopathy and 87 samples of neuopathic are correctly classified. And the percentage of accuracy can be calculated as equation (4.8) :

$$\frac{92+89+87}{100+100+100} \times 100\% = 89.3\% \tag{4.8}$$

The comparison between MLP and WNN in the group 5, it can be seen that MLP gets 86.3% for accuracy and WNN get 89.3% for accuracy. It can be shown that WNN classification techniques based on the input from PSD can produce better result than MLP when using Auto regressive.

The testing performance of neural network that found in this project is satisfied and this system can be upgraded to become a useful system to be used in clinical system. The strength of this method is its strict discipline in training procedure relating cross-validation, early stopping and a large number dataset of training repetitions. There are various techniques such as: Wavelet Neural Network (WNNs), K-nearest neighbor (Knn), Support Vector Machine (SVM). All these techniques can be used to compare the speed and the accuracy of classification during training and testing dataset. Each has different advantage and its limitation. However, the use of all these methods in general and MLP in particular are most practical to achieve better result during its application.

The result can be improved when other feature extraction techniques has been applied in this project. Power Spectrum Density is just only one of many techniques from frequency domain. There are lot of techniques that can help get the exact feature extraction from EMG signal, then the classification system can get better result than before.

4.6 The advantages and disadvantages between MLP and WNN

4.6.1 Advantages

4.6.1.1 Multilayer Perceptron (MLP)

- Adaptive learning: This is one of the important thing to make the advantage for MLP, a skill to learn how to perform works that based on the data and weights given for training or beginning experience.

- Self-Organization : The organization of information can be created by an ANN to receive during learning time .

- Real Time Operation : The computations from ANN can be hold in parallel in order to design a special hardware devices which take advantage of this.

- Structure : MLP with three layer black-propagation network with sufficient hidden nodes can be an universal approximation to yield the required decision function directly through training.

4.6.1.2 Wavelet Neural Network (WNN)

- The combination between time and frequency characteristic of wavelet transformation can approach high accuracy of classification.

- Wavelet neural network inherits all the characters from wavelet analysis so that it has stronger approximation, tolerance and classification capacity than conventional neural network.

- The use of nonlinear Morlet wavelet at the basic function combines with error back-propagation algorithm to train the network may overcome the defect of conventional back-propagation neural network.

4.6.2 Disadvantages

4.6.2.1 Multilayer Perceptron (MLP)

• Overfitting: An extreme potential for overfitting occur during training data , there will be excellent result accuracy on training data but poor accuracy on unseen data.

• Local minimum: During training data, there will be error surface that make more than one local minimum , the system may converge to a local minimum and stuck from there. The Figure 32 will represent the local minimum error.

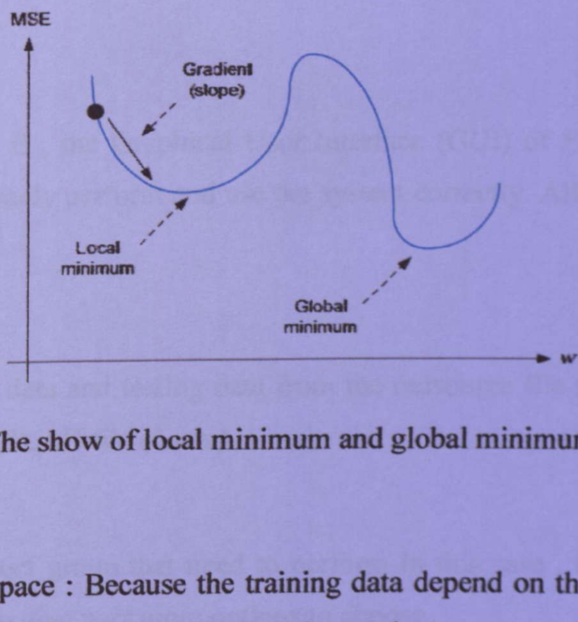


Figure 32: The show of local minimum and global minimum

• Starting search space : Because the training data depend on the weight , so that different initial weights can deeply effect to the result.

4.6.2.2 Wavelet Neural Network (WNN)

• Because the wavelet frames can be linearly correlated so when wavelet has been used at time-frequency domain, there will be the interception of the frame of wavelet bases function as the neuron function of the hidden layer node. So that it will effect to the result.

4.7 E-class system user interface

The name of E-class comes from "Electromyography Classification", E-class is an automated system that used to perform classifying three different types of Healthy, Myopathy and Neuropathy based on Electromyography signals.

There are two techniques that have been used in E-class system such as: Multilayer Perceptron (MLP) and Wavelet Neural Network (WNN), by applying training data file and testing data file to the system, there will be two options to choose how to perform the classification. After finish performing, an error analysis will be used to show the percentage of accuracy between three different types of Neuromuscular Disorders.

Based on the Appendix B , the Graphical User Interface (GUI) of E-class will be shown to help user get easily perform and use the system correctly. All the steps will be explained as below

Step 1: Choose training data and testing data from the outsource file such as Excel (*.xls or *.xlsx) and MATLAB file (*.mat)

Step 2: Choose the correct group that need to perform in this case , there are five different groups button to give user more options to choose.

Step 3 : Normalize the training and testing data using normalize button.

Step 4 : Choose different technique to perform classifying such as MLP and WNN

Step 5: Choose Error analysis button to perform the percentage of accuracy after finish classifying.

CHAPTER 5
CONCLUSION

ANN architecture is successfully developed for identification of EMG signals. Furthermore, three different groups of EMG signal such as Healthy, Myopathy And Neuropathy were used in order to analyze and diagnostic performance of this system. For faster computation, coefficient with their specifications has been extracted from EMG signals with various feature extraction methods, and Multilayer Perceptron (MLP) is useful tool to classify the EMG signal with the Back-propagation algorithm.

MLP is useful to classify the EMG signal with the algorithm back-propagation. There are many kind of method such as: Fuzzy logic, PID… However, MLP method still get the a good result for training input signal. The development of the project will take more time to do research in order to improve the algorithm and can be used in purposes. However, the accuracy of this method maybe not high compared to other methods, so that's why it needs to do more research and find another methods to increase the accuracy of the classification.

By using different feature extraction techniques, the classification can give the different results; Autoregressive is still the good method that can be applied in feature extraction to get high accuracy for classification. The other methods such as Root mean square, zero crossing, wavelength, mean absolute value still are suitable methods to use in feature extraction and then apply in classified system.

Wavelet Neural Network (WNN) can be shown that the better technique when compared to MLP, this technique based on the feature extraction in frequency domain. Based on the result of accuracy from the result and discussion, WNN can approach higher result than MLP. In the future, this technique can be updated to improve the percentage of accuracy by using different feature extraction to approach higher accuracy and use widely in different industry.

REFERENCE

[1] Sangit Sasidhar, Sanjib Kumar Panda, Xu Jianxin, "*A Real Time Control Algorithm for a Myoelectric Glove for the Rehabilitation of Wrist and Elbow of Stroke Patients.*" *8th IEEE International Conference on Control and Automation (2010), pp. 745-749.*

[2] Sabri Koçer, *"Classifying Myopathy And Neuropathy Neuromuscular Diseases Using Artificial Neural Networks",International Journal of Pattern Recognition and Artificial Intelligence Vol. 24, No. 5 (2010) ,pp. 791-807*

[3] Shady Gadoue, *"Industrial Automation – Artificial Neural networks" , Newcastle University , School of Electrical, Electronic & Computing Engineering*

[4] Dr. Scott Day, *"Important Factors in Surface EMG Measurement"*

[5] Girish Kumar JHA, *"Artificial Neural networks"*

[6] Priyanka Mehtani, Archita Priya , *"Pattern classification using artificial neural network"*

[7] R. Rojas, *"The Backpropagation Algorithm", Neural Network , Springer-Verlag, Berlin (1996).pp. 151-184.*

[8] *"Multilayer Perceptron Neural Networks"* http://www.dtreg.com/mlfn.htm

[9] "Neural Networks" , *http://en.wikipedia.org/wiki/Neural_network*

[10] *"Complexity- NET"*, *http://www.complexitynet.eu/about/Pages/default.aspx*

[11] Neural Networks' Role in Predictive Analytics, "*http://www.information-management.com/specialreports/2008_61/-10000704-1.html?zkPrintable=true*"

[12] Quian Huang, Dong Xiang Jang, Liangyou Hong, *"Application of Wavelet Neural Networks on Vibration Fault Diagnosis for Wind Turbine Gearbox", ISNN 2008 , pp.313-320, 2008*

[13] R.Istenic, M.Lenic, P.A.Kaplanis, C.S.Pattichis, D.Zazula, *"Classification of Neuromuscular Disorders Using Wavelets and Entropy Metrics on Surface Electromyograms", 7th WSEAS International Conference on Signal, Speech and Image Processing, Benjing, China, Sep 15-17 (2007), pp. 159-163.*

[14] *"Database source for EMG signal of healthy, myopathy and neuropathy from website"*, http://www.emglab.net

[15] Constantinos S. Pattichis, Andreas G. Elia, *"Autoregressive and cepstral analyses of motor unit action potentials", Medical Engineering & Physics 21 (1999), pp. 405–419.*

[16] Ramaswamy Palaniappan, *"Biological Signal Analysis", Journal of Neuroscience Methods 156 (2006) .*

[17] Abdulhamit Subasi, Mustafa Yilmaz, Hasan Riza Ozcalik, *"Classification of EMG signals using wavelet neural network", Journal of Neuroscience Methods 156 (2006) 360–367*

[18] Rahime Ceylan, Yüksel Özbay , *"Wavelet Neural Network for Classification of Bundle Branch Blocks", Proceedings of the World Congress on Engineering 2011 Vol II*

[19] Terry Windeatt, *"Ensemble MLP Classifier Design", Comp. Intel. Para.: Innov. Applications, SCI 137 (2008), pp. 133–147,*

[20] Markus Reischl, Lutz Groll, Ralf Mikut, *"Optimized classification of multiclass problems applied to EMG-control of hand prosthese", 0-7803-8359-1/04/2004 IEEE.*

[21] Omry Paiss, Ajat Gideon f. Inbar, *"Autoregressive Modeling of Surface EMG and Its Spectrum with Application to Fatigue", IEEE transactions on biomedical engineering, vol. bme-34, no. 10, October 1987*

[22] Abdulhamit Subasi, M. Kemal Kiymik, Ahmet Alkan, Etem Koklukaya, *"Neural Network Classification Of EEG Signals By Using AR With MLE Preprocessing For Epileptic Seizure Detection", Mathematical and Computational Applications, Vol. 10, No. 1, (2005), pp. 57-70.*

[23] Hugo Simões, Gabriel Pires , Urbano Nunes, Vitor Silva ,*"Feature Extraction And Selection For Automatic Sleep Staging Using EEG"*

[24] Philip Chrapka, *"EMG Controlled Hand Prosthesis: EMG Classification System", (2010). EE 4BI6 Electrical Engineering Biomedical Capstones.*

[25] Robert Bos, Stijn de Waele, and Piet M. T. Broersen, *"Autoregressive Spectral Estimation by Application of the Burg Algorithm to Irregularly Sampled Data", IEEE Transactions on Instrumentation and measurement, vol. 51, no. 6, December 2002*

[26] John Ashmead , *"Morlet wavelets in quantum mechanics", January 1, 2010*

APPENDICES

Appendix A : Gantt chart for the 2 semesters of Final Year Project

Appendix B : E-class system with user interface

APPENDIX A

GANTT CHART FOR THE 2 SEMESTERS OF FINAL YEAR PROJECT

I. Timeline for FYP I

Week Number Activities	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
FYP Title selection	D	D													
Literature Review			D	D	D	D	D	D							
Methodology									D	D					
Submission of Extended Proposal											D				
Signal Acquisition												D			
Proposal Defense													D		
Project work continues														D	
Submission of Draft Report														D	
Submission of Final Report															D

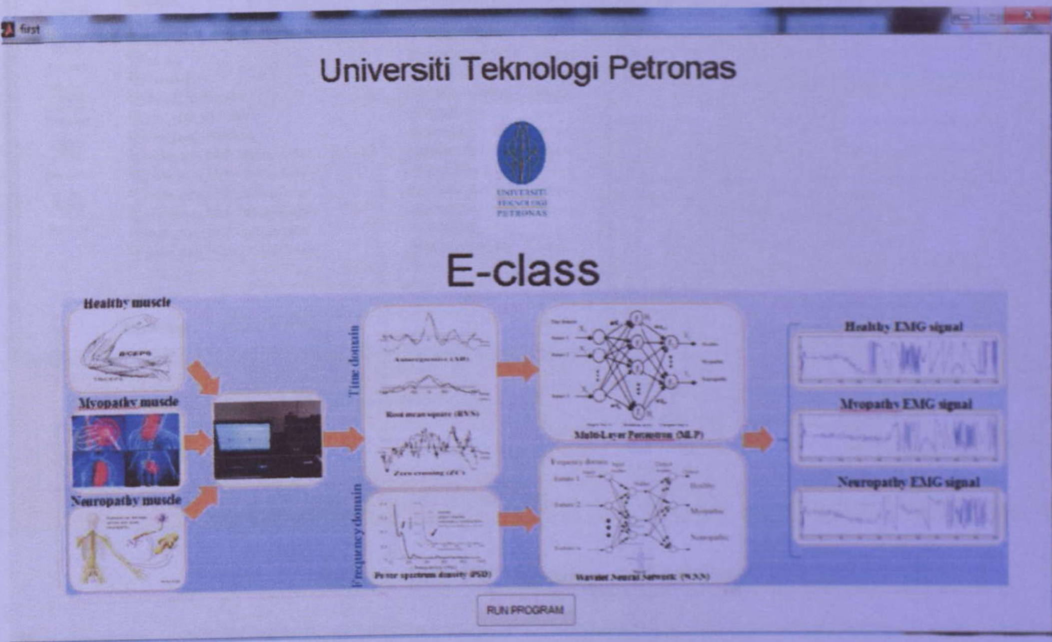
II. Timeline for FYP II

D: Task has been done

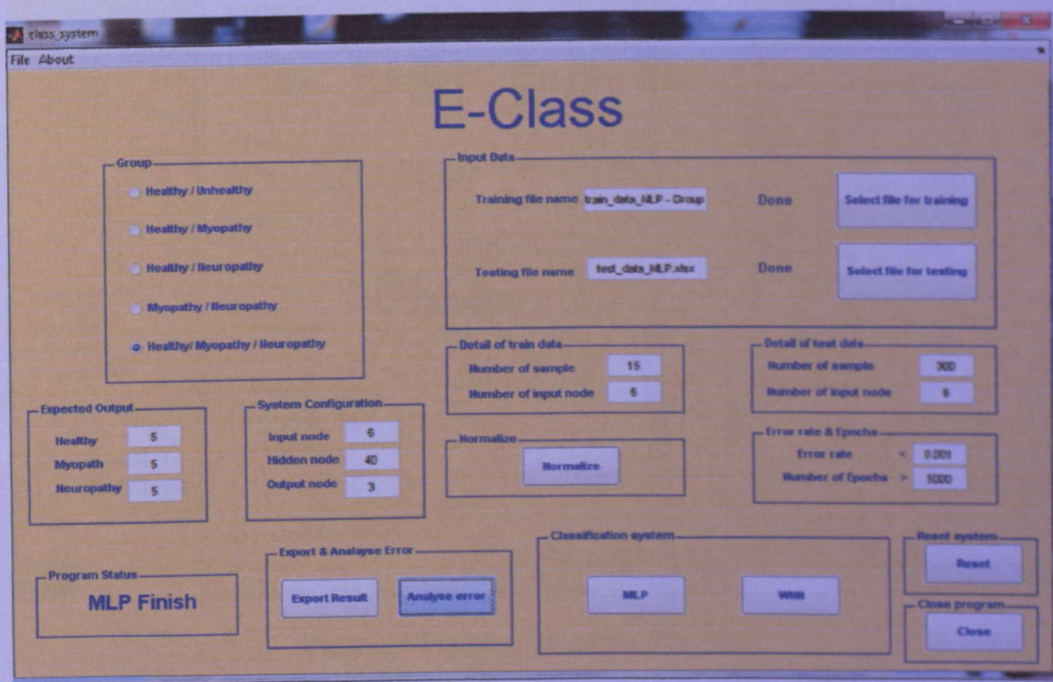
Week Number Activities	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
MLP and Wavelet Classification	D	D	D	D	D	D	D								
Submission of Progress Report								D							
Wavelet classification continue									D	D		D			
Submission of Draft Report											D				
Project work continues (data)											D				
Pre-SEDEX											D				
Submission of Final Report (soft cover)													D		
Submission of Technical paper													D		
VIVA														D	
Submission of Final Report (hard bound)															D

APPENDIX B

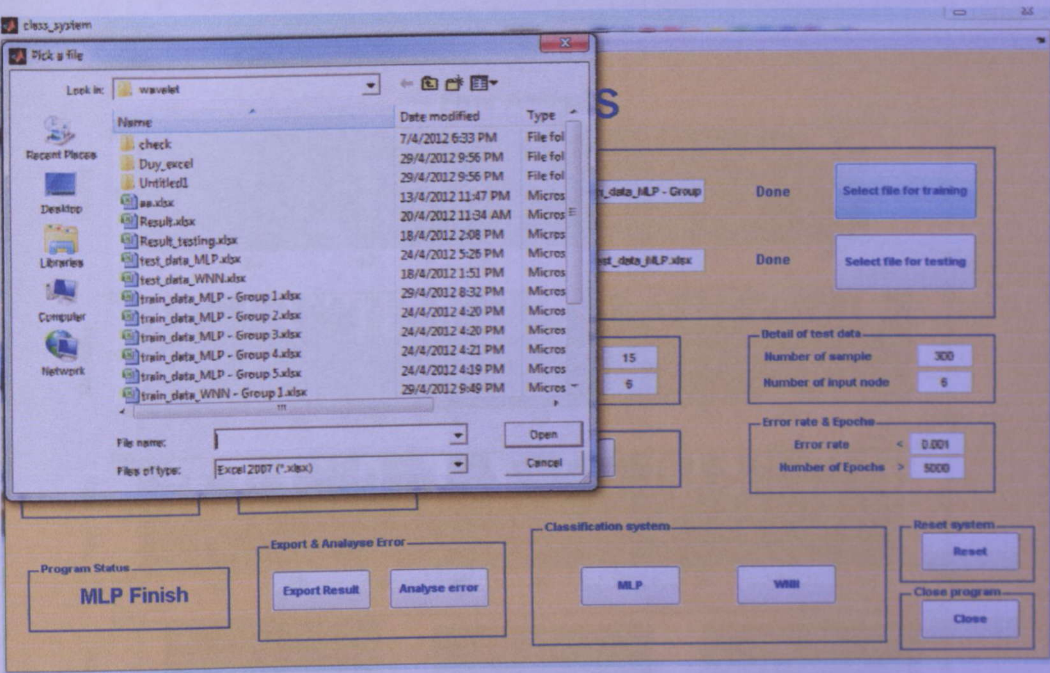
E-CLASS SOFTWARE WITH USER INTERFACE



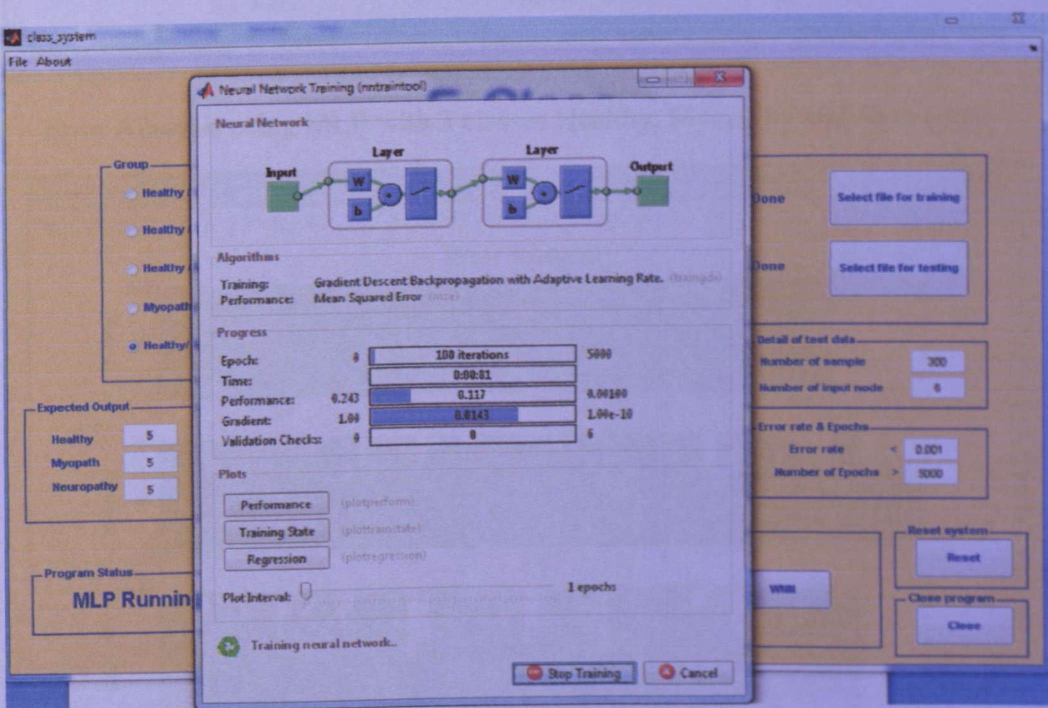
E-class introduction page



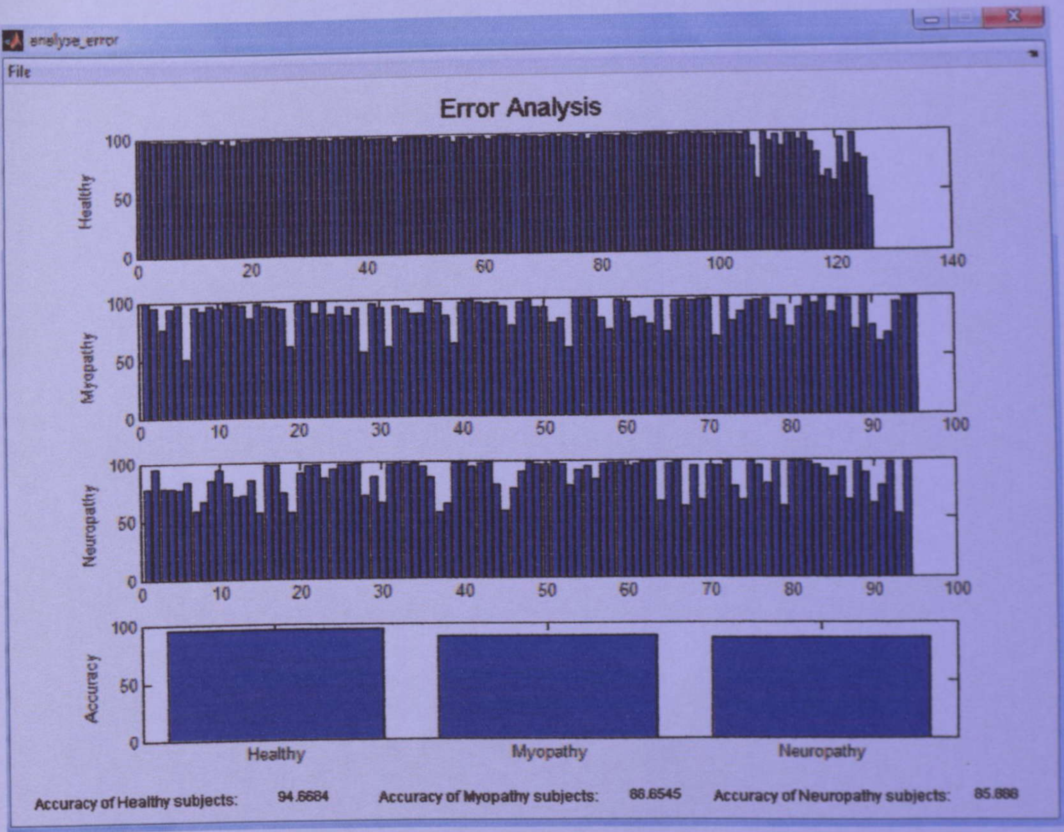
E-Class main page



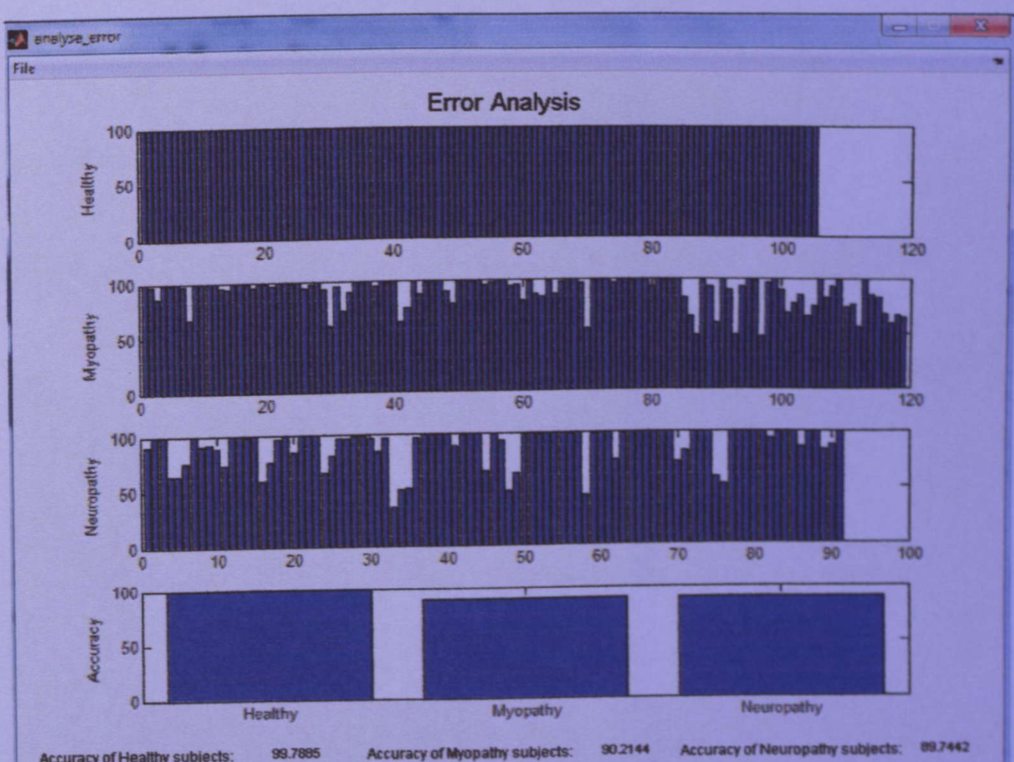
Select data for training and testing



Program Training using MLP system



Error Analysis using MLP with 3 classes Healthy, Myopathy and Neuropathy



Error Analysis using WNN with 3 classes Healthy, Myopathy and Neuropathy