

## BORANG PENGESAHAN STATUS TESIS

JUDUL: AN IMPLEMENTATION OF FCM-RBF TECHNIQUE FOR ELBOW JOINT FLEXION USING SINGLE CHANNEL SURFACE ELECTROMYOGRAPHY (SEMG) SIGNALS

SESI PENGAJIAN: 2013/2014

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AN IMPLEMENTATION OF FCM-RBF TECHNIQUE FOR ELBOW JOINT  
FLEXION USING SINGLE CHANNEL SURFACE ELECTROMYOGRAPHY  
(SEMG) SIGNALS

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This report is submitted in partial fulfilment of the requirements for the  
Bachelor of Computer Science (Artificial Intelligence)


FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY  
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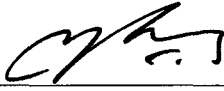
2014

## DECLARATION

I hereby declare that this project report entitled  
**AN IMPLEMENTATION OF FCM-RBF TECHNIQUE FOR ELBOW JOINT  
FLEXION USING SINGLE CHANNEL SURFACE ELECTROMYOGRAPHY  
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is written by me and is my own effort and that no part has been plagiarized  
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(DR. CHOO YUN HUOY)

## DEDICATION

To my beloved parents, Mr. Soh Hai Lun and Mrs. Tee Poh Geok, my love and support are my greatest inspiration upon accomplish this project.

To my dearest supervisor, Dr. Choo Yun Huoy for being responsible, receptive and always by my side to encourage and motivate me.

To my dear friends, especially Yap Tian Bee, Liew Siaw Hong, Shidah and Loke Kien Yeow for your support and motivation throughout this project.

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## ABSTRACT

Muscle force to every joint position movement is very important. Human movement involves the activation and control of muscle force. Therefore, EMG evaluation had been recorded from movement activity produced by skeletal muscles to predict the muscle force from human motion. This study mainly aim to predict the muscle force during elbow joint flexion using single channel surface Electromyography (sEMG) signals. However, the challenge of using the single channel sEMG signals was it facing the problem of accuracy in prediction although it is cheaper than using multi-channel signals. Therefore, a good prediction method had been carried out using the technique of Radial Basis Function (RBF) Network hybrid with technique of Fuzzy C-means (FCM). Most of the researched were used RBF and Multilayer Perceptron (MLP) technique only to predict the muscle force. Anyway, the technique of RBF in prediction is better than MLP. To improve the performance of RBF, FCM was used to find the cluster centres and used in hidden layer of RBF network so that it can improve the performance during the prediction of muscle force. The result shown that the FCM did the clustering according to the pre-set category, so the hidden node in the hidden layer had been cluster in the different node and it affect the high Root Mean Square Error (RMSE) values produced. MLP using nntoolbox also had been carried out in this research to compare the RMSE results with the technique of RBF based on FCM. The result had proof that the technique of RBF based on FCM is better than MLP technique.

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## LIST OF ABBREVIATIONS

EMG	-	Electromyography
sEMG	-	Surface Electromyography
AI	-	Artificial Intelligence
RMSE	-	Root Mean Square Error
RBF	-	Radial Basis Function
FCM	-	Fuzzy C-means
FCM-RBF	-	Radial Basis Function based on Fuzzy C-means
NN	-	Neural Network
ANFIS	-	Adaptive Neuro Fuzzy Inference System
MLP	-	Multilayer Perceptron
SVM	-	Support Vector Machine
MAE	-	Mean Absolute Error

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# CHAPTER I

## INTRODUCTION

### 1.1 Project Background

The human movement involves the activation and control of muscle force. In human body, the static and dynamic balance can be represented by articulated segments. Movement can be arising from internal force in the body, acting outside the joint axis and causing the external force to the body. The muscle force to joint position movement is vitally important for every muscle activity and also the coordination of muscle activities during functional movement. However, the generation of force by a muscle is associate with electrical signal closely by placing the electrode to the surface of the human skin to detect the electricity activity and the waveform show on screen is called electromyogram and it called as Electromyography (EMG).

Electromyography (EMG) is a technique to test and record the bio-signal activity produce by human or animal skeletal muscles and the nerves cell which control them (Aik & Zainuddin 2008); (Oludolapo 2012); (Kuriki & Azevedo n.d.). EMG uses a tiny device called electrodes to transmit or detect bio-electrical signals. The devices translate electrical signal which cause the muscles to contract into graph, sound or numerical value that a specialist interprets. The signals can be analyzed to detect activation level, abnormalities, or recruitment order or to analyse the human or animal motion. In the result, EMG signals is often used as control signals in rehabilitation robotic systems and virtual models which mimic the human upper or lower limb (Marcos et al. 2008). The analysis of EMG signals has been largely used

to detect human physical movement intent, control various human-machine interfaces, diagnose neuromuscular disease, and model neuromusculoskeletal system. The association between EMG and human muscle forces is the basis for many application of EMG to allow inferences according to various aspects of muscle physiology. However, it is impossible to measure muscle force directly using EMG bio-signal.

EMG signals are hard to recreate because these may influenced by some source of noise, such as from the quality of the EMG amplifier, environment may overlay and the quality of the given detection condition (Oludolapo 2012).

Since the accuracy of signal channel prediction will be affect by variety source of noise, an uncertainty and hybridization method called adaptive neuro fuzzy inference system (ANFIS) common and popular method to predict the muscle force of human arm among the methods of neural-fuzzy hybridization because the accuracy of prediction is high (Crd 1997). Thus, ANFIS is a kind of neural network structure based on Takagi-Sugeno fuzzy inference system which it is capable of learning to approximate any non-linear function (Petković et al. 2013). ANFIS is mostly used for the two or above number of channels when doing prediction method so that the experiment result provide a vast amount of useful information and it avoid noise and also increase the accuracy for the prediction (Khezri et al. 2007). If signal within 16 channels, it needs the technique of Fuzzy C-mean (FCM) to select certain wavelet features that maximized the class separability (Tang et al. 2012). Therefore, FCM is suitable for single or multi-channel because classify the signal data when the data is complicated or contain many of channels. Based on the Sugeno type fuzzy rule base, when come to hybridization with radial basis function (RBF) technique neural network, it allow the system to learn from the training data (Phinyomark et al. 2012b).

Therefore, the hybrid method between FCM and Radial Basis Function (RBF) was proposed. Fuzzy system used, FCM will be choosing because it selects those wavelet features that maximized the class separately(Awad et al. 2009). RBF will be used in neural network due to RBF is a single hidden layer and because it allowing the system to learn from the training data.



## 1.2 Problem statements

Muscle force plays an important role to move our limbs. These forces must be predicted with indirect techniques, as direct measurements are neither generally possible nor practical. EMG is always applied to estimate muscle activation, force and moments from the signal's amplitude. However, they are always towards using multi-channel EMG signal data (Tang et al. 2012). Most studies of multifunctional myoelectric control system (MCSs) have used multi-channel to get more information to increase the classification and estimation performance. This is because the ability of EMG to classify movements is based on information obtained from different muscle positions and information contained in feature of signal (Staudenmann et al. 2006). The use of single channel EMG signal is benefit also for estimate and classify low-level muscle activation because it does has the further advantage of lower cost and lower computational complexity. But, the use single channel EMG signal in estimation of force, the challenge of using single channel is the information is very limited, and identifying of EMG signal difficult in classification due to no single muscle has a major correspondent to different kind of movement. The signals derived from one of a selected group of muscles will contain both high-level and low-level EMG signals. Therefore, the ability of the feature extraction methods needed to solve the problem of loss of signal detection sources (Phinyomark et al. 2012a; Phinyomark et al. 2012b).

## 1.3 Objectives

This project embarks on the following objectives:

- i. To identify signal features for single channel force prediction using sEMG signal.
- ii. To propose the FCM-RBF hybrid method for modeling muscle force in human arm using single channel EMG signal.
- iii. To compare the proposed method with Multilayer Perceptron (MLP) prediction method.

## 1.4 Scope

The prediction will be focus on the single channel, which is bicep to control the movement of elbow joint. The use of single channel and multi-channel of muscle signal will totally affect the accuracy of the prediction of the data. So a prediction method will be use proposed to solve the problem of prediction.

The weight of the object is constant when the hand lifts up, which separate into 4 type of weight: 0 kg, 2kg, 4 kg and 6kg. While, the degree also will be fix which the subject will bent up at 45°, 90° and 145°. For each experiment, 11 seconds will be fix. For example, when a people test with lift up 2kg object until 45°, the will not move for initial 2 seconds, and it will spend another 2min to lift up until 45°, then remain constant at 45° at the following 4 seconds so that we can observe the changes on the graph. Each experiment will be repeat until 10 time iteration to increase the accuracy of data. The optimum force needed will be predicted when the hand bent up.

The sample will be test for 10 people. 3 basic method of feature extraction will be carrying out, which are time domain analysis method, frequency domain analysis method and time-frequency analysis method. Hence, muscle v3 sensor will be chosen to reduce the noise data when doing the experiment.

## 1.5 Project Significance

The project significance for this project is to propose muscle force prediction of human arm using EMG signals. Apart from that, the combination of FCM and RBF are chosen and implementation in Matlab R2013a in order to do clustering and predicting sEMG signal for muscle force estimation.

## 1.6 Conclusion

As a conclusion, FCM-RBF is proposed to predict sEMG data based on the single channel of EMG signal. It is believe that with the hybridization of FCM and RBF can produce a better result compared to the others in term of accuracy prediction. At the end of this project, the expected output is to get a set of coding for prediction of EMG signals and a best predict method will be determined in order to predict EMG signals prediction result for muscle force of human arm.

## CHAPTER II

### LITERATURE REVIEW

#### 2.1 Introduction

In this chapter, a literature review of muscle force prediction models with single channel of EMG signal and a literature review on a various type of artificial intelligence techniques to cluster and predict the EMG signals have been studied. It is because artificial intelligence techniques are believed to get better result in accuracy and use less time to cluster and predict the EMG signals. This chapter contain 8 sections. The first section presents the introduction of this chapter. Second session present the importance of EMG signals in muscle force prediction and session three present the important of muscle force. The following session will discussed about all the existing techniques in estimate muscle force. All the existing using artificial will be compare so that the best technique will be apply or continue to do new hybridization method among two high accuracy methods. The fifth session will describe the parameter measurement. And, the sixth session will descript about the EMG signal dataset. At last, a summary or conclusion will be made to give the reason and choose a best technique in predict force.

#### 2.2 Muscle Force Estimation

Skeletal muscle responsible generates force for movement (Kuriki & Azevedo n.d.). No matter what motion, when we want to move any part of our body,

we apply force. When the muscle is stimulated, they contract will causing the muscle become shorter, the force applied is therefore a tension (Rosen et al. 1999). The force generated by muscle action and the most basic type of force is weight, which is the product of mass and acceleration. To overcome the inertia of an object, we have to apply a force so that the force will exceed the weight (Bodlne-fowler 1993). Muscle force from our body is needed to estimate due to different load when push or pull an object (Dasanayake et al. 2013). Muscle force is important so that can control the movement according to the weight (Biscarini et al. 2003). Information of muscle force is used to control the physical movement of human or animals. Within this movement control, one of the movement of robot design is it can be used to design robot arm system so that we able to control it when the system get the information of object to bent up and lift down the arm (C. et al. 2012); (Pujana-Arrese et al. 2010). Movement can arise from internal forces acting outside the joint axis, causing force external to the body. When the muscles begin to develop force, the tendon start to carry load or weight as well and transfers force from muscle to the bone (Staudenmann et al. 2006).

However, muscle force cannot easily measure directly because it is highly nonlinear system. It must be assessed, calculated or modeled. The use of force sensors for interface normal operation is often inconvenient and not practical for direct measurement of forces (Franz & Mallot 2000). Other than that, the high cost of commercially available force sensor makes the alternate method of force prediction from a group of muscles using electromyography (EMG) signals (Rosen et al. 1999). EMG signal is directly proportional to muscle strength for isometric and isotonic contraction with constant speed. In most cases, EMG rises non-linear with increasing force of muscle contraction. For isometric contraction, angle does not vary in the isometric case, the relationship between EMG and force must be different for each angle, and depends on the level of strength and speed of contraction (Choi & Hong 2010). While for isotonic contraction, a movement implies change in joint angle over which the muscle acts.

## 2.3 Electromyography (EMG)

Electromyography (EMG) is proposed so that to measure muscle force using EMG signals. EMG signals are the bio-signals collected on human skeletal muscle (Franz & Mallot 2000). The bio-signal appeared when muscle membrane movement or excitation allowed the muscle to go through the process of depolarisation and repolarisation. This process was called action potential. The muscle membrane potential will be produced when sodium ( $\text{Na}^+$ ) influx exceeded a certain threshold voltage and will cause a depolarisation process occur (Sidek et al. 2012). This action potential for raw electromyography (EMG) signal normally will increase from  $-80\text{mV}$  to  $30\text{mV}$  as shown in Figure 2.1.

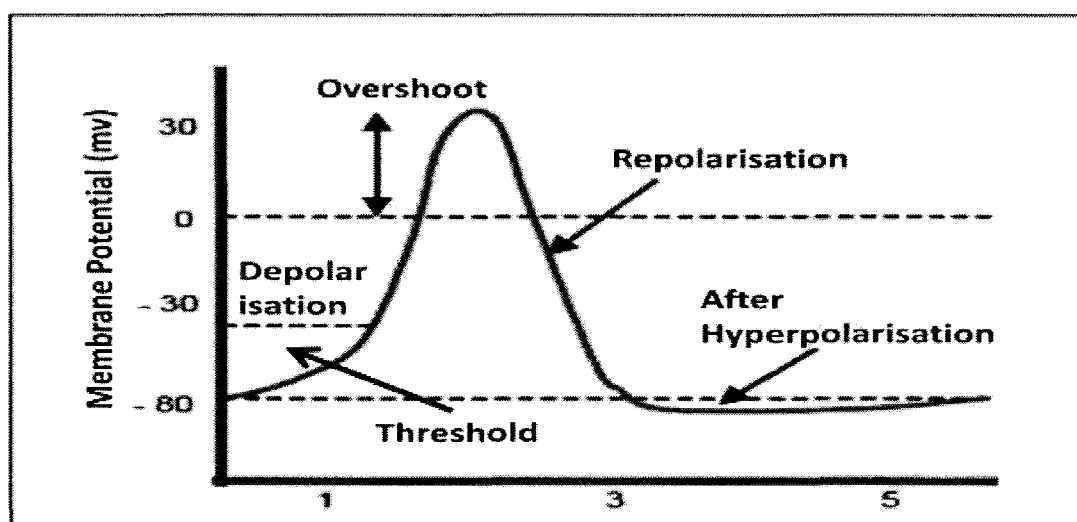


Figure 2.1 : The Action Potential of EMG signal (Gheab & Saleem 2008)

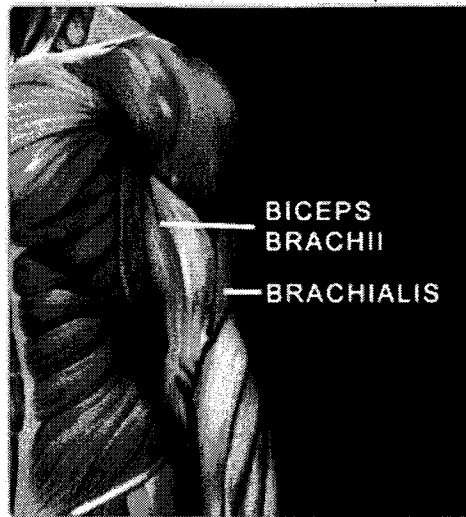
For surface EMG (sEMG) signals, it is hard to apply as a main EMG signal because of the noise and several factors that were present in the surrounding of the raw EMG signal, The inner and external environment will affect the changes of EMG signal, the example of inner affect are the temperature of the skin, the physiological changes and thickness varies with electrical conductivity, while the external noise also will caused the EMG signal to be distorted (Antfolk et al. 2010). The prevention method of this external noise is to run EMG experiment in a Noiseless room or compartment within using the sensor when collect the EMG signals data

which can reduce the noise until minimum so that it won't affect the accuracy of EMG (Mankar 1995).

The EMG signals can be collect by placing electrodes on the skin surface to detect underlying electrical activity and the signal will displaying the associated waveform on a computer monitor (Khushaba & Al-jumaily n.d.). EMG signals are directly proportional to muscle strength for contraction with constant speed and nonlinear motion (Oludolapo 2012); (Padmavathi 2011). Due to the relationship of EMG and muscle force is not linear and a bit of environmental changes will affect the accuracy of prediction computing method for processing and analyzing EMG signals had been proposed and applied before such as Radial Basis Function (RBF) and Multilayer Perceptron (MLP) in Neural Network, Fuzzy logic and Adaptive Neuro Fuzzy Inference System (ANFIS). The used of ANFIS is a hybridization of fuzzy logic and neural network which integrated the best features of both techniques (Crd 1997).

#### **2.4 The effect of multi-channel and single channel in EMG signals prediction**

During the prediction of EMG signals, single channel will be choosing in predict muscle force of hand arm. The single channel, biceps muscle that will be choosing in this research is biceps brachii and the position of muscle is as shown in Figure 2.2.



**Figure 2.2 : Position of Biceps Brachii**

Number of multi-channel channel and single channel has some affection on prediction. For multi-channel in EMG signals prediction, most studies of multifunctional myoelectric control system (MCSs) have employed multi-channel sensors to deal with the problem in increase the classification performance (Staudenmann et al. 2005); (Phinyomark et al. 2012b); (Sidek et al. 2012). The multichannel sensor ring is a kind of redundant sensor that provides a large amount of useful information. Between, it is enough to cover circumference of the posterior side and can record the contraction information of the muscle and also detect other redundant information. When the collecting enough information from many channel, it will improve the estimation of muscle force (Kuriki & Azevedo n.d.). While, increasing number of channel increase its complexity and take time in classify action too (Staudenmann et al. 2005); (Phinyomark et al. 2012b).

In this research, single channel will be using in estimate muscle force of EMG signals. This is bicep for single channel, it is very convenient to control human-computer interface (HCIs), but the information obtained from the muscle is limited to a single channel (Phinyomark et al. 2012a). Besides that, there is no any single channel that has a major correspond in many different kind of movement. When single channel provide the information is limited, the ability of the feature extraction method is needs to be increase to balance for the loss of signal detection sources (Phinyomark et al. 2012b) . The example of feature extraction can reduce the