Faculty of Information and Communication Technology

FCM-RBFN INTEGRATION TECHNIQUE FOR IMPROVING ISOTONIC MUSCULAR ENDURANCE LOAD PREDICTION

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FCM-RBFN INTEGRATION TECHNIQUE FOR IMPROVING ISOTONIC MUSCULAR ENDURANCE LOAD PREDICTION

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A thesis submitted in fulfilment of the requirements for the degree of Master of Science in Information and Communication Technology

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DECLARATION

I declare that this thesis entitled “FCM-RBFN Integration Technique for Improving Isotonic Muscular Endurance Load Prediction” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in the candidature of any other degree.

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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Information and Communication Technology.

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Supervisor Name	: Associate Professor Dr. Choo Yun Huoy
Date	: …………………..………………………

DEDICATION

Dedicated to:

Mama, & Ayah.

Mil & Fil

Husband, Khairul Anuar.

Aten & family, Along & family.

Dr Choo & Siaw Hong

Asmah

Thank you for all you love.

May Allah bless us.

ABSTRACT

In sports training, muscle endurance training using surface electromyography (sEMG) analysis is manually monitored by human coach. Decisions rely very much on experience. Hence, the endurance training plan for an athlete needs to be individually designed by an experienced coach. The pre-designed training plan suits the athlete fitness state in general, but not in real time. Real-time muscle fatigue monitoring and feedback helps in understanding every fitness states throughout the training to optimise muscle performance. This can be realized with muscle fatigue prediction using computational modelling. This research proposed an integrated Fuzzy C-Means and Radial Basis Function Network (FCM-RBFN) technique to model the relationship between muscle loads versus the muscle fatigue using the sEMG signals. The Fuzzy C-Means techniques aims to cluster similar sEMG signal patterns into three separate groups based on muscle strength level, to facilitate the Radial basis function network in future muscle load prediction. The scope of the research limits the non-invasive EMG acquisition to only the isotonic arm lifting task, involving four electrodes on biceps brachii and flexor carpi radialis muscles group. Three sessions of training data, each with a gap of at least three days' rest, were acquired from a group of volunteer undergraduate athletes. The research follows the experimental research methodology, including problem investigation, experimental paradigm design, signal pre-processing analysis, feature extraction, model construction, and performance validation. Due to the higher amount of motion artefact, research in isotonic muscle fatigue prediction is very much lesser than the isometric prediction. Hence, the Butterworth high-pass noise filter on isotonic muscle fatigue data were studied using three cut-off thresholds, 5 Hz, 10 Hz, and 20 Hz. The best prediction performance was achieved by the 10 Hz filter with 0.028 average mean square errors. A total of seven popular feature extraction methods, namely, the mean absolute value, the root mean square, the variance of EMG, the standard deviation, the zero crossing, the median frequency, and the mean were explored to construct the predictive feature vectors. The mean square error was used to benchmark the experimental results with the Artificial Neural Network. The experimental result shows that the proposed FCM-RBFN technique is able to predict different load intensity efficiently according to real time muscle condition against fatigue. The experimental findings suggest that a long isotonic training task induces fatigue, hence it contributes to data noise that will affect muscle load prediction in overall. Therefore, training load should be reduced on the first detection of muscle fatigue sEMG signal, in order to prolong the muscle resistance against fatigue. Future research should study on dynamic cluster number instead of the fixed cluster initialization in FCM technique. Also, the proposed model should be validated using multiple sessions in different periods of time length to further support the hypothesis of muscle endurance.

ABSTRAK

Dalam latihan sukan, latihan daya tahan otot menggunakan surface Electromyography (sEMG) *analisis yang dipantau secara manual oleh jurulatih manusia yang berpengalaman. Oleh itu, pelan latihan daya tahan untuk atlet perlu direka secara individu oleh jurulatih. Pelan latihan dirancang terlebih dahulu sesuai dengan keadaan kecergasan atlet secara umum, tetapi tidak dalam masa nyata untuk membantu dalam memahami setiap tahap kecergasan sepanjang latihan untuk mengoptimumkan prestasi otot. Ini dapat direalisasikan dengan ramalan keletihan otot menggunakan pemodelan komputasi. Kajian ini mencadangkan satu teknik* Fuzzy C-Means *dan* Radial Basis Function Network (FCM-RBFN) *untuk model hubungan antara beban otot berbanding keletihan otot menggunakan isyarat* sEMG. *Teknik* Fuzzy C-Means *bertujuan untuk mengelompokkan pola isyarat* sEMG *yang sama ke dalam tiga kumpulan berasingan berdasarkan tahap kekuatan otot, untuk memudahkan* Radial Basis Function Network *meramal beban otot. Skop penyelidikan mengehadkan kepada* EMG *yang tidak invasif dan untuk tugas mengangkat lengan isotonik, yang melibatkan empat elektroda pada kumpulan otot* biceps brachii *dan* flexor carpi radialis. *Tiga sesi data latihan, masing-masing dengan jurang rehat sekurang-kurangnya tiga hari, diperoleh daripada sekumpulan atlet siswazah sukarela. Penyelidikan ini mengikuti metodologi penyelidikan eksperimen, termasuk penyiasatan masalah, reka bentuk paradigma eksperimen, isyarat analisis pra-pemprosesan, pengekstrakan ciri, pembinaan model, dan pengesahan prestasi. Oleh kerana jumlah artefak gerakan yang lebih tinggi, penyelidikan dalam ramalan* isotonic fatigue *adalah jauh lebih rendah daripada ramalan isometrik. Oleh itu*, Butterworth high-pass noise filter *pada data keletihan otot isotonik telah dikaji menggunakan tiga* cut-off thresholds, *iaitu 5 Hz, 10 Hz, dan 20 Hz. Prestasi ramalan terbaik dicapai oleh* filter 10 Hz *dengan* average mean square errors, 0.028. *Sejumlah tujuh kaedah pengekstrakan ciri popular, iaitu*, mean absolute value, root mean square, variance of EMG, standard deviation, zero crossing, the median frequency, *dan* mean *diteliti untuk membina vektor ciri ramalan*. Mean square error *telah digunakan untuk penanda aras keputusan eksperimen dengan* Artificial Neural Network. *Hasil eksperimen menunjukkan bahawa teknik* FCM-RBFN *yang dicadangkan dapat meramalkan intensiti beban yang berbeza dengan cekap berdasarkan keadaan otot masa nyata terhadap keletihan. Penemuan eksperimen menunjukkan bahawa tugas latihan isotonik yang panjang mendorong keletihan, oleh itu ia menyumbang kepada* data noise *dan menjejaskan ramalan beban otot secara keseluruhan. Oleh itu, beban latihan perlu dikurangkan pada pengesanan pertama isyarat* sEMG *keletihan otot, untuk memanjangkan rintangan otot terhadap keletihan. Penyelidikan masa depan perlu mengkaji nombor* cluster *dinamik dan bukannya permulaan* cluster *tetap dalam teknik* FCM. *Juga, model yang dicadangkan perlu disahkan menggunakan pelbagai sesi dalam tempoh masa yang berlainan untuk menyokong hipotesis ketahanan otot.*

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TABLE OF CONTENTS

		PAGE
DECLARATION		
APPROVAL		
DEDICATION		
ABSTRACT		**i**
ABSTRAK		**ii**
ACKNOWLEDGEMENTS		**iii**
TABLE OF CONTENTS		**iv**
LIST OF TABLES		**vii**
LIST OF FIGURES		**ix**
LIST OF APPENDICES		**xii**
LIST OF ABBREVIATIONS		**xiii**
LIST OF PUBLICATIONS		**xv**
CHAPTER		
1.	**INTRODUCTION**	**1**
1.1	Overview	1
1.2	Project background	1
1.3	Problem statement	3
1.4	Research question	5
1.5	Research objective	5
1.6	Hypothesis	6
1.7	Research scope	6
1.8	Research significance	7
1.9	Expected output	9
1.10	Thesis organization	9
1.11	Summary	12
2.	**LITERATURE REVIEW**	**13**
2.1	Introduction	13
2.2	Bio-signals	14
2.3	Endurance training and fatigue in sport science	17
2.4	sEMG characteristic during isometric and isotonic muscle contraction	22
2.5	Surface electromyography signal (sEMG) on muscle analysis	24
2.6	Surface electromyography signal (sEMG) placements	27
2.7	Surface electromyography (sEMG) experimental paradigm	29
2.8	Inherent noise in raw sEMG signal and signal pre-processing for isotonic muscle task	31
2.8.1	Inherent noise in the electrode	32
2.8.2	Movement artefact	33
2.8.3	Electromagnetic noise	33
2.8.4	Cross talk	34
2.8.5	Internal noise	34
2.8.6	Inherent instability of the signal	35
2.8.7	Electrocardiography (ECG) artifacts	35
2.9	sEMG signal processing and features extraction	36
2.9.1	Time domain features	40

2.9.2 Frequency domain features 40
2.10 Predicting techniques in muscle fatigue load 42
2.11 Original Fuzzy C-Mean (FCM) 50
2.12 Radial Basis Function Network (RBFN) 50
2.13 Fuzzy C-Mean based Radial Basis Function Neural Network (FCM-RBF Neural Network) 51
2.14 Benchmark techniques 53
2.15 Performance measurement 56
2.16 Problem situation and solution concept 57
2.17 Summary 60

3. RESEARCH METHODOLOGY 61
3.1 Introduction 61
3.2 Overview of research methodology 61
3.2.1 Overall research design 62
3.2.2 Investigation component 63
3.2.3 Implementation component 64
3.3 Operational procedure 66
3.3.1 Phase 1 and 2: Data acquisition and data processing 68
3.3.2 Phase 3 and 4: Data clustering and predicting (FCM-RBFN technique) 71
3.3.3 Phase 5: Performance measurement and validation test 72
3.4 Summary 75

4. SURFACE EMG EXPERIMENT DESIGN AND DATA ACQUISITION 76
4.1 Introduction 76
4.2 Participants 76
4.3 Hardware and software 78
4.4 Electrode types and placement 80
4.5 Experiment location 82
4.6 Experiment setup 83
4.7 Signal processing procedure 87
4.8 Summary 88

5. INTEGRATION FUZZY C-MEAN BASED RADIAL BASIS FUNCTION NETWORK (FCM-RBFN) TECHNIQUE 89
5.1 Introduction 89
5.2 Operational research design 89
5.3 Proposed integration Fuzzy C-Mean based Radial Basis Function Network 92
5.3.1 Proposed Fuzzy C-Mean 94
5.3.2 Proposed Radial Basis Function Network 96
5.3.3 Selection of Radial Basis Function Network Model 99
5.4 Summary 101

6. EXPERIMENTAL RESULTS AND ANALYSIS 102
6.1 Introduction 102
6.2 Butterworth high pass filter cut-off threshold analysis using integration FCM-RBFN 103

6.3 Predicted load analysis 107
6.4 Comparison between integration FCM-RBFN and ANN technique 112
6.5 Comparison between 2 group datasets using integration FCM-RBFN and ANN technique 116
6.6 Comparison between predicted load and actual load using integration FCM-RBFN and ANN technique 120
6.7 Discussion 125
6.8 Summary 127

7. CONCLUSION AND FUTURE WORK RECOMMENDATION 129
7.1 Introduction 129
7.2 Summary and discussion 129
7.3 Threats of validity 130
7.4 Contribution 131
7.5 Future work and recommendation 132
7.6 Summary 133

REFERENCES 134
APPENDICES 154

LIST OF TABLES

TABLE	TITLE	PAGE
2.1	sEMG signal noise type	36
2.2	Mathematical representation of widely used sEMG feature extraction methods	41
2.3	Summary of literature review of predicting technique in muscle fatigue load	49
3.1	Summary of investigation component	64
3.2	Summary of implementation component	65
3.3	Simple square integral (SSI) and waveform length (WL) equation	69
3.4	The criteria for selection of the subject	70
3.5	Different outcomes of Trial/Class 2 and 3 for Artificial Neural Network (ANN) and integration FCM-RBFN	73
4.1	The subject details	77
4.2	The tasks for the experiment	85
5.1	sEMG data for a subject with even presentative predicted class	99
5.2	sEMG data for a subject with odd presentative predicted class	100
6.1	Prediction performance of Butterworth high pass filter with cut-off threshold at different frequency ranges	104
6.2	Normality test result for prediction performance of Butterworth high pass filter with cut-off threshold at different frequency ranges	104

6.3	Validation test of prediction performance for 5, 10, and 20 Hz cut-off threshold filtering	105
6.4	Prediction performance of integration FCM-RBFN and ANN technique for Class 1	114
6.5	Normality test result for prediction performance at Trials/Class 1	115
6.6	Validation test on MSE between integration FCM-RBFN and ANN technique for Class 1	115
6.7	Summary of prediction performance of integration FCM-RBFN and ANN technique for Class 2 and Class 3	117
6.8	Normality test result for prediction performance at Trials/Class 2	118
6.9	Validation test on average MSE value between integration FCM-RBFN and ANN techniques for Class 2 and Class 3	119

LIST OF FIGURES

FIGURE	TITLE	PAGE
2.1	Literature review on purpose, technique, type and feature extraction under bio-signal in human	15
2.2	Literature review on sport conditioning using surface EMG in isotonic muscle contraction	16
2.3	Types of muscle contraction (Boundless.com, 2018)	23
2.4	The action potential of EMG signal (Ashcroft, 2014)	25
2.5	The biceps brachii and flexor carpi radialis muscles position (Sharawardi et al., 2014)	29
2.6	The present of noise inside the raw EMG signal	32
2.7	Summarised of past studies of statistical based feature extraction method for sEMG signal	39
2.8	Pseudo code for Fuzzy C-Means (Amin et al., 2005)	45
2.9	FCM-RBFN flowchart (Woo et al., 2008)	53
2.10	Artificial Neurons model	54
3.1	Overall research design	62
3.2	Research methodology	67
4.1	Trigno™ wireless 4-channel sensor (A), size of Trigno™ wireless 4-channel sensor (B) and Trigno™ Base Station (C) (TrignoTM Wireless EMG, 2018)	78

4.2	Block diagram of the myoelectric interface system	79
4.3	The correct position to lift the dumbbell	81
4.4	Muscles type on human hand	82
4.5	The sEMG data collection setup for isotonic muscle contractions	83
4.6	The experiment design process	84
4.7	The endurance training schedule	84
5.1	Operational research design of integration of FCM-RBFN technique	90
5.2	Integration FCM-RBFN flowchart	93
5.3	Network RBFN net stimulate in testing phase algorithm	95
5.4	Architecture of RBFN	98
5.5	RBFN modelling algorithm	99
5.6	Selection of RBFN model	100
6.1	Average prediction MSE performance of Butterworth high pass filter with cut-off threshold at different frequency ranges	106
6.2	Normal raw sEMG signal of right biceps decreasing muscle activation	108
6.3	Decreasing predicted load of the sEMG signal	108
6.4	Raw sEMG signal of right biceps with increasing muscle activation	109
6.5	Increasing predicted load of the sEMG signal	110
6.6	Raw sEMG signal of right biceps with difference muscle activation	111
6.7	Predicted load of the sEMG signal, (a) and (b)	112
6.8	Prediction performance of integration FCM-RBFN and ANN techniques	113
6.9	Hypothesis of finding total ‘true’ and total ‘might true’	116
6.10	The standard deviation and mean of predicted and actual/original load and fatigue level by FCM-RBFN vs ANN across 3 classes	121

6.11	Comparison of Class 1 between predicted load and original load for integration FCM-RBFN technique	122
6.12	Comparison of Class 2 between predicted load and original load for integration FCM-RBFN technique	122
6.13	Comparison of Class 3 between predicted load and original load for integration FCM-RBFN technique	123
6.14	Comparison of Class 1 between predicted load and original load for ANN	123
6.15	Comparison of Class 2 between predicted load and original load for ANN	124
6.16	Comparison of Class 3 between predicted load and original load for ANN	125

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	Source code	154
B	Sample of dataset and result of FCM-RBFN	160
C	Sample of dataset and result of ANN	162
D	Lab attachment request for data collection	164
E	Consent form (participant information sheets)	167
F	Consent form (participant consent form)	171

LIST OF ABBREVIATIONS

1RM	-	One repetition max
AI	-	Artificial Intelligence
ANFIS	-	Adaptive Neuro Fuzzy Inference System
ANN	-	Artificial Neural Network
AUC	-	Area under the curve
BMI	-	Body Mass Index
c	-	Cluster centre
cm	-	Centimeter
ECG	-	Electrocardiogram
EEG	-	Electroencephalogram
EMG	-	Electromyography
EOG	-	Electroretinogram
FCM	-	Fuzzy C-Mean
FCM-RBFN	-	Fuzzy C-Mean based Radial Basis Function Neural Network
FFT	-	Fourier transformation
Hz	-	Hertz
kg	-	Kilogram
LB	-	Left Biceps Brachii muscle
LF	-	Left Flexor Carpi Radialus muscle
MAV	-	Mean Absolute Value

MDF	-	Median Frequency
MF	-	Mean Frequency
MLP	-	Multilayer Perceptron
MMG	-	Mechanomyogram
MSE	-	Mean square error
PSO	-	Particle Swarm Optimization
PURELIN	-	Linear Transfer Function
RB	-	Right Biceps Brachii muscle
RBF	-	Radial Basis Function
RF	-	Right Flexor Carpi Radialus muscle
RMS	-	Root Mean Square
ROC	-	Receiver operating characteristic
sEMG	-	Surface Electromyography
STD	-	Standard deviation
SVM	-	Support Vector Machine
TANSIG	-	Hyperbolic Tangent Sigmoid Transfer
TRAINLM	-	Levenberg-Marquardt algorithm
VAR	-	Variance of EMG
ZC	-	Zero Crossing

LIST OF PUBLICATIONS

Sharawardi, N.S.A., and Choo, Y., 2018. Isotonic Muscle Fatigue Prediction for Sport Training. *Hybrid Intelligent Systems*, 3 (SoCPaR 2016), pp.232–241.

Sharawardi, N.S.A., Choo, Y., Chong, S., and Mohamad, N.I., 2018a. Integration FCM-RBFN with Butterworth Noise Filteration Frequency for Isotonic Muscle Fatigue Analysis. *International Journal of Computer Information Systems and Industrial Management Applications*, 10, pp.47–56.

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Sharawardi, N.S.A., Choo, Y., Chong, S., Muda, A.K., and Goh, O.S., 2014. In: *4th World Congress on Information and Communication Technologies (WICT 2014)*, pp.320–325.

CHAPTER 1

INTRODUCTION

1.1 Overview

Chapter 1 briefly describe the overall focus of the study, including the background of study, problem statement, research questions, research objectives, research scope, research significance and the contribution of the research. At the end of this chapter, a summary is provided to describe the organization of the chapters in this thesis.

1.2 Project background

Muscle endurance training serves the purpose of building up human muscles strength to the optimum level. This physical exercise is used in physiotherapy and rehabilitation for restoring the condition of injured muscle to regain its' strength. It is also commonly used in sport science during muscle building workout. Muscle endurance training involves stimulating the contraction and relaxation in targeted muscles to build strength against resistance. Muscle contraction against resistance in which the length of the muscle remains the same is called isometric contraction. In opposite, isotonic contraction is the length of the muscle changes. Various loads are used as resistance in both isometric and isotonic endurance training to stimulate the body muscles for a predetermined time length to make sure the targeted muscles are properly trained up. Muscle endurance training will only achieve the best results when the targeted muscles are stimulated optimally. Light training will definite not achieving the training objective. However, overstressing the muscles will also cause muscle fatigue and injury. To achieve the best outcome, a trainer usually needs to study and prepare a training programme according to individual body fitness state.

The success stories in biomedical technologies have driven the effort of health status monitoring using various biomedical sensors. The electromyography (EMG) signals analysis is one of the basic methods in checking the muscle activities in the sport training programs. Continuous monitoring on muscle training performance has proven promising results in assisting the trainer to design and adjust the training program to suit individual trainee's needs. This promising approach relies heavily on the computational intelligent algorithms to make smart suggestion based on trainee's muscle states. However, most of the current muscle endurance training applications are partially intelligent. They are able to recognise different muscle states based on EMG signals, but very few are able to give good recommendation to alter the training programme at real time. Thus, human intervention is still needed in regulating the training programme by observing the EMG signals changes. Hence, a fulltime coach is required for each trainee to achieve real personalised sport training.

On the other hand, various efforts have been researched to increase the automation of personalised sport training towards the paradigm of personalised self-monitoring. This includes the invention of more accurate data acquisition procedures (Gini et al., 2012; Samarawickrama et al., 2018) lightweight wearable sensors (Sharma et al., 2016; Majumder et al., 2018) intelligent monitoring models (Xi et al., 2018) robust interfacing (Kim et al., 2018; Phinyomark et al., 2018) higher level of analytics on monitoring results (Christopher et al., 2018) and many more. Many of the research work are to model the dynamic muscle states and to provide the simple yet meaningful solutions. Some higher level analytical applications aim to prescribe suitable EMG biofeedback to the trainee through machine learning experiment (Merletti and Parker, 2004).

Computational modelling is broadly utilized in different human related issues understanding, for example, in physiotherapy, rehabilitation programme or even in sport training. In muscle endurance training, variable-load intensity model is usually suggested either to improve the muscle strength or for rehabilitation purposes (Nazmi et al., 2016). Variable-load solution requires close monitoring by trainer onto its trainee. Limitation in expert availability hinders the realisation of personalised sport training. Fuzzy C-Means (FCM) technique has been long proven good in surface electromyography (sEMG) muscle fatigue prediction due to its simple network structure and processing speed. FCM offers good adaptive strength but the cluster number remains predefined by expert either through thresholds or fixed cluster number methods. Initialized cluster number is important in variable-load intensity modelling by aligning muscle force, endurance and load intensity to individual physical status. Thus, a prediction technique based on short-term historical data is crucial in predicting the nonlinear intensity needs for different types of sport training program.

1.3 Problem statement

To date, computational models are focusing on the isometric muscle contraction instead of isotonic muscle contraction (James et al., 2018). Movement noise in isotonic contraction increases the challenges of computation modelling significantly. Since many sport training sessions involve isotonic muscle strength drill, modelling the isotonic muscle endurance is essential in encouraging personalised sport training. Monitoring muscle contraction using sEMG is common but vulnerable to data noise influence. Extracting good features are proven beneficial in various biomedical classification tasks (Phinyomark et al., 2018). Likewise, similar effort can be done to identify features which are immune to movement and environmental noises for isotonic sEMG muscle signals modelling. The initiative of variable load intensity prediction was leverage on modelling human expert knowledge (Reaz et al., 2006; Leu, 2016). The advancement of biomedical applications enables computational modelling through historical data to overcome the major shortcomings of expert system. However, there is only limited report from literature on designing the dynamic biofeedback approach for isotonic muscle prediction. Almost all of them are focusing on predicting muscle fatigue instead of muscle endurance (Rostami et al., 2018; Wang et al., 2018).

The frequency and time domains are the features that be used by past studies to predict the muscle fatigue. However, before extracted the raw data, the best noise filtering will be determined. A noise filter is designed to attenuate the specific ranges of frequencies while allowing other informative and meaningful data to pass. There are several types of the frequency spectrum of a signal filters such as low pass filter, high-pass filter, band pass filter and band stop filter and all of them need a specific cut-off frequency threshold during implementation. The movement artifact is the most critical noise in dynamic task and fundamentally important issue since noise filtration will directly affect the quality of data feeding into the learning model. A recommended filter method and its cut off threshold is needed especially for modelling isotonic muscle task.

The most common method used by many sport science coaches is still the 1RM prediction formula, which lacks of approximation strength to produce continuous prediction. To the knowledge of this study, it is yet to be found any solid conclusion on trustworthy computational modelling approach for muscle endurance modelling. Therefore, proposition on reliable and consistent modelling approach and techniques are essential to boost the computational personalised isotonic muscle endurance initiative.

1.4 Research question

The primary research question for this study is "how can the variable-load intensity model enhance the muscle endurance against fatigue?" Derivative questions are as follows:

1. How to quantify muscle resistance and muscle fatigue in repetitive concentric contractions or also called isotonic contractions at different intensity levels?
2. How to produce the good feature vectors with the good feature extraction methods for endurance training during isotonic task and muscle fatigue analysis using surface electromyography signals?
3. How to capture dynamic biofeedback for weight's load prediction in integration FCM-RBFN technique?
4. How to design the variable-load intensity model based on integration FCM-RBFN technique for muscle endurance against fatigue?

1.5 Research objective

The essential objective of this exploration is to propose an upgraded variable-load intensity model based on sEMG biofeedback using the Fuzzy C-Mean based Radial Basis Function Network (FCM-RBFN) technique against muscle fatigue for isotonic muscle endurance training. The derivatives of the objective are as follows:

1. To propose the noise filtering threshold for isotonic sEMG signals cleaning.
2. To construct an integrated FCM-RBFN integration technique for muscle load prediction.
3. To evaluate the proposed FCM-RBFN integration technique for muscle load prediction.

1.6 Hypothesis

The hypotheses of this research are as follow:

1. The proposed noise filtering threshold is able to improve the isotonic sEMG signals for muscle endurance modelling.
2. The proposed feature vectors are able to quantify muscle fatigue in isotonic muscle endurance training.
3. FCM-RBFN technique is able to accommodate dynamic changes from biofeedback through sEMG signals.

1.7 Research scope

The bio-signal is selected as a main focus in this study. This is because bio-signal is widely used mainly in the clinical application, rehabilitation and even in sport training program. There are two type of method for capturing the muscle activity, which are EMG and sEMG. In this research, we are focusing the weak sEMG signal whereby is an electrical potential recorded by electrodes from above the skin. In additional, the electrodes are safe to be used. This experiment procedure uses the upper part of the body because the load weight setting and electrodes placing are easy to manage. In addition, the use of oxygen mask is for monitoring the current breathing condition of the participant during the experiment to avoid lack of the oxygen.

The experiment design has been done using Delsys Trigno sEMG wireless electrode. This modelling can handle sEMG isotonic muscle signal with the different physical of the subjects and load align with the current muscle activation signal input. This integration FCM-RBFN will be compiled in MATLAB R2013a. In addition, the integration FCM-RBFN technique is for variable load intensity modelling in personalized sport training. The wireless electrodes are easy to be used due to the high movement that involves during experiment.

In this research, the main direction is to measuring the endurance of the muscle and to measuring the load and time that will correspond to the endurance muscle condition of a person. But due to the short time of study, we managed to measure the load of weight that is predicted from the isotonic sEMG muscle feedback signal that will lead to the endurance muscle. The endurance measuring with time will be in the further study due to the effectiveness of muscle endurance in a person need to be observed with more time with different period, test, and scale up the endurances scoring. Furthermore, isotonic contraction muscle contraction involves the concentric and eccentric contractions. Therefore, isotonic contraction is focused in this research.

The study will explore and validate a set of feature extraction methods proposed in the literature studies, namely the Mean Absolute Value (MAV), Root Mean Square (RMS), Variance of EMG (VAR), Standard deviation (STD), Zero Crossing (ZC), Median Frequency (MDF) and Mean Frequency (MF) features for isotonic. The seven features then will be classified by integration FCM-RBFN technique. The integration FCM-RBFN is been choose because due to the suitability to be used in real-time sEMG recognition system and the ability with low computational time.

1.8 Research significance

The significance of this research lies in the cross-fertilization in three main disciplines, such as the sport science domain knowledge, the signal processing engineering, and the intelligent computational modelling. All these three domains are identified with one another so as to fulfil the goals of this study. In the sport domain, the condition of the muscle contraction is one of the important part that need to be trained with a proper way in order to observe the athlete muscle condition for archives their muscle endurance and resistance level. There are many sports that stimulate the isotonic contraction such as lifting weight, badminton, and taekwondo. However, the sEMG signal that been capture from the isotonic muscle contraction are noisier than isometric contraction due to high movement artefact. Therefore, the improved proposed technique will enhance the performance in order to achieve the objectives.

Continually with the above statement, this research is expected to propose a feature vectors set using suitable features extraction methods to quantify the muscle endurance in isotonic sport training. However, the proper signal processing such as filtering the noise in sEMG signal before extracting the features are need to be consider. The proper filtering will enhance the noisy signal and will help in the proposed technique to enhance the performance in order to achieve the objectives.

In another side, to propose an integrated Fuzzy C-Mean based Radial Basis Function Network (FCM-RBFN) for the personalized isotonic muscle load prediction. The proposed model can foresee the lifting load by analysing the muscle fatigue states acquired through sEMG signals during isotonic training task. The proposed FCM-RBFN technique performs successfully in predicting the load, and is able to align with the current muscle feedback signal of a subject.

The proposed integration of FCM-RBFN technique is a combination of classification and prediction modelling. As in Chapter 2 later, an FCM technique is a simplest classification technique with fast computational performance. The main purpose using the FCM modelling, which make it differ with other techniques, is it can personalize classification the fatigue level state due to each person or athlete will have varied current muscle state condition. In addition, FCM modelling trained with sEMG isotonic muscle, varied type of fatigue state and different gender of participant resulting in classifying personalized fatigue level; fatigue, moderate fatigue or normal.

Next, the RBFN techniques is a simplest prediction technique and also with fast computational performance same as FCM technique. The differences of improved RFBN modelling with another technique is that it can predict load intensity from the continuously feedback of current personalized isotonic muscle condition of a person. As widely known that sEMG signal of isotonic muscle contraction has highly movement artefact which is highly noise than isometric contraction.

1.9 Expected output

This study is to propose an integrated Fuzzy C-Mean based Radial Basis Function Network (FCM-RBFN) for the personalized isotonic muscle endurance training. The proposed model is able to predict the work out load by analysing the muscle fatigue states acquired through sEMG signals during isotonic training task. The proposed FCM-RBFN technique performs successfully in predicting the next load, and is able to align with the current muscle activation of a subject. In addition, this research is expected to propose a feature vectors set using suitable features extraction methods to quantify the muscle endurance in isotonic sport training.

1.10 Thesis organization

This thesis consists of 7 chapters. The brief outlines of each chapter are described as follows:

Introduction of this research are been explain in Chapter 1. This chapter picture the general concept of the overall research. This chapter explain clearly the problem statement and research questions. In addition, the research objectives, scopes, contribution significance and expected output are stated in this chapter.

Next, in Chapter 2 is the literature review of the previous studies in sEMG signal method, signal processing and features studies, soft computing techniques especially in sport domain and related to it. This section starts with the literature review on the bio signal especially in surface EMG signal. The literature review continue with endurance training and fatigue in sport science, sEMG on muscle analysis, sEMG placements, and sEMG experimental paradigm. The different types of noise that can inherent into the raw sEMG signal and the signal pre-processing for isotonic muscle task are also been study in this chapter. Next, literature review studies in sEMG signal processing and feature extraction, more details in soft computing techniques and last literature review in the performance measurements that suitable for this research.

Chapter 3 illustrates methodology of this research. This chapter discusses the phases of methodology involved in carrying this research. The methodology comprises of fundamental stages, which are Investigation phase and Implementation phase.

The following Chapter 4 defines the experimental design for sEMG data collection. This chapter focusing on the selection of participants; hardware and software used in this experiment; electrode types and placement; the experiment location; experiment setup; and signal processing procedures. A result and discussion is provided in the last section in this sEMG experiment design and data acquisition of Chapter 4.

Chapter 5 represents the proposed integration of Fuzzy C-Mean based Radial Basis Function Network (FCM-RBFN) technique. This chapter start with the operational research design of the integration of FCM-RBFN technique and followed with the details and algorithm of FCM-RBFN, Fuzzy C-Mean (FCM) and Radial Basis Function (RBF) are presented in request to have a superior comprehension of the proposed technique.

Furthermore, in this chapter will highlight the details and algorithm of integration of Fuzzy C-Mean based Radial Basis Function Network technique. The integration FCM-RBFN is divided into 4 parts which explained more in details of proposed technique. The first part, explain on FCM, the integration of FCM with the RBF in testing phase which is the important phase in the proposed integration FCM-RBFN technique, the sub-RBFN in the RBFN and last part which is the selection of Radial Basis Function Network Model (example: sub-RBFN).

The last chapter of this thesis is Chapter 6 which discusses the experimental results and validation test. The experimental results are further analysed with the validation test. This chapter consists of 3 major parts which are the results discussion on the Butterworth high pass filter cut-off threshold analysis (example: 5, 10, 20 Hz) using RBF and compared with ANN, comparison of MSE values between proposed technique and popular prediction technique in sEMG domain technique: the integration Fuzzy C-Mean based Radial Basis Function Network (FCM-RBFN) technique and Artificial Neural Network (ANN) technique and lastly, comparison between similarity of predicted load and original load using integration FCM-RBFN and ANN techniques to graphical illustrates the most identify predicted load value to the original load. The similar predicted load's value to the original load shows that the technique can mimic the human expert in athletes training during the endurance training.

Chapter 7 draws the conclusion of this research. A summary and discussion on the overall research is provided. Besides, this chapter discusses the threats of validity of this research. Furthermore, the contributions of this research are likewise depicted in this part. Finally, the recommendations are presented as guidelines for further work that can be continue in this research area.

1.11 Summary

In this chapter, the overview of this research is presented. Positive results of this study will advance the frontier of clustering in signal analysis especially in solving dynamic learning problem in muscle endurance prediction model based on integration FCM-RBFN technique through muscle fatigue measurement. In summary, the research outcomes are expected to produce an integration FCM-RBFN technique to predict different load intensity efficiently in sport training to prolong muscle resistance against fatigue. In addition, the feature vectors with the suitable features extraction for quantifying muscle endurance in isotonic sport training are provided. According to the matter, two hypotheses have been made, first, the FCM-RBFN technique is able to accommodate dynamic changes from muscle biofeedback and variable-load intensity training can enhance muscle endurance against fatigue. Apparently, this study is feasible and will support the communication, content and infrastructure development, fulfilling NKEAs' aim to provide well-founded backbone for application developments especially towards the inspiration of personalized healthcare.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, a literature review of muscle fatigue sEMG signal with different sEMG electrodes placements and muscle contractions on various types of soft computing techniques to prediction the value of muscle load intensity for sports domain during isotonic muscle task have been studied. Soft computing techniques are one of the promising tools that provide practical and reasonable solutions to the muscle load prediction; the example is the isotonic muscle fatigue sEMG signal. This chapter consists of 10 sections. Section 2.2 presents different types of bio-signals. Section 2.3 consists of a critical review on endurance training in sport science for both the isometric and isotonic. Section 2.4 discusses the sEMG characteristic during isometric and isotonic muscle contraction. Next, Section 2.5 reviews the surface electromyography signal (sEMG) on muscle analysis. Then, Section 2.6 reviews the past research studies of sEMG muscle electrodes placement. Section 2.7 describes about the sEMG experiment paradigms. Section 2.8 explains the presents of noise in the raw sEMG signal, especially in isotonic muscle task and the review liberating of pre-processing on isotonic sEMG signal. Review on features technique that available in this field will be discussed in Section 2.9. Section 2.10 provides literature review on the soft computing techniques in handling the isotonic muscle task data. On the second last section, the review on the performance measurements to evaluate the prediction performance. Last but not least, the summary is provided in Section 2.12.

2.2 Bio-signals

Geospatial data biofeedback has been long used for the treatment of different restorative issue, chronic pain, headaches, and many others. Today, it is been picking up noticeable in an increasingly proactive limit such as physiotherapy, rehabilitation (Singh and Chatterji, 2013), and even for sport science, due to the importance of sEMG study (Zeng et al., 2013; Chowdhury et al., 2014). People, going from competitors to craftsmen, business pioneers and then some, are taking advantage of the advantages of biofeedback to advance wellbeing, mental, physical, passionate, and to improve execution in different physical exercises. The common practice involves capturing biofeedback from different muscle group of the human’s body (Watanabe et al., 2015; Sharma et al., 2016) using isolated sEMG electrodes.

Currently, bio-signals applications are commonly used in research studies refer Figure 2.1, including Electroretinogram (EOG), Mechanomyogram (MMG), Electroencephalogram (EEG), Electrocardiogram (ECG), and Electromyogram (EMG). EMG signals are the popular ways of data acquisition method in muscle analysis among athletes and patients either for rehabilitation or for sport purposes. In view of athletes’ training purpose with bio-signal feedbacks interfere; there are two types of categories, with load or without load to fulfil the requirement of muscle force in this experiment.

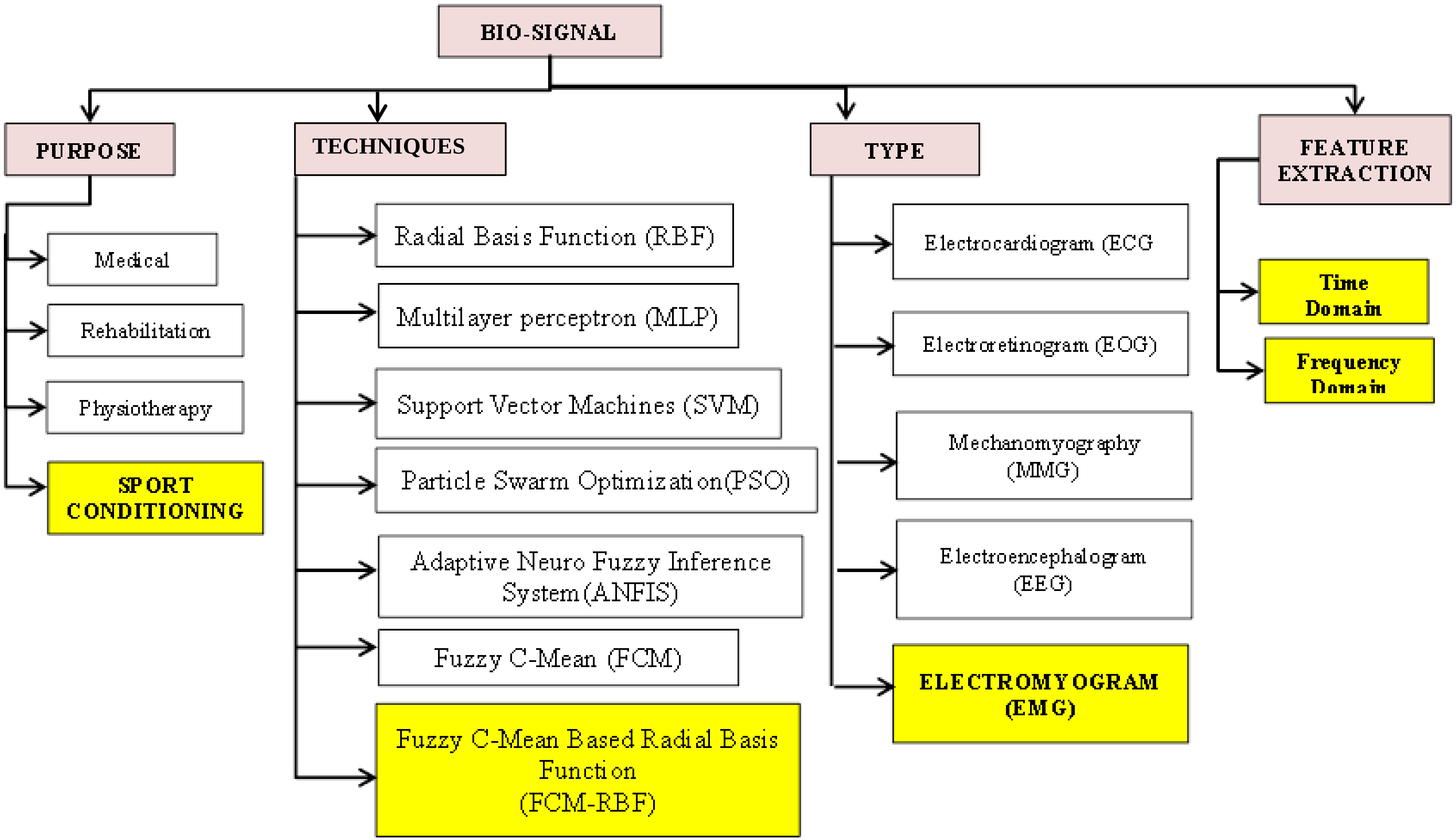


Figure 2.1: Literature review on purpose, technique, type and feature extraction under bio-signal in human

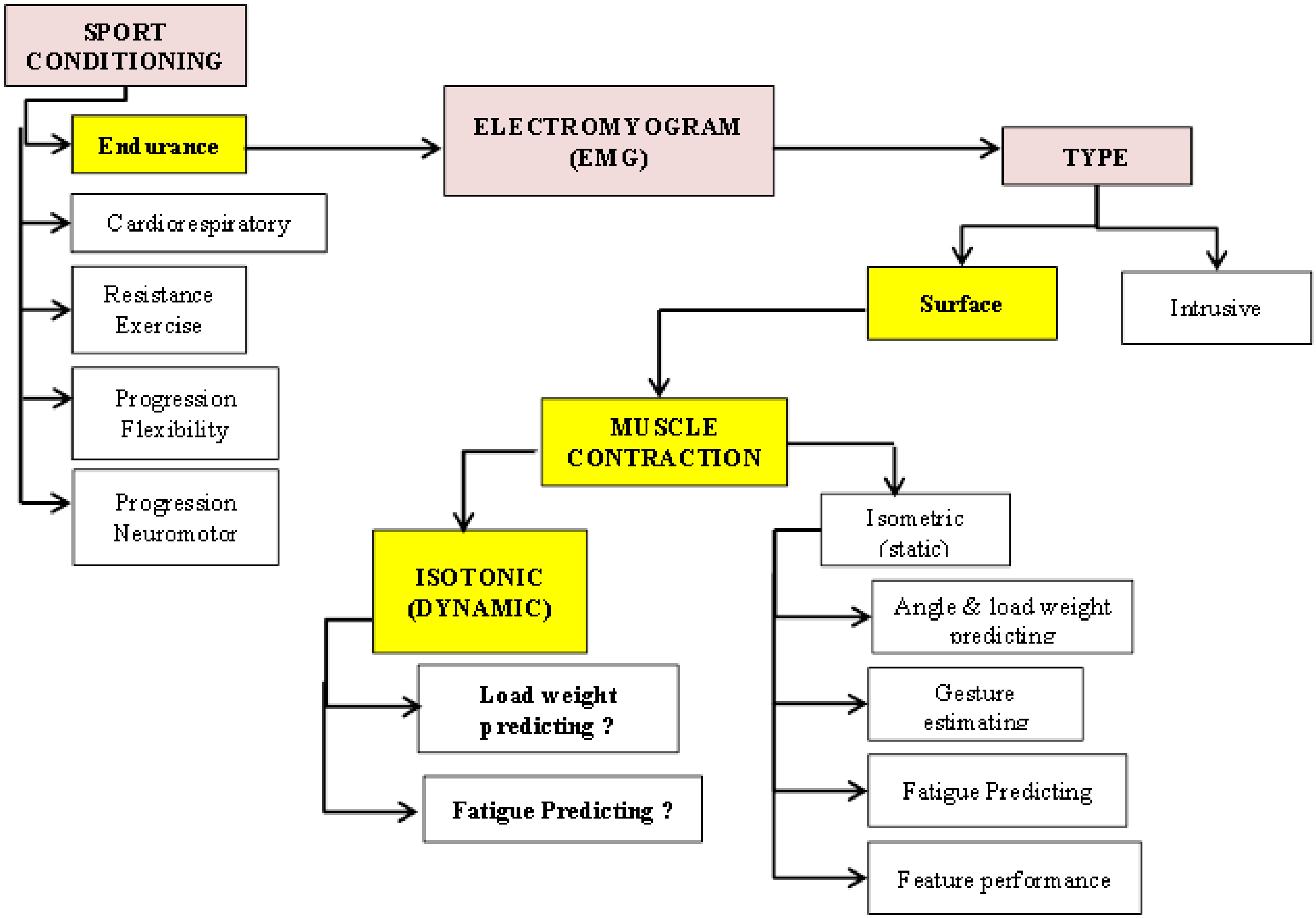


Figure 2.2: Literature review on sport conditioning using surface EMG in isotonic muscle contraction

2.3 Endurance training and fatigue in sport science

Sports science is characterized as concentrates on how the solid human body functions amid exercise, and how sport and physical action advance wellbeing and execution from cell to entire body points of view. It consists of five disciplines such as, the exercise physiology, the sport nutrition, the sports biomechanics, the strength and conditioning, and the sport psychology. Wide range study on sports and science gives great impact on understanding about body nature during exercise and training with different environment and movement which lead to the numerous benefits in physical and mental health in adults (Garber et al., 2011). At the same time, mostly of the sport technologies that have been applied in sport science includes injury surveillance and prevention, diagnostics, injury management, and performance enhancement. The performance enhancement will be focus on this paper. In Figure 2.2, literature review on sport conditioning using surface EMG in isotonic muscle contraction.

The endurance training under category of disciplines of strength and conditioning is the training that enhancing endurance of the body specific to certain sports such as marathon, bicycle and many others. Endurance training that usually has been done by athletes is cardiovascular training and muscle training. Lots of training equipment that can be used to gives intense and challenge the muscle such as bikes, rowing machine, treadmills and many more. Nowadays, lots of training equipment have been produced and been commercial but still not have the automated muscle biofeedback as the same meaning that machine will gives feedback automatically to subject (Ujihashi et al., 2008).

Endurance refers to the capacity to apply or stay dynamic after some time. It also refers to the capacity to withstand weakness, stress or pain. Endurance exercise enhances cardiovascular, respiratory and muscular endurance during any aerobic or anaerobic exercise (Peck, 1958). While the vast majority solely relate swimming, running and biking with intense exercise, there's something else entirely to it than only three games.

Muscular endurance refers to the muscles' ability to contract repeatedly over a lengthy period of time and resist fatigue. For example, keeping legs moving for the duration of a long run takes muscular endurance. Running additionally tests the cardiovascular endurance. Cardiovascular endurance refers to your heart, blood vessels and lungs' ability to pump oxygen steadily for long periods of movement or work. The ability to keep your breath steady throughout a long run without needing to stop demonstrates one type of cardiovascular endurance.

Endurance not only enhances your performance while working out, but also contributes to the overall health, providing you with energy, improved heart function and increased metabolism. Many team sports including soccer, lacrosse, ultimate frisbee and basketball require endurance as do activities like hiking, snowshoeing, skiing, climbing and snowboarding (Endurance Training, 2015).

The previous study show that the addition of heavy weight lifting and explosive jump training to endurance running training as a way to improve running performance (Beattie et al., 2014) and strength and plyometric or the jump-type exercises training can improve neuromuscular efficiency for example the brain muscle communication ability, increase force production capacity, delay the recruitment of fast twitch muscle fibers and help convert plastic fast-twitch type IIx fibers into fatigue resistant type IIa fibers (Rønnestad and Mujika, 2013). The benefits to running are expressed as improved running economy, running speed and time to exhaustion (Beattie et al., 2014).

Currently in sport field, the endurance training usually has a specific training interval schedule for each of the individual fitness. Thus, in this study we are focusing on the muscle signalling feedback to prolong the endurance training for assist every athlete to fulfil their needs and energy limit using the variable load intensity in their endurance training. sEMG signals are complex and highly nonstationary by nature, and it is very difficult to classify these signals in dynamic contraction (Marri and Swaminathan, 2016). In this research, the biofeedback signal capturing on brachiali, bicep and triceps muscle and asked the subject by doing the muscle training using the dumbbell due to the easy use, cheap, and will provide the lesser interference between other muscle. The interference between other muscles will lead to additional noise in the sEMG signal.

Endurance training is the demonstration of increasing the endurance of the body muscles. The requirements of endurance training, especially in sports science, are fulfilled through personalised training program with appropriate skills and techniques. The correct techniques should be advised and monitored by a sport conditioning expert to avoid muscle injuries. The goal of endurance training is two-fold, like an example is to maximize the muscle strength, while prevent muscle fatigue. Fatigue muscles absorb less energy before they are stretched out, until a certain degree when muscle injury happens (Mair et al., 1996). Hence, optimum training is the key to endurance. This can be realised through condition training where customised designed training program is used to achieve preferred endurance level. Besides, continuous monitoring is essential to avoid muscle injuries, and to alter the training program to best suit the conditioned athletes (Yessis, 2008; Marri and Swaminathan, 2016).

The requirement of continuous monitoring to achieve optimum training makes fatigue analysis an important component in endurance and conditioning training. Fatigue prediction (Marri and Swaminathan, 2016; McCrary et al., 2018) quantify fatigue states, and predict before it happens. The terms exhausted or tired are usually used instead of fatigue. Exhausted and tired are overall feelings of fatigue. Symptoms of body fatigue include short breath, misstep in exercise training, and muscle weakness. On the other hand, muscle fatigue relates to localised muscle state which is difficult to detect early through sensory observation (Wedro, 2017). Muscle fatigue in athletes will affect muscle activity such as decreases the sEMG amplitude and the muscle force (Abd-Elfattah et al., 2015). Hence, automated fatigue monitoring using sEMG data is popular in fatigue detection. In addition, short term fatigue, such as failure to lift weight is also an interesting research in muscle signal analysis domain (Hernandez et al., 2010; Taylor, 2012; Takeda et al., 2016).

Fatigue is a state when a person generally feeling tired and lack of inspiration that effect physically and mentally. Persons with fatigue condition always related to insufficient sleep, tired, exhausted, malaise, weary, lack of energy and feeling run down. (Davis, 2018). There are two types of fatigue which are chronic and acute fatigue.

Chronic fatigue syndrome which is the tiredness isn't soothed by rest. The indications of incessant weariness disorder are like this season's cold virus, last longer than a half year and meddle with specific exercises.

Meanwhile, acute fatigue is consequences from the short-term deficient of sleep or from short times of heavy physical exercise or mental work. The impacts of intense exhaustion are just for brief period and for the most part can be toppled by having enough rest and rest. Therefore, this research is focused on short term fatigue which it involving the heavy physical exercises (endurance training with lifting loaded dumbbell) and it leads to the several of challenges in analysing the short term fatigue using sEMG.

The challenges are include making sure the muscle condition is not in fatigue state for each experiment session for sEMG signal data collecting. Fatigue level state is changeable from the first session to the last session of training. Usually the last session, the participant should be in the fatigue state and can be monitored through sEMG signal reading by expert. However, interference with participant’s activities such as classes and daily routine as a student will lead to early fatigue and it will affect the sEMG signal. In

(Garber et al., 2011) suggested that the rest intervals of 2-3 minutes between each set repetitions and 48 hours or more between sessions for any single muscle group is effective for individualized exercise prescription in endurance training.

In another hand, the isotonic contraction involves the shortening and lengthening of muscle and it has movement in each lifting of load. The collecting sEMG signal data during isotonic contraction will leads to high noise such as movement and misplaced of sEMG electrodes. This can cause interference with useful fatigue information. Therefore, the suitable noises filter and feature extraction need to be determining to overcome this problem.

However, current research works focus mainly on localised muscle fatigue as the process of a decline in the force during a sustained activity, which gives a definition of physiological fatigue as the inability to exert any more force or power (Barry and Enoka, 2007). Barry (Barry and Enoka, 2007) argues that this definition indicates that fatigue occurs rapidly after the onset of a sustained exercise although the subject may be able to sustain the activity. Merletti and Parker (Merletti and Parker, 2004) argue that muscle fatigue can be defined as an engineering approach to fatigue, where fatigue develops over time and is progressive, which defines muscle fatigue as all the physiological changes that occur in the muscle before reaching the inability to exert force. Physiological manifestations of fatigue relate to the exhaustion of the metabolic reserves in the contracting muscle. The amount of waste is increased, and the muscle has difficulty in continuing its task. As a result, the muscle fatigues due to the accumulation of lactic acid in the muscle tissue and the depletion of glycogen (stored glucose), which reduces the contractile properties of the muscle.

2.4 sEMG characteristic during isometric and isotonic muscle contraction

In general, sport training involves the muscle flexion exercise to increase the muscle strength against resistance. Complete muscle training includes three different types of muscle tensions, example, the concentric contractions, eccentric contractions, and the isometric contractions. The concentric (shortening) and eccentric (lengthening) contractions interchange in sequence makes up the isotonic muscle workout. Figure 2.3 shows the types of contraction of types of contraction of muscle. An isotonic concentric contraction results in the muscle shortening, while an isotonic eccentric contraction results in the muscle lengthening. During an isometric contraction the muscle is under tension but neither shortens nor lengthens (Boundless.com, 2018).

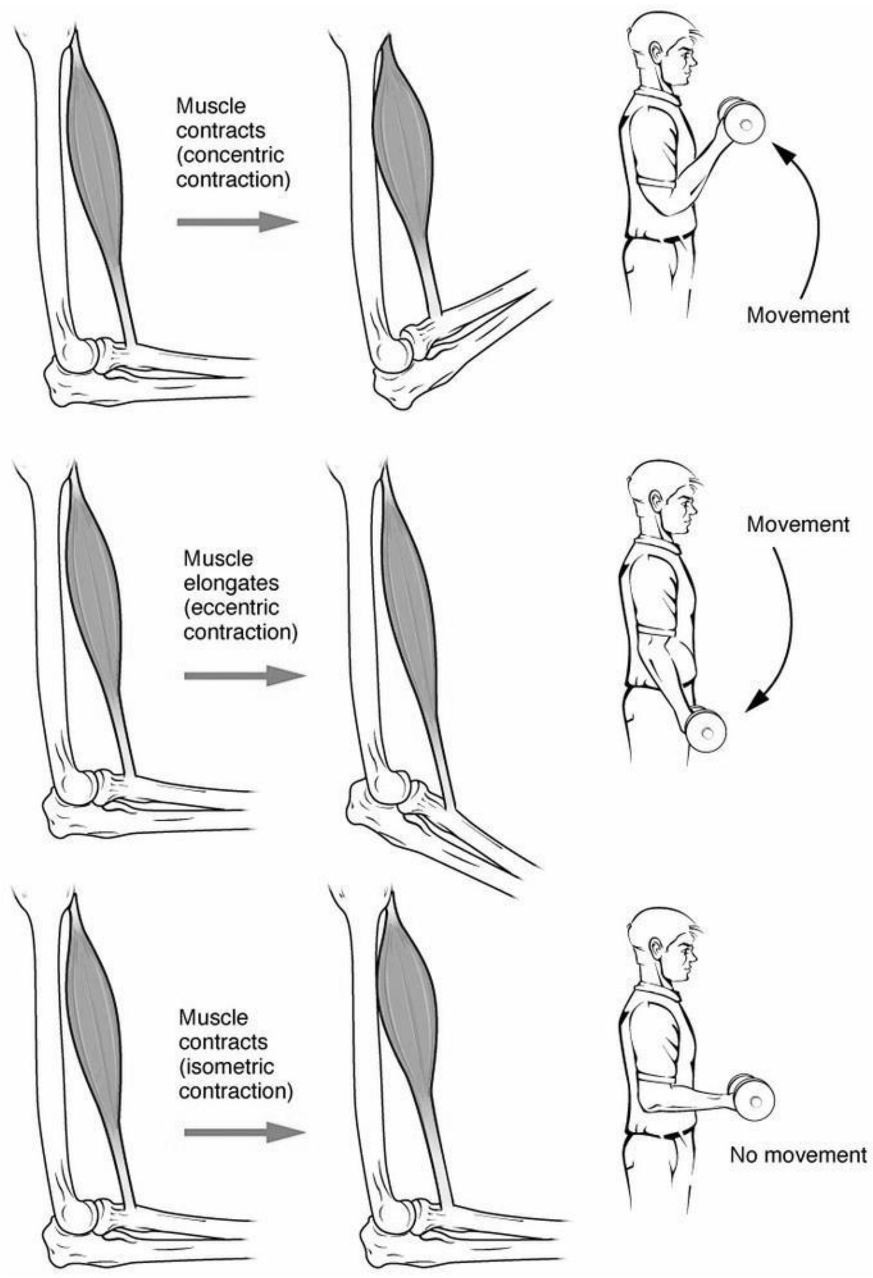


Figure 2.3: Types of muscle contraction (Boundless.com, 2018)

Comprehensive training on all three types of muscular contractions is important for athlete in sport training. Among all muscular contractions, the eccentric contraction is easier to cause muscle damage when the weight or resistance is unintentionally overloaded for a particular muscle to accommodate. This condition, also known as involuntary eccentric contraction is harder to control because athlete is normally less conscious on overloaded weight during eccentric contractions until it happens (Schmitz et al., 2002). Therefore, many sport training programs today are designed by experts. Trainings are conducted under the monitoring of muscle signal analysis tool to assure optimum results, and to reduce the risk of muscle damage (Garber et al., 2011).

Many analysis tools use computational automated methods to assist human decision in sport training. Fatigue prediction has emerged to be an important research component in this area. Although the isotonic signal analysis is equally important in sport training, many researches on muscle fatigue prediction are still concentrated on isometric training as compared to isotonic training. This is because isotonic training generates larger volume of motion artefact. Thus, it imposes greater challenge of noise management on signal analysis (Kuriki et al., 2012). In addition, fatigue analysis using sEMG signals were usually carried out for isometric contraction task to identify good predictors, predictive model performance, muscle force prediction, angle estimation, and others (Kuriki et al., 2012; Amarantini and Bru, 2015; Scott et al., 2017).

2.5 Surface electromyography signal (sEMG) on muscle analysis

Electromyography is an electro diagnostic modality, which records the electrical activity produced by skeletal muscles contractions. The introduction of surface EMG (sEMG) with non-invasive electrodes has offered many advantages in biomedical engineering research. The sEMG signals analysis is currently the most common way to assist sport training, especially in sport conditioning for bio-signal feedbacks monitoring. The raw sEMG signal can be acquired by attaching sEMG electrodes on the targeted muscle during exercise.

Muscular biofeedback is measured using the electromyography (EMG) in either invasive or non-invasive ways. The non-invasive EMG acquisition named surface electromyography (sEMG) which is needless becoming popular among the practitioners especially for muscle force prediction. EMG signals are the bio-signals collected during muscle membrane movement or excitation when the muscle go through the depolarisation and repolarisation processes as shown in Figure 2.1. This transient change in the voltage across the cell membrane is called action potential. The stronger the stimulus on the muscle, the larger the number of action potentials per second (Ashcroft, 2014). The EMG signals can be collected by placing electrodes on the skin surface to detect underlying electrical activity and the signal is an associated waveform shown on a computer monitor (Franz and Mallot, 2000). EMG signals are directly proportional to muscle strength for contraction with constant speed and nonlinear motion. In the previous studies, to measure the muscle force, it must be assessed, calculate or modelled (Heloyse et al., 2012). However, it is not possible to measure force directly using EMG. The relationship of EMG and muscle force is nonlinear and minor environmental changes will affect the accuracy of prediction. Hence, lots of studies for detecting and processing the captured signal from EMG have been refined considerably, with the availability of computational techniques.

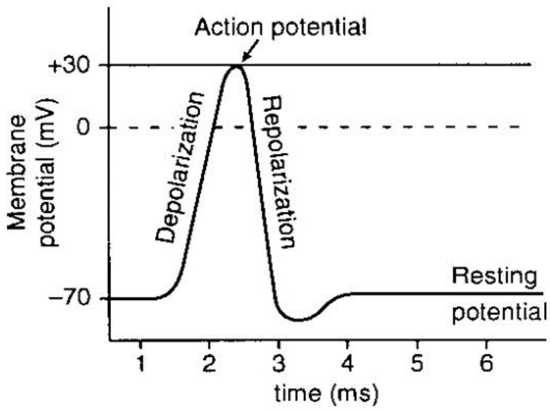


Figure 2.4: The action potential of EMG signal (Ashcroft, 2014)

In the previous research, the study that has been done by (Sharawardi et al., 2014) is to use a single channel sEMG to access the performance of LS-SVM model to predict the muscle fatigue on the dynamic and static subjects. In this study, the researcher uses three features; RMS, MDF and MF, but it has limitation and hope can enhance the signal representation in differentiating the dataset and to improve the algorithm to better adapt with the vagueness during modeling process. Continuing with the limitation of the limitation of the previous research, this research will use 8 channel sEMG to enhance the signal representation on the certain muscle and use automated clustering FCM-RBFN technique to adapt to variable load intensity modeling. With this in mind, the muscle activities capturing on the brachiali, triceps brachii, and biceps brachii muscle for both female and male of subjects as followed in research (Li et al., 2009) which is for capturing accurately the feedback information from arm wrestling athletes' forearm force training.

The usage of sEMG, especially in the high potential of the sEMG as a non-invasive tool in the rehabilitation, clinical and also gives a great benefit in sport training is increasing by time to time. Endurance training usually has been done around 2-3 times weekly continuously long training to enhance the endurance and gives effect to muscle activity. However, the study that has been done in (Singh et al., 2006), where the researcher aimed to capturing sEMG signal dynamic contractions on vatus lateralis, vatus medialis, and rectus femoris where the subject asked to performs cyclic dynamic contractions for a long duration shows that for long period athletics exercise, sEMG isn't an appropriate measure to spot the onset of muscle fatigue.

In addition, the research involves sEMG analysis with the subjects with neuromuscular has been done by (Marri and Swaminathan, 2016). Muscle fatigue is commonly experienced in both normal and subjects with neuromuscular disorders especially during dynamic contraction. The researcher uses three different of classification techniques the Logistic Regression and *k*-Nearest Neighbour classifier performance gave an accuracy of 84% and 82% respectively. The Naïve Bayes have a lowest accuracy value with 80%. However, observed that the performance of the classifier did not increase significantly which may be due to improper selection of fitness values method. These gaps in feature selection can be addressed by using nature inspired feature selection methods in future work. In this study did not predict the intensity of weight load. The using of both female and male subject in collecting data by sEMG will give variable types of data and has been proven in (Vinod and Da, 2013) that each male subjects are more effective than female subjects in using lesser dynamism for a given pressure level. However, female subjects presented lower flare-up power or faster response than male subjects. In addition, in (Singh et al., 2004) stated that the significant variation of the magnitude of the sEMG between subjects representative that magnitude of SEMG can't be related between subjects throughout maximal contraction muscle activity. Therefore, this unique characteristic is the one of the factors that need to be focus in proposed the modelling on muscle resistance performance against muscle fatigue towards personalized sport training so that it can be optimized.

2.6 Surface electromyography signal (sEMG) placements

Human body is a complex system supporting by different sub-systems, such as the nerve system, skeletal system, muscular system and so on. Different muscles group on human body are meant to exert force in order to move the body. Skeletal system and muscles are connected to each other by tendons. Combination of muscle and bone is brought about by the tendon intermeshing with the skeletal periosteum sheath. Tendons are the strong connective tissue composed of three layers. And this extends the length of all the muscle and collagen protein. Epimysium, perimysium and endomysium are the connective tissues forming each tendon (Turker and Sze, 2013).

For non-sport condition, upper limb as often as possible loaded for everyday activities (Fischer et al., 2009). In sport environment upper limb muscle are exceedingly essential in sports such as swimming, combat sports and racquet sports. Because of these reasons, the upper limb muscles were chosen for this test. sEMG data of upper limb provides the strength and conditioning coaches guidelines on which muscles were initiated in every variety of activities included (Engineering et al., 2014). In (Al-Mulla et al., 2011a) to avoiding the estimated innervation zone and toward the distal tendon to acquire sEMG signal, the sEMG electrodes were located on the subjects biceps brachii lower belly.

(Sarmiento et al., 2011) and (Ahamed, 2012) suggest the skin need to be cleaned and rubbed with alcohol to limit impedance of the electrical contact of the electrode. According to SENIAM references, the sEMG electrodes were placed in the following muscles of the dominant side of the subject's biceps brachii. The longitudinal axis of the electrodes were positioned parallel to the fibers of these muscles, and the reference sensors were placed in the patient's wrist as recommended in (Hermens et al., 2000).

Experimental setup in (Sharawardi et al., 2014) where the participants were told to experience a static action, where they are to grasp on the handgrip dynamometer on the sEMG recording within the tests. The sEMG electrodes were placed on the participant's flexor carpi radialis muscle as in Figure 2.5. In this paper, the ROC value shows better result in static activity than dynamic activity.

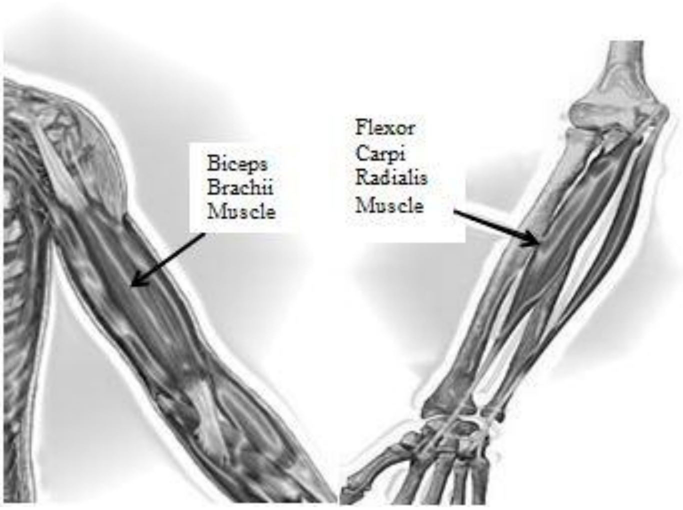


Figure 2.5: The biceps brachii and flexor carpi radialis muscles position (Sharawardi et al., 2014)

2.7 Surface electromyography (sEMG) experimental paradigm

The original raw sEMG signal from human muscle contaminated with the various noise signal or artifacts. The factors effected the contaminated signal that cannot be avoid such as individual skin formation, measured skin temperature, the tissues structure and others (Chowdhury et al., 2013a). These factors provide different types of noise in the sEMG signal and will affect the result performance and hence will affect the whole experiment result. However, the movement artifact cannot be avoid effecting the sEMG signal when isotonic task are been applied. The isotonic produces much more movement artefact than isometric. This have been proved in (Sharawardi et al., 2014) where the isometric have higher ROC value than isotonic muscle task.

The development of the link associating the electrode to the amplifier and the interface between the identification surface of the electrode and the skin deliver development relic. At the point when the muscle is actuated, the lengths of the muscle reduce, skin and electrodes move with respect to each other. Around then, the electrodes will show demonstrate movement artefacts.

This is an important issue in prediction the value of muscle load intensity for sports. This movement noise a difficult to be avoided. Therefore, the suitable features extractions and prediction model techniques will enhance the performance result and helps in prediction the value of muscle load intensity. In addition, constructing experiment dataset is an important step before any learning model could be tested and verified.

sEMG signal are captured by placed the sEMG electrode onto the surface of the skin after a few produces in cleaning step such as shaves the hair, alcohol swap and others. sEMG is a device that measures the amount of electrical activity that be produces by human muscle when muscle are contracting. The significant phase in every experiment that includes capturing signal with sEMG is the skin. The attachment of electrode on the skin need to be sure that there were no any small barrier between it (Clarys et al., 2010).The sEMG electrode is a non-invasive and does not cause pain or irritation. Therefore, it is safe for all age stage and subject conditions.

In addition, during the experiment, the armrest is used to avoid the muscle contraction of the lower part of body such as lower back and leg to be stimulated by load's weight. Therefore, the strain in the muscle as the muscle changes length in the upper piece of body which are biceps and flexor can be maximised (Phinyomark et al., 2018).

A high performing equipment Trigno wireless sEMG sensor from Delsys Inc is aimed to make EMG signal detection dependable and easy. The capability of the system to streaming data digitally into EMGworks® and a Trigo wireless 4-channel system (Delsys Inc.) to detect the sEMG signal is beneficially. The trigno sensor is furnished with the transmission range of 20m and inter-sensor latency < 500us (< 1 sample period). In addition, EMG signal bandwidth 20-450 Hz with EMG signal sampling rate of 2000 samples/sec. The base stations are equipped 64-channel analog output connector (16 EMG, 48 ACC) and ± 5V analog output range. The skin was cleaned by gently scouring it with

70% isopropyl alcohol. The sensors were attached to the skin with a double-sided adhesive interface tailored to match the contours of the sensor. The informational data collected from the sEMG were saved in digital format using EMGworks and end up with acquisition software then be analyst in the Matlab R2013a.

2.8 Inherent noise in raw sEMG signal and signal pre-processing for isotonic muscle task

The muscle activity is controlled by the nervous system. Hence, the EMG signal is dependent on the anatomical and physiological properties of muscles. Moreover, the raw sEMG signals captured from different muscle at a time will generate interaction of different signals and will actually lost due to the mixing of several of noise signal from the different source such as from the subject's skin formation, blood flow, measured skin temperatures, the tissue fat, the measuring site and more are the contributors to the existent noise in the EMG signal collected.

These contributors produce many types of noise signal that can be found. Therefore, many methods of noise filtrations have been proposed during the EMG signal acquisition (Clancy et al., 2002; De Luca et al., 2010; Wang et al., 2013) and the subject continues to be popular one among practitioners. The electrode sensors placements in certain experiment were an important things to be concern, mainly in classification type for hand motion pattern (Ahsan, 2011), and multifunction myolectronic hand for real time control of robotic arm (Chowdhury et al., 2013a) and others. The main challenges in analysing the EMG signal in each type of noises are explained below.

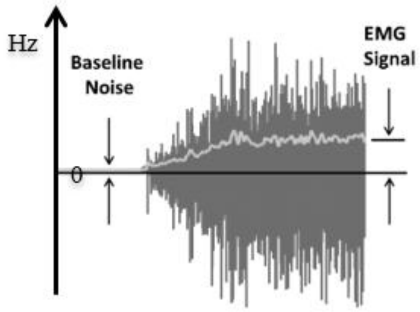


Figure 2.6: The present of noise inside the raw EMG signal

2.8.1 Inherent noise in the electrode

The inherent noise in the electronics equipment in the recognition and recording equipment is one of the attributes that generates electrical noise in EMG signal. The noise has frequency components that range from 0 to several thousand Hz. The widely use of surface EMG that more accepted in mostly clinical and physiological application (Mannion et al., 1997; Clancy et al., 2002; Al-imari and Jordan, 2003; Norali et al., 2009; De Luca et al., 2010; Chowdhury et al., 2013a, 2013b; Vinod and Da, 2013; Wang et al., 2013; Darak and Hambarde, 2015) instead of invasive electrode. The advantages of using the non-invasive are that the user does not need to be anesthetized before placing the electrode and the placement is easy and painless.

For capturing the EMG signal from surface electrode, the surface electrodes are applied to the skin of the subject which the electrode is made of silver/silver chloride (10 × 1 mm) that gives adequate signal-to-noise ration and are electrically very steady. When the electrode size enlarges, the impedance decreases. However, electrode size should not be very large. On the other hand, high electrode impendence effectively reduces the signal quality and gives low signal-to-noise ratio. Therefore, both parameters should be taken into consideration (Kappenman and Luck, 2010).

2.8.2 Movement artefact

In collecting or recording EMG signal during the density of an EMG signal depends on the strength of the contraction, whether the muscle is in isotonic or isometric state which lead to inherent the movement artefacts. Muscle fibres produce electric pulse whenever muscles are active (See, 2006).

The frequency range of the motion noise is usually 1–10 Hz and has a voltage comparable to the amplitude of the EMG. In addition, virtual movement in the innervations zones of the underlying motor units can cause another type of motion artefacts too. In addition, moving artefact also can degrade the quality of signal and this disadvantage is the current problems that need to overcome. Researchers that has done experiments during isotonic muscle contraction task as their sEMG signal data where proposed a new fatigue state using FIR filters and not by a frequency analysis (Kim et al., 2012). In addition, others studies fatigue state (Li et al., 2009), muscle force studies (Chakraborty and Parbat, 2016) and using Artificial Neural Network (Bai and Chew, 2013).

2.8.3 Electromagnetic noise

Electromagnetic also been produced by living cell, tissues or organisms. Human living is also concluded. The electromagnetic will be produces and changed the original signal with useless information in with continuously existing of electric and magnetic radiation from the human body. In addition, this unwanted signal is somehow greater than the EMG signal of the real information. Therefore, in demand to eliminate the capturing artefact, additional processing is needed (Clancy et al., 2002). Thus, a high pass filter is one of the filtering methods that can eliminate the interfering.

2.8.4 Cross talk

The limitation of surface EMG can cause by crosstalk while capturing the signal. Cross talk can be happen when an electrical activity of a single muscle directly underlying the sEMG electrode. Because of that, it may overlook the electrical activities of neighbouring muscles (Day, 2002). While signal sources near to the electrode, it will overwhelm the detailed sEMG signal, increasing distant of sources from different muscles may encounter the problem. Huge contact areas and electrode distances >10 mm acquaint the factor of crosstalk.

In addition, specific anatomical features that affect the length of muscle fiber, muscle fiber type and muscle compartments may vary between muscles and can lead to into the crosstalk (Turker and Sze, 2013). EMG signals may be affected by crosstalk if there were no anatomical differences are been giving consideration. EMG signal that inherent from crosstalk cannot be eliminated from the selected muscle. The small inter-electrode distance of electrode sensors and the changing of the distance between trials and across subjects can introduce artificial variability in the recorded data.

2.8.5 Internal noise

Noise is the unwanted electrical signal that degrades the quality of signal. The anatomical, biochemical and physiological factors take place due to the number of muscle fibres per unit, depth and location of active fibres, and amount of tissue in the body. All of the attributes are the internal noise. The skin has a relatively low conductivity and high permittivity such that capacitive effects would be expected to be significant and the dispersive effects of permittivity will be more pronounced (Chowdhury et al., 2013b). Therefore, the capacitive effects such as the amount of the tissue between contracting muscles and electrodes and the thickness will affect the amplitude of the EMG signal.

Hemingway et al. suggested that if the thickness of the tissue between the surface electrode and active muscles increases, then the electromyography activity decreases (Hemingway et al., 1995). The experiment has been done by examining 20 normal participants who contracted their muscle force for 45s and all the subjects had different capacity of dermal tissue. The quantity of extra body fat is reflected as an internal noise for EMG signal. This is because it increases the departure between the active muscle and the electrode. Under the recording sites, surgical fat layer reduction increases surface EMG signal amplitude (Kuiken et al., 2003). These effects can be partly reduced by using high pass spatial filters (Farina and Rainoldi, 1999).

2.8.6 Inherent instability of the signal

The frequency sEMG signal of components between 0 and 20 Hz are mostly unstable because they are affected by the quasi-random nature of the firing rate of the motor units which, in most conditions, fire in this frequency region. The amplitude if the sEMG signals are usually quasi-random. Because of the unstable nature of these components of the signal, it is advisable to consider them as unwanted noise and remove them from the signal (Luca, 2002).

2.8.7 Electrocardiography (ECG) artifacts

Electrocardiography or known as ECG artefact is a main unwanted noise that embedded in the EMG signal that can degrade the important information in the signal. This usually happen when EMG signal is recorded from the upper trunk muscles (Abbaspour and Fallah, 2014). This noise is overlapped with the frequency of the signal. Most of the previous techniques in reduce the level of noise are including the amplitude clipping, gating techniques and high pass filtering, or even which have proved effective (Abbaspour and Fallah, 2014).

Table 2.1: sEMG signal noise type

Noise Type	
Inherent noise in the electrode	Noise from the electronics equipment in the recognition and recording equipment.
Movement artefact	Movement of the muscle during collecting the signal.
Electromagnetic noise	Living cell, tissues or organisms include human living changed the original sEMG signal.
Cross talk	Overlook the electrical activities of neighbouring muscles.
Internal noise	Anatomical, biochemical and physiological factors take place.
Inherent instability of the signal	Affected by the quasi-random nature of the firing rate of the motor units.
Electrocardiography (ECG)	Present of heart beat noise. Usually happen when EMG signal is recorded from the upper trunk muscles.

2.9 sEMG signal processing and features extraction

Naturally, biomedical signal processing goals captures the importance information from biomedical signals. Therefore, the signal processing the is the most required analysis tools for analysing the EMG signal (De Luca et al., 2010; Wang et al., 2013). However, the ideal filter types are important in order to clean the noise out from the contaminated EMG signal. A filter is a devise aimed to eliminate ranges of frequencies while allowing others to pass. There are different types of the frequency spectrum of a signal filters. For examples are band pass, low pass, high pass, and band stop filter. Each of the filtering types, have their certain Hz cut off frequency. The determination of Hz cut off frequency is according to the signal's types and the stage of the contaminated EMG signal. However, noise in fatigue muscle during isotonic task exercise can be filtered easily using the high-pass filter due to its amplitude's range between 0Hz to 20Hz. The comparing cut-off filter threshold is crucial, especially with significant changes in motor unit recruitment of biceps muscles after strength training interventions was hard to find (Watanabe et al., 2015). It is because to numerous reasons such as a much slower rate of movement, typically less than 1Hz (Yang and Hunt, 2014) and smaller cross-sectional area (less motor-neuron) compared to lower limb muscles. Therefore, Butterworth filters is a popular filter used in sports science and human movement studies. It come with different filters range (Schoenfeld et al., 2014; Amarantini and Bru, 2015; Balshaw et al., 2017; Scott et al., 2017) and was commonly used to clean the undesired noises before prediction model building (Fratini et al., 2007). Thus, further investigations needed to verify which range is the best.

In sports training, fatigue prediction using surface electromyography analysis is manually monitored by human coach. Decisions rely very much on experience. Hence, the endurance training plan for an athlete needs to be individually designed by an experienced coach. The pre-designed training plan suits the athlete fitness state in general, but not in real time. Real-time muscle monitoring and feedback help in understanding every fitness states throughout the training to optimize muscle performance. This can be realized with muscle fatigue prediction using computational modelling. Due to the higher amount of motion artefact, research in isotonic muscle fatigue prediction is very much lesser than the isometric prediction. Fatigue prediction studies are popular domain nowadays (Marri et al., 2016). Moreover, many researches on muscle fatigue prediction are still concentrated on isometric training as compared to isotonic training. This is because isotonic training generates larger volume of motion artefact. Thus, it is giving a greater challenge of noise management on signal analysis (Kuriki et al., 2012). The noise artefacts in isotonic muscle fatigue can be easily cleaned using the high-pass filter because the noise amplitude normally falls in the range between 0 Hz to 20 Hz and the Butterworth filters has been widely used in sports science and human movement studies with varied filter range (Schoenfeld et al., 2014; Amarantini et al., 2015; Scott et al., 2017; Balshaw et al., 2017). It was commonly used to clean the undesired noises before prediction model building (Fratini et al., 2007).Thus, the Butterworth high-pass noise filter on isotonic muscle fatigue data will be use and the investigation on three cut-off thresholds, which are 5 Hz, 10 Hz, and 20 Hz, were compared using the Fuzzy C-Mean Radial Basis Function Network model. Several features of time and frequency domains, the median frequency, mean frequency, mean absolute value, root mean squares, simple-square integral, variance length, and waveform length were used as model predictors. The cut-off threshold at 10 Hz is the best frequency with the lowest average mean squared error of 0.0282 and best validation performance at epoch 972.

The rapid growth in using of EMG in multivariate fields makes many studies in features extraction. In addition, the requirement information remains in the raw data together with the main factors related to the various noise and artifacts detected among the EMG signals. Thus, if this raw signal data inserted as an input in the sEMG classification or prediction, the efficiency of the classifier will be decreases. However, to improve the efficiency of the classifier, many researchers have been studies for the EMG features as an input to the classifier. There are 3 types of EMG features in different domain, such as, frequency domain, time domain and time-frequency domain as shown in Figure 2.4.

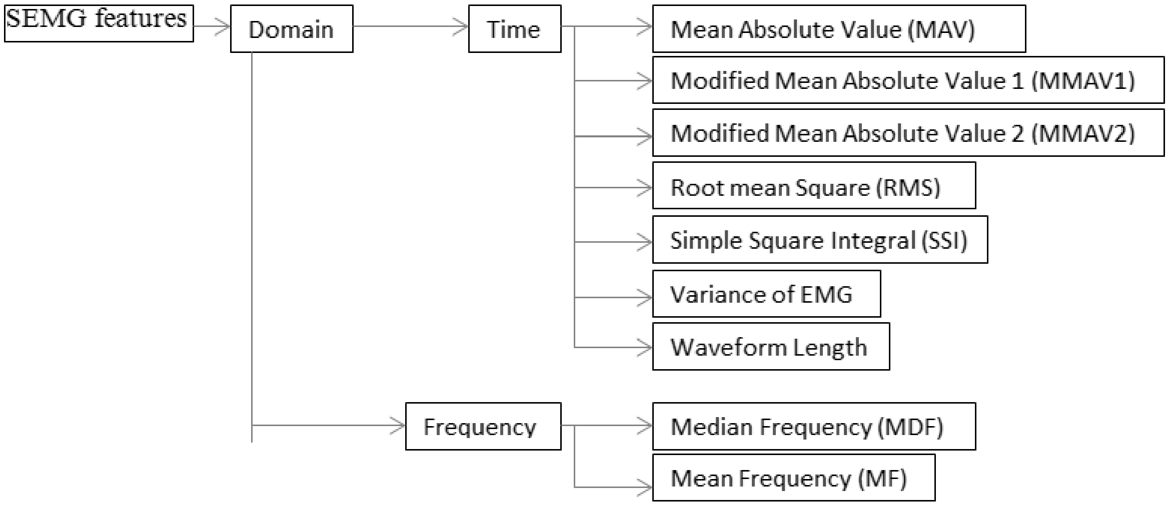


Figure 2.7: Summarised of past studies of statistical based feature extraction method for sEMG signal

The electrode sensors placements in this experiment are at brachiali, triceps brachii, and biceps brachii with six channels to capturing the muscle activities signal data according to the previous study with the classification type for hand motion pattern (Ahsan, 2011), multifunction myolectronic hand control eight classes of hand movement for real time control of robotic arm (Chowdhury et al., 2013a) and others. There are many types of sEMG features are popular been used especially in the dynamic activities. However, in the previous study that has been done by FKE's undergraduate by using all the features shows in Figure 2.7 above, results shows that MAV, MF, and MDF gives a good performance in dynamic force changing among the others. Therefore, only seven features be implement in this study due to the frequent use of this seven features in the previous study related to the dynamic motion studies (Singh et al., 2006; Li et al., 2009; Sarmiento et al., 2011; Chowdhury et al., 2014).

2.9.1 Time domain features

Time domain analysis is used in analyzing data over a time period. Time domain features are established by Hudgins in year 1993. Features in time domain are used in signal classification due to its easy and fast employment. Moreover, it does not have need of any renovation, which the features can be calculated based on raw EMG signal. For sEMG signal, the time domain analysis is mainly based on the amplitude of signal measured against time. Due to the uncomplicatedness in computation of time domain features, therefore it is the most common been used by previous researcher in studying the sEMG signal.

2.9.2 Frequency domain features

Frequency domain analysis is used in analyzing data with respect to the frequency. It indicates the amount of signal lie in the frequency range. Some researchers claim that frequency domains features show the better performance than other-domain features in case of the assessing useful fatigue (Phinyomark et al., 2012). MNF and MF are the most advantageous and general frequency domain features and frequently used in the assessment of muscle fatigue in sEMG signal. The important pre-requisite before doing the frequency domain analysis is transform a time domain function to a frequency domain function. For sEMG signal, the most popular transformation used is the Fourier transformation (FFT). Therefore, FFT are being done before extracting the frequency features from the sEMG signal.

Table 2.2: Mathematical representation of widely used sEMG feature extraction methods

Features Extraction	Formula	Domain area
Mean Absolute Value (MAV)	MAV = $\frac{1}{N}\sum_{n=1}^{N}\lvert x_n\rvert$ (2.1)	Pattern recognition (Jali et al., 2015)
Root Mean Square (RMS)	RMS = $\sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n \hat{} 2}$ (2.2)	Muscle fatigue detection (Singh et al., 2006)
Variance of EMG (VAR)	VAR = $\frac{1}{N-1}\sum_{n=1}^{N} x_n \hat{} 2$ (2.3)	Pattern recognition (Jali et al., 2015)
Median Frequency (MDF)	MDF = $\frac{1}{2}\sum_{n=1}^{N} P_n$ (2.4)	Muscle fatigue detection (Lee et al., 2009)
Mean Frequency (MF)	MF = $\sum_{n=1}^{N} f_n P_n$ (2.5)	Muscle fatigue detection (Singh et al., 2006)
Standard deviation (STD)	STD = $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2}$ (2.6)	Pattern recognition (Jali et al., 2015)
Zero Crossing (ZC)	ZR= $\sum_{n=1}^{N-1}[sgn(x_n \times x_{n+1}) \cap \lvert x_n - x_{n+1}\rvert \geq threshold]$ (2.7)	Hand motion (Zhaol et al., 2012)

As summary, all features inside Table 2.1 above are feature extraction techniques as attributes which represent the important information in order to improve the performance of the prediction techniques.

2.10 Predicting technique in muscle fatigue load

Intelligence computing technique to process and analyse EMG signals, like example the Radial Basis Function (RBF) and Multilayer Perceptron (MLP) in Neural Network, Fuzzy Logic, Support Vector Machine (SVM) and Adaptive Neuro Fuzzy Inference System (ANFIS) had been proposed and applied for various purposes. Among all, the ANFIS, SVM and the RBF model showed encouraging results for muscle force prediction (Padmavati, 2011). The RBF model is a popular option to take the advantage of neural network structure, but using only a single hidden neuron layer and the Gaussian activation function. It opposed to an MLP network that can have more than one hidden layer. With the simpler network structure, RBF has been proven good at modelling nonlinear data and can be trained in one stage rather than using an iterative process like those in MLP. This advantage enables RBF model to learn faster with lower processing time in its learning environment. In the past study on breast cancer (Padmavati, 2011; Subasi, 2013) and energy efficiency (Oludolapo et al., 2012), prediction using RBF and MLP, the percentage of correct prediction for RBF is marginally higher than MLP with less learning and prediction time. The Gaussian function was used to minimize the error appropriately using the concept of probability.

Fatigue analysis using sEMG signals were usually carried out for isometric training to identify the good predictors set as well as for prediction muscle force and angle estimation. For isotonic training, the onset of contractile fatigue was successfully predicted in (Mobasser and Hashtrudi-zaad, 2005) using Radius Basis Function Neural Network (RBFN) model and Multilayer Perceptron (MLP) model. Research from (Mobasser and Hashtrudi-zaad, 2005) recommended the use of Artificial Neural Network (ANN) model for muscle fatigue prediction due to the capable to predict the level of fatigue. At the same time, many studies has proven empirically that models from ANN family such as RBF

(Mobasser and Hashtrudi-zaad, 2005) and MLP (Bravo et al., 2015) are good for isometric muscle fatigue prediction with mean squared error recorded between 1.76E-11 to 0.5.

Another past studies, SVM model also showed encouraging results for muscle force prediction and is a widely used machine learning technique with many biomedical signal classification (Subasi, 2013). However, SVM have a high computational time and have problems by need to setting up the SVM model on how to decide on the kernel function and its parameter values. Improper parameter setting and the unsuitable features-selection may lead to inaccurate classification result (Keerthi and Lin, 2003; Lin et al., 2008). Furthermore, the use of the kernel-induced feature spaces generally can lead to the misclassification result if wrong in the using of kernel function (Subasi, 2013). A study for supervised classification of the sEMG signal for the purpose in recognizing drivers' lumbar muscle fatigue during prolonged driving has been done in (Tao et al., 2013). In this study, the use of C typed support vector machine with radial basis function (RBF) kernel (RBF-SVC). Result of using RBF-based kernel gives the improvement of performance with respect to a priori of parameter (Tao et al., 2013). The accuracy prediction of SVM could be strongly affected by the adaptability between kernel function and data structure (Davy et al., 2002). The advantages of being insensitive to the order of appearance of the adjust signal gives the reason why choosing RBF-based are the wisely advised.

Meanwhile, in a paper that are focusing on diagnosis of neuromuscular disorders, his purpose a hybrid of Particle Swarm Optimization (PSO) optimized the SVM classification techniques by using a extracted EMG signals data. This optimization and population-based search algorithm by Reynolds are based on the simulation of the bird flocking. In this paper, the PSO-based are significantly influences the classification accuracy (Subasi, 2013) but in contrast, PSO algorithm are not suitable for the problem that included the non-coordinate system such as the solution to the energy field and moving rules of particles in the energy field (Bai, 2010).

There are a lot of studies that related on FCM clustering technique in different domain, such as electric engineering (Wang et al., 2011), healthcare and many more. (Chattopadhyay et al., 2007, 2008, 2009,). The FCM technique classifier the signal processing by grouping the similar data that are present in the future points into clusters. One of the studies shown that a hybrid of Quantum-behaved Particle Swarm Optimization (QPSO) and FCM had been used to detect unwanted intrusions in the network (Wang et al., 2011). The gradient descent of FCM had been used to import stronger global search capacity and preventing local minimum issues with FCM, The studies also confirmed the robustness in that studies. In addition, from the studies to segment MRI images as manual segmentations are highly time taking process, the FCM-based segmentation work faster and accurate (Ramathilagam et al., 2011) and the objectives of the study to remove the noise are successfully accomplished with FCM technique (Li and Weng, 2011). Others studies to segment MRI images have been advanced by automated the FCM to automate the segmented volume were analysed by the physician and by manually segmenting it which have been done with the real time data. The result shows that it is possible to function as predictors of future development (Satapathy et al., 2014). Thus, FCM is one of the most commonly used fuzzy clustering techniques for different degree estimated problems. Its strength over the famous k-means algorithm is that, given an input point, it yields the point’s membership value in each class (Amin et al., 2005). The efficiency ability of FCM techniques to gives best result for overlapped data, such as, sEMG signal, and comparatively better than k-means algorithm. Unlike k-means where data point must exclusively belong to one cluster center here data point is assigned membership to each cluster center as a result of which data point may belong to more than one cluster center. In another word, FCM is easy to get a fuzzy rule base and robust to noise. However, original FCM is sensitivity to the initial guess.

Furthermore, (Amin et al., 2005) do a research to estimate the degree to which a face expresses a given emotion which are less happy, moderate happy and very happy. This research has been successfully determining the strength or degree and FCM clustering is also used to choose the best description of faces in a reduced dimension. In this signal processing study, we implement the FCM for determine the variable load intensity or estimate the degree of fatigue for biofeedback personalized sport training to prolong the endurance sport training. There are few researcher and studies that have been done in the signal processing especially in variable load intensity modelling but not giving a feedback in predicting the load on the certain types of fatigue. In addition, the original FCM is randomly initializing the membership matrix which can lead to different performance result and might not correct. The pseudo code for Fuzzy C-Means is as follows:

1. Randomly initialize the membership matrix (U).
2. Calculate centroids (c_1).
3. Compute dissimilarity between centroids and data points.
4. Stop if its improvement over previous iteration is below a threshold.
5. Compute a new U.

Figure 2.8: Pseudo code for Fuzzy C-Means (Amin et al., 2005)

Otherwise, the research findings showed that the limitation of RBF model lies in the inefficiency of the network in large dimensional dataset. However, RBF, one of the neural networks families has several advantages such as better approximation capabilities, simple network structure, and fast learning (Niros and Tsekouras, 2008). In addition, The RBF algorithm is a popular muscle fatigue prediction technique due to its capability in improving the performance with respect to a priori of parameter (Tao et al., 2013; Sharawardi et al., 2016). Commonly, the estimated the parameters is carried out using two stages learning strategies; a) cluster analysis is implemented to calculate the appropriate values of the centers and the widths, and b) the supervised optimization procedures such as the optimal estimation of the connecting weight. Fuzzy C-Means based Radial Basis Function Neural Network (FCM-RBFN) was introducing to propose a clustering phase before the learning algorithm in RBF model (Maeda et al., 2006a, 2006b; Woo et al., 2008). The FCM clustering technique was used to optimize the center of RBF in order to increase the learning accuracy while maintaining the low computational time since it is able to detect meaningful structures in the available data set. Nevertheless, the current implementation of FCM-RBFN model cannot determine the number of cluster automatically, but has to be predefined either by thresholding method or fixed cluster number method (Maeda et al., 2006a, 2006b).

A good prediction technique based on short-term historical training data is crucial in predicting a nonlinear intensity program suitable for individual physiotherapy users. Radial Basis Function Network (RBFN) has been proven good in many real world applications (Xiao and Wang, 2004; Maeda et al., 2006a; Woo et al., 2008; Meng et al., 2009; Nanda et al., 2012; Rostami et al., 2013; Ferrari et al., 2014; Hamedi et al., 2014; Xie et al., 2014; Zainuddin and Lye, 2014) due to its simple network structure and processing speed. RBFN has been improved to adapt to dynamic changes using FCM clustering techniques which is able to identify cluster centres by training from data. However, the current implementation of FCM-RBFN model cannot determine the number of cluster automatically, but has to be predefined either by thresholding method or fixed cluster number method (Maeda et al., 2006a). Besides, determining the training time interval is a vital issue in designing the variable-load intensity model. Common practices are to determine the interval length according problem and rely on expert’s experience. To the knowledge of the researcher, very little research work was done on determining a good training time interval for prolonging muscle resistance against fatigue.

Variable-load intensity model is one of the suggested models aims to prolong muscle resistance against fatigue rehabilitation (Palmer et al., 1999; Veeger et al., 2002; Fry, 2004; de Vos et al., 2005). In (Tibold and Fuglevand, 2015), the predictions involves the complex multi joint movement include interaction with objects in the environment is crucial. It uses ANN to predict EMG activities of 12 arm muscles while human subjects made a free style of movement.

Nevertheless, in (Chan, 2007), an experiment has been done with trunk and upper limb as participants lifted a load from floor to a shelf using squat, stoop and freestyles lift techniques. At the same time, the sEMG signal and kinematic data are been recorded. model was successfully developed for the squat lift posture using the area, peak and mean of the zero-normalized EMG LE recorded from the erector spine (L4 level), with a prediction error of ± 1.03kg and for the stoop posture, a prediction error of ± 2.34kg. However, they are no computational technique involves.

In addition, a studies are been done in evaluation of hand force prediction using ANN regression models using sEMG for hand wear devices with different numbers of neurons and hidden layers and evaluated handgrip forces by using a dynamometer (Yokoyama et al., 2017). It contains of six different levels of forces from 0N to 200N and maximum voluntary contraction (MVC) is measured to train and test the ANN regression models. It shows that ANN family are good prediction techniques.

Meanwhile, in (Yokoyama et al., 2017), a study was done to show that 1RM can measured by a small load and EMG. The sEMG signals were captured on quadriceps during performed leg press exercise from 5kg to 6 kg load with interval 7.5kg. When subjects exercised with a small load, with increased load, the slope was gradually decreased. There was no significant change in the median frequency of the measured EMG. Thus, prediction equation can be used only in appropriate weight and repetition. If there are too many repetitions, 1RM determined by the equations are not accurate (Yokoyama et al., 2017). Therefore, in proposed objectives of the research, with the help of computational techniques, it can help to predict load according to current muscle fatigue state without worries about the repetitions.

Recent forecasting studies in a variety of domains have shown the many benefits of this model using machine learning approach but the problem of determining the suitable learning data time frame is still remained an open issue. Many real-time applications are facing difficulties in determining the time interval length of training data. Generally, different researchers suggested different optimum time interval and it is mostly based on expert knowledge.

From the Table 2.3 below shows the summary of literature review of predicting technique in muscle fatigue load. In this research focusing the robustness of the technique, fast learning, simple and can give excellent performance with the real time data. Therefore, from the table below its shows that RBF and FCM techniques fulfilled the objectives of this research. Thus, the next sub topic will explain more into these two techniques.

Table 2.3: Summary of literature review of predicting technique in muscle fatigue load

Technique	**Purpose**			**Data**		**Machine Learning Task**		**Performance**		
	Muscle Force predicting	Fatigue prediction	Load Prediction	sEMG	Real time data	Clustering	Classification	Accuracy	Robust	Fast Computation Time
RBF	/	/		/	/		/	/	/	/
MLP		/		/			/			/
ANN	/	/	/	/			/			
ANFIS	/			/						
SVM	/									
(RBF-SVC)				/			/	/		
PSO + SVM				/			/			
RBF + Gaussian function							/	/		
QPSO+FCM						/				
FCM			/	/	/	/		/	/	

2.11 Original Fuzzy C-Mean (FCM)

The original FCM is be developed by (Dunn, 1974) and improved by (Bezdek, 1981). In fuzzy clustering, each point has a probability of belonging to each cluster, rather than completely belonging to just one cluster as it is the case in the traditional k-means. FCM specifically tries to deal with the problem where points are somewhat in between centers or otherwise ambiguous by replacing distance with probability, which of course could be some function of distance, such as having probability relative to the inverse of the distance. FCM uses a weighted centroid based on those probabilities. Processes of initialization, iteration, and termination are the same as the ones used in k-means. The resulting clusters are best analysed as probabilistic distributions rather than a hard assignment of labels.

2.12 Radial Basis Function Network (RBFN)

In another hand, RBFN is an approximation process can also be interpreted as a simple kind of neural network; this was the context in which they originally surfaced, in work by David Broomhead and David Lowe in 1988, RBFs are also used as a kernel in support vector classification. The intuitive RBFN performs prediction by measuring the input’s similarity to examples from the training set. Each RBFN neuron stores a membership function, which is just one of the examples from the training set. To classify a new input, each neuron computes the Euclidean distance between the input and its membership function which have the most similar.

The advantages from both techniques are the main reasons to proposed integration FCM-RBFN technique to predicting the next load weight from a sEMG signal during isotonic muscle training task.

2.13 Fuzzy C-Mean based Radial Basis Function Neural Network (FCM-RBF Neural Network)

FCM-RBFN proposed by (Woo et al., 2008) consists of three steps. The first step is to classifying training objects into several clusters using FCM clustering. The second step is training each cluster with a sub-RBF neural network. The third step is combining several RBF outputs to obtain the final result using membership function. These techniques use training data for traffic flow modelling were generated using a well-known macroscopic traffic flow model at different densities and average velocities.

Three layers RBFN has consists hidden layer H hidden neurons, with radial activation function as following equation:

$$Z_h = \phi(\|x - C_h\|) = \exp\left(-\frac{x - C_h{}^T(x - C_h)}{2\sigma_H^2}\right) \tag{2.1}$$

The set of hidden neurons is designed to cover all the significant regions of the input vector space. The network output y is given by the following equations:

$$y = \sum_{h=1}^{H} W_h Z_h \tag{2.2}$$

FCM clustering is an unsupervised classification algorithm which uses a certain objectives function as following equations:

$$J_m(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m d_{ij}^2(X_i, V_j) \tag{2.3}$$

Where C is the number of clusters, N is the number of training objects. The objectives function is a weight within group sum of distance d_{ij}. Cluster centers are given by the following:

$$V_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} X_i}{\sum_{i=1}^{N} u_{ij}^{m}}, \forall j \quad (2.4)$$

Membership values compute as in the following:

$$u_{ij} = \frac{1}{\sum_{l=1}^{C} \left(\frac{d_{ij}}{d_{il}}\right)^{\frac{2}{m-1}}, \forall j} \quad (2.5)$$

With the Euclidean distance as following formula:

$$d_{ij}^{2}(X_i, V_j) = (X_i - V_j)(X_i, V_j)^{T}, \forall j \quad (2.6)$$

The new membership value of memberships is computed using the following equation along with the chosen distance measure. The membership value for a new vector is:

$$u_{N+1,j} = \frac{1}{\sum_{l=1}^{C} \left(\frac{d_{N+1,j}}{d_{N+1,l}}\right)^{\frac{2}{m-1}}}, \forall j \quad (2.7)$$

And output y of the distributed FCM-RBFN compute as following:

$$y = \sum_{j=1}^{C} u_{N+1,J} f_j(X) \quad (2.8)$$

Where f_j is the output of the jth RBF sub-network, C is the number of sub-networks in the distributed network such as the number of cluster of FCM. Figure 5.2 shows the FCM-RBFN flowchart proposed by (Woo et al., 2008).

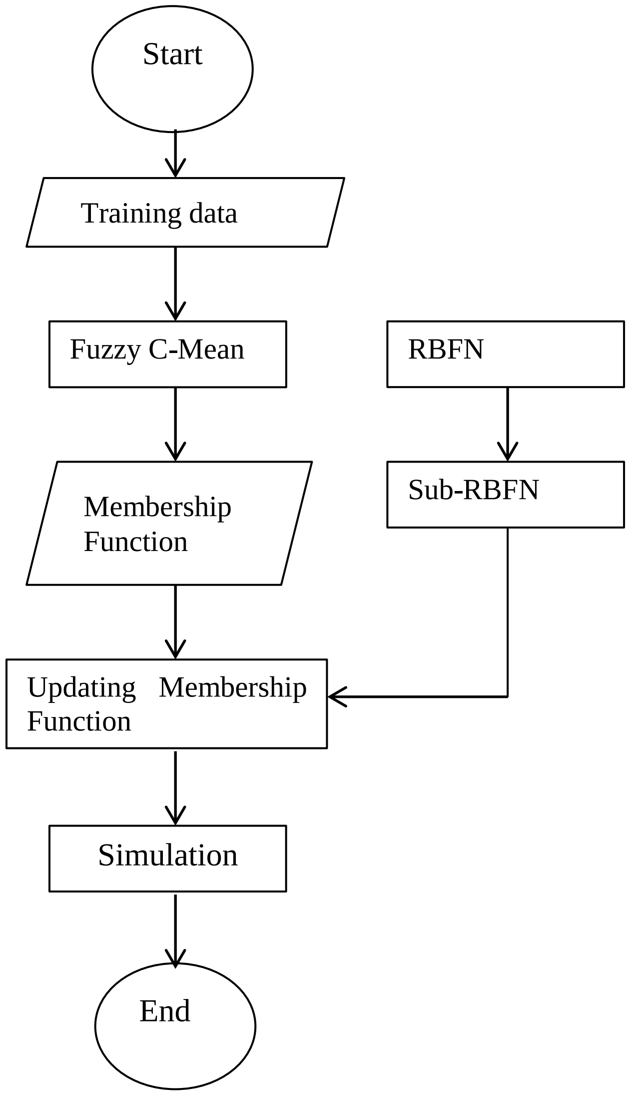


Figure 2.9: FCM-RBFN flowchart (Woo et al., 2008)

2.14 Benchmark techniques

The proposed technique was tested with the isotonic muscle fatigue dataset. The proposed technique is experimented on dataset to evaluate the load intensity performance against the benchmarking technique. The Artificial Neural Network (ANN) technique proposed by Warren McCulloch and Walter Pitts in (McCulloch and Pitts, 1943). ANN can be found in ANN tool in Matlab environment. The key expected an outcome from this phase is the classification results.

ANN is a computational model that inspired by the biological neural networks in human brain which is nervous system functions. ANN consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weight connections. The knowledge is stored within inter-neuron connection strengths known as synaptic weight.

ANN is a well-known prediction technique and useful for solving several problems such speech recognition, computer vision and text processing. Nowadays, a study in bio signal recognition, sEMG signal is widely using ANN as a prediction technique. ANN acquires knowledge through learning. Therefore, ANN provides a powerful tool to help researcher to analyse, modelling and predicting especially in bio signal recognition.

ANN model are at their core simplified models based on the biological neurons. This allows them to capture the essence of how a biological neuron functions.

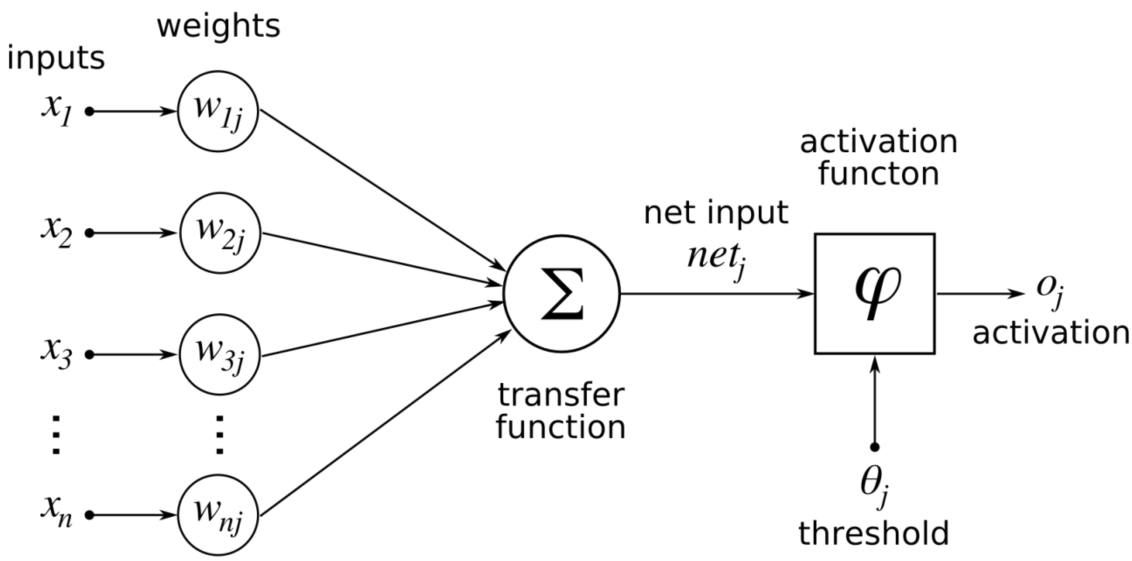


Figure 2.10: Artificial Neurons model

As shown in the Figure 3.3 above, there a several data or known as input and all these inputs are all individually weighted. The weight can either amplify or deamplify the original input signal. Next, the weighted signal is then added together and passed into the activation function. The activation function is used as the conversion input into the more important output. There are many different types of activation function but one of the simplest would be step function. In this research, the step function is used. A step function will typically output a 1 if the input is higher than a certain threshold, otherwise its output will be 0.

There are some initial setting needs to be set in order to performance the proposed integration FCM-RBFN prediction technique in Matlab environment. According to the literature, the class of the fatigue level is from 2 to 5. But in this study, the number of *c* is set to; such as, fatigue, transition-to-fatigue, and non-fatigue (Al-Mulla et al., 2009) due to the basic fatigue level. The number of *c* is set to 3 for the FCM in the proposed integration FCM-RBFN. On the other hand, the value weight and bias for RBFN in proposed techniques is automatically setting in Matlab environment.

Otherwise, for the benchmark technique, a 2-layer-10-neuron feed forward backpropagation ANN was used to predict the muscle fatigue state using 4 sEMG channels (Sharawardi and Choo, 2018). The hyperbolic tangent sigmoid transfer (TANSIG) function and the linear transfer function (PURELIN) were used for the first and second layer respectively. The implementation was run with the NNTool in Matlab using the Levenberg-Marquardt (TRAINLM) algorithm. Early stopping conditions for training after 1000 epochs (Mobasser and Hashtrudi-zaad, 2005) was imposed to improve the generalization of the network and to avoid over fitting. The ANN model was trained with 3 clusters and each of the cluster data have 81 samples data on different percentage of 1RM load with 7 input vectors corresponding to their output vectors. The target dataset for this benchmark technique will be the original cluster dataset which according to the trial. In addition, the load's weight also will be the second target data set. The performance was measured by using mean square error and the load value of predicted are be use for performance validation.

2.15 Performance measurement

Performance measurement is an important to measure the outcomes and a result, which produces a reliable data on the effectiveness and efficiency of the techniques used in a research or study. The most popular of performance measurements are the receiver operating characteristic (ROC), area under the curve (AUC), and mean square error (MSE). Each types of performance measurement choose are varies according to implemented techniques.

The area under the receiver operating characteristic (ROC) curve (AUC) is by far the most popular index of discrimination ability (Hanley and McNeil, 1982). AUC is a value between 0.5 and 1.0, with a higher value indicating better prediction performance. A prediction model with an AUC value of a 1.0 AUC value is a perfect prediction model, with 100% accurate predictions and in another word, an AUC value of a 0.0 is the lowest prediction model performance. However, AUC has been criticized as insensitive to the addition of strong marker, typically resulting in only small changes in value (Cook, 2008; Cook, 2011).

However, the MSE is the most used in the predicted performance such as in (Ahsan et al., 2012; Chowdhury et al., 2013b; Jali et al., 2014; Jali et al., 2015; Alba-Flores et al., 2016). The performance evaluation the predicted performance is based on the mean squared error (MSE) of the training data between the target outputs and the prediction model outputs. The prediction model is considered has the best prediction performance if it has lowest MSE value to 0.0 exhibits the smaller error (Jali et al., 2014) which in other words, which has a higher accuracy. The mean squared error (MSE) is calculated by squaring the value of predicted load and summing them. The value is interpreted in how far the result residuals are from zero or as the average distance between the observed values and the model predictions.

The MSE analysis had been used in (Zhaol et al., 2012) for the performance evaluation of an Artificial Neural Networks (ANN) techniques in sEMG data prediction. In addition, a research study in (Jali et al., 2015) used MSE as suitable performance measurement technique to evaluate the prediction performance. Moreover, ANN tools in Matlab are already implements the MSE as one of its performance measurement and it is easy to use. Therefore, the most popular performance measurement technique for prediction model is MSE.

2.16 Problem situation and solution concept

There are many ways, traditionally, in formal fatigue prediction by expert at different indicators such as physical changes in appearance, breathing, muscle contraction patterns, and most of the time on past experience, and later predicts muscle fatigue by analysing and comparing sEMG signals pattern changes across two different states, the non-fatigue and fatigue states in the workout session. Thus, this common practice in sport training by having the expert assistance approach to observing and predicting the fatigue state will lead to vary in terms of judgements because the prediction is made by different experts with various experiences. İn addition, the fatigue condition can be different from one person to another due to individual fitness level. On the other hand, the automatic prediction based on sEMG signal is more consistent in statistical perspective because is it based on quantitative measurement of signals pattern changes in oppose to human opinions. The purpose of this project is to predict fatigue level on muscular endurance training during isotonic muscle task for sport application.

The sEMG signal is been captured by electrode on the surface of the human skin for a weak electrical potential signal. This signal is very useful to analyse the human's muscle endurance against fatigue. However, sEMG signal have a very high noise that can annihilate the inherent of important information of the signal. Thus, it is giving a greater challenge of noise management on signal analysis. Therefore, there a lot of filtering techniques that eliminates the noise from the raw signal. The use of inappropriate filtering techniques will eliminate the important information in the raw signal. Therefore, the determination which type of filtering techniques that should be used are still a question mark due to varies types of filters suites to certain characteristics of raw sEMG signal.

Typically, sport training involves the muscle contraction exercise to increase the muscle strength against resistance. To complete muscle training includes three different types of muscle contraction, such as the concentric contractions, eccentric contractions, and the isometric contractions. All these contractions are needed each other to complete the isotonic muscle contraction workout and comprehensive training on all three types of muscular contractions is important for athlete in sport training. However, muscle injured during concentric contraction contently happen because athlete is normally unaware about it (Schmitz et al., 2002).

Currently, many researches on muscle fatigue prediction are still concentrated on isometric training as compared to isotonic training even though mostly sport training are in isotonic muscle contraction task. The importance of studying on isotonic muscle contraction is less attention due raw sEMG generates larger volume of motion artefact than isometric muscle contraction task. Nowadays, analysis tools use automated techniques to assist human decision especially on muscle fatigue prediction are conducted under the monitoring of muscle signal analysis tool to assure optimum results, and to reduce the risk of muscle damage (Garber et al., 2011) many researches on muscle fatigue prediction are still concentrated on isometric training as compared to isotonic training.

sEMG signal is a unique and varies between a another human being. Fatigue analysis using sEMG signals were usually carried out for isometric con-traction task to identify the good predictor's performance set as well as for prediction muscle force and angle estimation (Mobasser and Hashtrudi-zaad, 2005; Bravo et al., 2015). For isotonic training, the onset of contractile fatigue was successfully predicted using Radius Basis Function Neural Network (RBFN) model and Multilayer Perceptron (MLP) model. Research from (Mobasser and Hashtrudi-zaad, 2005) recommended the use of Artificial Neural Network (ANN) model for muscle fatigue prediction. At the same time, many studies has proven empirically that models from ANN family such as RBF (Mobasser and Hashtrudi-zaad, 2005) and MLP (Bravo et al., 2015) are good for isometric muscle fatigue prediction with mean squared error recorded between 1.76E-11 to 0.5. However, the capability of ANN models in isotonic muscle fatigue prediction is but it does not per-form comparatively well for isotonic fatigue analysis as it has achieved for isometric fatigue analysis (Sharawardi et al., 2016) but is able to perform muscle fatigue analysis on isotonic training. Therefore, RBF is proposed in this study as a prediction model.

In other term, FCM is one of the most popular fuzzy clustering techniques for different degree estimated problems. The successfully to determine the strength or degree and at the same time, FCM clustering is also used to choose the best description of faces in a reduced dimension (Amin et al., 2005). Its strength over the famous k-Means algorithm is that, given an input point, it yields the point's membership value in each class (RICHARD, 1999). The FCM and k-Means clustering algorithm have been reported to the best of knowledge but no similar study has been carried out in the isotonic muscle task using sEMG signal for sport application and it is still unclear which technique can provide better clustering.

Therefore, in this study, the proposed FCM-RBFN will be compared with k-Mean-RBFN to prolong muscular endurance training during isotonic muscle task for sport application. The choose of the popular RBFN algorithm as a predicting techniques is because of the improvement of performance with respect to a priori of parameter (Tao et al., 2013).

2.17 Summary

In this chapter, a wide-ranging and inclusive literature review has been conducted and its discoveries are presented in this chapter, ranging from the endurance training in sport science field, sEMG signal and features selection, and its existing techniques and framework with a brief overview of the result and findings. The gaps in this research that can be concluded are little studies in using isotonic muscle contraction in sport science due to high influents noise in raw signal and lack of data mining use in this particular research. In addition, from the literature review concluded, the combination of two soft computing is performed better than single techniques especially in prediction the different degree of certain subject. The literature review has provided an extensive perception into the current topics specifically to enhance the variable load clustering in endurance training task for sport training. In another side, the popular prediction modelling techniques among sEMG signal studies, ANN will be the benchmark technique against proposed technique.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This is a study of short-term personalized load prediction based on muscle fatigue status using sEMG signal analysis. This chapter describes the methodology of the proposed solution in details to achieve the overall objectives of this study. The experiment is focusing on isotonic muscle contraction. Experimentation data were collected among volunteer subjects from undergraduate sport science faculty students. This chapter contains 4 main sections. Section 3.1 describes the problem situation and solution concept. Section 3.2 explains the overall research methodology in this research. These sections contain the overall research design, investigation phase and implementation phase. Section 3.3 describes the operational procedure involved in the experiments that have been conducted throughout the research development in this study. It includes signal pre-processing, features extraction, Butterworth high pass filter threshold analysis, data acquisition and data preparation, construct the proposed technique, benchmarking analysis, performance measurement and validation test. Finally, the summary of this chapter will be written down in Section 3.4.

3.2 Overview of research methodology

This section discusses the research methodology adopted in this study. It involves the research development phases and the investigation procedures of operational framework in this research. An overall research plan is outlined to conduct the research development phases that been described in Chapter 1.

3.2.1 Overall research design

This research design in this study involves 2 main phases which are investigation component and implementation component. The overview research design is shown in Figure 3.1 below.

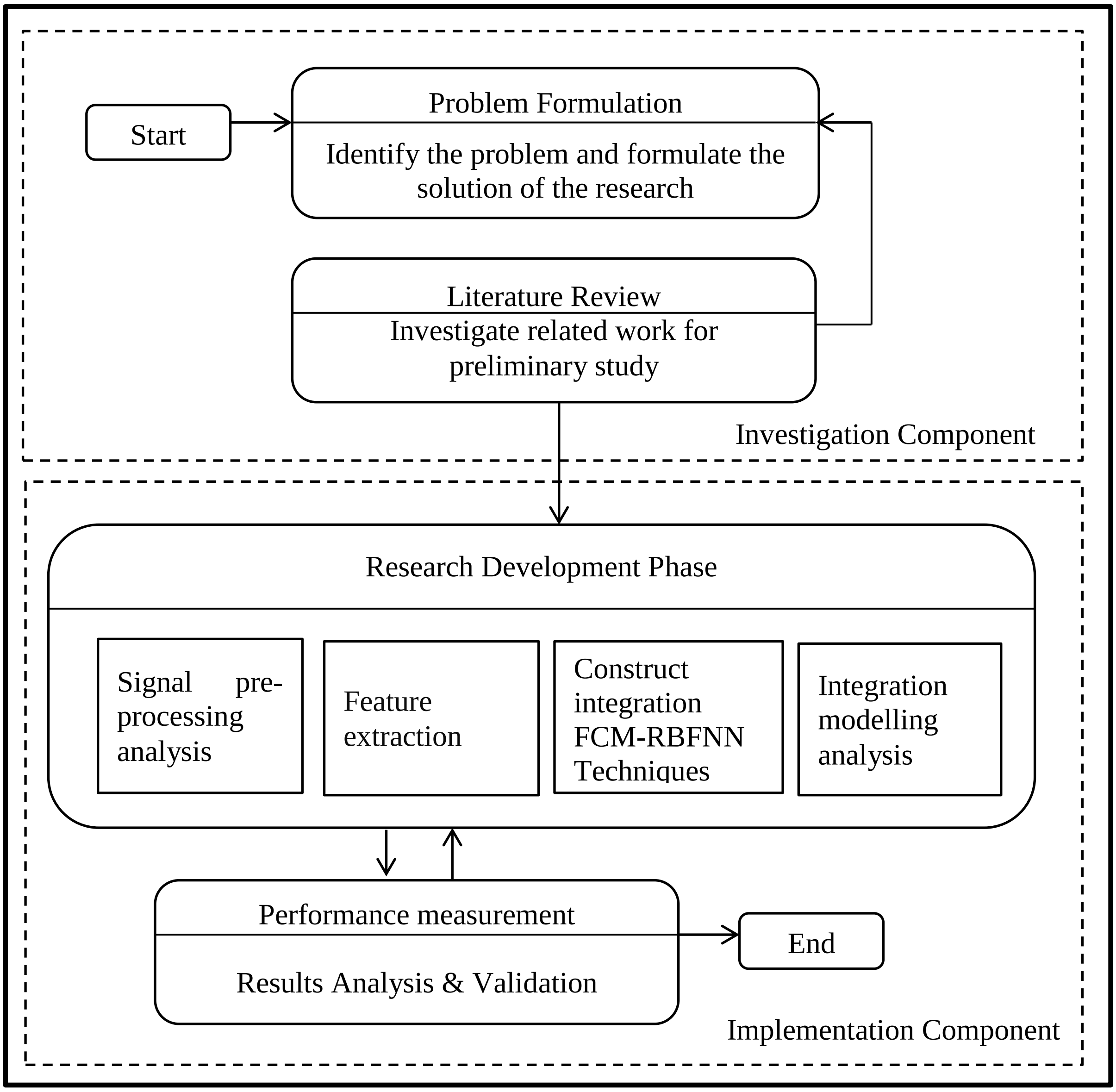


Figure 3.1: Overall research design

Based on the literature review in Chapter 2, a research study starts with the problem formulation. From literature review, the preliminary studies in problem domain and related area of the research can be explored and solutions can be proposed in order to find the suitable solution of the research gap. It is followed by the four main modules that have been investigate for research development component in order to address the solution of problem that has been define on the early stage. These four modules are Signal pre-processing analysis, feature extraction, construct integration FCM-RBFN techniques and integration modelling analysis. Lastly, in order to complete this research, the performance measurement with validation and analysis of the results process are presented in the last component of the research design in this study.

3.2.2 Investigation component

The preliminary studies have been done of the earlier of this research. This component, an open literature review of the research area has been studied in order to deeper understand the problem background, trends, and issues in the problem domain and other related area of this research. This literature review is needed to identify the specific domain to be explored in this research. Therefore, literature review is important in order you underline the problem statement and objectives for this research as be stated in Chapter 1. Results from literature study, the scope, importance of the research contribution has been identified and briefly presented in Chapter 1. The proper technical report on the problem background and related research to subject studies are then provided in Chapter 2. Table 3.1 shows the summary of the subject studies in the Investigation component.

Table 3.1: Summary of investigation component

Item and Description of Subject's Studies	
1. Subject Area :	sEMG signal analysis
2. Domain	Personalize load predicted for endurance training in sport
3. Issue	1. Person's sEMG signals are different and difficult to predict. 2. Person's muscle easily injured without sEMG signal monitoring from human expert.
4. Problem	Current predicted techniques lack of predicted load's weight value method which depends on the current muscle's conditions.
5. Solution	Enhance predicted techniques to automatically predict continuously next load's weight value according to subject's muscle current conditions in order to muscular endurance training.
6. Solution Model	Bio-signal pattern recognition
7. Solution Approach of Object	Integration between clustering technique and predicting modelling techniques.
8. Solution Method	sEMG signal pre-processing, feature extraction, integration method, model analysis.
9. Solution Technique	Fuzzy C-Mean (FCM), Radial Basis Function Neural Network (RBFN), integration, membership function update, sub-RBF network.
10. Data Resource	Collected sEMG dataset
11. Introduced	Integration FCM-RBFN techniques
12. Contribution in Domain	Personalize load predicted for endurance training in sport using sEMG signals, enhance integration between two techniques for personalizes load predicted modelling.

3.2.3 Implementation component

The stated justified problem in the investigation phase is addressed and applied into the Implementation phase in order to solve the problems. There are two phases in this phase which are the research development and performance measurement. The proposed solutions concept with justified approach, method, technique and model are adopted into this stage with a proper research guideline. The table shows as in Table 3.2, is an overall research plan in order to achieve the objectives in this research. It summarizes the problem statement, research questions, research objectives, performance measures and outcome.

Table 3.2: Summary of implementation component

Problem Statement	Research Question	Research Objectives	Performance Measure	Outcome
1. Too few experts to meet the demand of each person in personalized sport training 2. The need for the application the machine learning techniques for detection and classification for enhance variable load intensity modelling to muscular endurance for personalized sport training	1. How to quantify muscle endurance and muscle fatigue in isotonic contractions at different intensity levels? 2. What are the good feature extraction methods for muscle endurance and muscle fatigue analysis using surface electromyography signals?	1. To propose the predictive feature vectors to quantify muscle fatigue in isotonic muscle endurance training.	• Average Mean Square Error • Anderson – Darling Test for normality test • Wilcoxon Paired Signed-Rank Test for validation test	• Five time domain features: mean absolute value (MAV), root mean square (RMS), simple square integral (SSI), variance of EMG (VAR) and waveform length (WL). • Two frequency domain: median frequency (MDF) and mean frequency (MF). • The proposed electrode placed at biceps brachii and flexor carpi radialis muscle
	3. How to capture dynamic biofeedback for load prediction in FCM-RBFN technique?	2. To construct an integrated FCM-RBFN integration technique for muscle load prediction.		This integration FCM-RBFN prediction modelling technique can handle sEMG isotonic muscle signal with different types of subjects and sEMG signal characteristics align with the current subject’s muscle conditions.
	4. How to design the variable-load intensity model based on integration FCM-RBFN technique to enhance muscle endurance against fatigue?	3. To evaluate the proposed FCM-RBFN integration technique for muscle load prediction		The muscle load prediction model is been tested and the integration of FCM-RBFN is better that its benchmark, ANN technique.

3.3 Operational procedure

The main drive of this chapter is to explain the research methodology, in order to accomplish the main objectives of this study. The major objective of this research is to quantify muscle endurance and muscle fatigue in isotonic contractions at different intensity levels which led to designing the variable-load intensity model based on dynamic FCM-RBFN load prediction technique, equivalent to the Objective 1 and 2 in this research.

Continually from Objective 2, the validation the proposed model on muscle endurance performance against muscle fatigue towards sport training will be established, corresponding to the Objective 3. Hence, the research framework of this research will include 5 phases; data acquisition, data processing, data clustering, value predicting and results validation phase.

The research will follow the experimental methodology as follows at Figure 3.2 on the next page:

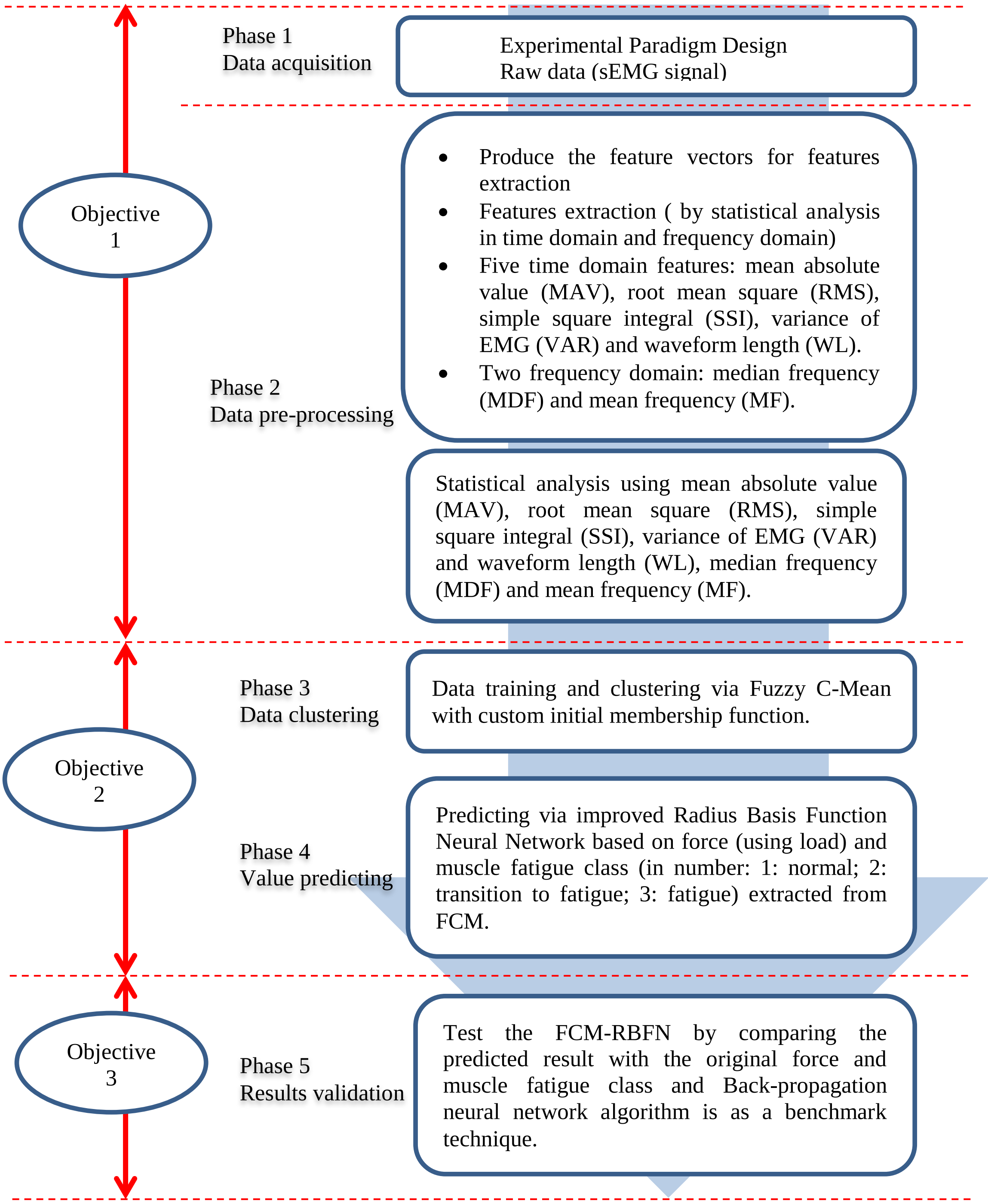


Figure 3.2: Research methodology

3.3.1 Phase 1 and 2: Data acquisition and data processing

The main purpose of this phase is to identify all the related variables needed for design and experimental phases. This phase starts with thorough literature reviews on muscle endurance state, muscle states quantification methods, load intensity parameters and the feature extraction methods related to the solutions. Among the potential outcomes at the end of this phase are the proposed muscle endurance states and the quantification method, load intensity measurement parameters and the suitable feature extraction methods. The results in this phase support Objective 1.

Muscle fatigue sEMG signal during isotonic task data set was used in this study with consists of 27 subjects with 4 electrodes. Each individually is completes with a total number of 81 trials and sampled at 2000Hz/sec. The sEMG dataset was recorded for sport students. The classifier was being trained with 3 clusters; fatigue, transition-to-fatigue, and non-fatigue.

Raw sEMG signal tends to different in each epoch in the signal especially when subjects tend to be fatigue. The repetition and the amplitude will be lower due to the lower electrical energy inside subject's muscle. Therefore, feature extractions are important in order to identify muscle endurance state. These features extract the new version which represents the load intensity for the certain pattern of signal.

Thus, it is a vital process to extract the important and relevant information from the sEMG signal. Feature extraction stage involves the transformation of the new signal from the raw data into a relevant data structure which is known as feature vector. All the feature vectors that extracted were used as input attributes for the classification purpose. Different features provide different discriminative power for different subjects. Most popular feature of the studies in sEMG domain are RMS, MDF and MF due to efficacy of these features to extract important information in sEMG signal than others.

Therefore, from the literature review, there are total seven features techniques are selected from time and frequency domain for feature extraction. Five techniques are selected from time domain which are mean absolute value (MAV), given by equation (2.1), root mean square (RMS), given by equation (2.2), simple square integral (SSI), given by equation (3.1), variance of EMG (VAR), given by equation (2.3) and waveform length (WL), given by equation (3.4). In the other hand, the techniques which used in frequency domain are median frequency (MDF), given by equation (2.4) and mean frequency (MF), given by equation (2.5). The Table 3.3 shows the seven features used in this project.

Table 3.3: Simple square integral (SSI) and waveform length (WL) equation

Time Domain	
Features	**Formula Number**
Simple Square Integral (SSI)	$\text{SSI} = \sum_{\text{n}=1}^{\text{N}} \lvert x(n)^2 \rvert$ (3.1)
Waveform Length (WL)	$\text{WL} = \sum_{\text{n}=1}^{\text{N}} \lvert x_{\text{n}} - x_{n-1} \rvert$ (3.2)

Raw sEMG dataset was obtained in this phase. This phase involves the design of experiment, ethics approval, data acquisition, experimentation and results analysis. The proposed variable-load intensity model from phase 2 and phase 3 will be tested in this phase. The isotonic muscle fatigue sEMG signals will be used for training and testing steps. The experimental dataset will be acquired from a test group of 27 healthy subjects with variable-load intensity force prediction. The isotonic muscle contractions paradigm will be carefully designed to demonstrate the anticipated dynamic condition of different intensity levels in the experiments. Suitable features extraction methods will be identified to maximize the prediction effort of the test subjects in processing the muscle resistance signal presentation in the experiments. A group of 27 student subjects of predefined requirements, such as gender, health, age, and others will be recruited to develop the case study.

Ethical approval application will be forwarded to Centre for Research and Innovation Management Ethics Committee at UTeM as well as the MOH Medical Research and Ethics Committee (MREC) at www.nmrr.gov.my. A total of 27 separate sessions of sEMG data of 4 channels acquisition will be recorded as training data. The raw data will be pre-processed accordingly to filter noise and perform feature extraction process. Next, the processed datasets will be divided into training and testing data using the 10-fold cross validation method to ensure an unbiased learning function of the proposed model.

The 27 undergraduate Sport Science students from Faculty of Sport Science and Coaching, Sultan Idris Education University were recruited to participate in the experiment based on voluntary basis. From the subject group, there were 9 healthy male subjects (age = 22-24 years; body weight = 50-75 kg; height = 152-180cm) and 18 healthy female subjects (age = 22-24 years; body weight=42-67 kg; height = 145-164 cm). All of the subjects are having normal body mass index. None of them has any history of neuromuscular disorder. The criteria for selection of the subject are shown in Table 3.4.

Table 3.4: The criteria for selection of the subject

Criteria	**Male**	**Female**
Number of subject	9	18
Age (Years old)	22-24	22-24
Weight (kg)	50-75	42-67
Height (cm)	152-180	145-164
Health Condition	Normal and Healthy	Normal and Healthy
BMI	Normal	Normal

The experiment dataset was collected by recording the sEMG signal activities based on isotonic muscle contractions during the dumbbell lifting workout session. A muscle contraction from two muscle types was observed during the experiment, the flexor carpi radialis and biceps brachii from both right and left hand.

Experimental results will be reported in suitable statistical and graphical presentations to ease the analysis and evaluation process. The last phase in the research emphasises on the analysis, validation and evaluation of the experimental results to investigate the capability of the proposed model and its performance against the benchmarking techniques in prolonging the muscle resistance against muscle fatigue during physiotherapy session.

3.3.2 Phase 3 and 4: Data clustering and predicting (FCM-RBFN technique)

Phase 2 is the beginning of the design phase. It aims to construct a dynamic FCM-RBFN technique which is able to adapt to continuous muscle biofeedback for dynamic load prediction. The expected outcome of this phase is the new version of dynamic FCM-RBFN technique and its algorithm to partially achieve Objective 2. The main purpose of this phase is to enhance the current techniques to design the variable-load intensity model based on integration FCM-RBFN load prediction modelling technique.

FCM technique is an unsupervised clustering which the ‘c’ numbers are set to 3. The efficiency ability of these techniques to gives best result for overlapped data and robust to noise. However, original FCM is sensitivity to the initial guess. In order to enhance the original FCM, this study proposed, the initial guess is fixed set according to expert knowledge. Therefore, the outputs of FCM are in supervised data set.

In addition, RBF is more fast learning which will complementary the limited of a long computation in FCM techniques. RBF also is claimed that the hidden layer is easier to interpret than the hidden layer in other ANN predicted techniques. In addition, RBF are a special class of hidden layer deep forward neural networks for application to problems of the supervised learning. The integration FCM-RBFN algorithm and flowchart will be discussed in details in Chapter 5.

3.3.3 Phase 5: Performance measurement and validation test

The last phase in the research emphasizes on the analysis, validation and evaluation of the experimental result to investigate the noise management capability of the proposed integration FCM-RBFN technique and its benchmark ANN technique in a sEMG signal prediction. The experimental results are analysed based on mean square error (MSE) and average mean square error (MSE) for both techniques. However, these performance measurements are suitable only for trial/class 1. This is because the original load is only valid for only first trial. When the second trial is about to be done, the original load should differ and lesser than the original load on the first trial due to the current muscle's condition is getting fatigue that the first trial. Therefore, MSE is not suitable be compute for the second and third trial. As known, the original loads provided are from 1RM formula for each of the subjects taken before the first session experiment.

In order to validate the second and third trial in a session, the other measurement has been produces according to the condition of muscle that will be fatigue over time with the continuing doing isotonic training task. Therefore, the load's weight should be lesser that 1 RM for the first trial. The true positive cannot be use because the expected original load is only for second and third trail might be true, or might be false.

Based on Table 3.3 as shown below, when either one of predicted load value of integration FCM-RBFN or its benchmark technique ANN are lesser than the original load, the techniques that got the lowest predicted load value is accepted. Then, either one of the predicted load value of integration FCM-RBFN or ANN is higher than original load, the highest value predicted load is rejected. However, there are problems when either prediction techniques have higher load values or both values have lower load values. As shown in Table 3.5 below, the mark (*) indicate the problems. The way to solve the problem is the nearest predicted load value to the original load in between ANN and integration FCM-RBFN will be accepted and otherwise, the predicted load is rejected. The accepted technique will get 1 mark. As to calculate the total ‘true’ and ‘might true’, the overall mark has been sum up and the average are calculated.

Table 3.5: Different outcomes of Trial/Class 2 and 3 for Artificial Neural Network (ANN) and integration FCM-RBFN

		Predicted Load	
		Lower	Higher
Original Load	Lower	*	rejected
	Higher	accepted	*

All the accepted predicted load value will be compute to get the average mean squared error, which is calculated as follow:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\bar{y}_i - y_i)^2 \quad (3.3)$$

When $\bar{Y}$ is a vector of n predictions, and y is the vector of observed values corresponding to the inputs to the function which generated the predictions, then the MSE if the predictor can be estimated. The mean squared error (MSE) is a measurement of the quality of the estimator. The MSE is always non-negative and the values nearer to zero are better. The MSE is also known as the finding average of a set of errors mostly popular in predicting techniques.

The normality distribution of the data must be determined before perform a validation test. A validation test is performed to determine the confidence level of the dataset that can be in reaching conclusions. In addition, most statistical tests rest upon the assumption of normality. A deviation from normality is called non-normality. If the data sets are non-normality, then a non-parametric test is performed. It is to test group medians. If the data are normally distributed a parametric test is performed and the group means is tested. It is important to make sure the type of data distribution is being tested on the correct test as the result will not be accurate. Parametric test, paired sample t-test is chosen when the data are normally distributed while non-parametric test, Wilcoxon signed-rank test is chosen when the data are not normally distributed.

The paired sample *t* test is a parametric test. The paired samples *t* test is to compares the two means that are from the same related group. The two means represent the before test and after test or two different but related condition. In this case, the original load is being compared with predicted load. The purpose of this test is to determine whether there is statistical evidence that the mean difference between paired observations on a particular outcome is significantly different from zero.

In another hand, the Wilcoxon signed-rank test is a non-parametric test that usually used in statically test. The Wilcoxon signed rank is to compare the two dependent samples and it is quite similar to samples t-test. In Wilcoxon signed rank test, when the *p*-value is less than 0.05, the null hypothesis is rejected and it is a significant difference between the paired samples. Otherwise, the null is accepted if the *p*-value is more than 0.05 and there no significant difference between the paired samples. The *p*-value is the probability of finding the observed which when the hypothesis is being tested. P is also described in terms of rejecting H_0 when it is actually true, however, it is not a direct probability of this state.

3.4 Summary

This chapter explains the research methodology used for obtaining the solution in this research. In addition, the research methodology to make sure the research development follows the schedule and can avoid any unexpected problem. Research methodology has been explained in this chapter which consists of 4 phases: data acquisition, data processing, data clustering, value predicting, and result validation. The next chapter will discuss the experiment design in details, which the important process to fulfil the objectives in this research.

CHAPTER 4

SURFACE EMG EXPERIMENT DESIGN AND DATA ACQUISITION

4.1 Introduction

This chapter will describe the experimental setup or design, in order to collecting sEMG signal data to fulfil the objectives of this study. The focus of this research is to design the experiment process so that the processing in collecting data of sEMG signal will smoothly will be done. Hence, this chapter will clarify in details for each subchapter and has been organizes of this subchapter as follows. The participant's details will be discussed in Section 4.2, hardware and software that have been used in Section 4.3, electrode types and placement in the participant's body in Section 4.4, the experimental venue that took place will be elaborate in Section 4.5, experiment setup in Section 4.6, and followed the signal processing in Section 4.7. Finally, the result and discussion of this chapter will be drawn in Section 4.8.

4.2 Participants

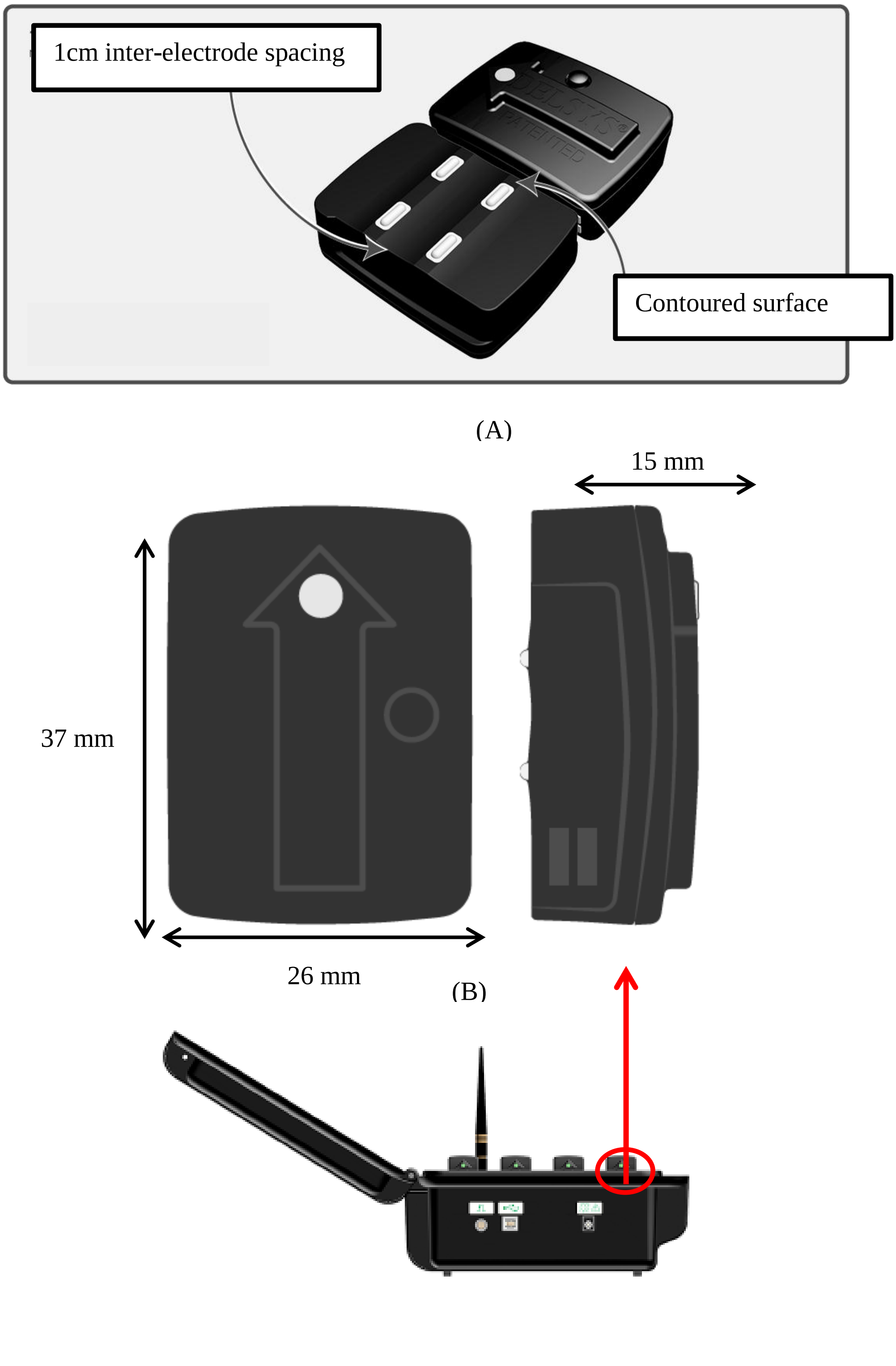
The SEMG signals will be recorded from a group of 27 subjects by using standard sEMG equipment with the non-invasive electrodes. There were 9 healthy male subject (age = 22-24 years; body weight =50-75 kg; height = 152-180cm) and 18 healthy female subject (age = 22-24 years; body weight=42-67 kg; height=145-164 cm) volunteered to participate in this study. The main focus for using both sex (9 males and 18 females) sEMG signal data is for the proposed modal techniques can tolerate in each user with minimal error. In addition, the imbalanced total number of subjects (more than 70% are from healthy female) is due to the lack of time for having a full 3 session experiment for a subject to be completed. The imbalanced total numbers of subjects are not being focused in this research. No participant had a history of neuromuscular disorder, and all participants were aware of experiment purposes and procedure. The participants were required to lift a dumbbell in the position described (Balshaw et al., 2017) in Figure 4.6. Human subject ethical approval was obtained from the Centre for Research and Innovation Management Ethics Committee at UTeM as well as the MOH Medical Research and Ethics Committee (MREC) at www.nmrr.gov.my and an informed consent was obtained from the subject prior the experiment.

Therefore, it will provide maximum comfort and painless for the subject during the experiment has been done. In order to collecting the required signal, the volunteer subjects recruited to join this experiment with college age ranging between 22 to 24 years old. All details for the subjects are in Table 4.1. Subjects were asked answering the PAR-Q questionnaire, done the determination of value one-repetition maximum (1RM) test, and asked to sign written consent before participating in the study.

Table 4.1: The subject details

Sex	**Age**	**Weight**	**Height**	**BMI**
M	22-24	50-75	152-180	Normal
F	22-24	42-67	145-164	Normal

4.3 Hardware and software



(C)

Figure 4.1: Trigno™ wireless 4-channel sensor (A), size of Trigno™ wireless 4-channel sensor (B) and Trigno™ Base Station (C) (Trigno™ Wireless EMG, 2018)

Figure 4.1(C) shows the Trigno™ base station that has been utilized as a devise interfacing with PC to analyse muscle signal that been capture by Trigno™ wireless EMG sensors to monitor the muscles activities. Engine neurons transmit electrical signs that make muscles contract. An EMG makes an interpretation of these signs into diagrams, sounds or numerical qualities that a master deciphers in PC. Each Trigno™ sensor attached to this Trigno™ base station is equipped with features such as the transmission range of 40m, with 48mS fixed group delay, sEMG signal bandwidth 20- 450 Hz and sample rate at 2000 samples/sec. The Trigno™ sensor utilizes Delsys' patented parallel-bar technology with proprietary stabilizing references and fixed 1cm spacing. The result is a high quality EMG signal that limits muscle crosstalk and motion artifacts while providing consistency through reliable hardware as shown in Figure 4.1 (A). In Figure 4.1 (B) shows the Trigno™ sensors measure 37mm x 26mm x 15mm and weight approximately 14 grams.

In addition, the use of software in this study such as Matlab R2013a, Microsoft Excel 2010 and also Microsoft Word 2010 are also employed in helping for signal processing and documentation. The experiment was implement on Intel ® Xeon® CPU E5-1620 v2 3.70GHz processing running on Microsoft Windows 7 Professional with 8GB of main memory.

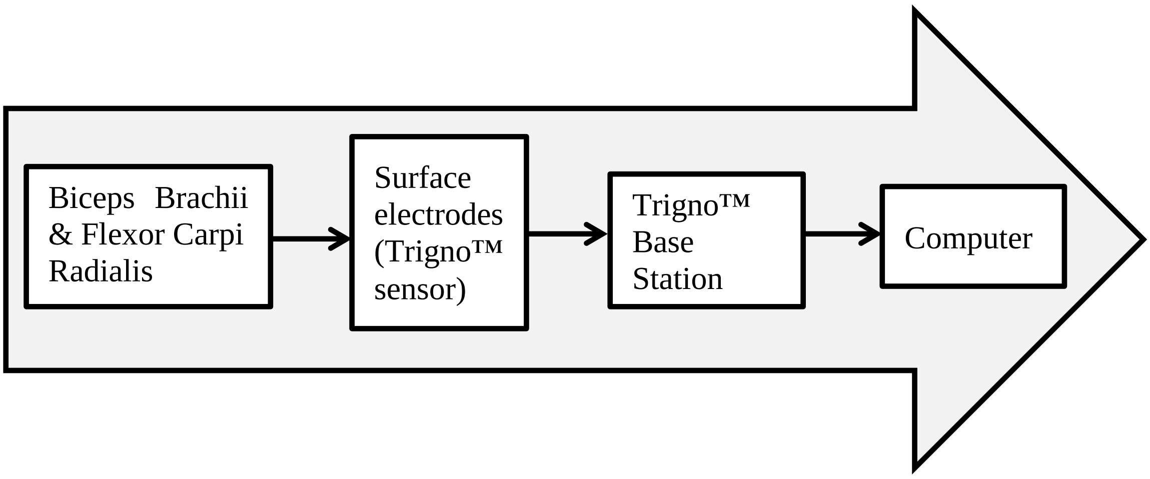


Figure 4.2: Block diagram of the myoelectric interface system

Figure 4.2 shows the block diagram of EMG interface system. The Trigno™ Sensors are attached to the participant skin which located at the biceps brachii and flexor carpi radialis Muscles. The sEMG signal are been analyses by Trigno™ Base Station and displays at computer for monitoring.

4.4 Electrode types and placement

In this study, the non-invasive surface electrodes are used to capture the EMG muscle activities signal from the human muscle. The selection of electrodes depends on the experimental setup and the objectives in this study. The main reasons are the non-invasive surface electrodes are easy and convenient to be use in any place and environment.

The recording of SEMG can be captured with electrodes that are attached to the skin surface. SEMG be captured by a 4 channel of electrodes. More than one electrode is needed because SEMG recordings display the potential difference between two separate electrodes. The skin preparation for each of the subjects must been done. The skin preparations for SEMG are including the removing of the subject's hair around the electrode site to improve the electrode adhesion. In addition, the use of fine sandpaper to abrade the skin surface combined with alcohol swabbing to clean the dead skin, oil and or dirt to lower the skin impedance. This is because sEMG electrodes are sensitive to artefacts. Then, the electrode will attach to the skin surface of the subjects.

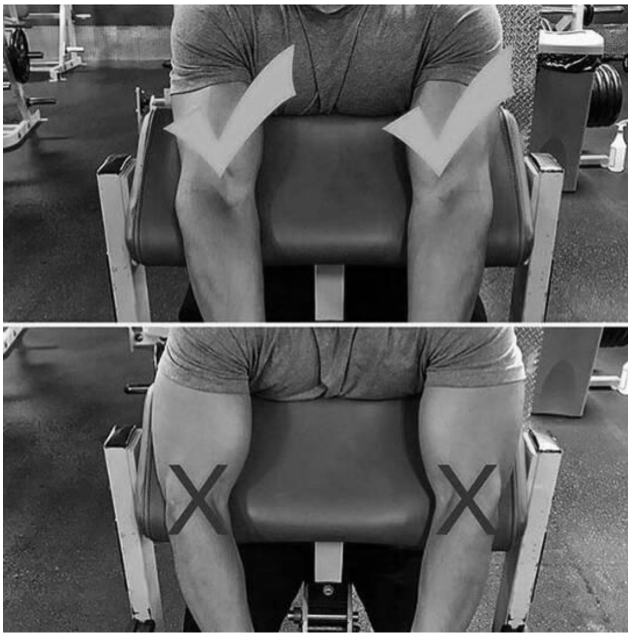


Figure 4.3: The correct position to lift the dumbbell

In this experiment, sEMG sensors were placed on the both hand of the subject's biceps brachii and after we do the cleaning on the skin surface. This placement is normally used to measure the sEMG signal during Dumbbell Curls Seated exercises and the correct position to lift the dumbbell to avoid muscle injury as in Figure 4.3. Selection of the muscle depends on the objectives and the experimental setup. Biceps brachii muscle is selected because it is the most visible part of the biceps brachii and the flexor carpi radialis muscle is selected because of it is included muscle and involves in uplifting the dumbbell. The position of muscle is located as shown in Figure 4.4. In addition, the placement of the sEMG electrodes on the skin are been referring to the sEMG for non-invasive assessment of muscle as state in SENIAM. The SENIAM project (Surface Electromyography for the Non-Invasive Assessment of Muscles) is a European concerted action in the Biomedical Health and Research Program (BIOMED II) of the European Union. The SENIAM project has resulted in European recommendations for sensors and sensor placement procedures and signal processing methods for SEMG.

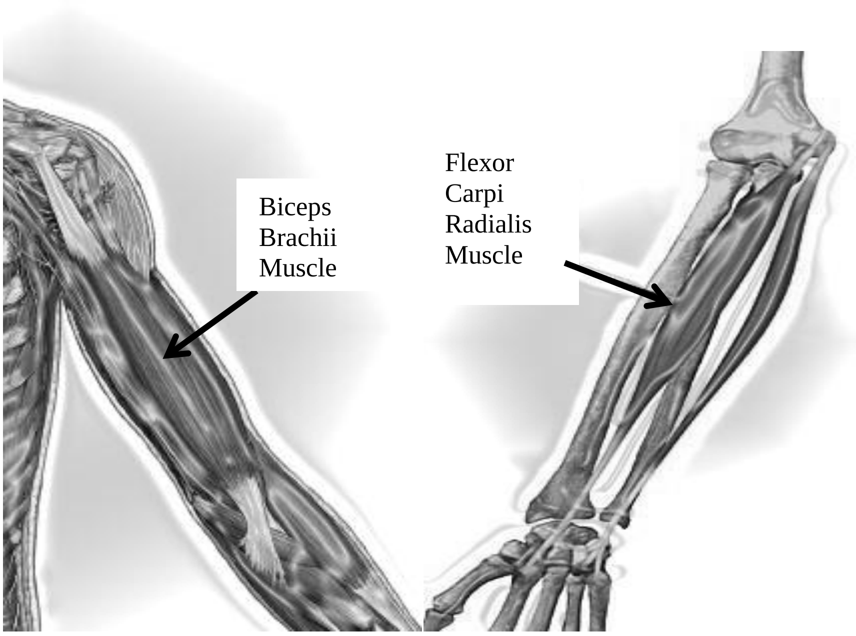


Figure 4.4: Muscles type on human hand

4.5 Experiment location

The experiment conducted in Faculty of Sports Science and Coaching (FSSK), Universiti Pendidikan Sultan Idris (UPSI). All the subjects are students of FSSK. This experiment is design a sEMG where the subject's asked to do dumbbell curls seated exercises for three sessions. The recording sessions were carried out in a normal gym hall in FSSK, UPSI. The experiment recordings were recorded in the morning and evening. There a study about the differences muscle activation level on the morning and evening. As a result, there are slightly different of muscle activation level. But, in this research, this concern is not in our focus. This is due to the availability of the gym hall, equipment and subject's schedule and also lack of time that need to fulfilled. All the subjects were recorded in the same gym hall and experimental setup to maintain the consistency in data acquisition.

4.6 Experiment setup

The experiment dataset was collected by recording the sEMG signal activities based on isotonic muscle contractions during the dumbbell lifting workout session. Muscle contractions from the flexor carpi radialis and biceps brachii for both right and left hand were observed during the experiment. The Figure 4.5 shows the experiment setup for data collection.

Figure 4.5: The sEMG data collection setup for isotonic muscle contractions

The subject must follow the endurance training for 1 day a week for 3 sessions as in Figure 4.6. For the first session, subjects will be asked to run a 1 RM (One-repetition maximum) test, then, at the next session, 3 set of training will be held around 30 minutes per session for each of the subjects. Each session have a different of training intensity, which are 30% of estimated 1RM, and 50% of estimated 1RM (Garber et al., 2011). Figure 4.7 show the endurance training schedule for a session with 50% of estimated 1RM. There are no specific reps and the subjects will be asked to maintain the 90^{o} elbow angle as closely as possible. There are 5 minutes break intervals for this experiment to make sure the subjects are not in the fatigue condition by sEMG signal produced. In addition, the 5 minutes' rest break intervals from one set to another in order to prevent muscle injuries. Throughout the experiment, metabolic analyzer as a key tool for analyzing the metabolic produces by body is use for further investigation. Table 4.2 shows the tasks that the subjects need to be complete for three sessions. A session must be completed for a day. Then, the participant need to take a few days rest with minimal 48 hours (Garber et al., 2011).

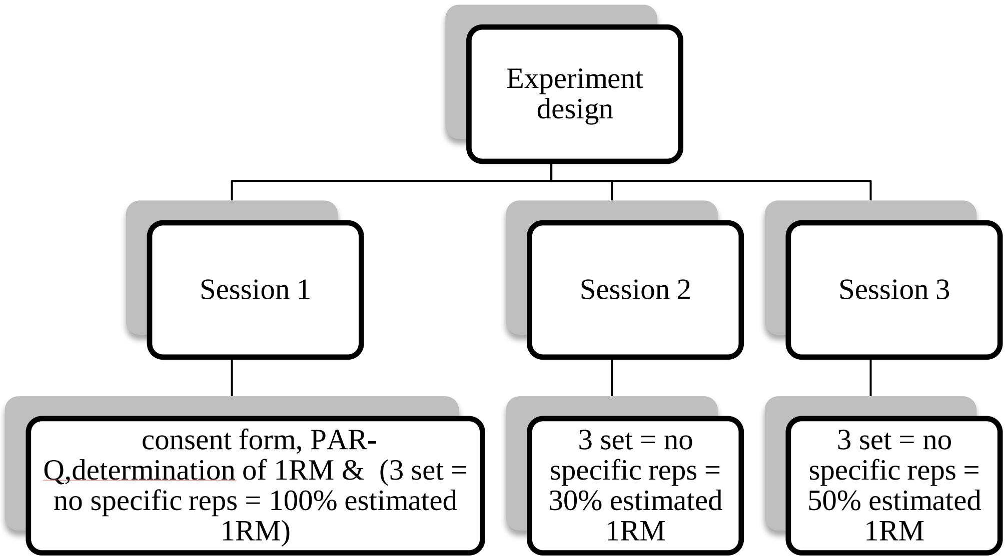


Figure 4.6: The experiment design process

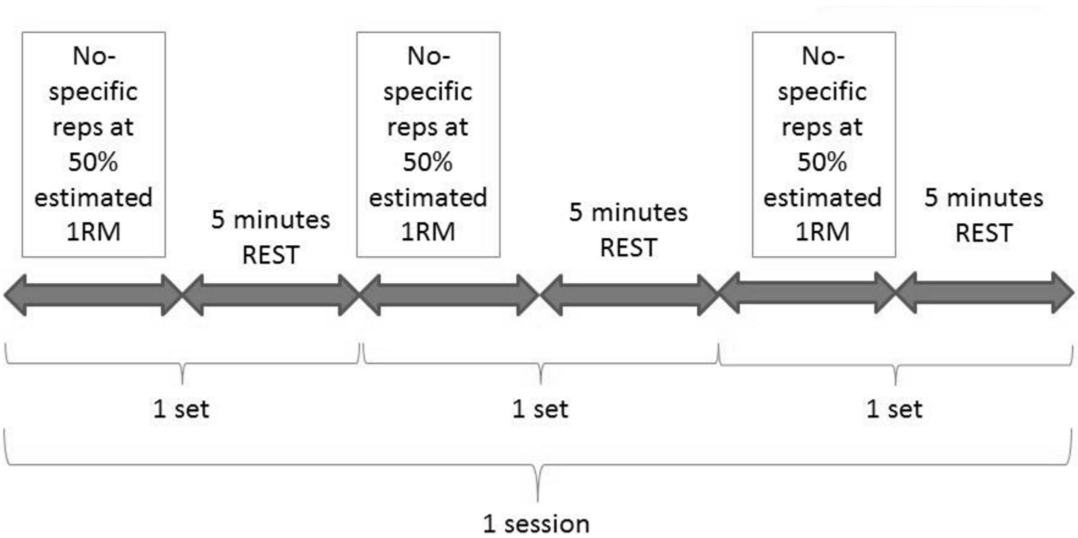


Figure 4.7: The endurance training schedule

Table 4.2: The tasks for the experiment

Task	Description
Session 1 (1 day)	
1	• consent form, PAR-determination of 1RM
2	• 1 set = no specific reps = 100% estimated 1RM
3	• 5 minutes rest
4	• 1 set = no specific reps = 100% estimated 1RM
5	• 5 minutes rest
6	• 1 set = no specific reps = 100% estimated 1RM
Rest for at least 3 days	
Session 2 (1 day)	
1	1 set = no specific reps = 30% estimated 1RM
2	5 minutes rest
3	1 set = no specific reps = 30% estimated 1RM
4	5 minutes rest
5	1 set = no specific reps = 30% estimated 1RM
Rest for at least 3 days	
Session 3 (1 day)	
1	1 set = no specific reps = 50% estimated 1RM
2	5 minutes rest
3	1 set = no specific reps = 50% estimated 1RM
4	5 minutes rest
5	1 set = no specific reps = 50% estimated 1RM

For non-sporting environment, upper limb frequently loaded for daily tasks (Fischer et al., 2009). In sporting environment upper limb muscle are highly important for sports such as swimming, combat sports and racquet sports. Due to these reasons upper limb muscle was selected for this experiment. sEMG data of upper limb provides the strength and conditioning coaches guidelines on which muscles were activated in each variations of exercises involved (Engineering et al., 2014). However, those sEMG data need to be meaningful. Thus, comparing cut-off filter threshold is essential, especially with significant changes in motor unit recruitment of biceps muscles after strength training interventions was hard to detect (Watanabe et al., 2015) due to several reasons such as a much slower rate of movement, typically less than 1Hz (Yang and Hunt, 2014) and smaller cross-sectional area (less motor-neuron) compared to lower limb muscles. Butterworth filters has also been widely used in sports science and human movement studies, with varied filters range (Schoenfeld et al., 2014; Amarantini and Bru, 2015; Balshaw et al., 2017; Scott et al., 2017). Thus, further investigations needed to verify which range is the best.

The purpose of using armrest in the experiment was to optimize the arm muscles utilized during dumbbell lifting task. The armrest is able to ensure only the targeted arm muscles are used, not the other body muscles, especially lower body muscles. The amount of oxygen consumption was monitored throughout the whole workout session to avoid cardiovascular overload. However, these data merely serve the purpose of monitoring but were not use as one of the predictors in the proposed model. In addition, video recording was used throughout the data acquisition sessions when the subjects were performing the workout to aid results validation especially in data exploration phase. The Delsys Trigno Wireless system was used as interfacing between EMG machine and the computer for sEMG signal acquisition. Four channels of electrode with 48ms fixed group delay were applied on the surface of flexor carpi radialis and biceps brachii muscles. The sampling rate of 2000 samples per second was used. The EMG signal recorded with surface electrodes could be sampled as slow as 1000 Hz for signal analysis, but the optimum sample rate is between 2000 to 2500Hz (Sys, 2009).

The dumbbell weight was predefined according to individual subject's one-repetition maximum (1RM) load. The measurement of 1RM is used to calculate the maximum load that a subject can lift in one maximal muscle contraction (Ability et al., 2007). The subjects were asked to performed dumbbell lifting using the maximum load until fatigue in the trial experiment set. The Wathan formula (Schoenfeld et al., 2014), as shown in equation below was used in the experiment.

$$1\mathrm{RM} = 100\mathrm{w}/(48.8 + 53.8\ \mathrm{e}^{-0.075\mathrm{R}}) \tag{4.1}$$

where w is the amount of weight used, and R is the number of repetition performed. To obtain the 1RM estimation, the subjects were tested with the maximum dumbbell weight load which he/she can afford to complete a full 10 repetitions. This is trial and error estimation although the amount of weight used can be guided by past experience and also the best practice in sport science (Garber et al., 2011; Charulatha et al., 2013). Hence, the more accurate the maximum weight used, the more realistic the 1RM measurement will estimate the true strength.

4.7 Signal processing procedure

Signal processing is an empowering innovation that incorporates the basic hypothesis, applications, calculations, and usage of preparing or moving data contained in various physical, typical, or theoretical configurations extensively assigned as signals. In this study, signal handling or signal processing is an important stage for noise cleaning and to extracted valuable meaning data that we can interpreted to useful data.

Raw data were pre-processed such as filtration. Filters are applied in the raw data to eliminate the unwanted noise in the signal. However, filtering can lead to information lost. Therefore, in this study, Butterworth high pass filter was used with high pass filter with 10 cut-off threshold. The reason for choosing high pass filter with 10 Hz will be explained in Chapter 6 later.

From the previous researchers, the easiest way to deal with noise in the surface EMG is to filter with the high pass filter (Najarian and Splinter, 2006; Allouch et al., 2013), and thus the use of Butterworth filter to remove noise from the raw sEMG signal was a very popular choice candidate amongst the researchers (Luca, 2003; Norali et al., 2009). In addition, the optimal value for the cut-off frequency as be proposed in the previous studies would be around 30Hz (Norali et al., 2009). After cleaning the data, the signal will be extracted to time domain and frequency domain.

4.8 Summary

This chapter describing the experiment requirement and design for obtaining the sEMG signal data. A detail of participants, devices that has been used and experimental design has been explaining. Besides, to keeping the subject’s schedule in track are essential. In addition, the condition of subjects and electrodes and the placement of electrodes must be appropriate to avoid misleading noise or even unable to record the sEMG signal. The next chapter will be continue explaining in details the proposed the integration techniques, which will achieve objectives in this study.

CHAPTER 5

INTEGRATION FUZZY C-MEAN BASED RADIAL BASIS FUNCTION NETWORK (FCM-RBFN) TECHNIQUE

5.1 Introduction

This chapter discusses about the proposed integration Fuzzy C-Mean based Radial Basis Function Network technique. This chapter consists of 4 sections. Section 5.1 describes the operational research design. Section 5.2 describes the structure of FCM and RBFN techniques. Section 5.3 explains the FCM-RBFN technique in detail which highlights the integration part in FCM-RBFN technique. The combination steps between FCM and RBFN will be explained briefly in this section. Lastly, this chapter ends with summarization.

5.2 Operational research design

This chapter highlight the contribution of this study using proposed integration Fuzzy C-Mean based Radial Basis Function (FCM-RBFN). In this research, the proposed techniques FCM-RBFN is designed by integrating Fuzzy c-Mean and Radial Basis Function Network techniques and bring into a next level of predicting model. The data has been studied, filtered and feature extracted.

The proposed integration FCM-RBFN techniques imposes integration strategies in combination of two techniques in order to enhance the techniques in load predicted of sEMG muscle fatigue signal during isotonic training task.

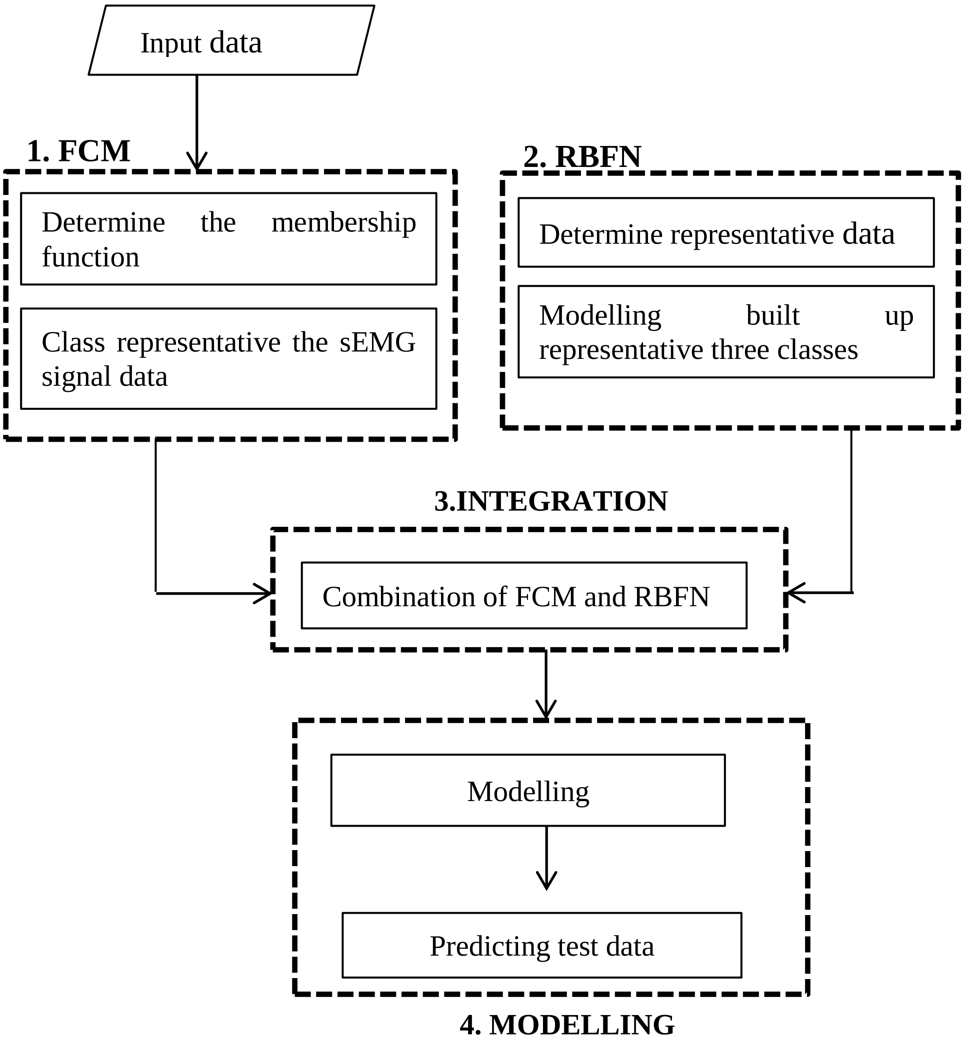


Figure 5.1: Operational research design of integration of FCM-RBFN technique

This technique has four components which complement each other as shown in the Figure 5.1. The contribution that is being proposed in this study are been highlight with dotted box. The first part is the training component where the FCM determine the membership function started with the fixed initialize membership values according to the original load's fatigue level which traditionally the initial membership values are random. Then, the output results where the training sEMG signals data has been labelled or grouped to the representative class.

The second component is integration between FCM and RBFN. This is an important part and mainly focused in order to complete the integration. The membership function updated from FCM in training phase are been calculate using Euclidean distance then replaced it to the new one to dividing the testing data into 3 fatigue stage. Meanwhile, the predicted class resulting from FCM are been use as target together with original load in RBFN.

Next, the third component was the training phase in RBFN. It is to determine the representative training data into their suitable modelling built up. The modelling has been divided into three classes according to class predicted by FCM in first phase. Hence, this phase build the Network RBFN net for each of the divided data according to their class from the training data sEMG signal. However, some of the data (x) will have more than one Network RBFN net and it lead to bias. It should be only one class for a set of data. A set of signal data contain 4 signals from different electrodes places on different muscles collected at the same time. Therefore, to overcome this problem, the forth phase in selection of RFBN model will take place. This phase will determine the modelling net and predicting the sEMG signal test data.

The determined Network RBFN net after the selection of RBFN model phase will predict the next load. Integration of FCM-RBFN modelling will be use continuously and the predicted load is depending on the muscle’s endurance of the subject on that time. The measurement performance average MSE of predicted load will be compared with the benchmark technique, Artificial Neural Network.

5.3 Proposed integration Fuzzy C-Mean based Radial Basis Function Network

An electro diagnostic medicine, Surface EMG can analyse to detect muscle activation level and biomechanics of human. Classification of sEMG signal is non-trivial and varies over time since endurance training tends to endure the muscle. In addition, sEMG signal may vary over different acquisition sessions even for the same subject doing the same experiment task due to the currently body conditions of the subject on current time. This is because of the high noise embedded in the raw sEMG. The raw sEMG signal having positive and negative components and contains outliers with high dimensionality. Therefore, integration prediction modelling is the best solution to enhance current techniques to predict the next load consistent with muscle activation of the subject.

The proposed integration Fuzzy C-Mean Radial Basis Function Network (FCM-RBFN) in this studies are been enhanced from FCM based RBFN (Woo et al., 2008) by employing Euclidean Distance calculation in the testing phase, input training data into RBFN, and selection of RBFN model which strengthen the proposed technique and compatible with sEMG muscle fatigue signal during isotonic training task. In addition, these FCM-RBF enhancements suites the output results in predicting the next load to endure muscle against early muscle fatigue. In addition, the original FCM based RBFN (Woo et al., 2008) is for traffic flow modelling and vary in domain with this research.

Training data containing vary of athletes which capable in different types of sports, genders, and ages as explain in Chapter 4. Therefore, the integration FCM-RBFN modelling is capable to predict the next load for different other testing subject even though have a different physical condition and high noise embedded in the sEMG muscle fatigue signal during isotonic training task. These modelling can work in MATLAB 2013a. The flowchart of the proposed integration FCM-RBFN is shown in Figure 5.3.

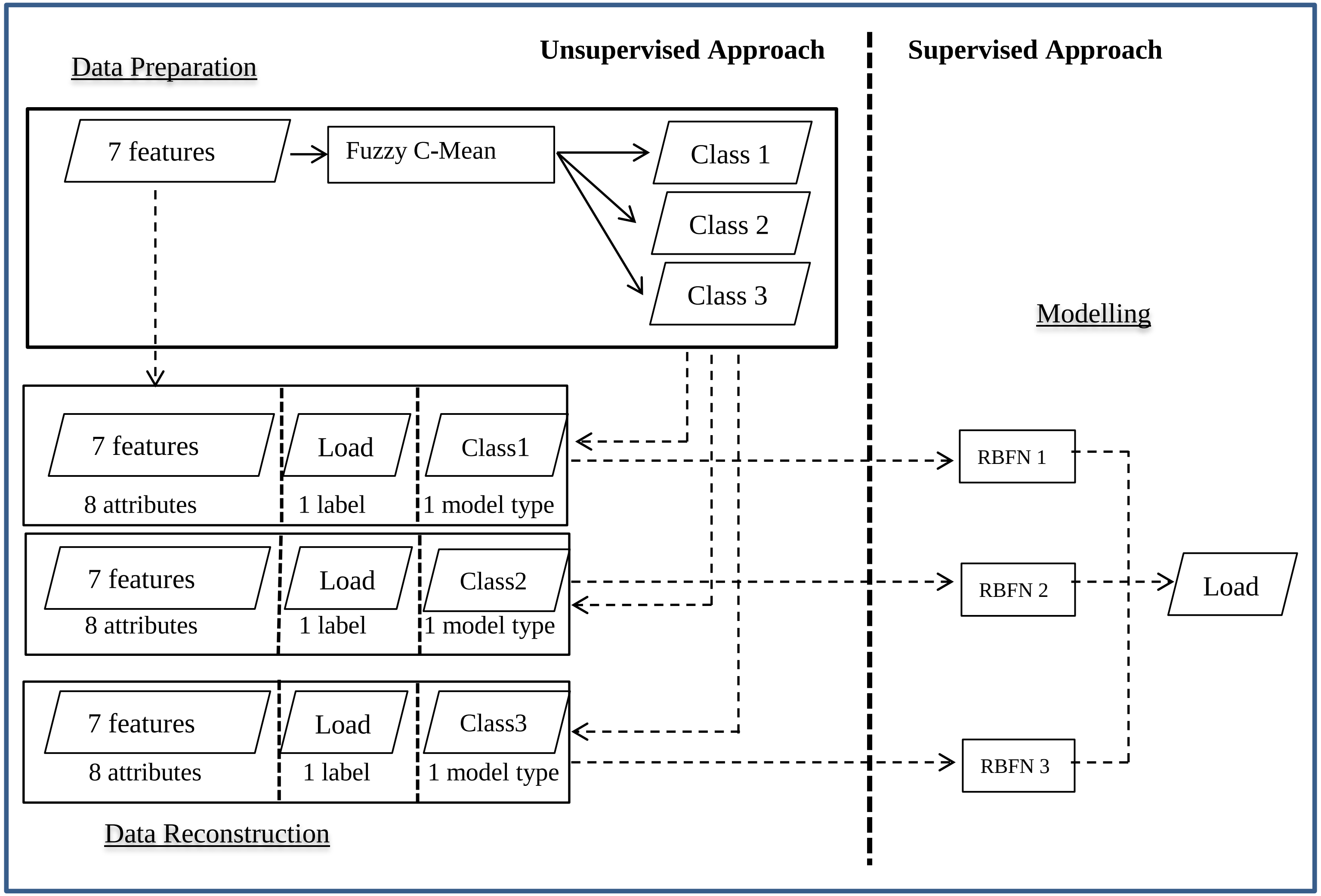


Figure 5.2: Integration FCM-RBFN flowchart

5.3.1 Proposed Fuzzy C-Mean

The fuzziness of the C-Mean is the main advantage in clustering sEMG signal data. Fuzzy in this research is to reconstruct the data from unsupervised to supervised data. Each point data in sEMG signal has a probability of belonging to each cluster. In this proposed FCM still the same as original. But the updated membership function will be use in section 5.4.2 and the initialize cluster membership values have been fixed according to the original load's fatigue level. The original FCM formula commonly randomly initializes the membership matrix. The following is the FCM formula:

$$J_m = \sum_{i=1}^{D} \sum_{j=1}^{N} \mu_{ij}^{m} \left\| x_i - c_j \right\|^2, \tag{5.1}$$

Where D is the number of data points. N is the number of clusters. m is fuzzy partition matrix exponent for controlling the degree of fuzzy overlap, with $m > 1$. Fuzzy overlap refers to how fuzzy the boundaries between clusters are, that is the number of data points that have significant membership in more than one cluster. x_i is the ith data point. c_j is the center of the jth cluster. μ_{ij} is the degree of membership of x_i in the jth cluster. The given data point, x_i, the sum of the membership values for all clusters are one. The FCM performs the following steps during clustering:

1. Fixed initialize the cluster membership values, μij.
2. Calculate the cluster centers according to the fixed initialize membership function:

$$c_j = \frac{\sum_{i=1}^{D} \mu_{ij}^{m} x_i}{\sum_{i=1}^{D} \mu_{ij}^{m}} \tag{5.2}$$

3. Update μ_{ij} according to the following:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \tag{5.3}$$

4. Calculate the objective function, J_m.

5. Repeat steps 2–4 until J_m improves by less than a specified minimum threshold or until after a specified maximum number of iterations.

The updated μ_{ij} from FCM will be use in testing phase (α) to create a new membership function according to the following:

$$d_{ij} = \sum_{i=1}^{n} \left(\mu_i - \alpha_j\right)^2 \tag{5.4}$$

Where d_{ij} is an updated membership function for testing data α and it will determine the representative center of the cluster for α resulting grouping the data point in Class α 1, Class α 2, and Class α 3. The reason only testing data uses the Euclidean distance is because the FCM already calculate the membership function from the training data. Thus, by calculated it distance using Euclidean, the testing data doesn't need to undergo FCM again and it will save time. In addition, Euclidean distance known as popular distance calculation than others. Figure 5.4 below shows the network RBFN net stimulate in testing phase algorithm which been code to determine the representative center.

```
IF data point α = = class α 1
    Network RBFN net 1 stimulate
    Display the predicted load
ENDIF
IF data point α = = class α 2
    Network RBFN net 2 stimulate
    Display the predicted load
ENDIF
IF data point α = = class α 3
    Network RBFN net 3 stimulate
    Display the predicted load
ENDIF
```

Figure 5.3: Network RBFN net stimulate in testing phase algorithm

The Network RBFN net 1, Network RBFN net 2, and Network RBFN net 3 are formed from RBFN in Section 5.3.3.

5.3.2 Proposed Radial Basis Function Network

Radial basis Function techniques were originally developed for exact interpolation of a set of data points in a multidimensional space. The aim of exact interpolation is to project every input vector x_i , onto the corresponding target y_i, to find a function $f(x)$such that:

$$y_i = f(x_i) \ where \ i = 1, \dots m, m - number \ of \ objects \tag{5.5}$$

According to the radial basis function approach, exact mapping can be performed using a set of m basis function with one for each data point with the form $\phi(\|x_i - x_j\|)$, where $\phi(.)$ is some nonlinear function, and $\| \quad \|$ denotes distance between x_i and x_j with Euclidean distance. Then the output of the mapping can be presented as linear combinations of these basis functions:

$$f(x_i) = \sum_{j=1:m} w_j \, \phi(\|x_i - x_j\|) \tag{5.6}$$

Where w_j denotes weights, x_i and x_j denote input object and the center of basis function respectively.

The Gaussian functions:

$$\phi(\|x_i - x_j\|) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{5.7}$$

The network is simulated in MATLAB R2013a. Therefore, *newrb* creates a two-layer network. The first layer has *radbas* neurons, and calculates its weighted inputs with *dist* and its *net* input with *netprod*. The second layer has *purelin* neurons, and calculates its weighted input with *dotprod* and its net inputs with *netsum*. Both layers have biases.

Initially the *radbas* layer has no neurons. The following steps are repeated until the network's mean squared error falls below goal.

1. The network is simulated.
2. The input vector with the greatest error is found.
3. A *radbas* neuron is added with weights equal to that vector.
4. The *purelin* layer weights are redesigned to minimize error.

These steps are repeated for each of the data point which represents each group class. The main reason to dividing the data point which supervised data from FCM is to ready the Network RBFN $net$for training phase, meanwhile the Network RBFN net that already ready for the next testing phase with another different testing data (α). After data reconstruction, the data will load into RBFN modelling. This modelling is for load prediction.

Experimental work for data pre-processing and prediction through RBFN is done by writing MATLAB program under window 7 environment. A predefined formula of RBFN as newrb()is used to add neurons to the hidden layer and to simulate the work of a radial basis network until it meets the specified mean squared error goal (eg).

$$\text{Net} = \text{newrb}\,(X, y, eg, sc) \tag{5.8}$$

Above function takes matrices of input and target vectors X and y respectively, and parameters goal with value 0.02 and spread as radius of the RBFN. The large value of spread smoother the function approximation and too small value of spread means many neurons are required to fit approximation function, simulation result of above function returns RBF network as net as shown in Figure 5.4 with randomly selected 100 neurons at hidden layer.

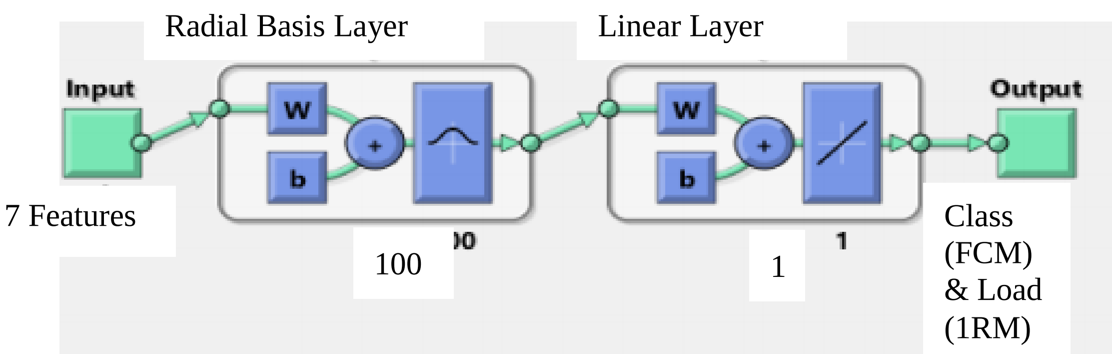


Figure 5.4: Architecture of RBFN

The use of 1 net are resulting higher MSE, therefore, the need to create separate model for RBFN is to get higher accuracy and it been detail describes at chapter 6 RBFN. The conditions each group class is as Figure 5.5 at the next page:

```
IF data point x = = class x 1
    Run RBFN for class 1
    Save Network RBFN net 1
ENDIF
IF data point x = = class x 2
    Run RBFN for class 2
    Save Network RBFN net 2
ENDIF
IF data point x = = class x 3
    Run RBFN for class 3
    Save Network RBFN net 3
ENDIF
```

Figure 5.5: RBFN modelling algorithm

5.3.3 Selection of Radial Basis Function Network Model

The selection of Radial Basis Function Network has been created when there are two group class in the same subject's data trial such as in Table 5.1. LB and RB muscle in the same group and RF and RB muscle in the same group and in another hand, Table 5.2 show RB, RF and RB muscle in the same group and LB muscle the only member in group class 2. The problems raised when the model predicted two different classes, hence, needs to decide on the nearest correct and most reliable class.

Table 5.1: sEMG data for a subject with even presentative predicted class

Muscle	MDF	MF	MAV	RMS	SSI	VAR	WL	Predicted class
LB	0.2903	0.2132	0.3812	0.2487	0.0472	0.0472	0.2534	2
LF	0.3911	0.4004	0.1260	0.0757	0.0055	0.0055	0.1302	3
RB	0.3101	0.2481	0.3158	0.2280	0.0401	0.0401	0.2315	2
RF	0.3074	0.2415	0.1331	0.0903	0.0074	0.0074	0.1027	3

Table 5.2: sEMG data for a subject with odd presentative predicted class

Muscle	MDF	MF	MAV	RMS	SSI	VAR	WL	Predicted class
LB	0.3389	0.3517	0.1006	0.0753	0.0025	0.0025	0.0416	2
LF	0.5960	0.5946	0.0721	0.0449	0.0010	0.0010	0.0471	3
RB	0.3842	0.3559	0.3526	0.2517	0.0236	0.023	0.1496	3
RF	0.8454	0.8711	0.0567	0.0366	0.0007	0.0007	0.0508	3

Therefore, to solve the above problems, the nearest distance between data point with the center point of its group class is been compute with Euclidean distance as in the following formula:

$$d(p,q) = \sum_{i=1}^{n}\left(p_i - q_j\right)^2 \tag{5.9}$$

Where d denotes distance, p denotes respectively data point, q denotes membership function regarding to p's class. The group class with the lowest value of Euclidean distance or the majority group class (for an example: Table 5.2, Group class 3) will be a dominant on another group class. The dominant group class will be the indicator for predicted the next load with the two conditions as described as in Figure 5.6 below.

```
IF Representative predicted class group = 2
        LOOP Calculate Euclidean Distance
                FIND The majority of representative class
        END LOOP
ELSE IF Representative predicted class group = 1 or class group = 3
        LOOP The minority of representative class
        END LOOP
ELSE Automatically start with the lowest class load ∴ class 1
END IF
```

Figure 5.6: Selection of RBFN model

5.4 Summary

As a summary, this chapter describes the proposed integration FCM-RBFN algorithm mainly for integration of both techniques in predicting the next load. The enhancement predicted modelling have improved the original techniques and correspond to sEMG muscle fatigue signal during isotonic training task even though isotonic have higher movement artefact than isometric. Thus, the performance analysis can be improved. The next chapter will be discussing on the experimental results, validation test and analysis.

CHAPTER 6

EXPERIMENTAL RESULT AND ANALYSIS

6.1 Introduction

Experimental result, validation test and analysis are being discussed in this chapter. This chapter consists of 7 sections. Section 6.1 presents the comparisons on Butterworth high pass filter at different level of thresholds. This comparison is to improve the prediction performance. This is because of the sEMG muscle fatigue signal during isotonic training task having high noise and can attenuate the signal. Thus, the prediction performance of the best Butterworth high pass filter at certain level of threshold is proposed using FCM-RBFN techniques as classification technique is selected to be use for proposed integration FCM-RBFN prediction technique. Section 6.2 discusses the predicted load analysis between classes. This comparison is to shows the pattern of the predicted load for each trial in sessions. It's should be parallel with the prediction performances in Section 6.3 and 6.4. The varying repetition and amplitude of each trial or class will affect the prediction performance. There are several factors due to the varying of the number of repetition and amplitude such as blood flow and oxygen taken of the subject. Thus, the lower prediction performances are relaying to different level of muscle condition types. Section 6.3 discuses on comparisons between integration FCM-RBFN and ANN techniques in term of prediction performance for class 1. Section 6.4 discuses on comparisons between integration FCM-RBFN and ANN techniques in term of prediction performance for class 2 and 3. Next, Section 6.5 is a comparison between predicted load and original load using integration FCM-RBFN and ANN technique. This comparison is to shows graphically the pattern of the predicted load and original load for each data of sEMG signal during isotonic task. The closer original load with the predicted load, the better of the technique's performance is. Section 6.6 provides a discussion to discuss the overall findings in this research. Lastly, the summary of the chapter will be provided.

6.2 Butterworth high pass filter cut-off threshold analysis using integration FCM-RBFN

The sEMG raw data were collected as mentioned in Chapter 4. The same classification technique and performance measures were used throughout this experiment to ensure a fair comparison on cut-off threshold at different frequency range. After the raw signal has been filtered with cut-off threshold the 7 features were applied and FCM-RBFN classifier was used to measure the classification performance. The main purpose to carry out this experiment is to identify the cut-off threshold for sEMG muscle fatigue during isotonic training task. The input are 7 features.

Table 6.1 shows the prediction performance for 5, 10, 20 Hz in FCM-RBFN modelling. The best prediction performance (Average MSE) was achieved by using 10 Hz with MSE average of 0.028. In another hand, the highest average prediction MSE value is sEMG signal filter with 5 Hz cut-off threshold. Next, the prediction average performance MSE was in between 5 Hz and 10 Hz, with MSE value 0.033. Base on the experimental result as shown in Figure 6.1, it is obviously see that 10 Hz has the best prediction performance of average MSE value. But, a validation test was performed to test the significance between the three sets of cut-off filtering threshold.

Table 6.1: Prediction performance of Butterworth high pass filter with cut-off threshold at different frequency ranges

HZ	5Hz		10Hz		20Hz	
FCM-RBFN	Epoch	MSE	Epoch	MSE	Epoch	MSE
1	972	0.0740	972	0.0301	196	0.0199
2	683	0.0199	377	0.0195	255	0.0199
3	637	0.0199	972	0.0311	255	0.0199
4	972	0.0740	385	0.0198	972	0.0380
5	972	0.0741	972	0.0301	972	0.0380
6	972	0.0740	972	0.0311	972	0.0380
7	972	0.0740	972	0.0301	972	0.0380
8	972	0.0220	972	0.0301	972	0.0380
9	972	0.0740	972	0.0301	972	0.0380
10	637	0.0199	972	0.0301	972	0.0380
MSE Average		0.0526		0.0282		0.0325

Table 6.2: Normality test result for prediction performance of Butterworth high pass filter with cut-off threshold at different frequency ranges

Anderson – Darling Test				
Hz (MSE)	Statistic	Adjusted statistic	Probability associated (Sig.)	Result
5 (N=10)	1.6922	1.8572	0.0001	Not normally Distributed
10 (N=10)	2.1124	2.3184	0.0000	Not normally Distributed
20 (N=10)	2.0331	2.2314	0.0000	Not normally Distributed

Table 6.2 shows the normality test from the Anderson-Darling for prediction performance of Butterwort high pass filter with cut-off threshold at different frequency ranges observed that distribution does not fit the normal distribution. The p value for both normality tests is less the 0.05 ($p < 0.05$), thus, the hypothesis is rejected. Therefore, the non-parametric test, Wilcoxon signed-rank test is chosen as a validation statistical test for this result.

Table 6.3: Validation test of prediction performance for 5, 10, and 20 Hz cut-off threshold filtering

	Mean	Standard Deviation	Minimum	Maximum	p-value (2-tailed)	Null Hypothesis	Statistical Test
5Hz	0.053	0.028	0.020	0.074	0.059	Accept	Significantly no different
10Hz	0.028	0.005	0.020	0.031			
5Hz	0.053	0.028	0.020	0.074	0.033	Reject	Significantly different
20Hz	0.033	0.009	0.020	0.038			
10Hz	0.028	0.005	0.020	0.031	0.278	Accept	Significantly no different
20Hz	0.033	0.009	0.020	0.038			

According to the validation test in Table 6.3, the p-value between the MSE of 5 Hz and 10 Hz is 0.059, which is higher than 0.05. Thus, the validation test is to accept the null hypothesis. Therefore, Wilcoxon Paired Signed-Rank Test indicated that the 5 Hz were significantly no different than 10 Hz, p <0.059. Next, the p-value between the MSE of 5 Hz and 20 Hz is 0.033, which is higher than 0.05. Thus, the validation test is to reject the null hypothesis. Therefore, Wilcoxon Paired Signed-Rank Test indicated that the 5 Hz were significantly different than 20 Hz, p <0.033. And the third test, the p-value between the MSE of 10 Hz and 20 Hz is 0.278, which is higher than 0.05. Thus, the validation test is to accept the null hypothesis. Therefore, Wilcoxon Paired Signed-Rank Test indicated that the 10 Hz were significantly no different than 20 Hz, p <0.278.

For that reason, showing that the 10 Hz have a lower mean of MSE than others two. There are significant differences between 5 and 20 Hz but not for 10 Hz. Assume that 10 Hz is in the middle safe zone of cutting the noise from the raw signal meanwhile, 5 Hz is too low and 20 Hz is too high. Therefore, 10 Hz are chosen for be use as a filter cut off threshold in this study. The Figure 6.1 shows the average prediction MSE performance of Butterworth high pass filter with cut-off threshold at different frequency ranges.

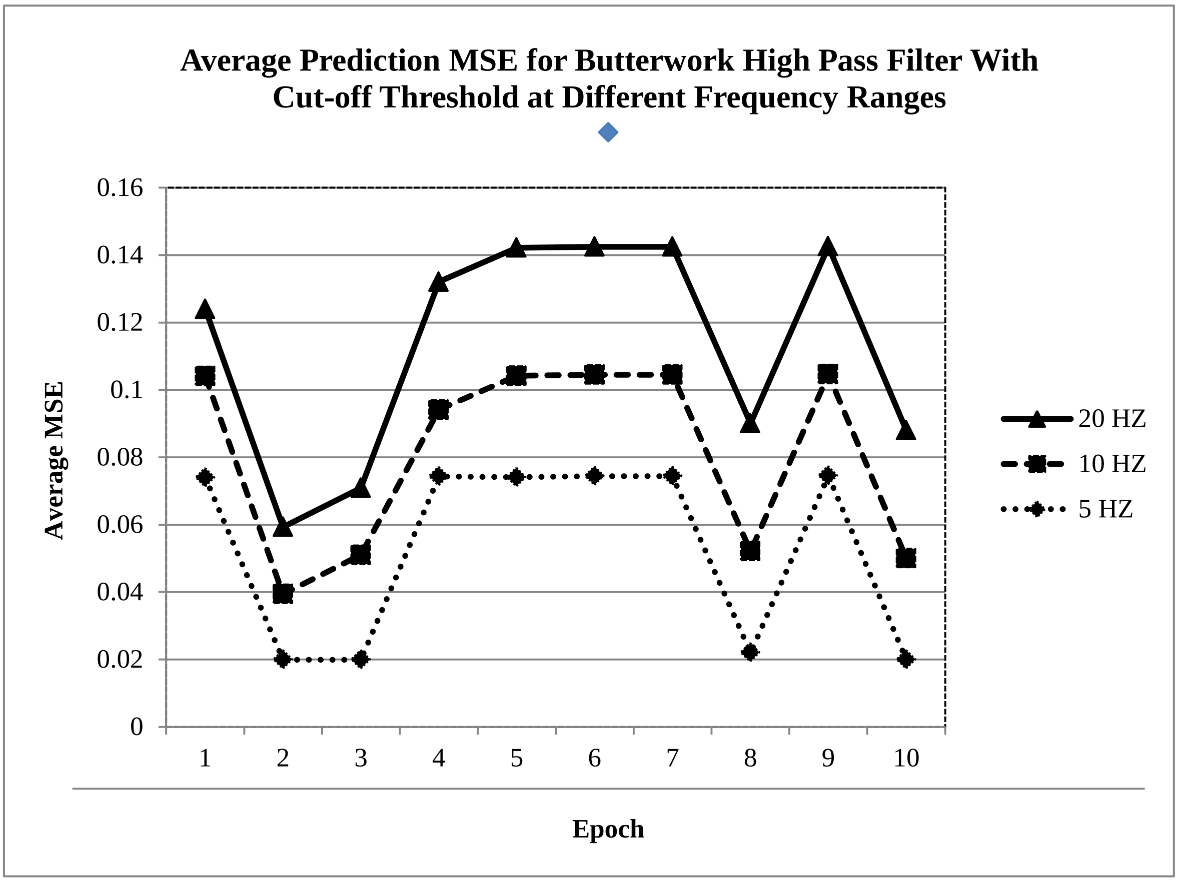


Figure 6.1: Average prediction MSE performance of Butterworth high pass filter with cut-off threshold at different frequency ranges

As shown in 6.1 shows line graph of the average prediction MSE performance of Butterworth high pass filter with cut-off threshold at different frequency ranges of 20, 10 and 5 Hz. The noise in the sEMG signal can be filtered using the high pass filter because the amplitude normally falls in range of 0 to 20 Hz. However, there is no specific literature review on isotonic muscle fatigue prediction. Therefore, this test is to make sure which level of threshold for Butterworth high pass filter with cut-off is suitable.

Different high pass filter threshold can give effect towards the MSE. If it is too low, it may not enough to clean the raw signal and if it too high, it may laminate the important information in the raw signal. Thus, the performances of MSE are affected. According to results in Figure 6.1, it shows that 10 Hz get the best MSE than 5 and 20 Hz. Therefore, 10 Hz of Butterworth high pass filter with cut-off threshold will be use in this thesis.

6.3 Predicted load analysis

In this section, different types of raw sEMG signal from the whole session is been observed. The muscle activation level from the first trial, second trial and last trial are being observed in order to describe the predicted load of the proposed technique modelling, integration FCM-RBFN, the predicted load versus the raw sEMG signal. In addition, the percentage different between 3 groups in Figure 6.3, 6.5, and 6.7 (a) and (b) are to show that clustering according to FCM groupings is sensible. The experimental data were pre-processed with 7 feature extraction.

We can observe the effects of these fatigue processes, by examining the amplitude or repetition of the EMG signal during a muscle contraction. As fatigue progresses, the firing rate of motor neurons falls, which in turn drops the number of action potentials the muscles themselves then fire, leading to a decline in strength, and muscles can often also continue generating action potentials due to neural drive, but the muscle is unable to contract due to molecular fatigue events in the muscle fibers, which in turn leads to a reduction in strength (Gage et al., 2016).

In addition, the blood flow to the muscle can be reduced because of 1) muscles intensely contracting can reduce blood flow and thus oxygen availability, or 2) the muscle is simply working so intensely that there literally is not enough oxygen to meet demand.

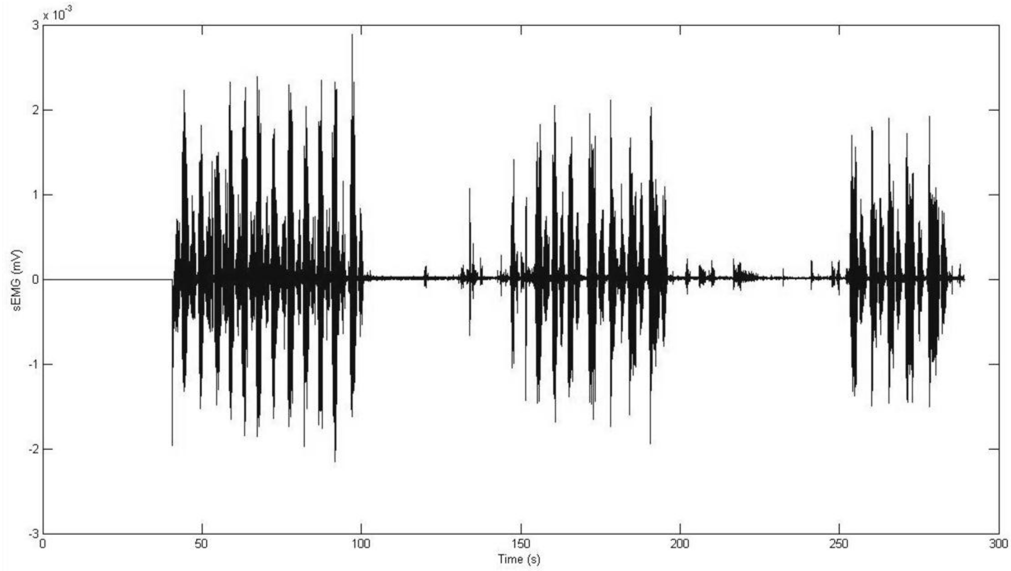


Figure 6.2: Normal raw sEMG signal of right biceps decreasing muscle activation

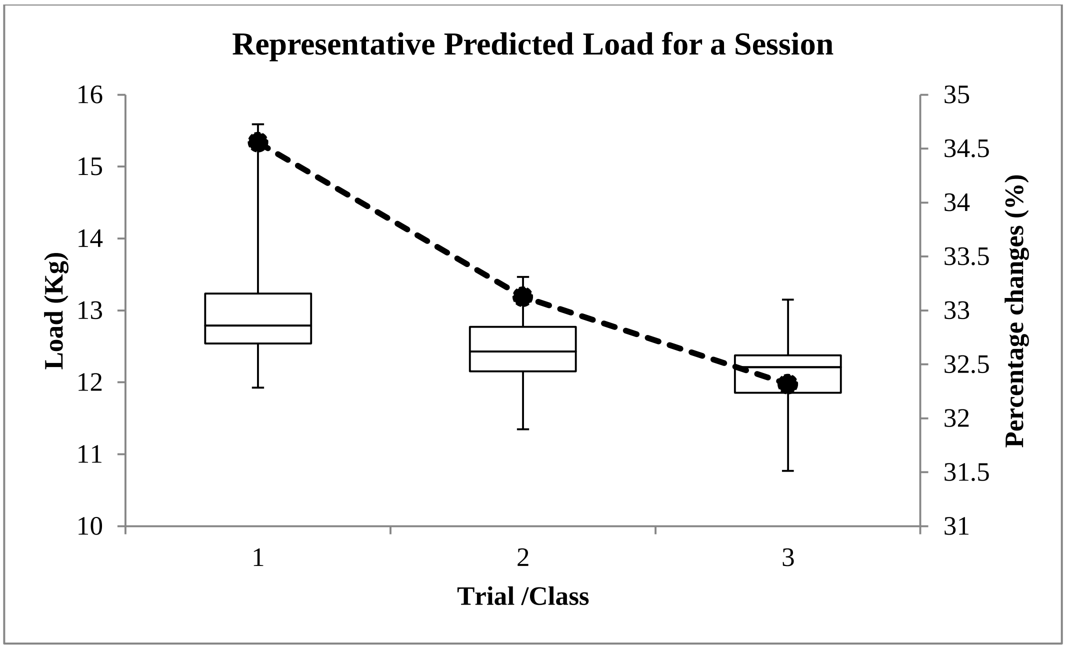


Figure 6.3: Decreasing predicted load of the sEMG signal

Figure 6.2 shows that the three trial of normal raw sEMG signal of right biceps. The first trial has more repetitions than trial 2 and trial 2 have more repetitions than trial 3. In term of amplitude, the first trial has higher amplitude than trial 2 and trial 2 have higher amplitude than trial 3. This signal showing that subject gives a good effort on the first trial and getting fatigue on the following trial. In addition, this is a good example of signal that proven that the hypothesis is true.

Figure 6.3 shows that the decreasing of the predicted load over trial. This graph shows the predicted load of the above raw sEMG signal. The decreasing of the plot showing that the load is varies for each of the trial according to the current muscle activation rate. The decreasing of the load from this modelling at the firing rate declined, will help subjects to endure much longer and continues training without having muscle tears.

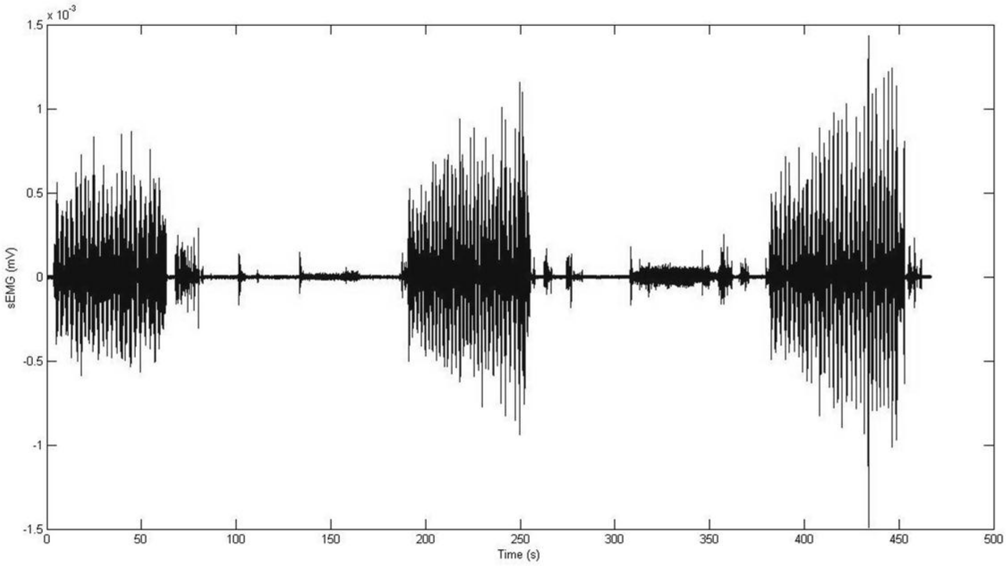


Figure 6.4: Raw sEMG signal of right biceps with increasing muscle activation

Figure 6.4 shows the raw sEMG signal of right biceps with the increasing muscle activation. The third trial has more repetitions than trial 2 and trial 2 have more repetitions than trial 1. In term of amplitude, the first trial has lower amplitude than trial 2 and trial 2 have lower amplitude than trial 3. This signal showing that subject not giving full effort on the first trial. The repetitions the following trials are increasing and the subject can continue this exercise for the forth trial without worrying for the muscle tear. This shows that every subject has a different muscle ability and strength.

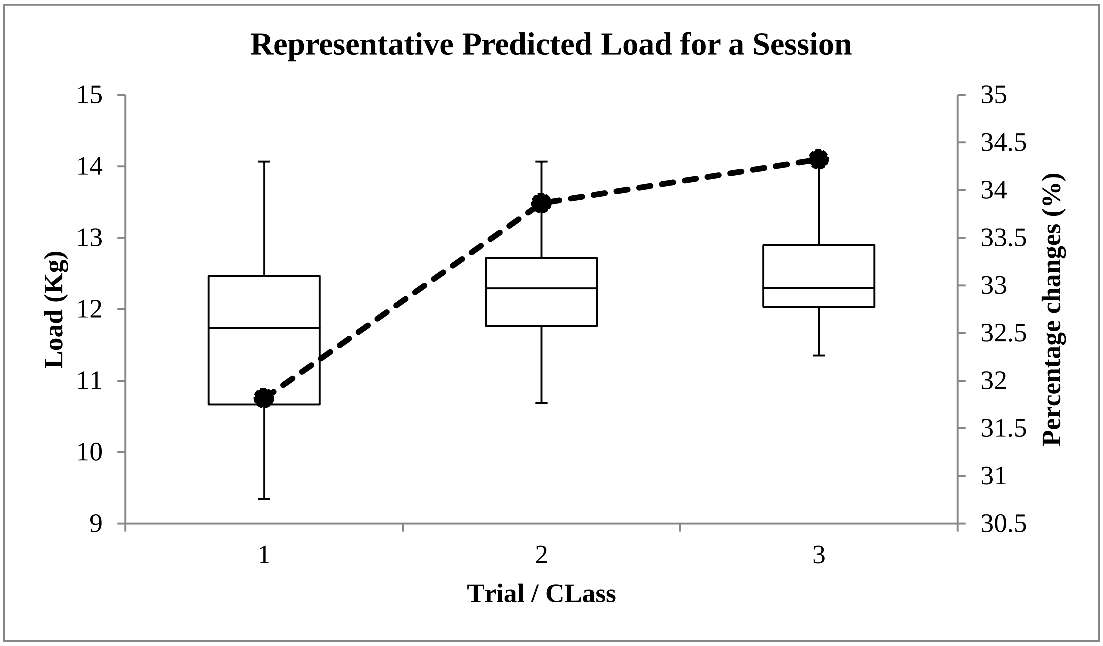


Figure 6.5: Increasing predicted load of the sEMG signal

Based on the experimental result as shown in Figure 6.5, the predicted load of the next following trial is increasing. This graph shows the picture of the predicted load of the above raw sEMG signal, Figure 6.4, the firing rate of motor neurons increased, leading to an increased in strength, therefore, the load of the lifted weight at that time should be higher.

As known, the isotonic muscle training task has varied activation levels in each of the lifting of the weight over time. Based on the experimental result as shown in Figure 6.6, its shows that subject is already fatigue at the second trial. In other case, another pattern of raw sEMG signal which have lower amplitude and many repetitions in the middle session of training as in Figure 6.7, this figure shows the representative predicted load of the sEMG signal. Figure 6.7(a) shows, the predicted load of the first and third trial are higher than the second trial. In another hand, Figure 6.7(b) shows, the predicted load of the first and third trial are lower than the second trial and it's make a 'U' shape.

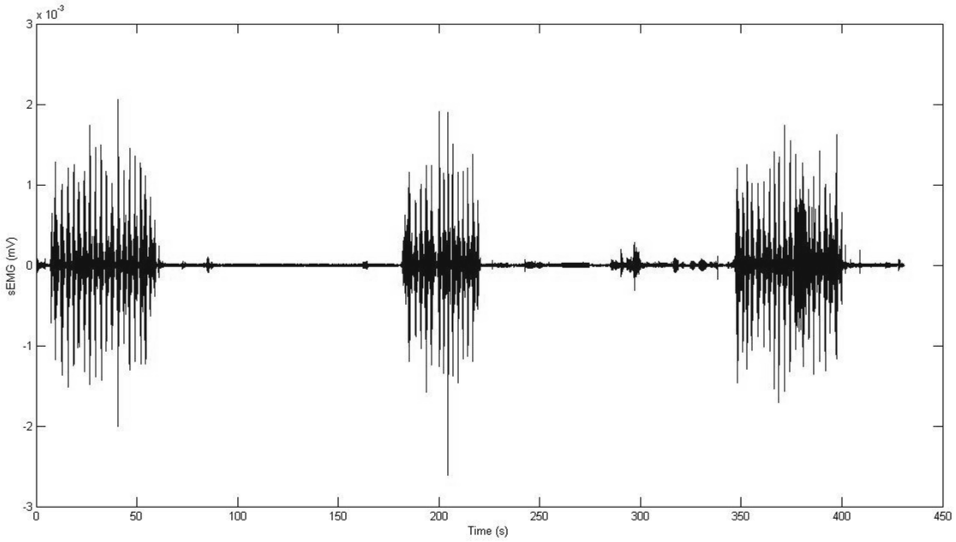
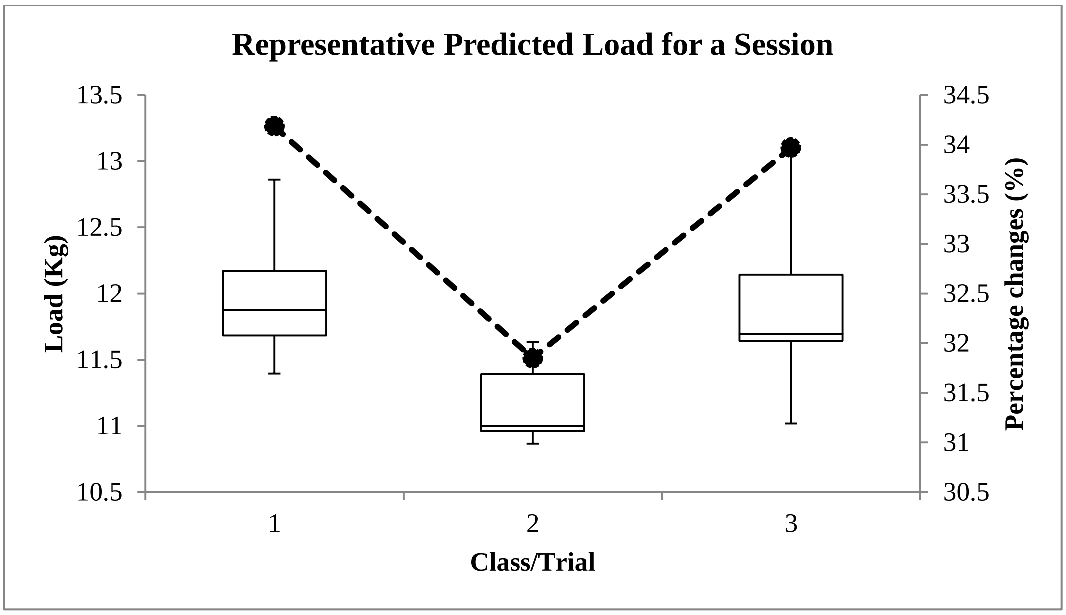
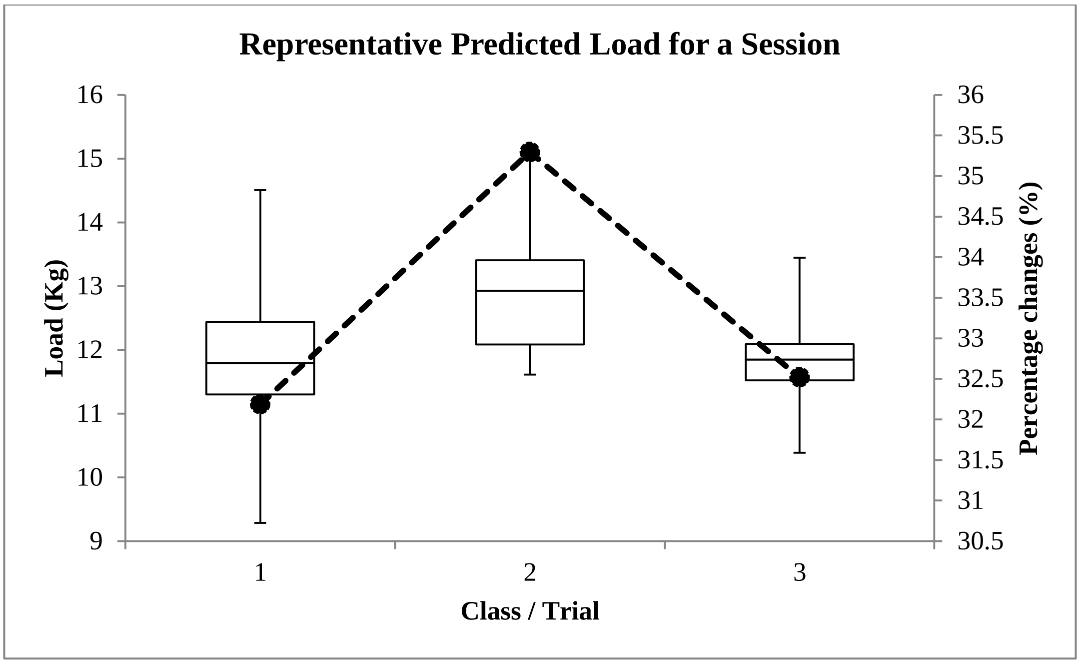


Figure 6.6: Raw sEMG signal of right biceps with difference muscle activation



(a)



(b)

Figure 6.7: Predicted load of the sEMG signal, (a) and (b)

6.4 Comparison between integration FCM-RBFN and ANN technique

After confirmed 10 Hz is better cut-off filtering threshold, the sEMG signals data that were pre-processed with the feature vectors. In this section, a comparison between integration FCM-RBFN technique and ANN technique was be carried out. Most of the studies in the same domain sEMG signal were carried with Artificial Neural Network prediction techniques as been discussed in Chapter 2 and it is shows that ANN is a good prediction technique. However, the result will be exposed below.

In this stage, only Class 1(Trial 1) will be compared for techniques performance comparison. The subjects are required to run the 1RM test before perform one full session of the experiment. Therefore, in order to compute average MSE value (between original load and predicted load) the only trial 1 is valid to be compared. This is because of the class 2 and 3, trial 2 and 3 respectively, might have different original load and MSE performance might not be valid. The performance for trial 1, 2 and 3 will depends on Table

3.5 that has been discussed in Chapter 3. Therefore, the prediction performance of trial 1 was being compared based on average MSE value. As shown in Table 6.4, shows that the integration FCM-RBFN has best performance average MSE than ANN, which is a good sign. However, a statistical test was carried out to test the significance difference between the two techniques.

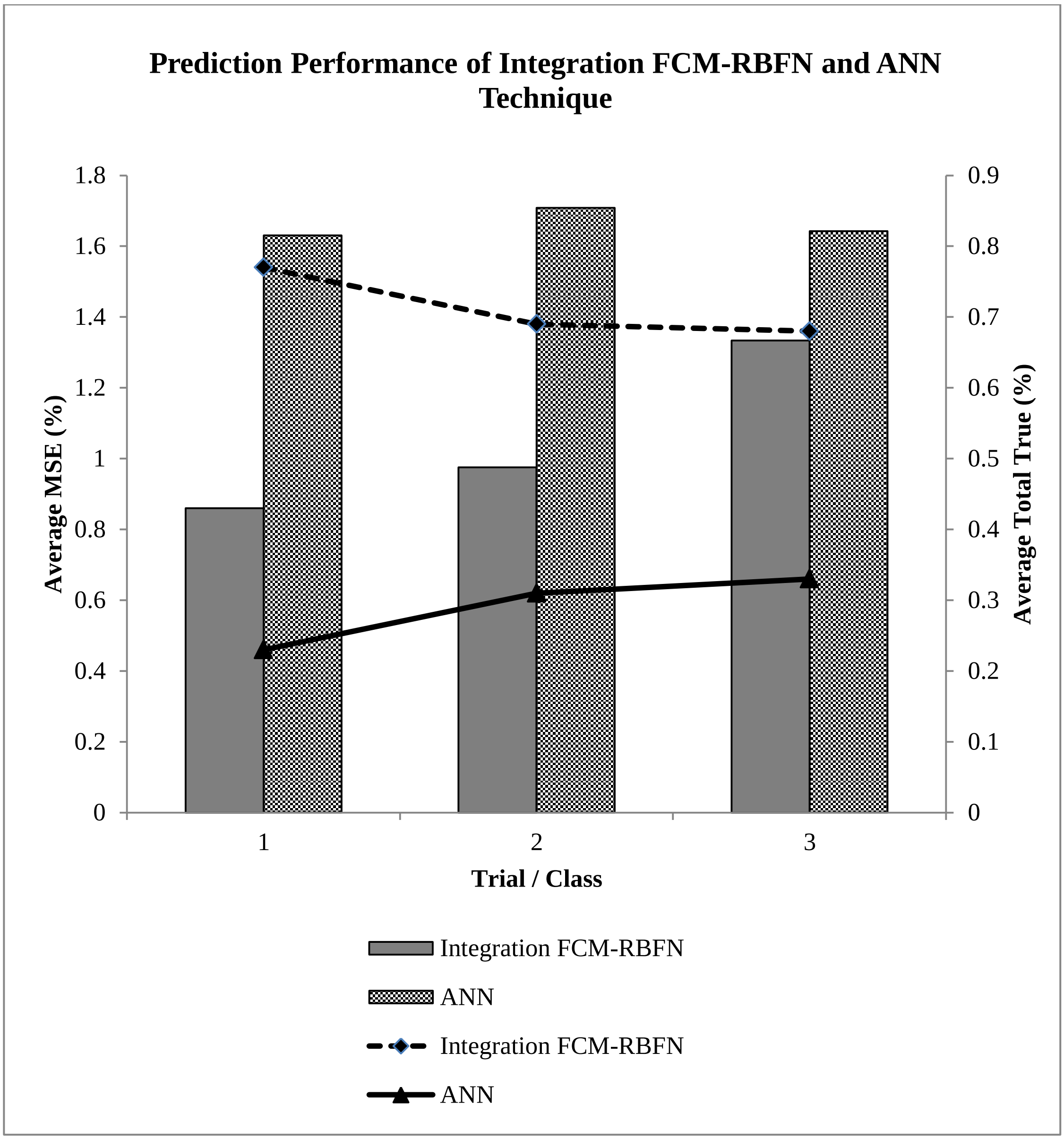


Figure 6.8: Prediction performance of integration FCM-RBFN and ANN techniques

Figure 6.8 above shows the average total 'true' (has been explained in Chapter 3) and average MSE performance value for integration FCM-RBFN and ANN techniques. Each class are graphically shows in that graph and the results of different classes are been discuss individually. The result shows that integration FCM-RBFN is better than ANN and it is able to accommodate the dynamic changes from biofeedback through sEMG signal. In addition, the graph shows that the average MSE for each class are increasing and followed with slightly decreasing of average total true. This shows that integration FCM-RBFN is sensible to the data compare to ANN technique. Even though the averages MSE of integration FCM-RBFN is still lower than ANN, but it slightly increased. However, it supports hypothesis in Figure 6.9 and it's prove that, integration FCM-RBFN can variable-load according to the muscle fatigue stage.

Table 6.4: Prediction performance of integration FCM-RBFN and ANN technique for Class 1

Technique	FCM-RBFN	ANN
Class/Trial	1	1
Total 'true'	62	19
Average (%)	0.77	0.23
Performance Average MSE (%)	0.86	1.63

Table 6.4 above shows the average total 'true' and average MSE performance value for integration FCM-RBFN and ANN techniques. The average total 'true' is considered better when the value is higher than other but vary with average MSE value where the lower value is better than other. As we see, the average total 'true' for integration FCM-RBFN is better than ANN with 0.77 and 0.23, respectively. Same goes to average MSE performance value of integration FCM-RBFN is lower than ANN with 0.86 and 1.63, respectively. In other words, integration FCM-RBFN technique yielded good results while

ANN technique only acquired moderate result for high embedded noise sEMG muscle signal.

Table 6.5: Normality test result for prediction performance at Trials/Class 1

Anderson – Darling Test				
Techniques (MSE)	Statistic	Adjusted statistic	Probability associated (Sig.)	Result
	Class 1/ Trial 1			
Artificial Neural Network (N=81)	2.2613	2.2831	0.0000	Not normally Distribution
Integration FCM-RBFN (N=81)	2.0786	2.0985	0.0000	Not normally Distribution

Based on the prediction normality test result as shown in Table 6.5 shows the normality test from the Anderson-Darling test at trials 1 show that the observed distribution does not fit the normal distribution. The *p*-value for both normality tests is less than 0.05 ($p < 0.05$). Thus, the hypothesis is rejected. Therefore, the non-parametric test, Wilcoxon signed-rank test is chosen as a validation statistical test for this research.

Table 6.6: Validation test on MSE between integration FCM-RBFN and ANN technique for Class 1

Wilcoxon Paired Signed-Rank Test							
	Mean	Standard Deviation	Min	Max	*p*-value (2-tailed)	Null Hypothesis	Statistical Test
ANN (N=81)	1.632	0.711	0.142	4.140	0.000	Reject	Significantly different
Integration FCM-RBFN (N=81)	0.861	0.749	0.024	3.985			

Based on the validation test as shown at Table 6.6, the p-value between the MSE of ANN and integration FCM-RBFN prediction techniques is 0.000, which is lower than 0.05. Thus, the validation test is to reject the null hypothesis. Therefore, Wilcoxon Paired Signed-Rank Test indicated that the ANN were significantly different than and integration FCM-RBFN, p <0.000. In addition, from the mean value shown in Table 6.6, it is clearly proved that the MSE of integration FCM-RBFN technique is better than MSE of ANN technique. Therefore, prediction performance of integration FCM-RBFN is better than ANN.

6.5 Comparison between 2 group datasets using integration FCM-RBFN and ANN technique

This this section, Class 2 (Trial 2) and Class 3 (Trial 3) will be compare as techniques performance comparison. The class 2 and 3 (trial 2 and 3 respectively), might have different original load and MSE performance might be invalid. This is because of the human muscles tending to getting more tired and fatigue over time as hypothesis in Figure 6.9. Even though, there a rest time interval between two trials in a training session, human muscle will fatigue in the end. Therefore, the original load is valid only for trial 1, which in contrast, trial 2 and 3 will be lower than the original load and trial 3 is lower than trial 2.

Hypothesis: The longer time of isotonic training task, the more tired subject will be.
*Human muscle considers fatigue, when subjects are unable to lift the weight anymore.

Figure 6.9: Hypothesis of finding total ‘true’ and total ‘might true’

The average total ‘might true’ are same as calculated in Section 6.2 and followed the condition as explained in Chapter 3, Table 3.5. The MSE is from the comparison of trials the original load. Therefore, this is only as a benchmark to shows the techniques performance is also relevant to hypothesis that has proved that the average MSE value for Trial 2 and Trial 3 are higher compared to trial 1. The result will be elaborate later. The prediction performance was being compared based on average MSE value. In additional, a statistical test was carried out to test the significance difference between two techniques.

Table 6.7: Summary of prediction performance of integration FCM-RBFN and ANN technique for Class 2 and Class 3

Technique	Integration FCM-RBFN		ANN	
Class/Trial	2	3	2	3
Total ‘might true’	56	55	25	26
Average (%)	69	68	31	33
Performance Average MSE (%)	98	133	171	164

Based on the experimental result as shown in Table 6.7, the average ‘might true’ and the average MSE performance of integration of FCM-RBFN techniques for class 2 is higher than ANN predicted technique. The average total ‘might true’ of integration FCM-RBFN class 2 achieved 69%. However, the average total ‘might true’ of ANN technique class 2 achieved only 31%. Next, average MSE of integration FCM-RBFN and ANN techniques achieved 98% and 171%, respectively. This is shows that an integration FCM-RBFN technique is better than ANN technique.

Next, the average total ‘might true’ of integration FCM-RBFN technique achieved 68% for class 3. Thus, the average MSE of integration FCM-RBFN technique achieved 133%. In contrast, ANN technique yields 33% and 164% for average total ‘might true’ and the average MSE respectively. Therefore, the integration FCM-RBFN yield a better prediction results in term of average total ‘might true’ and average MSE than ANN technique. Table 6.7 shows the prediction performance of integration FCM-RBFN and ANN technique for class 2 and class 3. As we can see, the integration FCM-RBFN is better than ANN technique. Future test, validation test was carried out to test the significance difference between these two techniques.

Table 6.8: Normality test result for prediction performance at Trials/Class 2

Anderson – Darling Test				
	Class 2/ Trial 2			
Techniques (MSE)	Statistic	Adjusted statistic	Probability associated (Sig.)	Result
Integration FCM-RBFN (N=81)	1.0706	1.0809	0.0078	Not normally Distribution
	Class 3/ Trial 3			
Artificial Neural Network (N=81)	4.2942	4.3354	0.0000	Not normally Distribution
Integration FCM-RBFN (N=81)	1.4025	1.4159	0.0012	Not normally Distribution

Based on the prediction normality test result as shown in Table 6.8 shows the normality test from the Anderson-Darling test at trials 2 and 3 shows that the observed distribution does not fit the normal distribution for both. The *p*-value for both normality tests is less than 0.05 ($p < 0.05$). Thus, the hypothesis is rejected. Next, the non-parametric test, Wilcoxon signed-rank test is chosen as a validation statistical test for both techniques to test the significance difference in each class.

Table 6.9: Validation test on average MSE value between integration FCM-RBFN and ANN techniques for Class 2 and 3

Wilcoxon Paired Signed-Rank Test							
	Mean	Standard Deviation	Min	Max	*p*-value (2-tailed)	Null Hypothesis	Statistical Test
Class 2							
ANN (N=81)	1.709	0.661	0.461	4.345	0.000	Reject	Significantly different
Integration FCM-RBFN (N=81)	0.975	0.658	0.021	2.566			
Class 3							
ANN (N=81)	1.642	0.668	0.507	4.174	0.002	Reject	Significantly different
Integration FCM-RBFN (N=81)	1.334	1.010	0.037	4.010			

Based on the validation test as shown at Table 6.9, the *p*-value between the MSE of ANN and integration FCM-RBFN prediction techniques for class 2 is 0.000, which is lower than 0.05. Thus, the validation test is to reject the null hypothesis. The results pairs were shown significantly different for both techniques with the p value 0.000, $p < 0.000$. In addition, from the mean value shown in Table 6.9, it is clearly proved that the MSE of integration FCM-RBFN technique is better than MSE of ANN technique. Therefore, prediction performance of integration FCM-RBFN for class 2 is better than ANN.

In addition, as shown at Table 6.9, the *p*-value between the MSE of ANN and integration FCM-RBFN prediction techniques for class 3 is 0.002, which is also lower than 0.05. Thus, the validation test is to reject the null hypothesis. The results pairs were shown significantly different for both techniques with the p value 0.002, $p < 0.002$. It has proven to be good for integration FCM-RBFN prediction technique than ANN with better mean MSE.

6.6 Comparison between predicted load and actual load using integration FCM-RBFN and ANN technique

In this section, a graphically comparison between the output result of predicted load between integration of FCM-RBFN and ANN techniques was carried out to clearly shows the nearest predicted load to the original load. Both predicting techniques were run in MATLAB R2013a. ANN techniques were run in the Neural Network Toolbox. The purpose of this study is to enhance modelling to cover the limitation of the isotonic muscle fatigue sEMG signal such as varies activation levels in each of trial weight as been describing in Section 6.4 above.

Figure 6.10 below shows the standard deviation and mean of predicted and actual load by FCM-RBFN vs ANN across 3 classes to show how much deviation in it. Standard deviations for prediction load of integration FCM-RBFN are 4.332, 4.332 and 4.332 and compared to actual load, 3.628, 3.875 and 3.827 for each class 1, 2 and 3 respectively. The slightly error in similarity is good when refer to Figure 6.9, the hypothesis of finding total 'true' and total 'might true'. Meanwhile, standard deviations for prediction load of ANN are 1.078, 0.915 and 0.688 and compared to actual load, 4.332, 4.332 and 4.332 for each class 1, 2 and 3 respectively.

Therefore, the actual load for integration FCM-RBFN is similar to its predicted load value than ANN. In the same time, the predicted and actual fatigue level shows that proposed technique got higher total of true than ANN with total 124 and 80 respectively. Therefore, the result shows that integration FCM-RBFN is better than ANN and it is able to accommodate the dynamic changes from biofeedback through sEMG signal. At the next paragraph, there will be a discussion for the results of different classes individually.

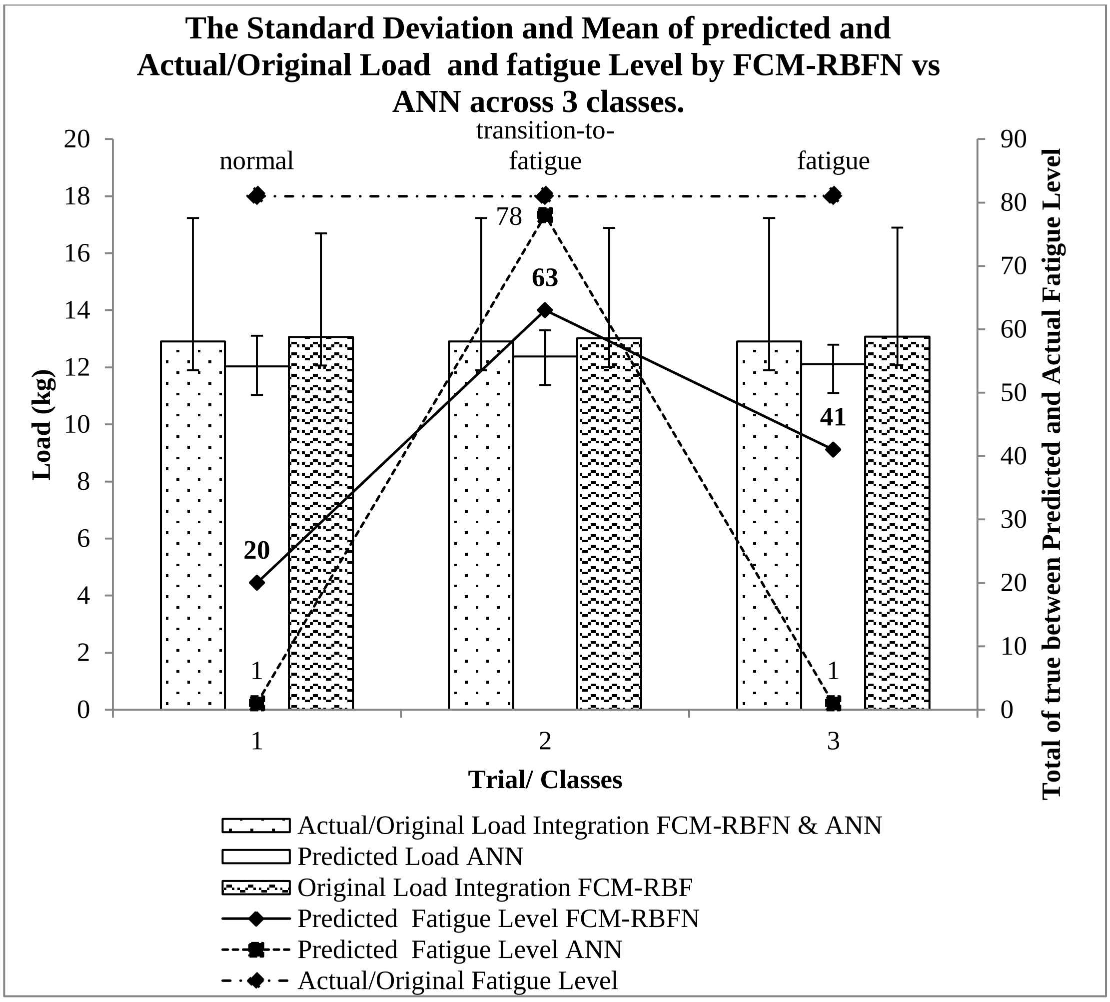


Figure 6.10: The standard deviation and mean of predicted and actual/original load and fatigue level by FCM-RBFN vs ANN across 3 classes

Based on the graph as shown in Figure 6.11, this graph shows the comparison of class 1 for integration FCM-RBFN modelling technique between predicted load and original load. This graph shows the predicted load is nearer to the original load. There are errors in predicting the original load but yet still accepted. Same goes to Figure 6.12, this graph shows the comparison of class 2 for integration FCM-RBFN modelling technique between predicted load and original load. The graph shows clearly the predicted load is nearer to the original load too even though there are also having errors. For the last class or known as trial 3, this graph shows that the predicted load and original load have a same result as class 1 and 2 as shown in Figure 6.13. Therefore, integration of FCM-RBFN are flexible to the limitation of the isotonic muscle fatigue sEMG signal with the average MSE value as been describe in Section 6.2 and Section 6.3.

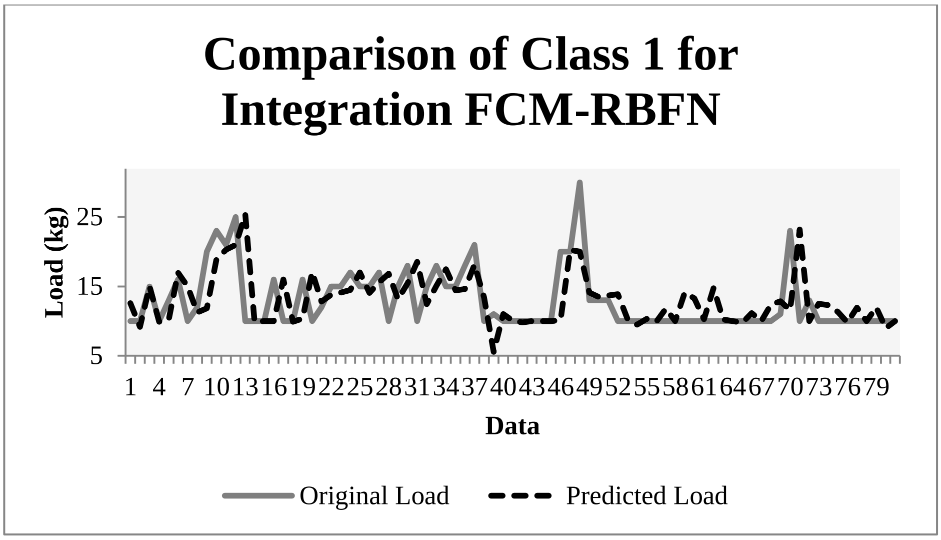


Figure 6.11: Comparison of Class 1 between predicted load and original load for integration FCM-RBFN technique

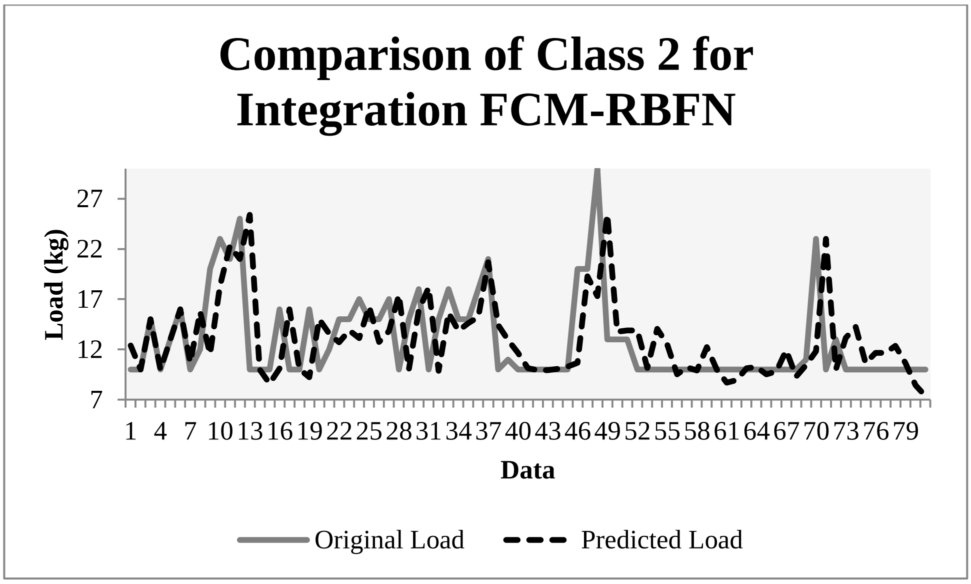


Figure 6.12: Comparison of Class 2 between predicted load and original load for integration FCM-RBFN technique

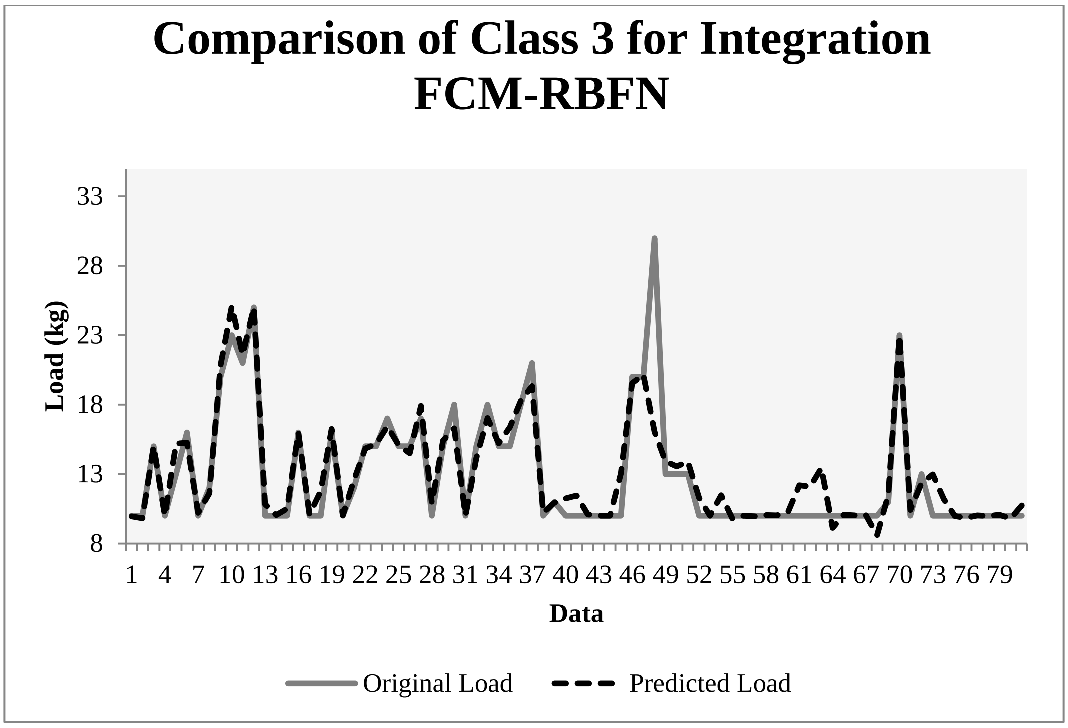


Figure 6.13: Comparison of Class 3 between predicted load and original load for integration FCM-RBFN technique

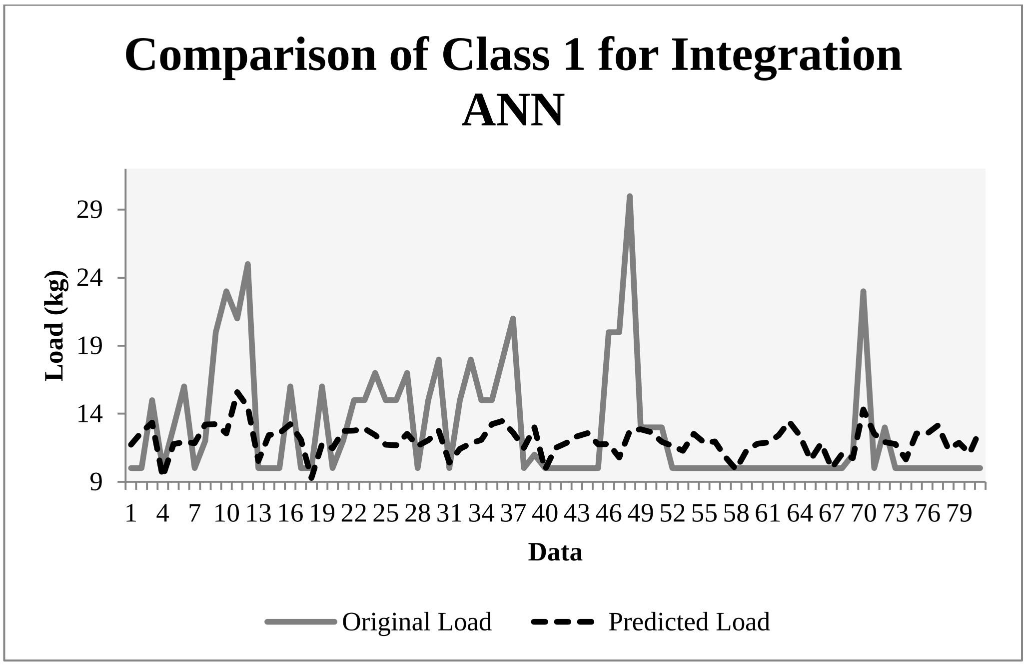


Figure 6.14: Comparison of Class 1 between predicted load and original load for ANN

In contrast, based on the graph as shown in Figure 6.14, this graph shows the comparison of class 1 for ANN modelling technique between predicted load and original load. This graph shows the predicted load is far from the original load. In Figure 6.15 and Figure 6.16 shows the comparison of class 2 and class 3 for ANN modelling technique between predicted load and original load, respectively. Thus, this technique is not stable with the limitation of isotonic muscle fatigue. The average MSE value for ANN performance has been described in Section 6.2 and Section 6.3.

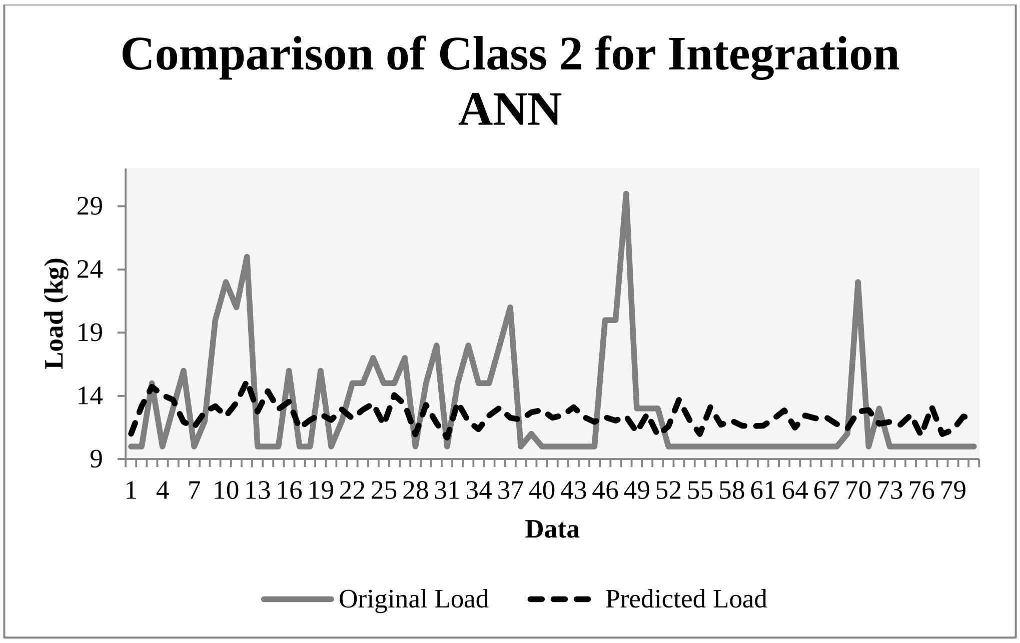


Figure 6.15: Comparison of Class 2 between predicted load and original load for ANN

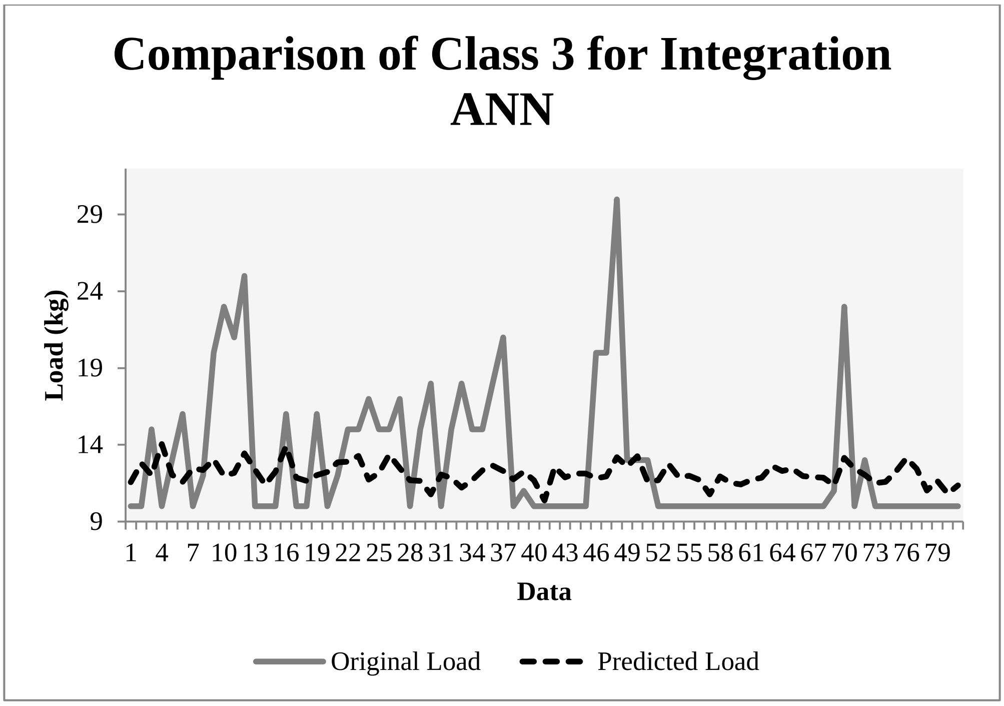


Figure 6.16: Comparison of Class 3 between predicted load and original load for ANN

6.7 Discussion

As been explained in above section, the experimental and validation test results have shown that the integration FCM-RBFN prediction technique performance better as compared to its benchmark technique, ANN. This concludes that integration between FCM and RBFN has enhanced the prediction performance of sEMG especially during isotonic muscle task which has a very high movement artefact noise. Each individual human being has different sEMG characteristics due to the individual muscle fire rate activation. Therefore, the proposed technique can be relying on the varying of sEMG limitation.

In this experiment, the combination between an unsupervised clustering technique and a predicting technique that produces a modelling that enhanced the previous technique. This modelling will predict the next load and will use continuously and the predicted load is depending on the muscle's endurance of the current muscle condition.

The determination of choosing clustering process for the first step in the proposed techniques is because to cluster the unsupervised feature extracted sEMG signal data into 3 stage of fatigue and has been long proven good in surface electromyography (sEMG) muscle fatigue prediction due to its simple network structure and processing speed. Initialized cluster number is important in variable-load intensity modelling by aligning muscle force, endurance and load intensity to individual physical status, therefore, according to expert and literature review, 3 stage of fatigue are crucial (Al-Mulla et al., 2011b).

In addition, FCM offers a good adaptive strength compare to RBNN. These predicted classes will help in predicted load value in RBFN. Even though RBFN is quite unstable as ANN, RBFN techniques is a simplest prediction technique and also with fast computational performance same as FCM technique. The difference of improved RFBN modelling with another technique is that it can predict load intensity from current personalized isotonic muscle condition of a person. The use of three sub-network of RBFN is to enhance the performance of the prediction if compare to ANN alone. So, the next new data will be used directly in the prediction modelling without wasting computational time and updating the membership function so its continually predict the next trial load according to the subject's muscle condition immediately.

The new membership values calculate from the Euclidean distance will combine the both techniques. Every time a new input of sEMG signal data will learn from the integration FCM-RBFN modelling and will give predicted load output for the next trial's load. This is because of the muscle endurance will increase over time with fixed endurance training schedule. Thus, with the continually use of this modelling will give varies load's weight parallel with the current subject's muscle condition and will help athletes to control their muscle from injuries and help to endure much longer.

In addition, the integration FCM-RBFN is been choose because due to the suitability to be used in real-time sEMG recognition system and the ability with low computational time. With the help of good proposed feature vectors are able to quantify muscle fatigue in isotonic muscle endurance training and at the same time can enhance the result of performance.

Various efforts have been researched to increase the automation of personalised sport training towards the paradigm of personalised self-monitoring and computational modelling is widely used in various human related problems solving but the limitation in expert availability hinders the realisation of personalised sport training. Therefore, the need of short term load predictions is necessary**.** Thus, in muscle endurance training, variable-load intensity model is usually suggested to improve the muscle endurance. Human muscle will achieve it maximum fatigue state when it can't lift any load anymore. Therefore, with the help of load prediction during current endurance training will gives many benefits. First, it does avoid the risk of injuries due to over load lifting. Even though, they have a traditional way to calculate the potential load lifting according to a person, but it might not suitable when it already reaches person's fatigue limitation. Second, it's help to enhance endurance with increasing the repetition according to suitable load with the current fatigue stage in endurance training. This can avoid for a person to get tired easily and at the same time enhance it endurance training.

6.8 Summary

As summary, the experimental results achieved the objectives in this study. A set of feature vectors were identified and the Butterworth high pass filter cut-off at 10 Hz threshold was selected. In addition, the clustering technique of FCM and prediction technique of RBFN is been enhance with integration of these both techniques to improve the next load's weight prediction and the prediction performance since the sEMG muscle fatigue during isotonic muscle task have a higher noise than isometric muscle task. The integration FCM-RBFN is able to self-adapt to the changing of the current athletes muscle's condition to predict the next load's weight for the next trial. Thus, integration FCM-RBFN prediction technique is suitable for all personalized endurance training for athletes using sEMG signals.

CHAPTER 7

CONCLUSION AND FUTURE WORK RECOMMENDATION

7.1 Introduction

This chapter explains briefly the summary of the overall thesis. There are 5 sections are provided in this chapter. The first section which is Section 7.2 provides the discussion on this study. Next, Section 7.3 explains the threats of validity of this study. Next, the contribution at Section 7.4 and the following section is Section 7.5 which is the future work and recommendation arising from this study will be explained. Finally, a summary of the chapter will be provided in the last section which in Section 7.6.

7.2 Summary and discussion

The sEMG signal pattern which is representing the individual muscle condition will change over time. Eventually body muscle will get fatigue when a person did certain sport training and each person will be different. So, the need an expert for each person is impossible. The needs to meet the demand of each person in personalized sport training where there are too few experts which lead to this study.

The output clustering techniques from FCM are the labelling cluster class and updated membership function. The initial membership function for FCM is been custom fixed. The importance of clustering first using FCM is because of the FCM is due to the suitability to be used in real-time sEMG recognition system and the ability with low computational time. In addition, this clustering technique is much stable than Neural Network family. The stability of FCM will enhance the clustering technique performance and complimentary the limitation of RBFN.

As a prediction technique, RBFN suitable for build the network modelling. The output from FCM then be used in the predicting technique. RBFN are dividing the sub-net of RBFN into three which represent the 3 classes that has been produce by FCM earlier .In addition, by employing Euclidean Distance calculation in the testing phase, the input training data for RBFN with the selected of RBFN modelling network will strengthen the proposed technique and compatible with sEMG muscle fatigue signal during isotonic training task if compared to ANN alone. So, the next new data will be used directly in the prediction modelling without wasting computational time and updating the membership function so its continually predict the next trial load according to the subject’s muscle condition immediately.

From the positive result of this study, the combination of 2 techniques an integration FCM-RBFN prediction modelling technique successfully predict different load intensity efficiently in sport training for muscle endurance against fatigue according to current muscle condition is produced. The main objective of integration of both techniques is to propose a muscle endurance prediction model based on dynamic FCM-RBFN technique through muscle fatigue measurement. In addition, the feature vectors with the suitable features extraction for quantifying muscle endurance in isotonic sport training are produced. Therefore, integration FCM-RBFN technique is able to accommodate dynamic changes from muscle biofeedback which variable-load intensity training can enhance muscle endurance against early muscle fatigue.

7.3 Threats of validity

There are limitations that must be taken account in our controlled experiment for a better understanding to what extend our experiment is valid for its results and findings. The limitations are as below:

1. The cluster for integration FCM-RBFN techniques on the value of the FCM's clusters is fixed to 3. With the optimal value of cluster, a better prediction performance result can be produced. The determination of choosing the 3 classes are based on past literature which represent 3 classes; fatigue, moderate and normal.
2. Selection of 7 features extraction methods are based on past literature. However, the performance of prediction may vary due to the different number of electrodes, electrode placements and noise inherent.
3. The data acquisition for endurance training need a long time with enough rest time. Thus, subject may be tired even though have enough time due to their own personal schedule such as personal sport training and classes during intersession variability.

7.4 Contribution

The contributions of this study are listed below:

1. A set of feature vectors with the suitable features extraction for quantifying muscle endurance in isotonic sport training. The 7 features extraction methods are Mean Absolute Value (MAV), Root Mean Square (RMS), Variance of EMG (VAR), Standard deviation (STD), Zero Crossing (ZC), Median Frequency (MDF, and Mean Frequency (MF). A quality features vector will enhance the prediction performance.
2. In this study, an integration technique of FCM-RBFN technique for weight's load prediction is been design. The uses of fixed initial membership function in FCM then produce the updated membership function and labelled class. The output then is used in prediction technique, RBFN.

3. From the combination of 2 techniques, a muscle endurance prediction model based on integration FCM-RBFN technique through muscle fatigue measurement using sEMG signal is produced. This modelling can enhance the current techniques for predicting the weight's load of the dumbbell in order to help a person or athletes to enhance their endurance training in sport. Thus, when a new unsupervised data set (a sEMG signal that has been extracted to features vector) arrived, the modelling will update the membership ship function in FCM and determine the class (change the unsupervised data into supervised). Then, the supervised data is directly to the certain class net to proceed for the load's prediction.

7.5 Future work and recommendation

In this thesis, the integration FCM-RBFN predicting technique is proposed. In order to get relevant features vectors, the features method is being selected based on past literature. In the earlier chapter, there a 7 features that has been used. Therefore, it is recommended that to reduce the number of feature extraction methods. The lesser the number of the feature vectors, the more convenient it is to the prediction technique. The number of vector will be reduced.

The integration FCM-RBFN predicting technique is the combination of clustering and prediction techniques. The cluster for integration FCM-RBFN techniques on the value of the FCM's clusters is fixed to 3. Instead of using a fix number of the cluster, it is recommended that to automate the integration of FCM-RBFN clustering. The automate FCM clustering will enhance the proposed techniques in order to predict more fatigue level which now just for 3 fatigue level. Hence, it is able to enhance the experimental result.

In addition, another recommendation is on the quality of the raw sEMG itself. Although the best filtering has been identified among other filtering techniques for isotonic muscle task, it is should conduct more test on finding the suitable sEMG signal filtering for the better result. The noises inherent in the raw sEMG are cannot be neglect due to the many factors. Therefore, the most suitable filter techniques especially for dynamic muscle are welcomed.

7.6 Summary

This study has been carried out successfully with the use of suitable research methodology and finally achieved the objectives successfully. As summary, the integration FCM-RBFN technique performed better than ANN. Hence the integration FCM-RBFN technique performance better, the isotonic muscle task sEMG signal can be used even though have higher noises than isometric muscle task. The proposed technique successfully predicts weight’s load value on the current subject’s muscle condition. The muscle condition during isotonic muscle task training will be fatigue at the end of the time, the predicted value of load will help athletes to prolong the endurance training according to the muscle's condition. Therefore, the proposed integration FCM-RBFN technique can be further improved to incorporate attribute variation and attribute value variation for a better performance in real world applications.

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APPENDIX A

Source code

```
% ======== 1)FCM-RBF ========

% Clear all existing variables from the workspace.
clc
clear all
rng default  % For reproducibility
% ====================================
%     Train FCM
% ====================================
 t = cputime;
disp('Training the FCM...');
data1 = load('FCM_10Hz_normalized.csv');
data = data1(:, 1:7);
% target = data1(:, 8); %output
c = 3;
options = [NaN 100 0.001 0];
[U_data,V_data,iteration] = fcm_v1(data,c);

%FCM Train process end
% ========================================
%       Measure Training Accuracy
% ========================================
disp('measuring Training accuracy...');
pre_labels = zeros(length(data),1);
for i = 1:length(data)
    [C,index] = max(U_data(:,i));
    pre_labels(i) = index;
end
%1:323 324:648 649:972
flag = zeros(1,3);
for i = 1:3
    flag(i) = sum(pre_labels(1:323)==i);
end
[num1,index] = max(flag);
flag = zeros(1,3);
for i = 1:3
    flag(i) = sum(pre_labels(324:648)==i);
end
[num2,index] = max(flag);
flag = zeros(1,3);
```

```
    flag(i) = sum(pre_labels(649:end)==i);
end
[num3,index] = max(flag);
%
accuracy = (num1+num2+num3) / length(data) * 100;

disp(sprintf('Accuracy = %g%',accuracy))
disp(sprintf('iteration = %g%',iteration))

x = data(945:948,: );
% x = [1 2 3 4; 5 6 7 8; 9 10 11 12; 1 1 1 1]; %data baru utk test
% y = [8 9 10 11]

% v_data = [8 9 10; 13 9 15; 7 9 10; 1 1 1; 3 4 5; 2 2 2; 4 4 4]'; %mf from fcm


%7) Euc compare distance from (1)'s mbershipFx
%8) calculate distance for each cluster
for m = 1:4 %row

    d1(m) = sqrt(sum(  (x(m,:) - V_data(1,:)).^2  ));
    d2(m) = sqrt(sum(  (x(m,:) - V_data(2,:)).^2  ));
    d3(m) = sqrt(sum(  (x(m,:) - V_data(3,:)).^2  ));

    new_mf1 = [d1; d2; d3];
end
%9) label the class, which the lowest distance value are the most similar
pre_labels2 = zeros(length(new_mf1),1);
for i = 1:length(new_mf1)
    [C,index] = min(new_mf1(:,i));
    pre_labels2(i) = index;
end
%=====================================================
=============
% Load the data set.
% This loads two variables, X and y.
%   C - The dataset
%   y - The corresponding label (category 1,2, 3).
% The data is randomly sorted and grouped by category.


load = xlsread('Load.csv');
datacombine = [data load pre_labels];
%2)dividing the clustering data from FCM into each array
for m = 1:972
```

```
    if datacombine(m,9) == 1
        class1_(m,:) = datacombine(m,:);
    elseif datacombine(m,9) == 2
        class2_(m,:) = datacombine(m,:);
    elseif datacombine(m,9) == 3
        class3_(m,:) = datacombine(m,:);
    end

end

%3)delete all rows which has 0 label
del1 = class1_(:,9) ==0;
class1_(del1,:) = [];

del2 = class2_(:,9) ==0;
class2_(del2,:) = [];

del3 = class3_(:,9) ==0;
class3_(del3,:) = [];

%4) paremeters for RBF
eg = 0.02; % sum-squared error goal
sc = 1;    % spread constant

%5) run all three sub-RBF
% ====================================
%    RBF Network Class 1
% ====================================
% data1 = load('20Hz_class3.csv');
C1 = class1_(:, 1:7); %from data line 84
Z1 = class1_(:, 8:9); %outputload
X1= transpose(C1); %transpose input
y1 = transpose(Z1); %transpose target

disp('Training the RBFN...');
net_1 = newrb(X1,y1, eg, sc);
% ====================================
%    RBF Network Class 2
% ====================================
% data1 = load('20Hz_class3.csv');
C2 = class2_(:, 1:7);%from data line 84
Z2 = class2_(:, 8:9); %outputload
X2= transpose(C2); %transpose input
y2 = transpose(Z2); %transpose target
disp('Training the RBFN...');
net_2 = newrb(X2,y2, eg, sc);
```

```
% ===================================
%    RBF Network Class 3
% ===================================
% data1 = load('20Hz_class3.csv');
C3 = class3_(:, 1:7);%from data line 84
Z3 = class3_(:, 8:9); %outputload
X3 = transpose(C3); %transpose input
y3 = transpose(Z3); %transpose target

disp('Training the RBFN...');
net_3 = newrb( X3, y3, eg, sc);

%until here_________________________________________
%euclidean calculation


%9) The smallest weight of distance is represent which cluster it will be.

datacombine2 = [x pre_labels2]; %why 4 data rows only? bcs 4 rows represents 1 trial with 4 sensors at dfrnt muscle

%10)dividing the clustering data from FCM into each array

for m = 1:4

if datacombine2(m,8) == 1
class1_1(m,:) = datacombine2(m,:);
%11)delete all rows which has 0 label
Class1 = class1_1(:,8) ==0;
class1_1(Class1,:) = [];


class1_1_trans = transpose(class1_1); %transpose new input
%data sebelum. coloum ade 7, nak masuk dlm RBF row kne 7
%RBF
P_c1 = class1_1_trans(1:7,1 );
Y_1 = sim(net_1,P_c1);

class2_1_trans = transpose(class2_1); %transpose new input
%data sebelum. coloum ade 7, nak masuk dlm RBF row kne 7
%RBF
P_c2 = class2_1_trans(1:7,1 );
Y_2 = sim(net_2,P_c2);
```

```
elseif datacombine2(m,8) == 3
class3_1(m,:) = datacombine2(m,:);
%11)delete all rows which has 0 label
Class3 = class3_1(:,8) ==0;
class3_1(Class3,:) = [];
class3_1_trans = transpose(class3_1); %transpose new input
%data sebelum. coloum ade 7, nak masuk dlm RBF row kne 7
%RBF
P_c3 = class3_1_trans(1:7,1 );
Y_3 = sim(net_3,P_c3);
end
end

   elseif datacombine2(m,8) == 2
      class2_1(m,:) = datacombine2(m,:);
      %11)delete all rows which has 0 label
      Class2 = class2_1(:,8) ==0;
      class2_1(Class2,:) = [];

      class2_1_trans = transpose(class2_1); %transpose new input
      %data sebelum. coloum ade 7, nak masuk dlm RBF row kne 7
      %RBF
      P_c2 = class2_1_trans(1:7,1 );
      Y_2 = sim(net_2,P_c2);

   elseif datacombine2(m,8) == 3
      class3_1(m,:) = datacombine2(m,:);
      %11)delete all rows which has 0 label
      Class3 = class3_1(:,8) ==0;
      class3_1(Class3,:) = [];

      class3_1_trans = transpose(class3_1); %transpose new input
      %data sebelum. coloum ade 7, nak masuk dlm RBF row kne 7
      %RBF
      P_c3 = class3_1_trans(1:7,1 );
      Y_3 = sim(net_3,P_c3);
   end
end

c = pre_labels2; %1x4 represent pre_labels2 4x3
d = new_mf1; %4x1; represent new_mf1 3x4
counter1 = 0;
counter2 = 0;
counter3 = 0;
for m = 1:4

   if c (m) == 1
```

```
        counter1 = counter1 + 1;
        continue;
    elseif c (m) == 2
        counter2 = counter2 + 1;
        continue;
    elseif c (m) == 3
        counter3 = counter3 + 1;
        continue;
    end

end

if (counter1 == 2 || counter2 == 2 || counter3 == 2)
    disp('line 1 - even number');
%   calculation
    aemong = sqrt(sum ((d(1,1)).^2) + ((d(1,2)).^2) + ((d(1,3)).^2) +
((d(1,4)).^2));
    etot = sqrt(sum ((d(2,1)).^2) + ((d(2,2)).^2) + ((d(2,3)).^2) + ((d(2,4)).^2));
    anjang = sqrt(sum ((d(3,1)).^2) + ((d(3,2)).^2) + ((d(3,3)).^2) + ((d(3,4)).^2));
    kucings = [aemong; etot; anjang];
    for i = 1:3

      minvalue = min(kucings);

    end
    groupEven = find (kucings == minvalue);
    disp(sprintf('group = %g%',groupEven))
else
    disp('line 2 - xade');
    counter4 = [counter1; counter2; counter3];
    for i = 1:3

maxvalue = max(counter4);

    end
    groupNot = find (counter4 == maxvalue);
    disp(sprintf('group = %g%',groupNot))
end

%disp(sprintf('Predicted next Load = %g%',Y_2))


%12) output= load, computational time and MSE value

e = cputime-t;
disp(sprintf('Time = %gs%',e))

disp('END');
```

APPENDIX B

Sample of dataset and result of FCM-RBFN

SUBJECT	TRIAL	SESI 1	SESI 2	SESI3	PREDICTED FATIGUE		
1	1	12.58338	9.161502	14.99718	2	2	1
	2	12.39783	10.00912	15.00225	2	3	1
	3	9.950527	9.809902	15.002	3	3	1
2	1	9.904628	10.23767	16.98963	3	1	2
	2	10.00185	13.00234	15.99353	1	1	2
	3	10.00246	15.17713	15.2533	1	2	2
3	1	14.9701	11.24939	11.84119	2	2	2
	2	10.69275	15.73377	11.54431	2	2	2
	3	10.20252	11.60877	20.8451	2	2	2
4	1	18.93103	20.27283	21.00196	2	2	1
	2	18.30603	22.30408	21.00205	2	2	1
	3	25.07064	21.60291	25.00188	3	2	1
5	1	25.38806	9.908534	10.00103	1	3	1
	2	25.38806	10.00183	8.59119	1	1	2
	3	10.82947	10.03939	10.49549	2	3	2
6	1	10.00216	16.00443	9.890018	1	1	2
	2	10.09115	16.00276	10.0658	3	1	2
	3	16.00306	10.099	11.76306	1	2	2
7	1	10.36853	17.07166	12.80408	1	2	2
	2	9.233768	14.99718	13.57943	2	1	3
	3	16.25135	10.01498	12.58338	2	3	2
8	1	13.75721	14.11658	14.49158	2	2	2
	2	12.71814	13.87635	13.13611	2	2	2
	3	14.82947	15.15955	16.43299	1	2	2
9	1	17.00156	14.03549	15.60291	1	3	2
	2	16.29041	12.73572	13.81971	2	2	2
	3	15.09213	14.50495	17.91346	1	3	2
10	1	16.82576	13.14197	15.42073	3	2	1
	2	17.42713	10.00303	15.88611	2	1	2
	3	10.90412	15.42073	16.29041	3	3	1
11	1	18.55775	12.45252	15.07166	2	2	2
	2	18.1576	9.879619	15.64197	2	2	2
	3	9.998344	14.15168	17.02986	1	3	3
12	1	17.45838	14.44661	14.60681	2	3	2
	2	13.8451	14.60681	15.22205	2	2	2
	3	15.19905	16.38923	18.27088	3	3	2
13	1	18.10486	13.42585	5.557987	2	3	2

	2	20.67322	14.41541	12.94825	2	2	2
	3	19.34455	10.22006	10.95222	3	3	2
14	1	11.00437	10.02768	9.799159	1	3	3
	2	11.64197	10.11557	9.946636	2	3	2
	3	11.24177	11.44783	10.08041	3	3	3
15	1	10.00146	10.00248	10.00182	1	1	1
	2	9.936901	10.07361	10.27674	2	2	2
	3	10.00141	10.0032	13.04916	1	1	2
16	1	10.12439	20.25525	20.03846	2	2	2
	2	10.65852	19.29236	17.29236	3	2	2
	3	19.54431	20.16511	16.04236	2	3	2
17	1	14.11604	13.45838	13.69471	3	2	2
	2	25.4701	13.75721	13.88611	2	2	2
	3	13.91736	13.54041	13.90174	1	2	2
18	1	13.88611	10.33338	9.475955	2	2	2
	2	13.88611	10.14735	14.03549	2	2	3
	3	11.28455	10.00135	11.47791	2	1	2
19	1	10.32556	9.885097	11.79525	2	3	3
	2	12.5326	9.50642	10.22361	2	2	2
	3	9.780101	10.00912	9.950527	3	3	3
20	1	10.00188	14.08728	13.29377	1	2	3
	2	9.91975	12.21814	10.00339	2	2	2
	3	10.05307	10.02182	10.26985	3	3	3
21	1	10.2533	14.74353	10.22663	2	2	3
	2	8.700565	8.962283	10.13611	2	2	2
	3	12.17805	12.09626	13.43885	3	3	2
22	1	10.00087	9.761761	11.16736	1	2	2
	2	10.26111	9.515018	9.821514	2	2	2
	3	9.113597	10.05799	10.02475	3	2	3
23	1	9.999405	12.36658	12.84705	1	2	2
	2	11.92097	9.30994	10.45642	3	2	2
	3	10.04525	8.584316	11.49153	3	3	3
24	1	11.55408	23.2201	10.00248	2	2	1
	2	11.805	23.00043	10.00253	2	2	1
	3	23.01387	10.41439	12.35486	2	3	2
25	1	12.49158	12.28523	11.33924	2	3	2
	2	13.15564	14.24353	10.65174	2	2	2
	3	12.96518	11.17317	9.982738	3	3	3
26	1	9.808178	11.9532	10.00581	2	3	1
	2	11.67322	11.67322	12.35261	2	2	3
	3	9.83308	10.01619	9.964198	3	3	3
27	1	11.96814	8.981815	10.00114	2	2	1
	2	10.65955	8.423183	7.358768	2	2	2
	3	10.06478	9.780101	10.72688	3	3	3

APPENDIX C

Sample of dataset and result of ANN

SUBJECT	TRIAL	SESI 1	SESI 2	SESI3	PREDICTED FATIGUE		
1	1	11.73169	12.65403	13.34903	2	2	2
	2	11.00257	13.18988	14.71748	2	2	2
	3	11.5595	12.79644	12.01922	2	2	2
2	1	9.345194	11.769	11.92449	2	2	2
	2	14.06861	13.69007	11.94859	2	2	2
	3	14.04138	12.03654	11.58097	1	2	2
3	1	11.83605	13.21823	13.23425	2	2	2
	2	11.52728	12.73231	13.18002	2	2	2
	3	12.46226	12.35656	13.05376	2	2	2
4	1	12.54801	15.59051	14.50841	2	1	2
	2	12.40262	13.46651	15.18625	2	2	1
	3	11.98981	12.16955	13.44753	2	2	2
5	1	10.53339	12.44149	12.56492	2	2	2
	2	12.76249	14.38403	12.96526	2	2	2
	3	12.36848	11.40692	12.24872	2	2	2
6	1	13.23858	12.10791	9.287414	2	2	2
	2	13.53017	11.45001	12.09291	1	2	2
	3	13.89387	11.85656	11.64336	2	2	2
7	1	11.77769	11.47983	12.74459	2	2	2
	2	12.55001	12.08467	12.91655	2	2	2
	3	12.02766	12.22599	12.86588	2	2	2
8	1	12.75824	12.90567	12.43445	2	2	2
	2	12.21224	12.90567	13.37328	2	2	2
	3	12.90567	13.2813	11.72718	2	2	2
9	1	11.73169	11.67888	12.52997	2	2	2
	2	11.71133	14.07461	13.3183	2	2	2
	3	12.17473	13.34903	12.48064	2	2	2
10	1	11.63544	12.04954	12.75176	2	2	2
	2	10.94909	13.27817	11.83366	2	2	2
	3	11.68943	11.65054	10.76942	2	2	2
11	1	10.4146	11.41352	11.82783	2	2	2
	2	10.68861	13.49422	11.99685	2	2	2
	3	12.06961	11.82792	11.21722	2	2	2
12	1	12.08836	13.23461	13.47506	2	2	2
	2	11.34863	12.45188	13.05626	2	2	2
	3	11.69673	12.33968	12.6571	2	2	2
13	1	12.63314	11.49866	13.0016	2	2	2

	2	12.27806	12.11711	12.68864	2	2	2
	3	12.29727	11.76265	12.25181	2	2	2
	1	9.893911	11.4828	11.85659	2	2	2
	2	12.88294	12.27003	12.48053	2	2	2
14	3	11.68511	10.38408	12.55948	2	2	2
	1	12.34107	12.58577	11.7421	2	2	2
	2	13.10203	12.31011	11.94403	2	2	2
15	3	11.87319	12.12849	12.11839	2	2	2
	1	11.78271	10.79807	12.7422	2	2	2
	2	12.31749	12.0476	12.37781	2	2	2
16	3	11.81795	11.94425	13.20089	2	2	2
	1	12.8599	12.64842	11.94225	2	2	2
	2	11.11962	12.57811	10.86573	2	2	2
17	3	12.57811	13.25672	11.61251	2	2	2
	1	11.63544	11.28338	12.52544	2	2	2
	2	11.58417	13.68998	12.08693	2	2	2
18	3	11.69626	12.75176	11.90055	2	2	2
	1	11.87599	11.96845	10.80933	2	2	2
	2	10.98451	13.10638	11.71197	2	2	2
19	3	11.98649	11.71066	10.77084	2	2	2
	1	9.910694	11.30336	11.80114	2	2	2
	2	12.05486	11.63713	11.61312	2	2	2
20	3	11.94524	11.52286	11.42642	2	2	2
	1	11.88446	12.40377	13.41397	2	2	2
	2	11.63556	12.20195	12.84124	2	2	2
21	3	11.70409	11.84685	12.63227	2	2	2
	1	12.39904	10.61146	11.82352	2	2	2
	2	11.47933	12.45162	12.22963	2	2	2
22	3	12.29964	12.44667	11.95946	2	2	2
	1	10.02014	11.07672	10.74465	2	2	2
	2	12.30046	11.75289	11.44715	2	2	2
23	3	11.90012	11.85122	11.35079	2	2	2
	1	14.32118	12.53737	11.92534	3	2	2
	2	12.74646	12.88762	11.79517	2	2	2
24	3	13.15125	12.44536	12.04165	2	2	2
	1	11.76877	10.64191	12.54338	2	2	2
	2	11.93195	11.71651	12.48848	2	2	2
25	3	11.50951	11.58741	12.25983	2	2	2
	1	12.55235	13.13969	11.39475	2	2	2
	2	10.89013	13.13969	10.97029	2	2	2
26	3	13.13969	12.43681	11.01833	2	2	2
	1	11.87599	11.09269	12.83033	2	2	2
	2	11.3036	12.36731	12.17508	2	2	2
27	3	11.67056	10.80933	11.36318	2	2	2

APPENDIX D

Lab attachment request for data collection

UPSI/FSSK/D/419(38)
01 December 2015

Associate Professor Dr Yun-Huoy Choo,
Principal Research : RACE/F3/TK12/FTMK/F00252,
Computational Intelligence and Technologies Lab (CIT Lab)
Faculty of Information and Communication Technology,
Universiti Teknikal Malaysia Melaka (UTeM),
Hang Tuah Jaya, 76100 Durian Tunggal, Melaka.

Tel : 06-331 6606 Fax : 06-331 6500

Dear Assoc. Prof,

LAB ATTACHMENT REQUEST FOR DATA COLLECTION

Please refer to the above matter and the related letter dated 24th November 2016.

2. On behalf of the faculty management, we are content to your request for research collaboration between the Faculty of Sport Science and Coaching, Universiti Pendidikan Sultan Idris and Computational Intelligent and Technology Research Lab (CIT Lab), FTMK, UTeM.

3. The faculty is aware that the collaboration is mainly for the purpose of data collection that could share in terms of publication. We also allow your graduate research assistance to be attached at FSSK, UPSI for the stipulated period.

Thank you for your cooperation and kind attention.

Sincerely,

(ASSOCIATE PROFESSOR DR JULISMAH JANI)
Dean,
Fakulti of Sports Science and Coaching

s.k. -Assoc. Prof Dr Nur Ikhwan Mohamad (FSSK, UPSI)
-File

Associate Professor Dr. Julismah bt. Jani
Dean
Faculty of Sports Science & Coaching,
Sultan Idris Education University,
Tanjong Malim, Perak Darul Ridzuan 35900,
Malaysia.

24 November 2015

Dear Assc. Prof.,

LAB ATTACHMENT REQUEST FOR DATA COLLECTION
RESEARCH ASSISTANCE: NUR SHIDAH BINTI AHMAD SHARAWARDI (M031510004)

I am writing to request for research collaboration between the faculty of FSSKJ, UPSI and Computational Intelligent and Technology Research Lab (CIT Lab), FTMK, UTeM to partially fulfill the research work in my RACE project, entitled "Improving Variable-Load Intensity Modelling using Auto Clustering FCM-RBF Technique to Prolong Muscular Resistance for Personalized Physiotherapy".

2. For your information, our team had conducted a research visit to your respective research group lead by Associate Professor Dr. Nur Ikhwan Mohamad on 15 September 2015. The visit was a fruitful experience and have paved a way for future collaboration between both parties. Thus, we would like to request for an opportunity to allow my graduate research assistance as named above to be attached at FSSKJ, UPSI as follows:

Date: 4th January - 8th January 2016 (experiment protocol design)
22nd February - 5th April 2016 (data collection)
Place: Lab facilities related to Sport Science
Purpose: Data collection
Mentor: Associate Professor Dr. Nur Ikhwan Mohamad
Assistance Mentor: Azrena Zaireen Ahmad Zahudi

3. The attachment aims to complete the data collection involving 40 FSSKJ, UPSI sport science students using electromyography related sensors and devices. If permitted, Miss Nur Shidah will register at FSSKJ, UPSI on 4th January 2016, at 09:00am. The proposed attachment milestone is as attached overleaf.

4. In addition, I will be much appreciated if I could appoint Assoc. Prof. Dr. Nur Ikwan Mohamad and Miss Azrena Zaireen Ahmad Zahudi as the expert consultants to the our RACE project. However, due to the budget constraints, the project is not able to allocate any consultancy fees. We would be glad to share the related outcomes in terms of publication and an official expert appointment letters.

5. Besides, I would also like to request for your kind favour if FSSKJ could help to arrange a hostel for Miss Nur Shidah during the attachment period if possible. This is because her safety is always at our utmost concern and we believe staying in campus will provide her better experience to get along with the sport science students consequently benefit her studies. The hostel's fee will be paid by our RACE project.

I hope that this request will merit your most favorable response. Kindly let me know should you need further details regarding the attachment.

Thank you for your consideration on my collaboration request.

Sincerely,

Yun-Huoy Choo, PhD | Associate Professor
Principal Research: RACE/F3/TK12/FTMK/F00252
Computational Intelligence and Technologies Lab (CIT Lab)
Faculty of Information and Communication Technology
Universiti Teknikal Malaysia Melaka (UTeM)
Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
Email: huoy@utem.edu.my
Tel: +606 331 6606 Fax: +606 331 6500

c.c. to:

Professor Dr. Burairah Hussin
Dean
Faculty of Information and Communication Technology
Universiti Teknikal Malaysia Melaka (UTeM)
Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
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Associate Professor Dr. Zulkifilie Ibrahim
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Associate Professor Dr. Nur Ikhwan Mohamad
Deputy Dean of Research
Faculty of Sports Science & Coaching,
Sultan Idris Education University,
Tanjong Malim, Perak Darul Ridzuan 35900,
Malaysia
Email: nur.ikhwan@fsskj.upsi.edu.my

PROF. DR. BURAIRAH BIN HUSSIN
Dekan
Fakulti Teknologi Maklumat dan Komunikasi
Universiti Teknikal Malaysia Melaka (UTeM)
24/11/15

PROF. MADYA DR. TAY CHOO CHUAN
Timbalan Dekan
Pusat Pengajian Siswazah
Universiti Teknikal Malaysia Melaka

APPENDIX E

Consent form (participant information sheets)

Improving Variable-Load Intensity Modelling using Auto Clustering FCM-RBF Technique to Prolong Muscular Endurance for Sport Training.

We would like you to consider this research study and then decide whether or not you wish to take part. Before you decide whether to participate or not it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and decide to take part the experiment.

1. What is the purpose of this study?

Computational modelling is widely used in various human related problems solving such as in physiotherapy, rehabilitation programme or in sport training. In muscle resistance training, variable-load intensity Model is usually suggested either to improve the muscle strength or for rehabilitation purposes. Physiotherapy, rehabilitation programmes or in sport training uses electromyography signals as biofeedback to prolong muscle resistance against fatigue. Thus, it should be able to adapt to dynamic changes automatically with minimal human intervention.

Fuzzy C-Means Based Radial Basis Function Network (FCM-RBF) technique has been long proven good due to its simple network structure and processing speed. FCM offers good adaptive strength but the cluster number is still remain predefined by expert either through thresholding or fixed cluster number methods. Auto initialized cluster number is important in variable-load intensity modelling by aligning muscle force, resistance and load intensity to individual physical status. Thus, a prediction method based on short-term historical data is crucial in predicting a nonlinear intensity program suitable for different type of sport training.

The proposed new variable-load intensity Model incorporates auto cluster initialization in FCM-RBF technique to achieve prolong muscular resistance for sport training. Two major contributions in the proposed model are to:

(1) Enhance FCM-RBF technique to automatically identify suitable cluster numbers of load intensity using the muscle biofeedback.

(2) Identify a good learning time interval in variable-load intensity model for real-time prediction.

Positive results of this study will advance the frontier of auto clustering in signal analysis especially in solving dynamic learning problem. In summary, the research outcomes are expected to produce an adaptive FCM-RBF technique to predict different load intensity efficiently in physiotherapy training to prolong muscle resistance against fatigue. Apparently, this study is feasible and will support the Communication, Content and Infrastructure development, fulfilling NKEAs' aim to provide well-founded backbone for application developments especially towards the inspiration of personalized healthcare.

2. Do I have to take part?

The participations of this study are voluntary. It is up to you to decide whether or not to take part. You are free to withdraw at any time and without giving a reason. If you decide to take part, we will ask you to sign a consent form indicating your willingness to participate in the study.

3. What do I have to do?

In order to collecting the required signal, the volunteer subjects recruited to join this experiment with age ranging between 18 to 30 years old. Subjects were asked answering the PAR-Questionnaire, determination of 1RM test, and they signed written consent before participating in the study. In this experiment, sEMG electrodes were placed on the subject's biceps brachii and triceps after we do the cleaning on the skin surface. The subject must follow the endurance training for 4 days a week for 4 session. For the first day, subjects will be asked to run a 1 RM test, then, at the next day (1 session per day), 3 set of training will be held around 30 minutes per session for each of the subjects. Each session have a different of training intensity, there are 50% estimated 1RM, 70% estimated 1RM and last session is the subjects will be asked to do 3 set of estimated 1RM. There are no specific reps and the subjects will be asked to maintain the 90^{o} elbow angle as closely as possible. There are 2 minutes break intervals for this experiment to make sure the subjects are not in the fatigue condition by sEMG signal produce. Throughout the experiment, kinematic analysis using video as a key tool for capturing and recording the movements is use for further investigation, for example for calculate the angle, distance and others. In the recording phase, details of the subject's joints are marked with sign that can be seen later in the kinematic analysis.

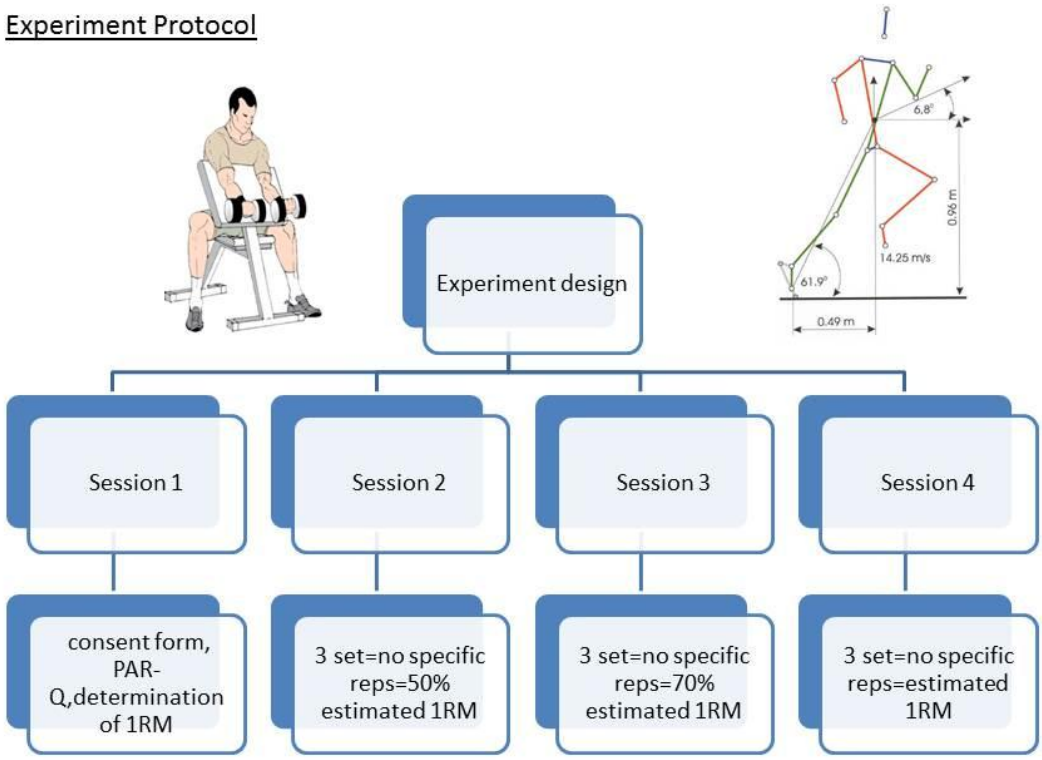

Figure1: The Endurance training schedule

4. Payment and insurance?

Subjects will not be paid and no insurance provided.

5. What are the possible risks of taking part?

The experiment does not bring any effects on the subjects. The subject requires attaching an eight channels electrode on their skin. The SEMG devices are non-invasive. Therefore, it is safe to use.

6. Will my taking part be kept confidential?

Subject's personal detail will be labelled with a number and subsequent analyses of the data will use the subject number rather than the subject's name. None of the data will be identifiable as any specific subject's. In addition, photos will be captured during SEMG signals recording but the facial image of the subjects will be censored and not to be disclosed.

7. How will the information I provide be used?

We plan to publish the results in a computer science journal, biomedical journal or other related journal so others can read about and learn from the results of the study.

8. Further information

If you require more information about this study, please email to one of the research team:

Dr. Choo Yun Huoy – huoy@utem.edu.my

Dr. Chong Shin Horng – horng@utem.edu.my

Ms. Nur Shidah Binti Ahmad Sharawardi – nurshidah.sharawardi@gmail.com

APPENDIX F

Consent form (participant consent form)

Consent of Participate in SEMG Signals Recording Experiment

I have been asked taking part in the SEMG Signals Recording Experiment. I have read the informed consent document for this experiment. I have received an explanation of the nature, purpose and duration of this experiment.

I, ____ hereby consent to participate in the SEMG Signals Recording Experiment.

I understand that:

a) I acknowledge that I have read the Participant Information Sheet, which explains the aims of the study and the nature of the investigation.
b) I understand that my participation is voluntary. I can stop participating in this survey at any time and I am free to not answer any particular question(s).
c) While information gained in this study may be used in conference presentation, and may also be published in a journal article, I will not be identified. Information concerning me will remain strictly confidential.
d) I can ask the investigator at any time for any additional information.

Participant's Signature:	Investigator's signature:
---	---
Participant's Name:	Investigator's name:
Date:	Date: