



**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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in fulfilment of the requirements for the degree of Master of Science in Information  
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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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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 mengoptimalkan 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 menghadkan 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-pemrosesan, pengekstrakan ciri, pembinaan model, dan pengesanan 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 cecap 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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## 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 Radialis 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 Radialis 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

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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 Filtration Frequency for Isotonic Muscle Fatigue Analysis. *International Journal of Computer Information Systems and Industrial Management Applications*, 10, pp.47–56.

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# 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, oversteering 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.