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Integration FCM-RBFN with Butterworth Noise Filteration Frequency for Isotonic Muscle Fatigue Analysis

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***Abstract*: In sport 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 optimise 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. Thus, this paper investigates the Butterworth high-pass noise filter on isotonic muscle fatigue data. Three cut-off thresholds, i.e. 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, i.e. 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 then trained in Integration FCM-RBFN model. The result shows that the proposed model can adapt the isotonic muscle.**

Keywords: Muscle fatigue, sEMG signal analysis, Butterworth cut-off threshold, Integration FCM-RBFN.

I. Introduction

Surface electromyography (sEMG) signals shows the muscle activity based on behaviour of electrical signal produced by human body movement. Nowadays, computational modelling is widely used in assisting human decision making, such as in biomedical and clinical application[1] due to the importance of sEMG study[2], [3][4]. The understanding of the characteristic of sEMG signal is usually recommended either improved the muscle strength or the muscle endurance for sport application purposes[5]. For example, sport training commonly use surface electromyography (sEMG) signals analysis that need a guide from human experts to prolong muscle endurance against fatigue.

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. 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 (e.g. RBF learning model). A recommended cut-off threshold is needed especially for modeling isotonic muscle task.

Typically, exercise training in sport is 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 contraction 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.

Fatigue prediction studies are popular domain nowadays [6]. 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 [7]. 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 0Hz to 20Hz. Butterworth filters has been widely used in sports science and human movement studies with varied filter range [8]–[11] and was commonly used to clean the undesired noises before prediction model building [12]. However, no literature has discussed and confirmed the best cut-off thresholds in isotonic muscle fatigue prediction, especially when different loads were imposed on a human subject.

Fatigue analysis using sEMG signals were usually carried out for isometric contraction task to identify the good predictor's performance set as well as for prediction muscle force and angle estimation[7][8][9]. For isotonic training, the onset of contractile fatigue was successfully predicted in [13] using Radius Basis Function Neural Network (RBFNN) model and Multilayer Perceptron (MLP) model. Research from [13] 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 [13] and MLP[14] are good for isometric muscle fatigue prediction [9,10] 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 perform comparatively well for isotonic fatigue analysis as it has achieved for isometric fatigue analysis [15] 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, Fuzzy C-Mean (FCM) is one of the most popular fuzzy clustering techniques for different degree estimated problems. The successfully to determine the degree and used to choose the best description of faces in a reduced dimension [16]. Its strength over the famous *k*-Means algorithm due ability to yields the point's membership value in each class [17]. The FCM clustering algorithm have been reported [18]–[22] 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 method can provide better clustering.

The RBFN algorithm is a popular muscle fatigue prediction technique due to its capability in improving the performance with respect to a priori of parameter [15][23]. Hence, combining the FCM and the RBFN techniques is a possible promising approach to predict muscle fatigue based on group similarity estimator. However, the capability of FCM-RBFN in isotonic muscle fatigue prediction is yet to be confirming in the past literature.

II. The Experimentation

In this study, the FCM-RBFN technique is used to predict muscle fatigue when different loads were imposed on human subject. We investigated the influence of three Butterworth high-pass filter cut-off thresholds towards the fatigue prediction performance. The cut-off thresholds, i.e. at 5 Hz, 10 Hz and 20 Hz frequency ranges were tested in the experiments. Then, the lowest average MSE among the 3 cut off frequency will be tested into the Integration of FCM-RBFN and ANN will be the benchmark. The following sections explain details of the experimental paradigm design, data acquisition, and sEMG signals preprocessing phases.

A. Experiment Setup

The important phase in every experiment that includes capturing signal with sEMG is the skin preparation is needed to reduce the resistivity of the skin and the electrode must attach to the skin surface without any small barrier. The process of the cleaning hair, dirt, shaving, and the implementation of alcohol swab will decrease the noise that will embed in the signal [24].

The electrodes sensors are used to detect the electrical activities in muscle during movement. Therefore, the participants are asked to not making any additional movement to give less motion artifact. The dataset collected based on isotonic muscle contraction during the dumbbell lifting workout session. Muscle contractions from two muscle types were observed during the experiment, i.e. the flexor carpi radialis and biceps brachii from both right and left hand (see Figure 1). The location of sEMG sensors on muscles are measured to ensure the position is fixed in each session. This is crucial to ensure data consistency. 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 and this monitoring is not use as one of the prediction 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.

For non-sporting environment, upper limb frequently loaded for daily tasks [25]. 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 were 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 [26]. 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 [27] due to several reasons such as a much slower rate of movement, typically less than 1Hz [28] 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 [8][9][10][11]. Thus, further investigations needed to verify which range is the best.

In order to collect sEMG signal, a total of 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.

Figure 1. The sEMG signal data collection setup for isotonic muscle contractions.

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 [26].The subjects were asked to performed dumbbell lifting using the maximum load until fatigue in the trial experiment set. None of them has any history of neuromuscular disorder. The participants were required to lift a dumbbell in the position described [10] (see Figure 1).The Wathan formula[11], as shown in equation (1) below was used in the experiment.

$$1RM = 100w / \left(48.8 + 53.8e^{-0.075R}\right) \quad (1)$$

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 [19]. Hence, the more accurate the maximum weight used, the more realistic the 1RM measurement will estimate the true strength. Each subject repeated the experiment for 3 trials with 2 minutes' rest in between trials (see Figure 2).

A total of 3 experiment sessions were conducted in three different days in orders of 1RM followed by 30%RM, and 50%RM. The orders of experiments for different percentage of RM measurement were designed as such to avoid performing the 1RM sEMG signal recording twice. Since the determination weight of 1RM for each subject needs to be performed in the initial trial, the sEMG signal for the particular trial will be used as one of the three trials in session 1RM to save time.

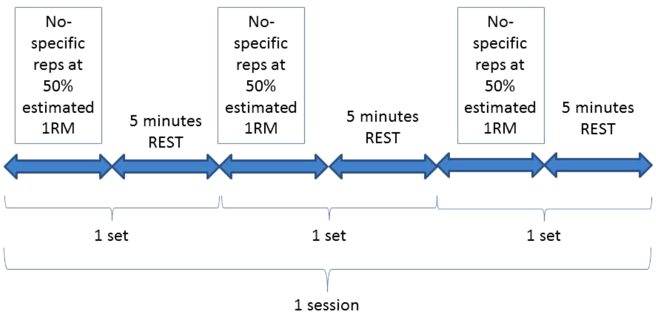

Figure 2. Experimental Paradigm and Design for individual workout session.

The experimental paradigm and design were approved by e Ethics Committee from the Centre for Research and ınovation Management, Universiti Teknikal Malaysia [elaka, as well as from the Medical Research and Ethics ommittee, Ministry of Health Malaysia. The participants ere informed of the experiment purposes and procedures. An ıformed consent was obtained from every subject prior to the experiment.

B. sEMG Signal Acquisition and Feature Extraction

After the experiment setup, sEMG signal can be acquired using acquisition device. 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 [26]. The experimental design and procedure are been explain as in [29].

C. Feature Extraction

The raw sEMG signal data were just an oscillation shown in amplitude across time. Thus, the raw data will normally less significance for classification and prediction task. Therefore, good feature extraction methods are able to produce a set of significant predictors to improve the fatigue classification result. Features extraction methods[30], such as the Median Frequency (MDF), Mean Frequency (MF), Mean Absolute Value (MAV), Root Mean Squares (RMS), Simple Square Integral (SSI), Variance Length (VL), and Waveform Length (WL) were used to extract meaningful data for fatigue prediction. Later, the extracted features are normalized before prediction analysis. Therefore, the data will be in 12x7 array size such as in Table 3.

III. Integration of FCM-RBFN

The 3 level of filter cut-off threshold are been tested with the original FCM clustering and directly been predicted in RBFN algorithm. The threshold which has the lowest average MSE value will be tested in this proposed technique to predict the load's weight value.

The integration overcomes the limitation by enhancing the original FCM- RBFN. These proposed techniques FCM-RBF is designed by integrating between these two techniques which lead to enhance the FCM and RBFN techniques and bring into a next level of predicting model.

A. Fuzzy C-Mean

In this proposed FCM still the same as original but the updated membership function in FCM clustering techniques will be used in RBFN. In addition, the initial membership function also has been fixed into a value according to the athlete's weight load data.

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:

$$c_j = \frac{\sum_{i=1}^{D} \mu_{ij}^{m} x_i}{\sum_{i=1}^{D} \mu_{ij}^{m}} \quad (2)$$

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

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N}\left(\frac{x_i - c_j}{x_i - c_k}\right)^{\frac{2}{m-1}}} \quad (3)$$

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.

B. Testing Phase

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

$$d_{ij} = \sum_{i=1}^{n}\left(\mu_i - \alpha_j\right)^2 \quad (4)$$

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 as shown in Figure 3. The Network RBFN $net\ 1$, Network RBFN $net\ 2$, and Network RBFN $net\ 3$ are formed from RBFN in the next section.

C. Selection of Radial Basis Function Network Model

The selection of Radial Basis Function Network part are be created when there are two group class in the same subject's data trial such as in Table 1. LB and RB muscle in the same group and RF and RB muscle in the same group and in another hand, Table 2 show RB, RF and RB muscle in the same group and LB muscle the only member in group class 2. The problems raised in when two group classes has been predict and which class will be the most nearest correct and reliable.

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:

$$d(p,q) = \sum_{(i=1)}^{n}(p_i - q_j)^2 \quad (5)$$

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 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 in Figure 4 below.

```
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 3. Network RBFN net Stimulate in Testing Phase Algorithm

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 1. sEMG data for a Subject with Even 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

Table 2. sEMG data for a Subject with Odd Presentative Predicted class

Muscle	**MDF**	**MF**	**MAV**	**RMS**	**SSI**	**VAR**	**WL**
1-LB	0.6567	0.8687	0.1377	0.0826	0.0054	0.0054	0.0114
1-LF	0.1109	0.1562	0.1377	0.0826	0.0054	0.0054	0.1305

1-RB	0.0894	0.1007	0.3257	0.2298	0.0385	0.0384	0.2305
1-RF	0.0887	0.0981	0.1452	0.0967	0.0073	0.0073	0.1026
2-LB	0.0966	0.1110	0.4256	0.2988	0.0421	0.0421	0.2054
2-LF	0.1101	0.1591	0.1600	0.0995	0.0050	0.0050	0.1017
2-RB	0.0898	0.0961	0.3276	0.2206	0.0233	0.0232	0.1477
2-RF	0.1743	0.2385	0.1582	0.0925	0.0043	0.0044	0.1338
3-RB	0.0990	0.1135	0.1654	0.1058	0.0087	0.0086	0.1305
3-LB	0.1691	0.2299	0.1373	0.08053	0.0052	0.0052	0.1714
3-RF	0.0883	0.1058	0.1338	0.0749	0.0045	0.0045	0.1007
3-RB	0.1653	0.2155	0.1375	0.0770	0.0047	0.0047	0.1621
1-LB	0.6567	0.8687	0.1377	0.0826	0.0054	0.0054	0.0114
1-LF	0.1109	0.1562	0.1377	0.0826	0.0054	0.0054	0.1305
1-RB	0.0894	0.1007	0.3257	0.2298	0.0385	0.0384	0.2305
1-RF	0.0887	0.0981	0.1452	0.0967	0.0073	0.0073	0.1026
2-LB	0.0966	0.1110	0.4256	0.2988	0.0421	0.0421	0.2054
2-LF	0.1101	0.1591	0.1600	0.0995	0.0050	0.0050	0.1017
2-RB	0.0898	0.0961	0.3276	0.2206	0.0233	0.0232	0.1477

Table 3. The normalized data sample for 1 session.

HZ	**5 Hz**		**10Hz**		**20 Hz**	
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 4. Prediction Performance of Butterworth High-Pass Filter With Cut-off Threshold at Different Frequency Ranges.

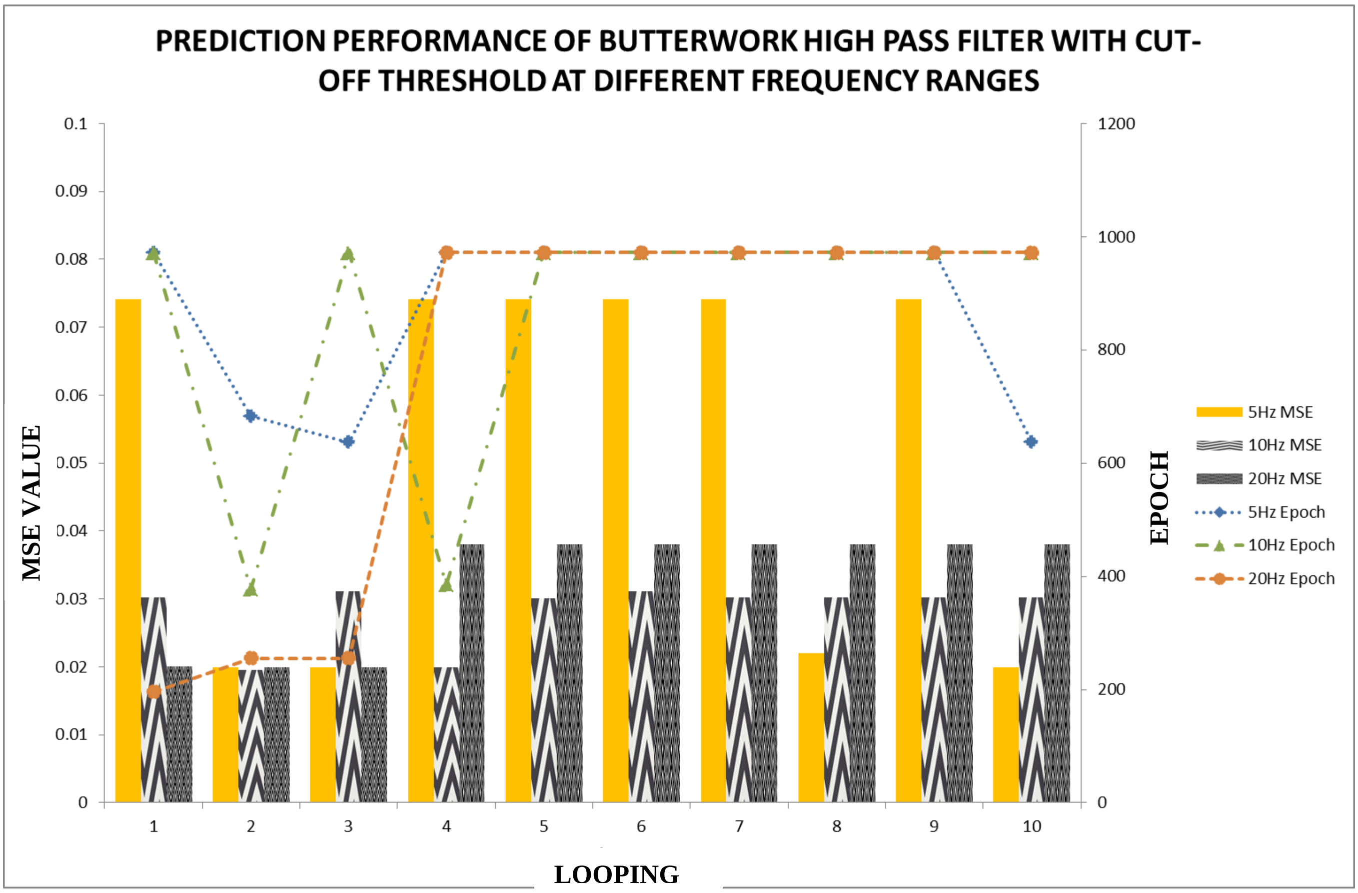

Figure 4. The performance of Butterworth high-pass filter with cut-off threshold at different frequency ranges.

```
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 Automatic start with the lowest class load ∴
```

Figure 5. Selection of RBFN model

I. Result and Discussion

Table 3 shows the normalized sEMG data sample of a single session used as the training data in the experiment. The trial indicates the signal data row of a subject for both biceps (B) and flexor (F) muscles on both left (L) and right (R) arms across 7 features vector. The overall training data were arranged according to the percentage from 1 RM, 30% and 50% of 1RM for session 1, 2 and 3 respectively. Table 4 shows the summary of average MSE comparison between FCM clustering techniques. RBFN technique was used for validating the clusters efficiency for classification.

A. The performance of Butterworth high-pass filter with cut-off threshold at different frequency ranges.

The results reveal that the best prediction results were produced by the data at 10Hz frequency cut-off with the lowest average MSE value of 0.0283. The raw signal that has been filtered with 5 Hz frequency high-pass filter may have not enough to filter the noise out for sEMG isotonic training task. This has been proved with highest MSE value in FCM-RBFN (0.526). The 20 Hz frequency cut-off filter performed better in FCM-RBFN with 0.0326 MSE value than 5Hz but had around 15% higher error rate as compared to the 10Hz frequency cut-off. Hence, data exploration from experiments suggested that in terms of cut-off frequency for muscle fatigue prediction during isotonic contraction task using sEMG signal Butterworth high-pass filter with cut-off threshold at 10 Hz for FCM-RBFN with a lower average MSE than others and 10 Hz suitable to filter off the unwanted noise while maintaining the useful information for constructing learning model at the next phase.

In terms of epoch value, the higher of epoch value, the higher computational time it could take. The training process uses training data-set and must be executed epoch by epoch, in order to calculate the MSE of the network in each epoch for the dataset. The best network model then used by training data for training process with the minimum MSE is selected for the evaluation process. Therefore, to compare the reproducibility, each algorithm was executed 10 times for the same batch of data. The question of the computational time requirements of each method needs to be addressed. Epoch for all 10 times are lower than FCM-RBFN where most of the executing process is nearest to the maximum epoch = 1000 that assuming optimization reaches some local minima and continues to move around the minima. At such state the objective function and validation performance should both become stationary distributions and the optimal value should occur with uniform probability anywhere between when the epoch when the local optimum is reached and infinity.

The results in Table 2 below show that each human subject has different optimum epoch values and different mean squared errors. Therefore, muscle prediction is proven to be better based on group estimates from people with similar strength. FCM algorithm tends to cluster the training data into different group of subjects to facilitate the personalized prediction in RBFN.

The cut-off frequencies at 5 Hz and 20 Hz were trapped in the local minima MSE values and continues to move around the minima at loop 4 while the cut-off frequency at 10 Hz was trapped at the local minimum MSE value starting from loop 5 but was fluctuated at loop 8 and loop 10 (see Figure 4). Among the three cut-off thresholds, the noise cut-off at 10 Hz has the most stable and lowest average MSE readings. The range of difference falls between 0.0116. The MSE fluctuation is the greatest when the 5 Hz cut-off threshold was used. The trend has showed that the noisy data influence has gradually softened when the cut-off threshold is set at 10 Hz and highest. However, it is not an advantage to increase the cut-off threshold just for the purpose of reducing the MSE values in any model building due to the overfitting issue. This is especially important during the data pre-processing stage. Hence, to preserve the original information at a satisfied model prediction is the best way to follows.

CLASS	Average MSE for Integration FCM-RBFN	Average MSE for ANN
1	0.86	1.63
2	0.98	1.71
3	1.33	1.64

Table 5. Average MSE for Integration FCM-RBFN and ANN Techniques.

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.

According to the Table 5 above, the average MSE of Integration FCM-RBFNN and ANN techniques achieved 0.98% and 1.71%, respectively for class 2. Same goes to class 3 where the average MSE for Integration FCM-RBFN and ANN are 1.33 and 1.64 respectively. This is shows that an integration FCM-RBFNN technique is better than ANN technique

The different between Integration of FCM-RBFN and ANN are the 3 sub-net in the proposed technique which specific predict the load's according to the signal's class in RBFN. In addition, the membership function in FCM will always update according to the current muscle condition.

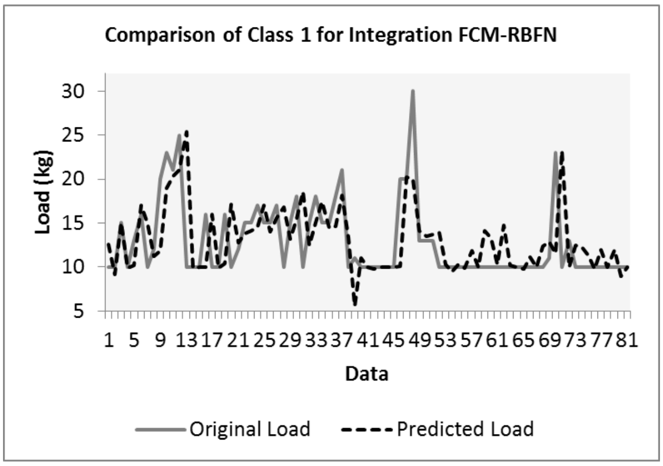

Figure 6 (a). Comparison of Class 1 between Predicted Load and Original Load for Integration FCM-RBFNN technique

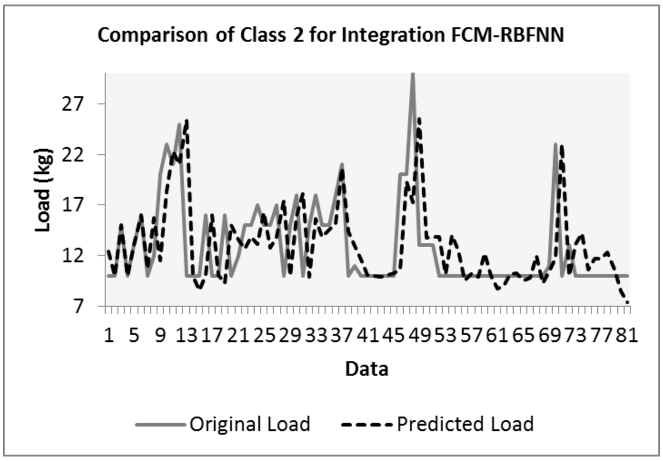

Figure 6(b). Comparison of Class 2 between Predicted Load and Original Load for Integration FCM-RBFNN technique

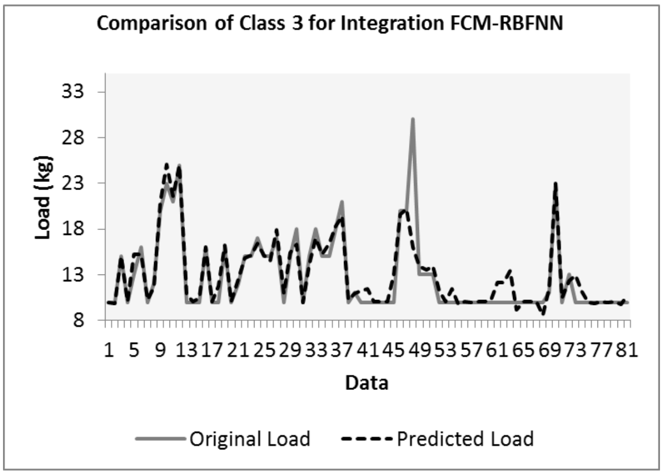

Figure 6(c). Comparison of Class 3 between Predicted Load and Original Load for Integration FCM-RBFNN technique

Based on the graph as shown in Figure 6 (a), (b) and (c) above, the graph shows that the comparison of class 1, 2 and 3, respectively, for Integration FCM-RBFNN modelling technique between predicted load and original load. The nearer the predicted load to the original load, it's shown that the modelling is accepting. There are errors in predicting the original load but yet still accepted. Therefore, Integration of

FCM-RBFNN is flexible to the limitation of the isotonic muscle fatigue sEMG signal with the average MSE value.

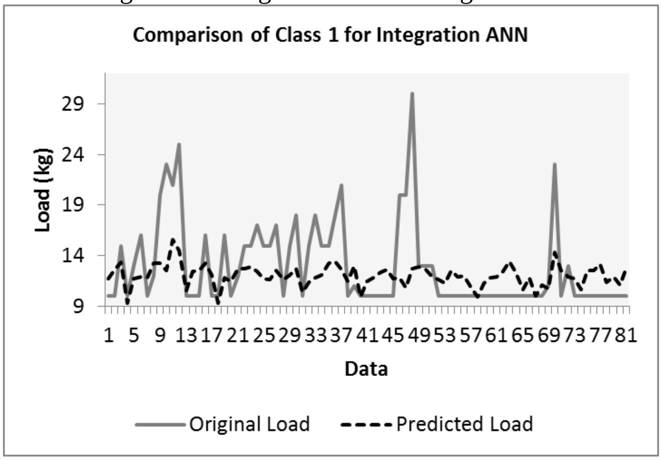

Figure 7(a). Comparison of Class 1 between Predicted Load and Original Load for ANN

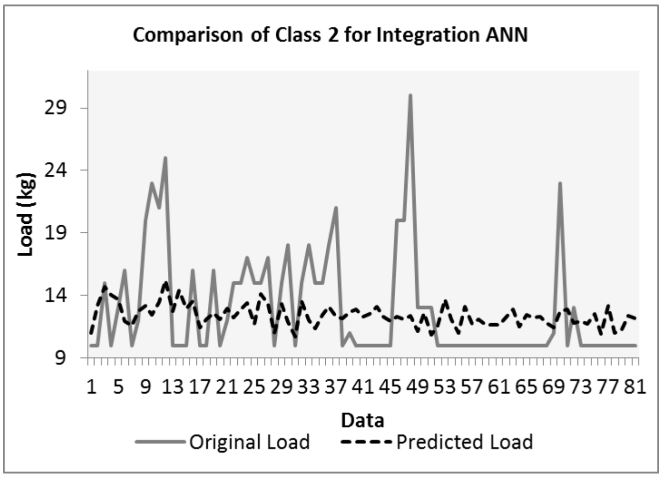

Figure 7(b). Comparison of Class 2 between Predicted Load and Original Load for ANN

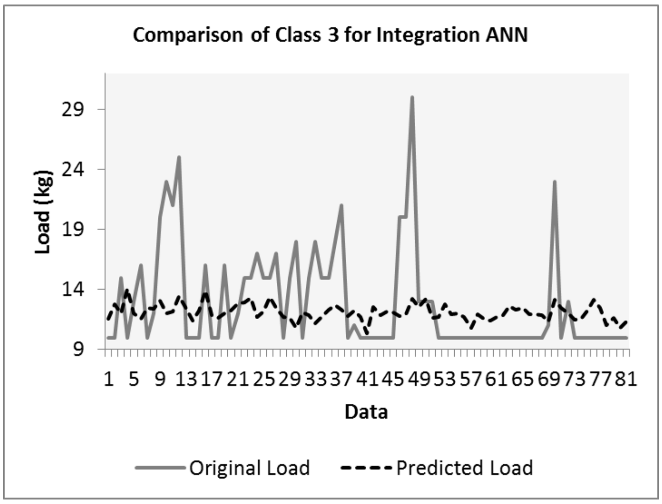

Figure 7(c). Comparison of Class 3 between Predicted Load and Original Load for ANN

Next, in contrast, based on the graph as shown in Figure 7 (a), 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 7 (b), and in Figure 7 (c), 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 dynamic muscle fatigue when compare to proposed technique. The average MSE value for ANN performance has been described in the previous section.

II. Conclusion

In this paper, we have investigated the performance of different cut-off frequency thresholds in Butterworth filter for isotonic muscle sEMG signal processing based on 2 biceps and 2 flexor arms' muscles. The research findings have recommended that the 10 Hz cut-off frequency threshold is the best setting in the proposed scenarios. The minimum average MSE value was recorded at 0.0282, with the maximum fluctuation range at 0.0116. Hence, the 10 Hz is also the most stable cut-off frequency compared with the 5 Hz and 20 Hz cut-off frequencies.

Thus, the most stable cut-off frequency, 10 Hz, is used as the noise filter for the raw sEMG signal. The extracted signal data is used as input data in the proposed technique, Integration FCM-RBFN. 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.

In summary, the proposed model FCM-RBFN can be used for sport training analysis especially for isotonic muscle contractions. The approach of personalized prediction based on similar group estimate is proven to be possible in predicting variable load intensity isotonic task. One of the limitations of this study is the availability of participants and number of sessions involved, as rest in between sessions for muscle recovery need to be taken into considerations [31][32][33]. The future work should look into the prediction model architecture to enable real-time prediction in different loads used to prolong the endurance of an athlete and conduct more cut-off threshold at different frequency ranges.

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