Isotonic Muscle Fatigue Prediction for Sport Training Using Artificial Neural Network Modelling

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Abstract. Fatigue prediction is part of the muscle endurance analysis, which is normally based on expert experience and guided by muscle signal chart such as surface electromyography. The overall endurance training plan is normally predetermined. Rapid updates on the training plan based on the athlete fitness state is hard to achieve in this case. Hence, this has resulted in inefficient muscle optimization during endurance training. Real time muscle monitoring and feedback can be realized through computational modelling. Many research has been done on isometrics muscle analysis. However, less attention was paid to the isotonic muscle fatigue prediction. This paper focuses on fatigue prediction using artificial neural network (ANN) model to support personalized sport training program. The ANN model aims to predict the fatigue state in isotonic muscle training. Selected feature extraction methods from 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 ANN model has achieved minimum mean squared error at 0.23 with overall regression value of 0.6571. The best validation performance has been attained at epoch 11. Although the result is not as good as the fatigue prediction for isometrics muscle analysis, it has shed light on the possibility of using computational modelling to predict muscle fatigue in isotonic training. Nevertheless, future work needs to be done on noise management in isotonic contractions to further improve the data quality for better prediction.

Keywords: Muscle fatigue · sEMG signal analysis · Artificial neural network

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1 Introduction

Computational modelling is widely used in assisting human decision making, such as for sport coaching. In muscle endurance training, fatigue prediction model is typically recommended either to boost the muscle strength or the muscle endurance for sport conditioning purposes. For example, physical therapy, rehabilitation programs, and sport coaching commonly use surface electromyography (sEMG) signals analysis as complementary guide to human experts to prolong muscle endurance against fatigue. Hence, predicting fatigue state is an important task in muscle signal analysis.

There are currently two common approaches to predict muscle fatigue in sport training, i.e. the expert assistance approach and the automatic prediction approach using sEMG signals pattern [1]. The formal predicts fatigue by looking at different indicators including physical changes in appearance, breathing, muscle contraction patterns, and most of the time on past experience, while the later predicts muscle fatigue by analyzing and comparing sEMG signals pattern changes across two different states, the non-fatigue and fatigue states in the workout session. The expert assistance approach is easy to implement, thus is a common practice in sport training. However, this approach is sometimes subjective because the prediction is made by different experts with various experiences. Also, 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 rest of the paper is organized as follows. Section 2 discusses some important literature on fatigue prediction using sEMG signal and artificial neural network model. Section 3 presents sEMG data acquisition, experimental setup, and some essential procedures when conducting the experiment. Section 4 illustrates the experimental component and process flow. Section 5 depicts the experimental results and discussion while Sect. 6 draws the conclusion and the direction for future work.

2 Literature

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, i.e. 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. 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 concentric contractions until it happens [1].

Today, many sport training programs 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 [2]. Many analysis tools use automated methods to assist human decision especially on muscle fatigue prediction. Although isotonic signal analysis is equally important in sport training, many research 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 [3].

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 captured by attaching sEMG electrodes on the targeted muscle during exercise.

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 [4–6]. For isotonic training, the onset of contractile fatigue was successfully predicted in [7] using Radius Basis Function Neural Network (RBFNN) model and Multilayer Perceptron (MLP) model. Research from [7] 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 [7] and MLP [8] 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 yet to confirm.

3 Experimentation and Data Acquisition

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 two muscle types was observed during the experiment, i.e. the flexor carpi radialis and biceps brachii from both right and left hand. Figure 1 shows the experiment setup for data collection.

Fig. 1. The sEMG data collection setup for isotonic muscle contractions.

The purpose of using armrest in the experiment was to optimize the arm muscles utilization 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 48 ms 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 2500 Hz [11].

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 = 152–180 cm) and 18 healthy female subjects (age = 22–24 years; body weight = 42–97 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 participants were required to lift a dumbbell in the position described in Fig. 1.

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 [12]. The subjects were asked to performed dumbbell lifting using the maximum load until fatigue in the trial experiment set. The Wathan formula, as shown in Eq. (1) below was used in the experiment.

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

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 a trial and error estimation although the amount of weight used can be guided by past experience and also the best practice in sport science [16]. 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 min' rest in between trials. The experimental paradigm is as shown in Fig. 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.

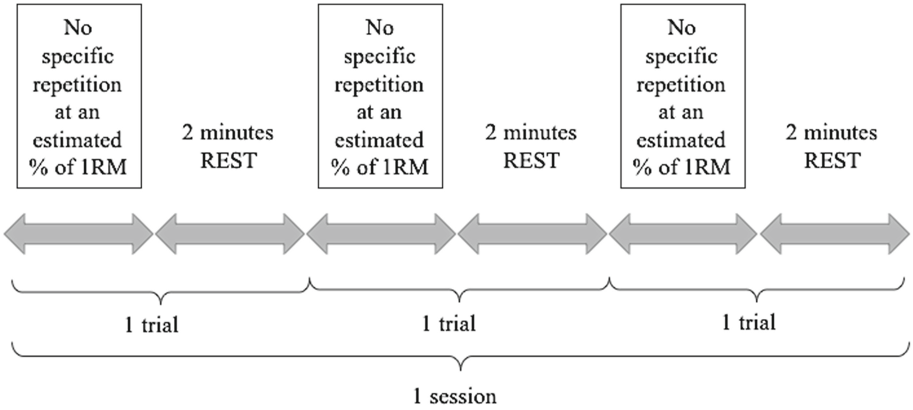

Fig. 2. The experimental paradigm for each individual workout session.

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

4 The Experimental Component and Process Flow

This research follows the experimental methodology as shown in Fig. 3. Raw sEMG signals captured in the experiments required two important pre-processing tasks to provide meaningful insights, i.e. the noise filtration and the feature extraction. The amount of muscle energy produced during the muscle contraction activities is in low amplitude (in mV) by nature [13]. Thus, the sEMG signals are normally amplified and digitized using the built in amplifier in the sEMG data acquisition devices. Hence, various noises including the inherent noise from the electrodes, the movement artefact

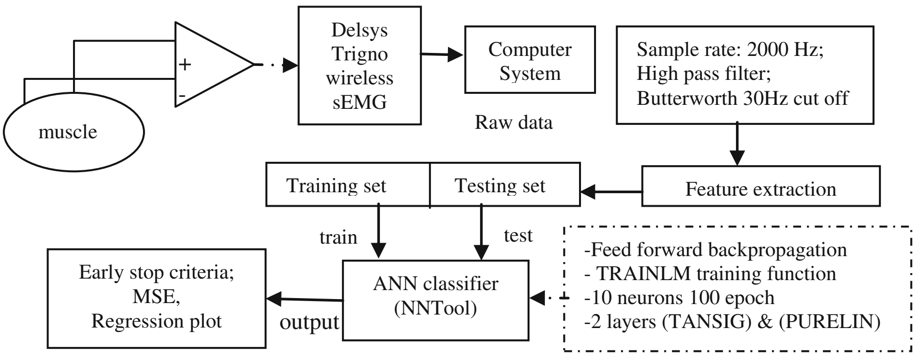

Fig. 3. The experimental component and process flow

such as the cables movement, the particles on the skin surface, cross talk, etc. are amplified concurrently. The Butterworth high pass filter with cutoff threshold at 30 Hz was used to remove the noise artefact [13, 14].

4.1 Noise Reduction

The present of noise during sEMG signal recording will deteriorate the data quality, and affect the prediction accuracy in the developed model. Preliminary data exploration as shown in Fig. 4 proves the existence of motion noise from arm stretching during rest time. This type of noise can be cleaned easily using the high-pass filter because its amplitude is range between 0 Hz to 20 Hz. Therefore, the Butterworth filter was used to clean the undesired noises before model building [16]. Figure 5 shows the signal comparison of before and after the noise filtration at 30 Hz. It is obviously seen that the motion artifact has been removed almost completely after the filtration process.

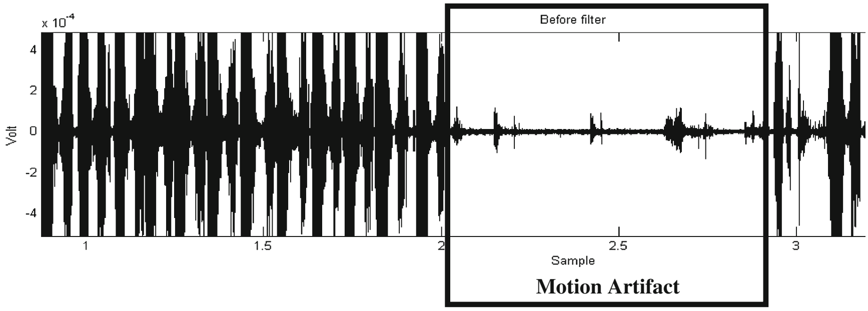

Fig. 4. Example of the present of the minor motion artifact

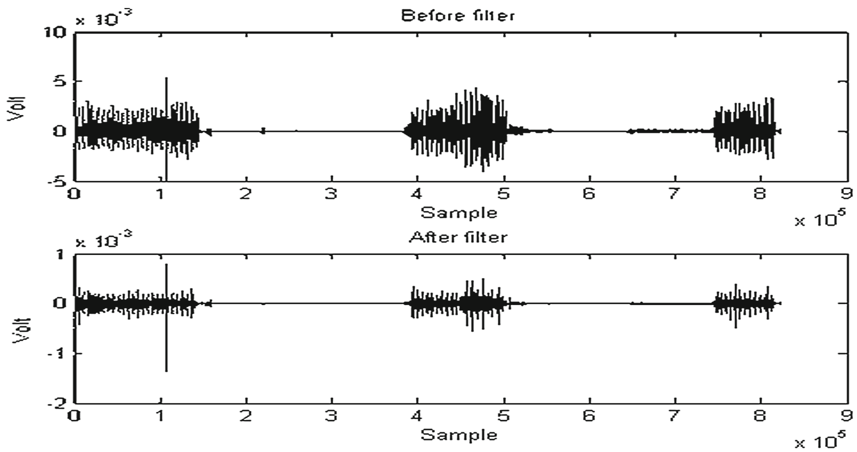

Fig. 5. The raw sEMG signal with presence of noise (above) and the after filteration (bottom) using Butterworth high-pass filter with 30 Hz cut off frequency.

4.2 Features 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 [17, 18], 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.

4.3 Feed Forward Backpropagation Neural Network

A 2-layer-10-neuron feed forward backpropagation ANN was used to predict the muscle fatigue state using 4 sEMG channels. 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 [7] was imposed to improve the generalization of the network and to avoid overfitting. The ANN model was trained with 72 sets of data on different percentage of 1RM load with 7 input vectors corresponding to their output vectors. The performance was measured by using mean square error and regression fit.

5 Results and Discussion

Table 1 shows the sample sEMG training data. 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 data were arranged according to the percentage from 1 RM, 30% of 1RM, 50% of 1RM for session 1, 2 and 3 respectively.

Table 1. The data sample for 1 session.

TRIAL	MDF	MF	MAV	RMS	SSI	VAR	WL
1-LB	6.8955	6.7176	5.49E-06	8.24E-06	8.15E-06	3.28E-08	0.5776
1-LF	7.7567	7.4630	9.14E-06	1.48E-05	2.62E-05	1.05E-07	1.0567
1-RB	7.0884	7.3024	7.83E-06	1.35E-05	2.18E-05	8.74E-08	0.8561
1-RF	7.8593	8.0138	5.12E-06	7.84E-06	7.38E-06	2.96E-08	0.6078
2-LB	7.5446	7.6328	4.60E-06	7.70E-06	5.34E-06	2.14E-08	0.3895
2-LF	8.9579	9.8330	3.96E-06	1.13E-05	1.16E-05	4.64E-08	0.3655
2-RB	7.4866	7.7445	6.63E-06	1.27E-05	1.44E-05	5.79E-08	0.5712
2-RF	8.0832	8.2433	3.62E-06	5.97E-06	3.21E-06	1.29E-08	0.3297
3-RB	7.5468	7.6696	4.82E-06	8.15E-06	4.32E-06	1.74E-08	0.2951
3-LB	7.6757	7.8812	7.77E-06	1.46E-05	1.38E-05	5.54E-08	0.4897
3-RF	8.2990	8.4814	4.51E-06	9.13E-06	5.42E-06	2.18E-08	0.2973
3-RB	8.2990	8.4814	4.51E-06	9.13E-06	5.42E-06	2.18E-08	0.2973

Figure 6 shows the model performance from the perspective of error function for training, validation and testing phases. Best validation performance was obtained in 11 epochs, at 0.23002, which is rather good in terms of convergence speed as compared to similar work which stopped around 14 epochs [19]. However, the training continued for 6 iterations before stopping.

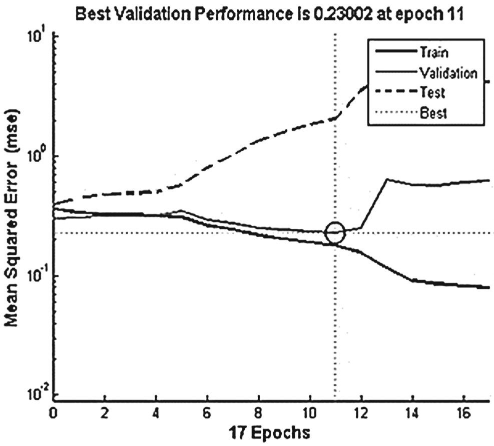

Fig. 6. The early stopping criteria

Regression plot in Fig. 7 illustrates the detailed relationship between inputs and targets of the proposed ANN model for training, testing, validation, and in overall.

The model training and validation have achieved a good fit with 0.84 and 0.88 respectively. However, the model testing has only record a weak performance of 0.33, which is not sufficient for fatigue prediction in real practice. When compare to the best performance in the past literature work [7], the MLP networks model for isotonic contraction analysis has achieved better estimation results with average RMSE between 0.03 to 0.3. Therefore, even though the designed neural network is simpler than the MLP network, but it does not perform comparatively well for isotonic fatigue analysis as it has achieved for isometric fatigue analysis.

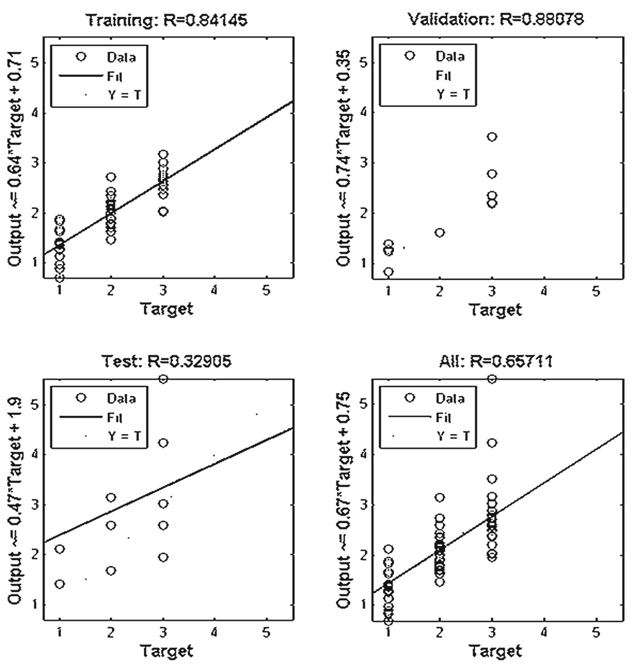

Fig. 7. The regression of the trained model

6 Conclusion

In this paper, we have investigated the performance of artificial neural network in muscle fatigue analysis for 2 biceps and 2 flexor arms' muscles on isotonic contraction training using 7 recommended features from past literature. The results show that the ANN model is able to achieve minimum mean squared error at 0.23 with overall regression value of 0.6571. It has attained the best validation performance at epoch 11. This has proven that the feed forward backpropagation neural network model is able to perform muscle fatigue analysis on isotonic training to a certain extend. The proposed model is compatible to MLP model in terms of convergence speed. However, further analysis need to be done using a standard data as well as noise management approach to confirm on the prediction performance. In summary, the proposed model can be used for sport training analysis especially for isotonic muscle contractions. However, future work needs to be done on noise management in isotonic contractions to further improve the data quality for better muscle fatigue prediction.

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