Analysis of Lower Limb Muscle Fatigue Based on Surface Electromyographic Signal

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Abstract. Surface electromyographic (sEMG) signal contains abundant information such as joint torque and joint motion, which is widely used in human-computer interactive intelligent rehabilitation equipment. In this work, the ankle torque of lower limb is taken as the research object, and the feature parameters of sEMG which represent the fatigue state are analysed. Advance prediction of fatigue features for specific time periods was performed using a normalized minimum average square (NLMS) filter. While the modified cerebellar model neural network (WFCMNN) is used to classify fatigue, which can be divided into three states, namely no fatigue, transition to fatigue, and fatigue. The results show that the accuracy of classification is 96.429%, which is better than other advanced models. At the same time, sEMG signal is used to predict fatigue in advance, which can solve the problem of differences between different individuals. Such strategy is helpful for doctors and physiotherapists to carry out rehabilitation treatment for patients, as a pre judgment and diagnosis index.

1. Introduction

Muscle fatigue is the state that the body cannot maintain the expected exercise intensity due to the temporary decline of the contractility of the muscle movement system [1]. In the actual rehabilitation training, it is necessary to monitor and predict the muscle fatigue state in real time to better understand the patient's muscle activities. The intelligent rehabilitation equipment enables to adjust the control strategy and provide fatigue warning timely according to the muscle fatigue state. Such equipment benefits to reduce the risk of muscle injury and thus serve a wider range of people. Surface electromyographic (sEMG) signal [2] is the performance of muscle activity, which contains a lot of motion control information. It has been considered as the best physiological feedback signal of intelligent rehabilitation equipment [3-4]. And a large number of studies show that sEMG can better reflect the information of muscle fatigue. Using sEMG for real-time monitoring and prediction of muscle fatigue in advance can help to understand the muscle fatigue of users in the process of rehabilitation, which can be used as an indicator for doctors and physiotherapists to judge the prognosis and diagnosis [5].

Many scholars analyse muscle fatigue by studying a variety of characteristic indexes and methods of sEMG signal. For example, Chowdhury et al. used db45 wavelet to analyse muscle fatigue and...
obtained the result of power spectrum moving to low frequency in gait test [6]; Krishnamani et al. developed an automatic muscle fatigue detection system by using the variational mode decomposition (VMD) feature of sEMG signal and random forest classifier [7]; The classification rate between the muscle fatigue and non-fatigue (88.4%) was detected by a genetic algorithm (GA)-based pseudo wavelet function which uses linear discriminant analysis (LDA) [8]; S. Edward Jero et al. Extracted the geometric features of sEMG for muscle fatigue analysis, and used a variety of networks to distinguish “fatigue” and “no fatigue” states, in which MLP had the highest classification accuracy, reaching 86% [9].

Grading according to modified Borg dyspnea score (Borg RPE), there may have three different states ("no fatigue", "transition to fatigue" and "fatigue") in the actual rehabilitation training [10]. The sEMG signals of each individual is different. The time-course and development of muscle fatigue varies between subjects, making the identification of a global muscle fatigue threshold difficult. It is therefore necessary to develop a method that is able to adapt to individuals and detect muscle fatigue ahead of time [11]. In daily life, the frequency of dynamic contraction is much higher than that of static, and the existing fatigue research mainly focuses on static contraction.

In this paper, we study the muscle fatigue of the subjects in the state of dynamic contraction. Both the physiological data (using sEMG) and the psychological data (Borg scale) were used to develop the muscle fatigue analysis model. Forecast the evolution of the fatigue features through adaptive signal processing (NLMS), and the modified cerebellar model neural network (WFCMNN) with fuzzy logic and wavelet function is used as the fatigue classification model to realize three classification ("no fatigue", "transition to fatigue" and "fatigue").

2. Data acquisition
It is unquestionable that the selection of muscles or muscle groups directly affects the outcome of subsequent prediction. The experimental results indicate that the fatigue state can be characterized by the signal of anterior tibial muscle which is selected for muscle fatigue analysis.

Delsys Trigno Wireless System is used for surface EMG signal acquisition, as shown in figure 1. The sampling frequency of the sEMG is 2000 Hz. Before collection, the muscle parts of the subjects were disinfected with alcohol with a concentration of more than 75%. The experiment required six subjects to perform two actions continuously, namely, back flexion and plantar flexion, and the fatigue state provided by the subjects was recorded. Each subject repeated the above experiment three times, with an interval of half an hour. The sEMG data were collected and shown in figure 2.
3. Data processing
The main steps of data processing are as follows: firstly, denoise the collected data by using filter, then conduct segmented and normalized processing; secondly analyze and select the features with good effect to form the fatigue eigenvector group; thirdly use NLMS algorithm to predict the fatigue feature in advance for a specific period of time, and finally train it as the input of WFCMNN.

3.1. Feature Extraction
The selected features should have enough sensitivity to the change trend of fatigue state as far as possible. In order to extract the appropriate fatigue feature for analysis, the fatigue feature of each action segment are fitted linearly separately, and the slope, root mean square error of the fitting curve are taken as the judgment index. Finally, mean power frequency, median frequency, wavelet packet entropy and Lempel-Ziv complexity are selected as the feature parameters of fatigue analysis.

3.2. NLMS Algorithm Predicts Feature Parameters in Advance
In order to predict these fatigue features in advance, NLMS algorithm is used to process each feature. NLMS algorithm is an adaptive filter capable of self-renewal at every time step [11-13]. The prediction time is set to 10 s, and the number of prediction points is \( l = 5 \). The specific steps of the NLMS algorithm are shown in algorithm 1.

**Algorithm 1** Using NLMS to predict feature vectors in advance

**Inputs:**
- feature vector - \( y \), training window size - \( m \), Advance predict
- learning rate - \( \mu \), Length of eigenvectors - \( N \)

**Output:**
- predicted eigenvectors - \( y' \)

Initialize \( w \leftarrow \text{zeros}(m,1) \)

While \( n > m + l \)

\[
x = y [ n - m - l : n - l ]
\]

\[
y' [n] = w^T x
\]

\[
E = y [n] - y' [n]
\]

\[
W = w + \mu * e * x / x^T x
\]

\[
y' [n + l] = w^T y [n - m : n]
\]

end while

Advance prediction Comparison graph of single fatigue feature (wavelet packet entropy) is shown in figure 3. It can be seen from the diagram that the prediction algorithm can adapt to the change of features quickly and can also predict the mutation situations well. It is very important for real-time monitoring of muscle fatigue and rapid adaptation to user activities.

According to figure 4 and figure 5, it can be seen that the algorithm has good reliability for predicting characteristic curves. Except for the large error of the first point prediction because the initial weight of the model is zero, and the latter error decreases rapidly with the real-time convergence of the algorithm. The average errors of wavelet packet entropy, MF, MPF and LZ complexity are 4.5%, 7.3%, 5.9% and 7.3%, respectively, and most of the data errors are less than 5%, which has little effect on the fatigue classification results.
Figure 3. Advance prediction graph of single fatigue feature (wavelet packet entropy)

Figure 4. Error percentage graph of actual and predicted feature curves

Figure 5. Prediction error violin graph of each feature
4. WFCMNN

In this part, WFCMNN, which combines wavelet function with fuzzy cerebellar model neural network, is proposed to improve the ability of dealing with nonlinear problems [14-15].

![Architecture of WFCMNN](image)

The architecture of the WFCMNN contains a five-layer network, as shown in figure 6.

**Input Space**: the input space used to accept input variables, the input signal is $x_i, i=1, 2, ... m$.

**Association Memory Space**: in this space, the input data will be analyzed (i.e. quantized), and the original m-dimensional data will be quantized into n discrete regions. Because wavelet function has the property of multi-resolution [16], it is easy to obtain the global and local behavior of any function [15], and because the integral of Gaussian function has been proved to be bounded convergent, So Gaussian wavelet function is used as membership function to achieve the desired input-output mapping. The first derivative of Gaussian function is selected as the wavelet function, and the relation is shown in formulas (1) and (2):

$$\phi_k = w_k x_i, i=1,2,...,m, k=1,2,...,n$$

$$r_k = \left(\frac{\phi_k - b_k}{a_k}\right) \exp \left(-\frac{(\phi_k - b_k)^2}{2a_k^2}\right), i=1,2,...,m, k=1,2,...,n$$

Where the $w_k$ represents the weight of the $i$-th input variable corresponding to the $k$-th layer, and the $b_k$ and $a_k$ are the translation and expansion parameters of the Gaussian mother wavelet, respectively.

**Receptive-field Space**: corresponding to fuzzy rule operation, "and" logic operation is used to realize fuzzy product reasoning.

**Weight Memory Space**: the weight of each rule $w_{kj}$ is stored in the space.

**Output Space**: corresponding to the defuzzification operation, the sigmoid function is used as the function of the layer to solve the problem of muscle fatigue classification.

In this part, the gradient descent algorithm is used to update and adjust the network parameters, including $b_k, a_k, w_k, w_{kj}$, to minimize the overall error.

5. Experimental result

In this paper, WFCMNN is used as the muscle fatigue classifier. Five subjects’ data were selected randomly for training, and the sixth data for testing. In order to verify the advantages of the network in
dealing with fatigue classification, BP, KNN, and SVM were used to classify muscle fatigue respectively. And ensure that the selection of structure and threshold of each network are consistent. The comparison classification results are shown in table 1.

Where Accuracy refers to the proportion of all samples with correct prediction in the total samples; Precision is relative to the prediction result, which refers to the proportion of the samples correctly predicted as a certain category in the total predicted as that category. Recall (i.e. Sensitivity) refers to the proportion of the sample correctly predicted as a certain type in all the actual samples.

Table 1. Comparison of Classification Results of Different Neural Networks

| Network | No Fatigue Precision | Transition to Fatigue Precision | Fatigue Precision | Accuracy   |
|---------|---------------------|---------------------------------|-------------------|------------|
| BP      | 0.9463              | 0.8333                          | 0.9474            | 0.92857    |
| KNN     | 0.7273              | 0.9231                          | 0.89286           |            |
| SVM     | 0.8750              | 0.8667                          | 0.9730            | 0.91667    |
| WFCMNN  | 1                   | 0.8571                          | 1                 | 0.96429    |

According to table 1, the classification accuracy of BP, KNN and SVM are relatively stable, and the accuracy is about 91%. In comparison, the WFCMNN shows the highest accuracy up to 96.4%.

By analyzing the classification results of different states, "fatigue" has the highest precision, which can be basically distinguished; the relative low precision of "transition to fatigue" may be due to the fuzzy definition of the state itself, which is easily interfered by "no fatigue" and "fatigue". When the WFCMNN is used as the classifier, the discrimination effect of each fatigue state can perform well.

Combining the data of precision and recall to analyze the classification effect of the WFCMNN. Table 2 shows that the precision rate of "no fatigue" and "fatigue" can reach 100%, while the recall rate of "transition to fatigue" can reach 100%. It can be seen that WFCMNN can accurately distinguish "transition to fatigue" among three states, but there is a remote possibility that the states of "no fatigue" and "fatigue" may be classified as "transition to fatigue". In general, WFCMNN has an apparent advantage in muscle fatigue state classification.

Table 2. Evaluation factors of the WFCMNN classification

| WFCMNN | No fatigue | Transition to fatigue | Fatigue |
|--------|------------|-----------------------|---------|
| Precision | 1          | 0.8571                | 1       |
| Recall   | 0.931      | 1                     | 0.973   |

6. Conclusion
This paper introduced the related experiments of muscle fatigue classification. The improved adaptive NLMS algorithm is used to predict the characteristic parameters in advance in a specific period of time. And the fatigue state is classified into three categories by WFCMNN. The experimental data show that the proposed method can achieve the purpose of fatigue prediction in advance, and the modified cerebellar model neural network (WFCMNN) can better classify muscle fatigue.

In order to apply this method to the practical rehabilitation equipment, we need to collect the data of different age groups and people who need lower limb rehabilitation training, and establish a complete database, so as to further enhance the feasibility and practicability of this method.

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