Muscle Fatigue Recognition Based on sEMG Characteristics

Xing FAN, Hai-bo XU, Wen-yu HUANG and Yu-feng LIN
School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, China
Corresponding author

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Abstract. In order to provide the best rehabilitation strategy for patients with neurological hemiplegia, this study collects the surface electromyography signal (sEMG) of the human body during exercise through MYO device to identify the muscle fatigue state. Firstly, the sEMG is filtered by a 4-step Butterworth filter with zero lag, and the 50 Hz power line interference is eliminated by the power line notch method. Then, the muscle fiber motion information contained in the multicomponent EMG signal is separated into the IMF components by empirical mode decomposition (EMD). The multi-scale entropy feature of sEMG is used to identify the fatigue of muscles, and it is found that the IMF5 component entropy of sEMG is most suitable for evaluating muscle fatigue. Finally, by comparing the IMF5 component entropy values of the biceps sEMG in four different exercise modes, it is found that the elbow joint movement has the most obvious training effect on the biceps.

Introduction

In the field of rehabilitation, doctors need to select different exercise modes for specific muscles when they perform rehabilitation training for patients. If the mode is not properly selected, it will not play a good training effect. At the same time, during the training process, the muscles need to maintain a certain degree of fatigue to effectively stimulate the muscles and nerves. Muscle fatigue refers to the fatigue of the body muscles during exercise. Low muscle fatigue can not play a training role, and excessive muscle fatigue can lead to muscle strain, muscle aches, weakness and other symptoms. The surface electromyographic signal (sEMG) is generated by the action potential of nerve impulses in the muscle fibers. Studies have shown that the eigenvalues of myoelectric signals also change with changes of muscle fatigue. Therefore, the eigenvalues of sEMG can be used to effectively identify the muscle fatigue state in different exercise modes, further provide guidance for the patient's rehabilitation training mode selection, and be used to judge the rehabilitation training effect.

Traditional analysis methods usually use sEMG features such as time domain features, frequency domain features, and time-frequency features. Inbar think that the process of muscle fatigue can be analyzed by zero-crossing rate. Liu Jian estimated the muscle fatigue by decomposing the frequency of sEMG and calculating the algorithm with spectral entropy[2]. In 1996, Luttmann established the sEMG signal amplitude-frequency joint analysis method for fatigue evaluation, and think that it can be attributed to fatigue only when the amplitude of the sEMG signal rises and the frequency domain index decreases simultaneously[3].

Approximate entropy and sample entropy have been widely used in the analysis and processing of sEMG signals. For normal sEMG, the approximate entropy and sample entropy values decrease with increasing fatigue. However, the approximation entropy and sample entropy of the signal under pathological conditions show lower adaptability. The reason may be that the approximate entropy and sample entropy are based on a single scale, and the physiological fatigue mechanism is composed of multiple spatiotemporal scales. Therefore, it is considered that the multi-scale entropy feature is more reasonable for the identification of muscle fatigue state.
Signal Acquisition and Preprocessing

Signal Acquisition

This study uses MYO of Thalmic Labs of Canada as the sEMG acquisition device. MYO has 8 sEMG acquisition channels with a maximum sampling frequency of 1000 Hz. Use the SDK provided by MYO to develop signal acquisition programs, data display programs, stored programs, etc. Two subjects were selected in the experiment, and each subject performed 4 kinds of rehabilitation actions in a 4s cycle for more than 10 minutes. In order to prevent mutual influence, each group of exercise modes is separated by more than four days. The exercise mode is shown in Table 1. The collection device and wearing method are shown in Figure 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Movement Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exercise mode 1</td>
<td>Elbow joint bending 0~90°</td>
</tr>
<tr>
<td>Exercise mode 2</td>
<td>Shoulder joint bending 0~90°</td>
</tr>
<tr>
<td>Exercise mode 3</td>
<td>Shoulder joint swing back and forth 0~90°</td>
</tr>
<tr>
<td>Exercise mode 4</td>
<td>Elbow joint bending 0<del>90° &amp; Shoulder joint bending 0</del>90°</td>
</tr>
</tbody>
</table>

Figure 1. sEMG acquisition.

Signal Preprocessing

The action potential of nerve impulses in the muscle fibers produces very weak sEMG on the skin surface and is susceptible to noise pollution, including the inherent noise of the acquisition equipment, ambient noise interference and 50 Hz power frequency interference. Therefore, before further processing of sEMG, noise interference must be filtered out. The surface EMG signal has a useful frequency range of 20Hz-500Hz. It is filtered by a 4-step Butterworth filter with zero lag, and the 50Hz power frequency interference is eliminated by the power frequency notch method. On the basis of noise reduction, the sEMG is subjected to 120 Hz resampling and 3 Hz low-pass filtering. The sEMG before and after filtering are shown in the Figure 2.

Figure 2. sEMG filtering.

SEMG Feature Extraction of Muscle Fatigue

During the process of continuous exercise, the muscle gradually enters the physiological fatigue state. As the fatigue process increases, the number of muscle fibers recruited by the exercise increases, and the signal tends to be regularized. As the degree of fatigue increases, the myoelectric signal shows a
decrease in complexity. There are many methods for calculating the degree of fatigue based on the sEMG, and the multi-scale entropy can comprehensively reflect the complexity information. Due to the external interference and sampling error in the acquisition process, there will be a small gap between similar signals, so the multi-scale entropy based on the sample entropy is still used in error[4]. Referring to the fuzzy entropy algorithm[5], the improved Gaussian distribution function is introduced to make the similarity discrimination more accurate. The complexity of the EMG signals is not the same and there is a clear distinction between the various frequency bands. Therefore, in order to reduce the interference of the muscle fiber information, the EMD decomposition of the surface EMG signals is performed which separate the muscle fiber motion information contained in one EMG signal into each IMF component and increases the accuracy of the analysis. The muscle fatigue analysis algorithm process is shown in Figure 3.

![Figure 3. Muscle fatigue analysis process.](image)

**EMD Decomposition**

The signal is EMD decomposed, and the first 8 layers of IMF components are extracted. The first 8 layers of EMD decomposition are shown in Figure 4.

![Figure 4. EMD decomposition results.](image)
**Improved Multi-scale Entropy Solving Algorithm**

Step1: Decomposed IMF sequences \( X_f = \{x(i), i = 1, 2, 3 \ldots N_1\} \). It is divided into 5 segments to obtain a segmented sequence \( Y^{(r)} = \{y^{(r)}_j, j = 1, 2, 3 \ldots N_2\} \), which is:

\[
Y^{(r)} = \{y^{(r)}_j, j = 1, 2, 3 \ldots N_2\}, \quad N_2 = N_1/5
\]  

(1)

In the formula: \( \tau - \) Scale factor;

Step2: For the segmented first segment sequence \( Y^{(r)} = \{y^{(r)}_j, j = 1, 2, 3 \ldots N_2\} \), reconstruct an m-dimensional vector \( Y^{(r)}_m(p) = \{(y^{(r)}_j(p+k))0 \leq k \leq m-1\} \), where \( Y^{(r)}_m(p) = \{(y^{(r)}_j(p+k))0 \leq k \leq m-1\} \) is a vector of \( y^{(r)}_j(p) \) to \( y^{(r)}_j(p+m-1) \);

Step3: Calculate the distance \( d^{(r)m}_{pq} \) of the two vectors, the expression is as follows:

\[
d^{(r)m}_{pq}[y^{(r)}(p), y^{(r)}(q)] = \max \left\{ \|y^{(r)}(p+k) - y^{(r)}(q+k)\| \right\}
\]  

(2)

Step 4: Using the improved Gaussian distribution function to find the similarity between vectors, \( Y^{(r)}_m(p), Y^{(r)}_m(q) \) similarity is defined as:

\[
D^{(r)m}_{pq} = \begin{cases} 
1 & 0 \leq d^{(r)m}_{pq} \leq 0.5r \\
\exp\left[ -\ln(2)\left( \frac{d^{(r)m}_{pq}-0.5r}{r} \right)^2 \right] & d^{(r)m}_{pq} > 0.5r
\end{cases}
\]  

(3)

Step5: Find the mean of the similarity between the \( Y^{(r)}_m(p) \) vector and all other vectors except itself:

\[
C^{(r)m}_p(r) = \frac{1}{N_2-m-1} \sum_{q=1,q \neq p}^{N_2-m} D^{(r)m}_{pq}
\]  

(4)

Step6: Find the mean of the similarity of all vectors \( Y^{(r)}_m(p) \) \( p = 1, 2, \ldots, N_2-m \):

\[
\phi^{(r)m}(r) = \frac{1}{N_2-m} \sum_{p=1}^{N_2-m} C^{(r)m}_p(r)
\]  

(5)

Step7: The mode dimension is increased by 1, that is, repeating steps (1)-(6) for \( m+1 \) dimensions:

\[
\phi^{(r)m+1}(r) = \frac{1}{N_2-m} \sum_{p=1}^{N_2-m} C^{(r)m+1}_p(r)
\]  

(6)

Step 8: Repeat steps (1)-(6) \( \tau \) times for other segment sequences that have been multi-scaled;

Step 9: Calculate the multi-scale entropy of each IMF component to be:

\[
EMD - MSE(f, \tau, m, r) = \ln \phi^{(r)m}(r) - \ln \phi^{(r)m+1}(r)
\]  

(7)

In the formula: \( f \) — the number of EMD decomposition layers is 8; \( \tau \) — the scale of segmentation is 20; according to the experimental study of Pincus, \( m \) — the dimension of the reconstruction vector takes 2, \( r \) — the similarity tolerance 0.25.

The improved multi-scale entropy of each IMF component is obtained using the above algorithm. The analysis shows that the sEMG's IMF component declines too fast in the first few layers. When the subjects have not felt fatigue, the entropy of the signal is close to zero, which does not reflect the
degree of muscle fatigue. The amplitudes of the latter layers of the IMF component fluctuate greatly, and it does not accurately reflect the change process of muscle fatigue state. The entropy value of the IMF5 component decreases uniformly with time and the degree of linearization is high. Therefore, the entropy value of the IMF5 component can be used to relatively accurately reflect the fatigue degree of the biceps muscle. The results of the IMF5 entropy of the sEMG of the biceps muscle in four different exercise modes are shown in Figure 5.

![Figure 5. Entropy of IMF5 stratification of sEMG in different motion modes.](image)

**Conclusion**

Studies have shown that the exercise effects on the biceps are different in different exercise modes. The exercise modes are sorted from more effective to less effective as Mode 4, Mode 1, Mode 3 and Mode 2. In mode 4 and mode 1, the sEMG of the biceps femoris has a significant decrease in the entropy of the IMF5 component, indicating that the flexion and extension of the elbow joint is more effective for the biceps than the shoulder joint. It is noted that the flexion and extension of the shoulder joint with the extension of the elbow joint can obtain better exercise effect, but the exercise of the shoulder joint alone is less effective for the exercise of the biceps. This study can provide scientific guidance for the rehabilitation training of patients with neurological paralysis, and it is convenient for doctors to select rehabilitation training methods and evaluate the training effect.

**References**


