Muscle Fatigue Classification and The Effect of Electrical Stimulation on Muscle Fatigue Recovery

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Abstract. The purpose of this work is to assess and grade muscle fatigue, and then reveal the different recovery effects of the three methods of natural recovery, electrical stimulation of acupoints, and electrical stimulation of non-acupoints based on the classification and changes in characteristics. Muscle fatigue mainly refers to the weakness of muscles and the weakening of working ability after long-term or high-intensity use. It is a problem that people often encounter in daily life. In this study, 20 subjects participated in the study. By collecting surface EMG signals, and then extracting time-domain features and frequency-domain features, three algorithms of KNN, LR, and SVM were used to classify muscle fatigue into three categories: good, transitional fatigue, fatigue. The average accuracy of KNN algorithm reached 83.2%, the average accuracy of LR reached 84.7%, and the average accuracy of SVM reached 88.6%. Afterwards, the SVM classifier was used to evaluate the subsequent three recovery effects. The experiment found that electrical stimulation of acupuncture points has a better recovery effect than natural recovery and electrical stimulation of non-acupuncture points, and has a more active recovery promotion effect.

1. Introduction
Muscle performance gradually declines after intensive use of muscles, and can basically recover after a period of rest [1]. This reversible phenomenon is called muscle fatigue. Evaluating the degree of muscle fatigue is one of the important ways to prevent muscle fatigue and evaluate the recovery effect. After the fatigue level is judged, the degree of muscle fatigue is quantified, and certain early warnings can be made according to the degree of fatigue to prevent further injuries due to muscle fatigue. The current research on fatigue levels is mainly focused on the two classifications of fatigue and non-fatigue, but when people reach the fatigue stage, muscle function declines and the risk of injury is still high. Therefore, if you join the transitional fatigue phase, and early warning of fatigue in the transition phase, this problem can be solved well [2].

Acupuncture is a medical essence that has been passed down in China for more than 2,000 years. It has excellent effects in terms of pain and treatment of certain diseases [3]. Studies have also shown that acupuncture has a certain effect on muscle fatigue recovery. However, the depth and angle of acupuncture are decisive for the effect of acupuncture. Therefore, the use of acupuncture is not a very convenient treatment. Studies have shown that acupuncture or specific frequency electrical stimulation of body parts can promote the release of specific neuropeptides in the central nervous system, produce physiological effects, and activate self-repair mechanisms [4]. Therefore, we turned our attention to electrical stimulation of acupuncture points to observe whether the effects of electrical stimulation of
acupoints and non-acupuncture points are the same. For electrical stimulation, it can be provided by electrodes placed on the skin (transcutaneous electrical stimulation) or by a probe inserted into the skin (transcutaneous electrical nerve stimulation) [5].

According to traditional Chinese medicine theories, Jianliao and Jianyu points are very effective in treating human upper limb muscle diseases or pain. Physicians often use acupuncture at Jianliao and Jianyu points to treat upper limb diseases. Therefore, in our experiment, we chose Jianlian and Jianhua as the stimulation points for electrical stimulation points, Control group selecting the muscles between the two acupoints. The corresponding acupoint positions are shown in Figure 1.

![Figure 1. Schematic diagram of the location of Jianliao and Jianyu points.](image)

We hope to find a way to use surface EMG signals to judge fatigue through research, as a reference to guide athletes and people in daily sports. The muscle fatigue level is divided by monitoring the surface electrical signal of the muscle during exercise, and the three algorithms of logistic regression (LR), support vector machine (SVM) and K nearest neighbor (KNN) are used to divide the muscle fatigue level into three levels: good, transitional fatigue, fatigue. At the same time, if the recovery of muscle fatigue can be accelerated, it will have a very positive effect on people's sports health. Therefore, we have studied electrical stimulation points and non-acupoint points to explore ways to accelerate muscle fatigue recovery, and use the muscle fatigue classification method to evaluate the recovery effect.

2. Method and equipment

2.1 Experimenter
We selected 20 healthy volunteers for the experiment, 12 males and 8 females, aged 24±3 years, height 167±15 cm, weight 60±15 kg, and signed informed consent before the experiment. Two days before the experiment, there was no strenuous exercise, no muscle injuries, such as tendinitis, sprains, fractures, etc., and no motor dysfunction. In order to ensure the accuracy of the selection of acupuncture points, we have invited an acupuncturist with many years of acupuncture experience to confirm the acupuncture points.

2.2 Equipment
The test uses the laboratory self-developed surface EMG signal acquisition board, the sampling frequency is 1000 Hz, two medical surface Ag/AgCl electrodes are attached to the two ends of the muscle belly, the surface EMG signal is introduced into the EMG signal acquisition board, and the reference electrode is placed on the wrist without muscles. The electrode placement position is shown in Figure 2. Then input the signal collected by the acquisition board to the PC and save it. The electrical stimulation equipment used is FlexHeat. The electrodes are attached to the previously determined
acupoints and non-acupoints, and the fourth intensity is used for electrical stimulation. FlexHeat electrical stimulation equipment is shown in Figure 3.

![Figure 3. FlexHeat electrical stimulation equipment.](image)

Figure 2. Electrode placement position

2.3 Method
In this study, the form of exercise is dumbbell lifting training, from the arm being lowered vertically to the elbow bending to the maximum angle, the whole process keeps the upper arm still to ensure the use of the biceps, the dumbbell weight is 5kg. Three experiments were performed, and there was a recovery time of more than three days between each experiment to ensure that the muscles returned to a normal state. The three experiments were after the exercise reached fatigue: 1. Simply rest for 15 minutes, and then perform a small amount of exercise to assess muscle fatigue. 2. Perform electrical stimulation of Jianliao and Jianyu points for 15 minutes, and then perform a small amount of exercise to assess muscle fatigue. 3. Perform 15 minutes of electrical stimulation of the muscles between Jianliao and Jianyu points, and then perform a small amount of exercise to assess muscle fatigue.

3. Algorithm and signal preprocessing

3.1 Signal pre-processing
Because each human body is different, the length of time to fatigue is different, so the length of the collected EMG signal is also different, and the time to fatigue is between 60 seconds and 240 seconds. After the data is collected, it is filtered. The filtering includes 50 Hz power frequency interference and high-order harmonic filtering, plus filtering of low-frequency components to remove the phenomenon of baseline drift. Use 2nd order Butterworth bandpass filter to filter out 50 Hz power frequency interference and higher harmonics. Use a second-order Butterworth low-pass filter to filter out signals
below 10 Hz. After the processing is completed, the data is divided into 7 segments evenly according to the length of the data. The first segment is considered good, the fourth segment is excessive fatigue, and the last segment is fatigue, as shown in Figure 4.

![Figure 4. Segmentation of filtered signal](image)

3.2 Feature extraction

Feature extraction in the three stages of good, transitional fatigue, and fatigue, including time domain features such as mean, variance, integrated electromyography (IEMG), root mean square coefficient (RMS), frequency domain features such as mean frequency (MNF), median frequency (MDF), average instantaneous frequency (AIF) and other characteristics.

- **Mean value ($\bar{X}$):** Extract the mean value from the surface EMG signal and observe the change in amplitude. The mean can be expressed as:

  $$\bar{X} = \frac{\sum_{i=1}^{N} x_i}{N}$$  \hspace{1cm} (1)

- **Variance (Var):** Extract the variance from the surface EMG signal and observe the degree of signal dispersion. The variance can be expressed as:

  $$\text{Var} = \frac{\sum_{i=1}^{N} (x_i - \bar{X})^2}{N}$$  \hspace{1cm} (2)

- **Root mean square coefficient (RMS):** Root mean square is related to constant force contraction [6], generally similar to standard deviation, which can be expressed as:

  $$\text{RMS} = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}}$$  \hspace{1cm} (3)

- **Integral electromyography (IEMG):** Integral electromyography is the sum of the absolute value of the amplitude of the EMG signal. Generally, the integral EMG is used as an indicator to detect the muscle activity generated by the control command. It is related to the trigger point of the EMG signal sequence and can be expressed as:

  $$\text{iEMG} = \sum_{i=1}^{N} |x_i|$$  \hspace{1cm} (4)

Mean power frequency (MNF) and median frequency (MDF): These two frequency domain features are the most common features of musculoskeletal conditions, expressed as:
The average instantaneous frequency (AIF) is used to express the state of muscle fatigue, which is defined as:

\[
\text{AIF} = \frac{\sum_{j=1}^{M} P_j}{M - 8}
\]  

(7)

In the frequency domain, the decrease in the action potential conduction velocity causes the electromyogram power density spectrum to move in the low frequency direction during a long time of maximum contraction [7,8].

3.3 Algorithm introduction

- **K Nearest Neighbor Algorithm (KNN)**, the core idea of KNN algorithm is that if most of the K nearest samples in the feature space of a sample belong to a certain category, the sample also belongs to this category and has Characteristics of samples in this category. In determining the classification decision, this method only determines the category of the sample to be classified based on the category of the nearest one or several samples. In this study, the K value is 5.

- **Logistic regression (LR)** LR is to model the conditional distribution of class labels based on features. Model parameters are obtained by maximizing the conditional likelihood. The model creates a linear boundary between regions corresponding to different categories in the feature space [9].

- **Support vector machine (SVM)** SVM is a classifier that classifies data in a supervised learning method. Its decision-making convenience is to solve the maximum margin hyperplane of the learning sample. Linear and nonlinear classification can be performed by selecting different kernel functions [10]. Here we choose the Gaussian kernel function.

4. Results and Discussions

4.1 Results

In this research, the entire data processing is done using python language, and the algorithm is implemented using standard library functions in the machine learning library scikit-learn. During training, K-fold cross-validation is used, and finally the results are counted in Table 1.

| Algorithm | Type | Accuracy |
|-----------|------|----------|
| **LR**    | Maximum | 86.4%    |
|           | Minimum | 82.3%    |
|           | Mean    | 84.7%    |
|           | Maximum | 92.6%    |
|           | Minimum | 85.5%    |
|           | Mean    | 88.6%    |
| **SVM**   | Maximum | 84.8%    |
|           | Minimum | 80.9%    |
|           | Mean    | 83.2%    |

Through comparison, it shows that SVM has the best accuracy in our research. The maximum accuracy reaches 92.6% and the average accuracy reaches 88.6%, which is the highest among the three algorithms. Therefore, in the subsequent evaluation of muscle fatigue recovery, we use the SVM model to judge the level of muscle fatigue.
After completing the classification algorithm for muscle fatigue levels, we observe the effects of the three recovery methods. The three recovery effects are shown in Table 2:

**Table 2. Distribution of people in three recovery methods**

| Number of people at each stage | Recovery Method               |                |                |
|-------------------------------|-------------------------------|----------------|----------------|
|                               | Simply rest                   | Electric stimulation non-acupoint | Electrical stimulation acupoints |
| Good                          | 0                             | 1              | 5              |
| Transitional fatigue          | 7                             | 12             | 11             |
| Fatigue                       | 13                            | 7              | 4              |

Figure 5.a, b plots the curves of iEMG and RMS of a tester. We can see that as exercise progresses, both iEMG and RMS are rising. After fatigue, after rest, we find three the time-domain characteristics of the rest method are significantly reduced. After continuing to exercise, the muscles reach fatigue again, and these two indicators rise again.

Figure 5. c, d plots the change trend curve of frequency domain characteristics MNF and MDF. From the beginning of exercise to fatigue, the median frequency and average frequency both decrease. After three types of rest, compare simple rest and electrically stimulate acupuncture points, Electrical stimulation of non-acupuncture points, three curves, we can see that after electrical stimulation of acupoints and non-acupoints, there is a more significant improvement compared to simple rest. At the same time, the effect of electrical stimulation of acupoints is better than that of electrical stimulation of non-acupuncture points. The value of the frequency domain feature is higher, and at the same time, during the process from recovering to a better state to fatigue again, the speed of electrical stimulation of acupuncture points is significantly slower than that of electrical stimulation of non-acupuncture points, that is to say, from the current state to fatigue the state will last longer and the recovery effect will be better. Considering the number of volunteers corresponding to each fatigue level, it is better to use electrical stimulation at acupoints to assist in recovery.
4.2 Discussions
After electrical stimulation of acupuncture points, the frequency domain characteristic recovery reached the state close to the beginning of exercise, but after electrical stimulation of non-acupuncture points, the frequency domain characteristic did not reach the initial state, indicating that the recovery effect is relatively poor compared to electrical stimulation acupuncture points. However, the effects of both electrical stimulation and non-acupoint stimulation were better than those of the control group that recovered naturally.

5. Conclusion
This paper collects the EMG signal after exercise, extracts the time-domain frequency-domain feature value, and divides the fatigue level algorithm. The KNN algorithm with K=5 has a three-classification accuracy of 83.2%, using LR three-classification accuracy of 84.7%, using Gaussian the nuclear SVM three classification reached an accuracy of 88.6%. By comparing the recovery effects of different resting methods after exercise, it is revealed that electrical stimulation of acupoints has a good effect on muscle fatigue. After many comparison experiments by many people, both electric acupuncture points and non-acupoints have a positive effect in the recovery of fatigue, but in comparison, the effect of electric stimulation of acupoints is longer and the effect of muscle fatigue recovery is better. From this study, we know that after muscle fatigue, we can use electrical stimulation of acupoints to assist in the recovery of fatigued muscles. This study also explained to some extent the difference in physiological functions between acupoints and non-acupoints, indicating that acupuncture points are indeed a body part with special effects.

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