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Design of Fatigue Grade Classification System Based on Human Lower Limb Surface EMG Signal

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***Abstract* - With the deepening of the aging of China's population, more and more people suffer from stroke. Stroke has three characteristics: high morbidity, high mortality, and high disability rate. At present, stroke has become one of the main causes of human death, and the population suffering from a stroke in China is gradually becoming younger, many patients can not work and live normally, destroying many happy families. However, stroke is not invincible. Once suffering from stroke, patients can still live and work independently as long as they actively carry out rehabilitation training. The surface EMG signal contains abundant physiological information and has remarkable effects on nerve rehabilitation and orthopedic rehabilitation. Patients with rehabilitation training less training can not play a rehabilitation effect, and excessive training is easy cause secondary injuries, therefore, this paper will design a fatigue state classification system based on surface EMG signals of human lower limb muscles, and analyze the fatigue state of patients' lower limbs by collecting surface EMG signals of target muscles of human lower limbs, to ensure that patients can not only carry out effective training but also not cause secondary injuries due to excessive training.**

Index Terms - Machine learning, surface EMG signal, fatigue analysis, rehabilitation training

I. Introduction

A. Research background and significance

Muscle fatigue is a very common phenomenon in life. People's intuitive feeling of fatigue is muscle pain and weakness, and people's work efficiency will be reduced, and their ability to work is weakened. Central theory thinks the inhibitive protection that cerebrum concerns area to bring about continuously excited and restrain the diffusion in the cerebrum is its produce fundamental reason. Metabolite accumulation theory believes that its generation is due to the work process of metabolites (such as lactic acid) continuously produced and accumulated so that the human body produces a similar poisoning eff. When people feel tired, they will be accompanied by changes in the muscle electrical signals on the surface of the human body, which reflects the current state of the human body. By detecting such changes, excessive fatigue can be prevented to effectively protect the health of bones and muscles.

Stroke patients are usually accompanied by unilateral limb weakness, numbness, and other symptoms so that they can not work and live normally, but active rehabilitation training can effectively improve muscle vitality, to improve their living conditions[1]. Late rehabilitation refers to the rehabilitation of patients with certain activity abilities, without the help of external forces, through their strength to complete the rehabilitation action. A fatigue test is very important for stroke patients[2]. Due to the lack of rehabilitation physicians in China, patients often need to use robots for rehabilitation, but the low intensity of rehabilitation training has little effect, high intensity training and will produce excessive fatigue, easy to make the patients with secondary damage[3]. Therefore, it is of great significance to judge the fatigue state of patients by the changes in surface EMG signal.

B. The research status

Muscle fatigue was put forward by scholars as early as 1912, but it was difficult to develop due to the limitations of the conditions at that time[4]. Because surface EMG signal is non-invasive and contains potential changes and information, it is a more suitable choice to use surface EMG signal to study fatigue. For nearly 30 years, studies of fatigue have achieved rapid development, the University of Essex in All - Mulla professor and his team studied the resting state, transition state, fatigue status, feature extraction, and classification of the classification accuracy reached 83%, and by extracting the characteristics of the different value, improve the classification results, at the same time high team developed a fatigue prediction system. The concept of the fatigue transition state is proposed[5]. Professor Mikel Izquierdo and his team at the University of Navarre in Spain studied muscle fatigue mainly in terms of signal power loss. They observed changes in muscle power output and apparent parameters (the amplitude and spectral index of muscle fatigue) caused by acute exercise under dynamic conditions[6]. The study focused on the lower limbs and legs. In China, Professors Wang Jian and Lu Ningyan from Zhejiang University conducted research on surface EMG and EEG response modes based on local muscle fatigue, and the physiological

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mechanism of surface EMG signal changes in the process of muscle fatigue induced by static exercise load[7]. Professor Zhang Yunkun of the Nanjing University of Physical Education conducted research on fatigue mechanisms based on a central mechanism[8].

Through the analysis of the current fatigue development, it can be found that the current research is only aimed at the prediction of fatigue, but there is no classification of fatigue degree. Therefore, by analyzing the surface EMG signals with different fatigue degrees, this paper finds the different eigenvalues of EMG signals under different fatigue states, designs a fatigue grade classification system based on surface EMG signals of human lower limbs, and designs the corresponding classifier to classify the fatigue signals, and obtains better classification results.

II. Acquisition Of Surface EMG Signal

This chapter mainly introduces surface EMG signal acquisition equipment, target muscle selection, signal acquisition process, and results.

A. Introduction of acquisition equipment

The acquisition system used in this paper is BIOFORCEN, which is developed by Eli Energy Technology, including hardware and upper computer software. The hardware part mainly uses the converter to convert the collected bioelectrical signals into ordinary electrical signals identified by computer software. The surface electrode has become the mainstream surface EMG signal acquisition method because of its small size and non-invasive advantages. The BIOFORCEN hardware system is equipped with two surface EMG collectors, two wireless interfaces, eight cables, and disposable patch electrodes. The BIOFORCEN system collects signals in a differential manner, with two recording electrodes and one black reference electrode for each channel. The system is equipped with a first-order high-pass filter and a second-order Butter Worth low-pass filter for all EMG channels, with cut-off frequencies of 10Hz and 3000Hz respectively. Input signal common-mode rejection ratio is greater than 100dB; Input impedance is greater than 1012 ohm; The maximum storage space is 8190K Bytes and stores a maximum of 20 records[9].

Fig. 1 Surface EMG acquisition system

The software system is used to analyze and process the data collected and transmitted by the hardware equipment. The parameters of the software system need to be set up in advance. The first step is to establish athlete files and select target muscles. Then the interface of the signal acquisition window is entered. The connection with hardware and the beginning of measurement is controlled by keys. The surface EMG software can also analyze the data according to the needs, including spectrum analysis and fatigue analysis[10].

B. Selection of the target muscle

The selection of the target muscle is very important for signal collection, and it is necessary to select the part with obvious changes in surface EMG signal after exercise. A surface EMG signal is an electrical signal generated by muscle contraction. Therefore, the lower limb muscle selected in this paper is the medial and lateral gastrocnemius muscle, and the gastrocnemius muscle is a large muscle in the superficial layer behind the lower leg. The lower end of the muscle forms the Achilles tendon to connect the calcaneus, which plays an important role in human upright and walking. With developed muscles, the changes in surface EMG signal are obvious. The medial and lateral sides of the gastrocnemius and the position of the electrode attachment are shown below.


Fig. 2 Schematic diagram of electrode placement

C. Acquisition of surface EMG signals

In the experiment, surface EMG signals were collected from the target muscles of five healthy subjects. Before collection, it was ensured that the subjects did not exercise violently and had no fatigue the day before. Before collection, the sweat hairs of the target muscle of the subject were removed, wiped with medical alcohol, and a new electrode patch was made. Collect EMG signals in the resting state, and then complete the routine rehabilitation training such as sitting posture bending legs, legs, leg holding, single foot standing, etc. 10 minutes is a group, three groups are carried out, and the groups rest for 2 minutes. When the subjects feel moderate fatigue and fatigue respectively, they stop exercising and collect the surface EMG signals of the target muscles.

Part of the collected results is shown in Fig.3, Fig.4, and Fig.5. Take the lateral gastrocnemius muscle of the right leg of one of the subjects as an example.

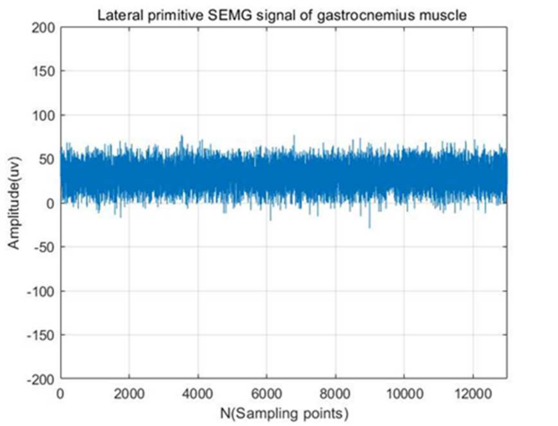

Fig. 3 the surface EMG signal at rest

Fig.4 shows the surface EMG signal of subjects after two groups of training.

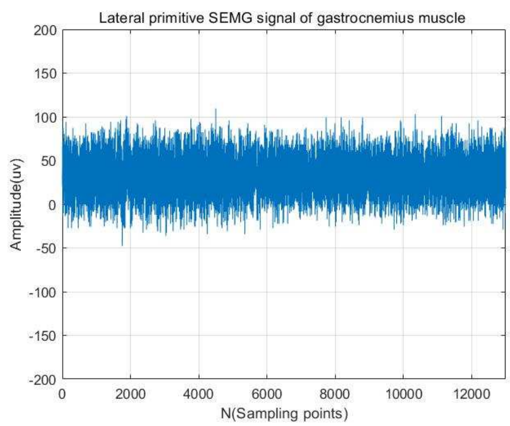

Fig. 4 the surface EMG signal under moderate fatigue

Fig.5 shows the surface EMG signal of subjects after five groups of training.

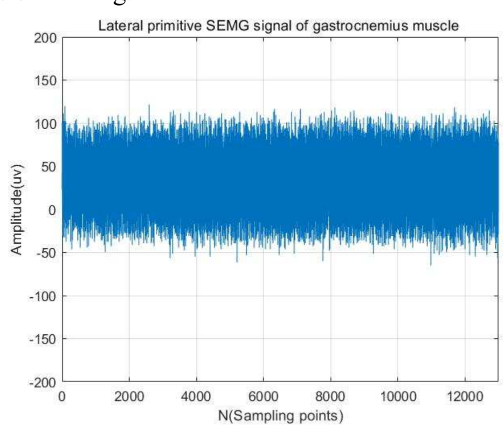

Fig. 5 the surface EMG signal under fatigue

By observing Fig.3, Fig.4, and Fig.5, we can intuitively see that the surface EMG of subjects before and after fatigue has obvious differences. Different fatigue degree results in different signal waveforms. With the deepening of fatigue degree, the fluctuation degree of surface EMG signal is bigger, and the burr sensation is stronger. In the next chapter, different EMG signals will be processed to make their respective characteristics more obvious.

III. Surface EMG Signal Processing

If we want to classify different fatigue levels more effectively, we need to denoise the collected original signals and extract characteristic values.

A. Denoising of surface EMG signal

Because there are many interference sources and many sensors in the collector, the signal we collect has a lot of noise. Only by removing these noises can we make better use of the effective signal. Butterworth filter is the filter with the highest frequency that we use. It has a relatively balanced linear phase and attenuation slope. The frequency response curve in the passband is flat to the maximum without fluctuation and gradually decreases to zero in the stopband[11]. The main frequency of the surface EMG signal is concentrated between 50-350Hz. However, the frequency distribution of surface EMG signals measured in experiments is about 0-800Hz, so a Butterworth bandpass filter is designed in this paper to eliminate high and low-frequency noises[12]. The steps of filter design are as follows:

1. Firstly, the index of the digital filter is determined, the sampling frequency is 1000HZ, the performance index of the digital filter is determined, sampling frequency FS= 1000HZ, the passband range fp is 50HZ-350Hz, and the stopband range FS is 40HZ-400Hz. The maximum passband attenuation is 1dB, and the minimum stopband attenuation is 30dB. The digital Angle frequency can be obtained from Equation (1), where ω is the digital angular frequency and F is the frequency range boundary of the passband stopband.
$$\omega = F * 2 * \frac{\pi}{FS} \tag{1}$$
2. The relation between simulated angular frequency ω and digital angular frequency ω is nonlinear, and there will be nonlinear distortion in the process of conversion. To overcome the problem caused by this, it is usually necessary to correct ω according to Equation (2):
$$\Omega = 2 * FS * \tan\left(\frac{\omega}{2}\right) \tag{2}$$
3. Through the filter design function Buttord function, the minimum order N and the natural frequency Wn of the converted simulated filter are calculated.
4. The Butter function was used to calculate the numerator and denominator of the converted simulated filter and to construct the butter worth bandpass filter.
5. The simulated filter is converted to a digital filter by the bilinear transformation method, and the frequency response of the digital filter is solved by the Freqz function.
6. The raw data is filtered.

After denoising, the original signal, the denoising effect in the time domain is shown in Fig.6.

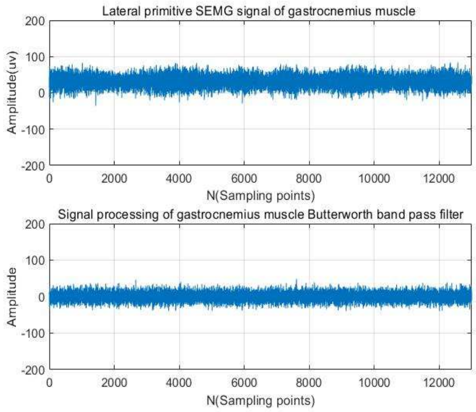

Fig. 6 Time domain comparison before and after denoising

It can be observed that compared with the original signal, the filtered signal waveform is more gentle and the noise is significantly reduced, and most of the effective signals of the surface EMG signal are retained. To see the effect of denoising more intuitively, we compare the signals before and after denoising in the frequency domain. The comparison results in the frequency domain are shown in Fig.7.

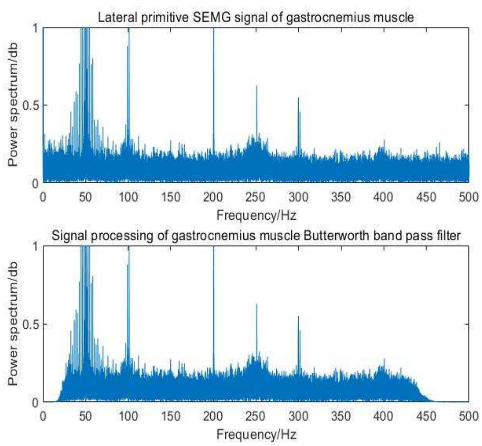

Fig. 7 Comparison diagram of frequency domain before and after denoising

We can see the noise below 50Hz and high-frequency noise are effectively eliminated, and the power frequency interference at 50Hz is also removed, which is conducive to the subsequent feature extraction and action classification.

B. Extraction of surface EMG signal eigenvalues

The extraction of eigenvalues plays a decisive role in the classification results of surface EMG signals, and the characteristic values of surface EMG signals with different fatigue levels vary significantly in the time domain and frequency domain[13]. In this paper, sliding Windows are used to obtain the characteristic values of surface EMG signals. The selection of the length of the data window is a key part. If the length of the data window is too large, the classification and recognition efficiency is too low due to a large amount of data. Therefore, the length of the sliding window is 100ms, the sliding size is 60ms, and the overlap time is 40ms. The eigenvalues in the time domain extracted in this paper are mean absolute value, variance, wavelength, and root mean square, and the frequency domain eigenvalues are mean power frequency and median frequency.

The mean absolute value (MAV) reflects the muscle activity, and its expression is shown as Equation 3, where N is the length of the sliding window and x(i) represents the surface EMG signal amplitude at the ith sampling point.

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x(i)| \tag{3}$$

Variance (VAR) represents the degree of variation of surface EMG signal intensity over time and reflects the intense intensity of muscle movement. Its expression is shown in Equation 4.

$$VAR = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \frac{1}{N}\sum_{i=1}^{N}x_i\right)^2 \tag{4}$$

Wavelength (WL) reflects the accumulated length of surface EMG signal in a certain time and its expression is shown in Equation 5.

$$WL = \frac{1}{N}\sum_{i=1}^{N}|x(i+1) - x(i)| \tag{5}$$

Root mean square (RMS) value represents the effective value of the surface EMG signal.

$$RMS = \sqrt{\int_{t}^{1+T}\frac{sEMG^2(t)dt}{T}} \tag{6}$$

The formula for calculating the mean power frequency (MPF) of the characteristic values in the frequency domain is shown in Equation 7:

$$MPF = \frac{\int_0^\infty f \cdot PSD(f)df}{\int_0^\infty PSD(f)df} \tag{7}$$

The calculation formula for median frequency (MF) of eigenvalues in the frequency domain is shown in Equation 8:

$$MF = \frac{1}{2}\int_0^\infty PSD(f)df \tag{8}$$

Where, PSD(f) represents the spectral density function of surface EMG signal at frequency F, and its calculation is as follows:

$$PSD(f) = \frac{1}{T}|x(i)|^2 \tag{9}$$

Partial results of feature extraction are as follows：

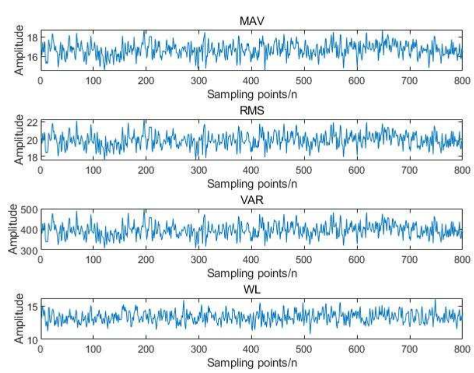

Fig. 8 Time domain eigenvalue results display diagram

After the eigenvalues are extracted, different classifications can be carried out by comparing the different eigenvalues of different fatigue degrees. The next section discusses the design and selection of classifiers.

IV. Design Of Classifier

A Classification basis of the surface EMG signal

At present, the main evaluation method of exercise fatigue is subjective self-evaluation, mainly from the subjects' feelings, such as fatigue, muscle pain, and so on. Based on this situation, Swedish psychologist Berg et al designed a Scale for Rating of Perceived Exertion, RPE scale. Because of its simplicity and practicality, RPE has become the main basis for fatigue evaluation.

TABLE I
DIVISION OF RPE SCALE

RPE scale	The body feeling	Subjective feeling
0	Very easy	No feeling of fatigue
1	No exertion at all	
2	Extremely light	
3	Very light	
4	Light	Medium fatigue
5	Somewhat hard	
6	Mezzo	
7	Hard(heavy)	Extreme fatigue
8	Very hard	
9	Extremely hard	
10	Maximal exertion	

As shown in Table I, the RPE scale was divided into three fatigue states in this paper. According to these three subjective feelings, surface EMG signals in the same feeling were classified into one class, thus surface EMG signals were divided into three categories altogether.

B. Selection of classifier for surface EMG signal

Choosing an appropriate classifier is very important for the result of classification. After a comprehensive analysis of the advantages of various classifiers, K-Nearest Neighbor (KNN) classifier is selected in this paper. KNN classifier is a simple and direct classifier, which is also one of the more mature classifiers at present. KNN is suitable for low-dimension analysis with low time complexity and high accuracy[14]. The algorithm idea of KNN is that if most of the K samples that are most similar in the feature space (that is, the most adjacent in the feature space, described by the distance formula above) belong to a certain category, then the sample also belongs to this category. This method only determines the classification of the samples according to the category of the nearest one or several samples[15].

KNN algorithm can be roughly divided into three steps:

1. Calculate the distance between the point you want to classify and the rest of the points.
2. Rank them in ascending distance order and select the first K (K of KNN) points, that is, the K points closest to the sample point.
3. A weighted average, get the answer[16].

C. Classification results.

The surface EMG signals collected above were made into data sets, and KNN was trained. Tenfold cross-validation was adopted in this paper[17], The ten-fold cross-validation means that the data set is divided into 10 parts, 9 of which are taken as training data and the other one as verification data in turn, and the average value of the 10 results is taken as the accurate value of the algorithm[18]. And the scatter diagram of classification results is shown in Fig.9.

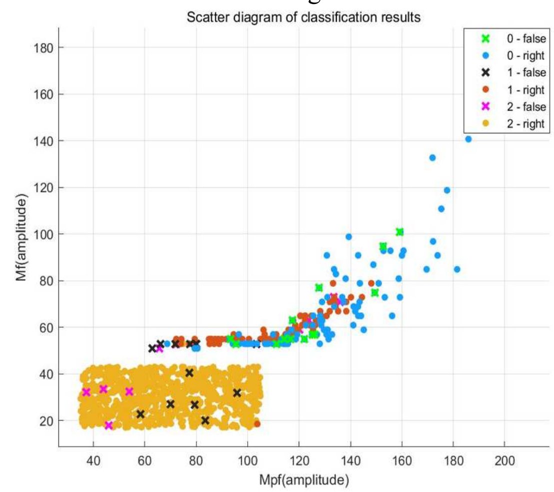

Fig. 9 Scatter diagram of classification results

Where 0 represents no fatigue, 1 represents moderate fatigue, and 2 represents extreme fatigue. The confusion matrix of classification results is shown in Fig.10. It can be seen from Fig.9 and Fig.10 that the accuracy of the KNN algorithm is very high. Among the 2600 samples, the classification accuracy reaches 98.4%, and the training time is not long. Therefore, the KNN classifier has quite a good classification effect.

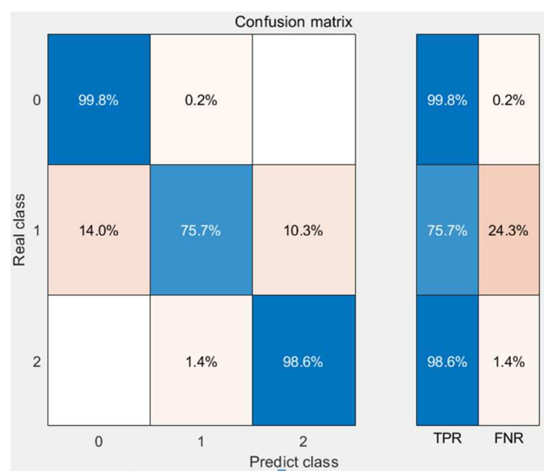

Fig. 10 Confusion matrix for classification results

V. Conclusions and Future Work

In this paper, surface EMG signals of two muscles of human lower limb gastrocnemius were collected, and the signals were classified according to different fatigue levels. Four-time domain eigenvalues and two-frequency domain eigenvalues were fused, and the KNN algorithm was used for classification, which improved the accuracy of general machine learning. It provides a basis for avoiding secondary injury of stroke patients during rehabilitation training.

In future work, more data collection is needed to achieve higher accuracy, and the system is transplanted into the robot of our research group.

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