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Research Article

Evaluation of Running Intensity and Fatigue Degree Based on Human Physiological Information

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Muscle fatigue represents a complex phenomenon including various causes, mechanisms, and forms of manifestation. It develops as a result of a chain of metabolic, structural, and energetic changes in muscles due to insufficient oxygen and nutritive substances supply through blood circulation, as well as a result of intensive physical exercise. In this study, a new method for frequency band energy of wavelet packet decomposition is proposed which combines normalized energy into wavelet packet decomposition and uses the frequency band energy quotient as physiological parameters for detecting muscles fatigue before and after human exercise. The operator's subjective fatigue test and surface electromyography (EMG) objective test were combined to design the experiment, and a computer program was used to control the operation interface and record the operation results. Three major operating fatigue variables, namely, the most comfortable initial position of the operator, the difference in operating direction, and the difference in operating distance, were evaluated. The surface EMG consumption of the operator was measured synchronously with the surface EMG meter. After variable control and error analysis, test results are analyzed, and the range of the operator's most comfortable initial position is summarized. The differences of operator fatigue degree in eight operating directions and operating fatigue degree in different operating distance variables are obtained. In the whole test process, the operator's subjective test results and objective test results remain consistent, which has proved the rationality of the experimental design and experimental results.

1. Introduction

A daily routine of physical activity is extremely effective in the prevention and treatment of many common chronic diseases, particularly those affecting the cardiovascular (CV) system. However, chronic, high-intensity endurance exercise can lead to structural changes in the muscles of the heart and other organs. Excessive and long-term exercise training and racing, such as marathons and ultramarathons, ironman triathlons, and very long-distance bicycling, can cause severe muscles fatigue and may cause adverse structural remodeling of the heart and large arteries [1].

With the development of society, people's pace of life is gradually accelerating, bringing more and more pressure from various aspects, and many people's sense of fatigue is aggravating. Therefore, fatigue has been recognized as a serious problem associated with excessive exercise. Fatigue will reduce people's work efficiency, cause accidents, and affect daily life, as well as physical and mental health. Therefore, real-time and accurate detection of human fatigue has become the focus of academic circles. Being able to get timely and accurate fatigue detection will bring a lot of benefits to people. Especially, in the field of medical technology, sports training, and sports fitness, the practical application value of fatigue detection is more prominent [2].

Human exercise intensity is closely related to the human body constitution. The strength of the constitution directly determines the size of people's exercise intensity. Due to the frequent occurrence of sudden death in sports, many schools have decided to simplify their physical training programs for students, eliminating long- and middle-distance running and other sports subjects [3]. Although, these measures may reduce the incidence of sudden death in sports, however, the reduction of physical exercise will inevitably lead to the decline of students' physique and normal fitness. Therefore, it is extremely urgent to test and evaluate the physical health and exercise intensity of people exercising and fitness in time so that people can have a detailed understanding of their physical condition and exercise ability, to avoid serious accidents. As the two most important physiological signals of the human body, heart sound and electrocardiogram contain a lot of physiological and pathological information about the human heart and blood vessels [4]. They can reflect cardiac contractile force and cardiac reserve well and have the characteristics of noninvasiveness, high sensitivity and specificity, repeatability, and objective quantification. Therefore, in the detection and analysis of heart sound, ECG signal is an indispensable method to determine the health of the human heart. Since heart health is directly related to the size of exercise intensity, the characteristics of the above two physiological signals can be applied to a variety of sports venues, to evaluate muscles fatigue and exercise intensity [5].

In this study, a method is proposed to measure fatigue and the intensity of exercise using the heart sound and ECG signals. Firstly, the characteristics of heart sound and ECG signal are analyzed. Then, a new method of wavelet packet decomposition frequency band energy quotient is employed using wavelet packet multiresolution analysis techniques. The aim is to combine the normalized energy into wavelet packet decomposition and use the frequency band energy quotient as physiological parameters for detecting cardiac sound and electrocardiogram signals before and after human exercise. Results show that the exercise intensity detection method described in this study has good classification and identification effect, simple and reliable operation of hardware equipment, and strong adjustable detection standard, which can evaluate the size of human exercise intensity well, can avoid the occurrence of cardiac disease emergencies caused by "excessive exercise," as far as possible, and prevent heart disease in the future.

The rest of the study is organized as follows. Section 2 provides an overview of the muscle fatigue and different techniques used for the identification of muscles fatigue. Section 3 illustrates the detection and evaluation of exercise intensity. The results are discussed in Section 4, and Section 5 is about the conclusion.

2. Background

Muscle fatigue represents a complex phenomenon including various causes, mechanisms, and forms of manifestation. It develops as a result of a chain of metabolic, structural, and energetic changes in muscles due to insufficient oxygen and nutritive substances supply through blood circulation, as well as a result of changes in the efficiency of the nervous system [6]. Fatigue is an important factor in a user gait change, and the research and quantitative gait fatigue have an important significance for a lot of problems. Fatigue can drastically alter gait features, increasing the likelihood of falls in the elderly; therefore, assessing elderly gait fatigue is critical for fall prevention in the elderly. In addition, the proper evaluation of gait fatigue is also of great significance for the training of athletes or the health monitoring of ordinary people [7].

Many current methods measure fatigue through users' self-expression or exercise conscious scale. This measurement method is largely determined by the subjective will of users and lacks objective evaluation criteria and basis. The experimental methods to obtain fatigue are also not accurate. For example, the fatigue obtained by running on a treadmill is mostly related to the user's cardiopulmonary function, rather than the user's gait fatigue caused by walking. Even the muscle fatigue caused by excessive exercise can mostly recover in a relatively short time, which is different from the long-term fatigue caused by walking [8]. The biochemical method can also be used to judge fatigue by examining the pH value of blood, urine, sweat, salivary fluid, human hormones, oil, enzymes, ions in the middle of cells, and other liquid components. Although this method is not affected by the physical or mental state of the testee, it often needs to be broken in the test process, which causes antipathy of the testee and also has certain harm to the testee's body, so it is not recommended to be adopted.

With the advancement of technology, fatigue is usually measured using a variety of biological signals including ECG signals, EMG signals, inertial sensor signals, and video signals, such as facial expressions and eye movements, which is followed by the classification of fatigue using machine learning methods. Systematic research on the effect of fatigue on the properties of myoelectric signals has begun around the 1950s. Knowlton et al. [9] observed an increase in the EMG signals' amplitude recorded from an individual during fatigue. Lindström et al. [10] proposed a mathematical model based on the power spectrum of surface EMG signals to evaluate the muscles fibers' conduction velocity. Kwatny et al. [11] employed digital signal processing techniques to explore properties of power spectrum density of sEMG signals' recorded during fatiguing tasks. They used the mean frequency of the spectrum to detect differences in the muscles signals before and during fatigue. Another fatigue indicator that has been used is the frequency shift of the raw EMG signals per time unit. This parameter is known to have similar properties such as mean frequency and median frequency [12]. Fatigue in dynamic conditions was explored intensively only during the last decade, using several time-frequency signals' processing methods to examine changes in the frequency contents of the myoelectric signals that are related to the development of fatigue [8]. Bonato et al. [13] proposed Choi–Williams distribution as the most appropriate method to be for estimating fatigue using sEMG signals. Karlsson et al. provided a comparison of the short-time Fourier transform, the Choi–Williams distribution, the Wigner–Ville distribution, and the continuous wavelet transform to examine EMG signals during dynamic contractions by estimating time-dependent spectral moments. The results have shown that the estimates provided by the continuous wavelet transform have better accuracy than those obtained by using other methods. The present study combines the normalized energy into wavelet packet decomposition and uses the frequency band energy quotient as physiological parameters for detecting cardiac sound and electrocardiogram signals before and after human exercise. Therefore, this topic will conduct in-depth research on the changes of human gait before and after fatigue, to be applied to the actual fatigue detection.

3. Study on the Detection and Evaluation of Exercise Intensity

Exercise intensity represents the amount of exercise per unit of time, that is, the amount of work done by human muscles per unit of time. It also describes the degree of physiological stimulation of the human body by exercise training. Exercise intensity is a very important index in the process of physical exercise or physical training. Studies have found that the high-precision response of the human body to exercise training is mainly determined by the intensity of exercise, followed by the time and frequency of exercise, human physiological state, and other factors [14].

3.1. Main Detection Methods and Evaluation Indexes. The indicators that can be used to describe and evaluate exercise intensity can be roughly divided into three categories: physical load, physiological load, and subjective sensory intensity. Physical load intensity refers to the amount of work done by the human body in a certain period. The physiological load intensity refers to sports activities completed by the human body. In addition, the intensity of other indicators such as exercise heart rate, blood lactic acid, oxygen uptake, and breathing rate can also be used as a measure of fatigue. This kind of indicator also has disadvantages; that is, the collection of physiological indicators needs to use various professional instruments, and the operation is tedious. The indicators related to biochemistry even need to be collected after the injury of the body, which lacks safety and cannot be obtained in time and is not suitable for daily exercise intensity detection. Subjective sensory intensity refers to the subjective perception evaluation of the exercisers and the level of exercise intensity during exercise [15].

The most accurate way to monitor exercise intensity is to monitor real-time oxygen consumption during exercise to obtain a %VO2 max value or to periodically measure blood lactate concentration during exercise to obtain a lactate threshold. VO2 max is the amount (volume) of oxygen your body uses while exercising. However, VO2 max needs to be measured in the lab with sophisticated instruments [16]. Therefore, if VO2 max data cannot be measured at the moment, exercise intensity can be monitored in real-time using indicators such as heart rate, metabolic equivalent, subjective intensity, and even speed of exercise. The most commonly used indicators and evaluation methods of exercise intensity are as follows.

3.1.1. Percentage of Maximal Oxygen Uptake (%VO2max). Maximal oxygen consumption (VO2max) is the maximum amount of oxygen used by our body when exercising at maximum intensity. Maximal oxygen uptake is the most direct and effective index to evaluate individual cardiopulmonary endurance and aerobic exercise ability, which can represent the human body's extreme exercise ability from the perspective of cardiopulmonary function. The detection method of VO2max can be divided into the direct detection method and the interconnecting detection method according to whether the components of breathing gas can be directly tested. Among them, the VO2max value of subjects is obtained by directly measuring the components of respiratory gases of subjects under the extreme intensity of exhaustion through specific professional equipment, such as a breath meter channel and glass airbag. The latter includes a step-by-step load test method based on Bruce protocol, the indirect test method based on PCI, and the indirect test method based on improved Bruce protocol PCIO. The Bruce protocol is a diagnostic test used in the evaluation of cardiac function. It is a standardized multistage treadmill test for assessing cardiovascular health [17].

VO2max expression refers to the individual's current oxygen uptake in the VO2max percentage value during exercise, that is, %VO2max, which is one of the most common indicators of exercise intensity evaluation. The reason is that exercise intensity is positively correlated with the energy consumed by individuals in movement, while energy consumption is positively correlated with oxygen uptake. Therefore, in current experimental studies, exercise intensity is mostly evaluated by the oxygen uptake of individuals per unit time and described by %VO2max to reduce numerical differences between different individuals. It is convenient for comparative analysis of experimental data.

3.1.2. Heart Rate (HR). Heart rate (HR) is the number of beats of the human heart in one minute. Heart rates can vary widely between different people. For a healthy adult, the resting heart rate usually varies from 60 to 100 bpm. In addition, the heart rate generally slows down as you get older. Multiple studies have shown that the heart rate can objectively describe exercise intensity and individual exercise state to a certain extent and even judge exercise fatigue. Scientists have conducted graded intensity tests through treadmill exercise for a long time and found that the heart rate has a linear relationship with intensity changes during subintensive exercise [18].

3.1.3. Percentage Representation of Maximum Heart Rate (% HRmax). HRmax refers to the maximum heart rate reached when the heart rate can no longer continue to rise when the maximum intensity of physical activity is reached [19]. Accordingly, HRmax is an important basis that judges the human body's maximum working ability. At the same time, the HRmax method is easy to operate, noninvasive, and personalized and has an important value in the detection and evaluation of exercise intensity. At present, the highly recognized calculation methods of HRmax and %HRmax are as follows:

$$\mathrm{HR\ max} = 220 - \mathrm{age}, \tag{1}$$

$$\%\mathrm{HR\ max} = \frac{\text{Exercise heart rate}}{\mathrm{HR\ max}}. \tag{2}$$

In addition, some scholars have found a close correlation between %HRmax and %VO2max. Therefore, %HRmax can be regarded as one of the most appropriate personalized indicators for real-time monitoring of sports training intensity for both the general public and professional athletes. Studies show that when %HRmax is used to guide physical exercise, exercise intensity, and corresponding exercise effect can be adjusted according to a certain suitable range, as shown in Table 1.

However, the %HRmax representation has some limitations. As can be seen from equation (1), this calculation method takes people's age as a single variable, so the values obtained by individuals of the same age are the same. However, in fact, due to the influence of many factors such as gender, exercise, habit, and physical condition of individuals, the HRmax of individuals of the same age may also be different to some extent. Therefore, this method is more suitable for the data collection and analysis of exercise experiments, which can exclude other variables except for age as much as possible, to improve the feasibility and accuracy.

3.1.4. Reserve Heart Rate Percentage Representation (%Hr Reserve/%HRR). To monitor exercise intensity more accurately by using the heart rate index, a group of new researchers believes that %HRmax is difficult to be modified according to different physical functions of each individual due to the limitations of the calculation method of maximum heart rate, and there are certain errors in monitoring and evaluating exercise intensity. So, researchers came up with the concept of heart rate reserve (HRR) to define exercise intensity. The concept of the reserve heart rate was first proposed by Karvonen et al. Compared with the maximum heart rate percentage index, the variable of athletes' quiet heart rate is added to monitor exercise intensity, and it can also be used to establish the target heart rate of exercise (bull's eye rate). The relevant calculation formula is as follows:

$$\text{HRR} = \text{HRmax} - \text{Quiet heart rate}, \tag{3}$$

$$\%\text{HRR} = \frac{(\text{HR} - \text{Quiet heart rate})}{\text{HR max} - \text{Quiet heart rate}}, \tag{4}$$

$$\begin{aligned}\text{Target heart rate} = {} & \text{Intensity of target heart\%HRR} \\ & \times (\text{HRmax} - \text{Quiet heart rate}).\end{aligned} \tag{5}$$

As the indicator of the resting heart rate can be used as the evaluation basis for aerobic fitness, generally speaking, the better the body function is, the lower the resting heart rate will be, and the worse the body function is, the higher the resting heart rate will be. Therefore, the reserve heart rate method to monitor and evaluate exercise intensity can better consider the individual physical differences of athletes. Moreover, it can reduce errors and better achieve personalized exercise intensity fitness guidance.

3.1.5. Blood Lactic Acid (BLA). Lactic acid is the metabolite of sugar and oxygen in the human body, and it is also an important index reflecting individual exercise ability. Blood lactic acid (BLA) is the concentration of lactic acid in the blood. After exercise fatigue, lactic acid accumulates in the body, leading to the increase of blood lactic acid concentration. The accumulation of lactic acid has a significant impact on individual exercise ability and subjective feeling of exercise, so blood lactic acid concentration is often used in the detection and evaluation of exercise intensity and fatigue. However, due to different body functions, the accumulation rate of blood lactic acid is also different in different individuals' exercising. At present, the use of heart rate, lactic acid concentration, and other indicators to evaluate exercise intensity is mostly based on empirical data obtained from a certain number of experimental samples.

3.1.6. Principles and Advantages of Wavelet Packet Decomposition. The wavelet packet method is a generalization of wavelet decomposition that provides a wider range of signal analysis options and allows for the most accurate signal analysis. It converts a signal from the time domain to the frequency domain on a level-by-level basis. It is calculated by repeating filter-decimation operations, which results in a decrease in time resolution and an increase in frequency resolution. Because the WPT divides both the low and high-frequency subbands, the frequency bins are of equal width, unlike the wavelet transform. A signal is split into an approximation and a detail coefficient in wavelet analysis. Therefore, while the wavelet transform has the property that the higher the frequency, the higher the time resolution, the frequency domain resolution is reduced, which is the wavelet transform's disadvantage. The two-scale equation of wavelet packet transform is as follows:

$$\begin{aligned} w_{2n}(t) &= \sqrt{2}\sum_{k\in Z} h_{0k} w_n(2t-k), \\ w_{2n+1}(t) &= \sqrt{2}\sum_{k\in Z} h_{1k} w_n(2t-k), \end{aligned} \tag{6}$$

where, when $n=0$, $w_0(t) = \phi(t)$ is the scale function.

The wavelet packet coefficient's recursion is

$$\begin{aligned} d_k^{j+1,2n} &= \sum_l h_{0(2l-k)} d_l^{j,n}, \\ d_k^{j+1,2n+1} &= \sum_l h_{1(2l-k)} d_l^{j,n}. \end{aligned} \tag{7}$$

The wavelet packet that can be reconstructed is

$$\begin{aligned} d_l^{j,2n} &= \sum_k \left[h_{0(2l-k)} d_l^{j+1,2n} + h_{1(2l-k)} d_l^{j+1,2n+1} \right] \\ &= \sum_k g_{0(l-2k)} d_l^{j+1,2n} \sum_k h_{1(l-2k)} d_k^{j+1,2n+1}, \end{aligned} \tag{8}$$

where h and g are low-pass and high-pass filters corresponding to scale function $\phi(t)$ and wavelet function $\varphi(t)$, respectively.

4. Experiment and Analysis

4.1. Statistical Processing

4.1.1. Conversion of Basic Experimental Data. During data collection, we recorded fatigue data of different subjects

Table 1: %HRmax intensity range and corresponding exercise effect.

%HRmax	Effect of movement
50%–60%	Can be used as a warm-up or post-run recovery exercise and less energy consumption
60%–70%	Start to burn fat, usually for jogging, calisthenics, and other light aerobic exercise or high-intensity exercise after the relaxation recovery zone
70%–80%	Medium and high aerobic range, moderate intensity, sugar metabolism, and fat utilization rate significantly improved, while training people's aerobic capacity, suitable for weight loss, and marathon running training
80%–90%	The body will have lactic acid accumulation in the high-intensity lactic acid threshold interval, which is mainly based on sugar metabolism, it is suitable for rhythm running and marathon pace running, and the exercise time should not be too long
90%–100%	Close to anaerobic metabolism and ultimate strength, heart burden, suitable for experienced runners to exercise their speed and ability, and training time should not be too long

during the quiet heart rate, running to get the real-time heart rate and the maximum heart rate. Equations (3) and (4) were used to compute the HRR and % HRR value and explore the subsequent index contrast and correlation analysis of the experimental data.

4.1.2. Time Standardization. Due to differences in physical condition and subjective fatigue evaluation results among different individuals, the time to exhaustion is also different. To better conduct data statistics and comparative analysis, it is necessary to conduct time standardization processing for experimental data of all subjects. The movement data of all the subjects are standardized one by one during the entire experiment by uniformly selecting points on individual exercise time, which is convenient for computing statistics such as mean and correlation analysis.

4.1.3. SPSS Statistical Analysis Method. After the above preprocessing, SPSS19.0 statistical software was used to conduct further statistical analysis on the experimental data. Correlation analysis, statistical mean, and other tools were used to verify the correlation index and significance between indicators, obtain the mean value and standard difference of indicators, and draw an information chart.

4.2. Statistics of Experimental Data of Increasing Load Exhaustion. In the experiment of increasing load running exhaustion, the longest exercise time of 12 subjects was 24 min and the shortest was 15 min, respectively. The maximum speed recorded was 12 km/h and the lowest speed was 9.5 km/h, respectively. There was no physical injury or abnormal condition during the exercise. The experimental data were complete, and there was no abnormal condition, so there was no need for screening. At the end of the experiment, 8 patients showed obvious muscle distension in lower limbs, waist, or other parts, and 5 patients showed mild symptoms of chest tightness or dizziness due to hypoxia, but all of them disappeared quickly after relaxation and adjustment. The 12 groups of complete experimental data were statistically processed, and the results are shown in Figure 1.

In the experiment, the percentage value of the heart rate signal index of the subjects' reserve heart rate increased gradually with the increase of exercise intensity. Since running speed was positively correlated with exercise time, the standardized time T% was used to represent exercise intensity in this experiment, and the trend in the changing relationship between T% and %HRR is shown in Figure 1.

As can be seen from the figure, the heart rate of the subjects increased rapidly to about 80%HRR, and then, the growth rate slowed down slightly until the subjects exhausted themselves and reached the maximum heart rate HRmax, i.e., 100%HRR. The correlation analysis showed that there was a very significant correlation between the two ($P < 0.01$), and the correlation coefficient (RT%−% $\mathrm{HRR} = 0.943$) indicates that there was a strong correlation between %HRR and exercise intensity.

With the increase of exercise time and intensity, exercisers gradually produce physical exercise fatigue, which creates a certain impact on exercise status and subjective fatigue feeling. In the experiment, observation was conducted every 1 min, and the RPE value of the subjects was recorded. There is a strong linear relationship between RPE value and exercise intensity, as shown in Figure 2. Correlation analysis shows that the correlation coefficient between RPE value and exercise intensity is $\mathrm{rT\%{-}RPE} = 0.986$, which is highly significant ($P < 0.01$).

During the experiment, EMG signals were collected using four lower limb muscles including rectus femoris (RF), tibialis anterior (TA), the biceps femoris (BF) muscle, and the surface of the lateral head of the gastrocnemius (GR). The signals were preprocessed to obtain MPF and root mean square (RMS) value of each muscle. Next, SPSS19.0 software was used to calculate the standardized index mean and standard deviation of the point in time. Statistical observation of the trend of index changes was carried out by plotting. In the experiment, with the increase of exercise intensity, the error bar chart for mean and standard deviation (mean ± standard deviation) changes of MPF and RMS of all muscles of all subjects is shown in Figure 3.

Figure 3 shows the changes of the MPF mean value of RF muscle of all subjects on a standardized time axis, that is, the trend of changes in the process of increasing exercise intensity. As can be seen from the figure, the mean value of MPF of RF showed a brief downward trend at the initial stage of running and then rose immediately. It showed a gradually accelerating upward trend in the 30%–70% standardized time after the start of running. After 70% standardized time, MPF showed a short-term obvious downward trend and then rose, presenting a significant upward trend in general.

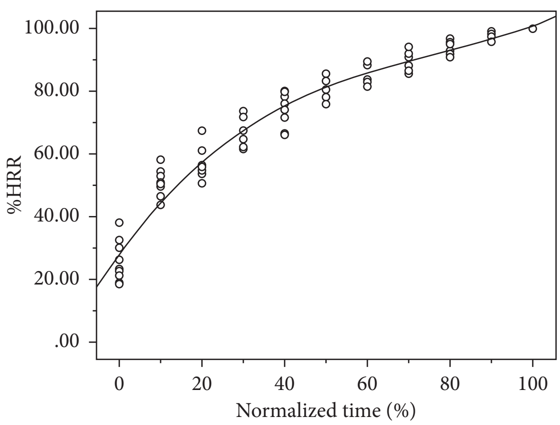

Figure 1: The trend of %HRR at a standardized time.

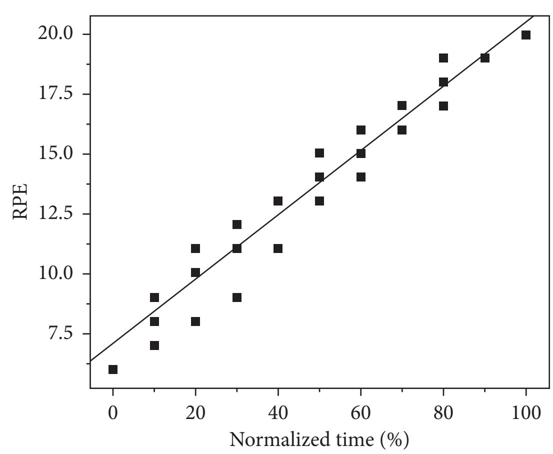

Figure 2: Scatter diagram of the RPE value at a standardized time.

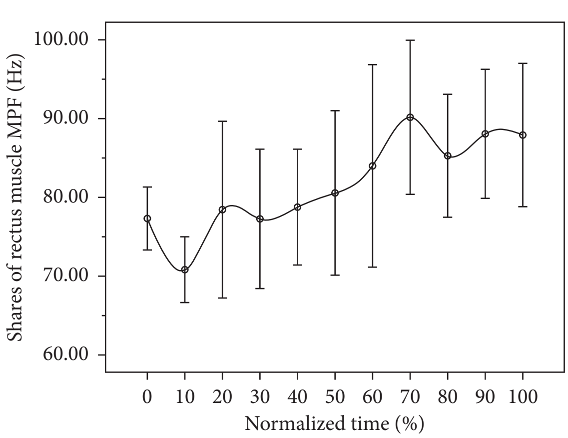

Figure 3: Mean value of MPF of RF muscle corresponding to standardized time (%).

Figure 4 shows the MPF mean value of subjects' BF muscle of the lower limb. It can be seen that the MPF value decreases gradually during the standardized exercise time from the beginning of the exercise to 30%, rises to the initial mean level within 30%–50%T, then drops slightly, and rises to a higher level. The overall trend is also on the rise. Table 2 shows the average values ("mean ± standard deviation") of

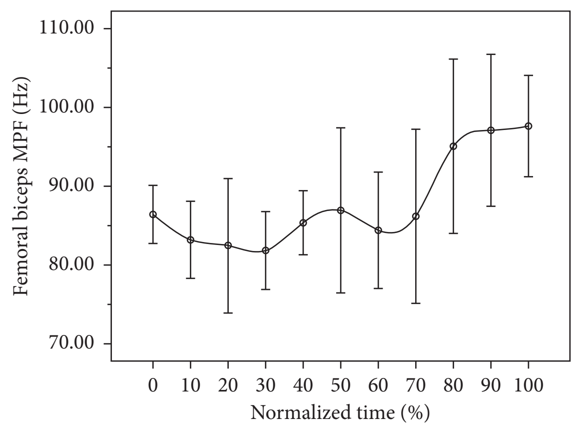

Figure 4: Mean value of MPF of BF corresponding to standardized time (%).

Table 2: Muscle RMS corresponding to each subjective fatigue level in the experiment.

RPE	RF	BF	TA	Lateral head of GR
6	51.79 ± 14.19	95.57 ± 43.19	91.83 ± 25.94	75.61 ± 45.53
7	46.67 ± 16.89	86.67 ± 25.45	89.09 ± 29.67	84.01 ± 43.79
8	60.34 ± 8.02	111.27 ± 46.97	90.06 ± 38.67	86.63 ± 46.91
9	58.09 ± 16.46	103.75 ± 44.56	90.59 ± 33.61	87.77 ± 44.68
10	54.56 ± 7.55	124.65 ± 47.63	101.28 ± 35.04	86.52 ± 47.69
11	50.75 ± 13.18	96.68 ± 37.62	87.92 ± 37.19	97.16 ± 45.81
12	46.73 ± 5.52	115.53 ± 29.71	98.14 ± 28.01	69.07 ± 27.54
13	44.53 ± 8.01	92.84 ± 40.12	94.42 ± 29.68	83.53 ± 40.47
14	40.24 ± 9.85	91.28 ± 48.59	95.35 ± 36.17	97.15 ± 53.12
15	42.65 ± 6.75	102.02 ± 38.25	95.99 ± 30.68	84.91 ± 36.67
16	37.74 ± 12.97	102.70 ± 47.02	95.61 ± 32.60	86.78 ± 45.23
17	37.92 ± 8.64	109.19 ± 48.28	93.81 ± 30.74	86.69 ± 46.32
18	33.21 ± 8.97	96.97 ± 50.43	92.69 ± 32.16	95.81 ± 54.34
19	35.47 ± 11.87	96.36 ± 45.86	93.26 ± 27.02	90.65 ± 54.17
20	37.94 ± 21.98	95.79 ± 50.69	103.63 ± 38.47	96.11 ± 56.70

EMG MPF on the target muscle surface of all subjects when they reach each RPE level in the incremental load exercise experiment.

From the numerical point of view, the RMS values of the muscles of the individual subjects were significantly different, especially the BF, TA, and GR. In addition, the RMS values of the three muscles were significantly greater than the rectus RF muscle, which shows that they can be used to measure fatigue.

5. Conclusion

Muscle fatigue occurs when the body's contractility of the muscle movement system temporarily declines, causing the body to be unable to maintain the expected exercise intensity. In the actual rehabilitation training, it is necessary to monitor and predict the muscle fatigue state to better understand the patient's muscle activities. A new method for frequency band energy of wavelet packet decomposition is proposed in this study, which incorporates normalized energy into wavelet packet decomposition and employs the frequency band energy quotient as physiological parameters for detecting cardiac sound and ECG signals before and after human exercise. After preprocessing the collected myoelectric signals, the time-domain correlation coefficient method is used to analyze the acceleration data before and after fatigue, and a good discriminating effect is obtained. The proposed method achieved the highest accuracy of 93% for muscle fatigue identification. This method is straightforward and effective because it does not rely on subjective judgment with the EMG meter on the surface. The method can be applied effectively for muscle fatigue identification in medical technology, sports training, and fitness [20].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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