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Human Exercise Intensity Monitoring Method Based on Smart Bracelet

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Abstract. The existing human movement intensity monitoring only rely on a single physiological data changes, with general standards to determine whether the intensity is too large, not only the lack of flexibility in monitoring, and monitoring accuracy and real-time poor. In order to monitor exercise intensity more conveniently and accurately and improve the curve existing in the above method, a human exercise intensity monitoring method based on smart wristband was studied. For PPG signal collected by smart bracelet, the artifact removal process is carried out by GAN After extracting PPG and ECG signal characteristics, human body motion posture was identified by combining the motion posture change data collected by the bracelet. According to the heart rate and load intensity range of standard setting is roughly, based on the SVM model to estimate abnormal physiological data of firefly algorithm, realization of human movement monitoring intensity. The experiment was carried out among 100 monitoring objects, and the accuracy rate of monitoring exercise intensity by using smart bracelet was higher than 97%, and the monitoring effect was better by giving feedback to the change of intensity of the monitoring object in real time.

Keywords. smart bracelet; Human exercise intensity; Intensity monitoring; Artifact removal; Attitude recognition; Abnormal judgment

1. Introduction

As the mobile hardware market continues to develop and wearable technology continues to improve, people will wear more and more smart devices. Smart bracelets and other wearable smart devices have become more frequently used in people's life and become a new consumption hotspot [1]. Since smart wearable devices such as smart bracelets require physical contact, they have the advantage of detecting body quality. They not only include fitness, health monitoring and location tracking, but also expand intelligent auxiliary functions such as communication. Fitness has increasingly become an indispensable part of people's life. Many manufacturers have launched intelligent wearable devices with fitness functions, which are welcomed by some sport-loving people [2]. People strengthen their bodies and improve their physical quality through sports training, but most people realize the health benefits of sports training, but it is difficult to control their own sports training from a professional point of view, and there are often injuries caused by excessive exercise intensity [3]. In the sports training, therefore, need to take some measures to monitor the movement of human body strength. Heart rate, as the easiest physiological data of human movement, has been widely used in physical education and training. Literature [4] collects the data of heart rate changes of students in the process of physical education teaching through smart bracelets to help teachers better guide training. Literature [5] estimated the

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oxygen consumption of diabetic patients in aerobic and resistance training with heart rate index as an index, so as to adjust the content of rehabilitation training. Literature [6] designed a system to monitor lactic acid changes in human skin based on real-time collection to monitor the evaluation of exercise intensity of objects. Although relatively accurate monitoring results were obtained, the accuracy of lactic acid data measurement and the reliability of lactic acid acquisition equipment determine the high cost and small scope of application of the monitoring method. In literature [7], physical activity tracker devices were used to monitor patients' exercise intensity at home, and this method had better monitoring effect for exercise with low intensity.

The existing monitoring methods for human exercise intensity mentioned above are not suitable for monitoring exercise intensity under different exercise types and have obvious limitations in application. With the growth of users' interest in sports and fitness, health monitoring smart bracelet has become the most acceptable product in the wearable product market. Movement on the bracelet is configured with a variety of common types of sensors, can collect in the process of movement human body posture, heart rate, such as sports physiological signal data, through the correlation algorithm into quantifiable value after processing, feedback to users of the bracelet. This study will use the smart bracelet to collect the data of human physiological data in real time to achieve accurate monitoring of human exercise intensity.

2. Research On Human Exercise Intensity Monitoring Method Based On Smart Bracelet

2.1 Smart bracelet data artifact removal

The smart bracelet can estimate human heart rate in different states by collecting Photoplethysmography (PPG) signal. Human motion causes Motion Artifacts (MA) from the wearable sensor to be in interspace contact with human skin, which makes PPG collected by the sports bracelet unreliable. In other words, the waveform form of PPG signal becomes worse in the time domain, and the MA band range overlaps with the PPG band range in the frequency domain. Which leads to inaccurate heart rate calculations. Therefore, it is necessary to process the human physiological data collected by the smart bracelet to improve the accuracy of data analysis and utilization.

According to the degree of overlap between the frequency band range of motion artifacts and PPG frequency band range, motion artifacts can be divided into two categories: weak motion artifacts caused by some small movements (such as walking and finger movements), and strong motion artifacts caused by some vigorous fitness activities (such as fast running, elliptical machine training and squatting). Among them, the frequency band range of weak motion artifact has little overlap with that of PPG, while the frequency band range of strong motion artifact has great overlap with that of PPG [8].

The real-time performance of data processing is very important for smart bracelets with limited computing capacity. In the actual wearable health monitoring, it is impossible to obtain the clean signal corresponding to the collected physiological signal containing noise. At the same time, various types of quasi-periodic pseudo-periodic motion of the human body tend to cause different types of strong motion artifacts, which makes motion artifacts very complex and makes it very difficult to remove different types of strong motion artifacts caused by various pseudo-periodic motions [9]. The PPG signal collected by smart bracelet has obvious interference information in the motion state, and the frequency of interference information overlaps with the frequency range of human pulse wave, so the effect of processing PPG data by filtering is not particularly obvious. Therefore, this study adopted an unsupervised learning method, that is, generating adversative networks to remove the interference of motion artifacts mixed with PPG signals collected by smart bracelets. In order to solve the problem that the GAN is too free in the generation process and may lose important frequency information, the real heart rate value is used as a conditional constraint to guide the PPG signal generation process. The loss function of adversarial network generation is as follows [10] :

$$\min_{G}\max_{D}\left(D,G\right)=E_{z}\left[\lg D\left(z|y\right)\right]+E_{s}\left[\lg\left(1-D\left(s|y\right)\right)\right] \tag{1}$$

Where, s is the original PPG signal; z is the output signal of the generated model; D and G are the discriminant model and generative model in generative adversarial network respectively. y is the real heart rate of human body under each exercise type. E_z is the function of network generation model; E_s is the function of the network discrimination model. The real heart rate is only used as a constraint condition to guide the generator in the process of generating clean PPG signals during training. Once the training is completed, the trained generator will not involve the information of the real heart rate during the test, that is, the actual denoising. The PPG signal with motion artifact interference is input to the encoder, and features are extracted through a series of convolution layers. In addition, in order to reduce the over-fitting of the model, a hidden layer gaussian white noise vector is added and superimposed, and then the superimposed features are input to the decoder. Denoised PPG signals generated by the generation model can be put into the discriminant model together with clean PPG signals for discrimination [11].

In the discriminant model, the correlation coefficient between the STFT amplitude of the original PPG signal and the STFT amplitude of the acceleration signal is calculated to determine whether the original PPG signal contains strong MA. If the calculated Pearson correlation coefficient is not high, it indicates that the original PPG signal does not contain strong MA, that is, PPG signal is considered to be clean. The original PPG signal and motion acceleration signal are converted to STFT amplitude domain according to the following formula, as shown below [12] :

$$\begin{cases} X=\left|\mathrm{STFT}\left(s\right)\right| \\ A=\left|\mathrm{STFT}\left(a\right)\right| \end{cases}, X, A\in R^{m\times n} \tag{2}$$

Where, X is the STFT amplitude of the original signal; A is the STFT amplitude of motion acceleration signal; m represents the components within the frequency range of 0 to 5Hz (the frequency range of the heart rate) in the STFT domain. n indicates the number of time Windows. Pearson correlation coefficient between the STFT amplitude of the original signal and the STFT amplitude of the motion acceleration signal is calculated. If the correlation coefficient is not greater than the preset threshold, the original PPG signal is judged as clean signal (or containing weak MA). After the discriminator updates the parameters, the generator also propagates back to train the parameters of the model, making the PPG signal generated by itself more and more like the clean PPG signal, until the discriminator determines that the signal is clean and the artifacts in the original signal are removed.

2.2 Analysis of human exercise heart rate data

This paper mainly uses artificial neural network algorithm to extract the heart rate of PPG signal. In the artificial neural network algorithm, self-coding neural network is used to extract the characteristic information of signals. After linear transformation of the PPG signal with artifact removal, a data set with label is formed and input into the stack self-coding network. If the input PPG signal has a total of k samples $S=\{s_1,s_2,\ldots,s_n\}$. SAE trains the network layer by layer from front to back [13] :

$$q^{v+1}=W^{v}J^{v}+p^{v} \tag{3}$$

Where, q^{v+1} is the weighted sum of input at layer $v+1$ of the stack autocoding network; W^{v} is the weight matrix between two adjacent layers; J^{v} is the activation value of the stack self-coding network; p^{v} is the output bias of the corresponding coding layer. Regularization terms were added to prevent overfitting, and stochastic gradient descent was used to find the minimum loss value of regularization function. Each iteration of gradient descent updates the weight matrix and output bias matrix of the coding network. Multiple iterations generate the minimum loss function, and the forward propagation algorithm is used to calculate the eigenvalues of neurons at each layer. Then, the partial derivative of regularized term function is obtained by back propagation algorithm, and the eigenvalues of neurons in each layer are adjusted. After obtaining clean PPG signal characteristics from autocoding, PPG signal characteristics are combined with ECG signal characteristics to obtain human heart rate data characteristics under different exercise states.

Because ECG signals are characterized by non-stationary random signals, the estimation of power spectral density by the period-graph method is usually achieved by fast Fourier transform of a finite sample sequence. But the data length for frequency domain characteristics of ECG signal analysis accurate read interference is larger. In this study, Welch power spectrum estimation method was used to extract ECG signal features.

ECG signal data segment of point M is divided into L segments with N samples in each segment and $N/2$ points overlapped between adjacent segments. To increase the number of segments and reduce variance, the data of each segment overlaps to a certain extent. The same smoothing window $w(m)$ is added to each segment of data, and the power spectrum of each segment of data is:

$$P_{ECG}^{i}=\frac{\left|\sum_{m=0}^{N}X^{i}(n)w(m)W^{-kn}\right|^{2}}{NG} \tag{4}$$

Where, $X^{i}(n)$ is the ECG signal after segmentation. W^{-kn} is periodic function; G is the normalized factor, which ensures that the obtained power spectrum estimation is unbiased. The average power spectrum of ECG signals can be expressed as:

$$P_{ECG} = \frac{\sum_{i=1}^{L}\left|\sum_{m=0}^{N} X^{i}(n)w(m)W^{-kn}\right|^{2}}{NGL} \tag{5}$$

The characteristics of heart rate data can only be used as one of the indicators to measure the physiological state of the human body under different conditions. Under different motion state of physiological data such as heart rate will appear obvious change, but by external stimuli, the physiological data such as heart rate will fluctuate. In order to avoid large errors in the monitoring results of motion intensity, the human body posture data collected by the smart bracelet was combined to identify the human movement state.

2.3 Human motion state recognition

The acceleration, displacement and other sensors on the smart bracelet can collect the changes of human body posture, and the data collected by these sensors can be used to identify the motion state of human body. Through joint judgment of acceleration, attitude angle, threshold and time difference of angular velocity data, it is used to identify running, walking, sitting, standing, falling and other motion states. The combined angular velocity is calculated from the X-axis angular velocity g_x, Y-axis angular velocity g_y and z-axis angular velocity g_z:

$$g_s = \sqrt{g_x{}^2 + g_y^2 + g_z^2} \tag{6}$$

The various motion waveforms of the human body obtained by the nine-axis inertial sensor contain a lot of information. When the difference between the combined acceleration and the static acceleration is less than 0.03g, the acceleration value of the sensor in 3000 samples is analyzed. If the acceleration value changes, it indicates that the sensor is in the static state.

In the analysis of motion data, wave peaks and troughs are used. In the process of human movement, motion signals such as boom acceleration, angular velocity and attitude angle are constantly changing. The maximum value in a period of time is the wave peak. Wave can reflect the actual changes in a period of time to exercise intensity, different actions of different frequencies, caused by wave is also different, so the wave can well reflect the change of human movement state; Trough is the minimum value of movement signal in a period of time, which can better reflect the movement of the human body down; The time difference is the time from the threshold before the peak to the threshold after the peak, or from the threshold before the peak to the threshold after the trough, or from the threshold before the trough to the threshold after the peak; Since each action is performed at a different cycle frequency, the time difference is different, which has a good effect in distinguishing periodic and aperiodic actions.

From the analysis of spectrum, the frequency of running is fast, and the peak amplitude of acceleration is large. When running normally, intelligent bracelet pitch angle in the acquisition of the attitude angle is less than 20 degrees, the change of roll angle is less than 40 degrees. However, both walking and running are periodic movements, which can easily cause misjudgment. This paper uses as many features as possible to reduce the misjudgment rate. Although the change of pitch angle and roll angle is similar, but the change of angular velocity is different, and the change of angular velocity is greater when running, there is a significant difference between the two. Because of the difference in motion frequency, time difference is a very important feature. In common motion scenes, human pose features collected by sensors are taken as the clustering center, and the clustering algorithm is used to cluster the pose data collected by smart bracelet in the actual monitoring process. In this study, cosine similarity formula is used to judge the similarity between attitude data collected by bracelet and cluster center. With highest similarity clustering center where clusters corresponding movement types as the basis, combined with the feature of exercise heart rate to identify human movement posture.

2.4 The realization of human movement intensity monitoring

A large number of studies on heart rate and exercise intensity show that there is a linear relationship between exercise intensity and heart rate, and exercise load can be classified according to different ranges of maximum heart rate. The maximum heart rate is not a fixed value, which will change with the physical condition of the exerciser. For heart rate data, this study based on maximum heart rate, heart rate associated with the intensity of load and the related theory of exercise load hierarchies. There are six levels of resting state, decompression state, fat burning state, cardiopulmonary exercise, anaerobic acceleration and extreme training. The classification rules are as follows: resting state corresponds to resting heart rate, decompression state corresponds to resting heart rate to 50% maximum heart rate, fat burning state corresponds to 50% to 69% maximum heart rate, cardiopulmonary exercise corresponds to 70% to 79% maximum heart rate, anaerobic acceleration corresponds to 80% to 89% maximum heart rate, and extreme training corresponds to more than 90% maximum heart rate. Exercisers can set corresponding exercise targets according to their training status and training objectives and exercise load levels. Exercise heart rate monitoring statistics will statistics the time required for each load range. The amount of exercise load can be preliminarily calculated by the time spent by the exerciser in the heart rate interval of different loads.

But the feelings of the human body to exercise intensity subjectivity is stronger, and heart rate only as a reference, cannot be measured muscle and so on for the rest of the body exercise intensity response. In this paper, SVM model based on firefly algorithm is used to judge the abnormal physiological data of human body to avoid large errors. The specific flow chart of abnormal physiological data judgment is shown in Figure 1.

The physiological values of the abnormality judgment model should be set according to the basic physiological data of the wearer, such as age, sex, height and weight, as well as the historical assessment of athletic ability. The standard value was used as the classification hyperplane of SVM model to judge abnormal physiological data. In the strength of human movement monitoring, sports bracelet in all kinds of physiological data after processing, the firefly algorithm of SVM identification model according to the figure 1 process. Will judge model to judge the results combined with heart rate scale, output current bracelet the user whether the exercise intensity of overload, complete the intensity of human movement monitoring method based on intelligent bracelet.

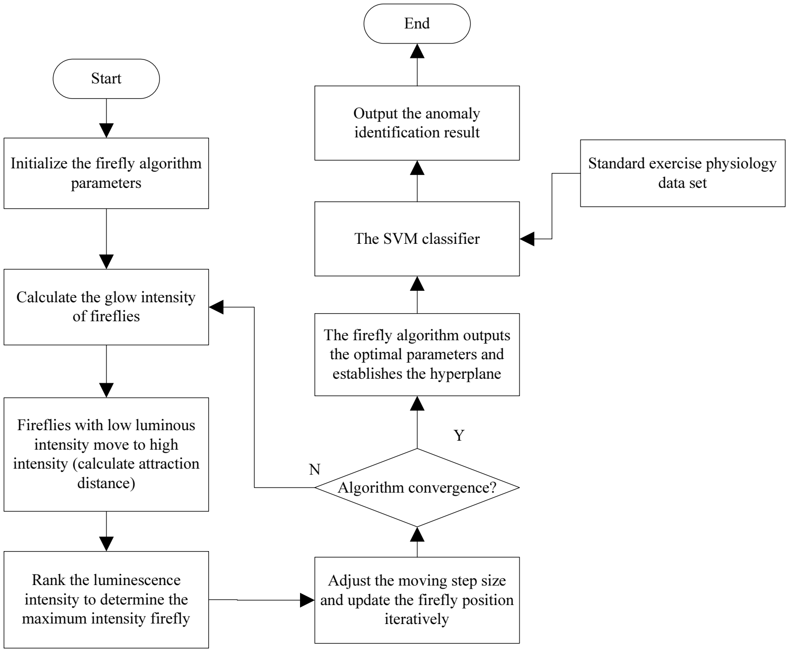

Figure 1. Flow chart of abnormal judgment of human motor physiological data

3. Experimental Study

Moderate intensity exercise can relieve human discomfort, improve human resistance and enhance physical fitness, but excessive intensity of physical training not only can not achieve the ideal training effect, but also have a negative effect. For a long period of time beyond the intensity range of motion, will have negative effects on the body's physiological and psychological, serious and even life-threatening. Based on the advantages that the smart bracelet with high popularity can collect relevant physiological data of human body, the monitoring method of human exercise intensity is proposed above. Before use in the monitoring method in large range, this section will open experimental research method for monitoring.

3.1 Experiment content

A total of 100 people were randomly selected to provide the relevant data of this monitoring method experiment, and the subjects participating in the data collection were different in age, gender, height, weight and exercise basis. The training intensity of 100 people was evaluated by a professional sports management team, and the evaluation results were used as the reference value of this experiment. A comparative experiment was conducted on the monitoring method proposed in this paper, the monitoring method based on lactic acid measurement and the monitoring method based on heart rate measurement from two aspects of the monitoring method's warning accuracy of intensity overload for the monitor and the response time of the monitoring method when the monitor's physiological data changes. In order to ensure the reliability of experimental results, the average value of 20 monitoring results for the same monitoring object was taken. In order to improve the universality of the experimental results, five periods of exercise training scenes were set up. During the experimental analysis, the influence of large deviation caused by the abnormality of relevant equipment should be excluded.

3.2 Experimental Results

Table 1 shows the statistical results of the experimental data of exercise intensity monitoring for 100 monitoring objects using three exercise intensity monitoring methods.

Table 1. Exercise intensity monitoring experimental data statistics

Serial number	Monitoring method based on smart bracelet		Monitoring method based on lactic acid measurement		Monitoring method based on heart rate measurement	
	Monitoring alarm accuracy /%	Response time /ms	Monitoring alarm accuracy /%	Response time /ms	Monitoring alarm accuracy /%	Response time /ms
1	98.5	124.5	97.2	457.9	95.4	334.8
2	97.6	131.2	96.8	416.8	89.2	351.9
3	97.4	119.6	97.5	439.7	70.6	362.5
4	98.4	126.8	96.9	502.3	83.0	390.2
5	99.1	128.0	98.0	478.4	79.3	346.4

Analysis of the data in the table 1 shows that when the monitoring objects of exercise intensity is beyond the scope of its can withstand the maximum, the method and measurement based on lactic acid monitoring method can very accurately alarm, monitoring accuracy were higher than 96%, and the small difference between the alarm accuracy of two methods. From the perspective of monitoring accuracy, the performance of the two methods is similar. However, the alarm accuracy of the monitoring method based on heart rate measurement fluctuates obviously, indicating that the reliability of the monitoring method is poor in different experimental scenarios. However, in terms of the response time of the method, the monitoring method cannot monitor the change of exercise intensity in real time due to the complexity of lactic acid measurement. In contrast, using smart bracelet for monitoring can respond more quickly to the change of the movement intensity of the monitored object, and reduce the possibility of the movement injury of the monitored object.

4. Conclusion

Wearable devices free the hands of users and can continuously monitor and other characteristics make it difficult to replace the role in many fields, opening up a new field of computer science. Smart wearable products such as smart bracelets are rapidly becoming commercial and mature, with gradually diversified types, and have penetrated into fitness, medical care, entertainment, security, office and other fields. The smart bracelet can help users record the real-time data of exercise data, sleep status, diet and other healthy life in daily life, and synchronize with relevant apps to present real-time periodic data information for users, help users to set exercise goals, urge exercise and fitness, and assist in guiding healthy living habits. In order to facilitate people to objectively evaluate the training intensity during sports training, this paper studies the human exercise intensity monitoring method based on smart bracelet, and verifies the validity of the method in the test object.

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