Revista de Psicología del Deporte/Journal of Sport Psychology Vol. 30. n.°2. 2021. pp. 87–100
Universidad de Almería / Universitat Autónoma de Barcelona. ISSN 1132–239X ISSNe 1988–5636

Research on Pre-Competition Mood State of Sports Athletes and Their Individual Differences

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Abstract
With the development of a country's economy and the progressive improvements in quality of life, sports and fitness are increasingly paid more attention. Regardless of the general sports and fitness-related needs, or the professional athletes who need a substantial amount of exercise, the scientific arrangement of exercise, training intensity and frequency, and monitoring of the athlete's mood state is an important topic. This paper uses bioelectric signals to study the mood state of male athletes during aerobic exercise, and analyzes the changes of the three signals of ECG, EMG and EEG in different physical mood states and the recovery period after exercise. This is done by constructing an objective recognition of the degree of mood state and the degree of recovery after exercise, while tracking and monitoring the changes of the athletes' red blood cell index, blood oxygen saturation, and heart rate indicators during the training process, to objectively evaluate the impact of the long-term training on the athlete's physical function, and provide suggestions for coaches to conduct scientific training. It is also hoped that further summarization of the variation rules of various physiological state evaluation indicators during long-term training of athletes will provide a certain technical support for athletes to avoid overtraining and damaging the body, and in doing so, scientifically restore their sports mood state.
Keywords: Sports; athletes; mood before competition; individual differences

Introduction

Modern high-level sports competitions show that sports athletes expend both, physical and psychological energy. If the athletes' psychological functions and personality characteristics are not well-developed in the competition and training, then even if they are well-trained in physical, technical, and tactical aspects, it is difficult to win the game (Ahmetov I I, et al 2019). With the continuous improvement of the level of college sports athletes, the influence of psychological factors on the competition is also increasingly being considered. At present, high-level sports teams at home and abroad attach great importance to pre-match psychological preparation and regard it as a key link in cultivating the best competitive state among athletes (De Moor M H M et al 2017). From the survey scores of international competitions, athletes who do not perform well in the competition have more than 70% of failures due to insufficient psychological preparation, and only about 20% of failures are due to insufficient technical and tactical preparation. (Scott R A, et al 2020). Therefore, it is necessary to engage in psychological training. These psychological qualities must be honed over time during the usual training and competition. When the exercise mood state occurs, the athlete's heart load will continue to increase, becoming more irritable than usual, leading to muscle aches and flexibility, and the development of necessary thinking ability in competitive sports such as judgment and reaction will also decrease (Scott R, et al 2019). To ensure that athletes can perform stably and achieve excellent results in the competition, coaches and athletes should develop overall training plans, methods and set goals before the competition according to the characteristics of the sport and combining various situations. Among them, the regulation of sports athletes' competitive state before the competition is an important link that determines whether athletes can perform stably and achieve success in the competition. Therefore, the state of exercise mood entails a comprehensive state of mind, mentality, and physical strength.

Athletes have different perceptions, attitudes, nature, and preparations for the game before participating in the competition, and they may be in various emotional states before the competition. Athletes also have different mental states before the game. In the traditional exercise mood state assessment, subjective (psychological) evaluation methods are often used to estimate the degree of the human body’s mood state quickly and directly (Rankinen T, et al 2020). However, because the state of movement mood is a complicated process, it is characterised by a lack of objectivity and can only be studied through subjective evaluation; for this reason, it is difficult to analyze and evaluate it comprehensively and accurately (Mikami E, et al 2019). The traditional view is that through the objective (physiological) evaluation method combined with the subjective (psychological) evaluation method, the state of

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the exercise mood is studied, and the relationship between the physiological mood state indicators and the mental state of the exercise is explored, and a variety of bioelectricity is constructed. We establish features of a model for objective recognition of the state of movement mood (Mikami E, et al 2019). Among them, the objective evaluation part selects the comprehensive analysis of several bioelectrical indicators of ECG, EMG, and EEG, and the subjective evaluation part selects the subjective exercise intensity scale (Rating of perceived exertion, RPE). The state of exercise mood is bound to cause changes in the biochemical conditions in the human body. Therefore, it will cause changes in the ion current in the body the state of exercise mood will lead to changes in the bioelectric signal of the human body, and the bioelectric signals are easy to collect, therefore, the bioelectric signal is used to study and monitor the state of exercise mood. At present, the research on the monitoring of sports mood state is still in its infancy, and a complete, mature, and effective monitoring system has not yet been formulated. Due to changes in the human body's environment during exercise, many physiological indicators of the human body will also show corresponding changes. Which of these indicators is more related to the trend of changes in the body's mood state? How to choose and calculate these indicators to better monitor and analyze the human movement mood state? These and other issues are still being explored through in-depth research (Heffernan S M, et al 2017).

This article designs and completes the aerobic exercise mood state experiment, collects the subjects' ECG, EMG and EEG signals, and uses the mood state scale to assess the subject's feelings of the subject's mood state as the degree of mood state during exercise. Aiming at the ECG motion artifacts that are affected by noise, an adaptive filter is designed. In the experiment, the three-axis acceleration data reflecting the motion state of the subject is synchronously collected as a reference signal, and input together with the noisy ECG signal. The filter uses the adaptive characteristics of the filter to continuously optimize the filter parameters and weights, so that the filter performance can automatically match the noise changes, and the noise can be better suppressed. The algorithm of adaptive differential threshold combined with adaptive amplitude threshold is designed to identify the R wave peak in the ECG and extract the heart rate variability signal. For EMG and EEG signals, noise is removed mainly by bandpass filter, notch filter, wavelet filter, threshold filter and other methods. The characteristics of ECG, EMG and EEG are extracted, and the changes of these characteristics in different mood states are analyzed. The EMG characteristics are normalized to reduce their individual differences. Based on the analysis and comparison, the parameters of the interval standard deviation, low-frequency power/high-frequency power, approximate entropy of the ECG in different mood states, the normalized rectification average value of the myoelectricity, and the normalized total power parameters are selected as the construction and the bioelectric characteristics of the motor state recognition model. The use of multiple bioelectrical multi-physiological parameters to identify the degree of mood state avoids the problems of low recognition rate and poor applicability caused by only using a single physiological index to study the mood state in some studies.

Related Work

The ECG research on the state of exercise mood is generally analyzed through the Heart Rate Variability (HRV) of the exercise process. (Kim et al. 2020) study the relationship between exercise and HRV and prove that HRV changes with the degree of exercise mood and is more sensitive. (Wolfarth et al. 2020) study the HRV characteristic changes of subjects riding power bicycles, and found that as the exercise deepened, the high-frequency power peak of HRV gradually increases from 0.25 Hz to 0.6 Hz, indicating that the main energy of HRV would gradually increase during exercise. (Isaac et al. 2019) study the changes in the subject's HRV under the conditions of the standard Bruce running test and found that as the number of running groups increases, the subject's HRV low frequency power (LF) and high frequency power (HF) both show an obvious downward trend. (Kim et al. 2020) study 33 ordinary personnel and 33 professional athletes, and by analyzing the HRV power spectrum curves of each experimenter, they find that professional athletes have higher heart rate variability due to increased parasympathetic nerve activity. Casadei et al. find that when the exercise load reaches 221W, the ratio of HF and LF to the total HRV power will decrease in the opposite direction. (Petróczi et al 2020) and others study electrocardiogram signals during the training process of football players, analyzing sports performance, mood state and the relationship with the various characteristic indicators of the electrocardiogram in the training of the athletes, and found that the heart rate and the mood state of the athletes, sports intensity is positively correlated, and it is an indicator that can directly and effectively reflect the degree of exercise mood. (Drozdovska et al 2019) and others, studying changes in HRV indicators of female handball players before and after exhaustive exercise, found that the subjects' HRV time-domain indicators

SDNN, RMSSD, and SDSD in a relatively quiet state after the end of exhaustive exercise are obvious. (Tahtinen et al. 2018) use HRV to study different types of mood states of healthy people, achieving substantial results. There is also a research team that uses HRV features to design a recognition model for monitoring the driving mood state, and the total classification accuracy rate reaches 86%. In short, studying the relationship between HRV and mood state and using it to monitor mood state is an important direction of mood state research.

In this study the relationship between mood state and surface electromyography has been studied, and it is believed that the integrated electromyographic value (IEMG) in the time domain index can better reflect the degree of the mood state of the muscle. The average power frequency (MPF) in the frequency domain index is better than the median frequency (MF) which can better reflect the change of mood state (Curry L A, et al 2017). Studies show that the surface EMG signal power spectrum changes before and after the isometric static load center state. It is found that the power spectrum after the mood state shifts to the left from the overall and peak values before the mood state (Pitsiladis Y P, et al 2020). Some researchers have found that as the muscular mood state increases, the MPF and MF values of EMG will decrease (Collins S. et al 2018). When analyzing the surface EMG signal of the squat exhaustion experiment, some researchers found that the time domain indicators of EMG, RMS and IEMG, will increase with the deepening of the mood state (Maciejewska-Skrendo A, et al 2019). Some scholars use regression analysis to find that the time series curves of MPF and MF from the biceps brachii to mood state induced by isometric load show obvious decreasing linear changes. The decreasing slope of MPF is 0.551±0.254, and the decreasing slope of MF is 0.297± 0.0313 (Castro M G et al 2017). In terms of non-linear analysis, foreign scholars have studied the Lyapunov index of surface electromyography and found that the Lyapunov index of the biceps brachii under the condition of eccentric contraction exercise load is significantly lower than that of concentric contraction (Ahmetov I I, et al 2018). Local researchers have also found that the one-dimensional time series of EMG has chaotic characteristics. They calculate the information entropy of various EMG signals in the reconstructed two-dimensional phase space, and analyze the results obtained to determine the relationship between muscles and movements (Ahmetov I I, et al 2018). Some teams also use chaotic and fractal methods to study surface EMG signals, and wavelet transform methods to identify surface EMG signals, and can achieve accurate results. There are also studies that use quantitative recursive analysis to determine the percentage of certain segments of the biceps brachii muscle as EMG continues to rise during the exercise mood state and is more sensitive than the median frequency MF to changes in mood state. All in all, ECG and EMG are bioelectrical signals that are highly correlated with exercise mood state and change sensitively with them, so this article chooses them to study exercise mood state. The central electrophysiology is intended to study its relationship with the state of exercise mood through three parameters in the time domain, frequency domain and non-linearity. The electromyography is intended to study the relationship between the time domain and the frequency domain.

Pre-Match Mood State of Sports Athletes and the Construction of Their Individual Difference Model

Classification Model Theory Based on Athlete Status

Studies have found that the ECG signal is a very weak bioelectric signal. Its amplitude is generally between 0-4mv, and its spectral energy is distributed in 0.5-100Hz, and most of the energy is distributed in 0.5-20Hz between. ECG baseline drift is noise caused by human breathing and changes in acquisition equipment. Its frequency is low and coincides with the low-frequency part of the ECG. It needs to be filtered out by a filtering algorithm. According to the power spectrum analysis of the baseline wandering noise and pure ECG signal, and following several experiments, we found that the fast median filtering method can effectively filter the baseline wandering noise in the ECG signal collected in this experiment.

The algorithm principle of the median filter algorithm: For the signal x=(x(1),x(2),...x(n)...), take a filter window length of 2T+1, then the signal x at a certain time n (N), the sequence in the window is y=(x(n-T),...x(n),...x(n+T)), and then the sequence in the window is reordered from small to large, Get a new sequence z=sort(x(n-T),...x(n),...x(n+T)), and then take out the element z(n) in the middle of the sequence z, which is the median value at time n of the output value of the filtering algorithm. After the signal at time n is calculated according to the above algorithm and the output value is obtained, the filter window is shifted to the back by one position, that is, with x(n+1) as the center of the window, continue to calculate according to the above algorithm, and so on. This computational time and resource consumption is relatively large, and the fast median filter algorithm which improves based on the median filter algorithm, can solve this limitation well.

$$u[x,y] = \iint x(i) * y(i)dxdy \tag{1}$$

The principle of fast median filter algorithm : For signal x, take a filter window with a length of 2T+1, and for the first time, first set the sequence y in the filter window = [x(n-T),...,x(n),... ,x(n+T)] re-sort from small to large, get z= sort[x(n-T),...x(n),...x(n+T)], here expressed as z=[z(1) , Z(2)...z(2T+1)], select the element in the middle position in z as the first output. Then, the filter window is moved one bit backward in x, and the previously sorted sequence z is used to remove an element in z that is equal to x(n-T), and then a new element x(n+T+1) is added to z. And find the sorting position of the new element in z according to the numerical value, and then insert it to get a new sequence z1. Take the element at the middle position of z1 as the second output of the algorithm. By analogy, in addition to sorting all elements in the filter window for the first time, you only need to remove one element leaving the filter window based on the previous sorting result and add a new element entering the window. And interpolate the new element into the previous sorting result according to the element size to get the sorting result of the current filtering window. The element in the middle position is taken as the current output value.

$$z(i,j) = x(i) * y(j) / \sum (x(i) * y(j))^T \quad (2)$$

It is based on the expected response (in this article, the input original noisy ECG signal is used as the expected response) and the minimum error mean square between the output signal as the criterion, and through the input signal (in this article, the input three-axis acceleration Signal) of a gradient vector estimate in the iterative process, and constantly updates the adaptive filter weight coefficients to achieve the optimal adaptive iteration. Suppose the input original noisy ECG signal is r(n), the three-axis acceleration signal is x(n), the output signal of the filter is y(n), the output error signal is e(n), each filter. The weight coefficient vector at time is (n). Then there are:

$$y(i) = x(i) * w(i)^T \quad (3)$$

Define the cost function as the mean square value of the error signal e(n), namely:

$$e(i) = r(i) - y(i) = r(i) - x(i) * w(i)^T \quad (4)$$

Since adaptive filtering is based on the error signal e (n) to adjust the filtering parameters to adapt to new unknown noise statistics at any time, it is like the stochastic gradient descent method, so the expected algorithm of the cost function can be ignored, that is:

$$F = E(e(i) * e(j)) \quad (5)$$

The gradient of the calculated cost function is:

$$\nabla F(i) = \partial y(i) \,/\, \partial w(i) = -e(i)xe(j) \quad (6)$$

In addition, the weight vector update rule of the LMS filter is:

$$w(i,j)w(i) * w(j) - dF(i,j) \quad (7)$$

Substituting Equation 5 into Equation 6, the update formula of the weight vector of the LMS filter can be obtained as:

$$w(s,t) = w(s,s+1) * w(t+1,t) + e(i,j) \quad (8)$$

Formulas 7-8 are the adaptive update process of the weight coefficient of the LMS filter. Through this process, the filter can adjust its filtering performance according to the real-time noise level, to better cancel the noise. In the formula, the value of μ is the step length parameter. In the LMS algorithm, it must satisfy 0< μ <2, and it must be a fixed number, where λ max represents the maximum value of the eigenvalue of the autocorrelation matrix of the input signal. However, in actual data processing, it is found that λ max cannot be accurately calculated, and the accurate value of μ cannot be obtained through λ max. For the LMS filter, if the μ value is too large, the convergence speed will be faster, but the steady-state error will also be greater; on the contrary, if the μ value is too small, its convergence will be very good, but the convergence speed will be slow. In actual application, each set of data needs to be manually debugged several times according to the results to determine a more appropriate μ value. For the above-mentioned traditional median filter algorithm, if the length of the input signal to be processed is M and the length of the filter window is 2T+1, the number of operations of the algorithm should be (2T+1) *(M-2T) times. However, the length of the ECG signal to be analyzed in this experiment is relatively long. If the traditional median filtering algorithm is used, it may lead too excessive calculations.

Linearly Inseparable Mood State EEG Algorithm

The LMS algorithm has a simple structure and low complexity. It has a wide range of applications in the field of adaptive filtering; however, its filtering effect is mainly affected by the value of μ , and the value of μ of the LMS algorithm is a predetermined value that needs to be set in advance. The appropriate value is troublesome. Addressing this shortcoming, it has made improvements and designed an LMS algorithm with a variable step size parameter μ value, that is, an NLMS filter, as shown in Figure 1, which is the linear and inseparable mood state EEG algorithm flow. The algorithm uses the input signal x(n) to adjust the μ value of the filter in real-time. The specific formula is as follows:

$$u(i) = \delta(i) \,/\, (x(i) * x(i)^T) \quad (9)$$

To avoid a situation where the denominator of the above formula is equal to zero, a correction factor ρ is added to the denominator. In the formula, ρ is a correction parameter to prevent the denominator from being 0, and

δ is a parameter to prevent the value of μ from being 0. They should all be a smaller positive number. In this paper, ρ is taken as 0.001 and δ is taken as 0.3. Good results can be obtained when processing all exercise ECG data collected in this paper. Therefore, the weight vector update formula of the NLMS algorithm is:

$$v(i) = \delta(i) \,/\, (x(i)^T * x(i) + r) \qquad (10)$$

Equations 9-10 are the algorithm flow of the NLMS algorithm. Compared with the LMS algorithm, the NLMS algorithm is more convenient, and the filtering effect is better. Therefore, it has been finally decided to use NLMS as a filter to filter out ECG motion artifacts and achieve good results.

According to Petróczi A, 2020, the R wave peak in the QRS complex of each heartbeat cycle is the point with the largest amplitude in a cycle, and the difference between the R wave peak and neighboring points is also the largest. Therefore, the R wave peak is selected as the representative point of each cycle, and the time interval between two adjacent R wave peaks (that is, the RR interval) is used as the time interval between these two adjacent heartbeat cycles. At present, there are many R-wave detection methods, including differential threshold method, wavelet transform method, neural network method and so on. Since the R wave peak has the characteristics of the largest amplitude and the largest difference in a cycle, this study uses the adaptive amplitude threshold combined with the adaptive differential threshold to design an algorithm to identify the ECG R wave peak. In addition, the EMG signal is a non-stationary random signal, and its mechanism determines that it has strong uncertainty and individual differences. It bears to note regarding the filtering of motion artifacts and baseline drift, motion artifacts and baseline drift noise in the EMG are the same as the two noises in the ECG.

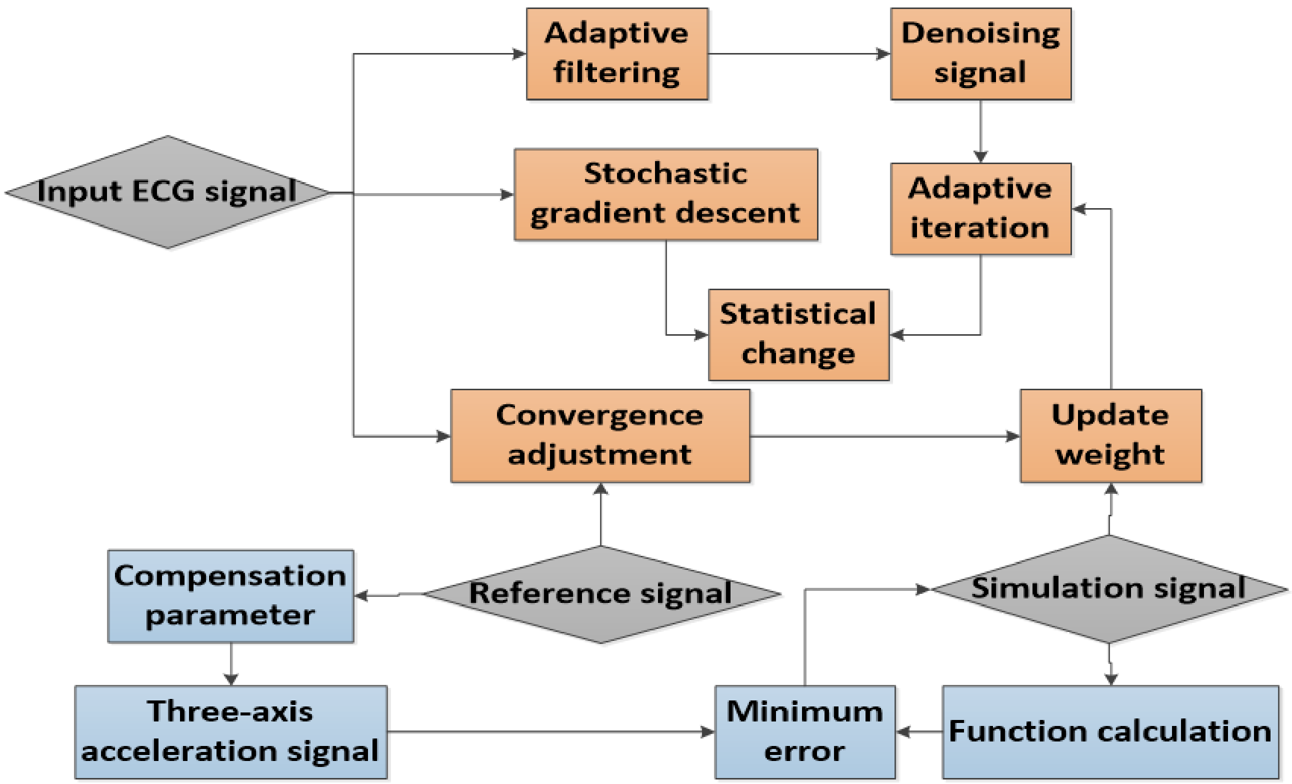

Figure 1. Linear inseparable mood state EEG algorithm flow

The flow chart of NLMS filter to filter out ECG motion artifacts is shown in paper. The input x(n) is the collected real-time three-axis acceleration signal in motion (as a reference signal). W(n)=(W1, W2, W3) is the real-time weight coefficient vector of the filter, which is continuously updated according to e(n) and real-time three-axis acceleration. The input r(n) is the noisy ECG signal to be denoised. e(n) is the denoised signal output by the filter and is also the feedback signal for updating the weight co-. The detailed expression of y(n) is:

$$\mathrm{w}(m,n)^T = \Sigma n(i) * m(j) + n(j) * m(i) \qquad (11)$$

Optimization of Model Weight Parameters

In the collected ECG signals, in addition to motion artifacts and baseline drift, there are two types of noise; power frequency interference and electromyographic interference. The main energy of power frequency interference is concentrated in the vicinity of 50 Hz, and in the vicinity of frequencies that are integral multiples of 50 Hz. As this noise does not coincide with the main frequency band of the ECG signal (0.5-20Hz), it is possible to directly design a buttworth low-pass filter with a pass band of 45 Hz and a stop band of 48 Hz to filter it out. The comparison before and after power frequency filtering is shown in the paper. And the ECG signals collected during exercise in this study will inevitably have EMG interference. For EMG noise, the author uses the wavelet threshold denoising method. The threshold form selects the maximum and minimum value threshold, the threshold selects the soft threshold, the wavelet function selects the sym4 function, and the decomposition layer is 4 layers. The detailed state of the sports athletes' mood before the game and the framework of the individual difference model is shown in Figure 2.

It can be seen from the above that HRV is a sequence of time intervals between adjacent cardiac cycles. Therefore, if you want to find the time interval between two adjacent cardiac cycles, you must first find a strong and easily identifiable point in each cardiac cycle as the characteristic point of each cycle to represent this cycle. Preliminarily, we think that the point n+4 is the point R, store its corresponding time into a sequence K, and the intermediate value of this point (the other two numbers remain unchanged), and then re-calculate their arithmetic averages h0, c0 , then update the difference threshold and amplitude threshold according to the rules of the step. When updating them, the parameters k1 and k2 are most suitable to be 0.35. After the update, continue to detect subsequent points and use the new threshold for the standard to perform detection. If not satisfied, skip to the next point to continue the above verification and operation. In order to prevent false detection points in the step, we finally make a first-order difference KK(n)=K(n+1)-K(n) for the sequence K from the beginning and traverse it. If KK(n)<0.25, then K(n +1) delete from sequence K, otherwise keep it. After the above steps, the R wave peak in a segment of the ECG signal can be successfully identified, and the final sequence K is the time sequence corresponding to the R wave peak of the ECG signal. This is illustrated in a schematic diagram of an ECG signal with R wave peaks identified and marked using the above algorithm. It can be seen from Figure 2 that all R wave peaks, regardless of their amplitudes, have been successfully identified and marked, thus verifying the above algorithm. reliability.

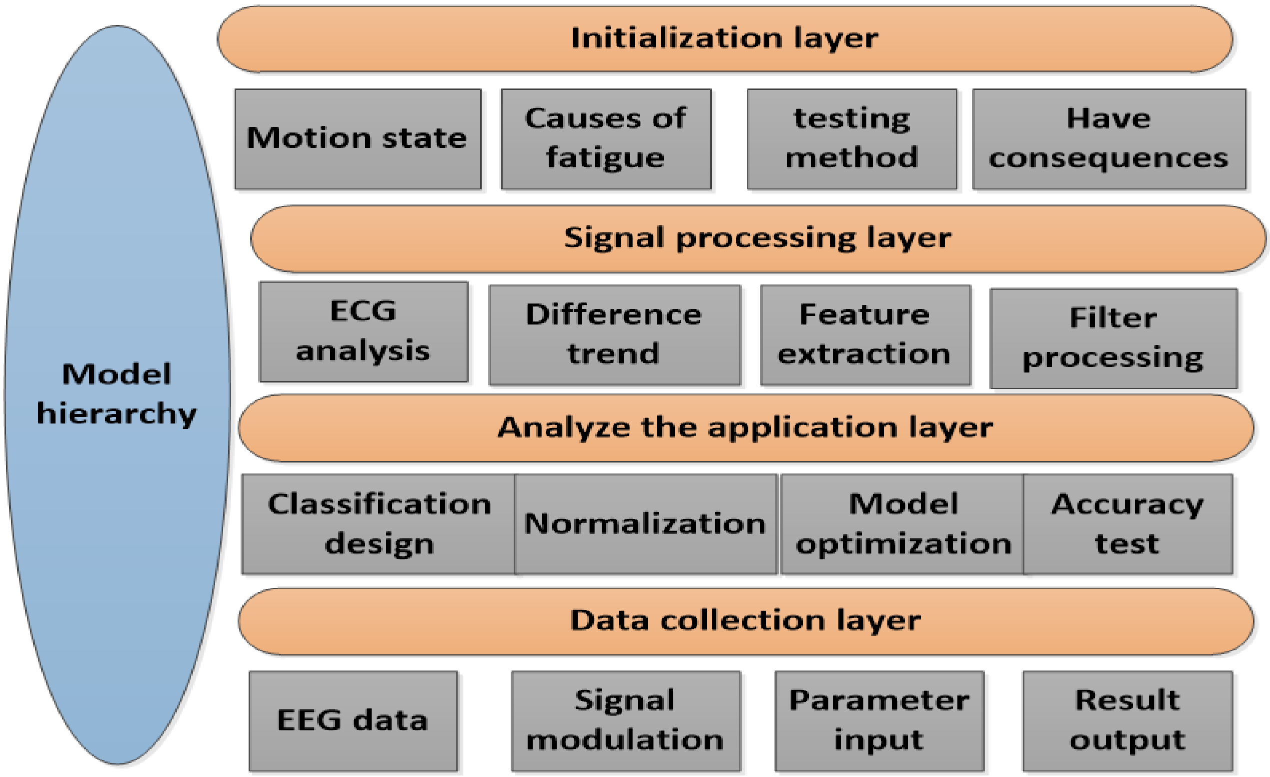

Figure 2. Pre-match mood state of sports athletes and their individual differences model framework

The time domain characteristics of HRV mainly include SDNN, RMSSD, SDSD, NNVGR, PNN50, HR, and NNVGR: the average value of the HRV sequence. PNN50: the percentage of the number of points with an absolute value greater than 50 in the 1-scale difference sequence of the HRV sequence to the total number of points. HR: the average number of cardiac cycles per minute. When the HRV signal is analyzed in the frequency domain, its power spectrum is inevitably required. However, the HRV signal is a time difference signal. It is not sampled at equal intervals in the time domain and does not have a fixed sampling rate. Therefore, when analyzing the HRV signal in the frequency domain, it must first be interpolated to make it an equally spaced sample signal before subsequent analysis. This article uses cubic spline interpolation to interpolate the HRV signal, and the sampling rate is 4 Hz. It is a comparison before and after 200-second HRV signal interpolation of a subject in a severe mood state. After the interpolation is completed, in order to avoid the influence of a large DC component, the HRV signal must be deaveraged, and then the power spectrum analysis of the HRV signal can be performed. In this paper, the periodogram method is used to find the HRV power spectral density curve, the window function is Hanning window, the window length is 256 points, and the window overlap length is 86 points. As shown in Table 1, the statistics of the power values of the 2-minute HRV signal in the resting state before exercise and in the mild, moderate, and severe mood states of the same subject in the same experiment. It can be seen that the state of exercise mood has a great influence on the HRV power spectrum curve. The frequency domain features extracted from the HRV signal mainly include low frequency power (LF), high frequency power (HF), total power (TP), and the ratio of low frequency and high frequency power (LF/HF), where LF refers to the power in the 0.04Hz-0.15Hz frequency band in the HRV power spectrum. TP is the total power of all frequency bands of the HRV power spectrum. As for HF, when the human body is completely resting, it breathes slowly, and the main energy of HRV is basically concentrated within 0-0.4Hz. Therefore, analyzing HRV under completely resting conditions often defines HF as the 0.15-0.4Hz frequency band.

Table 1.

Athletes' pre-match mood state corresponds to the HRV signal power value

State of mind	Low frequency power	High frequency power	Total frequency power	Low frequency /High frequency
Mild	0.6	0.9	1.5	0.67
Moderate	1.1	1.4	2.5	0.78
Severe	0.5	0.7	1.2	0.71

However, in the analysis and calculations performed as part of this study, it is found that in the state of human motion, the main energy distribution of the HRV power spectrum also shifts sharply to the right and extends to about 1.5 Hz in the severe mood state. Exercise state of mind aggravates the rapid increase in human respiratory rate. Therefore, in the state of motion, the power in the 0.15-1.5 Hz frequency band in the HRV power spectrum is taken as the high-frequency power HF. There are numerous methods for non-linear analysis of HRV signals, such as sample entropy method, approximate entropy method, and scatter plot method. In this paper, the approximate entropy value is selected as the characteristic index of the nonlinear analysis of HRV. Approximate entropy (Ap-En) is a non-linear dynamic parameter used to measure the regularity and unpredictability of time-domain signal fluctuations and reflects the possibility of new information in the time-domain signal. In other words, it is a physical quantity that reflects the complexity of the time domain signal; the more complex the time domain signal, the greater its Ap-En value.

Pre-Match Mood State of Sports Athletes and Application and Analysis of Their Individual Difference Model

EEG Simulation Based on the Athlete's Mood State

The EMG signal is the bioelectric signal generated during the muscle contraction and force, therefore, when the muscle relaxes, there is basically no EMG signal to be detected. The spectrum energy distribution of EMG signal is wider than EEG ECG, generally within 0-500Hz, and the main energy distribution frequency band is 20-150Hz. Its amplitude is generally in the range of 0-4mv. The motion artifacts originate from the friction between the electrode sheet and the skin, and the main frequency is 3-14 Hz; the baseline drift comes from changes in breathing and acquisition equipment, and the main frequency is 0.1 to 2 Hz. Therefore, these two kinds of noise are low-frequency noises, and do not overlap with the main energy frequency bands of the EMG signal. Table 2 shows the numerical comparison of the eigenvalues of HRV in different mood states. This paper designs a filter with a cut-off frequency of 15Hz to filter out these two types of noise.

Table 2.

Numerical comparison of various characteristic values of HRV in different mood states

	characteristic value 1	characteristic value 2	characteristic value 3	characteristic value 4	characteristic value 5
Good	47.22	32.71	48.44	52.62	49.21
General	3.71	8.36	5.29	7.31	6.54
Bad	0.36	1.41	3.18	2.19	1.86

The statistical values of the HRV characteristics of 28 subjects in the three states of mild mood state, moderate mood state, and severe mood state during exercise, and each value is based on the average value of the characteristic of 28 subjects in this state ± standard. The difference is given in the form. Figure 3 is a histogram of the mean values of some of the ECG characteristics of 28 subjects in different mood states. It can be seen that, except for the three characteristics of RMSSD, SDSD, and PNN50, which have no obvious differences in different mood states, the other characteristics all show a clear trend of change.

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states, the other characteristics all show a clear trend of change. Among them, the six characteristics of SDNN, NNVGR, LF, HF, TP, and LF/HF show a significant downward trend with the deepening of the mood state during exercise, while the two characteristics of ApEn and HR show a significant downward trend as the mood state of exercise increases. The aggravation shows a clear upward trend. In terms of time domain characteristics, SDNN has obvious changes in different states, so it can be used as the time domain characteristics of ECG for mood state recognition. In terms of frequency domain characteristics, TP can reflect the activity of the autonomic nervous system and the degree of cardiac load, which is a commonly used mood state. For condition monitoring index, its response physiological characteristics are highly consistent with SDNN, therefore, it is not selected as a frequency domain index. Figure 4 shows the average distribution of the athlete's ECG characteristics in different mood states. LF and HF can reflect the activity of sympathetic nerve and vagus nerve respectively, while LF/HF can comprehensively reflect the relative strength of sympathetic nerve and vagus nerve activity. It can also reflect the degree of mood state and the difference is obvious under different mood states, leading the author to choose LF/HF as an ECG frequency domain indicator for mood state recognition.

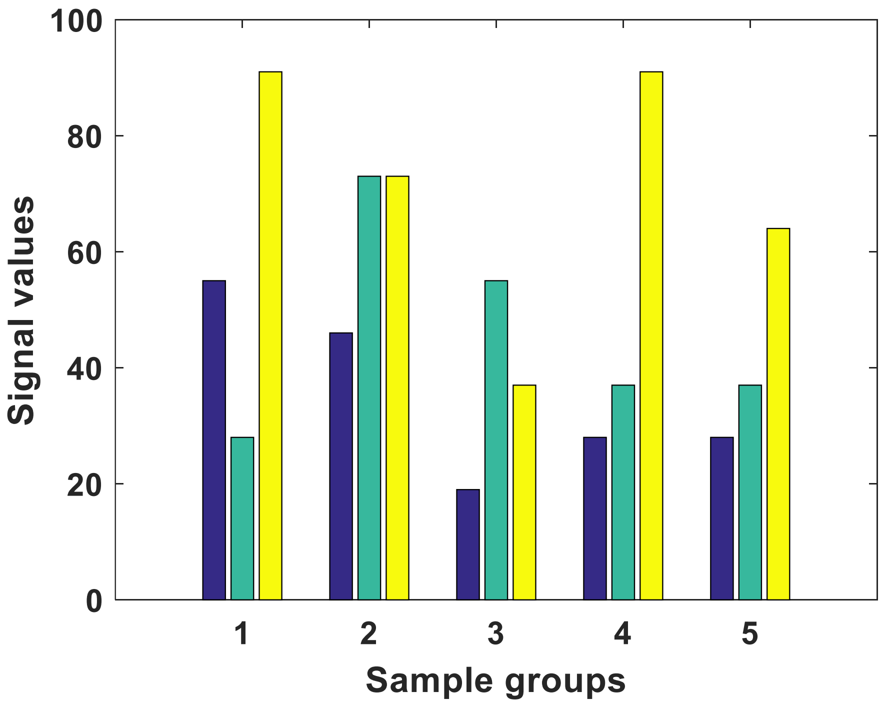

Figure 3. Histogram of EMG signal before and after denoising

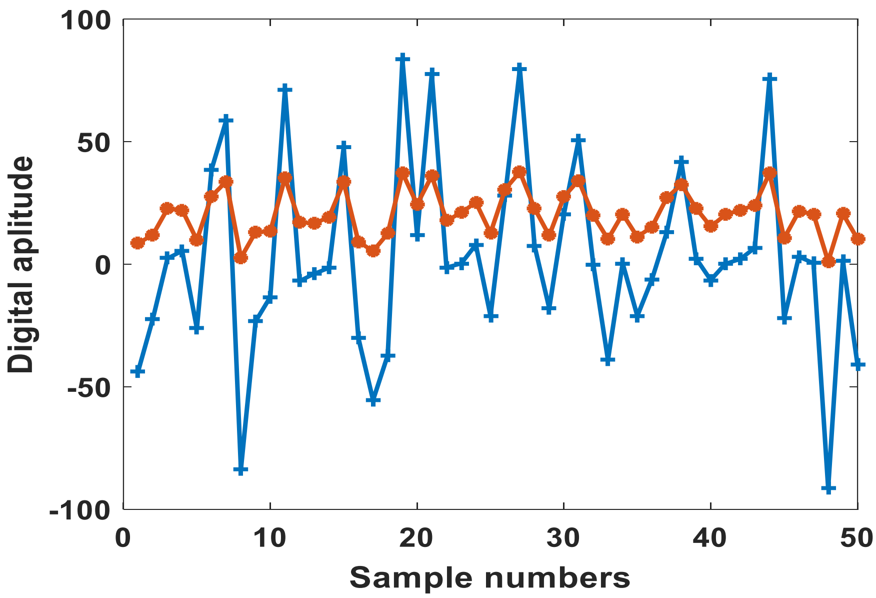

Figure 4. The average distribution of the athlete's ECG characteristics in different mood states

In terms of non-linear characteristics, ApEn changes significantly with the deepening of the mood state; for this reason, it is selected as the ECG non-linear index for mood state recognition. Most athletes show fighting spirit and self-confidence before the game. 30.6% of the athletes report that their emotional state before the game generally does not have much enthusiasm and motivation, and 13.7% of the athletes hold a negative attitude towards themselves. This part of the athletes may not fully recover due to fatigue or other reasons, say, they are not active enough before the game, indicating that the recovery and adjustment of the athletes before the game is particularly important. Due to the large individual differences in the feature values of each experiment, it is not possible to use a single feature to monitor the mood state, but to use multiple features to monitor together, in order to avoid individual differences as much as possible and improve the recognition accuracy. Figure 5 shows the 2-minute HRV time-domain waveforms of subjects under four states: pre-exercise, mild mood state, moderate mood state, and severe mood state. The horizontal and vertical axis units are seconds and milliseconds, respectively. It can be seen from the figure that as the state of mind deepens, the HRV value becomes smaller and the fluctuation range of HRV becomes smaller and smaller, which leads to a significant decrease in the overall frequency domain indicators TP, LF, and HF. The vagus nerve will gradually occupy a dominant position, and the heart load will gradually increase. The fluctuation range becomes smaller, and the standard deviation of the sequence also becomes smaller, therefore, the time domain indicator SDNN also decreases as the mood state deepens.

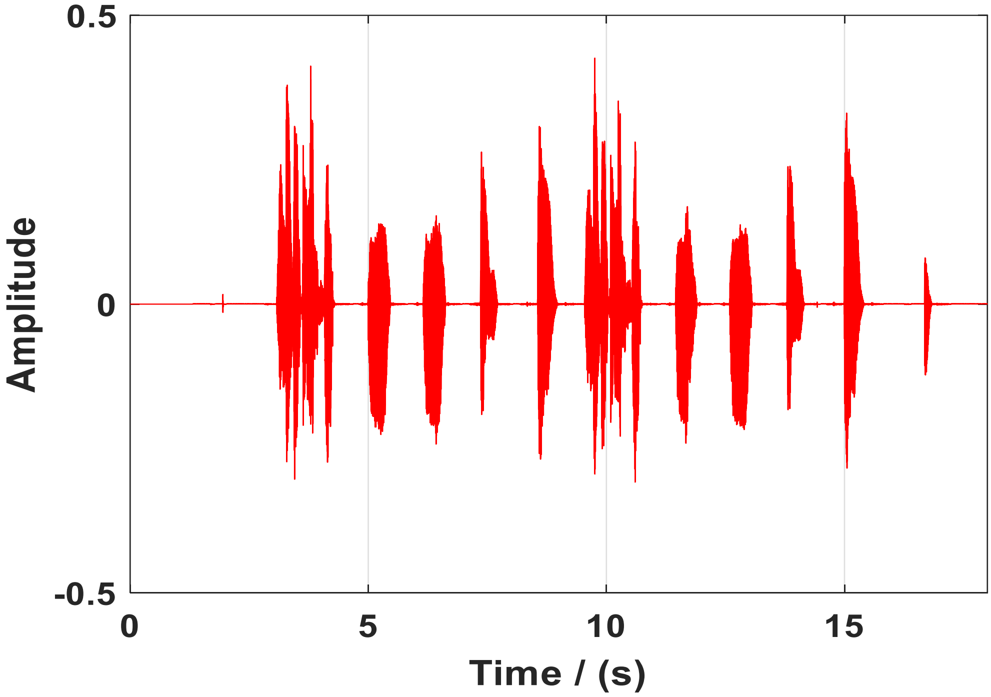

Figure 5. Time-domain waveforms of EEG signals in four states of different mood states

Studies show that the non-stationary components in the signal will reduce the complexity of the signal. At the same time, in terms of emotional stability before the game, the author finds that 38.6% of the athletes think that their stability is average, and 27.42% of the athletes think that they are unstable, which means that there are also varying degrees of differences in the psychological endurance of athletes. These reasons may be due to lack of experience in the field or the pressure of results. In terms of self-regulation, 38.6% of the athletes believe that their ability to self-adjust before the game is average, and 27.42% of the athletes believe that they are poor. These will directly affect the athletes' performance in the game. Generally speaking, the mental state of athletes is also an indicator of the pre-match competitive state that requires Chinese medicine research. As can be seen from the figure, when the mood state deepens, the non-stationary components in the HRV waveform gradually decrease, therefore, its approximate entropy ApEn also increases. Athletes' pre-match competitive state can be seen from the analysis of the above related factors from physical fitness, skills, tactics, intelligence and psychology, which are all important and related factors that can affect their state. Coaches and athletes' training time and content prior to the match need to reasonably grasp this one and make good use of the time at this stage to carry out an overall pre-match adjustment to the athletes.

Example Results and Analysis

In this experiment, after the subjects finish their exercise, they collect the ECG signals of their resting state for 10 minutes. Heart rate, as a commonly used index to assess the cardiovascular system of athletes, plays an important role in sports training. During training, the morning pulse can reflect the physical function of the athlete and play a positive role in determining whether the athlete adapts to the exercise load and whether he or she experiences fatigue. If the morning pulse suddenly accelerates or slows down, it indicates excessive fatigue or disease. During this time, the subjects sat on the chair and experienced a state of rest and recovery. In this section, we use the ECG during this period to explore the changes in the various characteristics of the human body's HRV during the recovery period after intense aerobic exercise. After the exercise, preparations such as getting off the car and wiping off the sweat are required, therefore, the ECG signal of the recovery period of 10 minutes is formally collected about 1.5 minutes after stopping the exercise. At this time, the subjects have entered a resting state. This experiment is designed to test the intensity of exercise with the characteristics of exercise, and it is of practical significance to obtain the inflection point of the heart rate. From the occurrence of heart rate inflection points of multiple subjects, there are obvious individual differences, that is, as exercise capacity increases, the heart rate inflection point drifts from left to right, which means that the stronger the aerobic capacity, the later the heart rate inflection point appears. Correlation analysis of the exercise intensity and crutches rate of multiple subjects found that the two have significant differences, indicating that the regular changes in the heart rate turning point in this study do reflect the differences in individual athletic ability and can give individual sports athletes maximum aerobic training to provide a reference.

Figure 6 shows the statistical values of the HRV characteristics of 28 subjects in several resting state phases. Each value is given in the form of "mean ± standard deviation". The heart rate inflection point is about 6A of maximum oxygen consumption and 88%-97% of maximum heart rate. The speed and heart rate inflection point are studied in two forms of treadmill and track. At the same time, blood is taken to determine lactic acid during two different forms of increasing intensity exercise, and the 99% track test of the subjects have heart rate inflection points, while running only 50% of athletes have heart rate inflection points. The characteristic value of each state is a truncated heart rate of 2 minutes. Moreover, the electrical signal is calculated, showing the HRV time-domain waveform of the resting state of the subject after exercise. After exercise, the ECG of 1.5-3.5min after the end of exercise is intercepted in the initial resting state, the ECG of 5-7min after the end of exercise is intercepted in the mid-term, and the ECG of 9.5-11.5min is intercepted after the end of exercise.

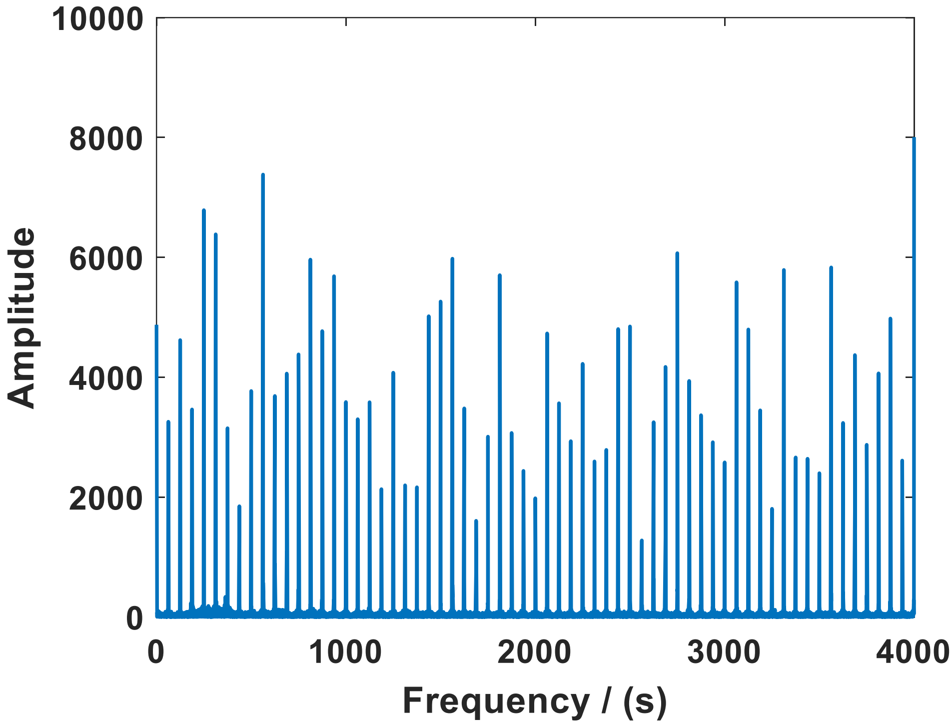

Figure 6. Frequency domain spectrum of athlete's ECG signal

The experiment records the change curve of five ECG characteristics at 8 recording points during exercise (given as the average value of 28 subjects at the corresponding stage). It can be seen from Figure 6 that after the athletes enter the plateau, the average value of the morning pulse in the second week increases by 2.73% compared to the first week when they went to the plateau at the beginning of the first week. During this period, the training intensity gradually increases with the extension of the time spent in the plateau. The athletes show the ups and downs of the morning pulse during the process of adapting to the environment and adapting to the exercise intensity. Coaches should keep close contact with other physiological indicators during this period to observe and analyze the physical state and sports state of athletes together. By the seventh week, the average value of the morning pulse is 8.18% lower than that of the first plateau ($P<0.05$). This may be due to the low-oxygen environment just entering the plateau. In order to maintain oxygen supply, the natural reaction of the body is mainly manifested in increased heart rate and increased myocardial contractility, which compensates the body's hypoxia by increasing blood circulation. The overall trends of SDNN, TP, LF/HF significantly decrease with the deepening of the exercise, and the overall trends of ApEn and HR increase significantly with the passage of exercise time, however it bears to note that the changing trends are not completely monotonous with the exercise time. In the process of oxygen exercise, you can reduce your mood state to a certain extent by adjusting your breathing and other means, so that you can continue to exercise.

In the pre-exercise period, the characteristic changes are the most obvious. This is because the human body is in the transition stage from the resting state to the exercise state in the pre-exercise period, and the changes in its biochemical reactions are greater than the changes in the long-term exercise state. Simultaneously tested 28 subjects' SDNN, LF/HF, ApEn, and HR in different mood states (the RPE value of subjects 23 and 24 did not reach more than 17 during the whole exercise process, signifying that there was no severe mood state. The content of the questionnaire establishes ten aspects of defensive awareness. The full score for each item is 10 points, and the total score is 100 points. The coaches of each sports team (1 head coach, 2 assistant coaches) will score each athlete's defensive awareness. Then, sort them manually according to personality type. The results are obtained by using SPSS15.0 software to perform non-parametric tests of the scores of two samples. During the trial exercise, the RPE value is not lower than 9 so there is no mild mood state). It can be seen that the three characteristics of SDNN, LF/HF, and ApEn in each subject have a consistent and more obvious change trend as the mood state deepens, so it can be used as a good classification feature.

The EEG collected at three points has the same characteristic change rule under the above four states and the difference in characteristic value is small. In each experiment, the power of resting β wave during exercise was generally improved relative to that before exercise, and the power of resting state β wave is lower in relative movement at the initial stage of resting state after exercise. There is also the power of theta wave. The resting state during exercise is generally greater than the resting state before exercise, and the resting state after exercise is generally smaller than the resting state during exercise at the initial stage. The alpha wave power also has the above trend in the three states but the individual differences are large. However, the approximate entropy ApEn in the resting state during exercise is generally lower than that in exercise. The value of the resting state before exercise, and the initial approximate entropy of the resting state after exercise is generally higher than that of the resting state during exercise.

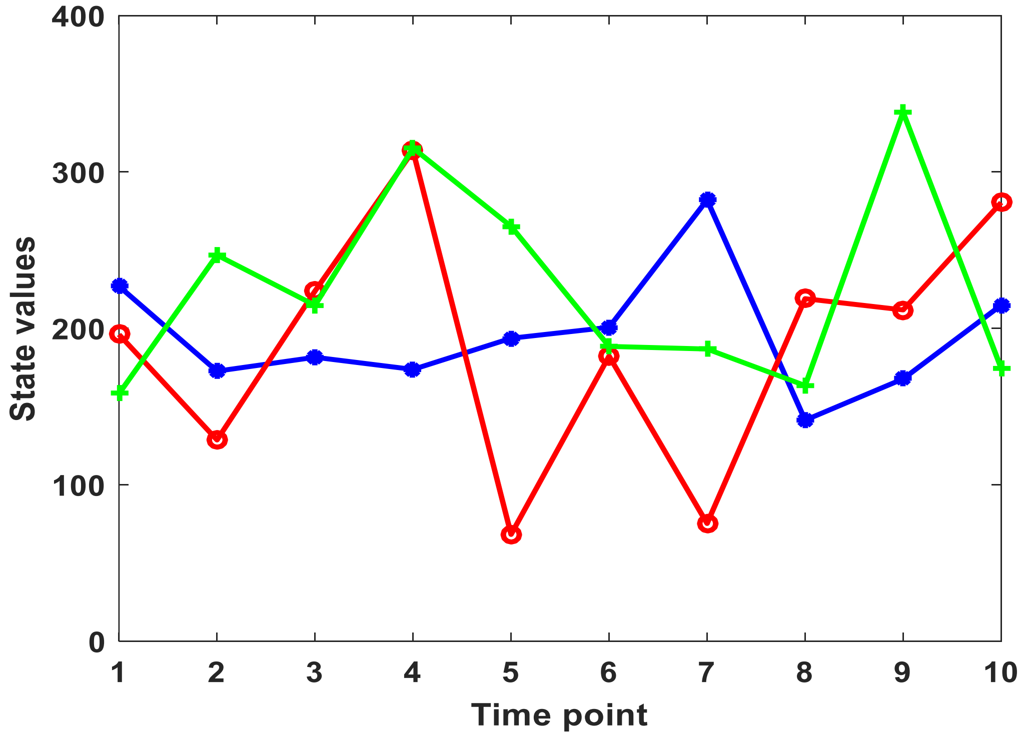

Figure 7. The broken line of the athlete's state recovery period over time

Figure 7 represents the change curve of each HRV feature in the post-exercise recovery period with time. It is given by a sliding time window algorithm. Each time window intercepts 2min of ECG signal for calculation, and the overlap time of adjacent windows is 110 seconds. The time at the beginning of each time window is taken as the time corresponding to the calculation result of each feature value in the time window. It can be seen that during the recovery period after a lot of exercise, the characteristic SDNN has a large initial value, then decreases, and finally shows an increasing trend. This is due to the rapid decrease in the subject's heart rate and the obvious HRV curve in the initial period after stopping the exercise of rising, resulting in a larger standard deviation SDNN.

Approximately 5 minutes after stopping the exercise, the subject's HRV curve stabilizes, so the standard deviation SDNN decreases. After 8 minutes since the end of the exercise, the degree of HRV fluctuation gradually increases, so the SDNN increases again. This article analyzes the results of the questionnaire, derives the personality type of each athlete, and classifies it. At the same time, a questionnaire is issued to the coaches of each team to evaluate the overall score of each athlete's defensive awareness. Combining the results of the personality survey to make a horizontal comparison of strengths and weaknesses, this study analyzes the differences in defensive awareness of athletes of different personality types. The results indicate that extroverted athletes show stronger desire and active awareness in defensive consciousness, and defensive actions are more aggressive; whereas, introverted athletes show more stable and passive awareness, and defensive actions are more passive sex.

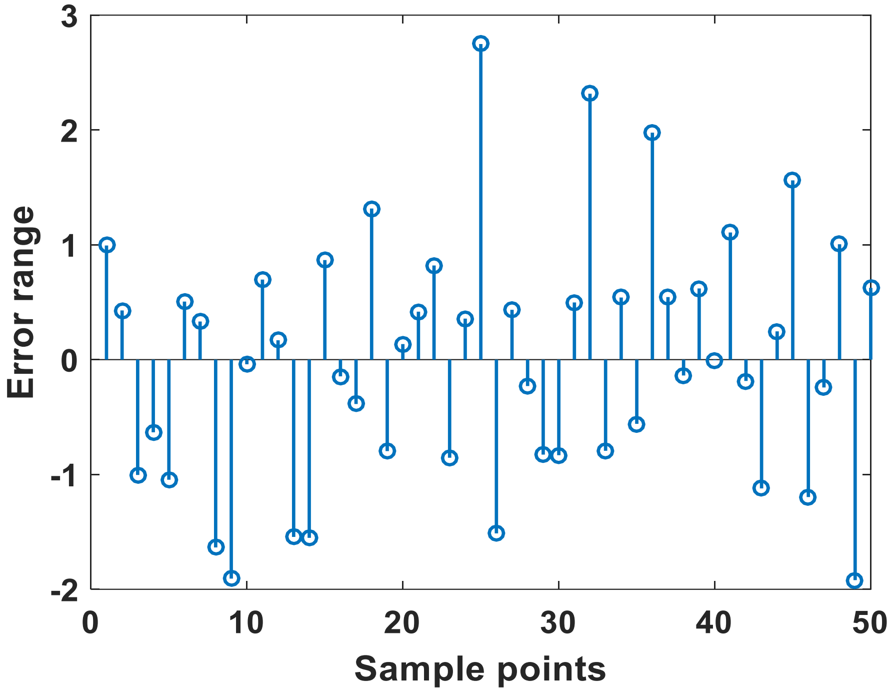

Figure 8. Athlete's ECG signal error distribution

At the same time, the two characteristics of RMSSD and SDSD increase with the passage of recovery time, indicating that the rapid changes in the heart rate component have been increasing during the recovery period. Figure 8 shows the error distribution of athlete's ECG signal. In terms of frequency domain indicators, the three characteristics of LF, HF, and LF/HF increase with the passage of recovery time. This is because during the recovery period, the activity of the vagus nerve and sympathetic nerve of the subject is increasing, and the sympathetic nerve activity becomes increasingly dominant. Analyzing the above data, it is not difficult to see that the difference in defensive awareness is caused by differences in personality types. For example, in terms of technical purpose, the techniques used by extroverted athletes are reasonable and clear, and the techniques used by introverted athletes are blindly ambiguous. In terms of the rationality of behavior, both extroverted and introverted athletes can perform appropriate and effective actions. In terms of movement flexibility, extroverted athletes are usually more decisive, while introverted athletes are more hesitant and slower. The characteristic TP during the recovery period after exercise shows an initial trend of decline and then rise. In the middle of the recovery period, all aspects of the human body tend to be stable, therefore, the autonomic nervous system activity will also decrease. The TP value also decreases; and at the end of the recovery period, the body's mood state is more and more diminished, the heart load is increasingly reduced, and the autonomic nerve activity is also lowered. Therefore, the TP value also increases (SDNN and TP have very similar physiological significance and mathematical significance, so the change trend is similar).

Conclusion

This paper uses extracted features to build a support vector machine and random forest-based aerobic exercise mood state recognition model and uses the multi-fold cross-validation method to test their classification accuracy. The support vector machine mood state recognition model algorithm is classic, reliable, simple and efficient; the random forest mood state recognition model algorithm is based on decision trees, and more than half of the decision trees need to make mistakes at the same time, and the number of votes for a certain misclassification is higher than the correct classification. Aiming at these influencing factors, this article uses the relevant theoretical knowledge of sports training to scientifically intervene and regulate the sports athletes' pre-competition conditions so as to make the athletes adjust to the best pre-competition conditions. The number of votes will produce incorrect classification results; therefore, the classification error rate is low and the stability is strong. After 5-fold cross-checking, the recognition rates of SVM and Random Forest classifier for the degree of mood state reaches 91.39% and 95.15%, respectively. At the same time, the ECG and EEG changes during the recovery period of the mood state are analyzed, and a recognition model of the recovery degree of the mood state based on the characteristics of the electrocardiogram is constructed, and the ECG signal of the last 2 minutes of the rest period after exercise is used to detect the state of mind recovery during that period.

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