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A Support Vector Machine Algorithm-Based Study on Detection of Mental Training Anxiety in Basketball Players in a Co-Court Confrontation Center

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Abstract Basketball as a high-intensity confrontational sport, athletes' psychological quality directly affects competitive performance. In this study, we propose a multi-physiological signal fusion detection method based on support vector machine algorithm to address the difficulty of detecting anxiety in the same-court confrontation of basketball players. METHODS: Electroencephalography (EEG), electromyography (EMG) and electrodermal (EDA) signals were collected from 10 basketball players, and 1000 sets of data samples were obtained by watching different emotion-evoking videos. The Relief algorithm was utilized for feature selection to reduce the original 100-dimensional features to key features, and combined with support vector machine and least squares support vector machine for classification and recognition. RESULTS: The Relief-SVM algorithm reduced the EEG EMG fusion features from 30 to 15 dimensions, and the recognition rate of anxiety reached 83.355%, which was 9.121% and 9.357% higher than that of EEG and EMG alone, respectively. The three-signal fusion of ECG, EMG, and SCL improved the recognition accuracy from 79.58% to 92.65% after feature selection by SBFS. CONCLUSION: The multi-physiological signal fusion method effectively improves the anxiety detection accuracy, and the support vector machine algorithm performs well in processing small-sample high-dimensional data. The method can realize real-time monitoring of basketball players' anxiety and provide technical support for scientific adjustment of training tasks.

Index Terms Support vector machine, Basketball players, Anxiety detection, Multi-physiological signals, Feature fusion, Mental training

I. Introduction

Basketball is a same-court competitive, open-ended sport characterized by technique, precision, height, strength and speed, and human confrontation ability is its attraction and winning factor. As modern sports are in the development of high competition, it is not only necessary for players to have more advanced sports technology, but also higher requirements for their psychological quality [1], [2]. Athletes' basketball skills, training level, participation experience, psychological tolerance, motivation, tournament scale, arena size, and sensory perception are all important factors that produce psychological changes, by generating emotions such as uneasiness, lack of self-confidence, stress, and anxiety, thus affecting the effectiveness of their confrontation and even causing physiological injuries, whereas anxiety has a non-linear relationship with the outcome of the game [3]-[7]. Therefore, in the field of today's basketball competition, timely psychological adjustment and psychological training of athletes has become an important part of the whole training process, which plays a key role in athletes' game by relieving anxiety and reducing pressure [8]-[10].

In the second decade of the 20th century, a large proportion of studies on athletes' mental skills training and psychological counseling were conducted in core sports journals. However, some of the research results in recent years have shown that the overall level of psychological quality of some basketball players is low, the level of psychological training is generally low, and the phenomenon of random, unstructured psychological training or no psychological training at all is serious [11], [12]. In addition, in the traditional psychological training method, the training scene is seriously detached from the actual game scene, and the training effect is not ideal. Scale-based psychological level testing is highly subjective and has a serious lag. As the anxiety fluctuation coefficient is high in the hourly segment, it is difficult to capture emotions such as anxiety of athletes in complex dynamic environments [13]-[16]. It highlights the urgency of researching psychological training to shift to intelligent technology.

With the addition of intelligent technology, although anxiety emotion detection performs well in terms of speed and comprehensiveness, factors such as the interference of body collision and mental-emotional camouflage in the same field of confrontation still lead to a decrease in the correct rate of detection and are more unfavorable to real-time emotion detection [17], [18]. The support vector machine (SVM) algorithm, as a classical machine learning algorithm, has the advantages of strong generalization ability, performs well in high-dimensional space, can deal with nonlinear problems, and is effective for small sample data, which points out a new direction for the above problems [19].

Basketball is a same-court competitive, open-ended sport characterized by technology, precision, height, power and speed, and human confrontation ability is its attraction and winning factor. Modern sports are in the stage of high competitive development, which not only requires athletes to have advanced sports technology, but also the requirements for their psychological quality are constantly improving. Athletes' basketball skills, training level, participation experience, mental capacity, motivation, event scale, arena size, sensory perception, etc. are all important factors that produce psychological changes, through the production of restlessness, lack of self-confidence, pressure, anxiety and other emotions that affect the effect of their confrontation, and even cause physiological injuries, and anxiety and the results of the game is a non-linear relationship. Therefore, in the field of today's basketball competition, timely psychological adjustment and psychological training of athletes has become an important part of the entire training process, through the alleviation of anxiety, reduce pressure and so on, plays a key role in the game of athletes. In the second decade of the 20th century, the core journals of sports accounted for a large proportion of the research on athletes' psychological skills training and psychological counseling. However, some of the research results in recent years have shown that the overall level of psychological quality of some basketball players is low, the level of psychological training is generally low, and the phenomenon of random, unstructured psychological training or no psychological training at all is serious. In addition, in the traditional psychological training method, the training scene is seriously detached from the actual game scene, and the training effect is not ideal. Scale-based psychological level testing is highly subjective and has a serious lag. As the anxiety fluctuation coefficient is high in the hourly section, it is difficult to capture the anxiety and other emotions of athletes in the complex dynamic environment. With the addition of intelligent technology, although anxiety emotion detection performs well in terms of speed and comprehensiveness, factors such as the interference of body collision and mental emotion camouflage in the same confrontation still lead to a decrease in the correct rate of detection and are more unfavorable to real-time emotion detection. In this study, we propose a multi-physiological signal fusion detection method based on the support vector machine algorithm, which acquires physiological signals such as electroencephalogram, electromyography, and electrodermography, applies the Relief feature selection algorithm to screen key features, and combines with the support vector machine classification algorithm to realize the accurate identification of anxious emotions. The study designed an emotion-evoking experiment to obtain the physiological signal data under different anxiety states, established a multimodal physiological signal database containing EEG, EMG, EDA, and pre-processed the signals and extracted the features. The combination of Relief-kNN and Relief-SVM algorithms was used for feature selection and classification recognition, and the effects of different physiological signal combinations on the recognition effect were verified through multi-signal fusion experiments, which finally realized the real-time detection of anxiety and dynamic adjustment of training tasks for basketball players.

II. Experimental design and feature extraction

II. A. Selection of experimental material

In this study, the subjects' emotions were induced by selecting different emotional videos (happy, sad, and fearful). The selection of experimental materials is crucial to the effect of emotion elicitation, and the combination of audio-visual stimuli is more effective in eliciting emotional fluctuations.

II. B. Experimental design

The experiment was conducted in a room with good sound insulation and lighting. The EEG and EMG signals of the subjects were collected using the new electrophysiological amplifier SynAmps2 and 66-lead silver/silver chloride electrode caps, and the EDA signals were collected using the Biopac MP160 multilevel physiological recorder from the U.S. The sampling frequency of the three physiological signals was 1000 Hz.

A total of 10 basketball players were recruited as volunteers to participate in this experiment, and all subjects were healthy. The whole experiment was divided into 3 groups, and each group consisted of 3 segments of the same type of evoked material, and the duration of each segment of evoked material was 240s.

Subjects stayed relaxed and sat quietly on a chair about 1m away from the screen, avoiding eye movements as much as possible, and three different emotions were induced by watching three different types of evoked materials, namely happy, sad and fearful, which were divided into four time periods of 265s. 0-3s was the cue for subjects to pay attention to, and subjects were resting at this time; 3-5s was the cue for the imminent commencement of the experiment on the screen, and the corresponding evoked materials were played from 5 to 245s, and the corresponding evoked materials were played from 5 to 245s. The evoked material was played from 5 to 245s. After the material was played, the subjects had 20s to adjust themselves and calm down, and then clicked the left mouse button to play the next evoked material.

II. C.Preprocessing and Feature Extraction

In order to ensure the accuracy and stability of the data, the acquired EEG, EMG, and EDA signals were preprocessed and feature extracted respectively in this study.

II. C. 1) EEG signal preprocessing and feature extraction

As a weak physiological signal, the EEG signal is susceptible to the interference of ocular and electromyographic as well as industrial frequency noise during the acquisition process, so it needs to be accurately preprocessed to ensure the quality of the signal. In this study, the EEG signal was preprocessed using the EEGLAB toolbox, and the power spectral density (PSD) analysis of the EEG signal was performed using the Welch period estimation method to extract the PSD features of the five frequency bands: delta, theta, alpha, beta, and gamma. The sampling value of each small segment of the signal sequence set corresponding to the EEG signal lead was used for power spectral estimation, and then the average value was taken as the power spectral estimation of the whole sequence, which together with the label to which the signal belonged to obtain the feature matrix of the five frequency bands of the 60 leads. According to the evaluation questionnaire in the pre-experiment to establish the corresponding label matrix, the final PSD features of all subjects constitute a vector space with the dimensions of number of subjects × number of trials × number of leads × number of frequency bands, and all the PSD feature samples are normalized to establish a data matrix with 1632 dimensions to constitute the sample space for training the classifiers.

II. C. 2) EMG signal, electrodermal preprocessing and feature extraction

Since EMG signals can reflect changes in facial muscle activity, they were similarly standardized and preprocessed in this study. First, the EMG1 and EMG2 lead signals associated with the emotional state were retained, and high-pass (20 Hz), low-pass (400 Hz) and notch filtering (50 Hz) were applied to remove the noise. The posterior 60s signals of the 5-245s data segment of the emotional excitation were intercepted for time-domain feature extraction. Specifically, five time-domain features were extracted, namely, the mean EMG value, transition rate, integral EMG value, zero-crossing rate, and maximum magnitude of the brow and zygomatic muscles. The EDA signals were preprocessed using the built-in filtering and denoising functions of the Biopac MP160 device. The latter 60s signal of the 5-245s data segment of the emotional excitation was intercepted and used for time domain feature extraction. For the characteristics of EDA signals, only time-domain features were extracted in this study, including skin conductance level, skin electrical response amplitude, and skin electrical response frequency as indicators of emotional state classification.

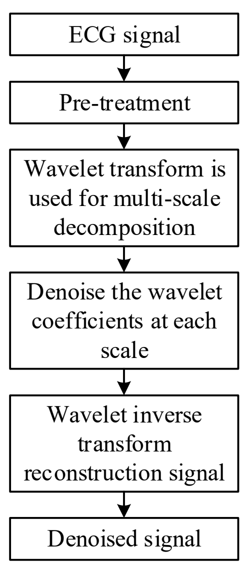

Figure 1: Flowchart of wavelet denoising

II. D.Database creation

II. D. 1) ECG signal preprocessing

In this study, wavelet transform is used to remove noise and interference. The wavelet transform provides the ability to analyze at multiple scales, capturing both local and global features of the signal. This makes wavelet thresholding denoising excellent in dealing with signals containing multiple frequency components and allows for more accurate localization and processing of noise [20]. The flow of ECG signal denoising using wavelet is shown in Fig. 1.

The wavelet transform of a continuous signal $x(t)$ is defined as:

$$WT_x(a,\tau) = \int_R x(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-\tau}{a}\right)dt \tag{1}$$

where $\psi_{(t)}$ is the wavelet function, and a and τ are the scale factor and translation factor, respectively.

The inverse transform of continuous wavelet transform exists on the premise that the chosen wavelet function must satisfy the tolerance condition. The tolerance condition formula is as follows:

$$C\psi = \int_{-\infty}^{+\infty}\frac{|\psi(\omega)|^2}{|\omega|}d\omega < \infty \tag{2}$$

The formula for the inverse transformation is then:

$$x(t) = \frac{1}{C\psi}\int_0^{+\infty} WT_x(a,\tau)\frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right)\frac{1}{a^2}d\tau \tag{3}$$

Continuous wavelet transform is computationally intensive and is not suitable for digital signal processing, therefore, it is necessary to transform the continuous wavelet into a discrete wavelet transform, which decomposes the signal into a series of wavelet coefficients on discrete scales.

The discrete wavelet transform of signal $x(t)$ is:

$$WTx(m,n) = \int x(t)a_0^{-m} /_2\, \psi(a_0^{-m}t - n\tau_0)dt \tag{4}$$

II. D. 2) Pre-processing of electrical skin signals

Similarly EDA signals also receive noise or other external factors interference during the acquisition process, so it is also necessary to denoise the EDA signals. The effective frequency of the EDA signals is between 0.02-0.2 Hz, so sym4 wavelet is chosen to perform a three-layer wavelet decomposition of the dermatoelectric signals. Subsequently, the signal is de-noised using the wdencmp function. The process of discrete wavelet transform (DWT) was performed to decompose the original signal into wavelet coefficients at different scales. After wavelet decomposition, the wavelet coefficients are thresholded. After thresholding, the processed wavelet coefficients are inverted. This gives the signal after removing the noise, thus realizing the reconstruction of the signal. Where A represents the low frequency component of the signal and D represents the high frequency part of the signal [21]. The three-layer wavelet decomposition structure is shown in Fig. 2.

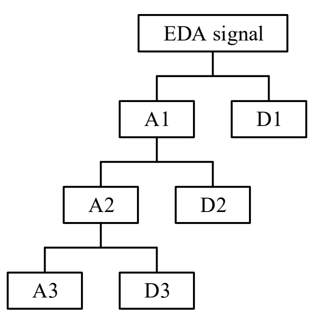

Figure 2: Three-layer wavelet decomposition structure diagram

II. D. 3) Data set construction

After preprocessing the ECG and EDA signals, valid samples were screened from the data of 10 participants, and samples with abnormalities such as electrode tabs falling off or missing signals during the experiment were excluded. Among these valid samples, the samples were screened based on the criteria that the mood ratings conformed to the 2D mood model (HAHV, HALV, LAHV, LALV), and only those samples whose rated moods corresponded to the music-induced moods were selected.

II. E. ECG Signal Feature Extraction

A typical ECG waveform consists of a P-wave, a QRS complex wave, and a T-wave. In order to extract the time domain features from the ECG waveform, it is necessary to first detect the P-wave, QRS complex wave, and T-wave from the electrical waveform. Detection of R-wave, P-wave, Q-wave, S-wave, and T-wave from the ECG waveform is shown in Fig. 3.

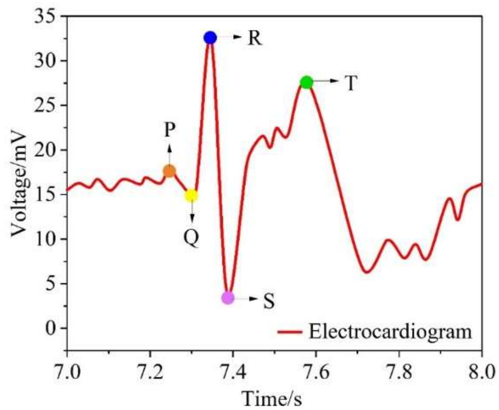

Figure 3: Electrocardiogram detection

II. E. 1) Respiratory signal characteristics

Before extracting the characteristics of the respiratory signal, the peaks and troughs of the respiratory wave are identified. Rising from the trough to the peak is the inspiratory segment, and falling from the peak to the trough is the expiratory segment. Due to the low frequency of the respiratory signal, the respiratory waveform has been smoothed after 0.45 HZ low-pass filtering in the pre-processing stage of the respiratory signal, and the location of the respiratory waveform peak (trough) can be obtained based on the first-order difference at the peak (trough) and the first-order difference at the point succeeding the peak (trough), and the peaks and troughs of the respiratory waveforms can be detected as shown in Fig. 4. A total of 156 time-domain or frequency-domain features are extracted from the respiratory waveform.

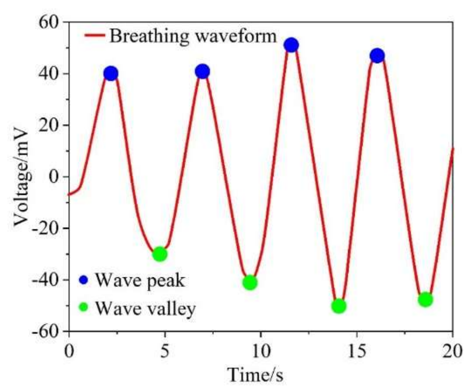

Figure 4: The wave and wave valleys are detected from the waveform of the breath

II. E. 2) Pulse wave characteristics

A typical pulse waveform contains a main wave, a pre-pulse wave, a descending mid-channel, and a re-pulse wave. Before extracting the features of the pulse wave signal, the locations of the main wave, the precession wave and the rewave of the pulse wave are determined. First of all, all main wave, precession wave and repulsive wave locations are obtained based on the first say difference at the wave crest and the first order difference at the point succeeding the wave crest, i.e., the dissimilar sign. Since a main wave is immediately followed by a heavy beat front wave and a heavy beat wave, and the main wave amplitude is the highest, the heavy beat front wave is the second, and the heavy beat wave is the lowest, we can connect all the wave peaks to form an envelope, and then find the wave peaks of this envelope, i.e., we get the position of the main wave. The top two waveforms among all the waveforms between the two main waves are the pre-pulsation waveform and the re-pulsation waveform, respectively. The detection of the main wave, the pre-pulse wave and the re-pulse wave from the pulse wave is shown in Fig. 5. After accurately locating the position of the main and heavy beat waves of the pulse wave, a total of 70 time or frequency domain features were extracted from the pulse wave.

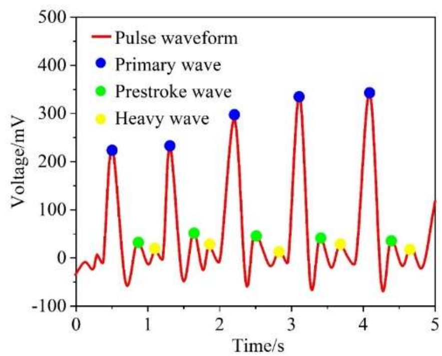

Figure 5: Main wave, prestroke and weight

III. Multi-physiological signal-based algorithm for recognizing anxiety mood states

III. A. Feature selection

Feature selection is to select the smallest possible subset of features while satisfying the two conditions of not significantly reducing the accuracy of classification and not significantly changing the class distribution. The feature selection framework is shown in Figure 6.

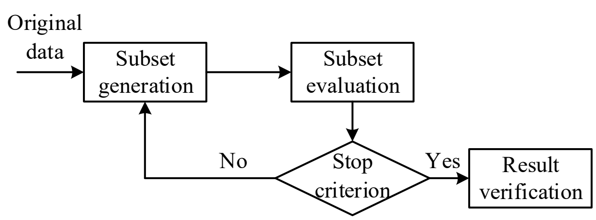

Figure 6: Feature selection framework diagram

III. B. Relief Feature Selection Algorithm

Relief algorithm avoids heuristic search by a statistical method. The computational complexity of Relief algorithm is $O(tmN)$ (t is the number of attempts, n is the number of samples, and N is the number of alternative attributes), and its computational effort is significantly reduced in comparison to other algorithms.

The sample interval is the minimum distance that represents the sample from the decision surface. It is assumed that the interval is the maximum distance that the decision surface can be moved if the sample classification is constant. That is:

$$\theta = \frac{1}{2}(\| x - M(x) \| - \| x - H(x) \|) \tag{5}$$

where $M(x), H(x)$ are the closest points to x of like and unlike respectively.

The hypothesis interval is simple to compute compared to the sample interval and evaluates the classification ability of various attributes of the features. The Relief algorithm uses the computation of the hypothesis interval of the samples to estimate the subset of features that are most favorable for classification.

The Relief algorithm randomly selects m samples from the training sample, computes the hypothesis interval and accumulates it as the weights of each dimension of the final feature, the update of the weights of the feature p of a dimension in the sample x is:

$$W_p^{i+1} = W_p^i - diff(p, x, H(x)) / m + diff(p, x, M(x)) / m \tag{6}$$

If p is discrete, then:

$$diff(p, x, x') = \begin{cases} 0, & x_p = x'_p \\ 1, & x_p \neq x'_p \end{cases} \quad x = (x_1, \ldots, x_N) \tag{7}$$

If p is continuous, then:

$$diff(p,x,x^{'})=\frac{|x_p-x_p^{'}|}{\max(p)-\min(p)} \tag{8}$$

where $\max(p),\min(p)$ are the upper and lower bounds of p, respectively.

III. C. kNN classification algorithm

In the field of pattern recognition, the kNN algorithm is a method of classification using the closest distance of the training samples in the feature space [22]. kNN algorithm is schematically shown in Fig. 7. In the figure triangles and squares are known categories of sample points, here we assume that triangles are positive categories and squares are negative categories. Circles are data of unknown category.

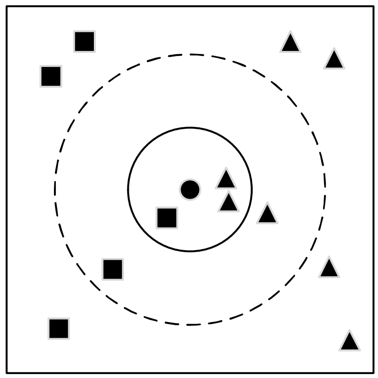

Figure 7: Schematic diagram of the KNN algorithm

III. D. Relief-kNN algorithm combined application

Since both Relief algorithm and kNN algorithm have relatively small computational complexity and are easy to implement, they are combined to perform the analysis of preliminary feature selection and classification of the physiological signal data collected from the experiment. The detailed procedure of the combination of the two algorithms is as follows:

Step 1 Initialize the feature weight values and set the number of selected similar and non-similar nearest neighbors.

Step 2 Calculate the weights of the features in each dimension using Relief, and eliminate the features with smaller weights.

Step 3 Classify the selected feature vectors using kNN algorithm.

Step 4 Get the classification result and compare it with the actual result to calculate the recognition rate.

Step 5 Adjust the parameters to know the optimal recognition rate, so as to determine the final algorithm model.

III. E. SVM Algorithm

III. E. 1) Classical Support Vector Machine Algorithm

The basic idea of support vector machine is to take sample points that are difficult to classify in N-dimensional space and distinguish different classes of sample points in higher dimensions by finding a plane that is most favorable for classification [23].

In this algorithm, the choice of kernel function has a crucial role. It exists mainly to improve the computational efficiency of the algorithm. This is because transferring the computation from a low-dimensional space to a high-dimensional space leads to an increase in computation and a decrease in computational efficiency. Therefore, it is necessary to choose a suitable kernel function that is conducive to improving efficiency, and the support vector machine algorithms applied using different kernel functions are also different.

In this paper, the Gaussian kernel function is used, namely:

$$K(x,x_i)=[(x\times x_i)+1]^q \tag{9}$$

The size of the kernel function depends on the size of the difference between x and z, if the two are close, the value of the kernel function is close to 1, if the difference between the two is larger, the value of the kernel function is closer to 0.

And the biggest difference between the least squares support vector machine and the classical support vector machine is the difference in their optimization problems, i.e., from:

$$\begin{aligned} &\min_{w,b,e} J(w,e)=\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum_{k=1}^{N}e_k^2 \\ &s.t.\quad y_k[w^T\varphi(x_k)+b]\geq 1-e_k,\quad k=1,2,...,N \end{aligned} \tag{10}$$

Shift to:

$$\begin{aligned} &\min_{w,b,e} J(w,e)=\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum_{k=1}^{N}e_k^2 \\ &s.t.\quad y_k[w^T\varphi(x_k)+b]\geq 1-e_k,\quad k=1,2,...,N \end{aligned} \tag{11}$$

III. E. 2) Least Squares Support Vector Machine (LS-SVM)

The least squares support vector machine method is derived as follows: $\left\{(x_k,y_k)\,|\,x_k\in R^n, y_{ki}\in\{-1,+1\}\right\}_{k-1}^{N}$ is the sample set, where x_k is the input vector (n-dimensional) and y_k is the output scalar (one-dimensional). The sample set is obtained by mapping nonlinearly into a higher dimensional space:

$$y(x)=w^T\phi(x)+b \tag{12}$$

Then the next step is to make it based on the principle of minimizing structural risk:

$$\begin{aligned} &\min_{w,b,e} J(w,e)=\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum_{k=1}^{N}e_k^2 \\ &s.t.\quad y_k[w^T\varphi(x_k)+b]=1-e_k,\quad k=1,2,...,N \end{aligned} \tag{13}$$

where $\gamma>0$, determines the degree of penalization for samples that exceed the error, and e_k serves to control the error.

The Lagrangian method is used to solve this problem, i.e.:

$$L(w,b,e;a)=\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum_{k=1}^{N}e_k^2-\sum_{k=1}^{N}a_k\left\{y_k\left[w^T\varphi(x_k)+b\right]-1+e_k\right\} \tag{14}$$

In the above equation, the Lagrange multiplier $a_k\geq 0,(k=1,2,...,N)$. Is obtained according to the optimization conditions:

$$\begin{cases} \dfrac{\partial L}{\partial w}=0\rightarrow w=\sum_{k=1}^{N}a_k y_k\varphi(x_k) \\ \dfrac{\partial L}{\partial b}=0\rightarrow \sum_{k=1}^{N}a_k y_k=0 \\ \dfrac{\partial L}{\partial e_k}=0\rightarrow a_k=\gamma y_k,(k=1,2,...,N) \\ \dfrac{\partial L}{\partial a_k}=0\rightarrow y_k\left[w^T\varphi(x_k)+b\right]-1+e_k=0 \end{cases} \tag{15}$$

Eq. then translates into solving the following matrix equation:

$$\begin{bmatrix} J & 0 & 0 & -Z^T \\ 0 & 0 & 0 & -Y^T \\ 0 & 0 & \gamma I & -I \\ Z & Y & I & 0 \end{bmatrix}\begin{bmatrix} w \\ b \\ e \\ a \end{bmatrix}=\begin{bmatrix} 0 \\ 0 \\ 0 \\ l_v \end{bmatrix} \tag{16}$$

where $Z=[\varphi(x_1)^T y_1,\varphi(x_2)^T y_2,\ldots,\varphi(x_N)^T y_N]$, $Y=[\gamma_1,\gamma_2,\ldots,\gamma_N]$, $lv=[1,1,\ldots,1]$, $e=[e_1,e_2,\ldots,e_N]$, $a=[a_1,a_2,\ldots,a_N]$.

The optimization problem is transformed into solving the linear equation, i.e:

$$\begin{bmatrix} 0 & Y^T \\ Y & ZZ^T + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ l_v \end{bmatrix} \tag{17}$$

Again, using Mercer's principle, it is obtained:

$$\Omega = y_k y_l \varphi(x_k)^T \varphi(x_l) = \psi(x_k, x_l) \tag{18}$$

III. F. Combined Relief-SVM Algorithm Application

Since the SVM algorithm performs well and has advantages in the processing of the small sample data obtained in this paper, the Relief-SVM algorithm is used in this paper for feature selection and classification recognition under the state of anxiety emotion by using the collected multi-physiological signal data, and the detailed process is as follows:

Step 1 Initialize the feature weight values and set the number of selected similar and non-similar nearest neighbors.

Step 2 Calculate the weights of the features in each dimension using Relief, and eliminate the features with smaller weight values.

Step 3 Train the selected feature vector with SVM algorithm for learning and compute the classification.

Step 4 Get the classification results and compare them with the actual results to calculate the recognition rate.

Step 5 Adjust the relevant parameters of Relief algorithm and repeat the test until the optimal recognition rate is reached, and establish the corresponding algorithm model.

IV. Empirical studies

IV. A. Performance testing experiments

IV. A. 1) Relief-kNN-based research and applications

In order to reduce the computational difficulty of the classifier as well as to improve the recognition rate, the fusion features need to be selected and the optimal fusion features need to be chosen. The method of this paper is used to select the optimal features for EMG and EEG data.

(1) Relief-kNN-based feature selection

Firstly, the features are individually tested to initially screen the features, and then the Relief-kNN is used to select the fusion features to finally find the optimal fusion features. Acquisition experiments to obtain two kinds of physiological signals of EMG and EEG, 10 testers collected a total of 1000 groups of data samples, 550 groups of calm state physiological samples, and 225 groups of anxiety samples of three different degrees. A total of 100-dimensional features were extracted from the raw data, respectively, 10-dimensional features of 2 EMG channels (IEMG, WL, SSI, DASDV, WAMP, MF, MPF, RMSF, IMDF, IMNF) totaling 20 dimensions, and 8-dimensional features of 10 EEG channels (WL, DASDV, WAWP, MF, MPF, SC, LZC, SampEn) totaled 80 dimensions. Both EEG and EMG signal data were acquired synchronously in a time series, but the sampling frequencies of the EEG and EMG acquisition devices were 500 Hz and 2000 Hz, respectively, to ensure the unity of EMG and EEG sample features in the time domain. To minimize the error, a five-fold cross-validation method was used. The samples D were randomly divided into five groups, and one group was randomly selected as the test set each time, and the remaining four groups were the training set, so that five classification models were finally obtained, and the classification recognition rate and the computation time obtained from the test were averaged, which were recorded as the final classification recognition rate CV, as well as the final computation time T. Individual Feature TestsThe results of the individual tests for the anxiety-emotion features are shown in Table 1.

Firstly, the individual feature data were input into the SVM classifier separately for classification to verify the feature classification effect, and the feature extraction time, classification time, and classification rate were taken as the indexes to screen the features. The highest classification rate of individual features is EMGRMSF is 69.65%. In terms of feature extraction time, the time domain and frequency domain feature extraction time of EMG signal is generally between 0.08-0.18 seconds, but the extraction time of IMDF, and IMNF features decomposed by VMD is more than 1 second, which is relatively time-consuming. The EEG signal channels are more, and the data volume is also relatively large compared to EMG, so the EEG signal extraction time is generally between 2.3-6.9s. In terms of classification time, the times are all relatively short. Although the feature extraction time of EEG signals is higher than that of EMG, the classification rate of some features of EEG signals is also higher, so this paper also needs to include EEG features in the combination analysis. The features with individual recognition rate above 65% are selected based on the classification rate, which are EMGRMSF, EMGIMNF, EEGLZC, EMGIEMG, EEGSampEn, and EMGIMDF.

Table 1: The anxiety emotion characteristics were tested separately

Feature name	Feature extraction average time (s)	Classification time (T/s)	Classification rate (CV)
EMG_IEMG	0.09894	0.01355	0.68307
EMG_WL	0.13955	0.01078	0.59447
EMG_SSI	0.10631	0.04612	0.58048
EMG_DASDV	0.19912	0.02955	0.46471
EMG_WAMP	0.18059	0.02273	0.56645
EMG_MF	0.14637	0.00733	0.56992
EMG_MPF	0.13852	0.01494	0.38931
EMG_RMSF	0.14567	0.02075	0.69651
EMG_IMDF	1.38494	0.06298	0.69007
EMG_IMNF	1.25719	0.00575	0.68499
EEG_WL	2.68322	0.0371	0.53749
EEG_DASDV	2.82737	0.00532	0.44414
EEG_WAMP	2.67108	0.04123	0.53493
EEG_MF	2.64246	0.05361	0.57069
EEG_MPF	2.54593	0.04149	0.44701
EEG_SC	5.67001	0.1008	0.55133
EEG_LZC	5.66641	0.0857	0.68031
EEG_SampEn	6.51125	0.03918	0.66144

(2) Relief-kNN feature selection

Four EMG features were obtained from the individual feature testing experimental trials as RMSF, IMNF, IEMG, IMDF, and two EEG features as LZC, SampEn. The EEG signals have 10*2=20 dimensional features, and the EMG signals have 2*4=8 dimensions, for a total of 28 dimensional features. The experimental data were compared in three separate experiments: a. Only the combined features of EMG signals were used as the sample set. b. Only the feature combinations of EEG signals were used as the sample set. c. The combined features of EMG and EEG were used as the sample set. d. The sample set of EEG signals was compared with the sample set of EMG signals. The above sample sets are individually implemented with Relief-kNN feature selection method for feature selection, and the selected features are input into the multiclassification support vector machine for classification. The classification results of the algorithm are shown in Table 2. The original features of EEG and EMG are reduced to 10 dimensions and 4 dimensions using the method of this paper, corresponding to an average recognition rate of 74.99% and 72.36%. And the original features of EEG and EMG can be reduced from 28 dimensions to 16 dimensions by the method of this paper, and the recognition rate is 77.05%, which is relatively improved by 2.06% and 4.69% compared to EEG and EMG alone. The following conclusion can be drawn that the experimental data of the combination of EEG and EMG has a higher recognition rate relative to a single signal. Using the method of this paper can reduce the feature dimensions to some extent and reduce the computational amount and difficulty of the classifier.

Table 2: Classification results

Physiological signal	Primary characteristic number	Selection characteristic number	Average recognition rate (%)
EMG	9	5	72.36
EEG	22	8	74.99
EEG+EMG	30	15	77.05

(3) Selection of EEG channels based on Relief-kNN features

The results of the optimal selection of EEG channels are shown in Table 3. The optimal EEG channels of different subjects are very different, indicating that there are individual differences between different subjects, but there is a common feature in the top six optimal EEG channels, which is that they all have PP1, FP2, FC5, and F8, which indicates that although there are individual differences between different subjects, the same EEG channels can be found to study the anxiety condition. This is similar to the results of feature selection via Relief-kNN above. In addition, it can also be seen from the table that the classification recognition rate of EEG multi-feature combination is improved compared to the classification recognition rate of single feature.

Table 3: The optimal choice of brain electric channel

Crew number	The optimal anterior hexone	Classification accuracy (%)
1	FP2, FP1, FT10, FT9, FC5, F8	75.27
2	F8, FC5, FC6, F3, FC2, FC1	72.38
3	FP1, FP2, F4, FT10, F8, FC5	74.05
4	FP2, F8, F3, FP1, FC5, FT10	72.25
5	FC5, FP1, FT9, F7, FP2, F8	76.43
6	FP1, F3, F4, F8, FC5, FP2	78.62
7	FP2, FP1, FT9, FT10, F8, FC5	74.68
8	FT10, F3, FP1, FP2, FC5, F8	70.27
9	F7, FP1, F8, FP2, FC5, FT10	76.69
10	FP1, F3, F4, F8, FC5, FP2	74.63

IV. A. 2) Anxiety state assessment based on Relief-SVM algorithm

The brain and EMG fusion feature vectors selected using the Relief-SVM algorithm are inputted into a multiclassification support vector machine to finally realize the anxiety state assessment. The results of different signal feature fusion recognition are shown in Table 4. The average recognition rates of EMG combined features alone and EEG combined features alone are 73.998% and 74.234%, respectively, and the average recognition rate of EEG and EMG fusion features is 83.355%. The recognition rates of both EEG and EMG fusion features are higher than those of EEG alone and EMG alone features, which indicates that the introduction of EEG signal features can improve the recognition rate of EMG signals, and also confirms that multimodal fusion features have a higher recognition rate than unimodal features. From the table, it can also be found that the recognition rate of anxiety state is relatively high for No. 10 tester and relatively low for No. 5 tester, indicating that individual differences between different testers can affect the recognition results.

Table 4: Different signals feature fusion recognition results

Tester number	Individual EMG fusion characteristics	Individual EEG fusion characteristics	EMG+ EEG fusion feature
1	73.45	72.73	82.15
2	75.68	76.85	84.83
3	74.38	73.32	82.97
4	72.66	72.64	81.34
5	69.46	70.77	78.48
6	71.33	72.53	82.21
7	75.03	76.35	85.2
8	72.88	70.19	81.63
9	76.36	77.95	86.85
10	78.75	79.01	87.89
Mean	73.998	74.234	83.355

IV. A. 3) Experimental protocol and analysis of training task adjustment based on online assessment of anxiety state

Take the training process of three cycles of the training task of one of the testers as an example, first of all, assume that the basketball training task T1 is a normal training task, after training the testers should produce moderate anxiety, through the collection equipment will be transmitted to the host computer, at this time, should be able to identify the anxiety state S1 for moderate anxiety state. As three consecutive cycles of training task difficult are training normal task, at this time the tester will think that the task difficulty is too light and produce mild anxiety, so S2, S3 emotion recognition state is moderate anxiety, mild anxiety, respectively. At this time, it is necessary to increase the difficulty, according to the rules set the task T4 as overweight task, after which the experimenter will recognize S4 as severe anxiety after training. Because the training difficulty of the overweight task is too heavy, even if the difficulty is reduced for a short period of time, it is still severe anxiety. According to the rule, it is necessary to reduce two difficulties to regulate, i.e., the training tasks of T5 and T6 are normal task and too light task, and the recognized state of S5 and S6 should be severe anxiety and mild anxiety. According to the previous analysis T7 will be set as a normal task, S7 state is the same as S1 as moderate anxiety, after that T8 and T9 are normal tasks, while S8 and S9 states are moderate anxiety and mild anxiety respectively. The training difficulty and anxiety in different cycles are shown in Figure 8. It can be seen that the method of this paper can identify the anxiety mood state and adjust the training difficulty according to the identified anxiety mood state, which can ensure that most of the time of the training task can be in the normal task stage, greatly improving the training efficiency of the experimenter.

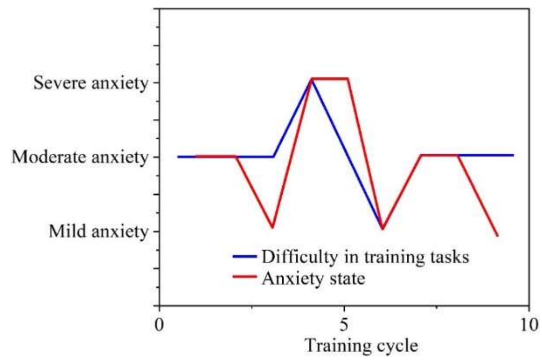

Figure 8: Training difficulty and anxiety in different cycles

IV. B. Multi-signal fusion experiment

The three physiological signals have different properties and there is an interaction relationship between them. In the following, we will try to group the three signals in a fusion experiment to explore the mutual influence relationship between the signals. The way of combination is to splice the features of the three signals, and there are four combinations of ECG+EMG+SCL, ECG+EMG, ECG+SCL and EMG+SCL. The best features of the three signals in the first experiment filtered by SBFS were spliced according to different combinations, and the resulting number of features were 24, 17, 14, and 17, respectively. The spliced features were then processed separately using SBFS to select more characterizing features. The three signal features in the control group were spliced without further SBFS feature selection. There were a total of eight SVM classifiers whose hyperparameters were grid-searched to achieve their respective better results. The comparison of different signal combinations (average accuracy) is shown in Fig. 9. The comparison of different signal combinations (accuracy and standard deviation) is shown in Table 5. As can be seen from the figure, without SBFS, the best accuracy of 79.58% is achieved by splicing 7 features of ECG with 10 features of EMG and 7 features of SCL. The performance is not improved but rather decreased compared to the best accuracy of 81.75% for ECG classifier alone. The redundant features affect the performance of the whole classifier. At this point, the performance of both SCL and EMG after splicing ECG features separately both classifiers are significantly improved, proving that ECG contains the richest information and plays a facilitating role for EMG and SCL. When SBFS is used, the performance of the classifiers for all four signal combination methods is substantially improved. Among them, the ECG+EMG+SCL classifier has the most performance improvement, from 79.58% without SBFS to 92.65%, with a total of 10 selected features, including Mean_cA_ECG, Max_cA_ECG, Min_cA_ECG, Var_cD_ECG, Mean_cA_EMG, Max_cA_EMG, Min_cA_EMG, Max_cD_EMG, Var_cD_EMG, and Max_cA_SCL. The combination of EMG+SCL has the least performance improvement of the classifier. The experimental results show that even if each of the three signals ECG, EMG and SCL is filtered with the optimal features, there is still redundancy after splicing the different combinations of features, and the spliced features need to be processed. The three signals ECG, EMG and SCL contain different information that can promote each other, and they reflect the change of emotions from different aspects. Among them, the combination of ECG+EMG+SCL contains the most information, and the most emotion-representative features can be selected from them by sifting out redundant features through SBFS, in which the statistical features extracted from the detailed and approximate signals after the signal wavelet transform are the most reflective of changes in emotion.

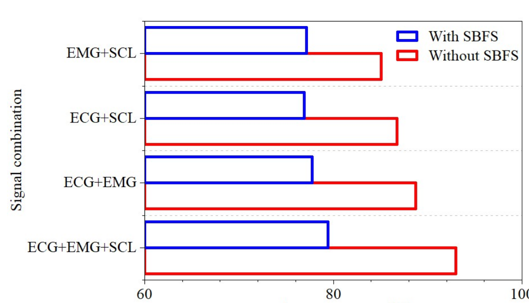

Figure 9: Comparison of different signals (Average accuracy)

Table 5: Comparison of different signals (Accuracy and standard deviation)

Signal combination	ECG+EMG+SCL		ECG+EMG		ECG+SCL		EMG+SCL	
Accuracy	92.65	79.58	98.65	78.65	86.66	76.98	86.98	77.84
SD	2.81	2.96	3.11	2.62	3.15	1.98	4.82	3.95

V. Conclusion

The support vector machine algorithm shows superior performance in the detection of basketball players' anxiety. The effectiveness of the multi-signal fusion method was confirmed by analyzing and processing 1000 sets of multi-physiological signal data from 10 basketball players. The average recognition rates of EMG combined features and EEG combined features alone are 73.998% and 74.234%, respectively, while the average recognition rate of EEG fusion features reaches 83.355%, which significantly improves the detection accuracy. The Relief-kNN method successfully reduces the original features of EEG and EMG from 28 dimensions to 16 dimensions, while maintaining a recognition rate of 77.05%. In the multi-signal fusion experiment, the three-signal combination of ECG, EMG, and SCL is screened by SBFS features, and the accuracy rate reaches 92.65%, of which the standard deviation is only 2.81%, which indicates that the system has good stability. The training task adjustment experiment based on the online assessment of anxiety state verifies that the method can monitor the changes of athletes' anxiety in real time, dynamically adjust the training difficulty according to the identification results, ensure that the training task is kept in the normal difficulty stage most of the time, and effectively improve the training efficiency. This technique provides a scientific and objective assessment tool for the psychological training of basketball players, which is of great value for improving athletes' competitive performance.

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