Scientific
Research

Mood States Recognition of Rowing Athletes Based on Multi-Physiological Signals Using PSO-SVM

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Abstract

Athletes have various emotions before competition, and mood states have impact on the competition results. Recognition of athletes' mood states could help athletes to have better adjustment before competition, which is significant to competition achievements. In this paper, physiological signals of female rowing athletes in pre- and post-competition were collected. Based on the multi-physiological signals related to pre- and post-competition, such as heart rate and respiration rate, features were extracted which had been subtracted the emotion baseline. Then the particle swarm optimization (PSO) was adopted to optimize the feature selection from the feature set, and combined with the least squares support vector machine (LS-SVM) classifier. Positive mood states and negative mood states were classified by the LS-SVM with PSO feature optimization. The results showed that the classification accuracy by the LS-SVM algorithm combined with PSO and baseline subtraction was better than the condition without baseline subtraction. The combination can contribute to good classification of mood states of rowing athletes, and would be informative to psychological adjustment of athletes.

Keywords

1. Introduction

For athletes, it is easy to have pressure and various emotional reactions in the competitive environment [1]. They can have different mood states during different periods of time of one week before competition [2]. Some emo-

tion can have positive impact on the athletes, such as vigor and confidence, but some can have just the opposite impact, such as tension, anger, fatigue, depression, confusion, etc. Different mood states have diverse impact on the competition results of the athletes [3]. If the positive emotion is intense and the negative emotion is not obvious, the mood states of the athletes are considered to be positive. Otherwise, the mood states of the athletes are negative. For the latter condition, the coach and other related staff should take some actions such as psychological intervention and adjustment training before competition to help the athletes to relieve from the bad mood and take good preparations for the competition. So the examination of athlete's behavioral, and emotional responses are an essential part of sport psychology [4].

As an outward manifestation of psychological states, people usually express their emotion through language, intonation, facial expression, behavior, breathe and other reactions of body [5]. It is convenient to judge the emotion of one person through the face expression or gestures, but the real internal mood states of one person cannot be observed in this way if they are reluctant to express themselves obviously. However, the physiological signals are a kind of bio-electricity signals or bio-impedance signals, which are regulated by human automatic nervous system and endocrine system, and cannot be easily influenced by the society features [6]. Ekman *et al.* proved that autonomic nervous system activity distinguishes among emotions [7]. Picard *et al.* first proposed a series of methodologies for the emotion recognition from the variation of physiological signals, through application of many effective algorithms in signal processing and pattern recognition, such as feature extraction and classification. They used Fisher Projection with Sequential Floating Forward Search to classify 40 original features extracted from 4 physiological signals to recognize 8 kinds of emotion, and reached the accuracy of more than 80% [8]. Based on the same physiological data, Healey and Picard extracted 11 original features and investigated Fisher linear discriminant and the leave one out test algorithm in recognizing emotions, and found that anger was well differentiated from peaceful emotions (90% - 100%), but positive and negative valence states were difficult to distinguish (50% - 82%) [9]. In recent years, along with the development of the non-invasive detecting methods and devices, more researches engaged in this field and proved the reliability of emotion recognition from the multi-physiological signals. Kim and his colleagues collected physiological signals of 50 subjects and used SVM classifier to recognize three kinds of emotions and reached the accuracy of 78.4% [10]. Lisetti with his team used a wireless noninvasive wearable computer to collect physiological signals and mapped these data to emotional states to model the patients' emotions for patient care [11]. To improve driving safety, Fatma and his co-workers developed a multi-model intelligent system to recognize the driver's emotions [12]. And according to its judgment, it would use some multi-media technologies to relieve the negative moods.

The mood states of athletes are usually estimated by the observation of coach through their facial expressions or behaviors, and the judgment correctness is influenced by the athletes' desire to express themselves [13]. Some researchers have estimated the mood states of athletes according to the function state of the athletes' brain through event-related potentials (ERP) [14] or Electroencephalograph (EEG) [15], and found that there are differences of characteristics of information processing, brain function and the brain nerve cell metabolic mode of athletes between different sport events and different technical levels, but the data collection and analysis are inconvenient. The traditional algorithms of feature selection are like Fisher, sequential forward selection and sequential backward selection, which are of the calculation slow and poor convergence shortcomings. The particle swarm optimization (PSO) algorithm can overcome these shortcomings with good robustness [16]. The support vector machine (SVM) is a kind of mature method of classification and the least squares support vector machine (LS-SVM) is of better speed of calculation and the same good learning performance with SVM [17]. So the combination of the two algorithms is reasonable. This paper focuses on recognizing the mood states of athletes by using their physiological signals. First, the features were extracted from the physiological signals which had been subtracted the baseline. Then the PSO algorithm was adopted to optimize the features selection from the features of multi-physiological signals, which proved to be useful to optimize the feature selection of signals, and combined with LS-SVM classifiers to recognize positive and negative mood states. A brief introduction of the algorithms is first presented, following the physiological signals collection and feature extraction method. Finally results are shown and discussed.

2. Method

2.1. Particle Swarm Optimization, PSO

The most important parts of emotion recognition are the algorithms of feature selection and classification. Fea-

ture selection includes the removal of non-informative terms according to corpus statistics, and the construction of new features. Eberhart and Kennnedy developed a kind of algorithm through simulating social behavior [16] [18]-[20], which was particle swarm optimization, since it resembled a school of flying birds. The concept comprised in PSO is very simple, and can be implemented in a few lines of computer code. So it is used in this paper to realize the optimal selection of features.

In a particle swarm optimizer, each particle treated as a point in a D-dimensional space, adjusts its flying according to its flying experience and its companion' flying experience. The *i*-th particle is represented as $X_i = (x_{i1}, x_{i2}, x_{i3}, …, x_{iD})^{\text{T}}$. The best previous position of any particle is recorded and represented as $Pbest_i = (pbest_{i1}, pbest_{i2}, pbest_{i3}, …, pbest_{iD})^{\text{T}}$. The index of the best particle among the parties in the population is represented as $Gbest = (gbest_1, gbest_2, gbest_3, …, gbest_D)^{\text{T}}$. The particles are manipulated according to the following equations:

$$V_i^{n+1} = w \times V_i^n + C_1 \times rand_1(\ ) \times \left(Pbest_i - X_i^{\ n} \right) + C_2 \times rand_2(\ ) \times \left(Gbest - X_i^{\ n} \right) \tag{1}$$

$$X_i^{n+1} = X_i^{\ n} + V_i^{\ n} \tag{2}$$

where w is a inertia weight factor, usually from 0.4 to 0.9. C1 and C2 are two positive constants; $rand_1()$ and $rand_2()$ are two random functions in the range of [0, 1]. In Equation (3), the inertia weight factor can regulate to insure convergence of the PSO, which is

$$w(t) = w_{\max} - \left(w_{\max} - w_{\min} \right) \times \frac{T}{T_{\max}}, T = 1, 2, ..., T_{\max} \tag{3}$$

In this paper, the original value was got by inertia weight factor algorithm, and *w* was initialized as 0.729, $C_1 = C_2 = 1.494$. Usually $V_i \in [-V_{\max}, V_{\max}]$ to make sure the particle's location is global and the possibility of get the best fitness.

Kennedy and Eberhart published the discrete binary version of PSO in 1997 [21], which used the binary variables to present the position of grain, and trajectories are changes in the probability that a coordinate will take on a zero or one value. The change in position then is defined by the following rule:

$$\begin{cases} x_{id} = 1, & if \quad rand < S\left(v_{id} \right) \\ x_{id} = 0, & \text{else} \end{cases} \tag{4}$$

where the function $S(v)$ is a sigmoid limiting transformation and *rand*() is a quasirandom number selected from a uniform distribution in [0.0, 1.0].

2.2. Support Vector Machine, SVM

Support vector machine was developed by Vapnik in 1963 [22] and had been introduced for solving pattern recognition problems in 1990s [23]. In this algorithm, one maps the data into a higher dimensional input and one constructs an optimal separating hyperplane in this space. This basically involves solving a quadratic programming problem, while the existence of many local minima influent gradient based training methods for neural network architectures. The essential part of this algorithm is the kernel function. Sample classification is hard to be done in a low dimensional space, but it is easy to be finished in a higher dimensional input. Using a right kernel function can reduce the computation complexity. In this paper, RBF function was used as the kernel function [24].

For the function estimation problem, a support vector interpretation of ridge regression has been given in. This means equality type constraints instead of inequalities from the classical SVM approach is considered. So the solution is got by solving a set of linear equations instead of quadratic programming. In least squares SVM (LS-SVM) [23] the support values are proportional to the errors, which is different from that in classical SVM, where many support values are zero. In this paper, LS-SVM was used to finish the classification.

2.3. The Combination of PSO and SVM

There are two parameters to be optimized in the LS-SVM using RBF kernel function. In this paper, the feature selection was realized at the same time. Thus, the grain is in the form of binarydigit string, with three parts, γ, σ^2 and feature mask to determine which feature is chosen, and the grain is as **Table 1** below.

Table 1. Particle design of PSO-SVM.

γ	σ^2	a_1	a_2	...	a_n

The combination of PSO and SVM, for optimizing the feature selection, improved the accuracy of classification and decreased the number of the features selected. In the PSO-SVM, bigger value of the fitness function g(x) represents better adaptive ability of the grains. In this paper, the fitness function was defined as

$$\text{fitness} = \frac{1}{RMSE\left(\gamma, \sigma^2\right) \times f + N} \tag{5}$$

where N is the number of feature subset of the sample; and f represents the equilibrium factor.

The flowchart of the combined algorithm is in **Table 2**.

3. Data Collection of Rowing Athletes

3.1. Subjects

It is considered that female athletes are more sensitive and easier to have negative mood states before competition [25]. Therefore, 22 female rowing athletes from the Rowing Team of Shanghai participated in the experiments. All subjects were native Chinese and 14 - 27 years of age. They didn't do strenuous exercise half an hour before the experiment and they haven't taken any drugs a week before. Consent was obtained from all subjects and awards were given for their participation. Experiments were conducted according to the ethical recommendations of the Declaration of Helsinki. The experiments were carried out twice during one week before and a few weeks after the National Rowing Championships.

3.2. Apparatus & Mood States Measurement

The portable physiological signals collecting device self-developed in our laboratory was used to detect and collect the physiological signals. It can collect electrocardiography (ECG), heart rate (HR), respiratory rate (RR), oxyhemoglobin saturation (SpO_2), pulse rate (PR) and so on. The HR signal measured by the instrument is from 30 to 240 times per minute, the errors of different signals are in **Table 3**.

Several kinds of methods, such as questionnaires, direct observation and measurement of biochemical signals, are used to assess emotion [26]. In this paper, Profile of Mood States Standard & Brief questionnaire (POMS questionnaire) was used to assess athletes' mood states [27] [28]. POMS questionnaire was modified and set up the norm standard for Chinese by Zhu in 1995, and it was considered as a good tool to assess emotion and its relationship with sports performance efficiency [29]. The reliability of POMS questionnaire is between 0.62 and 0.82, the average is 0.71. The POMS questionnaire measures six identifiable mood or affective states: 1) Tension, 2) Anger, 3) Fatigue, 4) Depression, 5) Vigor, 6) Confusion, 7) Esteem-related affect (Self-esteem).From the questionnaire, scores of Total Mood Disturbance (TMD) can be gotten. The higher the score is, the more negative the mood state is.

3.3. Procedures

One week before the competition and the period with no competitions, five kinds of physiological signals of the rowing athletes were collected as the baseline, which were BP, HR, RR, PR and SpO_2. Before the precompetition collection, athletes were required to finish the POMS questionnaire and the reliability of POMS questionnaire was analyzed. The questionnaire inquiry and the mood states related physiological data collection of the athletes were conducted in the Shanghai Water Sports Training Center. During each data collection before the competition, 22 questionnaires were sent out. The data was collected in a resting state, without any sports before the collection. Most subjects can finish the questionnaire in 3 - 5 minutes.

3.4. Preprocessing of Dataset

According to the POMS questionnaires, physiological signals of the 16 athletes were chosen and categorized into two mood states, which were 9 samples of negative mood states before competition, 7 samples of positive

Table 2. The flowchart of the PSO-SVM.

Begin

Initialize particle swarm, including the settlement of the original position X_i and original speed V_i.

Repeat

Transfer the form of the parameters of LS-SVM, according to the binary form of the grains.

Compare the value of the fitness function of every grain $f(x_i)$ with its optimum value $f(pbest_i)$.

If

$f(x_i) < f(pbest_i)$

Make the value of the fitness function take place of the value of the fitness function before, and so it is with the grain.

Compare the value of the fitness function of every grain $f(x_i)$ with the global optimum value $f(gbest_i)$.

If

$f(x_i) < f(gbest_i)$,

Make the value of the fitness **function** of that grain take place of the optimum value of
the fitness function before, and so it is with the grain.

Update the speed and value of the grains according to the Equations (1) and (2), and build the new population X_{i+1}.
Update the speed according to the rules: if $v_i > V_{max}$, $v_i = V_{max}$, if $v_i \leq -V_{max}$, $v_i = -V_{max}$.

Update the inertia factor w.

Update the binary digit of the grains.

Check whether the requirement of ending is satisfied. The requirement is reaching
the max iterations or the evaluation of estimate is less than the given accuracy.

Improve the iteration. Make $T = T + 1$.

Until

The requirement of ending is satisfied, end the selection for the best feature, and return the
best character subset and classification accuracy.

Table 3. The error of different physiological signals.

Signal	Error
HR	$\leq 2\%$
RR	$\leq 5\%$
SpO$_2$	$\leq 2\%$
PR	$\leq 3\%$

mood states before competition. Meanwhile, the psychological signals of all the 16 athletes in resting state after the competition were set as the baseline data. Considering the individual difference of different people, the baseline data was subtracted from the signal data collected before the competition. Then 27 original features were got by feature extraction, which are shown **Table 4**.

4. Results

The reliability of all finished POMS questionnaires was analyzed by internal consistency test, and the standard α coefficient of subscales are 0.7 - 0.8, and the average is 0.72, which means high reliability of POMS questionnaire. The scores of subscales and the whole questionnaire finished before and after the competition of 16 chosen subjects were analyzed by principle component factor analysis. There are significant difference of the scores of subscales and the whole questionnaire finished before and after the competition ($p < 0.01$). So the POMS questionnaire is of high reliability and validity.

Table 4. Feature extractions of physiological signals.

Physiological signals	Extracted features
BP	systolic pressure, diastolicpressure, blood pressure difference
HR, RR, PR, SpO$_2$	mean value, variance, average of first difference, maximum value, minimum value, difference between the maximum and minimum value

The TMD scores in each questionnaire were calculated and found out 9 athletes with high TMD scores and 7 athletes with relative low TMD scores, as shown in **Figures 1-3**.

If the scores of vigor and esteem-related affect are high and that of other emotions are low, and the TMD score is low at the same time. The figures of section of psychological state of athletes are like the iceberg profile, which means the mood states of the athlete is positive. Otherwise, means the mood states of the athlete is negative. The figures of S1 and S2 are just like this, and their TMD scores are lowest in all subjects.

The PSO-SVM was used to classify the positive and negative emotion before competition. In this paper, 10 samples were used as the training set (5 for positive emotions and 5 for negative emotions), and the other 6 were used as the test set (2 for positive emotions and 4 for negative emotions). The results of classification of the data with subtraction of the baseline data and the data without subtraction of the baseline data is in **Table 5**.

Table 5 showed that the best recognition accuracy (RA) is 100% and the average RA is 94.44%, through the PSO-SVM to recognize the emotion. The classification using the data with subtraction of baseline data is better than that without the subtraction. The results using combination of different physiological signals after the optimized selection is better than the single physiological signal. In the training phase of the feature selection, difference between systolic pressure and diastolic pressure, mean HR, difference between the maximum and the minimum of RR were chosen as the best set of features, which means that they are advantageous to the recognition of positive and negative emotion through physiological signals.

5. Discussion

Profile of mood states questionnaire is worked out by the team of McNair in 1971 [30]. It consists 6 subscales (Tension-Anxiety, Vigor-Activity, Depression-Dejection, Fatigue-Inertia, Anger-Hostility, Confusion-Bewilderment), and each subscale consists several adjectives. Morgan and his colleagues used this questionnaire to assess the mood states of athletes from 1978 and pointed it out that the POMS questionnaire was an useful tool to assess the mood states of athletes and predict the results of competition [31]. Then Grove and his team published the Profile of Mood States Standard & Brief questionnaire in 1992, and added the subscale of Esteem-related affect, with totally 40 adjectives [28]. The adjectives of different subscale are mixed. Subjects were required to choose the closely levels weighing the adjectives according to their own mood states in a week lately. The TMD scores of athletes before and after competition have significant difference using this questionnaire. Then the questionnaire we use was modified and set up the norm standard for Chinese by Zhu. The reliability is between 0.62 and 0.82, the average is 0.71, and it is a good tool to assess mood states of athletes in China. The application of POMS questionnaire in China showed the test-retest reliability of it was 0.428 - 0.680, which was satisfactory [32].

From **Table 4** we can see, the best RA is 100% and the average RA is 94.44%, through the PSO-SVM to recognize the emotion. Although the data of physiological signals are not exactly the same, the average accuracy of nearly 95% is an improvement, while the accuracy was no more than 90% in other researches [9] [10]. The classification using the data with subtraction of baseline is better than that without the subtraction, which demonstrated that the baseline data subtraction is meaningful for effective recognition of athletes' mood states.

The time of data collections in first phase was settled during one week before the competition, when most athletes' mood states were influenced by the coming competition seriously [2]. Considering not disturbing the athletes' preparation for the coming competition, the collection of physiological signals was only twice. This is relative small datasets for mood states recognition regarding training the classification algorithms. In the future, more emotion related multi-physiological data could be reliably obtained, to improve the recognition performance of the PSO-SVM model.

Due to the nature of emotion recognition problem, it is impossible to prevent the false recognition of positive and negative mood states. However we can try to integrate different modalities that the emotions can be recog-
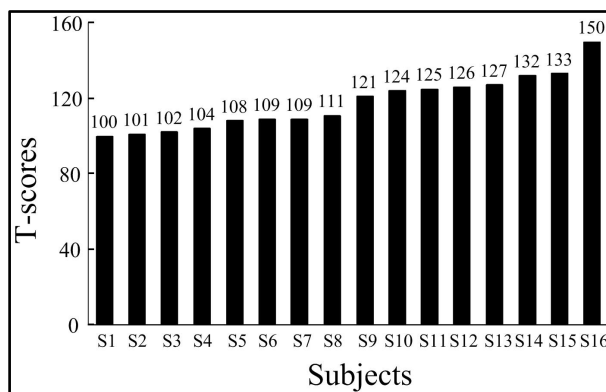
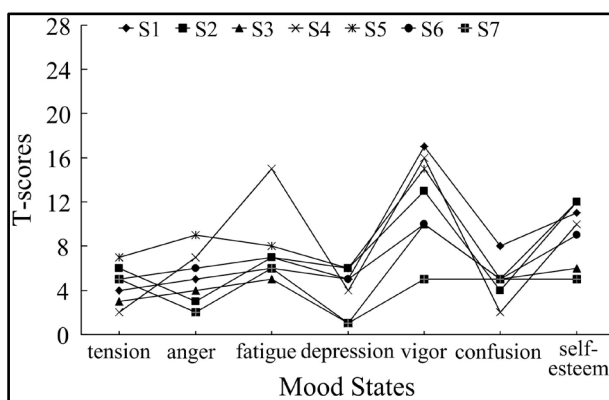**Figure 1.** Total mood disturbance of female rowing athletes.

Figure 2. Mood states of female rowing athletes with low TMD scores.
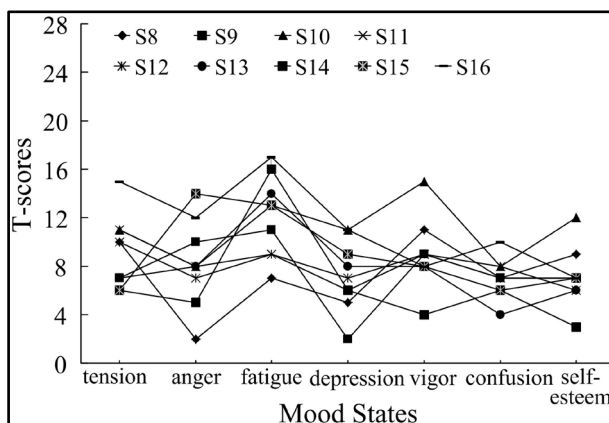

Figure 3. Mood states of female rowing athletes with high TMD scores.

nized from such as facial expressions, and vocal intonation and try to make a better combination of recognition algorithms for higher recognition accuracy.

6. Conclusion

The recognition of athletes' mood states can help athletes to have better adjustment before competition, which is necessary to have better competition performance. In this paper, mood states related multi-physiological data of

Table 5. Recognition accuracy of the mood states of the athletes before competition using PSO-SVM.

Signal	Number of features	Number of best features		Best RA/%		Average RA/%	
		PSO-SVM	PSO-SVM (Subtracted by baseline)	PSO-SVM	PSO-SVM (Subtracted by baseline)	PSO-SVM	PSO-SVM (Subtracted by baseline)
BP	3	2	1	83.33	100.00	72.22	94.44
HR	6	2	2	83.33	83.33	50.00	83.33
RR	6	1	2	83.33	83.33	77.78	83.33
PR	6	1	1	83.33	83.33	83.33	83.33
SpO$_2$	6	1	1	83.33	83.33	83.33	83.33
ALL	27	5	6	100.00	100.00	88.89	94.44

ALL: BP, HR, RR, PR, SpO$_2$.

female rowing athletes were collected before and after the competition, according to a standard questionnaire for evaluating mood states of athletes. The multi-physiological signals and implemented the baseline data subtraction were used, which finally were classified by the particle swarm optimization algorithm combined with least squares support vector machine classifiers. The result showed that the classification accuracy of the PSO-SVM model with baseline subtraction was better than the condition without baseline subtraction. Further, more subjects will be recruited in this study since the sample size is relatively small. And the relationship between physiological signals and pre-competition emotions of male athletes will be investigated. Also, other effective algorithms in pattern recognition are under investigation. It is hoped that these results are informative to pre-competition psychological adjustment of rowing athletes, thus making the PSO-SVM mood states recognition model more practical for athletes.

Acknowledgements

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