

Abnormal Emotion Detection of Tennis Players by Using Physiological Signal and Mobile Computing

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ABSTRACT

Emotion is an important research topic in the field of sports. The physiological changes caused by emotion have a great influence on the completion of sports. It cannot only fully mobilize the organism and maximize the exercise potential, but also lead to muscle stiffness, movement deformation, or muscle contraction weakness. Furthermore, it can affect the completion of exercise. In order to ensure the athlete can keep the best competitive level, it is necessary to estimate the athlete's emotion before competition. This paper adopts the pulse wave signal to implement the emotion estimation for the athletes. First, the pulse wave signals are collected by using a portable sensor via mobile computing. Then, the collected pulse wave signals have noises removed by wavelet transform. Last, the denoised pulse wave signals are represented as the features in time domain and frequency domain to input into a trained classifier for determining the current emotion status. The experimental results show that the proposed method can recognize more than 90% of the abnormal emotions.

KEYWORDS

Abnormal Emotion Detection, Mobile Computing, Pulse Wave Signal, Smart Health Sport

1. INTRODUCTION

Movement, emotion and cognition are three concepts in the field of sports psychology (Nesti et al. 2013) and play important role in the sports competition and training, such as tennis sports. The movement refers to the action or activity that an organism completes by means of the nervous system, bones, muscles, joints and other motor organs (Cust et al. 2019). Emotion is a kind of attitude experience of whether the objective things meet their own needs (Delbrouck et al. 2020). Cognition refers to people's understanding of objective things. Exercise connects emotion and cognition closely (Raab et al. 2019). Emotion is produced in the process of sports, whose source is sports. In turn, it can affect the quality and effect of sports. Cognition comes from movement and is the basis of emotion. Therefore, we must make a serious study of sports, emotion and cognition for both sport technology and sport competition.

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The research has found that emotion is controlled by the autonomic nervous system (Morris et al. 2020). Autonomic nervous system is a part of the whole nervous system. Its main function is to control the digestion, respiration, circulation, reproduction and other visceral activities of organism, and regulate the functions of viscera, smooth muscle and gland. The autonomic nervous system is controlled by the cerebral cortex. It reaches the internal organs through the spinal cord. People show many physiological reactions in emotional state. Respiration, circulation, bone, muscle, internal and external glands, as well as metabolic process, will have obvious changes. For example, in the emotional state of excitement and tension, breathing speeds up and deepens, heart beats strengthen, blood vessels dilate, blood pressure rises and blood sugar increases. Anxiety can lead to the decrease of blood sugar, muscle relaxation and digestive gland activity. In short, the physiological changes caused by emotion have a significant impact on the completion of sports. It cannot only make the organism fully mobilize, maximize the exercise potential, but also lead to muscle stiffness, movement deformation or muscle contraction weakness, thus affecting the completion of sports. The competition emotions can be classified as three categories: the movement emotion for fighting, the overheated status of competition, and the indifferent status of competition.

In the movement emotion for fighting (Poma et al. 2017), the physical state of the sportsman reaches the most suitable level for the competition, the physical function is brought into full play, and various psychological factors are at the best level, the technique movement coordination, the labor saving, the high movement effect.

In the overheated status of competition (Archer et al. 2020), the athletes are over excited, out of control, uncoordinated, hands and feet tremble, thirsty and frequent urination.

In the indifferent status of competition (Reitz et al. 2017), the athletes are lack of physiological energy, slow movement, slow thinking, depression.

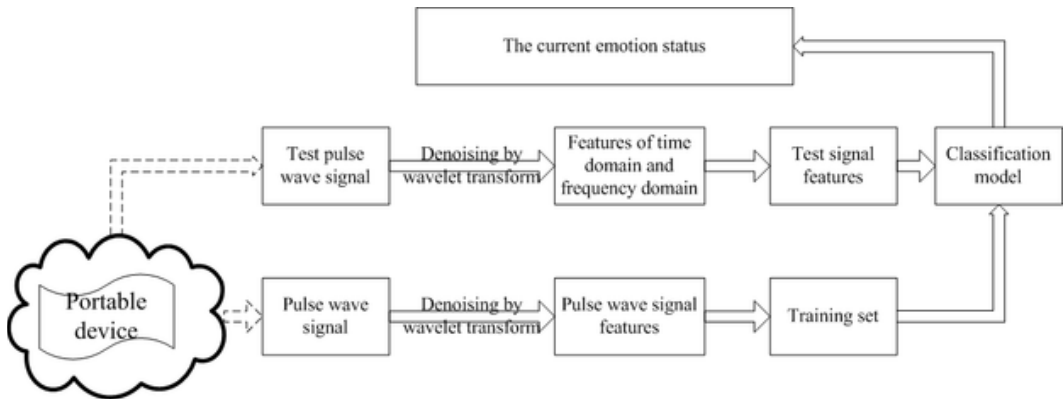
The inverted U theory (Chmiel et al. 2017) points out that both very high and very low wake-up levels of the movement emotion are unfavorable to the operation, and the appropriate wake-up level of the movement emotion is considered to be the most favorable for the operation. The high arousal level is necessary for endurance, strength and speed movement to achieve the best performance. The general attention operation of high arousal will interfere with complex skills, fine muscle activity, coordination, and stability. For all motor tasks, slightly higher than average arousal is more appropriate.

Recently, we can use portable devices to obtain effective information by detecting the changes of physiological signals such as ECG (Attia et al. 2019), pulse (Ma et al. 2018) and EEG (Craik et al. 2019), so as to achieve the purpose of detecting people's emotions. For the tennis players, the coach can remind them when their emotions are abnormal and help them to keep the best competition status. The emotion recognition is an interdisciplinary science between artificial intelligence and artificial psychology.

The pulse wave signal is one of the common and widely used signals for emotion recognition (Egger et al. 2019). The people's emotions fluctuate according to their physiological states, such as pulse rate and blood flow. Blood volume pulse is the change of heart rate and blood vessel contraction when light (infrared or red light) irradiates finger skin detected by blood volume pulse sensor plethysmograph. After each heartbeat, the blood flows through the blood vessels, and the changes of capillary congestion (pulse) and vasoconstriction can be detected under the light source. This paper adopts the pulse wave signal to detect the movement emotion of tennis players during sports. First, the pulse wave signals are collected by portable device in the mobile node; second, the noises in the pulse wave signals are removed by wavelet transform; third, the denoised signals are represented as the features from time domain and frequency domain; lastly, we learn a classifier by using the features of the denoised signals from training set and use the learnt classifier to monitor the emotions of tennis player. The procedure is summarized as the following figure.

The remaining part of this paper is organized as follows: the feature extraction for pulse wave signals are provided in Section 2; the abnormal emotion detection by using support vector machine

Figure 1. The architecture of emotion estimation by using pulse wave signal.



is provided in Section 3; the experimental evaluation is provided in Section 4; and the last section is the conclusion and discussion.

2. FEATURE EXTRACTION FOR PULSE WAVE SIGNAL

With the periodic activity of the heart, the pressure and volume in the artery changes rhythmically, and the pressure wave is formed by blood flow and propagates along the pulse wall. The pulse reflects the heart rate. The heart pumps blood in the body and flows to the whole body through the blood vessels. The blood pulse at the blood vessels is the pulse. People can feel the pulse at the blood vessels near the skin surface, such as the wrist, neck or upper arm.

The heart relaxes and contracts regularly. When the heart contracts, blood gradually flows to the aorta. Due to the existence of peripheral resistance, most of the blood still temporarily exists in the proximal end of the aorta. When there is too much blood in the aorta, it expands and the pressure rises. When the heart is diastolic, the aortic valve is temporarily close. As a result, the aorta regains its elasticity to contract and pushes blood to flow outward. Then, the pressure on the aorta decreases. With the relaxation and contraction of the heart, the aorta will expand and recover, and then the pressure will spread from the aorta to the branches in the form of pressure wave until it spreads to the whole arterial system, which makes the distal artery pulsating regularly. This is the process of arterial pulse wave propagation.

Pulse reflects the change of human heart rate, which is an important physiological index of human body. Because the pulse is easy to measure, it is often used in medical detection of physical condition. We can know the intensity and rhythm of the heart beat by the pulse beat. The occasional pause or extra beat of the pulse is normal. The systolic blood pressure can be determined by pulse. Usually, when breathing deeply, the heart rate will increase. Through the pulse beating intensity and speed changes, it can reflect a person's physical condition. Pulse rate can be checked by calculating beats over a period of time (at least 15 to 20 seconds) to obtain beats per minute. When individuals experience feelings of fear, they sweat, their limbs are cold, and their heart beats faster. The corresponding physiological index changes behave as follows: skin electricity increased, skin temperature decreased, finger blood volume decreased, heart rate increased and pulse quickened.

The pulse can be palpated by touching fingertips to feel heartbeat. The pulse rate can be measured by observing and touching the external part of the artery to record the pulse times per minute. Pulse is measured by palpating any artery that presses on the bone, such as carotid artery (neck), brachial artery (elbow), radial artery (wrist), etc. Heart rate is estimated by the number of arterial beats per minute. The pulse and heart rate of normal people are consistent. In normal people, the pulse is equal

in strength, and the time between pulses is conserved. When the fluctuation of emotion and pulse during exercise increase, the fluctuation of pulse slows down during rest and sleep. Tachycardia occurs when the pulse rate exceeds 100 beats per minute in normal adults. Bradycardia occurs when the heart rate is lower than 60 beats / min.

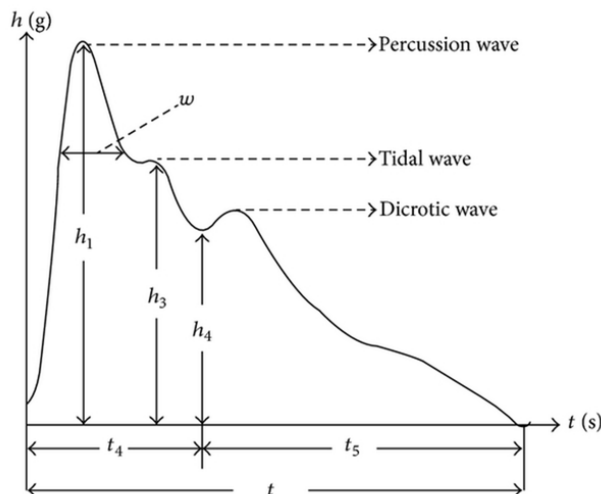
As a very important physiological index, pulse wave belongs to low frequency and weak bioelectrical signal (Chen et al. 2020). The regular activity of the heart changes the pressure and volume of the artery, and the pressure wave propagates outward along the artery wall to form the pulse wave. The pressure sensor is the most common way to detect pulse wave. The pulse wave detected by pressure sensor is pressure pulse wave, which is a typical pulse wave. The pressure sensor is very sensitive to pressure (Ruth et al. 2020). Pressure sensors can be placed in brachial artery, radial artery and other arteries with obvious pulse beating. Then the analog-to-digital converter, filter circuit and amplifier circuit are designed to process the signal to obtain the final pulse wave.

Another way to acquire pulse wave signal is the blood volume pulse (BVP) sensor (Blackford et al. 2018), from which the blood volume pulse signal is obtained. This paper adopts BVP sensor to collect pulse wave signal. Pulse wave detection by blood volume pulse sensor belongs to a non-invasive detection method, which detects the change of blood volume by irradiating arterial blood vessels with light. The detection needs a light source, a light sensor and a light receiver. BVP sensor is a kind of optical sensor, which can detect the change of arterial transparency and are non-invasively. The BVP sensor can be placed in any capillary near the surface of the skin in the human body.

Because the fingertip is very sensitive, the BVP sensor measures the pulse of the fingertip. The fingertip is placed in the plastic clip to minimize the interference of external light source, and the light emitter and detector are placed in the plastic clip to collect the original pulse wave signal. After each heartbeat, the blood flows through the blood vessels, and the changes of capillary congestion (pulse) and vasoconstriction can be detected under the light source. The signal is collected and converted into electrical signal, which is called blood volume pulse wave signal.

Figure 2 is the illustration of a typical pulse wave of a normal person in a complete cycle, which is obtained by detecting the radial artery. The curve between starting point and end point is the whole pulse cycle. Obviously, a whole pulse arterial wave is divided into ascending and descending branches. From the beginning to the end, the pulse wave is subdivided into percussion wave, tidal wave and dicrotic wave.

Figure 2. An illustration of a pulse wave cycle.



When the heart contracts, the ventricle will rapidly release blood and the blood volume of the aorta will increase rapidly. The vascular wall will expand and the blood pressure will rise to form the pulse wave ascending branch. Many factors, such as the speed of cardiac ejection, the size of resistance, and the elasticity of arterial wall, will more or less affect the length and amplitude of ascending branch. In short, the steepness of the ascending branch reflects the larger amount of blood loss or the smaller resistance during the onset of the heartbeat. On the contrary, if the rising speed is slow and the amplitude is small, it means that the blood loss is small or the resistance is large. In a word, the ascending branch takes a short time in the whole pulse cycle.

When the heart contracts and the ventricles rapidly release blood, the ejection rate will gradually slow down. As a result, the blood in the artery decreases and the blood pressure decreases, the amplitude of pulse wave will decrease gradually until the next ventricular re-ejection. With the end of the heart's systole, the aortic valve closes and blood gradually returns. The tidal wave is triggered, which shows that the pulse wave with a rapid downward trend delays the downward speed to form a notch on the downward branch waveform curve. At the same time, it also represents the beginning of diastole. Although the aortic valve is closed, the arterial blood can no longer return to the ventricle, but the return blood will still impact towards the ventricle. This makes the closed aortic valve still be impacted by the blood, so the blood in the artery will increase again, and then the blood pressure will rise, so a second notch will be formed. Then the pulse wave will stop falling, showing a small upward trend of the wavelet, that is, the double pulse wave, the trough in the middle is called the descending isthmus (double pulse wave notch).

Pulse wave contains a lot of physiological information, especially the inflection point of pulse wave and special waveform (percussion wave, tidal wave, dicrotic wave). We can accurately extract these key features to obtain some valuable and meaningful information for application in scientific research and medical field.

Wavelet transform is an effective way of frequency transform in time domain analysis (Zhang et al. 2019). Wavelet transform is developed from Fourier transform. Wavelet transform overcomes the limitation that the window size of short time Fourier cannot change with frequency. The wavelet transform consists two parts: decomposition and reconstruction. A signal is decomposed into several signals and then recombined after processing. In this way, we can get a higher quality signal than the original signal. Wavelet transform uses wavelet basis to decompose signal.

Actually, wavelet transform is a time-frequency localization analysis method, which can provide a time-frequency window which changes with frequency. It can focus on any detail of the signal. Wavelet transform is especially suitable for processing non-stationary signals. It uses a finite length and attenuating wavelet basis to obtain frequency and positioning time. The wavelet basis function can stretch and shift. For the signal $f(x)$, the continuous wavelet transform is written as follows:

$$W_f(a, \tau) = f(t), \psi_{a, \tau}(t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi^* \left(\frac{t - \tau}{a} \right) dt \quad (1)$$

In the Equation (1), $\Psi_{a, \tau}(t)$ is called wavelet basis function, in which a is the scaling factor to control the scaling and τ is the shift factor to control the shift time of wavelet function. The scaling function in wavelet transform is written as follows:

$$\Psi_{a, \tau}(t) = \frac{1}{\sqrt{a}} \Psi \left(\frac{t - \tau}{a} \right), a, \tau \in R, a > 0 \quad (2)$$

In the Equation (2), $\Psi(t)$ is called basic wavelet of parent wavelet.

The continuous wavelet transform has the following characteristics.

- Superposition. The wavelet transform is constituted the sum of each component of signal.
- Scale property. If the continuous wavelet transform of signal $f(x)$ is $W_f(a, \tau)$, the wavelet transform after stretching $f(ct)$ is written as $\frac{1}{\sqrt{c}} W_f(ca, c\tau)$ where $c > 0$.
- Time shift invariance. If the continuous wavelet transform of signal $f(t)$ is $W_f(a, \tau)$, the waveform transform $f(t - t_0)$ after shift is written as $W_f(a, \tau - t_0)$.
- Self-similarity. The continuous wavelet changes are similar for different scale factor and different translation factor.
- Redundancy.

The multi resolution analysis decomposes any function $f(t) \in V_0$ as low frequency part L_j and high frequency part H_j . The decomposition can be repeated to get the low frequency part and high frequency part on any scale. The decomposition is represented as follows:

$$f(t) = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} l_{i,j} \varphi_{i,j}(t) + \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} h_{i,j} \phi_{i,j}(t) \quad (3)$$

In the Equation (3), $l_{i,j} = \langle f(t), \phi_{i,j}(t) \rangle$ and $h_{i,j} = \langle f(t), \phi_{i,j}(t) \rangle$ represent scale coefficient and waveform transform coefficient.

The signal space can be divided into subspaces with different fineness, and the set of these subspaces is the scaling function or the scaling function after frequency transformation. Through the multi-resolution analysis, the low-frequency and high-frequency information of the signal can be obtained effectively, which is equivalent to the low-pass and high pass filter, respectively.

The signal can be compressed and filtered by using wavelet transform. The basic flowchart of wavelet transform is summarized as follows:

- Step 1. Select wavelet function and scale to decompose the signal to get low frequency coefficient and high frequency coefficient.
- Step 2. Treat the coefficient as needed.
- Step 3. Reconstruct the signal with the processed wavelet coefficients.

Reconstruction is the inverse process of wavelet decomposition, in which the original signal is reconstructed by wavelet reconstruction algorithm after the decomposed signals are processed. The reconstruction of wavelet transform is used to remove baseline drift of pulse wave signal. First, a proper wavelet basis is selected to decompose the pulse wave signal to be processed in multi-layer. Then, the remaining signal is reconstructed after the hierarchical processing to implement denoising.

The energy of the signal can be expressed by the energy of the expanded part in each frequency domain, which is written as follows:

$$\int |f(t)|^2 dt = \sum_{i=-\infty}^{\infty} |l(i)|^2 + \sum_{i=0}^{\infty} \sum_{j=-\infty}^{\infty} |h_i(j)|^2 \quad (4)$$

After removing the noises in the pulse wave signal, we need to extract the useful features in the denoised signal, which is further used in the emotion estimation and recognition. The paper adopts the time domain features and frequency domain features to represent the denoised signals. The time domain features include mean value, median value, standard deviation and minimum value of pulse wave and its first-order difference; the mean value, median value, standard deviation, minimum value and maximum value of peak value and descending gorge; the distance between wave crests and the mean value, median value, standard deviation, minimum value and maximum value of the first-order difference; the total number of peaks and the sum of the total peaks.

The frequency domain features are obtained by wavelet transform. The pulse wave signal is decomposed by wavelet transform to obtain the wavelet coefficients of each layer. The wavelet transform is a time-frequency localization analysis method, which can provide a time-frequency window changing with frequency. The window can focus on any detail of the signal during processing. The wavelet signal adopts a finite length and attenuating wavelet basis. The wavelet basis function can stretch and shift, analyze function or signal in multi-scale, decompose a signal into several signals in different frequency domain. It is especially suitable for processing non-stationary signals.

3. ABNORMAL EMOTION DETECTION BY USING SUPPORT VECTOR MACHINE

Let x_i represent the features of a denoised pulse wave cycle, y_i represent the associated label which denotes the corresponding emotion, X and Y represent the set of x_i and y_i respectively. Then, the aim of emotion detection needs to learn a classifier to recognize the emotions. The common used classifiers include: random forest, naïve Bayes, neural network, support vector machine, etc. This paper adopts weighted support vector machine which is an improved version of support vector machine (Zhu et al. 2016). Compared with classical support vector machine, weighted support vector machine is robust to the noises in the training set. The training sample in weighted support vector machine is reorganized as $\{x_i, \rho_i\}$ and the aim is to find a hyperplane $f(\mathbf{x}) = \mathbf{w}^T \mathbf{x}_i + b$ by minimizing the following optimal programming.

$$\begin{aligned} \min_{\mathbf{w}, \rho} \quad & \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^n \rho_i \xi_i \\ \text{s.t.} \quad & y_i (\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad i = 1, 2, \dots, n \end{aligned} \quad (5)$$

In the Equation (5), ρ_i is the instance weight of \mathbf{x}_i , n represents the number of training set. The Equation (5) is a convex optimal programming. The solution can be obtained by the dual form, which is written as follows:

$$\begin{aligned} \min_{\alpha} \quad & \alpha^T Q \alpha - \alpha \\ \text{s.t.} \quad & \sum_{i=1}^n y_i \alpha_i = 0, \quad 0 \leq \alpha_i \leq \rho_i C, \quad i = 1, \dots, n \end{aligned} \quad (6)$$

In the Equation (6), α is the vector form of the Lagrange multipliers which are associated with the constraints $y_i (\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i$ in the Equation (5), and Q is a $n \times n$ matrix whose element $Q(i, j) = \langle \mathbf{x}_i, \mathbf{x}_j \rangle$.

The solution of Equation (6) can be obtained by SMO algorithm. The weight \mathbf{w} and bias b are represents as follows:

$$\mathbf{w} = \sum_{\mathbf{x}_i \in SVs} \alpha_i \mathbf{x}_i \quad (7)$$

$$b = y_i - \mathbf{w}^T \mathbf{x}_i, \quad 0 < \alpha_i < \rho_i C \quad (8)$$

In the Equation (7), SVs is the set of support vectors whose Lagrange multipliers satisfy $\alpha_i > 0$.

When the training set is nonlinear separable, the sample is mapped into a high-dimensional kernel reproducing Hilbert space via an implicit function $\phi(x)$. Then, the optimal programming (5) is rewritten as follows:

$$\begin{aligned} \min_{\mathbf{w}, \rho} \quad & \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^n \rho_i \xi_i \\ \text{s.t.} \quad & y_i \left(\mathbf{w}^T \phi(\mathbf{x}_i) + b \right) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad i = 1, 2, \dots, n \end{aligned} \quad (9)$$

The dual form of Equation (9) is the same as that of optimal programming (6). The matrix \mathbf{Q} is called as kernel matrix whose element is $\mathbf{Q}(i, j) = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}_j) \rangle = k(\phi(\mathbf{x}_i), \phi(\mathbf{x}_j))$. The common used kernel functions include polynomial kernel, Gaussian kernel, Matérn kernel, exponential kernel etc.

The weight and bias for kernel form weighted support vector machine are rewritten as follows:

$$\mathbf{w} = \sum_{\mathbf{x}_i \in SVs} \alpha_i \phi(\mathbf{x}_i) \quad (10)$$

$$b = y_i - \sum_{\mathbf{x}_j \in SVs} \alpha_j k(\mathbf{x}_i, \mathbf{x}_j), \quad 0 < \alpha_i < \rho_i C \quad (11)$$

The instance-weight can be determined by prior nearest neighbor information (Zhu et al. 2014; Zhu et al. 2016) or estimated distance to decision hyperplane. This paper adopts the later one which is written as the following equation.

$$\rho_i = \frac{E_{margin}^i}{\max_{j=1, \dots, l-1} d_{i,j+1}} \quad (12)$$

In the Equation (12), E_{margin} is estimated margin between two boundary hyperplanes, $d_{i,j+1}$ is the distance between two adjacent nodes in the nearest neighbor chain of sample \mathbf{x}_i . The nearest neighbor chain is defined as follows (Zhu et al. 2017):

Definition (nearest neighbor chain): for sample $\{\mathbf{x}_i, y_i\} \in \mathbf{X} \times \mathbf{Y}$, the nearest neighbor chain is defined the sequence $\mathbf{x}_{i,1}, \dots, \mathbf{x}_{i,l}$. The first node $\mathbf{x}_{i,1}$ is \mathbf{x}_i itself. The following node $\mathbf{x}_{i,j}$ is defined as the nearest neighbor of its previous node $\mathbf{x}_{i,j-1}$ in $\mathbf{X} - \{\mathbf{x}_{i,1}, \dots, \mathbf{x}_{i,j-1}\}$.

The distance between two adjacent nodes is defined as $d_{i,j+1} = \mathbf{x}_{i,j} - \mathbf{x}_{i,j+1}$. Then, the estimated margin is defined as follows:

$$E_{margin}^i = \frac{\sum_{j=1}^l d_{j,j+1} - \max_{j=1,\dots,l-1} d_{i,j+1}}{l-2} \quad (13)$$

Obviously, when a sample is close to the decision hyperplane, the weight defined by Equation (12) will be close to 1; otherwise, the weight will be close to 0.

Both classical support vector machine and weighed version are mainly used to solved binary classification problem. For multi-class classification problem, the problem needs to be divided into several binary classification problems. The common used strategies to deal with multi-class classification problem include one against one and one against rest.

The one to one strategy is one of the most approaches to deal with multi-class classification problems. For a training set containing k classes, any pair classes i and j are used to learn a binary class support vector machine model. The class i is used as positive class, while class j is used as negative class. Therefore, the k -class classification problem is converted as $\frac{k(k-1)}{2}$ binary class support vector machines. The test sample is input into each binary class support vector machine model and the final label is determined by voting the results of $\frac{k(k-1)}{2}$ binary class support vector machine models.

The advantage of one to one strategy is that the scale of sub-problem is relative small and easy to solve. However, the number of binary class classifiers is quadratic with the number of classes. When the number of classes is very large, it needs to learn massive binary class classifiers, which is very time-consuming.

The one to rest strategy adopts one class in the training set as positive class and the rest classes are all used as negative class. Then, for a training set containing k classes, it needs to learn k binary class classification models in total. The test sample is input into each binary class support vector machine model and the final label is determined by the binary class support vector machine model whose decision function has the maximum value.

Compared with one to one strategy, the one to rest strategy only requires to learn k binary class classifiers and the decision stage is much easier. However, binary class sub-problem is obviously asymmetric, which may cause the optimal hyperplane to shift and induce the performance to be deteriorated. The scale of the binary class sub-problem is also larger than single sub-problem in one-to-one strategy. The illustration of one to one strategy and one to rest strategy for weighted support vector machine is shown in Figure 3 and Figure 4, respectively.

4. EXPERIMENTS AND SIMULATIONS

In this section, first a benchmark emotion dataset is adopted to evaluate the proposed emotion estimation method; then, we collect the emotion data from 20 tennis players via portable devices to verify the proposed method. The benchmark emotion datasets contain four emotions: anger, excitement, sadness and calmness.

The benchmark dataset is from MIT emotion dataset and each emotion contains the same number of samples. The time domain and frequency domain features of the pulse wave signals from wavelet transform are used to learn classification model. The MIT emotion dataset is randomly split as two parts. One is used as training set, while the other is used as test set. Both training set and test set

Figure 3. The illustration of the one versus one strategy for multi-class classification

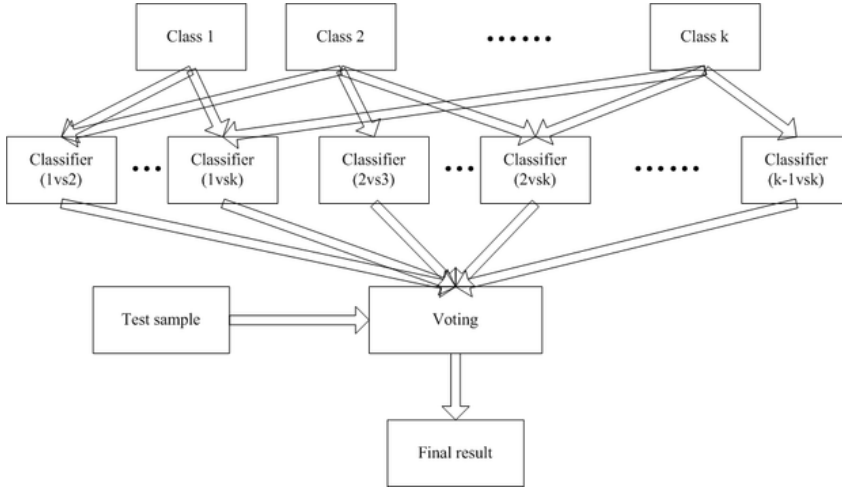
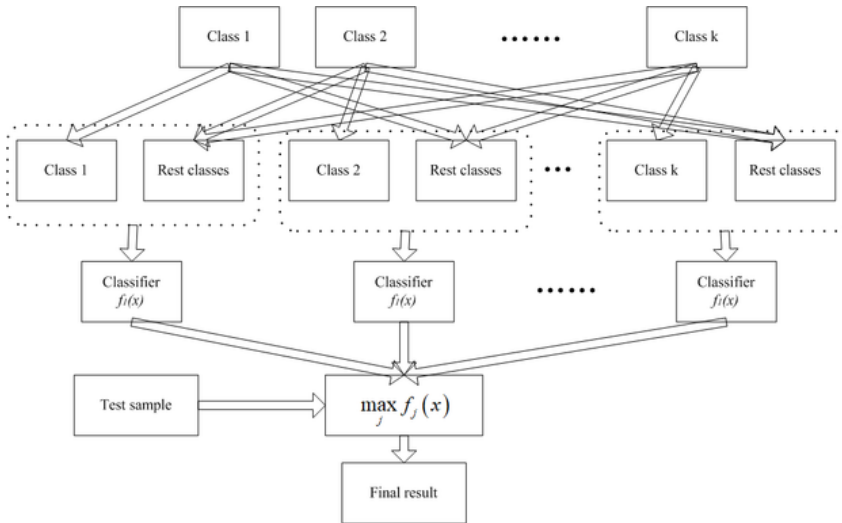


Figure 4. The illustration of the one versus rest strategy for multi-class classification



contains 1,440 samples and 360 samples per emotion. The classical support vector machine (Soentpiet et al. 1999) and weighted support vector machine (Zhu et al. 2016) are adopted as classification algorithm. The one to one and one to rest are used as the multi-class classification strategy. The methods are denoted as SVM (O-vs-O), SVM (O-vs-R), WSVM (O-vs-O), and WSVM (O-vs-R).

The Gaussian radial basis kernel function (RBF), $k(x_i, x_j) = e^{-\frac{x_i - x_j^2}{2\sigma^2}}$, is used as the kernel function. The accuracy of emotion estimation is reported in Table 1, 2, 3 and 4 in the form of confusion matrix.

From the results of Table 1, 2, 3 and 4, it can be found the whole recognition rate reaches 91.81%, 91.46%, 95.07%, and 93.89% for support vector machine (one versus one), support vector machine (one versus rest), weighted support vector machine (one versus one), and weighted support vector machine (one versus rest), respectively. The recognition rate of weighted support vector machine

Table 1. The confusion matrix when SVM (O-vs-O) is used as classification model on benchmark dataset.

	Anger	Excitement	Sadness	Calmness	Recognition rate (%)
Anger	329	13	7	12	91.14
Excitement	5	332	21	7	90.96
Sadness	19	6	324	4	91.78
Calmness	7	9	8	337	93.35
Recognition rate (%)	91.39	92.22	90.00	93.61	91.81

Table 2. The confusion matrix when SVM (O-vs-R) is used as classification model on benchmark dataset.

	Anger	Excitement	Sadness	Calmness	Recognition rate (%)
Anger	327	15	6	13	90.58
Excitement	6	330	19	7	91.16
Sadness	18	5	329	9	91.14
Calmness	9	10	6	331	92.98
Recognition rate (%)	90.83	91.67	91.39	91.94	94.46

Table 3. The confusion matrix when WSVM (O-vs-O) is used as classification model on benchmark dataset.

	Anger	Excitement	Sadness	Calmness	Recognition rate (%)
Anger	341	12	7	9	92.41
Excitement	3	339	4	3	97.13
Sadness	14	5	347	6	93.28
Calmness	2	4	2	242	97.71
Recognition rate (%)	94.72	94.17	96.39	95.00	95.07

Table 4. The confusion matrix when WSVM (O-vs-R) is used as classification model on benchmark dataset.

	Anger	Excitement	Sadness	Calmness	Recognition rate (%)
Anger	337	14	9	11	90.84
Excitement	5	334	3	4	96.53
Sadness	15	7	343	7	92.20
Calmness	3	5	5	338	96.30
Recognition rate (%)	93.61	92.78	95.28	93.89	93.89

is higher 3.26% than that of support vector machine when one versus one strategy is adopted, and 2.43% than that of support vector machine when one versus rest strategy is adopted. Compared with one versus rest strategy, the recognition rate of one versus one strategy is higher 0.35% and 1.18% for support vector machine and weighted support vector machine, respectively.

The emotion data collected from tennis players includes emotion for fighting, overheated emotion, and indifferent emotion. There are 1,500 samples as the training set in total, 500 samples

Table 5. The confusion matrix on real dataset by using WSVM (O-vs-O) as classification model.

	Fighting	Overheated	Indifferent	Recognition rate (%)
Fighting	268	5	4	96.95
Overheated	8	5	5	95.75
Indifferent	6	293	291	97.32
Recognition rate (%)	95.33	2	97.00	96.67

per emotion; and 900 samples as the test set, 300 samples per emotion. The emotion data of tennis players is collected by using portable devices. The weighted support vector machine is adopted as classification algorithm and the one versus one is used as the multi-class classification strategy. The confusion matrix is reported in Table 5.

From the result of Table 5, it can be found that the weighted support vector machine with one versus one strategy can recognize 95.33%, 97.67%, 97.00% of fighting emotion, overheated emotion, and indifferent emotion, respectively. The overall recognition rate can reach 96.67%.

5. CONCLUSION

This paper proposes a framework to estimate the emotion and recognize the abnormal emotion of the athlete before competition. The emotion status is closely related with the competition level of athlete. The proposed framework first collects the pulse wave signals of the athlete by using portable device, second removes the noise in the collected pulse wave signals by using wavelet transform decomposition and reconstruction, third extracts the features of the time domain and frequency domain of the denoised signals, last learns a classification classifier by using the training set consisting of the features of the pulse wave cycles. The learnt classification model is used to estimate the emotion status of the athlete. The experimental results show that the emotion recognition framework can correctly identify most of the emotion status of the athlete.

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