Study of Emotion Recognition Based on Surface Electromyography and Improved Least Squares Support Vector Machine

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***Abstract*— In order to improve human-computer interaction (HCI), computers need to recognize and respond properly to their user's emotional state. This paper introduces emotional pattern recognition method of Least Squares Support Vector Machine (LS_SVM). The experiment introduces wavelet transform to analyze the Surface Electromyography (EMG) signal, and extracts maximum and minimum of the wavelet coefficients in every level. Then we construct the coefficients as eigenvectors and input them into improved Least Squares Support Vector Machines. The result of experiment shows that recognition rate of four emotional signals (joy, anger, sadness and pleasure) are all more than 80%. The results of experiment also show that the wavelet coefficients as the eigenvector can be effective characterization of EMG. The experimental results demonstrate that compared with classical L_M BP neural network and RBF neural network, LS_SVM has a better recognition rate for emotional pattern recognition.**

***Index Terms*--Least Squares Support Vector Machine (LS_SVM); Emotion Recognition; Surface Electromyography (EMG); Wavelet Transform (WT)**

I. Introduction

Emotion recognition technology has become a research hotspot as people increase attention and concern on face information now. Emotion recognition is a key issue in emotion computing and one of the foundations to build a harmonious man-machine environment, whose purpose is to provide theoretical and experimental basis of the right choice of emotional signal and to provide a reliable raw data [1-3] for the understanding and expression of emotion.

As one interdisciplinary research topic, emotion recognition technology is related to psychology, physiology, computer science, cognitive science and other disciplines of knowledge. A challenging study in emotional expression recognition is to detect the change of Surface Electromyography (EMG) in various internal states. Emotional expressions are continuous because the expression varies smoothly as the expression is changed. The variability of expression can be represented as subtleties of manifolds such as amplitude, frequency and other parameters. Thus emotional recognition has to be detected subtleties of manifolds in the expression EMG.

Despite the complexity of the concept of emotion, most researchers agree that emotions are acute affective states that exist in a relatively short period of time and are related to a particular event, object, or action [4-5]. The roots of psycho-physiological aspects of emotions lay in Darwin's book "The expression of emotions in man and animals", which he wrote in 1872. The overall assumption is that emotion arouses the autonomic nervous system (ANS), which alters the physiological state. This is expressed in various physiological measures, often stimulated through the ANS; e.g., heart rate, blood pressure, respiration rate, galvanic skin response, and muscle activity [6].

Experimental media group of MIT led by Professor Picard proved that the method of physical signal emotion recognition is feasible. Professor Picard and Elias collected a 20-day physiological signal from eight kinds of emotions of an actor when performing deliberately, to extract the value of demographic characteristics using Fisher Projection [2, 5, 7].

In this paper, the method of Wavelet Transform is used in surface EMG with objective data, aiming for non-stationary features of surface EMG signal, to extract more effective, reliable, robust signal characteristics. This will help improve the recognition rate of the surface EMG. Also this paper uses the surface EMG signal for six-scale decomposition of surface EMG with the method of wavelet transform and extract the maximum and minimum of multi-scale wavelet coefficients, constructing 14-dimensional feature vector, then we input into the BP neural network, RBF neural network and the support vector machine classifier for emotion recognition, respectively. Experiment results show that the method can detect and identify four emotional signals (joy, anger, sadness and pleasure) on the surface EMG successfully,

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providing a more effective experimental method for the detection of emotional model.

II. Description of emotion Recognition Methods

A. Wavelet Analysis

The concept of Wavelet transform (WT), a signal analysis tool of commonly used non-steady-state analysis, was first proposed by the French engineer J. Morlet, who was engaged in oil signal processing in 1974. Wavelet transform overcome the shortcomings of the Fourier transform and the window Fourier transform with a window adaptive performance. Also it is capable of signal analysis for different scales, so it is widely used in signal processing. In this paper, we use the basic wavelet function: the Department of Daubechies wavelet, and the Daubechies wavelet mathematical expression is as follows:

$$P(x)=\sum_{k=o}^{N-1} C_k^{N-1+k} x^k \tag{1}$$

In equation (1), C_k^{N-1+k} is the binomial coefficient, then

$$\left|m_0(\omega)\right|^2=\left(\cos^2\frac{\omega}{2}\right)^N P\left(\sin^2\frac{\omega}{2}\right) \tag{2}$$

Where, $m_0(\omega)=\frac{1}{\sqrt{2}}\sum_{k=0}^{2N-1} h_k e^{-jk\omega}$.

According to MATLAB algorithm, the signal $f(t)$ can be decomposed into the sum of different frequency approximate components and details components named as $\{V_j, j\in z\}$ which is Hilbet space, and it can be decomposed into the orthogonal sum of wavelet subspace $W_j(j\in z)$, that is

$$L^2(R)=\bigoplus_{j\in z} W_j,\quad j\in z \tag{3}$$

The fast decomposition algorithm of MATLAB is as follows:

$$\begin{cases} c_{j+1,\ k} = \sum_{n\in z} c_{j,n}\bar{h}_{n-2k} \\ d_{j+1,\ k} = \sum_{n\in z} c_{j,n}\bar{g}_{n-2k} \end{cases},(k\in z) \tag{4}$$

In equation (4), c_j and d_j is the discrete approximation and discrete detail in different frequency, respectively. $\bar{h}_{n-2k}$ and $\bar{g}_{n-2k}$ is the wavelet and scale, respectively. Then the fast reconstruction algorithm of MATLAB is as follows:

$$c_{j,k}=\sum_{n\in z} c_{j+1,n}h_{k-2n}+\sum_{n\in z} d_{j+1,n}g_{k-2n},(k\in z) \tag{5}$$

The signal can be decomposed into the sum of signals in each frequency band with Wavelet Transform, which can select the appropriate frequency band for signal processing.

B. Pattern classification using Least Squares Support Vector Machine (LS_SVM)

Support Vector Machine SVM (Support Vector Machine) is a statistical learning theory that basis developed a new machine learning method is a professor from the Vapnik and his AT & T Bell Laboratories collaborators in resolving the issues raised by pattern recognition [8]. Support vector machine is mainly used in pattern recognition field, in addressing the small sample, nonlinear and high-dimensional samples of machine learning problems demonstrated a number of unique advantages, particularly in statistical learning theory to develop and improve research and development for the SVM provides a a solid theoretical basis.

Least Squares Support Vector Machine (LS_SVM) [9] is an improved support vector machine, which changes the inequality constraints into equality constraints in traditional support vector machines. We take the Sum Squares Error loss function as the loss of experience of a training set. So the problem of solving quadratic programming is transformed into problem of linear equations. The speed and convergence accuracy of problem solving has been improved. Supposed that sample is a n-dimensional vector, the sample of a region is expressed as: $(x_1,\ y_1),\cdots,(x_i,\ y_i)\in R^n\times R$, first the sample is mapped from the original space to feature space using nonlinear mapping $\psi(\cdot)$, in this high-dimensional feature space optimal decision function is constructed:

$$y(x)=\omega\cdot\phi(x)+b \tag{6}$$

Thus non-linear estimation function is transformed into a linear estimation function of high dimensional feature space. The use the principle of structural risk minimization, for ω, b is the minimum:

$$R=\frac{1}{2}\|\omega\|^2+c|\cdot R_{\partial mp} \tag{7}$$

In equation (7), $\|\omega\|^2$ is the complexity of the control model and c is the regularization parameter, controlling the degree of punishment beyond the sample error. $R_{\partial mp}$ is the error control function, or the loss function non-sensitive to ε. Commonly used loss function: linear ε loss function, quadratic ε loss function, Huber loss function. Selecting a different loss function can construct different forms of support vector machines. The optimizing objective of LS_SVM is a function with a quadratic error named ξ_i. Optimization problem turns as follows:

$$\min J(\omega, \ \xi) = \frac{1}{2}\omega \cdot \omega + c\sum_{i=1}^{l}\xi_i^2$$
$$st: y_i = \phi(x_i)\cdot\omega + b + \xi_i, \ i = 1,\cdots, \ l \tag{8}$$

In equation (8), ξ_i is the relaxation factor. We solve the optimization problem with the Lagrangian method:

$$L(\omega, \ b, \ \xi, \ \alpha, \ \gamma) = \frac{1}{2}\omega\cdot\omega + c\sum_{i=1}^{l}\xi_i^2 - \sum_{i=1}^{l}\alpha_i(\phi(x_i)\cdot\omega + b + \xi - y_i) \tag{9}$$

In equation (9), $\alpha_i (i = 1,\cdots, \ l)$ is the Lagrange multiplier.

The definition of kernel function $K(x_i, \ y_i) = \phi(x_i)\cdot\phi(x_j)$ is symmetric function to satisfy the conditions. The optimization problem becomes to a solution of linear equation:

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1, \ x_1) + 1/c & \cdots & K(x_1, \ x_1) \\ \vdots & \vdots & & \vdots \\ 1 & K(x_l, \ x_l) & \cdots & K(x_l, \ x_l) + 1/c \end{bmatrix} \cdot \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_l \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix}$$

(10)

At last, we calculate a and b with the method of least-square, thus least square support vector machine is named and the non-linear prediction model is endorsed:

$$f(x) = \sum_{i=1}^{l}\alpha_i K(x, \ x_i) + b \tag{11}$$

$K(x, \ x_i) = \Phi(x_i)\cdot\Phi(x_i)$ is the kernel function to satisfy the Mercer conditions of any symmetric kernel function correspond to dot product of the feature space. Kernel function has many types. Studies have shown that RBF kernel function can plan samples to a higher-dimensional space non-linealy. So as to achieve non-linear mapping; the RBF function has less value restrictive conditions, its value usually is limited between 0 and 1. In this article, the RBF function is selected as LS_SVM nuclear function, such as the expression shows as follows:

$$k(x_i, \ x) = \exp\{{-|x - x_i|^2}/{2\sigma_2}\} \tag{12}$$

III. Process of Emotion Recognition Experiment

Considering the experimental resource, this study designed and carried out experiments to find the mapping relations among EMG to four emotions: joy, anger, sadness and pleasure. The experimental factor is human emotion. It is hypothesized that physiological parameters change with human emotions.

Experiment was carried out in the MATLAB R2008 environment. The physiological signal data of EMG is from the Augsburg University in Germany, it is four kinds of emotions, joy, anger, sadness and pleasure, generated by a subject's conduct of music by Johannes Wagner and others through the selective emotional music, with a total of Record a 25-day EMG physiological signals whose signal sampling frequency is 32Hz [10].

This paper uses a compact quadrature Daubechies5 wavelet as the base function for six-scale decomposition of the EMG physiological signal data each day. Wavelet decomposition algorithm will decompose the signal into fuzzy components a_i and details components d_i in each scales. In the high-level wavelet decomposition, the high-level components a_i will be broken down into fuzzy components a_{i+1} and details components d_{i+1}.And fuzzy component consists mainly of the low-frequency signal components. Details components contains only high-frequency signals, also some high-frequency noise. High-frequency noise reduces as the decomposition scale increases. Wavelet coefficients of continuous signal increase as the scale of decomposition increases. And we extract the maximum and minimum values of each layer in wavelet decomposition as the feature vector of the surface EMG signal vector, constituting a 14-dimensional feature vector. The EMG signals Waveform of joy, wavelet transform coefficients Wf(a,b) in different scales, decomposition algorithm and the actual results are shown in Figure 1 and Figure 2. d1, d2, d3, d4, d5 and d6 in figure 2 are the details component and a6 is fuzzy component.

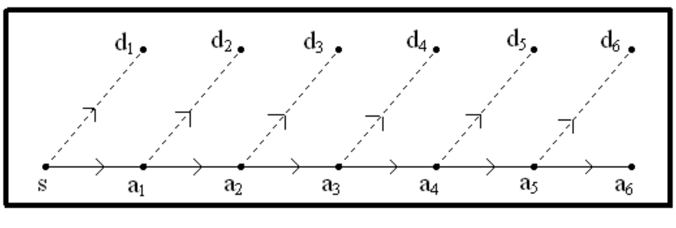


Figure 1. Schematic Diagram of Wavelet Decomposition Algorithm

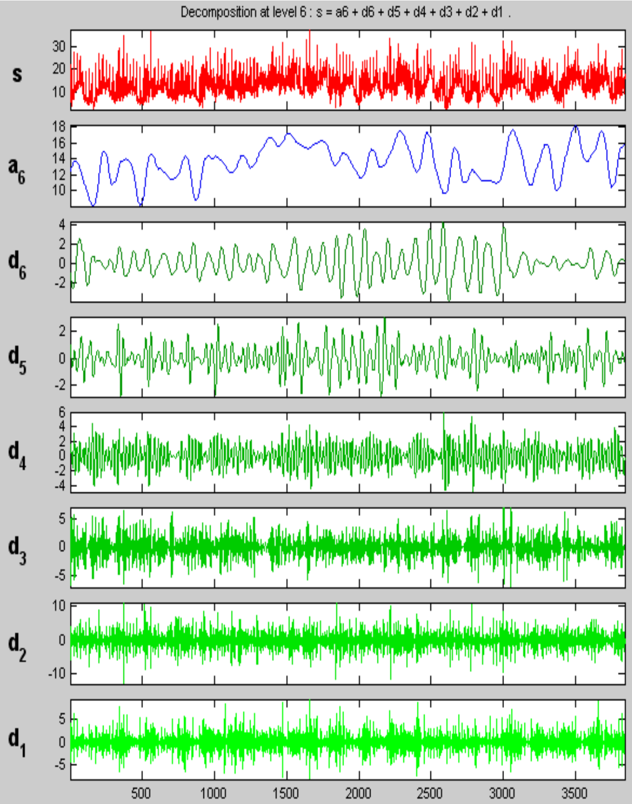
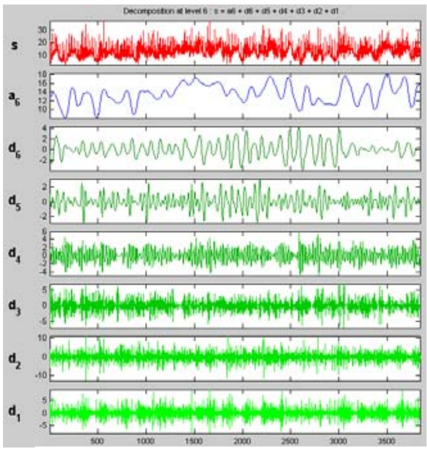
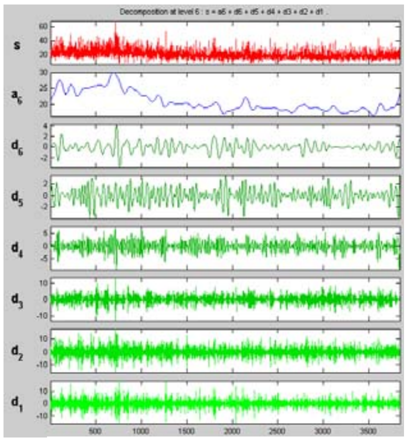


Figure 2. The EMG signals of joy with wavelet transform in six scales

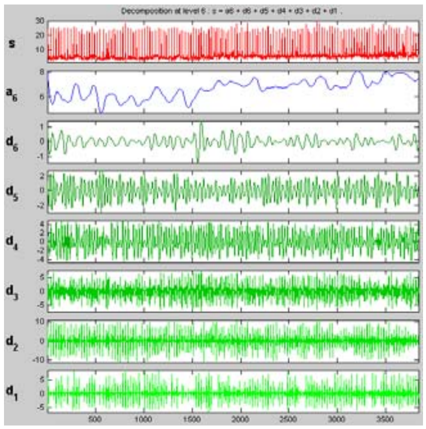
In this paper, the six-scale decomposition of the surface EMG of the four kinds of feelings is shown in Figure 3. Figure 3 (a) is a measure decomposition of the joy sample s1; (b) is a measure decomposition of the anger sample s2; (c) is a measure decomposition of the sadness sample s3; (d) is a measure decomposition of the pleasure sample s4.



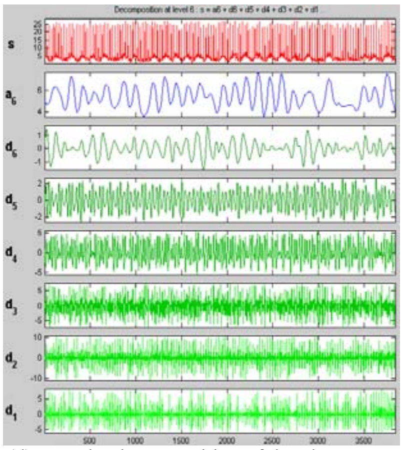
(a) Wavelet decomposition of the joy sample s1



(b) Wavelet decomposition of the anger sample s2



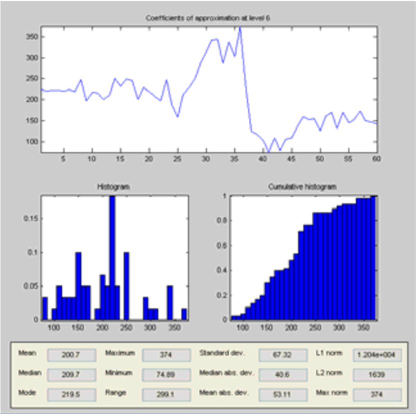
(c) Wavelet decomposition of the sadness sample s3



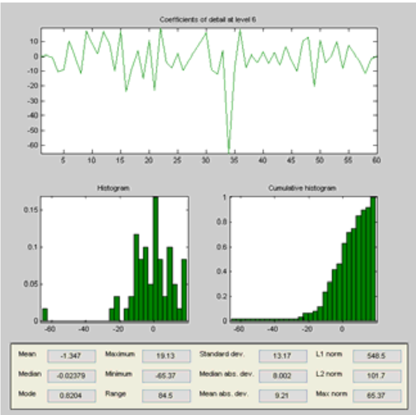
(d) Wavelet decomposition of the pleasure sample s4

Figure 3. Wavelet decomposition of four kinds of emotional signals

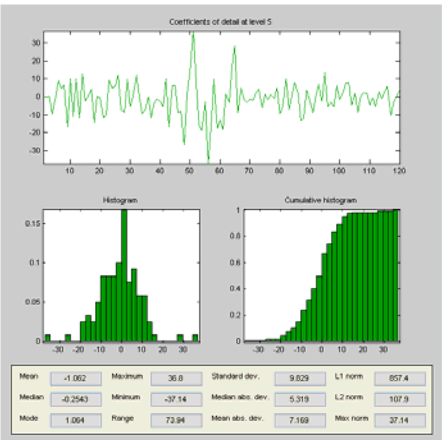
We extract the wavelet coefficients of each layer in the signal - the maximum and the minimum. Then we classify and save the wavelet coefficients of four kinds of emotion. Figure 4 is statistical analysis plan that shows the complete feature extraction process of joy sample s1, of which Figure 4 (a) shows the fuzzy component a6 of the joy sample s1; (b) shows the details component d6 of the joy sample s1; (c) shows the details component d5 of the joy sample s1; (d) shows the details component d4 of the joy sample s1; (e) shows the details component d3 of the joy sample s1; (f) shows the details component d2 of the joy sample s1; (g) shows the details component d1 of the joy sample s1. From the statistical analysis plan, you can extract the characteristics (such as maximum, minimum, standard deviation, mean, etc.) of the surface EMG signal.



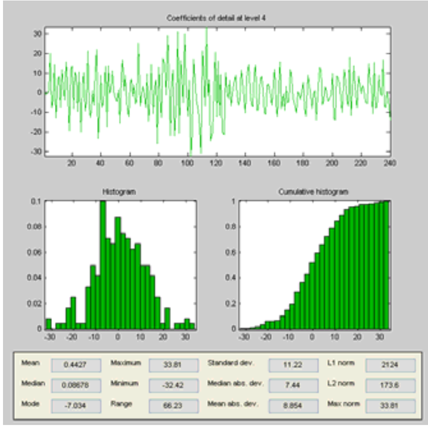
(a)Approximation component a6 of joy



(b) Detail weight d6 of joy

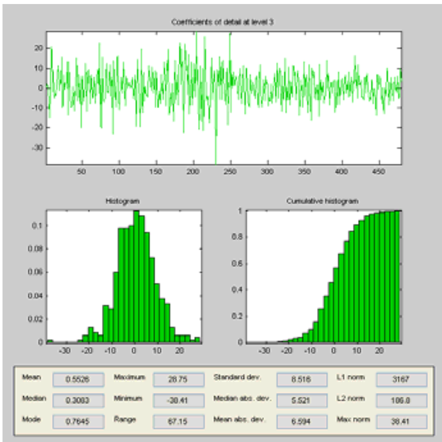


(c) Detail component d5 of sadness

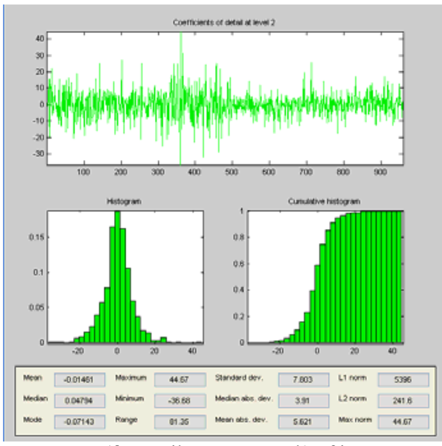


(d) Detail component d4 of joy

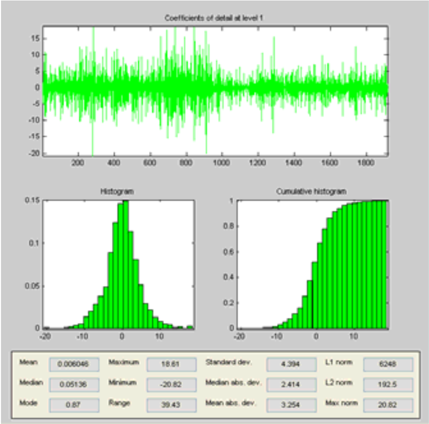
After the six-scale decomposition procedure, we get wavelet coefficients of maximum value and minimum value of a typical emotion pattern of joy. Table I and II show the maximum and minimum of six-scale wavelet decomposition in the six emotional joy experiments, respectively. Then the maximum and the minimum will constitute a 14-dimensional feature vector as the feature vectors of the surface EMG.



(e) Detail component d3 of joy



(f) Detail component d2 of joy



(g) Detail component d1 of joy
Figure 4. Complete feature extraction of sample joy from s1

TABLE I
THE MAXIMUM OF TYPICAL JOY OF SURFACE EMG SIGNAL

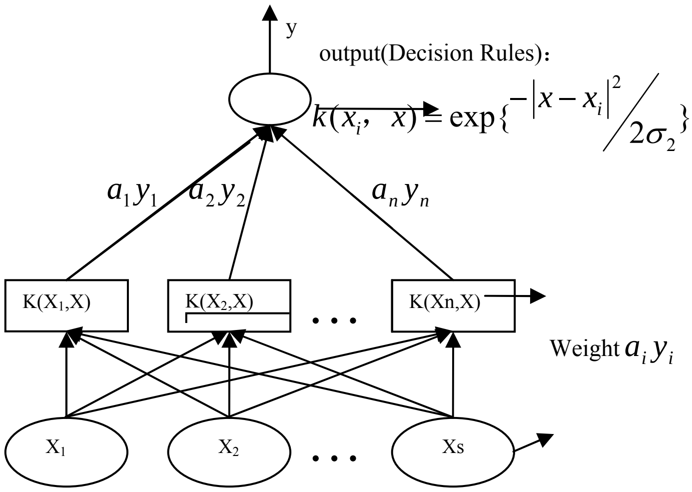
	joy						
	a6	d6	d5	d4	d3	d2	d1
1	137.9	29	11.99	14.38	16.67	13.76	7.097
2	130.6	24.51	10.11	40.3	27	50.58	27.75
3	209.8	20.83	40.21	18.28	18.53	17.68	18.77
4	133.4	24.95	11.21	23.47	16.94	18.01	9.231
5	91.27	21.91	9.811	13.92	8.421	8.224	8.942

TABLE II
THE MINIMUM OF TYPICAL JOY OF SURFACE EMG SIGNAL

	joy						
	a6	d6	d5	d4	d3	d2	d1
1	47.1	-33.4	-15.54	- 14.96	-15.6	- 16.23	-8.676
2	42.83	-21.21	-25.83	- 15.99	-49.37	- 16.81	-24.89
3	65.28	-20.76	-77.88	- 22.05	-17.72	- 22.19	-18.34
4	43.03	-18.79	-7.633	- 18.95	-16.37	- 17.89	-11.67
5	37.37	-13.92	-20.72	- 8.405	-7.798	- 15.76	-10.09

Then we use an improved LS_SVM, which belongs to black-box type model, shown as Figure 5. Its input and output mapping is entirely completed with LS_SVM. So we should understand its internal structure. For the specific model, we select a instrumental variable closely related to the leading variables as the LS_SVM input and the leading variables as the export. The nonlinear mapping of input and output is showing in equation (10).

In this paper, data in 19 days of 25 days is selected as the training set. And the other 6 days data is the test set. Then we have a training to get the statistical results. Its output parameter is the training results. It displays '1' with correct identification and '0' with error identification.



Based on n-support vector X1,X2,…,Xn Non-linear transformation Input vector

$$X = (X_1, X_2, \ldots X_s)$$

Figure 5. Structure model of LS_SVM algorithm

Also the recognition rate is included. Training and test samples is n1 and n2, which is 14 x 76 and 14 x24 matrix, respectively. That is the training and test samples of the 14-dimensional feature vector is 76 and 24, respectively. The number of input nodes is 14 and the output 4 , representing four kinds of emotional states: joy (1000), anger (0100), sadness (0010), pleasure (0001). Training samples is taken as negative training samples, which is the definition of 1-a-r algorithm. In this paper by setting codefct = 'code_MOC' we realize the multiple algorithms 1-a-r of support vector machine.

In the training process with the use of LS_SVM, there are many factors that influence the classification results, mainly the choice of feature vectors and the reasonable mode selection. That is, category selection of kernel function and quadratic programming preferences selection. This choice of kernel function in this paper is radial basis: set kernel_type as ‘RBF_kernel’, by setting the preprocess as ‘preprocess’. Right after pre-processing of the raw data, the output parameter is a train result. Its physical meaning is equivalent to the grid structure parameters, which is used in the testing and the input of new sample identification. But the greatest impact on the training effect is the setting of input parameter value. Here by setting the right value gam, sig2 the by the choice of several settings. Thus we choose the parameters with the largest correct recognition rate as the best gam and sig2. Table III is a record of SVM recognition rate through several times of choosing and setting a different gam and sig2.

TABLE III
PARAMETERS SETTING OF GAM AND SIG2

gam	Sig2	Total
0.1	0.1	83.33%
0.5	0.5	87.5%
0.5	1	87.5%
1	0.4	87.5%
1	0.5	91.67%
1	0.6	87.5%
1	1	87.5%
1	2	79.17%
2	2	75%

Figure 6 is the changes of the classification Effect of gam and sig2. When the gam is between 0.7 and 1.5 and sig2 is 0.5, four kinds of emotional effects can achieve a global recognition of 91.67%, which will ultimately determine that the value of gam is 1 and sig2 is 0.5. Thus we have a emotion recognition.

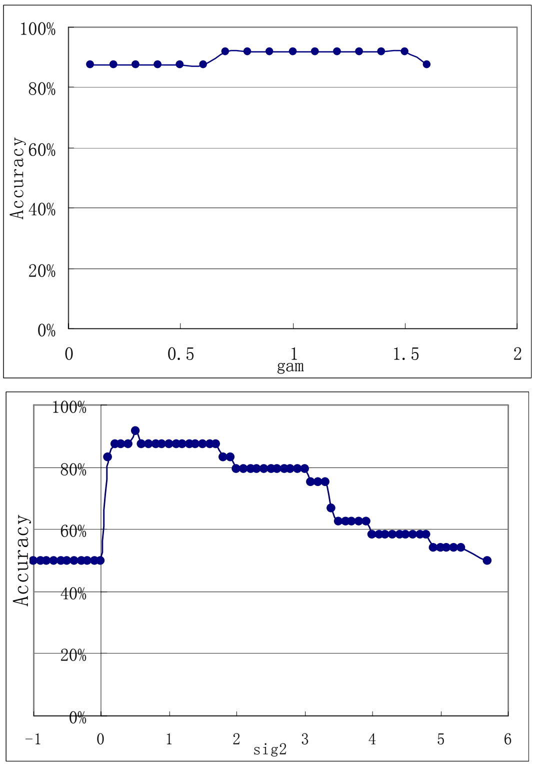


Figure 6. Relationship of gam and sig2 with accuracy in classification

The result after emotion recognition by the use of LS_SVM is shown in the Table IV, from which we can see that emotion recognition by the use of LS_SVM is feasible. And the recognition rate can reach 91.67%. The classification of Support vector machine by solving linear equations makes the time of training greatly reduced.

Then we compare the experiment result of the mode recognition for the four kinds of emotions with the recognition rate of the BP neural network classifier improved by L-M and RBF neural network, respectively. Table V is the recognition results of the same group of data in different classifier. It can be seen from Table V that the efficiency of the standard BP neural network classifier is 62.5%, while the efficiency of the L-M improved BP neural network classifier and RBF neural network are both 83.33%. The efficiency of LS_LVM classifier for four kinds of emotions can reach up to 91.67%, proving that the wavelet coefficients extracted from wavelet transform can characterize the type of emotion. Compared to the traditional BP network and RBF neural network, improved LS_SVM will increase system response speed and identification accuracy, effectively eliminating the phenomenon of over-fitting. Also it has a good ability of generalization and overcomes some shortcomings of the BP algorithm well. The experimental results of the emotion recognition process of the same data in different classifiers prove that LS_SVM has its unique advantages in a small sample classification fully. Also, in the experiment, we find that the emulation time of LS_SVM is much faster than BP neural network classifier with a good recognition effect.

TABLE IV
THE RECOGNITION EFFECT OF EMG SIGNALS IN LS_SVM CLASSIFIER

	Actual output						Error Number	Recognition Effect	Overall Recognition Rate
joy	1	1	1	1	1	1	0	100%	91.67%
anger	1	1	1	1	1	0	1	83.33%	
sadness	1	1	1	0	1	1	1	83.33%	
pleasure	1	1	1	1	1	1	0	100%	

TABLE V
RECOGNITION EFFECT IN THREE KINDS OF CLASSIFIERS

	Joy	Anger	Sadness	Pleasure	Total
BP	50%	66.7%	83.3%	50%	62.5%
L-M BP	66.7%	83.3%	83.3%	100%	83.3%
RBF	83.3%	83.3%	83.3%	83.3%	83.3%
LS_SVM	100%	83.3%	83.3%	100%	91.67%

IV. CONCLUTION

Emotion recognition is an issue with a promising development prospect [11]. This experiment multi-scale decomposes wavelet of EMG signals by wavelet transform. Then we extract the maximum and minimum of wavelet decomposition coefficients so as to constitute a signal feature vector. Then we input it to the standard BP neural network classifier and the L-M improved BP neural network classifier for emotion recognition method. These two kinds of classifiers are able to detect and identify the surface EMG of four kinds of emotions, joy, anger, sadness and pleasure. Compared to the BP neural network classifier, the emotion recognition have a better classification effect, higher recognition rate and better robustness. Experimental results show that the surface EMG feature extraction based on wavelet transform and emotional type recognition method using SVM as a classification tool is feasible and effective in application of emotion recognition.

In particular, the surface EMG is not only with human body movement and its physiological state and other objective factors, often the shape of signal guiding electrode and its location have a great influence on the results of testing and analysis. Therefore, it will be a further study that people strengthen the integration of multiple information technology, and integrate a wide range of information, such as ECG, pulse, body temperature, etc., to more accurately guess people's inner feelings [12, 13].

The main future work topics are not only related to this particular study, we will concern to EEG, ECG, Facial expression[14] and a more sensible and reliable GSR in next stage. The aims are extracting more bio-signals, namely pupil dilatation, voice analysis and facial expression recognition. What's more, many studies [15-19] for representing facial expression images have been proposed such as Optic flow, EMG(electromyography), Geometric tracking method, Gabor representation, PCA (Principal Component Analysis) and ICA (Independent Component Analysis). These methods would be plausible to perform automatic subject emotion classification with deeper detail levels. But there have been no reports about how to contribute the intrinsic features of the manifold based on various internal states on facial expression recognition. So, we will do some experiments and found some significative results next stage.

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These technologies provide human-machine interaction for emotion detection and further treatment of psychiatric problems [3â€“5]. Several researches measured the level of fatigue and stress from speech [6]. But the level of fatigue and stress does not lead to psychiatric disorder directly. Emotion change of a human can cause mental diseases.Â Early detection of disease improves the prognosis and is helpful to provide effective treatment at early stages. Emotion detection system can provide support to the clinicians to perform the task of emotion detection more efficiently.Â (NN), artificial neural network (ANN), and support vector machine (SVM) are widely used for emotion detection due to their excellent performance [8â€“13]. The support vector machine (SVM) proposed by Cortes and Vapnik2 is one of the most influential and powerful tools for solving classification and regression problems.3,4 but it does not have an online learning technique.Â Therefore we extended the standard SVM based on a pairwise coupling method to make it into a multiclass pattern recognition problem for s-EMG recognition. The number of SVMs necessary for an n-pattern classification, N, is defined by Eq. 6. N=.Â These results show that the recognition rate of the SVM improved after a period of online learning. 487.Â Technical Report IEICE PRMU, vol 99, No, 182, pp 45â€“52 6. Tamura H, Okumura D, Tanno K (2007) A study of motion recognition without FFT from surface-EMG (in Japanese). Diagnosis Model Based on Least Squares Support Vector Machine Optimized by Multi-swarm Cooperative Chaos Particle Swarm Optimization and Its Application. Guojun Ding, Lide Wang, Peng Yang, Ping Shen, Shuping Dang. JCP. 2013. An Improved PSO Algorithm with Object-Oriented Performance Database for Flight Trajectory Optimization. Sibin Zhu, Guixian Li, Junwei Han. JCP. 2012.Â Study of Emotion Recognition Based on Surface Electromyography and Improved Least Squares Support Vector Machine. Ying Guang Yang, Shanxiao Yang. JCP. 2011. Comparison of Support Vector Machine and Back Propagation Neural Network in Evaluating the Enterprise Financial Distress. Ming-Chang Lee, To Chang. ArXiv. 2010. 1 Excerpt.