Analysis of Physiological Signals for Emotion Recognition Based on Support Vector Machine

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Abstract. Emotion recognition is one of the important part to develop in human-human and human-computer interaction. In this paper, we focused on the experimental paradigm and feature extraction to extract features from the physiological signals. The experimental paradigm for data acquisition used MULTI module equipment of biofeedback 2000 x-pert which combined multi-sensor such as skin conductance, skin temperature, and blood volume pulse to collect physiological signals from the subject's fingertip of the non-dominant hand. And an approach for the emotions recognition based on physiological signals such as fear, disgust, joy, and neutrality that international affective picture system (IAPS) was used to elicit emotion. These were selected to extract the characteristic parameters, which will be used for classifying emotions. Support vector machine (SVM) is a popular technique for classifying emotion recognition and perform high accuracy for classification. The experiment results showed that the methodology by using experimental paradigm, feature extraction and especially multi-class support vector machine (MSVM) provided significant improvement in accuracy for classification emotion recognition states.

Keywords: emotion recognition, biofeedback system, physiological signals, international affective picture system (IAPS), support vector machine (SVM).

1 Introduction

Biofeedback system is an important autonomic nervous system (ANS) measure in psychophysiological signal for emotion recognition to develop human computer interaction. This system provides a service health care for human and proves to be a particularly successful new therapy. For emotion is a concept involving three components such as subjective experience, expressions and biological arousal. And it is a psychophysiological process that produced by the limbic system activity in response to a stimulus.

In this paper, multi-class support vector machine (MSVM) was employed to improve accuracy for emotion classification. There are many ways that the researcher used to express and elicit emotions through visualization, audition, gesture and tone of voice, body movement, facial expressions, and others to detect which respond to

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the affective state. In this work, visualization of IAPS was employed to elicit emotions for the experimental paradigm and it was an affective picture standard to induce the emotions for the subject [1]. And some emotions were difficult to induce and recognize by people, and inner emotional experiences was not expressed outwardly. Then, the physiological patterns may be used to recognize distinct emotions through the remained questions [2].

The physiological signals of interest in this analysis are: SC, SKT, and BVP. Skin conductance changing is related to the activity of sweat gland which is controlled by the sympathetic nervous system and skin conductance is used as an indication of psychological or physiological arousal.

SKT may be taken as a representative sample of bodily activity correlated with changes in affective states. A fall in the skin temperature of the extremities in response to mental work: stress, fear, and pain. Conversely, a rise in the skin temperature showed about the relaxation and sleep state.

BVP changes in the blood flow causes fluctuations in the brightness of the reflected or transmitted light. These fluctuations are filtered out, amplified, and displayed as the BVP parameter relative change in blood flow.

Statistical analysis is a crucial algorithm which used to extract the features of raw signals for processing emotion recognition classification. SVM is a popular algorithm which presented the ability with the good result of classifying to classify four emotions such as fear, disgust, joyful and neutral. The remains parts of this paper will be proved in the next step such as the related work, feature extraction, classification, the result of experimental paradigm, and the conclusion and future work.

2 Related Works

The emotion recognition system was recognized by using physiological signals through the different ways that this system was proposed by some researchers. The physiological signals can vary depending of the range of number of emotional categories and whether the systems are user dependent or independent as the following descriptions:

The emotion recognition system was able to recognize eight emotions and performed with the accuracy of 81.25% for a single subject. Four biometric sensors of physiological signals were collected over a period of 20 days. The statistical features were then calculated over a period of one-day, and hybrid of SFFS and FP were used to select and classify respectively. This system was developed by Picard et al. [3].

Posner et al. proved an analog, continuous mapping of emotions based on a weighted combination of arousal intensity and emotional valence which is represented by two-dimensional space [4].

The emotion recognition system was user-independent emotion detection system by utilizing three physiological signals that the physiological data were collected from 50 children aged from 5 to 8 years old to recognize 4 emotions of sadness, anger, stress, and surprise. The accuracy of 78.43% and 61.76% were achieved for three and four emotion respectively. In pattern classification, SVM was employed to classify emotion recognition. This system was developed by Kim et al. [5].

The emotion recognition system was used 5 types of bio-sensors to attach on the subjects to make the experiment. IAPS was used to elicit emotion for subjects and feature extraction employed six statistical features of physiological signals. To optimize the work procedure, genetic algorithm was used for feature selection. And four types of classification methods were employed to classify emotion after comparing the accuracy of these methods [6].

Our previous work, we used mean and standard deviation of raw signal to extract the features for classifying emotions. In the experimental paradigm was used another method to induce emotion for the subjects which was different to experimental paradigm in this work. And the experimental results proved that the accuracy of emotion recognition was low accuracy for classification.

Thus, our purpose in this work, throughout the researchers above and our previous work, we concentrate on experimental paradigm to get the meaningful data and eigenvalue with eigenvector to extract the features. And support vector machine was employed for classification to improve accuracy of emotion recognition.

3 Experimental Paradigm for Physiological Data Acquisition

In our work, we divide two steps for defining the method to extract the data collections that we describe as the following:

3.1 Equipment Method

The equipment for acquisition of emotion-specific physical signals is MULTI module of biofeedback 2000 x-pert combined multi-sensor such as SC, SKT and BVP. These three physiological signals are selected to record the raw data for extracting the emotion recognition features. This equipment is attached on the finger tip of the non-dominant hand of subject as the following figure 1. The temperature and relative humidity of the experimental room were between 20 ^{0}C and 26 ^{0}C.

SC is measured by recording the electrical potential and it has the sample rate of 2 KHz. It is a square wave signal with frequency 20 Hz and amplitude of ±1.42 V is applied to the skin. The maximum measuring range for SC is defined from 0 to 50μS and resolution 0.001μS with maximum error of 0.65 μS.

SKT is processed in the sensor and transmitted to the multi-module in digital form and data rate of 4 values per second. Within a range of 10-40 ^{0}C and the temperature is measured at a resolution of 0.01^{0}C and with an accuracy of 0.5^{0}C.

BVP is the measurement of the mean flow of blood near the surface of the skin with the range of the value is 0-100% at a resolution of 0.25%. And the range of parameter is 30-200 bpm (beats per minute) at a display resolution of 1 bpm. The sample rate is 500 Hz and integration time constant of 100 ms with 10 data rate per second.

Fig. 1. The experiment procedure in our laboratory

Figure 1 showed that the way how to attach the sensor, radio module, and connect the radio pyramid to the software biofeedback 2000X-pert in the computer.

3.2 Emotion Induction Method

Subjects and emotion elicitation protocol: four subjects (three males and one female, aged from 25 to 30 years old) graduate students are healthy subjects and not taken any medicine in a week for making the experimental paradigm. The participants were introduced how to induce emotions and make the experiment before we start the experiment. The consent form the participant is seated in a comfortable chair in front of a computer screen at an approximate distance of 70 cm. All target emotion states are elicited from the subject by using IAPS image slide-show to induce emotion.

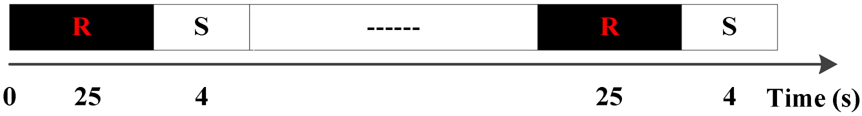


Fig. 2. The process of eliciting emotions for the subjects (R = rest and S = stimulus)

Data collection: One session takes the time of 4 minutes 50 seconds that each emotion displays 10 images and one image is displayed 4 seconds to induce emotion. In order to process the experiment, we first start showing the black screen which represent the rest time for the subject, after we show the image to elicit emotion. The black screen is also shown in the time duration of 25 seconds and it was shown between of the images to stimulus emotion that it was done 10 times until finish the experiment of each session. There are 10 trials in one session as shown in the Figure 2 and these 10 trials of image stimuli are displayed the same emotion in a session.

The accuracy strongly depends on the data sets or experimental data which were obtained in laboratory conditions because the observation and verification showed that the results were achieved for specific users in specific contexts and it is very difficult to label emotion classes in physiological signals such as waveforms without uncertainty.

4 Feature Extraction

4.1 Preprocessing

We first verify that the data were recorded properly during the experimental session by generating and examining plots of each of the channels over time as the following figure 3. The data acquisition of each physiological signal was segmented according to the time duration of the stimulating sections as you can see in the Figure 2. And these segments were prepared to process for the next step, means that we cut the meaningful signal as the trial from the session of the experiment procedure.

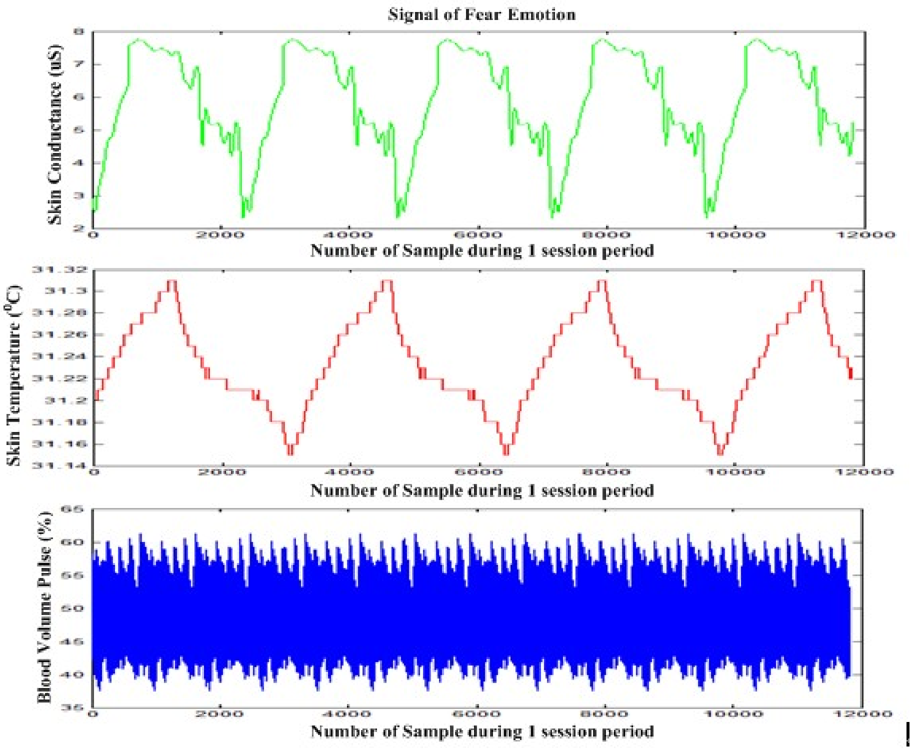


Fig. 3. The raw signal of fear emotion during one session period

Figure 3 showed characteristic raw signal of fear emotion which was plotted by physiological signals such as skin conductance, skin temperature, and blood volume pulse. This signal was cut in 10 trials subject to the time stimulus of the subject.

We will get the property of the raw signal of fear emotion for a trial as shown in below figure 4.

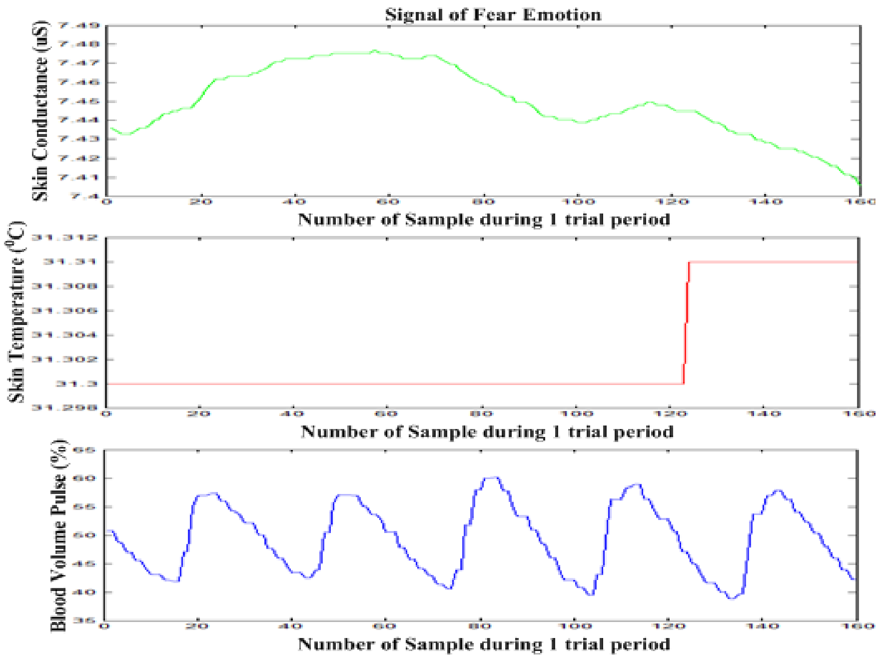


Fig. 4. The raw signal of fear emotion of one trial cut from the session

4.2 Feature Extraction Method

Eigenvalue and eigenvector were employed to extract the features from the raw data for feature extraction. The process of this method was calculated through the step as follows. After we got the raw data of each trial, we used the raw data of skin conductance (x), raw data of skin temperature (y), and raw data of blood volume pulse (z) to make a 3 dimensional data set (dimensions x, y, z) and the result was the calculation of covariance matrix between two dimensional space which were arranged as bellows:

So, we obtained 3 matrices (size: 160-by-2) that we got from the combination of x, y, and z. We assume that matrix *A* = [x y], *B* = [x z], and *C* = [y z].

Next, we calculated the covariance matrix *A*, *B*, and *C* which were given as the following formula (1).

$$Cov(X) = \frac{1}{n-1} XX^T \tag{1}$$

Where $Cov(X)$ is a covariance matrix. $\boldsymbol{X}$ is a matrix and $\boldsymbol{X}^{\mathrm{T}}$ is a transpose matrix. For n is the length of row of the matrix $\boldsymbol{X}$ that we make the covariance matrix to be a square matrix (n -by- n)

After that, we calculate the eigenvalue and eigenvector of the covariance matrix of all two separate dimensions by supposing:

$T = Cov(A),\ U = Cov(B),$ and $V = Cov(C)$ as the equation (2) can be written as:

$$\mathbf{P}\cdot\mathbf{v} = \lambda\cdot\mathbf{v} \tag{2}$$

Where $\mathbf{P}$ is a square matrix n-by-n and $\mathbf{v}$ is the eigenvector and λ is the eigenvalue

Thus, we receive 160 features from four subjects and four emotions for classification by using this method.

5 Classification Method and Experimental Results

The classification was most important step to recognize emotion. The multi-class support vector machine was used to classify emotional states of physiological signals and to improve the accuracy result of recognition.

5.1 Classification Method

In this paper, we use a tree-structure multi-class SVM, whose aim is to optimize the class patterns [7]. The process of this method will be shown as the following given steps.

First, we review a two-class pattern recognition problem. Given l labeled training data $\{(x_i, y_i)\}$, where $x_i \in R^n, y_i \in \{-1, 1\}$, and $i = 1, 2, ..., l$. The learning of a two-class SVM is formulated as a convex quadratic programing (QP) problem by calculating the Lagrange multipliers $\{\alpha_i\}_{i=1}^{l}$ that maximize the function:

$$\begin{aligned} Q(\alpha) &= \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \\ Subject\ to &: \sum_{i=1}^{l}\alpha_i y_i = 0,\quad 0 \le \alpha_i \le C\ \ for\ i = 1, 2, ..., l \end{aligned} \tag{3}$$

Where C is a user-specified positive constant and $K(x_i, x_j)$ is a kernel function

The Gaussian kernel is chosen in this condition and we can optimize the problem 1 by using the function:

$$f(x) = \sum_{i=1}^{l}\alpha_i^* y_i K(x_i, x_j) + b \tag{4}$$

Where b means the bias

In this section, we describe the SVM learning algorithm for a k-class pattern recognition problem as the following steps.

Step 1: Let $\Gamma = \{1, 2, ..., k\}$, and put Γ into a table which is indexed. Calculate the distances d_{ij} of all pairwise classes by equation below.

$$\begin{cases} d_{ij} = \dfrac{Ed_{ij}}{\gamma_i + \gamma_j} \\ \gamma_i = \dfrac{\sum_{m=1}^{n_i} \left\| x_m^i - c_i \right\|}{n_i} \end{cases} \tag{5}$$

Where Ed_{ij} is the Euclidian distance between *ith* class and *jth* class patterns, and γ_i is the distance between patterns in *ith* class and center point of *ith* class patterns.

Step 2: Find the furthest pair (i^*, j^*) in Γ, and let x^{i^*} belong to class1 and x^{j^*} belong to class -1.

Step 3: Compare d_{ii^*} with d_{ij^*}, where $i \in \Gamma \setminus \{i^*, j^*\}$. If $d_{ii^*} < d_{ij^*}$, x^i is distributed to Class1. If not, x^i is distributed to class -1. Thus, two subsets Γ_1 and Γ_{-1} are obtained.

Step 4: Calculate μ by using equation (6 (a)).

$$\begin{cases} \text{(a) } \mu = \dfrac{\min(n_1, n_{-1})}{\max(n_1, n_{-1})} \\ \text{(b) } \mu' = \dfrac{\min(n_1 + n_F, n_{-1} - n_F)}{\max(n_1 + n_F, n_{-1} - n_F)} \\ \text{(c) } v_e = \dfrac{d_{eA}}{d_{eB}} \end{cases} \tag{6}$$

Parameter μ represents the balance of distribution of four-class patterns, if $n_1 \prec n_{-1}$, calculate v_e by using formula (6(c)), where $e \in \Gamma_{-1}$. If not, calculate v_e where $e \in \Gamma_1$. Select a class x^e that the corresponding v_e is smallest. And calculate μ' by using formula (6(b)), where $n_F = n_e$.

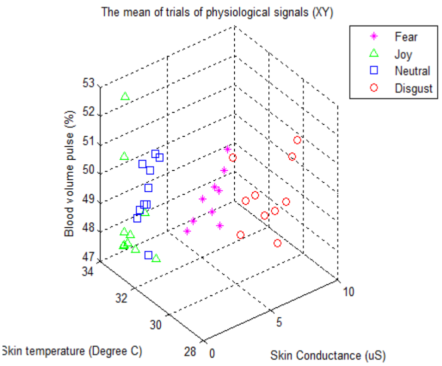
If $\mu \succ \mu'$, go to step 5, else, if $n_1 \prec n_{-1}$, put x^e in class 1, and let $\Gamma_1 = \Gamma_1 \cup e$ and $\Gamma_{-1} = \Gamma_{-1} \setminus e$, if $n_1 \succ n_{-1}$, put x^e into class -1, and let $\Gamma_1 = \Gamma_1 \setminus e$ and $\Gamma_{-1} = \Gamma_{-1} \cup e$. Then repeat to step 4.

Step 5: We solve the equation (3) with the subsets Γ_1 and Γ_{-1}, and get a classifier.

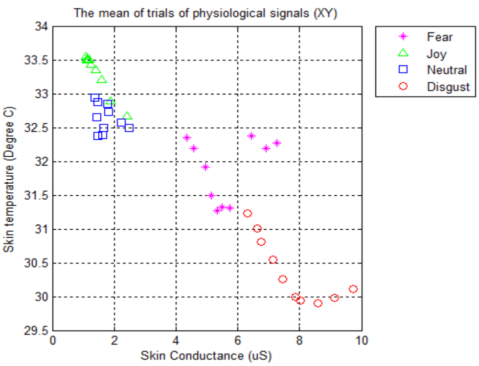
Step 6: Delete Γ from the table and put Γ_1 and Γ_{-1} into the table. If the number of elements in each subset listed in the table equals 1, stop the algorithm. Else, let Γ be one of subsets in the table, in which the number of elements is larger than 1. And then go to Step 2.

5.2 Experimental Results

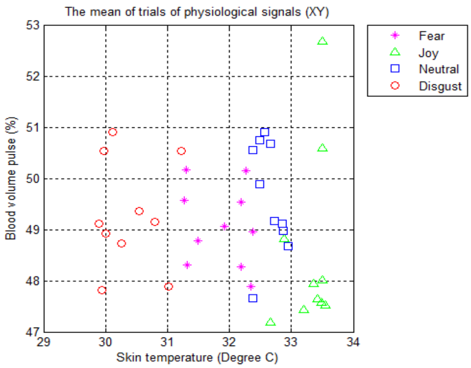
In Figure 5 represents the data of physiological signals of each emotion which is plotted in 2-D and 3-D space of single subject, it proves that the data of different emotions of single subject is separated and spread out for classification.



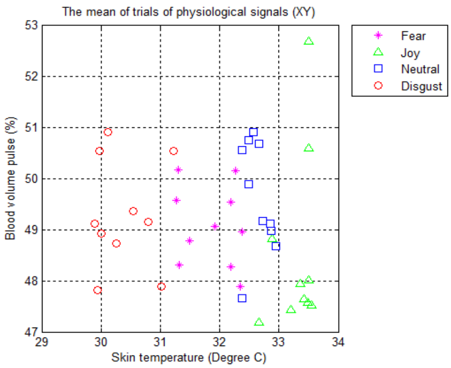
(a) Plotting data in 3-D space (SC-ST-BVP)



(b) Plotting data in 2-D space (SC-ST)



(c) Plotting data in 2-D space (SC-BVP)



(d) Plotting data in 2-D space (ST-BVP)

Fig. 5. Physiological data distribution for each emotional state

Table 1 proves the experimental results of four emotions of single subject, subject 1 exists the high accuracy of 100 % of fear and joy emotion from the 1st column but low accuracy of 40% of fear and disgust emotion from the 2nd column. Subject 2 has the high accuracy of 100% of disgust and neutral emotion in the 1st column with the low accuracy of 40% of neutral emotion in the 2nd and 3rd column, likewise the low accuracy of 40% of joy emotion is in the 4th column. For subject 3 proves that the 1st column shows the high accuracy of 100% of fear, joy, and neutral emotion but in the 3rd column proves the low accuracy of 40% of disgust and joy emotion. Subject 4 certifies that in the 1st column appears the high accuracy of 100% of joy and neutral emotion, in contrast the low accuracy of 40% of disgust emotion is in the 1st, 2nd, 3rd and 4th column.

Table 1. The accuracy of experimental results of each single subject, in this table: 1st, 2nd, 3rd columns represent the 2-D space which are combined by two axes of skin conductance-skin temperature, skin conductance-blood volume pulse, and skin temperature-blood volume pulse, respectively. And 4th column is a 3-D space which is constructed by three axes of skin conductance, skin temperature, and blood volume pulse.

Emotion	Subject 1				Subject 2				Subject 3				Subject 4			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Fear (%)	100	80	40	60	60	60	40	60	100	80	80	80	80	60	60	60
Disgust (%)	60	60	40	60	100	60	60	80	60	60	40	60	40	40	40	40
Joy (%)	100	60	60	80	40	60	60	40	100	60	40	60	100	60	60	60
Neutral (%)	60	60	60	60	100	40	40	60	100	60	60	60	100	60	60	60

Thus, according to the result in table 1 shows that the high accuracy of each subject in the 1st column is more efficient than the other columns in this experimental result, on the other hand the low accuracy is appeared in the 3rd column of this work much more than the other columns.

6 Conclusion

In this paper, we showed that using multi-class support vector machine was more efficient than other methods for classification in this work. And eigenvalue and eigenvector were used to optimize the feature for feature extraction. The accuracy of experimental result proved that the high accuracy of this work was located in the 1st column and low accuracy was located in the 3rd column. Although in this paper had a trouble with experimental paradigm in this time, we still make the progressive and will re-prepare the experiment for this work by improving the accuracy of emotion recognition. We assume that the methods are employed for feature extraction and classification in this paper, are efficient for emotion recognition.

In the future work, we will reach the experimental method to improve the meaningful data of elicited emotions such as video-clip and multi-modal stimuli (the combination of visualization and audition). And power spectrum as same as the other optimization methods for feature extraction will be used to optimize the feature for the feature extraction step as well as the comparison of classification methods with support vector machine will be employed to classify emotion recognition for improving the accuracy of classification. And we will show the way how to study multi-subjects classification in the next work.

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