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Remarks on Emotion Recognition from Bio-Potential Signals

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Abstract

This paper proposes an emotion recognition system from multi-modal bio-potential signals. For emotion recognition, support vector machines (SVM) are applied to design the emotion classifier and its characteristics are investigated. Using gathered data under psychological emotion stimulation experiments, the classifier is trained and tested. In experiments of recognizing five emotion: joy, anger, sadness, fear, and relax, recognition rate of 41.7% is achieved. The experimental result shows that using multi-modal bio-potential signals is feasible and that SVM is well suited for emotion recognition tasks.

Keywords: Emotion, EEG, Pulse, Skin Conductance, Support Vector Machine

1 Introduction

In human communication, nonverbal information, such as intention and emotions, plays an important role. Especially, by using information of emotion people can communicate with each other more smoothly. It is clear that the exchange of nonverbal information is important in all forms of communication and is sometimes more important than verbal information. This means that nonverbal communication is the basis of human communication. Recently, in addition to human-to-human communication, communication between humans and machines are becoming more and more common. To achieve more intimate and human-like interactions between humans and machines, the use of both verbal and nonverbal information will be essential in man-machine interface systems.

Emotion recognition is an interesting but difficult task. People can recognize emotional speeches with about 60% accuracy and emotional facial expressions with about 70-98%.[1] Studies on emotion recognition with computers differ on the number of categories and the kinds of categories to use. Some emotion recognition systems in speech or facial expressions which have been used include several emotional states such as joy, teasing, fear, sadness, disgust, anger, surprise, and neutral. In those studies, emotions that are consciously and purposefully expressed by the subjects are treated since consciously expressed emotions are easier to recognize, control and significantly to gather data on, however recognition rates are 50-60% in emotional speech recognition [2, 3, 4] and 80-90% in facial expressions [5, 6, 7]. On the other hand, physiological indexes are useful to evaluate emotions since they can be measured physically and objectively and can be easily applied to engineering approaches. Physiological changes according to exciting emotions can be observed on changes of the body surface and/or autonomic nervous system: e.g., skin conductivity, electrocardiogram, electromyogram, and blood volume pressure[8]. Furthermore, using brain waves, which are an index of the central nervous system, seems to be effective[9] since emotions are excited in the limbic system and are deeply related to cognition process. The authors have investigated emotion recognition from multi-modal physiological features [10]. By gathering data from multiple subjects and using learning based pattern recognition methods, we tried to achieve person independent emotion recognition and a recognition rate of about 60% was attained for two emotional states (pleasure and displeasure) by using support vector machines (SVMs).

In this paper, we investigate emotion recognition including five emotional states (joy, anger, sadness, fear, and relax) by using SVMs and discuss how multi-modal bio-potential signals are effective for emotion recognition. In section 2, collecting physiological signals using multi-modal sensors are described. The design of emotion recognition systems is shown in section 3 and results of our emotion recognition experiments are presented in section 4.

2 Emotional Data Collection

2.1 Experimental equipment

Figure 1 shows the experimental equipments for gathering bio-potential signals in emotion recognition experiments. The equipment is composed of three sensors and two personal computers; one PC is

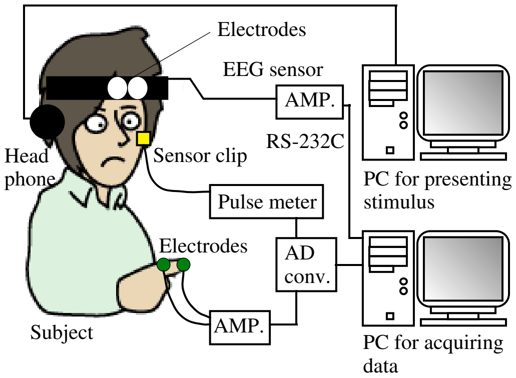

Figure 1: Experimental setup in emotion recognition.

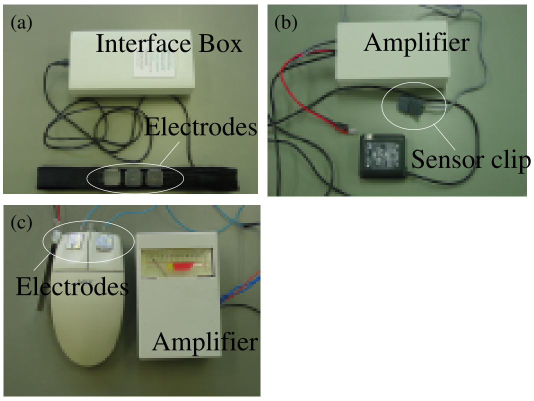

Figure 2: Overview of sensors ((a) EEG sensor, (b) pulseoxymeter, (c) skin conductance meter).

used to present stimulus for a subject and the other PC is used to acquire bio-potential signals: electroencephalographic (EEG), pulse, and skin conductance. A subject wears headphones, a headband on which electrodes are mounted, a clip sensor, and touch type electrodes. In order to excite emotions, audio-visual stimulations are presented to the subject.

The EEG signal is measured by using a simple brain-computer interface (The Cyberlink^{TM} Interface, Brain Actuated Technologies, Inc.) as shown in Fig.2(a). The interface system is optimized to pick up the subject's bio-potential signals from his/her forehead in real time with three dry electrodes that are embedded in the headband to of reduce the cost and protect the human body off from the risks of inserting electrodes. The gathered signals are separated using frequency domain analysis algorithm [11] into three bio-potential signals: EEG, electroocculargraphic (EOG) and electromyographic (EMG) signal. EEG is then analyzed in terms of three frequency bands: a low frequency band including δ and θ wave, a middle frequency band including α wave, and a high frequency band including β wave. These results are transferred into a personal computer (DELL Precision 420) via RS-232C.

The pulseoxymeter shown in Fig. 2(b) is composed of a sensor clip and amplifier. The sensor clip that is mounted on subject's earlobe is composed of an infrared light emitting diode and a photo detection sensor. Since the blood volume at the earlobe varies with the pulse, the infrared light passing through the earlobe varies. As a result, the pulse is detected by a variation of the light received in the photo detection sensor. The pulse measured with electrical current is amplified in the pulse meter and input to the personal computer via the AD converter (PCI-3133, Interface Inc.).

The skin conductance meter shown in Fig. 2(c) is composed of two electrodes and an amplifier. The electrodes are mounted on a mouse in order to contact the fingers of the subject naturally with ease. The variation of the skin conductance at the tips of fingers is measured by a variation of electrical current and the current is amplified and then input to the personal computer via the AD converter.

2.2 Psychological experiments

By using three sensors, the bio-potential signals were gathered under psychological experiments that used audio-video contents as a stimulus for exciting emotions. The experiments were carried out in a private room of our laboratory where the illumination, sounds, and room temperature were controlled to maintain uniformity. To stimulate emotions (joy, anger, sadness, fear, and relax), we used several commercial films that are broadcasted on TV. First we recorded five films in each emotion. To evaluate whether the film excite each emotion or not, we next carried out investigation using questionnaires by human subjects who don't take part in the experiment of acquiring bio-potential signals using the sensors. Then we selected the 10 films that have higher scores in the evaluation. Figure 3 shows examples of the film sequences used in our experiment. The audio-video content is presented to the subject by using a Web application coded in the HTML. We use Internet Explorer 6.1 and Real One Player 2 on Windows XP to browse the application.

To collect bio-potential signals, psychological experiments by human subjects were carried out. A total of 12 subjects (male, native Japanese, age: 21-25) were served. The raw bio-potential signals were collected from each subject two times, one time for each of the five emotions. Figure 4 shows the subject wearing the physiological sensors and Fig. 5 shows examples of bio-potential signals measured from a subject while he received audio-visual stimulus. Here, Fig. 5 is the results after each signal passes through a 50Hz low-pass filter. To investigate whether the subject can feel emotions or not in the experiment, the investigation using questionnaires was also carried out. Table 1 shows

Figure 3: Example of stimulus (Joy: entertainment institution ©Grand chateau 2004, Anger: news of war ©NHK 2004, Sadness: want of love to child ©Japan Advertising Council 2004, Fear: infectious disease ©Japan Advertising Council 2004, Relax: puppies ©NHK 2004).

the results of the questionnaires. As shown in this table, most subjects could feel each emotion by using the stimulus.

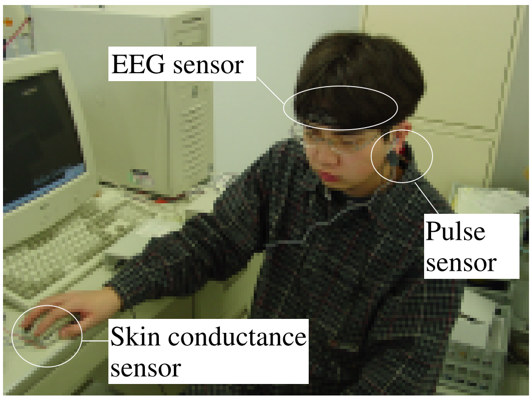

Figure 4: The subject wears physiological sensors.

2.3 Feature extraction

For emotion recognition training or testing, the features of each bio-potential data must be extracted. In this study, the following six values[8] are considered in each bio-potential signal.

$$\mu_X = \frac{1}{T}\sum_{t=1}^{T} X(t) \tag{1}$$

$$\sigma_X = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(X(t)-\mu_X)^2} \tag{2}$$

$$\delta_X = \frac{1}{T-1}\sum_{t=1}^{T-1}|X(t+1)-X(t)| \tag{3}$$

$$\bar{\delta}_X = \frac{1}{T-1}\sum_{t=1}^{T-1}|\bar{X}(t+1)-\bar{X}(t)| = \frac{\delta_X}{\sigma_X} \tag{4}$$

$$\gamma_X = \frac{1}{T-2}\sum_{t=1}^{T-2}|X(t+2)-X(t)| \tag{5}$$

$$\bar{\gamma}_X = \frac{1}{T-2}\sum_{t=1}^{T-2}|\bar{X}(t+2)-\bar{X}(t)| = \frac{\gamma_X}{\sigma_X} \tag{6}$$

where t is the sampling number and T is the total number of sample. By using these feature values, the feature vector x is defined as follow.

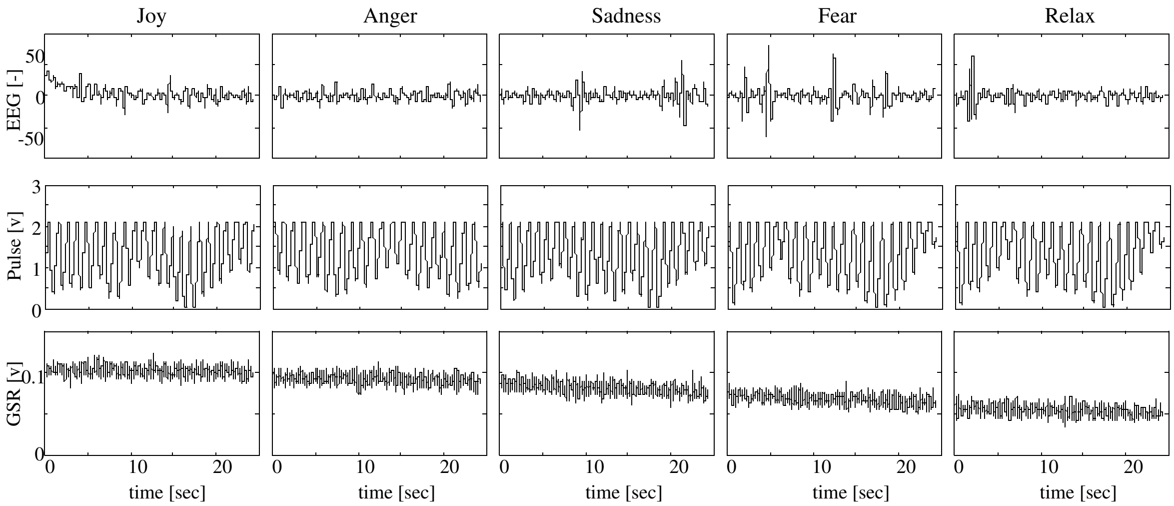

Figure 5: Example of bio-potential signals (top: EEG, middle: pulse, bottom: skin conductance, left to right: joy, anger, sadness, fear, and relax).

Table 1: Emotion recognition results by human subjects [%].

	Joy	Anger	Sadness	Fear	Relax	No emotion
Joy	**83.4**	8.3	0	0	0	8.3
Anger	8.3	**75.0**	0	0	0	16.7
Sadness	0	0	**91.7**	0	0	8.3
Fear	0	0	41.7	**58.3**	8.3	0
Relax	25.0	0	0	0	**75.0**	0

$$x^T = [\ \mu_e \quad \sigma_e \quad \delta_e \quad \overline{\delta}_e \quad \gamma_e \quad \overline{\gamma}_e \quad \mu_p \quad \sigma_p \quad \delta_p \quad \overline{\delta}_p \quad \gamma_p \quad \overline{\gamma}_p \quad \mu_s \quad \sigma_s \quad \delta_s \quad \overline{\delta}_s \quad \gamma_s \quad \overline{\gamma}_s\ ] \tag{7}$$

Here e indicates the power of EEG, p is the pulse, and s is the skin conductance.

3 Emotion Recognition Method

The SVM is a learning algorithm based on statistical learning theory[12]. Originally the SVM is designed for two classes classification by finding the optimal hyperplane where the expected classification error of test samples is minimized. There are several approaches to apply the SVM for multiclass classification. In this study, the one-vs-all method [13] is implemented. Figure 6 shows the processing flow of the emotion recognition using SVM. Five SVMs that correspond to each of the five emotions were used. The ith SVM is trained with all of the training data in the ith class with positive labels, and all other training data with negative labels. In the emotion recognition process, the feature vector is simultaneously fed into all SVMs and the output from each SVM is investigated in the decision logic that selects the best emotion; the SVM that gives the positive label is chosen, and the class of the SVM indicates the recognition result.

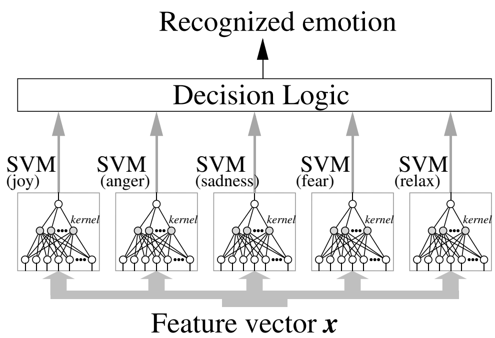

Figure 6: SVM-based emotion recognition system.

4 Computational Emotion Recognition Experiments

In the experiments of emotion recognition, training and testing of the classifier were carried out by the leave-one-out cross-validation method using the collected bio-potential signal data. In the SVM classifier, a Gaussian function was used as a kernel function that projects the data to high dimensional feature space. The kernel function parameter defining spread of a Gaussian cluster was 10^{-3}, and the margin parameter that quantifies the trade-off between training error and system capacity was chosen as 10^8. These parameters were defined by trial and error in order to achieve complete classification rate for training data.

Tables 2 to 8 are the emotion recognition results using SVM classifier. Here tables 2, 3, and 4 show the results in which the feature vectors are composed with EEG, pulse, and skin conductance, respectively. Tables 5, 6, and 7 are the results of using data from two sensors: (1) EEG and pulse, (2) EEG and skin conductance, and (3) pulse and skin conductance. Table 8 shows the emotion recognition result using all data from three sensors. Comparing the results leads to the following observations.

- 1sensor: Using EEG is feasible for emotion recognition task since the averaged recognition rate defined with the average of the diagonal element in the case of using EEG (table 2) is 41.7%, while emotion recognition seems to be hard only by the features obtained from pulse or skin conductance (tables 3 and 4).
- 2 sensors: Recognition rate of one emotions is improved by combining EEG and other sensors, but misclassification rate increases in the other emotions.
- 3sensors: The SVM classifier shows good recognition results in 'joy', 'anger', and 'fear' emotions while has some difficulty in recognizing 'sadness' and 'relax' emotions.

The averaged recognition rate in the table 8 is 41.7% while the average recognition rate for the teaching data is 100%. The recognition rates are relatively low in the case of 5 emotions recognition, however, these results indicate that using multi-modal bio-potential signals is feasible in emotion recognition.

5 Conclusions

This paper proposed an emotion recognition system from multi-modal bio-potential signals. For emotion recognition, SVMs were used to design the emotion classifier and its characteristics were investigated. Using gathered data under psychological emotion stimulation experiments, we trained and tested the classifier. In experiments of recognizing emotions, we attained a recognition rate of 41.7% for five emotions, such as joy, anger, sadness, fear, and relax. The results obtained in this study demonstrated: (1) using multi-modal bio-potential signals is feasible, (2) EEG is useful feature to achieve emotion recognition, and (3) SVM is well suited for this task.

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Table 2: Emotion recognition results using SVM [%] (1 sensor: EEG).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**58.3**	16.7	16.7	0	8.3
Anger	16.7	**33.4**	8.3	8.3	33.3
Sadness	33.3	0	**25.0**	16.7	25.0
Fear	0	8.3	25.0	**41.7**	25.0
Relax	8.3	16.7	8.3	16.7	**50.0**

Table 3: Emotion recognition results using SVM [%] (1 sensor: pulse).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**0**	25.0	25.0	16.7	33.3
Anger	8.3	**16.7**	25.0	16.7	33.3
Sadness	0	16.7	**25.0**	25.0	33.3
Fear	8.3	25.0	33.3	**16.7**	16.7
Relax	8.3	8.3	50.0	0	**33.4**

Table 4: Emotion recognition results using SVM [%] (1 sensor: skin conductance).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**0**	41.7	41.7	16.6	0
Anger	8.3	**41.7**	41.7	8.3	0
Sadness	8.3	33.4	**41.7**	8.3	8.3
Fear	8.3	33.4	50.0	**8.3**	0
Relax	8.3	33.4	50.0	8.3	**0**

Table 5: Emotion recognition results using SVM [%] (2 sensor2: EEG and pulse).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**33.4**	8.3	33.3	16.7	8.3
Anger	8.3	**50.0**	25.0	0	16.7
Sadness	25.0	0	**8.3**	25.0	41.7
Fear	0	33.3	16.7	**25.0**	25.0
Relax	0	33.3	33.3	0	**33.4**

Table 6: Emotion recognition results using SVM [%] (2 sensors: EEG and skin conductance).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**33.2**	16.7	16.7	16.7	16.7
Anger	8.3	**41.7**	16.7	0	33.3
Sadness	16.7	8.3	**41.7**	0	33.3
Fear	8.3	16.7	16.7	**25.0**	33.3
Relax	8.3	41.7	8.3	8.3	**33.4**

Table 7: Emotion recognition results using SVM [%] (2 sensors: pulse and skin conductance).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**0**	25.0	25.0	33.3	16.7
Anger	25.0	**16.6**	16.7	16.7	25.0
Sadness	8.3	25.0	**33.4**	8.3	25.0
Fear	16.7	16.7	25.0	**25.0**	16.6
Relax	16.7	25.0	33.3	8.3	**16.7**

Table 8: Emotion recognition results using SVM [%] (3 sensors).

In \ Out	Joy	Anger	Sadness	Fear	Relax
Joy	**58.4**	8.3	16.7	8.3	8.3
Anger	16.7	**50.0**	16.7	8.3	8.3
Sadness	33.3	8.3	**16.7**	16.7	25.0
Fear	8.3	25.0	8.3	**50.1**	8.3
Relax	8.3	25.0	8.3	25.0	**33.4**