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Facial Expression Mirroring-based Classification of Emotions using Electroencephalogram Signals

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Abstract

People have lived in a way delivering many messages through various non-verbal communicative means such as facial expressions and voice tones. Recently, many researchers have attempted to do tasks dealing with emotions conveyed through some immanent bio-signals for human-computer interaction or human-robot interaction. If we switch some applications of bio-signals dominantly occupied to cure the handicapped or the rehabilitant to entertainment areas including video games, artificial life and interactive theaters, this will provide us with a solution to overcome drawbacks caused by traditional interfaces in which it may allow us to more naturally experience human-oriented contents. In this paper, we present a mechanism to do analysis of electroencephalogram signals originated from emotional impulses and to carry out classification of the emotion. Also we have validated the methods to foresee usability for brain-computer interface. The partial derivatives of EEG are taken as features for some training data set gained from facial expression mirroring. Four emotions including neutral, anger, happiness, and surprise have been classified using the support vector machines. The experimental results can be extended in providing innovative potential in the areas including games, virtual reality, agents, and various entertainments.

Keywords: *Facial expressions; Emotion, Brain-computer interface, Human-robot interaction, Electroencephalogram*

1. Introduction

Human beings send and receive a great deal of messages through verbal and non-verbal communications. In particular, emotions in non-verbal messages can be thought of as being fundamental in which wordless signals including gesture, facial expression and eye contact seem to be rather critical than in verbal communication. In recent years, human-machine interaction or human-computer interaction has attempted to deliver emotions through facial expressions [1, 14-17] and voice recognition [18-20]. Davidson [2] presents a theoretical approach to the role of the two hemispheres in emotional processing. His study shows the activity on the left frontal temporal region of hemisphere when positive emotions are observed while the activity has been found on the right temporal region to negative emotions. In a case of children, the stronger activity has been seen on the left frontal region when the smile faces have been displayed. No distinctions between the left and right hemispheres are found when the sad faces are shown. Yoshida [10] investigates a pleasant feeling by observing the alpha frequency bands on the frontal lobes including *Fp1* and *Fp2* channels.

Heller [3] explores the correlation between spiritual emotions and active regions being composed of two dimensional structures. Musha et al. [4] present a method to quantify emotions by defining the emotion spectrum analysis method (ESAM) mapping that takes cross-correlation coefficients using feature parameters. Anderson [21] studies the classification induced by auto-regressive modeling for spiritual activities such as learning mathematics and writing letters. Aforementioned studies have shown meaningful achievements such as EEG asymmetric characters and difference of frequency bandwidth which are considered to be common results. However they seem to be not easy to realize those approaches since complex experimental setups, limits of the methods and feature variations. In addition, since newly emerging tasks beyond most dominant face-to-face communications have been increasing as such computer-to-computer or mobile-to-mobile, a new conceptual interface to comprehend emotions can be anticipated to improve communications more efficiently. For example, a robot can be controlled by an operator located in a remote place who is monitoring the mission of the robot. In a certain case, the operator wants to convey his or her emotion to the robot which is induced by the contents of the mission during the mission period. Recent studies however tend to focus on the recognition of facial expressions [5, 22] rather than bio-signals which surely represent genuine information. It is not difficult to seek the case that a genuine expression can be hidden or disguised in faked confessions. Hence, in this approach, we present a method to recognize genuine emotions from electroencephalogram (EEG) signals which have been collected during participants make facial expressions. Data acquisition process and preprocessing for noisy reduction are described. Feature extraction is defined to distinct each expression as well. Finally classification of expressions has been carried out.

2. Data Acquisition

In this study, we have decided to follow Ekman's six universal emotions [9] including happiness, surprise, sadness, anger, fear, and disgust. We have gathered EEG data from participants who are instructed to deliver internal moods as much as they could when performing facial expressions. In the experiments we follow a voluntarily emotion recoding that are widely used in capturing EEG data [6-8, 23]. The participants have been demanded to practice performing facial expressions as being asked to learn the example pictures of facial expressions which is referred to the Facial Action Coding System (FACS) [10] developed by Ekman. They are instructed to carry out internal moods as well as external expressions. We have recorded EEG data while the participants make and see their expressions through the camera at the same time.

2.1 The Experimental Setup

Six people (four males and two females) whose ages range between 18 and 25 participated in the experiments. They were asked to perform each expression five times. The participants were kept 1*m* far from the monitor while their brain activities wete recorded. Ongoing EEG signals were recorded using Ag/AgCl electrodes with a QEEG-4 amplifier (Laxtha Inc., Daejeon, Korea) in a quiet room that temperature was maintained around 20℃. No one was allowed to enter or exit during the experiments to accurately capture EEG data and help the participants focus on the making expressions. We selected *F4*, *T3*, *T4* and *P4* channels by referencing to the 10-20 system positioning as shown in Figure 1. The ground electrode was attached to mastoid process and the reference electrode was positioned at *Fp2* [13]. Throughout the experiment, EEGs were continuously obtained at a sampling rate of 512 Hz/channel.

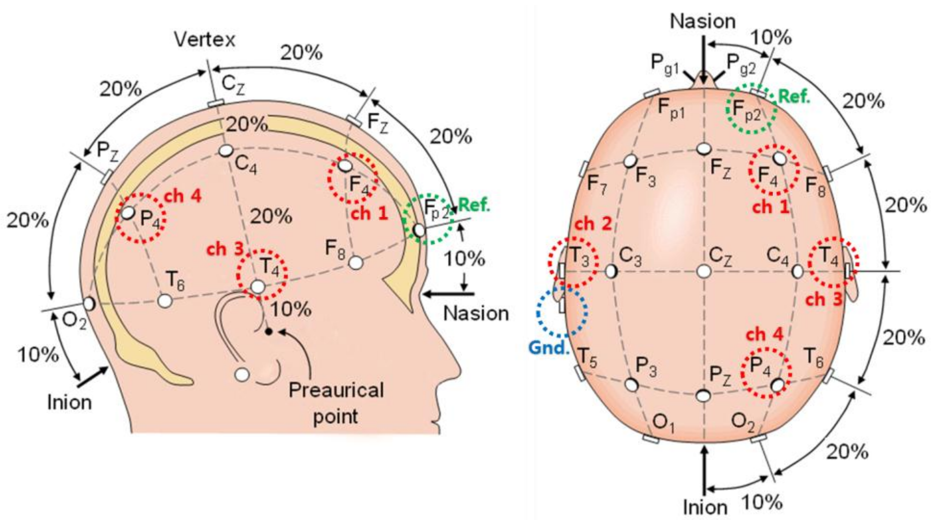


Figure 1. The Location of EEG Electrodes

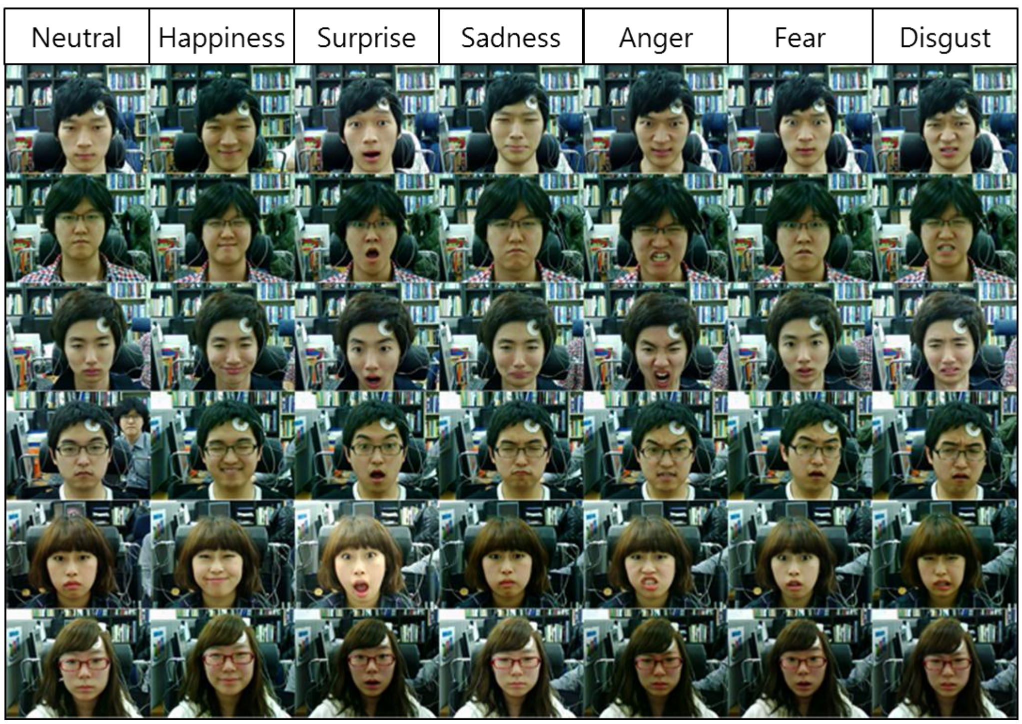


Figure 2. Screen Shots of the Recoded Videos for Facial Expressions

2.2 The Procedure of the Experiments

The participants had been learned about the purpose and mission of the experiments. They were also asked to care for avoiding eye blink or body motion that might cause noisy signals. When the experiments got started, the participants had been demanded to open eyes and keep the neutral expression for 20 seconds to record EEG data. The participants observed their expressions through a 23-inch LCD monitor while they were creating facial expressions. They had been asked to record each expression five times for three to five seconds. In addition, we recorded all procedures in order to utilize the video for preprocessing and data analysis. Each step needed to be recorded into the video files as capturing EEG data. The Figure 2 shows the examples of the screen shots of videos. The neutral expression, happiness, surprise, sadness, anger, fear and disgust are shown from the left.

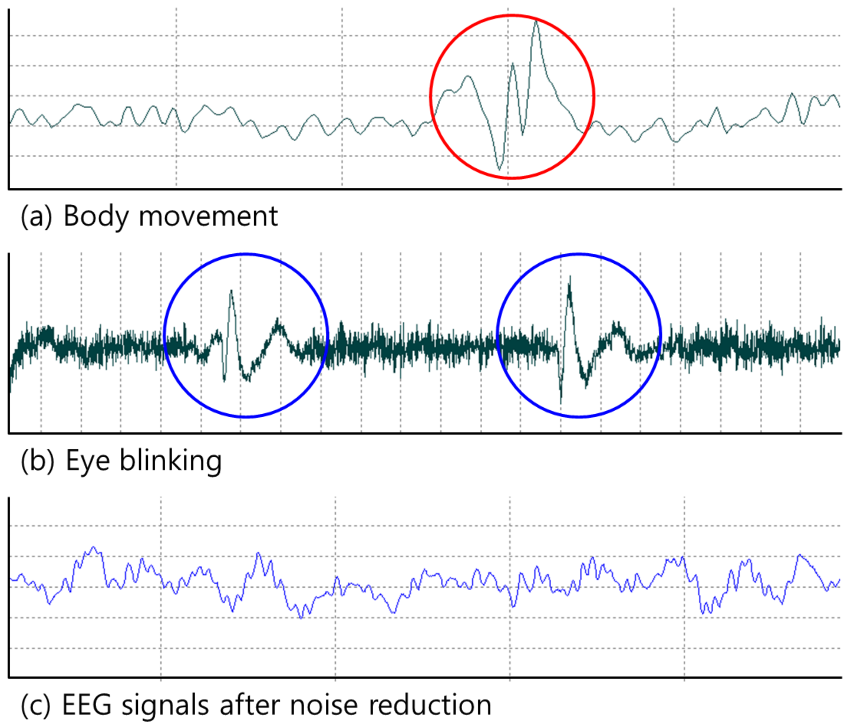


Figure 3. Preprocessing Results of EEG Data Showing Noise Caused by Body Motion on the Top, Eye Blink on the Middle and Noise Reduction Results on the Bottom

2.3 The Preprocessing

Prior to the data analysis, we need to fully delete distorted data or only part of noise data from the whole data. Independent component analysis as a blind source separation method can be widely used to get rid of only part of noise. However it might not be always robust in all EEG data. Hence we use the video data captured when obtaining EEG data. For instance, we figure out the frame that shows us that eye blink or body motion occur shown in Figure 3. For that frame, we delete the whole EEG data to be considered as noise contained data. We extract EEG data every two seconds shown in the bottom of Figure 3.

3. Feature Extractions

The goal of feature extraction is to extract distinctive characteristics that will be used to classify filtered data into the common sets. Emotions can be thought of as the internal responses to external stimuli. In EEG, physically observed magnitude can be measured after noise reduction. Intuitively speaking, each emotion from facial expressions has distinctive appearance. For instance, each facial expression shows various muscle movements contingent on the expression. Anger or surprise display more muscle movements than happiness. Even in a single expression, distinctive difference can be easily found when one of family member or an unknown person is dead. In this experiment, the partial derivatives can be observed differently between emotions. We use the partial derivatives of EEG data as feature vectors to classify facial expressions. Normalization that ranges EEG signals into 0 to 1 is obtained by Eq. (1).

$$E_K = \frac{X_K - \min(X_K)}{\max(X_K) - \min(X_K)}, \tag{1}$$

The partial derivatives can be defined using Eq. (2).

$$\delta(x) = \frac{1}{T}\sum_{t-0}^{T-1}\left|\frac{dE_K(t)}{d(t)}\right|, \tag{2}$$

4. Expression Classification

Support vector machine (SVM) that wants to figure out the maximize boundary between two interesting features is widely used as a classification tool. SVM is invented by Vladimir Vapnik and colleges from AT&T Bell Laboratory. Various kernels can be employed to make it possible to handle classification using non-linear hyper planes. SVM is based on the principle that minimizes structural risk with unknown probability distribution while traditional pattern recognition techniques are based on the empirical risk minimization method to achieve optimization of training time [11]. To verify the classification, *k*-fold cross validation has been use to report the performance. *K*-fold cross validation is one of statistical analysis tools broadly used in data mining for samples in which it divides a whole set into *k* sub-sets and compares one sample with others. We first divide initial samples into *k* sub-samples. Let one sub-sample be a model test sample for validation. The remaining *k*-1 sub-samples are treated as training data. *K* sub-samples repeat cross validation process *k* times until every sub-samples is used accurately once as validation data. Each step for the process produces *k* results whose average can be acquired to gauge the performance.

5. Experiments and Discussion

5.1. EEG Classifier

Feature vectors of all samples acquired from the participants have been displayed with respect to two dimensional features defined $\delta(x)$ by 1 and 3 channels (*F4* and *T4*) as shown in Figure 4. We chose $\delta(x)$ of these two channels as feature vectors since they are well distributed comparing to other channel pairs. After careful observation, we have decided to exclude fear, sadness and disgust expressions because the feature vectors of fear expression are much similar to surprise, and the ones of sadness and disgust do not show distinguishing distribution. Finally, neutral expression, happiness, surprise, and anger have been classified.

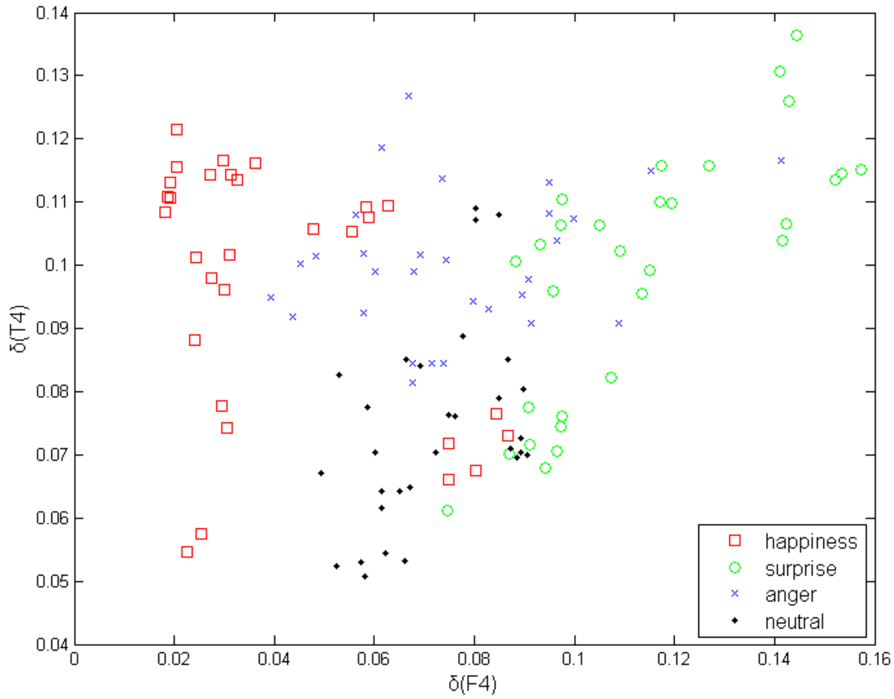
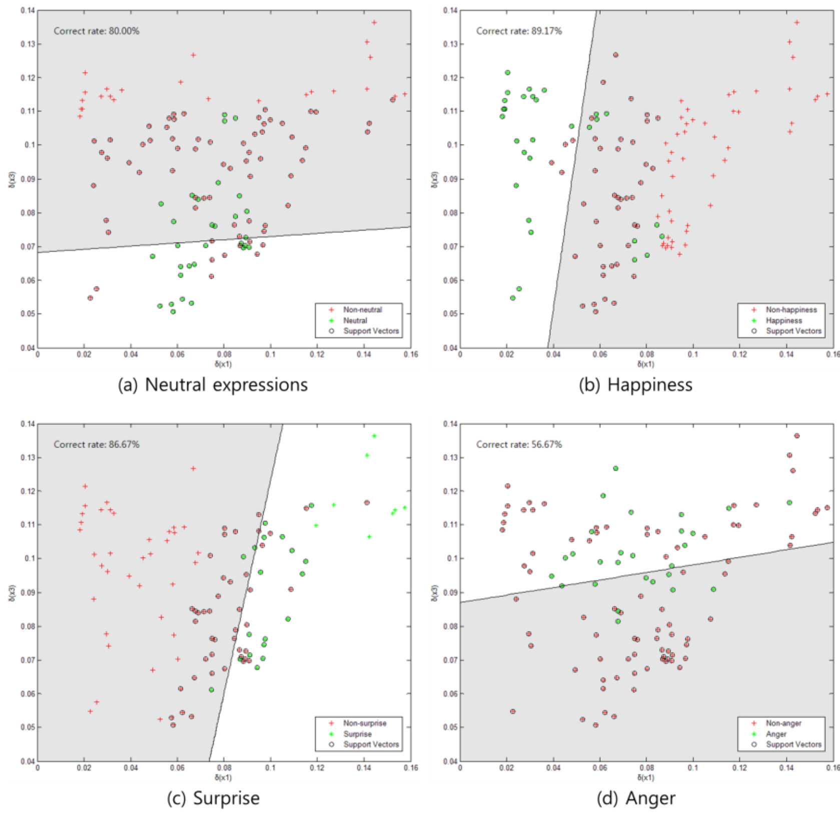


Figure 4. Distribution of each Emotional State's δ(x) in F4 and T4 Channels

5.2. Performance Test

The results of EEG classifier given k=10 for k-fold cross validation are shown in Figure 5 which have been carried out for the four facial expressions including neutral expression, happiness, surprise and anger. The green markers are ones belonging to the expression while the red ones represent other expressions. The circled markers show the support vectors. The green markers that fall into the white region can be considered as successfully classified ones. The green markers showing on the gray region are failed ones. The accuracy of classification appears 80.00% for neutral expression, 89.17% for happiness, 86.67% for surprise and 56.67% for anger. An integrated version of the classification is shown in Figure 6. The classifier starts with testing neutral expression first. If it does not belong to the neutral expression, the classifier does whether it is one of happiness, and surprise. If the result shows non-classification, we make a conclusion be the anger expression. This increases the accuracy almost 66.67% for the anger expression.



(a) Neutral expressions (b) Happiness

(c) Surprise (d) Anger

Figure 5. Classification Ratio and Result Plots using Features of Emotional States

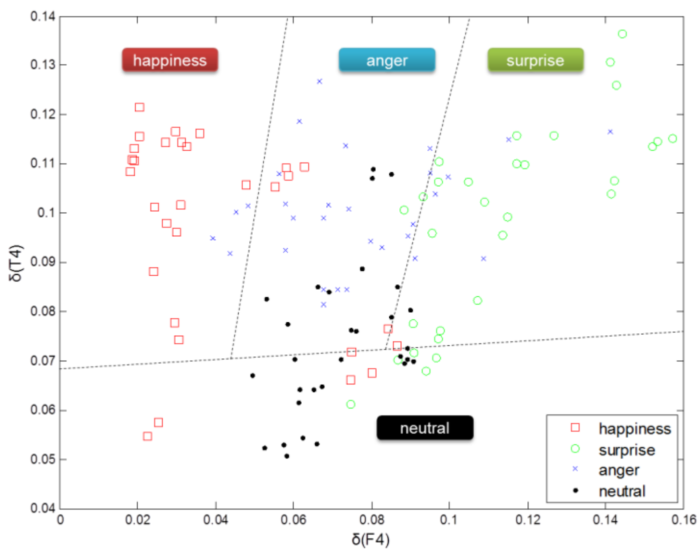


Figure 6. Emotion-EEG Classifier

6. Conclusions

In this paper, we present a emotion classifier for EEG data collected from facial expressions that would be utilized in brain computer interface. For this, we have gathered about 210 EEG data from six people. The partial derivatives are employed as feature vectors. The classifier is derived from SVM algorithm that makes it possible to group four expressions. The accuracy of classification of the integrated version achieves 80.00% for neutral expression, 89.17% for happiness, 86.67% for surprise and 66.67% for anger. For the future work, brain computer interface can be used in providing intelligent services for users. For instance, if we understand genuine emotions of customers for entertainment content services, more customized taking into account the current emotions intelligence services for the users can be utilized.

Acknowledgements

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