EEG-based emotion recognition using self-organizing map for boundary detection

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Abstract

This paper presents an EEG-based emotion recognition system using self-organizing map for boundary detection. Features from EEG signals are classified by considering the subjects' emotional responses using scores from SAM questionnaire. The selection of appropriate threshold levels for arousal and valence is critical to the performance of the recognition system. Therefore, this paper investigates the performance of a proposed EEG-based emotion recognition system that employed self-organizing map to identify the boundaries between separable regions. A study was performed to collect 8 channels of EEG data from 26 healthy right-handed subjects in experiencing 4 emotional states while exposed to audio-visual emotional stimuli. EEG features were extracted using the magnitude squared coherence of the EEG signals. The boundaries of the EEG features were then extracted using SOM. 5-fold cross-validation was then performed using the k-nn classifier. The results showed that proposed method improved the accuracies to 84.5%.

1. Introduction

Emotions are part of natural communication between humans. Automatic recognition of human emotion is an important research in behavioral science, computer games and medicine which is called affection computation [1]. Affective computing brings machines closer to humans by including emotional content in communication [2]. This can be achieved by enhancing the human-machine interface with autonomous recognition of emotional states. Hence, there is a growing interest in this field that led to the development of affective computation, which can potentially improve user experience of machines.

Emotion recognition mainly involves emotional perception of different stimuli, emotional expression in response to the stimuli. Traditional emotion studies were based on physical factors such as speech, facial expressions or combination of both. However, speech and facial expressions vary across cultures and nations [3-4]. In contrast, human biosignals are relatively more consistent across cultures and nations. Over the last years, emotion detection based on biosignals has attracted increased interest [5]. EEG data collected over the scalp approximately reveals the responses to external stimuli because these signals are a direct consequence of cognitive processes in our brain [6]. Therefore, EEG-based emotion recognition system of the basic emotions holds promise for affective computation. Basic emotions are defined as the emotions that are common across cultures and selected by nature because of their high survival functions. However, some complex emotions are a combination of some basic emotions. Nevertheless, commonly accepted basic emotions include: happy, sad, fear, anger, surprise and disgust, despite no coherent notion on the basic emotions [7].

Designs of emotion recognition systems usually employ classified affective responses of subjects using questionnaires. However, the affective responses are not easily mapped into distinctive emotion responses. The valence–arousal plane allows for a continuous representation of emotions on two axes: valence, ranging from unpleasant to pleasant, and arousal, ranging from calm to excited state (refer models of

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basic emotions in [7] and the valence–arousal space in [8]).

This paper presents an EEG-based emotion recognition system for four emotional states: happy, sad, fear and calm. These four emotional states were investigated in this work because they could be easily mapped from the affective responses [9].

The remainder of this paper is organized as follows: Section 2 describes the methodology employed in the proposed EEG-based emotion recognition system. Section 3 presents the experimental results. Finally, section 4 concludes this paper.

2. Methodology

This section describes the methodology behind the proposed EEG-based emotion recognition system. The brain signal in response to emotional stimuli was recorded using EEG. This section also describes the experimental protocol in acquiring the EEG data; and the signal processing steps that include preprocessing, feature extraction, boundary detection, classification and evaluation.

2.1. EEG data collection for 4 emotions

In order to collect EEG data from subjects with the four distinct emotional responses, pictures from International Affective Picture System (IAPS) were used together with synthesized musical excerpts from Bernard Bouchard [10-11]. These stimuli were employed to evoke four basic emotions of calm, happy, sad and fear. The emotion invoked in the subjects could differ from the expected emotion. Therefore, the subjects were asked to rate their emotional experience on a Self-Assessment Manikin [12], which is a standardized system to assess emotion on the valence and arousal scales. The time duration of invoking the emotional response is inline with the definition of ‘‘full blown emotions’’, of which applies the stimuli that last from seconds to minutes [13].

During data collection, the subject was seated in a comfortable chair in a room and the experimental protocol was explained to the subject. The subject was then asked to fill in a Perceived Stress Scale (PSS14) and handedness questionnaire. The PSS14 was used to measure the level of stress of the subject. 8 Ag/AgCl EEG electrodes were then attached bilaterally on the subject's scalp using the 10/20 system of electrode placement. Then the EEG data were recorded for 1 min of eyes closed condition, 1 min of eyes open condition, and 1 min from exposure to each of the 4 emotional stimuli. The visual stimuli were displayed on a 19 inch monitor and presented approximately 1 m from the participant's eyes. The emotional stimuli modalities were presented in a counterbalanced and random order so that each type of stimulus was presented once to every subject. After the presentation of each stimulus, the subject was asked to answer a SAM questionnaire. The protocol of the experiment is illustrated in Figure 1. The EEG data was recorded using the BMEC device with a sampling rate of 250 Hz. The impedance of recording electrodes was monitored for each subject prior to data collection to be below 5 kΩ .

The EEG data from 31 healthy female and male subjects was then collected. After analyzing the PSS14 and handedness questionnaire, 26 right-handed subjects were selected for the study in this paper.

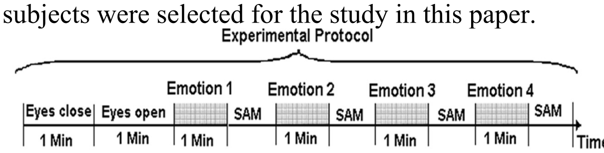

Figure 1. Paradigm for intersubjects experiment

2.2. Data processing

Data processing is then performed on the EEG data collected. In the first stage, the EEG data was normalized for each subject separately. Then the EEG data was filtered using an elliptic band-pass filter to yield EEG with frequencies below 35Hz for emotion recognition [14-15].

2.2.1. Feature extraction

Studies have shown that there exists different kind of connections between scalp regions for different emotions [15]. Thus in this work, EEG features are extracted using the magnitude squared coherence estimate (MSCE), which is often used as a method for detecting the presence of a common signal on two different channels [16]. The MSCE is given in Equation 1, which is a function frequency that yields a value between 0 and 1 to indicate how well x corresponds to y at each frequency.

$$C_{xy}(f) = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f)P_{yy}(f)} \qquad (1)$$

where C_{xy} is MSCE of the input signals x and y using Welch's averaged, modified periodogram method, P_{xy} is the cross power spectral density, and P_{xx} and P_{yy} are the power spectral density of x and y respectively.

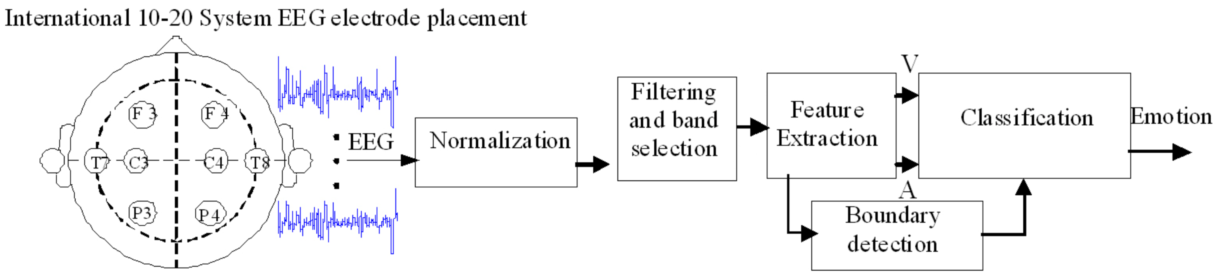

Figure 2. Protocol of data processing

2.2.2. Boundary detection

In order to train the classifier, the extracted features were labeled by two methods: crisp boundary selection and using SOM for boundary detection.

The crisp boundary selection method was applied by using the SAM scores of 1 to 9. By considering the category of applied stimuli, four classes of emotions were selected by considering the Arousal (A) and Valence (V) values. The procedure of region selection has been shown in Figure 3.

The emotion invoked in the subjects could differ from the expected emotion. Therefore in this work, the self-organizing map (SOM) is proposed for the boundary selection [17]. The result of crisp boundary selection is then compared with SOM boundary selection in the next section.

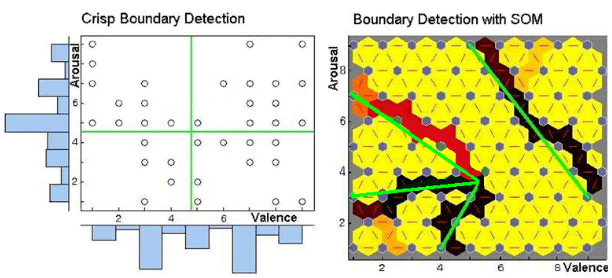

Figure 3. Crisp boundary detection vs. using SOM neighbor weight distances as boundary

3. Experimental results

This section describes the experimental study on the EEG-based emotion recognition system using the data processing steps described in Figure 2. The k-nearest neighbors classifier (kNN) [18] was applied to classify the extracted features and the performance of the emotion recognition system was evaluated using 5-fold cross- validation (on participant base) method.

Using the crisp boundary detection method, the frequency band of 2-30 HZ of EEG signal was evaluated for valence and arousal discrimination. The window length is 2 sec and the sampling rate is 250 Hz. The results of classification accuracies using the considered frequency band and altogether scheme is shown in Figure 3. The results are average of 5 times doing the same procedure.

Next, the boundary selection is then performed using SOM and Figure 3 shows the results. The results showed that four separable classes were recognized. These four classes were then extracted using the boundaries identified in Figure 3.

Figure 4 shows the results on the classification accuracies with boundaries identified using SOM.

The results are presented using three different time length: fast (2 sec), medium (10 sec) and slow (40 sec) triggering. However it should be mentioned that window size of 40 sec is a meaningful time length to process the QEEG signal in clinical research, so accuracy of classifier in different size of EEG signal can be compared with 40 sec window length.

It should be clarified that emotions are dynamic inherently. Using valence-arousal plane is to overcome the problems related to static emotion model. While the supervised method is used, for training the classifiers it is need to index the input features. This study shows using the identified boundaries by SOM gives better results. Comparison has been shown in Figure 4.

Another issue here is the considered timing. The results of different window sizes also have been presented in Figure 4 which shows that accuracy of classification based on 2 sec of EEG signal is as meaningful as 40 sec of that for emotion recognition.

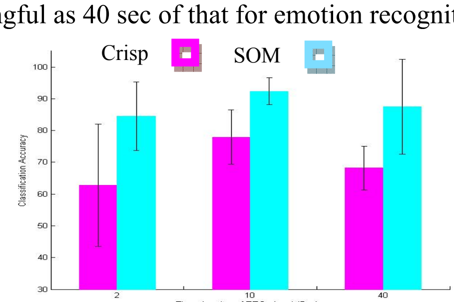

Figure 4. Classification accuracy for 4 classes of emotion in different window length (time in sec) with considering the SOM boundaries vs. crisp boundaries

The result of t-test shows significant improvement by SOM boundary detection method using 2sec of EEG signal (t-value=2.2047, df=8, P-value=0.0293).

4. Conclusion

This paper presents an EEG-based emotion recognition system. A study is performed using 8 EEG electrodes attached bilaterally on the subjects' scalp to record EEG data from 26 healthy right-handed subjects. The recognition of EEG in response to emotionally-related stimuli was investigated. Magnitude squared coherence estimation of EEG signals was used to extract EEG features for classification. Self-organizing map was employed to discriminate the labeled features with the SAM scores. Classification of the EEG features was then performed using the kNN classifier and the performance of the EEG-based emotion recognition system was then evaluated using 5-fold cross-validation. The results showed that considering the boundaries between classes improves the accuracy of the EEG-based emotion recognition system.

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