An EEG-Based Brain-Computer Interface for Emotion Recognition

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***Abstract*—In this paper, an EEG-based brain–computer interface (BCI) system used for emotion recognition is proposed to detect two basic emotional states (happiness and sadness). Selection of frequency bands plays a vital role in distinguishing brain patterns associated with emotions. This paper explores a new method to select suitable subject-specific frequency bands instead of using fixed frequency bands for the emotion recognition. Common spatial pattern and support vector machine were employed to classify two emotional states. Two experiments involving six subjects were conducted to validate our method and BCI system. An average online accuracy of 74.17% for two classes was achieved. The data analysis results demonstrated that the proposed method based on subject-specific frequency bands outperformed the method based on the fixed frequency bands in terms of accuracy.**

Keywords—Electroencephalogram (EEG); brain-computer interface (BCI); emotion recognition; frequency band

I. INTRODUCTION

Emotion recognition has emerged as a notable research topic in this field as it provides a window on the user's internal mental state. There existing many techniques used for automatic emotion recognition that are based on facial expressions, verbal speech, or body language. However, these techniques are limited by the observation of external indicators of emotion, which can be easily subject to deception. For this reason, researchers have been exploring the human emotion based on physiological signals such as electrocardiography (ECG), electromyogram (EMG), electroencephalograph (EEG), galvanic skin response (GSR), or multimodal approaches. These modalities capture the physiological changes associated with emotional states.

Compared to periphery physiological signals, EEG signals have been proven to provide more insights into the emotional processes and responses. Furthermore, since EEG has been widely used in BCIs, the study of EEG-based emotion detection may provide great values for improving user experience and performance for BCI applications. Currently, several studies have been initiated to recognize emotions from EEG signals [1]. Chanel et al. reported an average accuracy of 63% by using EEG time-frequency information as features and support vector machine (SVM) as a classifier to characterize EEG signals into three emotional states [2]. Choppin et al. used neural networks to classify EEG signals from three emotions and achieved 64% classification accuracy [3]. Ishino and Hagiwara categorized users' status into four emotional states using neural networks with accuracies range from 54.5% to 67.7% for each of four emotional states [4]. However, the use of EEG-based BCIs for emotional recognition is still in its infancy.

Power spectra of the EEG were often assessed in different frequency bands to examine their relationship with the emotional states [5]. Many studies have reported several spectral changes and brain regions, which are associated with emotional responses, such as the theta (θ: 4-7 Hz) power changes at right parietal lobe [6], the alpha (α: 8-13 Hz) power asymmetry at the anterior areas of brain [7], the beta (β: 14-30 Hz) power asymmetry at the parietal region [8], and the gramma (γ: 31-50 Hz) power changes at the right parietal regions [9]. Most of works focused only on EEG spectral power changes in a fixed frequency band, or in a large range of frequency bands covering from 4 to 50 Hz [1]. However, the most discriminative bands vary between subjects. Furthermore, neuropsychological research has shown the importance of asymmetric activation/ deactivation between the two cortical hemispheres for emotion processing [10]. Olofsson et al. reported the ERD/ERS responses to pictures of facial expressions in the gamma band [11]. The Common Spatial Pattern (CSP) algorithm is effective in constructing optimal spatial filters that discriminates two classes of EEG measurement in ERD/ERS patterns [12]. However, the success of CSP in BCI applications greatly depends on the proper selection of suitable frequency bands.

To address these problems, the objective of this study is to explore a new method to select suitable subject-specific frequency bands instead of using fixed frequency bands for the emotion recognition. An EEG-based BCI is proposed to detect two basic emotional states (happiness and sadness) during viewing facial expressions. We further evaluate the online performance for the emotion recognition.

II. METHODS

A. Stimuli and Graphic User Interface (GUI)

The stimuli used in this study are illustrated in Fig. 1. Facial expression pictures were used as stimuli to transmit emotions. The stimuli consisted of two kinds of emotional facial expression pictures, which are smiling and crying, corresponding to happiness and sadness emotional states. The smiling and crying facial pictures were taken of Chinese people. All pictures were cropped to remove extraneous background, but the outlines of faces, including hairstyles, were preserved. In addition, all of the pictures were modified using Adobe Photoshop 7.0 (Adobe, San Jose, CA) to produce identical overall luminance and contrast on a white background. The emotional contents of these pictures were measured by a self-assessment manikin (SAM) [13] containing 9 scales for both valence and arousal dimensions. Each subject was required to label every picture using SAM after the experiments. The evaluation results of the valence-arousal scales were (2.41±0.71, 4.37±1.31) and (7.33±1.73, 4.21±0.67) for smiling and crying facial pictures, respectively.

Fig. 1. Excerpt of a sequence of facial expression stimuli. The first two are pictures with happy facial expressions and the last two are pictures with sad facial expressions.

A facial expression picture was set at the center of a 22-inch LED monitor (the area ratio of the picture and monitor: 0.2). Each picture was presented for 8 seconds. The subject was instructed to focus on the smiling face or the crying one during its presentation.

B. Data *Acquisition* System

A NuAmps device (Compumedics, Neuroscan, Inc., Abbotsford, Australia) was used to capture scalp EEG signals for data acquisition. Each user wears an EEG cap (LT 37) with Ag–AgCl electrodes. The EEG signals are referenced to the right mastoid. Two channels, "HEOG" and "VEOG", for eye movements were excluded, and are not shown here. According to the standard 10–20 system, the EEG signals used for analysis were recorded from 18 electrodes ("Fp1," "Fp2," "F3," "F4," "FC3," "FC4," "C3," "C4," "TP7," "CP3," "CP4," "TP8," "P7," "P3," "P4," "P8," "O1," and "O2"). The impedances of all electrodes were kept below 5 kΩ. EEG signals were amplified, sampled at 250 Hz, and band-pass filtered between 0.1 and 60 Hz.

C. Data Processing and Algorithm

For our proposed BCI, the emotion recognition included three progressive stages: feature selection of frequency bands, feature extraction based on CSP, and classification using SVM. Fig. 2 shows the data processing procedure. The analysis methods and algorithms used in this study are described below.

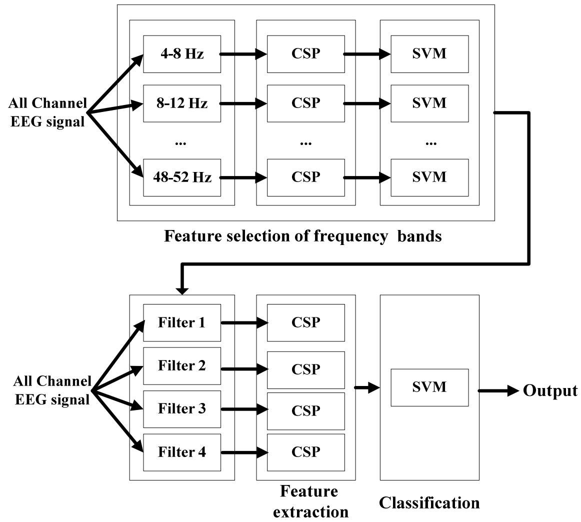

Fig. 2. Architecture of the proposed emotion recognition method including three progressive stages: feature selection of frequency band, feature extraction using CSP, classification using SVM.

1) Feature selection of subject-specific band: The objective of feature selection is to extract a subset of features by removing redundant features and maintaining the informative features. In this study, we focus on the feature selection of frequency bands. First, we employ a filter bank that bandpass filters the EEG signals collected in training phase into multiple bands. Speciafically, the multiple frequency bands cover frequency components from 4 to 52 Hz. In this study, the number of frequency bands is 12, and each of frequency bands has identical width of 4 Hz. Second, spatial filtering is performed on each of these bands using the CSP algorithm. Thus, each pair of bandpass and spatial filter yield CSP features that are specific to the frequency range of the bandpass filter. Next, a 10-fold cross-validation using SVM is applied to the CSP features of each frequency band. Specifically, in a 10-fold cross-validation, the whole EEG dataset is divided into ten subsets. The SVM is trained with nine subsets of CSP feature vectors, whereas the remaining subset is used for testing. Ten different accuracies are then obtained for the entire 10 folds. The average accuracy is taken as the performance evaluation criteria to sort the frequency bands. Four of the most discriminative frequency bands corresponding to the four highest accuracies are selected. Note that the number of the seleted frequency bands is empirically set to four for all subjects in this paper.

2) Feature extraction using CSP: In this process, the EEG data are copied and bandpass filtered over the four selected frequency bands. After bandpass filtering, we extract a segment (0–8000 ms for the facial picture presetation) of EEG data for each channel and each frequency band. A CSP transformation is then applied to this EEG segment to obtain features for classification as below. First, a CSP spatial filter, W , is obtained using two emotional classes of training data that correspond to the emotional states of happiness and sadness, respectively. We then extract the CSP features using this filter for each trial:

$$\text{fm} = \log_{10}(diag(\overline{W}EE^T\overline{W}^T))$$

where fm denotes the feature vector, $\overline{W}$ is a submatrix composed of the first three rows and the last three rows of W, and E is an EEG data matrix corresponding to one trial. In Eq. (1), $diag(\overline{W}EE^T\overline{W}^T)$ is a vector composed of all entries on the diagonal line of the matrix $\overline{W}EE^T\overline{W}^T$, and the operator $\log_{10}(.)$ is used to calculate the logarithm of each entry of the vector. In this study, we select the top three components and the bottom three components from W, which best separate the two emotional state classes. Furthermore, their logarithm variances are calculated and a 6-D feature vector is constructed for each frequency band. A feature vector of a trial is then obtained by concatenating all CSP feature vectors of all frequency bands.

3) Classification using SVM: SVM is a linear discriminant that maximizes the separation between two classes based on the assumption that it improves the classifier's generalization capability. An SVM classifier is first obtained based on the two classes of feature vectors of training data associated with happy and sad emotion states. For a trial of test EEG, a feature vector is first obtained as above and then fed into the SVM classifier to determine the emotion state.

D. Experimental procedures

Two experiments including an offline and online experiments were conducted in this study. In this study, the data of the first experiment were used for training. Six 20 to 33-year-old healthy subjects from the local research unit attended the experiments. During the experiments, the subjects were seated in a comfortable chair and instructed to avoid blinking or moving their body.

1) Experiment 1 (offline): The collected data in this experiment consisted of 40 trials, with 20 trials for happy facial expressions and 20 for sad facial expressions. The two emotional states appeared in a random order. At the beginning of each trial, a fixation cross was first presented at the center of the GUI to capture the subjects' attention. After 2 s, a picture of happy or sad facial expression was presented at the centre of the GUI. The subjects were asked to pay attention to the picture for 8 s. There was a 10 s break between two consecutive trials. We used this dataset to identify the most effective frequency bands for each subject, and further trained an SVM classifier, which were then used in the BCI algorithm in the online Experiment 2.

2) Experiment 2 (online): This experiment was composed of 40 trials, with 20 trials for happy facial expressions and 20 for sad facial expressions. The procedure of each trial was similar to that in Experiment I. However, after the facial expression presentation for 8 s, the BCI algorithm predicted/determined the emotion state. If the detection result was correct, a positive feedback consisting of a smiling or crying face (the same as the stimulus in this trial) and an auditory applause appeared for 4 s; Otherwise, no feedback was given.

3) Performance evaluation: In this study, the online accuracy was calculated as the ratio of the number of all correct predictions among the total number of presented trials. Furthermore, we compared the online accuracies of subject-specific frequency bands with those of theta (θ: 4-7 Hz), alpha (α: 8-13 Hz), beta (β: 14-30 Hz), gamma (γ: 31-50 Hz), and the wide frequency band (4-50 Hz). Here, for each frequency band and each subject, the data of Experiment 1 were used for training an CSP spatial filter and an SVM classifier, whereas the data of Experiment 2 were used for test. In this way, the accuracies of the fixed frequency bands were calculated.

III. RESULTS

A. Results of Experiment 1

The results of twelve frequency bands based on the 10-fold cross-validation for the six subjects were summarized in Table 1. We found that accuracies varied much with the frequency bands and the suitable frequency bands were not always the same for different subjects. We determined four frequency bands with the highest accuracies for the online evaluation (Experiment 2).

TABLE I. ACCURACY BASED ON 10-FOLD CROSS-VALIDATION FOR EACH FREQUENCY BAND AND EACH SUBJECT IN EXPERIMENT 1

Frequency band range (Hz)	**Accuracy based on 10-fold cross-validation (%)**					
	Subject1	***Subject2***	***Subject3***	***Subject4***	***Subject5***	***Subject6***
4-8	52.5	50	55	47.5	52.5	45
8-12	60	**65**	60	**67.5**	55	55
12-16	**72.5**	**62.5**	52.5	**72.5**	45	40
16-20	**67.5**	57.5	57.5	60	57.5	62.5
20-24	52.5	52.5	**65**	57.5	50	62.5
24-28	37.5	**67.5**	62.5	40	**67.5**	**70**
28-32	50	50	42.5	47.5	65	62.5
32-36	55	42.5	**65**	52.5	62.5	**70**
36-40	**65**	52.5	62.5	60	65	**67.5**
40-44	62.5	57.5	**67.5**	**62.5**	**72.5**	55
44-48	**67.5**	60	**65**	**65**	**67.5**	**65**
48-52	55	**62.5**	60	57.5	**75**	60

a. Numbers in bold represent the top four accuracies based on an individual band for each subject

B. Results of Experiment 2

The average online accuracies for six subjects were 70%, 65%, 75%, 80%, 82.5% and 72.5%, respectively. Table 2 summarized the online accuracies based on subject-specific frequency bands and those based on fixed frequency bands. The results in Table 2 showed that subject-specific frequency bands yielded a superior average test accuracy of 74.17%, whereas the average accuracies of all subjects for fixed frequency bands were 50.42%, 61.25%, 57.92%, 62.92%, and

58.33% for theta, alpha, beta, gamma, and the whole range of frequency band, respectively. A paired *t*-test was performed to the accuracies shown in Table 2. A significant difference of accuracy rates was observed between subject-specific frequency bands and each of the other fixed frequency bands (all $p<0.05$).

TABLE II. ONLINE ACCURACIES BASED ON SUBJECT-SPECIFIC BANDS AND THE ACCURACIES BASED ON FIXED FREQUENCY BANDS.

Subjects	Accuracy based on different frequency bands (%)					
	Theta	***Alpha***	***Beta***	***Gamma***	***All***	***Subject-specific bands***
Subject1	50	65	50	52.5	57.5	**70**
Subject2	50	62.5	52.5	50	57.5	**65**
Subject3	55	57.5	60	72.5	62.5	**75**
Subject4	47.5	70	55	62.5	57.5	**80**
Subject5	52.5	60	65	77.5	57.5	**82.5**
Subject6	47.5	52.5	65	62.5	57.5	**72.5**
Average	50.42	61.25	57.92	62.92	58.33	**74.17**

b. Numbers in bold represent the best accuracy based on different frequency bands for each subject

IV. DISCUSSION AND CONCLUSION

For real-time emotion detection, an important task is to distinguish the emotional states based on the ongoing EEG signals. In this paper, we proposed a new BCI method to classify two different emotion states (happiness and sadness). Unlike the conventional method based on the fixed frequency bands, our proposed method selected the subject-specific frequency bands with informative features. Two experiments involving six subjects were conducted to validate our method and BCI system. The data analysis results demonstrated that our method based on subject-specific frequency bands outperformed the method based on the fixed frequency bands in terms of accuracy.

Based on the results of Experiment 1 (Table 1), several important observations could be drawn. First, we found that the accuracies varied much with the frequency bands for each subject and the frequency bands suitable for classification varied for different subjects. Therefore, it is necessary for searching the suitable frequency band for each subject. Second, most of the selected frequency bands were in the gamma band. This result confirmed that compared to the other bands, the gamma band was more related to the emotion states of happiness and sadness.

For the results of Experiment 2 (Table 2), an averaged online accuracy of 74.17% for two-class emotion recognition was achieved. Superior performance was obtained compared to the state-of-the-art results in [14], [3] and [13]. In fact, the authors of [14] reported an average accuracy of 73% by using EEG signals to categorize users' status into two emotional states during image viewing. In [3], Chanel et al. proposed an emotion recognition system that uses EEG to classify two emotional states. Their system achieved an average accuracies of 72% for naïve Bayes and 70% for Fisher discriminant analysis. Bradley et al. classified arousal and valence emotions and obtained an average accuracy of 70% for two classes [13]. Overall, the results of our method are promising, which has verified our hypothesis that the frequency band for emotion recognition may be subject-specific. The future study will be focused on a large number of subjects to further validate our method and BCI system.

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