Emotion Classification Based on Gamma-band EEG

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Abstract— In this paper, we utilized EEG signal to classify two emotions—happiness and sadness. These emotions are evoked by showing subjects pictures of smile and cry facial expressions. We propose a frequency band searching method to choose an optimal band into which the recorded EEG signal is filtered. We use common spatial patterns (CSP) and linear-SVM to classify these two emotions. To investigate the time resolution of classification, we explore two kinds of trials with lengths of 3s and 1s. Classification accuracies of $93.5\% \pm 6.7\%$ and $93.0\% \pm 6.2\%$ are achieved on 10 subjects for 3s-trials and 1s-trials, respectively. Our experimental results indicate that the gamma band (roughly 30–100 Hz) is suitable for EEG-based emotion classification.

I. INTRODUCTION

Emotions play an essential role in many aspects of our daily lives, including decision making, perception, learning, rational thinking and actions. Assessing emotions is a key to understanding human being. Therefore, emotion classification[1] provides a great step towards aiding people, e.g. disable care, brain-computer interfaces.

A. Emotion model

As mental and physiological states, emotions associate with a wide variety of feelings, thoughts, and behaviors. The modern study of emotions began in the 19-century. Various models and theories have been proposed in psychology, cognition, neuroscience and other disciplines. There is, however, much controversy concerning how emotions are to be defined and discriminated. Whether emotions are cognitive or non-cognitive is one major question of interest. The former claims that cognitive activities are necessary for an emotion to occur [1]. while the latter argues that emotional experience is largely due to the experience of bodily changes [2].

Another question is about whether emotions are distinctive discrete states or continuous ones? One opinion is to divide emotions into basic and complex ones, where the latter are blended with the former [3]. Another opinion is to let emotions vary along several scales with respect to the relations between them. A well-known continuous model is the valence-arousal model [4], in which the valence dimension represents the scale from pleasant to unpleasant and the arousal dimension states the intensity of excitement.

B. The Gamma Band

The EEG under different frequency band has gained much research interest. Typically, low frequencies are related to vigilance and motion (e.g., alpha, mu) while high EEG frequencies, e.g. gamma, are relevant to high cognitive processes. Recent years, researches continue to suggest connections between gamma band activities (GBA) and emotions [5][6]. Further, ERD/ERS responses to pictures of facial expressions in the gamma band have been reported [7], which showed ERD decreased during 150–350 ms after presenting the stimuli.

II. RELATED WORKS

In neuroscience and psychology, event related potential (ERP) is popularly used to research the brain rapid processing of affective stimuli [8]. While in computer science, researches are focused on detecting human emotions from affective displays or physiological signals. Several studies [9] have utilized facial expressions, the tone of voice, and body movement to recognize emotions. However, those signals share an disadvantage—they are not reliable affective displays. Some emotions can occur without corresponding facial emotional expressions, or emotional voice changes and body movements, especially when the emotion density is not very high. On the contrary, such displays could be faked easily, e.g. when people are lying.

Many studies [10] utilized signals from peripheral neurons system, e.g. electrocardigonram, and skin impedance. Nevertheless, EEG, the signal directly recorded from central neurons system, has not received much interest. There are only a few studies using EEG to classify emotions. Choppin [11] used neural network to classify EEG signals from three emotions and got 64% classification accuracy. Chanel [12] also confirmed that EEG and other physiological signals can be used to recognize emotions along one arousal dimension. The classification results are around 70% using two classes and 60% using three classes. Bos [13] classified arousal and valence emotions and received average accuracy of 70% for two classes.

III. METHOD

A. Subjects

The study protocal conformed with local ethics guidelines. 10 subjects (2 females; mean age 25; all normal sight and right handed) participated in our experiment, all were paid for participation. Subjects were informed about the purpose of this experiment.

[1]The term emotion classification is also used as the meaning of taxonomy of emotions, but we refer it as the machine learning approach to classify the emotions which the subject is experiencing using related signals.

B. Stimuli

Fig. 1. Excerpt of a sequence of stimuli. The first two are smile facial pictures and the last two are cry facial pictures.

The stimuli, an excerpt is shown in Fig. 1, consisted of two kinds of emotional facial expression pictures—smile and cry. The smiling people were mainly Asian actors and the others pictures were taken of people who lost family members. Pictures were resized into similar size.

We chose this kind of stimuli to evoke emotions for two reasons. One is, the main channels humans use to transmit emotions are facial expressions, which are universal and reliable to evoke other people's emotions. The other is that smile and cry expressions are easier to touch humans than other facial expressions [3].

The emotional contents of these pictures were measured by self-assessment manikin (SAM) [14], which contained 9 scales for both valence and arousal dimensions. We required each subject to label every picture using SAM after the experiments. The results of valence-arousal scales were $(2.51 \pm 0.91, 4.60 \pm 1.41)$ and $(7.41 \pm 1.03, 4.37 \pm 1.94)$ for smile and cry pictures, respectively.

C. Protocol

The pictures covering a visual angle of approximately $6 \times 6°$ were shown on a black background. Each picture was presented for 6 seconds, before a small horizontal bar was presented for 1s to require attention. Between two trials, there was a 3s long black screen to allow subjects to rest. To prevent subjects from feeling discomfort due to high frequency change of different emotional pictures, we did not adopt a completely random stimuli sequence. Instead, we divided the pictures into groups, each group consisted of 5 randomly chosen pictures from the same class. Then we randomly ordered 12 groups into a stimuli sequence as a session. Each experiment consisted of 2 sessions, between the sessions there was a 10 minute long rest to make sure subjects could maintain high attention during each session.

The experiment was carried out in an illuminated and sound proof room. The temperature of the room was about 27 degrees and the humidity was between 40% and 60%. During the experiment, subjects were asked to focus their attention only on the facial expressions.Additionally, they were also required to keep their head and body steady during the presentation of the pictures.

D. Data recording

Subjects were fitted with a 62-channel electrode cap during the experiment. The Ag/AgCl electrodes were mounted inside the cap with bipolar references behind the ears. The electrodes were arranged according to the international 10-20 system. The contact impedance between electrodes and skin was kept to a value less than 10kΩ. The EEG data were recorded with 32-bit quantization level at a sampling rate of 1000Hz.

IV. Method

A. Artifact Detection

The time wave and energy of each trial (the segment of EEG when one picture was present) were visually checked. Trials seriously contaminated by electromyogram (EMG) were removed manually. Those trials typically showed larger amplitude wave and energy (about 10 times), compared to normal ones. We removed an average of 3 trials from each experiment.

B. Filter

The EEG signal was filtered into a specific frequency band after removing artifacts. We utilized Fourier transform (FT) to do filtering instead of using the widely used IIR or FIR filters. We firstly transformed the signal into frequency domain, then set the unwanted frequency components to zero. After that, we performed inverse FT to transform the signal back to time domain if necessary.

Since we did not know the optimal band to filter, we needed to search various ones. The IIR or FIR approach needs to perform filtering every time for each bands, therefore the time complexity is high. For FT, however, we only need to perform it once. [15]. This is why we used FT instead of IIR and FIR.

C. Common Spatial Patterns

Common Spatial Patterns (CSP) [16] is a surpervised dimension reduction method, which is suitable to extract ERD/ERS features. CSP searches directions to maximize the variances of two kinds of signals after being projected to these directions. More specifically, denoted by $D_{i_1}^{(1)}$ and $D_{i_2}^{(2)}$ the two kinds of signals, where $i_1 = 1, \cdots, n_1$, $i_2 = 1, \cdots, n_2$, and n_1 and n_2 are the numbers of trials for each kind of signal, respectively. For each trial $D_{i_k}^{(k)}$, which is a time $\times$ channel matrix, its covariance matrix $\Sigma_{i_k}^{(k)}$ is calculated by considering channels (column) as variables. Denote the mean covariance matrix $\Sigma^{(k)}$ for each class by $\Sigma^{(k)} = \frac{1}{n_k} \sum_{i=1}^{n_k} \Sigma_i^{(k)}$. Now, CSP finds the directions w, which is a channel $\times 1$ vector, to minimize or maximize $\frac{w^T \Sigma^{(1)} w}{w^T \Sigma^{(2)} w}$. This optimization problem equals to the generalized eigenvalue equation, $\Sigma^{(1)} w = \lambda \Sigma^{(2)} w$. The eigenvalue λ stands for the ability of the direction w to discriminate these two classes trials—strong when λ is large or small and weak when λ is near 1. Let $w_1, \cdots, w_c$ be the directions according to the eigenvalues sorted in ascending order, where c is the number of channels. Then, m directions $W = [w_1, \cdots, w_{\frac{m}{2}}, w_{k-\frac{m}{2}+1}, \cdots, w_c]$ are selected to deduce the dimension.

D. Classification

After deducing the dimension using CSP, we fed the logarithm of variance of the dimension-deduced trials as the features into a linear support vector machine (linear-SVM) [17]. Let the feature of a trial D be f, then f was computed as

$$f = \log(\mathrm{Var}(DW)) = \log(\mathrm{diag}(W^T \Sigma W)),$$

where $\mathrm{Var}(\cdot)$ computed the variance of each column, and $\mathrm{diag}(\cdot)$ denoted the diagonals of a matrix.

To obtain reliable classification result, we randomly divided the trials into training set and testing set with ratio $7:3$. The parameters, frequency band and m, were selected using 5-fold cross validation on the training set. After that, we performed CSP on the training set and calculated the features for both training set and testing set. The former was fed into a linear-SVM and the latter was used to test the classification accuracy.
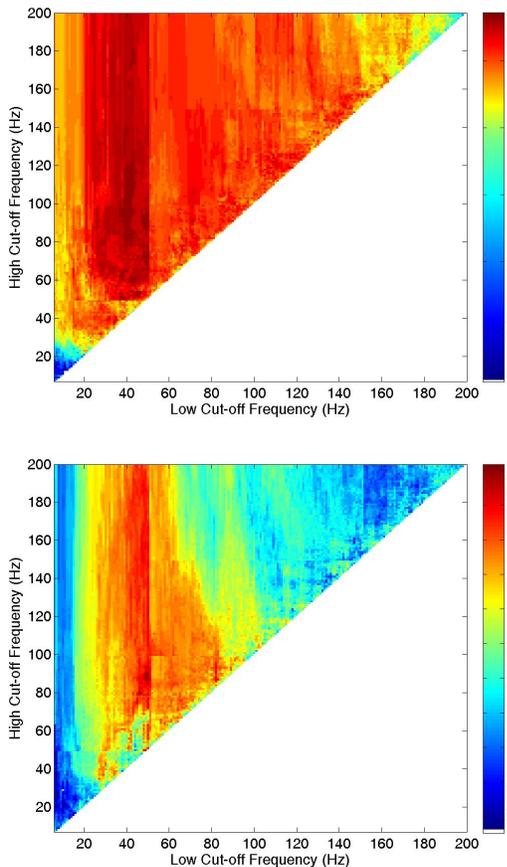
Fig. 2. Classification accuracies using different frequency bands for two subjects. The low and high cut-offs are presented in X-axis and Y-axis, respectively. The intensity represents the accuracy.

V. RESULTS

We divided the original 6s length trials into two kinds of short trials, 3s and 1s, to increase the number of classification trials and demonstrate our ability of classifying emotions with high time resolution. Thus, each experiment consisted

of around 240 trials (several EMG contaminated ones were removed, Sec. IV-A) for 3s-trials and around 720 trials for 1s-trials.

A. Frequency band selection

The cross validation results on the training set of 3s-trials for frequency bands under 200Hz are shown in Fig. 2. One can observe four interesting facts from the figure. First, the high performance areas are of vertical strip shape. The optimal strips always reach the region whose band width are at most 50Hz. Secondly, the low cut-offs of the optimal strips in the figure are both around 40–50 Hz, despite that the highest accuracies are different. But we should claim that this fact does not hold for other subjects. Actually, the positions of the optimal strips vary accross subjects. Thirdly, the high cut-offs of bands which give satisfied accuracy are always above 30 Hz; this holds for all subjects. Fourthly, for some subjects, the suitable bands could be high—both low and high cut-off frequency— up to the range 100Hz–150Hz for some subjects. We did not expect this surprising phenomenon. Finally, one can clearly note that the accuracy varies much with the frequency band and the suitable frequency band distribution varies across subjects. Therefore, searching the suitable band for each subject is necessary.

Inspired from the observations, we propose a band selection method. The basic idea is that, if we have chosen a suitable low cut-off, then we can consider only serveral high cut-offs which are not very far away from the low cut-off. Since it is not practical to search every low cut-off for each experiment, we only choose several bands with the low cut-off of $\{31, 36, \cdots, 91\}$ Hz and a width of $\{5, 10, \cdots, 50\}$ Hz. Denote $r(i, j)$ the cross validation results on these bands, where $i = 1, \cdots, 25$ and $j = 1, \cdots, 10$. We calculate the mean result for each low cut-off, that is, $\overline{r(i)} = \frac{1}{10} \sum_j r(i, j)$. Then we select the low cut-off with maximal $\overline{r}(i)$, namely $\mathrm{argmax}_i \overline{r}(i)$. At last we select the band width such that $\mathrm{argmax}_j r(i, j)$. Thus, we get the optimal band.

B. Classifier parameters

We need to choose the dimension reduction m for CSP, which is used to control the complexity of the classifier. We used the default settings of the linear LibSVM [17]. Though SVM can efficiently avoid over-fitting, considering the number of trials, feature dimension, and the low signal-noise ratio of EEG signal, the curse of dimension is still a big problem. In our method, four different values, $m = 2, 4, 20, 40$, were considered. We chose m with average good cross validation performance.

C. Classification Accuracy

Using the selected parameters, we performed CSP on the filtered training set. Next, the features of the training set were used to train a linear-SVM. Then we obtained the testing accuracy on the testing set features.

TABLE I

CLASSIFICATION RESULTS FOR 10 SUBJECTS. EACH EXPERIMENT CONTAINED AROUND 240 3S-TRIALS OR 720 1S-TRIALS, OF WHICH 70% WERE USED TO SELECT PARAMETERS BY 5-FOLD CROSS VALIDATION AND THE REST WERE USED FOR TESTING. THE PARAMETERS, LOW AND HIGH CUT-OFF FREQUENCY, NUMBER OF CSP FEATURES, AND TESTING ACCURACY WERE SHOWN IN ROWS FOR EACH SUBJECT.

Subject	Trial length = 3s				Trial length = 1s			
	Low (Hz)	High (Hz)	m	accuracy(%)	Low (Hz)	High (Hz)	m	accuracy(%)
1	46	50	4	98.96	46	55	4	100
2	51	80	40	91.7	71	85	40	91.0
3	36	55	20	82.9	81	115	40	81.4
4	61	80	40	97.8	76	100	40	95.3
5	41	60	40	100	36	85	40	89.7
6	26	40	4	87.1	66	110	20	86.2
7	56	70	20	100	86	105	20	98.1
8	31	80	40	98.6	51	100	40	97.2
9	21	55	4	83.8	56	95	20	91.4
10	66	115	20	93.8	66	95	20	100
Total	43.5±15.1	68.5±21.5	23±16	93.5±6.7	63.5±16.0	94.5±16.9	26±13	93.0±6.2

The testing accuracy of 3s-trials, see Table I, is $93.5\% \pm 6.7\%$, with 5 subjects (1, 4, 5, 7, 8) above 95%, and of 1s-trials is $93.0\% \pm 6.2\%$, with 6 subjects (1, 4, 5, 7, 8, 10) above 95%.

VI. DISCUSSION

Note that there are subjects whose results are greater than 95% and ones whose results less than 85%. This phenomenon is partly due to the diversity of subjects and qualities of experiments—some claimed that they were totally touched by stimuli while some others said they experienced only little emotions.

The average optimal frequency bands are 43.5–68.5 Hz and 63.5–94.5 Hz for 3s- and 1s-trials, respectively. Most bands are in the gamma band. The result confirms that GBA is related to the emotions of happiness and sadness.

Comparing the results of 3s- and 1s-trials, one can note that using short length trials does not reduce the classification accuracy much, but even causes improvement for several subjects. That means 1s length EEG signals are enough to classify emotions.

VII. CONCLUSION

In this paper, we utilized smile and cry facial expression figures to evoke emotions from subjects. The validity of the stimuli was tested using SAM. These two different emotions were classified based on EEG signals. We received $93.5\% \pm 6.7\%$, and $93.0\% \pm 6.2\%$ classification accuracies on 10 subjects for 3s length and 1s length trials using CSP, SVM and sophisticated frequency band selection strategies. Our experimental results indicate that the ERD/ERS activities in gamma band EEG can be used to classify happiness and sadness with high time resolution.

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