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Emotion Classification Based on Gamma-band EEG

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***Abstract*— In this paper, we use EEG signals 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 behavior. Assessing emotions is key to understanding human nature. Emotion classification[1] is a step towards aiding people such as in care taking and designing brain-computer interfaces.

As a mental and physiological state, emotion is associated 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.

Another question is whether emotions are distinctive discrete states or continuous ones. One opinion is to divide emotions into basic and complex emotions, 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 indicates the intensity of excitement.

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[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.

The EEG signals under different frequency bands have gained much research interest. Typically, low frequencies such as alpha and mu rhymes are related to vigilance and motion while high EEG frequencies, like gamma, are relevant to high cognitive processes. Researches continue to suggest connections between gamma band activities and emotions [5][6]. Further, ERD/ERS responses to pictures of facial expressions in the gamma band show that ERD decreased 150–350 ms after presenting the stimuli [7].

II. RELATED WORK

In neuroscience and psychology, event related potential (ERP) is popular in the research of the brains rapid processing of affective stimuli [8]. In computer science, research is focused on detecting human emotions from affective displays or physiological signals. Several studies [9] have utilized facial expressions, tone of voice, and body movement to recognize emotions. However, those signals share a disadvantage—they are not reliable affective displays. Emotions occur without corresponding facial emotional expressions or tone changes and body movements, especially when the emotion intensity is not very high. In addition, such displays could easily faked, as when one is telling a lie.

Many studies [10] utilized signals from peripheral nervous system, e.g. electrocardiogram and skin impedance. Nevertheless, EEG–the signal directly recorded from central nervous system–has not received much interest[11]. There are only a few studies using EEG to classify emotions. Choppin [12] used neural networks to classify EEG signals from three emotions and got 64% classification accuracy. Chanel *et al.* [13] 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 [14] classified arousal and valence emotions and obtained an average accuracy of 70% for two classes.

III. EXPERIMENT

A. Subjects

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

B. Stimuli

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

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

others pictures were taken of people who recently lost family members. Pictures were resized to be of similar size.

This type of stimuli was chosen for two reasons. Facial expressions are the main channels with which people use to transmit emotions, and are universal recognized. Moreover, smiling and crying are the expressions most likely to evoke empathy [3].

The emotional contents of these pictures were measured by a self-assessment manikin (SAM) [15] containing 9 scales for both valence and arousal dimensions. Each subject was required to label every picture using SAM after the experiments. The results of the valence-arousal scales were (2.51 ± 0.91, 4.60 ± 1.41) and (7.41 ± 1.03, 4.37 ± 1.94) for smiling and crying pictures, respectively.

C. Protocol

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

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.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 was 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 a single picture was present) were visually checked. Trials seriously contaminated by electromyogram (EMG) were manually removed. Trials that were removed 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 filter 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.

Since we did not know the optimal band to filter, we needed to search many bands. The IIR or FIR approach requires a separate filtering every time for each band; and thus has a high time complexity. For FT, however, we only need to perform FFT once since we only need to calculate the covariance matrix in the following steps [16].

C. Common Spatial Patterns

Common Spatial Patterns (CSP) [17] is a surpervised dimension reduction method that is suitable for extracting ERD/ERS features. CSP searches directions to maximize the variances of two kinds of signals projected to these directions. Denote these two kinds of signals by $D_{i_1}^{(1)}$ and $D_{i_2}^{(2)}$, 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. 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. The mean covariance matrix $\Sigma^{(k)}$ for each class is

$$\Sigma^{(k)} = \frac{1}{n_k} \sum_{i=1}^{n_k} \Sigma_i^{(k)}.$$

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 is equal 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 two classes trials—weak when λ is near 1 and strong when λ is larger or smaller. 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 variance of the dimension-deduced trials as the features into a linear support vector machine (linear-SVM) [18]. 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.

In order 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 classification accuracy.

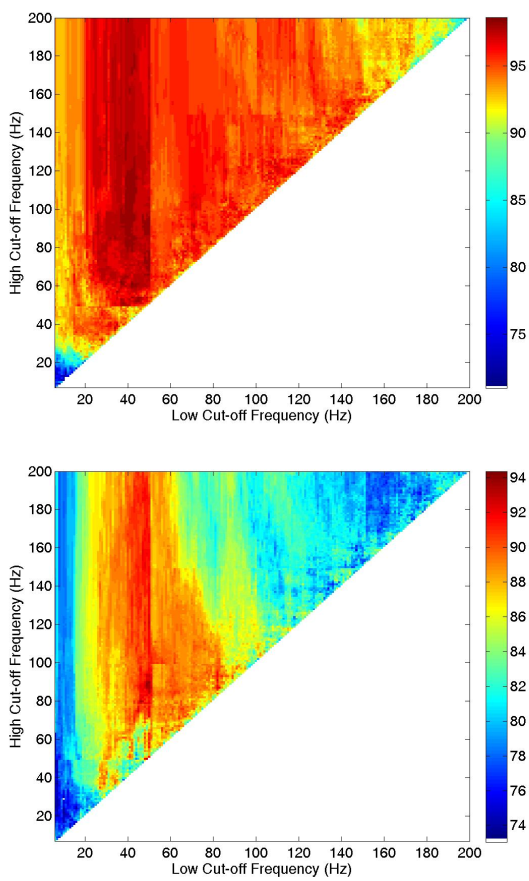

Fig. 2. Classification accuracies using different frequency bands for two subjects. The low and high cut-offs are presented in X-axis and Y-axis, respectively. The intensity represents the accuracy.

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 to classify emotions with a high time resolution. Each experiment consists of around 240 trials for 3s-trials and around 720 trials for 1s-trials (several EMG contaminated ones were removed, Sec. IV-A) .

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 five interesting facts from the figure. One, the high performance areas are in the shape of a vertical strip. The optimal strips always reach the region whose band width is at most 50Hz. Two, the low cut-offs of the optimal strips in the figure are both around 40–50 Hz, despite the fact that the highest accuracies are different. This fact does not hold for other subjects. Three, the high cut-offs of bands with acceptable accuracy are always above 30 Hz; this holds for all subjects. Four, both low and high cut-off frequencies of suitable bands are enough to enter into the 100Hz–150Hz range. This was surprising. Five, one can clearly note that 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 by these observations, we chose a band selection method. The basic idea is that, if we have chosen a suitable low cut-off, then we are limited to a few several high cut-offs not far 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 maximum $\overline{r}(i)$, namely $\mathrm{argmax}_i \overline{r}(i)$. At last we select the band width such that $\mathrm{argmax}_j r(i, j)$ and 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 [18]. 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. Then, the features of the training set were used to train a linear-SVM. We then obtained the testing accuracy on the testing set features.

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%.

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	99.0	46	55	4	100.0
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	100.0	36	85	40	89.7
6	26	40	4	87.1	66	110	20	86.2
7	56	70	20	100.0	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	100.0
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

VI. DISCUSSION

The subjects whose results are greater than 95% and ones whose results less than 85% point to the diversity of subjects and quality of experiments—some claimed that they were emotional arosed by the stimuli while others said they experienced little emotion.

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

When comparing the results of 3s- and 1s-trials, it is interesting to see that using short length trials does not reduce the classification accuracy by much, and even induces improvement for several subjects. This means that 1s EEG signals are enough to classify emotions.

VII. CONCLUSION

These two different emotions—smiling and crying— were classified based on EEG signals. We received $93.5\%\pm6.7\%$, and $93.0\%\pm6.2\%$ classification accuracies on 10 subjects for 3s length and 1s length trials using CSP, SVM and 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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