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EEG-based Emotion Recognition during Watching Movies

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Abstract— **This study aims at finding the relationship between EEG signals and human emotions. EEG signals are used to classify two kinds of emotions, positive and negative. First, we extracted features from original EEG data and used a linear dynamic system approach to smooth these features. An average test accuracy of 87.53% was obtained by using all of the features together with a support vector machine. Next, we reduced the dimension of features through correlation coefficients. The top 100 and top 50 subject-independent features were achieved, with average test accuracies of 89.22% and 84.94%, respectively. Finally, a manifold model was applied to find the trajectory of emotion changes.**

I. INTRODUCTION

Emotion is essential for humans. It not only contributes to communication between humans, but also plays a critical role in rational and intelligent behavior [1]. Its functions can be seen in many aspects of our daily lives. Thus, the study of emotion recognition is indispensable.

In the past few decades, many studies have been done on emotion recognition. Anderson and McOwan utilized facial expressions to recognize emotion [2]. Ang and colleagues did emotion recognition based on prosody [3]. However, these signals shared the same disadvantage. They are not reliable to detect emotion, especially when people want to conceal their feelings.

Other signals were introduced into emotion recognition research in order to overcome this disadvantage. Picard *et al.* used peripheral neurons system including heart rate variations, skin conductivity and respiration to do this work [1]. In recent years, more and more researchers have started to use EEG signals in recognizing emotion because they are reliable. However the classification results are often not good enough. Choppin confirmed that EEG signals can be used for emotion recognition and got a classification accuracy of 64% based on neural network [4]. Bos obtained an accuracy of 70% for two classes based on naive Bayes classifier [5].

One of the main goals of emotion recognition is to find the brain regions and frequency bands most related to emotions. Many studies have been done on it. The study of Sarlo *et al.* showed that activation for unpleasant emotions was prominent over the right posterior regions in the alpha band [6]. Schmidt and Trainor found that frontal brain electrical activity contributed much to musical emotions [7]. Li and Lu confirmed that gamma band also played a crucial part in this field [8].

In our research, we mainly try to find the relationship between EEG and human emotions. Instead of using the features directly, we apply a linear dynamic system to smooth them. The purpose of this operation is to reduce the influence of factors irrelevant to emotion. In order to find the features which are most related to emotion, we reduce feature dimension by correlation coefficients while keeping a stable classification performance, and figure out the brain regions and frequency bands according to the coefficients. In addition, we try to find the trajectory of emotion changes with a manifold model.

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II. DATA COLLECTION

A. Subjects

EEG data in this study were recorded from 3 women and 3 men aged around 22, who were healthy and right-handed. All of the subjects were undergraduate or graduate students from Shanghai Jiao Tong University and were informed about the purpose of this experiment.

B. Stimuli

As stimuli, we chose several kinds of movie clips, about 4 minutes each, including musical, romantic, war, disaster and landscape films. Most of the films were from Oscar movies, such as Chicago, Titanic and Pearl Harbor. The reason why we chose movies as stimuli is that audiovisual stimuli is highly benefit for arousing human emotion [9]. In this experiment, we were mainly concerned about positive and negative emotions, because emotion usually emerged in a mixed form. Even the subject could not properly distinguish his feelings, i.e. disgusted and horrible. Thus each of the movie clips was classified into these two kinds of emotions.

To measure the emotional content of each movie clip, the self-assessment manikin (SAM) [10] was used, with nine scales for valence, arousal and dominance dimensions.

C. Procedure

About 12 movie clips were used in each experiment, approximately 6 clips for each emotion. During the experiment, all of these movie clips were presented at random. After the presentation of each clip, the subject was asked to fill in a SAM form. The process of the experiment is as shown in Fig. 1.

Each subject was alert and was asked to focus on the clip during its presentation. Each subject was fitted with a 62-channel electrode cap, whose electrodes were arranged

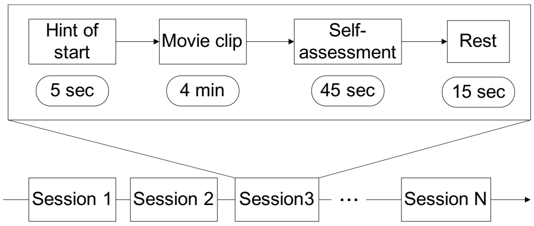

Fig. 1. Block diagram of the experiment.

according to the extended international 10-20 system with a reference on the top of the scalp. The EEG data were recorded with 32-bit level at a sampling rate of 1000HZ.

III. METHODS

A. Feature Extraction

According to the SAM forms, we only chose the sessions whose dominance scores were equal to or larger than 3. The reason is that if the dominance score was smaller than 3, we assumed that this session did not successfully arouse a certain emotion of the subject. As mentioned before, we only cared about two kinds of emotion, positive and negative, so we labeled the selected sessions according to their valence scores. If the valence score was smaller than 5, then this session belonged to the class of negative emotion, else it belonged to the class of positive emotion.

The time waves of the EEG data were visually checked. The recordings seriously contaminated by electromyogram (EMG) were removed manually. A series of band pass filters were applied to translate the EEG data to delta (1-4HZ), theta (4-8HZ), alpha (8-13HZ), beta (13-30HZ) and gamma (36-40HZ) bands. These five bands had been confirmed to reflect the physical activities in a way by many researches. Next a Fast Fourier Transform (FFT) with a 1 s non-overlapping window was used to compute the spectrogram of each channel and each band. Then the log band energy of FFT was calculated for each sample. We chose log band energy of each channel as feature, instead of traditional band energy, considering its stability. After these operations, we obtained about 2500 ($\leq 12 * 4 * 60$) samples for each subjects. Each sample had 310 ($= 62 * 5$) features.

B. Feature Smoothing

Since the features extracted directly from EEG data always have strong fluctuations and contain some information unrelated to our emotion task, we applied a linear dynamic system (LDS) approach to smooth the features. The details of this smoothing method can be found in [11]. The comparison of features before and after smoothing by the LDS approach is shown in Fig. 2. It can be seen that there is a general trend in feature before smoothing by using the LDS approach, but disordered in details. On the contrary, even the details are smooth after using the LDS approach. The noise irrelevant to emotion is mostly removed.

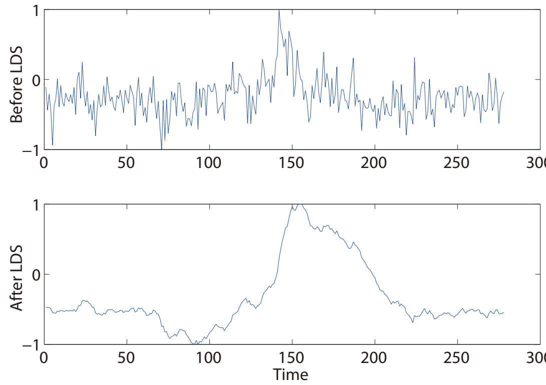

Fig. 2. Comparison of the features before and after using the LDS approach. The EEG signal is obtained from channel P8 at alpha band in session 8 of subject 1.

C. Classification

In this study, we divided the sessions into training set and testing set with a ratio 7:3, so that there was not even one session which belonged partly to training set or partly to testing set.

Totally 5 groups of features were available for each subject, according to the 5 bands and each group contained 62 features. We used 5 linear support vector machines (linear-SVMs) with linear kernel to train and test these groups of features. At last, we combined these features together into a long vector, so that each sample had totally 310 features. Then the 6th linear-SVM was used on them. The best parameters of each linear-SVM were obtained through a 10-fold cross-validation.

D. Feature Selection

The main purpose of our study is to find the relationship between EEG and human emotion. This relationship can be applied to normal life in order to provide help to people. For that, a 62-channel electrode cap is not convenient, so selection of relevant brain regions and bands is particularly important.

In our study, we found that the unsupervised dimension reduction methods, such as Principal Component Analysis (PCA), did not work always well. Instead, we calculated the correlation coefficients between features and labels for each channel and each band on training set. Then, we ranked the correlation coefficients in descending order. Every time the features corresponding to the top N coefficients were chosen to use together with a linear-SVM.

E. Manifold Learning

With the feature selection method introduced above, the dimension of features was reduced a lot. Then we put the selected features into an unsupervised manifold learning model and reduced the features to only one dimension. The purpose of this operation is to find the trajectory of emotion changes in nature.

TABLE I

CLASSIFICATION RESULTS OF DIFFERENT FREQUENCY BANDS

Subject	Delta (%)	Theta (%)	Alpha (%)	Beta (%)	Gamma (%)	ALL (%)
1	68.23	66.21	92.38	82.83	100	99.63
2	57.58	87.09	86.30	72.86	73.65	81.95
3	91.30	77.74	84.06	85.82	91.20	87.16
4	38.80	74.28	65.63	100	88.47	91.13
5	45.81	74.19	90.48	77.42	62.26	82.90
6	71.24	84.65	94.35	82.71	89.82	82.39
Average	62.16	77.36	85.53	83.61	84.23	87.53

In this part, we chose Isomap method for its global characteristics. The details of Isomap algorithm can be found in [12].

IV. RESULTS

A. Classification

The classification accuracies of SVMs across different frequency bands are presented in Table I. The classification accuracies of alpha, beta and gamma bands are obviously better than those of delta and theta bands. This result partly reflects that high frequency bands play a more important role in emotion activities than low frequency bands. But for different subjects, the frequency band mainly related to emotion may be different. In our experiment, the average testing accuracy of using all of the features reached 87.53%.

B. Feature Selection

In the last section, we used totally 310 features to train and test the linear-SVM, but in the normal life a 62-channel cap is obviously inconvenient. For this reason we tried to find a smaller number of features while keeping the classification performance stable with a high percentage.

First we ranked the correlation coefficients between features and labels (positive: 1, negative: -1) of each channel in all the 5 frequency bands in descending order for each subject, on the training set. Then, we selected the features corresponding to the top N coefficients as the useful set. Every time an extra 30 features were added to the set. Last, a linear-SVM was used to work on the useful set. The changes of classification performance for each subject are as shown in Fig. 3.

It is shown that when the dimension of features reaches a certain amount, the accuracy of classification becomes almost stable. Obviously this amount is much smaller than that of the original features.

In order to reduce dimension and find the features independent of subject, we calculated the average correlation coefficients of all the subjects across all channels and frequency bands. Then we chose the top 100 features having the largest coefficients and sorted them in descending order. The first 10 features were selected as the useful set. An extra 10 features were added to the useful set every time until all the 100 features were selected. A linear-SVM was used to work with the useful set every time and the classification performance is as shown in Fig. 4.

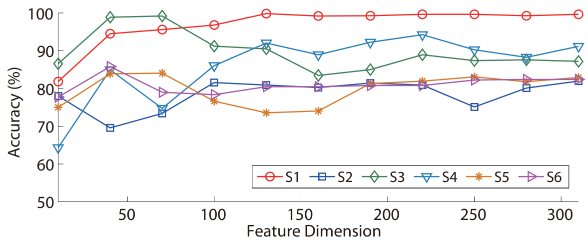

Fig. 3. Changes of classification performance for each subject

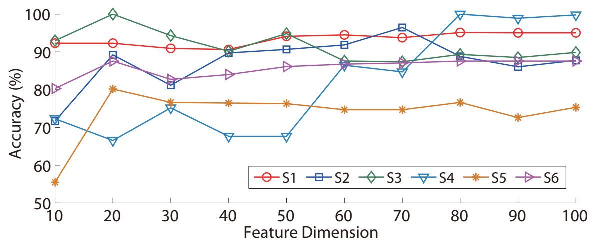

Fig. 4. Classification performance of subject-independent features

Comparing with Fig. 3, the classification performance using the subject-independent features has not degraded much. On the contrary, the classification accuracies of subject 2, 3, 4 and 6 have increased a little. The average accuracy with the top 100 subject-independent features is 89.22%. The classification accuracies of most subjects become stable after the dimension reaches about 50 and the average accuracy is 84.94%. The distribution of the top 50 subject-independent features is as shown in Fig. 5. It was drawn using correlation coefficients. We only retained the coefficients of the top 50 features and set others' as zero. This is the reason why most regions of Fig. 5 are dark blue. None of the top 50 features is in the delta band and few are in the theta band. This suggests that delta and theta bands have little relationship with emotion. The selected subject-independent features are mainly in the right occipital lobe and parietal lobe for the alpha band, the central site for beta band, and the left frontal lobe and right temporal lobe for gamma band. This finding is nearly consistent with the studies of other researchers in [6]-[8].

C. Manifold Learning

In order to find the trajectory of emotion changes during the experiment, we put the selected 50 subject-independent features into the manifold model and reduced the dimension to 1. The trajectory of emotion changes is as shown in Fig. 6.

In Fig. 6, positive emotion is labeled as 1, while negative emotion is labeled as -1. The red line only represents for variation tend, but not for threshold value. During the experiment, movie clips of positive and negative emotion were presented at random and two clips of positive emotions were removed according to the SAM forms of subject 6. The trajectory of emotion changes is almost consistent with the true changes of emotion during the experiment.

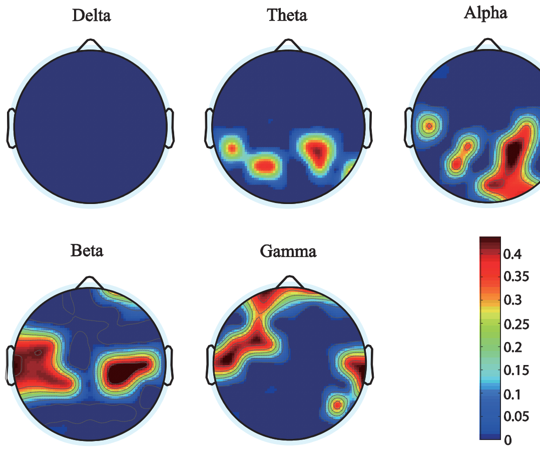

Fig. 5. Distribution of the top 50 subject-independent features

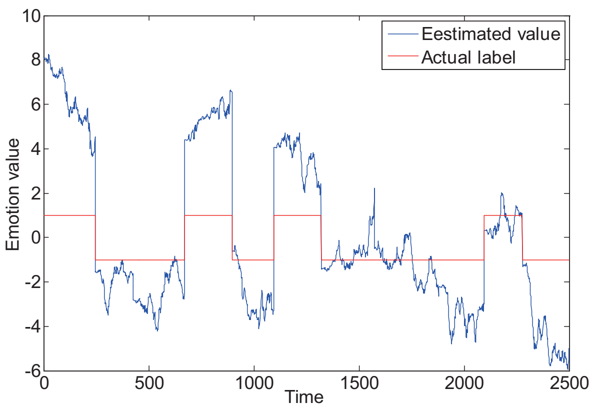

Fig. 6. The trajectory of emotion changes during the experiment from subject 6

V. DISCUSSION

In the experiment, we did our best to arouse subjects' positive and negative emotions through the movie clips, but not everyone was successfully aroused. This is the reason why classification accuracies of some subjects are greater than 90% while those of others are less than 80%.

Although we try to find the common features of all the subjects, individual differences do exist. Thus when we used the subject-independent features to compute the classification accuracy, not everyone got a good result, e.g. subject 4.

The selected subject-independent features are mainly on right occipital lobe and parietal lobe in alpha band, central site in beta band, left frontal lobe and right temporal lobe in gamma band. This suggests that human emotional response is mainly related to high frequency bands rather than low bands.

VI. CONCLUSION

In this work, we designed an experiment with movie clips as stimuli and SAM as label. Two classes of emotion, positive and negative were mainly concerned about. First we averaged the EEG data into delta, theta, alpha, beta and gamma bands, and computed the log energy of each sample. Next a LDS-based approach was applied to smooth the original features. Last a linear-SVM was used to work on the training and testing set. The average test accuracy with all the features was 87.53%.

For the purpose of practicability, we reduced the dimension of features using correlation coefficients and found the top 100 subject-independent features with an average test accuracy of 89.22%. When reducing the dimension further to 50, results were stable for most subjects. The average test accuracy with these 50 features was 84.94%, not much less than that of all the features. With these subject-independent features, we found the brain regions and frequency bands most relevant to emotion. At the end of the study, we used an unsupervised manifold model to draw the trajectory of emotion changes and the trajectory was almost consistent with the true changes.

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