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Classification of Five Emotions from EEG and Eye Movement Signals: Discrimination Ability and Stability over Time

Tian-Hao Li, Wei Liu, Wei-Long Zheng and Bao-Liang Lu* *Senior Member, IEEE*

***Abstract*— This paper explores the discrimination ability and stability of electroencephalogram (EEG) and eye movement signals over time for classifying five emotions: happy, sad, fear, disgust and neutral. We develop a multimodal emotion dataset called SEED-V with 16 subjects. Two classifiers are trained based on the EEG and eye movement signals. Topographic maps are used to depict the neural patterns of EEG signal. The classification result based on EEG, eye movement, and feature level fusion (FLF) reaches the average accuracies of 70.8%, 59.87% and 75.13%, respectively. The experiment result indicates that: a) the EEG and eye movement signals have good discrimination ability for five emotion classification problem; b) the beta and gamma bands of EEG signal have better discrimination ability than the delta, theta and alpha bands; c) the stable neural patterns of different emotions do exist and are common across sessions; and d) the neural pattern of disgust emotion has high gamma response in the frontal area, while fear emotion has low activation at the top of brain in the gamma band.**

I. Introduction

The last few years have seen the progress of physiological signals based affective brain-computer interaction [1] and emotion recognition [2]. There are two kinds of categorical models of emotions: the discrete model, which distinguishes a fix number of basic emotions, and the dimensional model, which depicts emotions in a two- or three-dimensional space [3]. One of the most famous discrete models of emotion is proposed by Ekman, which consists of six basic emotions, namely, fear, anger, surprise, disgust, sadness and happiness [4]. In this paper, we adopt the discrete model to investigate the five emotions (happy, sad, fear, disgust and neutral) classification problem using EEG and eye movement signals. The discussion mainly focuses on two aspects: the discrimination ability and stability over time.

In Zheng *et al.*'s work [5], the discrimination ability of EEG and eye movement signals for happy, sad, fear and neutral emotions is studied, and related discrete neural signatures of basic emotions are also found in the functional magnetic resonance imaging (fMRI) [6]. However, as far as we know, there is no related research about the five emotions using EEG and eye movement signals, neither related multimodal emotion dataset. The discrimination ability of EEG and eye movement signals for the five emotion classification problem needs further investigation. In our previous work [7], the stable neural patterns of sad, neutral and happy emotions have been discovered. The finding [8] indicates that the emotions of fear and disgust are related to core symptoms of depression, but the stable patterns of EEG signal for disgust and fear emotions are still unknown.

In this paper, we develop a new multimodal emotion dataset called SEED-V, which contains EEG and eye movement signals for five emotions (happy, sad, fear, disgust and neutral). Furthermore, we explore the discrimination ability of EEG and eye movement signals for the problem of classifying five emotions. We verify that the critical frequency bands of EEG for classification are identical to those in three emotions classification task [9]. To investigate the stable patterns of different emotions over time, different affective models are trained on different sessions. In addition to the neural patterns of happy, sad and neutral emotions mentioned in [7], the stable neural patterns of the fear and disgust emotions are investigated in this paper.

II. Experiment Setup

In order to obtain the EEG and eye movement signals of the five emotions, video clips with audio were used to elicit specific emotions of the subjects' emotion. Each subject was required to watch video clips wearing EEG cap and eye tracking glasses alone in a quiet room. To investigate the stability of neural patterns over time and the performance of affective models across sessions, all of the subjects participated in our experiment three times at an interval of three days or longer.

A. Stimuli Material

In the preliminary stage, we selected a set of video clips for the five emotions as our stimuli material pool. Twenty participants were recruited to assess the stimuli materials with a rating score from 0 to 5 according to the elicitation effect after watching each video clip. As a result, nine video clips for each emotion were selected from the pool as our stimuli material in the descending order of their mean scores, and the selected video clips have mean scores of 3 or higher. The durations of the video clips range from two to four minutes.

For each session, three video clips from each emotion were included in the stimuli with fifteen clips in total. The playing order of video clips is designed as follows: a) try to avoid sudden emotion transform such as happy emotion after

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Tian-Hao Li, Wei Liu, Wei-Long Zheng and Bao-Liang Lu are with the Center for Brain-Like Computing and Machine Intelligence, Department of Computer Science and Engineering, the Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, and the Brain Science and Technology Research Center, Shanghai Jiao Tong University, 800 Dong Chuan Road, Shanghai 200240, China.

*Corresponding Author (bllu@sjtu.edu.cn)

sad emotion, since human's emotion changes gradually; b) neutral emotion video clips could be used as a buffer between two opposite emotion video clips.

B. Subjects

Participants enrolled in our experiments were asked to fill out the Eysenck Personality Questionnaire (EPQ) in the beginning of the experiments. Those who turned out to be stable extraverts were selected as the subjects. Therefore, 16 subjects (6 males and 10 females, aged from 19 to 28, mean: 23.27, std: 2.37) with self-reported normal or corrected-to-normal vision and normal hearing took part in the experiments.

C. Procedure

Each session of the experiment contained 15 trials, and a brief abstract of the content and the emotion to elicit is prompted for 15 seconds before each clip started. After each clip, there were 15 or 30 seconds left for rest and self-assessment with relaxing background music. The length of rest and self-assessment period depended on the emotion type of the video clip. If the emotion type of the video clip was disgust or fear, 30 seconds was given to make the subject better recovered from that emotion, otherwise 15 seconds was given. Each session last about 55 minutes. The protocol of each session is shown in Fig. 1.

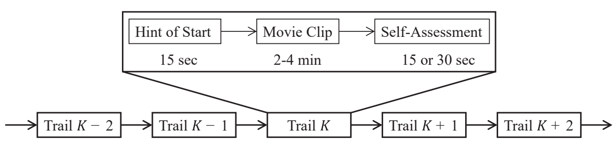


Fig. 1: Experiment protocol

The 62-channel active AgCl electrode cap and SMI ETG eye-tracking glasses were used to record EEG and eye movement signals simultaneously. The EEG signal was recorded using ESI NeuroScan System at a sampling rate of 1000 Hz according to the international 10-20 system. The electromyogram (EOG) signal was recorded at the same time from the electrode cap. The impedance of each channel in the cap was controlled to less than 5 KΩ.

A rating scale was given to the subject before each session started. The subjects were required to give a score (0-5) based on the elicitation effect during the rest and self-assessment period after watching each clip. Meanwhile, the subjects were instructed to sit comfortably in front of the screen, watch the forthcoming video intently, and refrain from body movement to avert the impact of muscle artifacts.

D. Ethics Statement

This study was approved by the Scientific & Technical Ethics Committee of the Bio-X institute at Shanghai Jiao Tong University. All the subjects signed up an informed consent, which described the experiment procedure, before the first session.

III. Methods

A. Preprocessing

We preprocessed the EEG signals with Curry 7, and carry out a baseline correction, then we applied a bandpass filter between 1 to 50 Hz to each channel. Finally, the signals from EOG and FPZ channels were used to detect and remove eye movement artifacts.

The spectral power of EEG signal has been shown to have highly correlation with emotions [10]. In our previous work [11], we proposed differential entropy (DE) feature for EEG-based emotion recognition. Various studies demonstrated that the DE feature is more suitable for EEG-based emotion classification in comparison with the power spectral density (PSD) feature [5][7][9][12]. In this paper, we use the DE features.

EEG signals were first downsampled from 1000 Hz to 200 Hz before feature extraction to speed up the data analysis procedure. The Short Time Fourier Transform (STFT) with a time window of 4 seconds and no overlapping Hanning window was used to extract the DE feature in the five frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (31-50 Hz). Moreover, the linear dynamic system algorithm was used for feature smoothing [13]. As for the eye movement signals, we used SMI BeGaze to extract features. The statistics of pupil diameter (X and Y), dispersion (X and Y), fixation duration, blink duration, saccade and other eye-movement related events were calculated as the final 33-dimension eye movement features as described in [14].

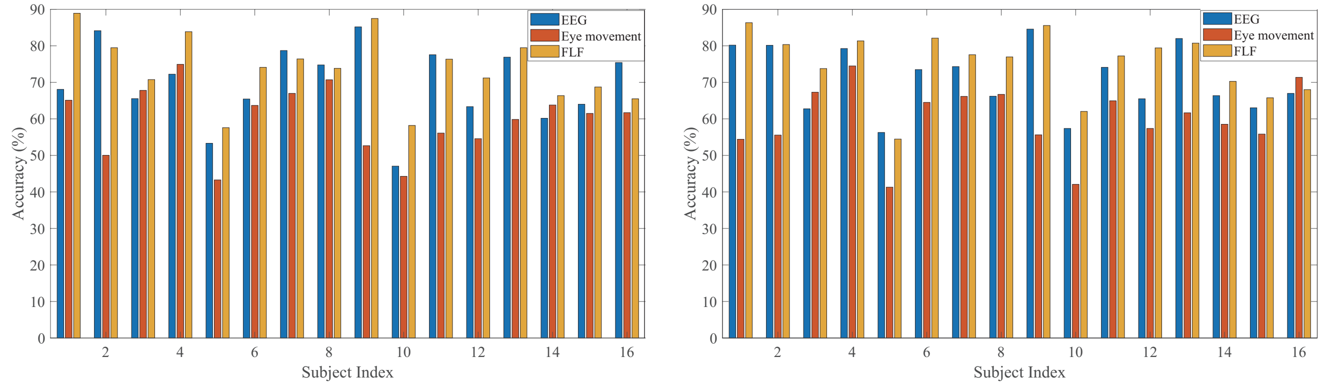
B. Classifier Training

We used Support Vector Machine (SVM) with linear kernel and Multilayer Perceptron (MLP) as the classifiers. To investigate the discrimination ability of EEG and eye movement signals, we trained classifiers for each subject using EEG and eye movement features. The parameter C of SVM is searched within the range of -10 to 10 with a step size of 1 using three-fold cross validation. The MLP contains two hidden layers and one softmax output layer with 128, 64 and 5 cells, respectively. We further utilized a feature level fusion (FLF) approach, which directly concatenated the EEG and eye movement features, in comparison with the classification performance achieved by single modality. In the purpose of exploring the stability of EEG signals across sessions, we used one session data as the training dataset and the data from another session as the test dataset to train the SVM classifiers for each subject.

IV. Result & Discussion

A. Discrimination Ability

1) Discrimination of EEG and eye movement signals: To evaluate the classification performance for the five emotions, we trained the classifiers using EEG features, eye movement features and the FLF approach, respectively. As shown in Fig. 2, the means and standard deviations of accuracy rate (%) for EEG features, eye movement features and the



(a) SVM (b) MLP

Fig. 2: The classification accuracy rates (%) for each subject based on the features of EEG, eye movement and FLF.

FLF approach are 69.50/10.28, 59.81/8.77, 73.65/8.90 for SVM , respectively, and 70.79/8.63, 59.87/8.98, 75.13/8.57 for MLP. For most subjects, the FLF approach achieves higher performance than the EEG features, and the EEG features tend to have better discrimination ability than the eye movement features.

2) Discrimination of Different Frequency Bands: In this part, we evaluate the performance of the SVM classifiers trained with the features in the separate and total frequency bands. Table I shows that high frequency bands have better discrimination than low frequency bands but with higher standard deviations, which is consistent with our previous findings in [9]. The total frequency band can achieve the highest accuracy rate of 69.50%.

TABLE I: The classification accuracy rate (%) of different frequency bands for each subject. The frequency band that reaches highest accuracy is marked out for each subject.

Subject index	Delta	Theta	Alpha	Beta	Gamma	Total
#1	59.79	55.29	**70.21**	62.21	59.68	68.07
#2	52.93	58.53	63.96	72.02	**72.90**	84.15
#3	48.22	53.21	59.74	**67.64**	66.76	65.55
#4	39.93	60.61	64.29	**71.31**	61.99	72.24
#5	48.66	50.25	46.96	53.98	**56.56**	53.32
#6	42.02	**64.89**	42.35	54.64	45.53	65.44
#7	39.44	30.28	39.17	73.83	**79.10**	78.72
#8	39.22	65.99	55.95	64.18	**70.38**	74.77
#9	64.18	50.74	72.13	75.04	**78.00**	85.19
#10	45.26	44.82	**63.03**	41.09	41.58	47.07
#11	51.62	54.20	53.54	**67.96**	63.80	77.56
#12	48.33	49.59	**62.53**	44.98	47.23	63.36
#13	58.86	42.02	64.62	**69.61**	67.20	76.91
#14	43.23	45.58	**55.95**	51.40	49.26	60.18
#15	44.32	56.66	52.66	**57.10**	47.23	64.02
#16	36.20	50.80	57.49	**70.87**	59.08	75.43
Avg	47.64	52.09	57.79	**62.37**	60.39	69.50
Std	7.86	8.64	9.00	10.27	11.40	10.28

B. Stability

1) Stability of Emotion Classification Model over Time: The stability of the emotion classification model over time is important for the practical applications of affective brain-computer interactions (aBCIs) [1]. Since subjects are required to participate in the experiments three times and the interval between each session is at least three days, the EEG data from different sessions are used to investigate the stability of emotion classification model over time. Table II shows the average accuracies of the classifiers. For each session, EEG data from this session is used to train one SVM classifier for each subject. Then, the performance of the models are evaluated on the EEG data from another session. In Table II, a mean classification accuracy of 55.84% is achieved by our model, which implies that EEG signal is stable over time for emotion classification.

TABLE II: The mean accuracy rate (%) of emotion recognition model across sessions

	Train	Test		
		First	Second	Third
Avg	First	60.61	53.58	46.71
	Second	50.98	70.98	58.95
	Third	48.48	50.32	62.00
Std	First	13.28	16.84	17.50
	Second	20.04	20.37	14.25
	Third	7.93	14.98	19.22

2) Neural Signature and Stable Patterns: Fig. 3 describes the neural patterns of different frequency bands for disgust, fear, sad, neutral and happy emotions, which is obtained by averaging the DE features from all subjects in each channel. As depicted in Fig. 3, the differentiation of the topographic maps of each emotion in different frequency bands demonstrates that the neural signatures corresponding to the five emotions do exist.

In general, the differences of neural signatures are shown in the degree of activation across different frequency bands and brain areas. Specifically, the neural patterns of happy emotion have significant high energy level in the lateral temporal area and low energy level in the frontal part in the beta and gamma bands, while the disgust emotion has a moderate activation in the lateral temporal part but strong activation in the frontal part. In fact, except for the frontal part in the beta and gamma bands, happy emotion has

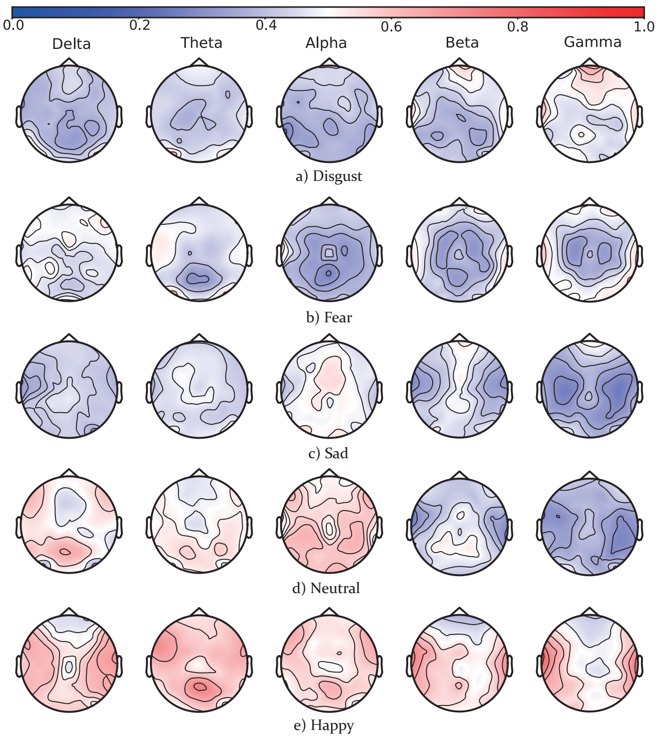


Fig. 3: The average neural patterns for all subjects for different emotions

commonly strong activation in all five frequency bands. In addition, the neural patterns for both sad and neutral emotions have a weak response in the lateral temporal area in the beta band. However, the neutral emotion shows much stronger brain activity in the delta, theta and alpha bands than the sad emotion, especially in the parietal and occipital area of the alpha band. The most distinguishable neural signature of fear emotion lies in the topographic map of the gamma band which has a low activation level in the partial area and a relatively high activation level in the frontal, lateral temporal and occipital areas. The most important brain regions to distinguish the neural patterns of each emotion are similar to and complementary to the brain regions from the fMRI analysis in [6].

It is worth noting that all five emotions exhibits specific activation degree in the lateral temporal and frontal areas in the beta and gamma bands. Although the neural patterns of sad and neutral emotions are similar in the beta and gamma bands, sad emotion has a medium level activation in the frontal area whereas neutral emotion simply has a weak response. These results indicate that high frequency bands (alpha, beta, and gamma) have better discrimination ability than low frequency bands (delta and theta).

V. Conclusions

In this paper, we have evaluated the discrimination ability of EEG and eye movement signals for the five emotions classification problem and the stability of EEG signal over time. Experimental results have indicated that EEG signal has better discrimination ability than eye movement signal, and the feature level fusion method achieves the best classification performance.

The stability of the emotion classification model over time has shown that the neural patterns are stable across sessions. The frontal area has high gamma response for disgust emotion. The fear emotion has a low gamma response in the partial area, and relatively high gamma response in the frontal, lateral temporal and occipital areas. Although sad and neutral emotions have similar neural patterns in the beta and gamma bands, neutral emotion has stronger activation in the parietal and occipital sites. As for happy emotion, stronger neural activities are observed in most brain areas in all five frequency bands compared to the other emotions, especially in the lateral and temporal area. The neural patterns found in this paper are consistent with the findings in [6]. The main difference among the neural patterns of emotions lies in the alpha, beta, and gamma bands, which indicates that high frequency bands have better discrimination ability than the low frequency bands.

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