FAST EMOTION DETECTION FROM EEG USING ASYMMETRIC SPATIAL FILTERING

Dong Huang, Haihong Zhang, Kaikeng Ang, Cuntai Guan, Yaozhang Pan, Chuanchu Wang, Juanhong Yu

Institute for Infocomm Research, A*STAR, Singapore

ABSTRACT

The injection of emotional intelligence in human-computer interfaces is necessary for computer applications to appear intelligent when interacting with people. With the recent development of brain imaging techniques and brain-computer interfaces, computers can actually take a look inside users' head to observe their emotional states. This paper presents an EEG-based emotion detection system which detects emotional states based on short EEG segments of 1s. A novel feature extraction algorithm termed asymmetric spatial filtering is proposed to extract features from high dimensional EEG data. The effectiveness of the proposed method is tested for two types of emotion detection problems on data from five subjects.

***Index Terms*—** emotion detection, BCI, EEG, feature extraction

1. INTRODUCTION

Emotion plays a critical role in rational and intelligent behavior. The injection of emotional intelligence in human-computer interfaces (HCI) is necessary for computer applications to appear intelligent when interacting with people. With meager understanding of the complex mechanism of human emotion recognition, machine emotion recognition has remained as an extremely challenging task. The design of a machine emotion detector should be guided by emotion studies from psychology, neuroscience, as well as tools from machine-based learning approaches.

Traditionally adopted approach of affect recognition is based on audio-visual signals [1]. However, there are a number of issues regarding their realization during HCI interaction. For example, a person has to look directly to the camera all the time or the recognition of emotion through voice in a noisy environment. Facial and voice expressions do not always reflect the true emotional state of the user.

Recently there have been studies on emotion detection from physiological signals, like skin resistance, skin temperature, blood pressure, and respiration [2]. These signals can reflect the influence of emotion on autonomic nervous system, but are also significantly influenced by other factors whose effect is similar with an emotion derived one. For instance, perspiration due to physical activity rather than emotions would affect a skin response based systems.

With the recent development of brain imaging techniques and brain-computer interfaces (BCI), there has been intense interest in relationships between emotion and brain activities. Investigating emotions through brain signals would be a look at internal aspect of emotions, since emotion is not just what is expressed. As electroencephalogram (EEG) has been widely used in BCI, the study of EEG-based emotion detection provides great values for improving user experience and performance for BCI applications. Currently, few efforts have been initiated to recognize emotions from EEG signals. This is mainly due to the lack of a neural model of emotion. Chanel et al. in [3] asked the participants to recall past emotional events, and obtained the best result 79% using EEG for 3 categories, 76% for 2 categories. [4] used self-elicitation and extracted EEG time-frequency features and pairwise mutual information which resulted in 63% for 3 classes. In [5] classification accuracies of 72% were obtained for 2 classes and 58% for 3 classes. It is difficult to make comparisons between these studies because they differ on several criterions, such as the number of subjects, the number of emotion categories, emotion elicitation method, and the way of labeling data.

In contrast to other physiological signals, EEG has very good temporal resolution and therefore could be potentially used for fast emotion detection. As fast emotion detection is necessary for real-time monitoring of emotional states, we investigated in this paper the feasibility of using EEG for fast emotion detection based only on short segments of 1s.

2. AFFECTIVE DATA COLLECTION

Emotions are notoriously fuzzy, ill-defined, subjective, and possibly indeterminate. The gathering of high quality affective data for the study of EEG-based emotion detection requires special care to be paid to the selection of emotion stimuli, stimuli presentation procedure, and ground truth labeling.

2.1. Experiment protocol for affective data collection

In our work, we adopted the dimensional view of emotions for the study of two types of emotion detection tasks: high arousal (HA) vs. low arousal (LA), and high valence (HV) vs.

e-mail: dhuang@i2r.a-star.edu.sg

low valence (LV). Arousal measures the intensity of emotion, while valence describes emotions from positive (pleasant) to negative (unpleasant).

We selected videos as emotional stimuli because videos seem more effective and close to the real-life situation in eliciting emotions than pictures, or music. In total 80 video clips are collected from youtube with 40 neutral, 20 positive, and 20 negative video clips. The video clips were censored and manually edited such that the lengths of neutral video clips are approximately 30s and the lengths of positive and negative clips are approximately 60s. Emotional clips are longer than neutral clips because we found more time is needed to effectively build up the desired high arousal emotional states (positive or negative) than neutral emotions.

The video clips are viewed in 5 sessions such that each session lasts for less than 20 minutes to avoid negative bias in the induced emotion resulting from prolonged viewing process. An emotional (positive or negative) video clip is always preceded and succeeded with neutral videos to reset of the subject to neutral emotional state. Before the viewing of each video clip, a cross is displayed on the screen for 3s to let the subject prepare for the viewing. A 15s rating period immediately follows the played video clip for the subject to report the induced emotions during watching the video clip. Subjects were instructed to sit comfortable and minimize body movement during the viewing.

32 EEG electrodes were attached to subjects' scalp according to the international 10-20 system. A diagram of the used electrodes and their position is shown in 1. EEG signals are acquired with a sampling rate of 250Hz.

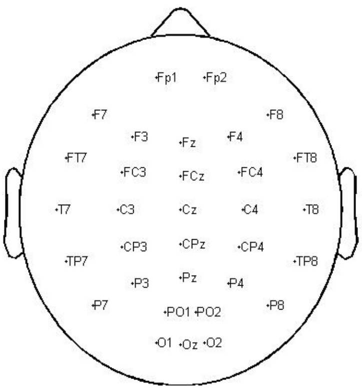

Fig. 1. The set of 32 EEG channels used in the experiment.

2.2. Affective data labeling

Emotions are known to be very dependent on past experience. One can never sure in data collection the expected emotion is elicited or not. To ensure the labeling of data genuinely corresponds to the ground truth, we used both the labels of video stimuli and subject's self assessment for the labeling and selection of EEG data. An EEG trial is selected only if its video label and subject ratings are consistent to minimize the effects of subjectiveness. To ensure that each EEG segment is associated the desired emotional state, we further selected EEG segments from 8s to 27s for neutral videos, and EEG segments from 18s to 57s for emotional videos.

3. ASYMMETRIC SPATIAL FILTERING

Neuropsychological research has shown the importance of asymmetric activation/deactivation between the two cortical hemispheres for emotion processing [6, 7, 8]. For example, the asymmetric involvement of prefrontal cortical regions in positive and negative affect was suggested over 70 years ago by observations of persons who had suffered damage to the right or left anterior cortex [8].

To extract features that are associated with hemispherical asymmetry, we propose a feature extraction algorithm termed asymmetrical spatial filter (ASF), which aims to maximize the difference in the variance of band-pass filtered EEG signal between the two cortical hemispheres. Let $\Sigma_h^{(c)} \in \mathbb{R}^{C\times C}$ denote the estimates of the covariance matrices of the band-pass filtered EEG signal from one of the two hemispheres $h \in \{L, R\}$, under one of the two conditions $c \in \{+,-\}$ (i.e., positive emotional state and negative emotional state):

$$\Sigma_h^{(c)} = \frac{1}{\mid \mathcal{I}_c \mid} \sum_{i\in\mathcal{I}_c} X_i X_i^T, \tag{1}$$

where $\mathcal{I}_c(c \in \{+,1\})$ is the set of indices corresponding to trials belonging to each condition and $\mid \mathcal{I} \mid$ denotes the size of the set. Σ gives a pooled estimate of the covariance of each hemisphere under each condition because EEG signals X of each trial is centered and scaled.

To maximize the difference in the activation of the two hemispheres, we can solve the following maximization problem:

$$\max\left\{\frac{w^T\Sigma_A w}{w^T\Sigma_D w}\right\}. \tag{2}$$

That is, we maximize the Rayleigh quotient of variances between the more activated hemisphere (Σ_A) and the less activated hemisphere Σ_D. Since there are two conditions, (2) can be expressed as:

$$\max\left\{\frac{w^T\Sigma_A^{(+)} w}{w^T\Sigma_D^{(+)} w}\right\} + \max\left\{\frac{w^T\Sigma_A^{(-)} w}{w^T\Sigma_D^{(-)} w}\right\}. \tag{3}$$

With a simple assumption of $w^T\Sigma_A^{(c)}w + w^T\Sigma_D^{(c)}w = 1$ for $c \in \{+,-\}$, we have

$$\max\left\{\frac{w^T\Sigma_A w}{w^T\Sigma_D w}\right\} \propto \max\{w^T\Sigma_A w\}, \text{ or}$$
$$\max\left\{\frac{w^T\Sigma_A w}{w^T\Sigma_D w}\right\} \propto \min\{w^T\Sigma_D w\}, \tag{4}$$

and (3) can be transformed to:

$$\max\{w^T\Sigma_A^{(+)}w\} + \min\{w^T\Sigma_D^{(-)}w\}, \text{ or}$$
$$\min\{w^T\Sigma_D^{(+)}w\} + \max\{w^T\Sigma_A^{(-)}w\}. \qquad (5)$$

Since the simultaneous maximization of A and minimization of B can be expressed as the maximization of the Rayleigh quotient of A over B, (3) is now equivalent to

$$\max\left\{\frac{w^T\Sigma_A^{(+)}w}{w^T\Sigma_D^{(-)}w}\right\} + \max\left\{\frac{w^T\Sigma_A^{(-)}w}{w^T\Sigma_D^{(+)}w}\right\}. \qquad (6)$$

Without loss of generality, we can let $\Sigma_A^{(+)} = \Sigma_R^{(+)}$, $\Sigma_D^{(+)} = \Sigma_L^{(+)}$, and $\Sigma_A^{(-)} = \Sigma_L^{(-)}$, $\Sigma_D^{(-)} = \Sigma_R^{(-)}$. (6) can be written as

$$\max\left\{\frac{w^T\Sigma_R^{(+)}w}{w^T\Sigma_R^{(-)}w}\right\} + \max\left\{\frac{w^T\Sigma_L^{(-)}w}{w^T\Sigma_L^{(+)}w}\right\}. \qquad (7)$$

From the above derivation, we formulate the criterion function of ASF as follows:

$$f(w) = \max\left\{\frac{w_R^T\Sigma_R^{(+)}w_R}{w_R^T\Sigma_R^{(-)}w_R}\right\} + \max\left\{\frac{w_L^T\Sigma_L^{(-)}w_L}{w_L^T\Sigma_L^{(+)}w_L}\right\}. \quad (8)$$

Note that there is actually no restriction for the spatial filters to be the same for the two hemispheres. The algorithm is termed asymmetrical spatial filtering because different spatial filters w are applied to the two hemispheres.

The unity constraint on $w^T\Sigma_h^{(c)}w$ can be easily satisfied by scaling of the spatial filters w_R and w_L. Let $w'_R = aw_R$ and $w'_L = bw_L$, it is always possible to find a and b to satisfy

$$w_R'^T\Sigma_R^{(+)}w'_R + w_L'^T\Sigma_L^{(+)}w'_L = a^2S_R^{(+)} + b^2S_L^{(+)} = 1$$
$$w_R'^T\Sigma_R^{(-)}w'_R + w_L'^T\Sigma_L^{(-)}w'_L = a^2S_R^{(-)} + b^2S_L^{(-)} = 1. \quad (9)$$

The scaling of w_R and w_L is trivial and can be discarded because the asymmetric feature obtained by ASF is the log ratio of the variances between the two hemispheres:

$$y = \log\left(\frac{w_R^T\Sigma_R w_R}{w_L^T\Sigma_L w_L}\right). \qquad (10)$$

4. CLASSIFICATION

To test the effectiveness of the proposed algorithm, we applied it on the data described in section 2 for two types of emotion detection problems: HA (strong) vs. LA (calm), and HV (positive) vs. LV (negative). We also implemented some other popular feature extraction algorithms including: short-time Fourier transform (STFT)-based time-frequency features, wavelet packet transform (WPT)-based time-frequency features, and filter bank common spatial pattern (FBCSP) [9], which is an enhanced variant of CSP method. For STFT, a window length of 1s and no overlap is used. Each window of EEG data is transformed to 16 sub-bands, with 2Hz resolution from 2 to 22Hz, 4Hz resolution from 22 to 42Hz, and 8 Hz bandwidth from 42 to 50Hz. For wavelet packet transform, discrete Meyer wavelet is selected. 16 sub-bands are obtained with 4 levels of decomposition. In FBCSP, a filter bank of 8 sub-bands is employed ranging from 0.5-4Hz, 4-8Hz, 8-12Hz, 12-16hz, 16-24Hz, 24-32Hz, 32-40Hz, and 40-50Hz, which roughly correspond to the typically defined EEG frequency bands such as delta, theta, alpha, and gamma bands. ASF is also applied after filter bank, with the same 8 sub-bands as used in FBCSP.

Each feature extraction method is tested with 4 popular classifiers: linear, Naive Bayes (NB), K-nearest neighbor (KNN), and support vector machine (SVM). The classification performance of each combination of feature extraction and classifier is obtained by the standard 10 $\times$ 10-fold cross-validation.

5. RESULTS AND DISCUSSION

Figure 2 and 3 show the mean classification accuracies of the 10$\times$10-fold cross-validation obtained with ASF features for arousal and valence recognition, respectively. It can be observed that linear classifier generally shows good performance compared to other classifiers across different subjects for both types of emotion detection problems.

Figure 4 and 5 show the mean classification accuracies of different feature extraction methods with linear classifier for arousal and valence recognition, respectively. The comparison of different feature extraction methods for the two types of emotion detection problems across different subjects is also shown in Table 1 and 2. ASF achieves higher classification accuracy for both type of emotion classification problems compared to time-frequency features and CSP features. Based only on 1s of EEG data, ASF can achieve an average accuracy of 83% and 79% for arousal and valence classification, respectively.

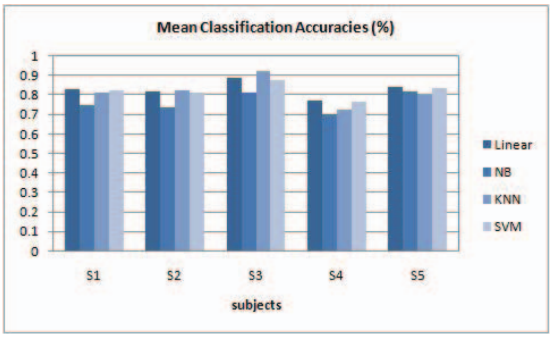

Fig. 2. Mean classification accuracies for arousal recognition with different classifiers for each subject.

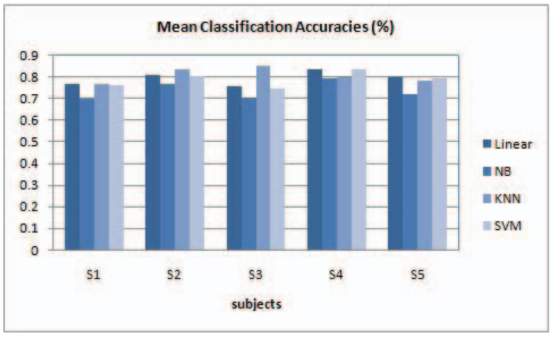

Fig. 3. Mean classification accuracies for valence recognition with different classifiers for each subject.

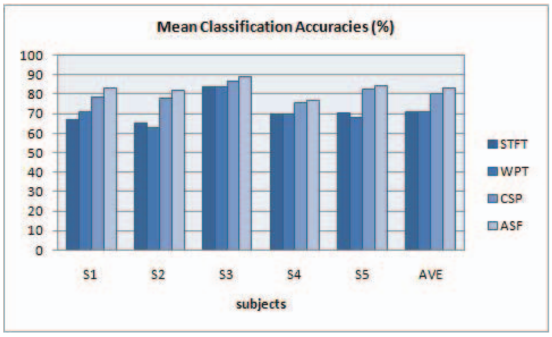

Fig. 4. Mean classification accuracies for arousal recognition with different feature extraction methods for each subject.

6. CONCLUSION

A novel feature extraction method termed asymmetric spatial filtering is presented, which compares favorably to time-frequency features and CSP features for two types of emotion detection problems: HA (strong) vs. LA (calm), and HV (positive) vs. LV (negative). Based only on 1s of EEG segment, our experimental results show that EEG-based emotion detection can achieve an average accuracy of 83% and 79% with ASF features for arousal and valence classification, respectively.

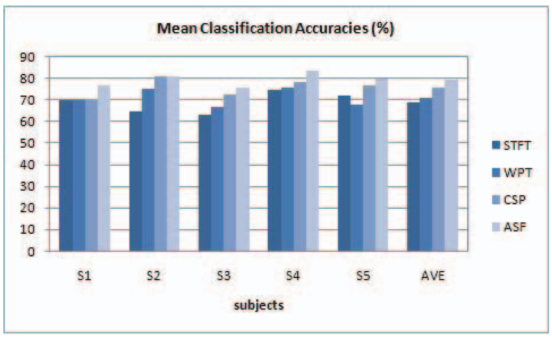

Fig. 5. Mean classification accuracies for valence recognition with different feature extraction methods for each subject.

Table 1. The mean classification accuracies (%) for arousal recognition of different feature extraction methods with linear classifier.

subjects	S1	S2	S3	S4	S5	ave
STFT	66.67	65.07	83.59	69.75	70.13	71.04
WPT	70.92	62.70	83.54	69.94	67.97	71.01
CSP	78.26	78.07	86.70	75.34	82.82	80.24
ASF	83.19	81.88	88.72	76.95	84.37	83.02

Table 2. The mean classification accuracies (%) for valence recognition of different feature extraction methods with linear classifier.

subjects	S1	S2	S3	S4	S5	ave
STFT	69.84	64.99	62.99	74.88	72.08	68.96
WPT	70.03	75.40	66.86	75.72	67.73	71.15
CSP	70.68	80.80	72.75	78.54	76.92	75.94
ASF	76.93	81.19	75.60	83.66	79.84	79.44

7. REFERENCES

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