

# Asymmetric spatial pattern for EEG-based emotion detection

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**Abstract**—Feature extraction has been a crucial and challenging task for EEG-based BCI applications mainly due to the problems of high-dimensionality and high noise level of EEG signals. In this paper we developed a novel feature extraction algorithm for EEG-based emotion detection problem. The proposed algorithm is derived from viewing EEG signals as the activation/deactivation of sources specific to the brain activities of interest. For binary classification problem, to be more specific, we consider the EEG signals for the two types of brain activities as characterized by the activation/deactivation of two discriminatory sources in the brain, with one source activated and the other one deactivated for one particular type of brain activities. The proposed algorithm, termed Asymmetric Spatial Pattern (ASP), extracts pairs of spatial filters, with each filter corresponding to only one of the two sources. The idea of ASP is neurologically plausible for certain situations. For example, according to the valence hypothesis of emotion, the left hemisphere is more activated in positive emotions and the right hemisphere is more activated in negative emotions. The effectiveness of the proposed algorithm is confirmed by application to real data for two types of EEG-based emotion detection problems: arousal detection (strong v.s. calm), and valence detection (positive v.s. negative). Experimental results on the real data also show that some of the asymmetric spatial patterns by ASP are consistent with the current neurophysiological findings on brain emotion processing.

## I. INTRODUCTION

It has been well known that emotional responses are inherently important for the survival of individuals and their species. After decades of neglect, neuroscience has embraced emotion as an important research area. After decades of development of machine intelligence, the importance of emotion has been acknowledged and has been motivating the research work in affective computing. However, with meager understanding of the complex mechanism of human emotion recognition, machine emotion recognition has remained as an extremely challenging task. With the recent development of brain sensing techniques and brain-computer interface (BCI) technologies, the use of brain signals for emotion detection has become a new and hot topic.

With its purpose first proposed for assisting the physically challenged, BCI research has now expanded to a wider range of applications. The interest in BCI technology stems from the unique advantage of having access to the user's ongoing brain activity which enables applications spanning a variety of domains such as entertainment (e.g. brain-activity based gaming [1]), safety (e.g. detecting the level of alertness [2]), security (e.g. brain activity based biometrics [3]), and neuro-

economics (e.g. neural correlates of consumer choices for marketing [4]). As for HCI applications, BCIs can also benefit from adapting their operation to the emotional state of the user. The use of BCI for emotion recognition has its special advantage as compared to other modes (e.g., audio-visual signals) by having access to brain activity which can allow significant insight into the user's emotional state. In neuroscience various brain imaging technologies have been utilized to understand emotions in the brain [5]. The range of signals that can be measured to monitor the brain activity include electrical potentials to hemodynamic measurements, including invasive eCoG, non-invasive EEG and MEG, fMRI, PET, and fNIRS. Of particular interest in the current BCIs is the electroencephalogram (EEG) due to its high time resolution, noninvasiveness, ease of acquisition, and cost effectiveness. In this paper, we present our work on EEG-based emotion detection.

Currently, few efforts have been initiated to recognize emotions from EEG signals. Chanel et al. in [6] asked the participants to recall past emotional events, and obtained the best result 79% using EEG for 3 categories, 76% for 2 categories. [7] used self-elicitation and extracted EEG time-frequency features and pairwise mutual information which resulted in 63% for 3 classes. In [8] 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 criteria, such as the number of subjects, the interested emotion categories, emotion elicitation method, selection of emotion stimuli, and the way of labeling data.

The volume of work published on EEG-based emotion detection is relatively small compared to emotion detection based on other modalities such as audio-visual signals. This is mainly due to a lack of neural emotional model and the high dimensionality and high noise level of EEG signals. Similar to other EEG-based tasks (e.g., EEG-based motor imagery classification), feature extraction plays a crucial and challenging role for a good performance. In this paper, we propose a novel feature extraction algorithm, termed Asymmetric Spatial Pattern (ASP), for EEG-based emotion detection problem. The proposed algorithm is derived from viewing EEG signals as the activation/deactivation of sources specific to the brain activities of interest. The idea of the proposed ASP is neurologically plausible for certain situations. For example, according to the valence hypothesis of emotion, the left hemisphere is more

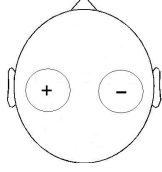


Fig. 1. A simple illustrative example where two sources corresponding to two classes  $\{+, -\}$  have a local distribution on the left and right side of the cortex.

activated in positive emotions and the right hemisphere is more activated in negative emotions.

The rest of the paper is structured as follows: Section II describes the proposed feature extraction procedure. Section III presents the procedure for affective data collection and ground truth establishment. Experimental results of the proposed method on data from four subjects are presented in section IV. Finally, some conclusions are drawn in section V.

## II. FEATURE EXTRACTION BY ASYMMETRIC SPATIAL PATTERN (ASP)

We first consider EEG signals as characterized by two discriminatory sources  $S_{1,2}$  for a binary classification problem  $\omega = \{+, -\}$ . Without loss of generality, we suppose that  $S_1$  is more activated when it is class  $+$ , while  $S_2$  is more activated for class  $-$ . If these two sources have different spatial locations on the cortex and have a local distribution on the multi-channel EEG signals, we can divide the group of EEG channels covering the two sources into two subgroups:

$$X = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} = \begin{bmatrix} f_1(S_1) \\ f_2(S_2) \end{bmatrix}, \quad (1)$$

where  $X$  denotes the EEG signal,  $X_{1,2}$  denotes the two subgroups of  $X$  covering the two sources  $S_{1,2}$ , and  $f_{1,2}$  are some unknown transfer functions relating  $S$  to  $X$ . A simple illustrative example which visualizes the distribution of two sources is shown in Figure 1. With the above assumption, the following asymmetric feature is formulated to decide the label of a single EEG trial  $X$ :

$$AF(X) = \frac{P(S_1)}{P(S_2)}, \quad (2)$$

where  $P(S)$  denotes the power of a source signal  $S$ . The asymmetric feature defined in (2) measures the difference in the activation level between the two sources. It would have a large value if the EEG signal  $X$  is from one class and a small value if  $X$  is from the other class. Since the underlying sources  $S_{1,2}$  are unknown, (2) can only be estimated from  $X$  as

$$AF(X) = \frac{P(g_1(X_1))}{P(g_2(X_2))} \quad (3)$$

where  $g(X) = f^{-1}(X)$  is some inverse transfer function from  $X$  to  $S$ . For linear transfer functions between  $X$  and  $S$ , we have  $g(X) = W^T X$ .

The objective of ASP is to maximize asymmetry in the activation level between the two sources by pairs of spatial filters, one for each of the two sources. To derive the objective function of ASP, the asymmetric feature in (2) and (3) is formulated as the following Rayleigh quotient of the two sources:

$$AF(X) = \frac{w_1^T \Sigma_1 w_1}{w_2^T \Sigma_2 w_2}, \quad (4)$$

where  $\Sigma_{1,2}$  are the covariance matrices of band-pass filtered EEG signals of the two sources, which can be estimated by:

$$\Sigma_i = \frac{1}{N} X_i X_i^T, \quad i = 1, 2 \quad (5)$$

where  $X_i \in \mathbb{R}^{M \times N}$  is the subgroup of EEG signals for source  $i$ ,  $M$  and  $N$  are the number of channels in the subgroup and the number of time samples of an EEG trial, respectively.

As there are two conditions under which EEG signals are recorded, there are in total four covariance matrix estimates for  $\Sigma_{1,2}$ , which we write as follows:

$$\Sigma_{1+} = \Sigma_{A+}, \Sigma_{2+} = \Sigma_{D+}, \text{ for class } +, \quad (6)$$

$$\Sigma_{1-} = \Sigma_{D-}, \Sigma_{2-} = \Sigma_{A-}, \text{ for class } -. \quad (7)$$

Note that the covariance matrices in the above two equations are the pooled estimates of the covariance matrices for the two sources under the two conditions. They are computed as the average across all samples from the same class:

$$\Sigma_{i+/-} = \frac{1}{|\mathcal{I}^{+/-}|} \sum_{X \in \mathcal{I}^{+/-}} \Sigma_i, \quad i = 1, 2 \quad (8)$$

where  $\mathcal{I}^{+/-}$  denotes the set of EEG trials from class  $+/-$ , respectively.  $|\mathcal{I}|$  is cardinality of the set.  $\Sigma_i$ , as defined in (5), is the covariance matrix estimated from a single EEG trials  $X$ .

The asymmetry between the two sources can be maximized by the following criterion function:

$$\max \left\{ \frac{w_1^T \Sigma_{1+} w_{1+}}{w_2^T \Sigma_{2+} w_{2+}} \right\} \cap \min \left\{ \frac{w_1^T \Sigma_{1-} w_{1-}}{w_1^T \Sigma_{1-} w_{1-}} \right\},$$

or equivalently,

$$\max \left\{ \frac{w_{A+}^T \Sigma_{A+} w_{A+}}{w_{D+}^T \Sigma_{D+} w_{D+}} \right\} \cap \max \left\{ \frac{w_{A-}^T \Sigma_{A-} w_{A-}}{w_{D-}^T \Sigma_{D-} w_{D-}} \right\}. \quad (9)$$

The criterion function (9) contains two parts, one for each condition. The intersection sign  $\cap$  indicates the optimization of both of the two terms. We observe that (9) is a function of four  $w$ 's and is determined by four covariance matrices.

To simplify the criterion function (9), we first make the following constraint on the pair of  $w$ 's:

$$w_A^T \Sigma_A w_A + w_D^T \Sigma_D w_D = 1, \quad (10)$$

for the two classes  $\{+, -\}$ . Later we show that this simple constraint can be easily satisfied. With this constraint, we have

$$\begin{aligned} \max \left\{ \frac{w^T \Sigma_A w}{w^T \Sigma_D w} \right\} &\propto \max \{ w^T \Sigma_A w \}, \text{ or} \\ \max \left\{ \frac{w^T \Sigma_A w}{w^T \Sigma_D w} \right\} &\propto \min \{ w^T \Sigma_D w \}, \end{aligned} \quad (11)$$

and (9) is equivalent to:

$$\begin{aligned} & \max\{w_{A+}^T \Sigma_{A+} w_{A+}\} \cap \min\{w_{D-}^T \Sigma_{D-} w_{D-}\}, \text{ or} \\ & \max\{w_{A-}^T \Sigma_{A-} w_{A-}\} \cap \min\{w_{D+}^T \Sigma_{D+} w_{D+}\}. \end{aligned} \quad (12)$$

Since the simultaneous maximization of  $A$  and minimization of  $B$  can be expressed as the maximization of the Rayleigh quotient of  $A$  over  $B$ , (9) is now equivalent to

$$\max \left\{ \frac{w_{A+}^T \Sigma_{A+} w_{A+}}{w_{D-}^T \Sigma_{D-} w_{D-}} \right\} \cap \max \left\{ \frac{w_{A-}^T \Sigma_{A-} w_{A-}}{w_{D+}^T \Sigma_{D+} w_{D+}} \right\}. \quad (13)$$

From (6) and (7), we can see that the first term in (13) is related only to source 1, while the second term is related only to source 2. The two covariance matrices in each term correspond to the activation/deactivation of the same source. We can therefore reduce the four spatial filters  $w$ 's to two spatial filters by making  $w_{A+} = w_{D-}$  and  $w_{A-} = w_{D+}$ .

From the above derivation, we formulate the pair of criterion functions of ASP as follows:

$$J_1(w_1) = \max \left\{ \frac{w_1^T \Sigma_{1+} w_1}{w_1^T \Sigma_{1-} w_1} \right\}, \quad (14)$$

$$J_2(w_2) = \max \left\{ \frac{w_2^T \Sigma_{2-} w_2}{w_2^T \Sigma_{2+} w_2} \right\}. \quad (15)$$

(14) finds a spatial filter  $w_1$  for source 1 which maximizes the difference between the activation and deactivation status of source 1, while (15) finds another filter  $w_2$  for source 2.

The unity constraint (10) can be easily satisfied by scaling of the spatial filters  $w_1$  and  $w_2$ . Let  $w'_1 = aw_1$  and  $w'_2 = bw_2$ , it is always possible to find  $a$  and  $b$  to satisfy

$$\begin{aligned} w_1'^T \Sigma_{1+} w'_1 + w_2'^T \Sigma_{2+} w'_2 &= a^2 S_{1+} + b^2 S_{2+} = 1, \\ w_1'^T \Sigma_{1-} w'_1 + w_2'^T \Sigma_{2-} w'_2 &= a^2 S_{1-} + b^2 S_{2-} = 1. \end{aligned}$$

The scaling of  $w_1$  and  $w_2$  is trivial and can be discarded because the asymmetric feature obtained by ASP is the log ratio of the variances between the two sources:

$$y = \log \left( \frac{w_1^T \Sigma_{1+} w_1}{w_2^T \Sigma_{2+} w_2} \right). \quad (16)$$

### III. AFFECTIVE DATA COLLECTION & GROUND TRUTH ESTABLISHMENT

The gathering of high quality affective data for the study of EEG-based emotion detection requires special care to be paid to the experiment design of emotion elicitation, ground truth labeling, and EEG data collection.

#### A. Emotion elicitation

1) *Emotion categories of interest:* 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. low valence (LV). Affective arousal measures the intensity of emotion ranging from calm to excited, while affective valence ranging from unpleasant to pleasant. Three categories of emotions are thus of interest: high-arousal low-valence (HALV, or strongly negative), high-arousal high-valence (HAHV, or strongly positive), and low-arousal neutral-valence (LANV, or neutral).

2) *Emotion stimuli selection:* We selected motion pictures as emotion stimuli because they seem to be more effective and close to the real-life situation in eliciting emotions than pictures, or music [9]. A total of 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 length of each neutral video clip is approximately 30s and the length of each emotional (positive or negative) video clip is 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 than neutral emotions.

3) *Emotion stimuli presentation:* The video clips are viewed in 5 sessions such that each session lasts for less than 20 minutes to avoid negative bias to the elicited emotion due to 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 assess the induced emotions during watching the video clip.

#### B. Emotion ground truth establishment

Although the video clips are selected to elicit emotions belonging to one of the three emotion categories, there is little way of knowing whether the intended emotion is successfully elicited or not. This is because emotions are very dependent on the subject's past experience. We may have tried to please, but the subject was irritated because of something she remembered unrelated to the task. We may have tried to irritate and not succeeded. During our data collection process, self-assessment is used to measure the induced emotions. Self-Assessment Manikin (SAM) [10], which is a pictorial assessment technique for measuring emotion, is presented to the subject immediately after the viewing of each video clip. The measurement using SAM is in terms of ratings from 1 to 9 for emotion dimensions: arousal, and valence (dominance is not used in this paper). Before the start of the data collection experiment, the subject was informed to rate her emotions as honestly as she can and there is no right or wrong answers.

To enhance the reliability of the emotion ground truth of EEG data, we discarded EEG trials if the subject ratings are not consistent with the video stimuli's labels. By "consistent" we mean the label of a video stimulus is the same as the crisp ground truth from the subject ratings. As the intended emotion may not have been fully developed yet during the start of each video clip, we discarded EEG segments within the first few seconds of viewing to further enhance the reliability of the ground truth for our data. We selected EEG segments from 8s to 26s for neutral videos (30s long), and from 18s to 54s for emotional videos (60s long).

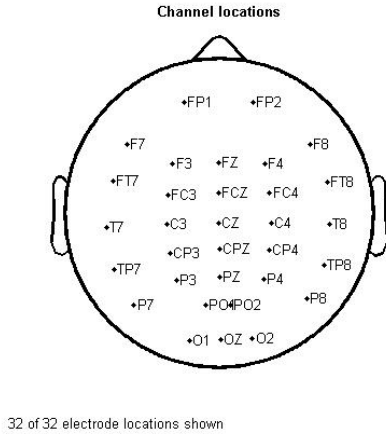


Fig. 2. The set of 32 EEG channels used in the experiment.

### C. EEG signal recording

EEG signals are acquired with a sampling rate of 250Hz. 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 Fig. 2. During the setup, we tried our best effort to ensure the impedance of electrodes to be below 10 k $\Omega$ , with only very few exceptions in the range of 10-50 k $\Omega$  for some subjects. Subjects were instructed to sit comfortably and minimize body movement during the viewing of motion pictures. The recording of 5 sessions for each subject is done on different days.

## IV. EXPERIMENTS

### A. Evaluation methods

To evaluate the performance of the proposed algorithm, we applied it on the affective data described in section III for two types of emotion detection problems: arousal detection (HA v.s. LA, or strong v.s. calm) and valence detection (HV v.s. LV, or positive v.s. negative). The affective data were collected from 4 subjects and in 5 sessions on different days for each subject. The EEG signals from a video clip were cut into trials, that is, segments of 6s. There is no overlapping between different EEG trials from one video clip. To avoid classification bias, we used a "leave-one-video-out" strategy for the evaluation of classification accuracy. In "leave-one-video-out", each time all trials that are extracted from one video clip are taken out as the test set, while the training set is comprised of trials from other video clips.

### B. Feature extraction & Classification

Two other feature extraction algorithms are also implemented and selected as the benchmark algorithms: asymmetric features and filter bank common spatial pattern (FBCSP) [11], which is an enhanced variant of CSP method. Asymmetric features are used in [8] for EEG-based emotion detection. We selected 5 pairs of EEG channels from the frontal lobe to get 5 asymmetric features in our experiments. The 5 pairs of

EEG channels selected are: FP1/FP2, F7/F8, F3/F4, FT7/FT8, and FC3/FC4. FBCSP is proposed by Ang et al. [11] and is the winner algorithm for single-trial EEG motor imagery classification on datasets Ila and I Ib from BCI competition IV. For all the feature extraction algorithms, the same pre-processing method is used. EEG signals are decomposed by a filter bank into 8 sub-bands: 0.5-4Hz, 4-8Hz, 8-12Hz, 12-16Hz, 16-24Hz, 24-32Hz, 32-40Hz, and 40-50Hz. These frequency bands are selected because they roughly correspond to the typically defined EEG frequency bands such as delta, theta, alpha, and gamma bands. The filter bank is implemented using a zero-phase Chebyshev Type II Infinite Impulse Response (IIR) filter so that no phase distortion is introduced between different channels by the band-pass filtering.

After feature extraction, Recursive Fisher linear discriminant (RFLD) [12] is applied to further reduce the dimensionality of feature vectors. RFLD employs Fisher linear discriminant (FLD) to find discriminant features that best separate different classes. A recursive strategy is integrated into FLD to overcome the feature number limitation of  $C - 1$ , where  $C$  is the number of classes. For binary classification problem, the number of features by FLD is 1, which is obviously a limitation for FLD. In the case of RFLD, the number of features can be extracted is not limited.

The performance of various feature extraction algorithms for EEG-based emotion detection are tested with 3 popular classifiers: K-nearest neighbor (KNN), Naive Bayes (NB), and support vector machine (SVM) with RBF kernel. We tried all combinations of the three feature extraction algorithms and the three classifiers. The experiment results are shown below.

### C. Results

The classification performance of each combination of feature extraction and classifier is obtained by the "leave-one-video-out" strategy. The classification error rates are summarized in Table I. The error rates for each combination of feature and classifier shown in Table I are averages across the 4 subjects. From the table, we observe that ASP achieves an average of 17.54% and 33.95% for arousal and valence recognition, respectively. An reduction of 21.8% and 9.13% in average error rate is achieved by ASP compared to the best of CSP and AF for arousal and valence recognition, respectively. The performance of ASP with all the three classifiers are significantly better than those of AF and CSP with the corresponding classifiers. The classification accuracies of the three feature extraction algorithms and the three classifiers are plotted in Figure 3 and 4 for arousal recognition, and Figure 5 and 6 for valence recognition. Figure 3 and 5 group different feature extraction algorithms together, while figure 4 and 6 group different classification algorithms together. It can be observed that ASP improves the classification performance significantly compared to AF and CSP. The comparison between the three classifiers shows that the three classifiers have similar performance.

TABLE I  
MEAN CLASSIFICATION ERROR RATES FOR EMOTION DETECTION BY  
DIFFERENT FEATURES AND CLASSIFIERS.

Arousal classification (mean error rates (%))				
	KNN	NB	SVM	ave
AF	37.48	29.13	30.58	32.40
CSP	23.02	21.99	22.28	22.43
ASP	17.75	16.90	17.97	17.54
ave	26.09	22.68	23.61	24.12

Valence classification (mean error rates(%))				
	KNN	NB	SVM	ave
AF	37.99	35.99	38.11	37.36
CSP	41.77	42.79	42.46	42.34
ASP	33.49	33.76	34.61	33.95
ave	37.75	37.51	38.39	37.88

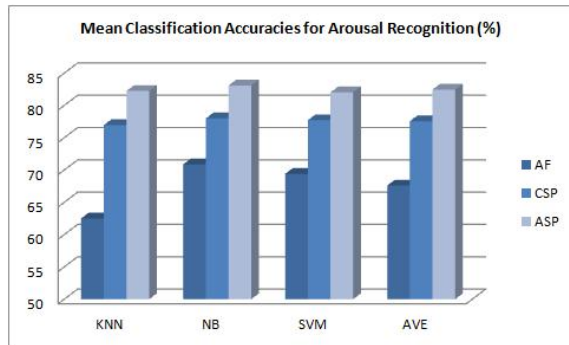


Fig. 3. Mean classification accuracies for arousal recognition. Accuracies for different feature extraction algorithms are grouped together.

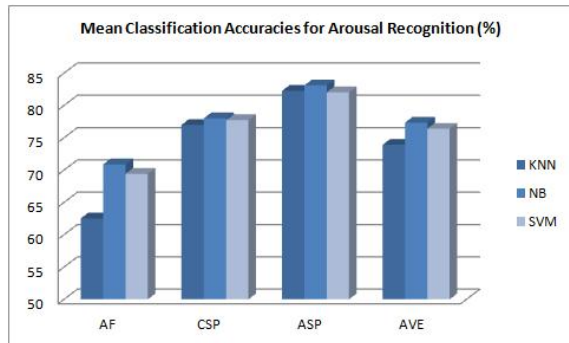


Fig. 4. Mean classification accuracies for arousal recognition. Accuracies for different classification algorithms are grouped together.

#### D. Discussion

Much evidence from neuropsychological study has shown the asymmetric cortical activity for emotion processing [13], [14], [15], [16], [17], [18], [19], [20], [21], [22]. The valence hypothesis predicts right hemisphere dominance for negative and lateralization towards the left hemisphere for processing of positive emotional material. For example, the asymmetric

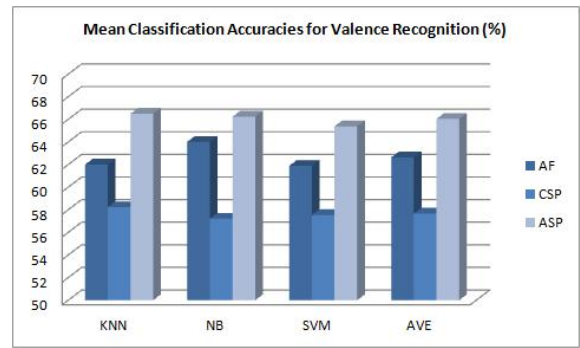


Fig. 5. Mean classification accuracies for valence recognition. Accuracies for different feature extraction algorithms are grouped together.

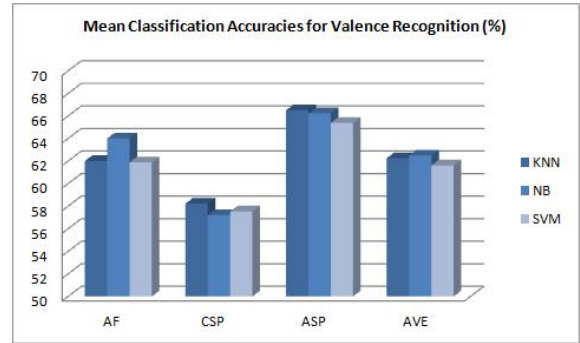


Fig. 6. Mean classification accuracies for valence recognition. Accuracies for different classification algorithms are grouped together.

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 [19]. [23] showed relatively more power for negative valence over the left temporal region as compared to the right and a laterality shift towards the right hemisphere for positive valence. In addition, emotional processing enhanced gamma band power at right frontal electrodes regardless of the particular valence as compared to processing neutral pictures. [24] reported greater right parietal activation, as measured by alpha power, occurred during viewing of both negative and positive stimuli. [25] showed higher right parietal beta power for positive emotions compared to negative emotion.

Based on the neurophysiological studies on brain asymmetry for emotion processing, we examine the spatial patterns obtained by ASP. The spatial patterns of ASP can be easily obtained by calculating the inverse transpose of the spatial filter matrix  $P = W^{-T}$ , where each column of  $P$  is a spatial pattern and each column of  $W$  is its corresponding spatial filter. In this paper, we show the spatial patterns as well as the spatial filters obtained by ASP for one of the subjects in our experiment. The spatial filters/patterns for arousal and valence recognition is topographically visualized in Figure 7, 8, 9, and 10. Figure 7 and 9 show the spatial filters/patterns in alpha band, while figure 8 and 10 show the spatial filters/patterns in gamma band. The spatial filters/patterns are scaled by its maximum absolute value so that the values at each electrode

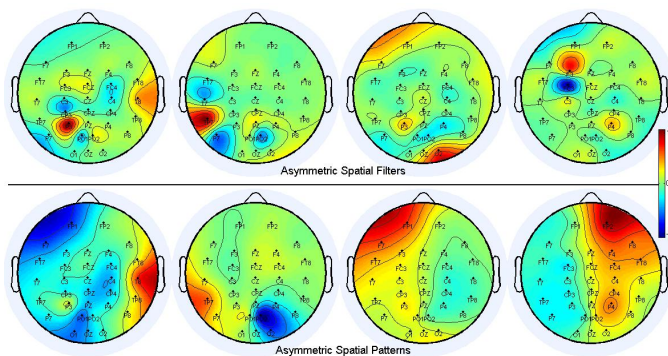


Fig. 7. The spatial filters/patterns obtained by ASP for arousal recognition in alpha band. Each pair of spatial filters (or spatial patterns) are combined together to show a full-head topographic map. The maps in the upper panel show the first 4 pairs of spatial filters, while the maps in the lower panel show the first 4 pairs of spatial patterns.

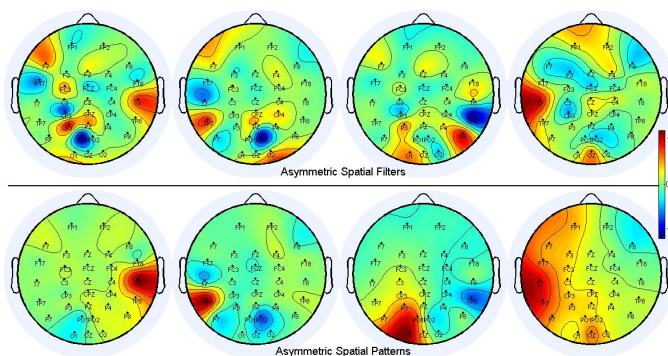


Fig. 8. The spatial filters/patterns obtained by ASP for arousal recognition in gamma band. Each pair of spatial filters (or spatial patterns) are combined together to show a full-head topographic map. The maps in the upper panel show the first 4 pairs of spatial filters, while the maps in the lower panel show the first 4 pairs of spatial patterns.

position fall into range  $[-1,1]$ . Position in-between electrodes are interpolated and may have a value out of the  $[-1,1]$  range. As we used to ASP to obtain pairs of spatial filters, each covering one hemisphere, each full-head topographic map in these figures are obtained by combining a pair of spatial filters (or a pair of spatial patterns). From the ASP spatial patterns shown in these figures, we can generally see that prefrontal asymmetry in alpha band and temporal asymmetry in gamma band are observable for arousal recognition, and prefrontal and parietal asymmetry in alpha band and temporal asymmetry in gamma band are present for valence recognition.

## V. CONCLUSION

This paper presents an EEG-based emotion detection system, which is important for improving the machine emotional intelligence, especially for BCI applications. A novel feature extraction algorithm, termed asymmetric spatial pattern (ASP), is derived from viewing EEG signals as the activation/deactivation of sources specific to the brain activities of interest. The proposed algorithm extracts pairs of spatial filters, with each filter corresponding to only one of the

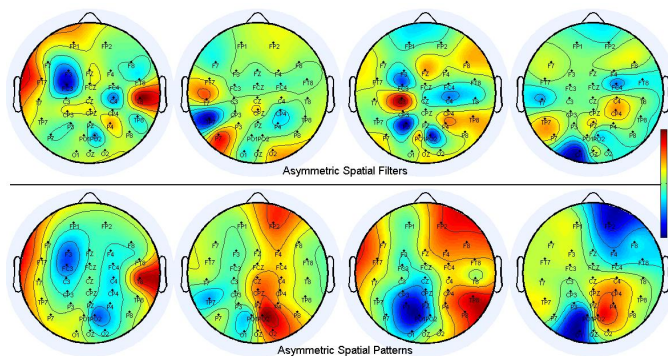


Fig. 9. The spatial filters/patterns obtained by ASP for valence recognition in alpha band. Each pair of spatial filters (or spatial patterns) are combined together to show a full-head topographic map. The maps in the upper panel show the first 4 pairs of spatial filters, while the maps in the lower panel show the first 4 pairs of spatial patterns.

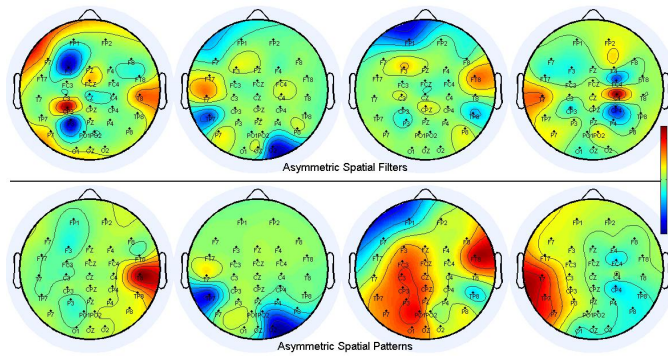


Fig. 10. The spatial filters/patterns obtained by ASP for valence recognition in gamma band. Each pair of spatial filters (or spatial patterns) are combined together to show a full-head topographic map. The maps in the upper panel show the first 4 pairs of spatial filters, while the maps in the lower panel show the first 4 pairs of spatial patterns.

two sources. The idea of ASP is neurologically plausible for certain situations. For example, according to the valence hypothesis of emotion, the left hemisphere is more activated in positive emotions and the right hemisphere is more activated in negative emotions. The effectiveness of the proposed algorithm is confirmed by application to real data for two types of EEG-based emotion detection problems: arousal detection (strong v.s. calm), and valence detection (positive v.s. negative). The performance of the proposed algorithm is significantly better than the benchmark feature extraction algorithms. Experimental results on the real data also show that some of the asymmetric spatial patterns extracted by ASP for are consistent with the current neurophysiological findings.

## REFERENCES

- [1] K. K. W. Wong, *Player adaptive entertainment computing*. ACM, 2007, p. 13.
- [2] T. P. Jung, S. Makeig, M. Stensmo, and T. J. Sejnowski, "Estimating alertness from the EEG power spectrum." *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 1, pp. 60–69, 1997.
- [3] S. Marcel and J. D. R. Millan, "Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 743–752, 2007.

- [4] N. J. Lee, A. J. Broderick, and L. Chamberlain, "What is "neuromarketing"? a discussion and agenda for future research," *International Journal of Psychophysiology*, vol. 63, no. 2, pp. 199–204, 2007.
- [5] J. E. LeDoux, "Emotion circuits in the brain." *Annual Review of Neuroscience*, vol. 23, no. 1, pp. 155–184, 2000.
- [6] G. Chanel, K. Ansari-Asl, and T. Pun, "Valence-arousal evaluation using physiological signals in an emotion recall paradigm," in *IEEE International Conference on Systems, Man and Cybernetics*, Montreal, Que., Oct. 2007, pp. 2662–2667.
- [7] G. Chanel, J. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm," *Int. J. Human-Computer Studies*, vol. 67, pp. 607–627, 2009.
- [8] T. Pun, T. Alecu, G. Chanel, J. Krongegg, and S. Voloshynovskiy, "Brain-computer interaction research at the computer vision and multimedia laboratory, university of geneva," *IEEE Trans. On Neural Systems and Rehabilitation Engineering*, vol. 14, no. 2, June 2006.
- [9] J. J. Gross and R. W. Levenson, "Emotion elicitation using films," *Cognition & Emotion*, vol. 9, no. 1, pp. 87–108, 1995.
- [10] P. Lang, M. Bradley, and B. Cuthbert, "Emotion, attention, and the startle reflex," *Psychological Review*, vol. 97, pp. 377–398, 1990.
- [11] H. Z. Kai Keng Ang, Zheng Yang Chin and C. Guan, "Mutual information-based selection of optimal spatial-temporal patterns for single-trial eeg-based bcis," *Pattern Recognition*, May 2011.
- [12] D. Huang and C. Xiang, "Recursive bayesian linear discriminant for classification," in *Lecture Notes in Computer Science*, vol. 4492, 4th International Symposium on Neural Networks, ISNN 2007. Nanjing, China: Springer Verlag, Heidelberg, D-69121, Germany, Jun 2007, pp. 1002–1011.
- [13] E. Harmon-Jones, P. Gable, and C. Peterson, "The role of asymmetric frontal activity in emotion-related phenomena: A review and update," *Biological Psychology*, vol. 84, pp. 451–462, 2010.
- [14] M. Kringelbach, J. O'Doherty, E. Rolls, and C. Andrews, "Activation of the human orbitofrontal cortex to a liquid food stimulus is correlated with its subjective pleasantness," *Cerebral Cortex*, vol. 13, pp. 1064–1071, 2003.
- [15] R. Davidson and K. Hugdahl, *Brain Asymmetry*. Cambridge, MA: MIT Press, 1995.
- [16] D. Tucker, "Lateral brain function, emotion and conceptualization," *Psychological Bulletin*, vol. 89, pp. 63–75, 1981.
- [17] E. Siberman and H. Weingartner, "Hemispheric lateralization of functions related to emotion," *Brain Cog*, vol. 5, pp. 322–353, 1986.
- [18] R. Davidson, *Cerebral asymmetry, emotion and affective style*. Cambridge, MA: MIT Press, 1995.
- [19] K. Goldstein, *The Organism: An holistic approach to biology, derived from pathological data in man*. New York: American Book, 1939.
- [20] T. H and C. C, "Determination and study of hemisphere dominance by means of intracarotid sodium amytal injection in man: Ii," *Electroencephalographic effects, Bolletino della Societa Ztaliana Sperimentale*, vol. 35, pp. 1626–1630, 1959.
- [21] R. GF and R. GR, *Brain Mechanisms Underlying Speech and Language*. New York: Grune & Stratton, 1967, ch. Experimental analyses of cerebral dominance in man.
- [22] C. IA, O. R, U. SHJ, M. M, and L. AF, "Assessing the accuracy of topographic eeg mapping for determining local brain function," *Electroencephalography and Clinical Neurophysiology*, vol. 107, pp. 408–414, 1998.
- [23] M. M. Muller, A. Keil, T. Gruber, and T. Elbert, "Processing of affective pictures modulates right-hemispheric gamma band eeg activity," *Clinical Neurophysiology*, vol. 110, no. 11, pp. 1913–1920, 1999.
- [24] D. RJ and F. N, "Asymmetric brain activity discriminates between positive and negative affective stimuli in 10 month old infants," *science*, vol. 218, pp. 1235–1237, 1982.
- [25] K. Takahashi, "Remarks on emotion recognition from biopotential signals," in *2nd Int. Conf. on Autonomous Robots and Agents, 2004*, 2005.