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Frontal EEG Asymmetry Based Classification of Emotional Valence using Common Spatial Patterns

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Abstract—**In this work we evaluate the possibility of predicting the emotional state of a person based on the EEG. We investigate the problem of classifying valence from EEG signals during the presentation of affective pictures, utilizing the "frontal EEG asymmetry" phenomenon. To distinguish positive and negative emotions, we applied the Common Spatial Patterns algorithm. In contrast to our expectations, the affective pictures did not reliably elicit changes in frontal asymmetry. The classifying task thereby becomes very hard as reflected by the poor classifier performance. We suspect that the masking of the source of the brain activity related to emotions, coming mostly from deeper structures in the brain, and the insufficient emotional engagement are among main reasons why it is difficult to predict the emotional state of a person.**

Index Terms—**Emotion, Valence, EEG, Common Spatial Patterns (CSP).**

I. Introduction

MOTIVATED by a range of possible applications in the field of human-computer interaction, research on emotion recognition from facial expressions, speech and physiological signals receives increasing attention. Many application areas can benefit from emotion recognition systems, ranging from applications that track the user's affective states and give corresponding feedback (e.g., automatic tutoring applications) to personalized photo or music selection applications. Furthermore, they can be useful in exploring reactions to advertisements, for monitoring emotional states in the healthcare area or in detecting which product aspects cause frustration.

The correlates of emotion in human EEG have been discovered more than two decades ago. In particular, the phenomenon of "frontal EEG asymmetry" has played a prominent role in the emotion research. According to Davidson's influential approach/withdraw motivational model of emotion [1] left frontal activity indicates a positive or approach-related emotion, whereas higher right frontal activity indicates a negative or withdrawal-related emotion. The degree of activation is inferred from the spectral power in the alpha band (8-12 Hz), with lower values in alpha power being associated with a higher degree of activity.

In the review of over 70 published studies Coan and Allen [2] examined the relationship between emotion and asymmetries in EEG over the frontal cortex. They suggest that asymmetrical cortical activations are ubiquitous and can be observed with different emotion elicitation procedures (e.g. films, pictures, voluntary emotional facial expression, emotional recall). However, in the affective picture studies the conclusions are adverse. The correlation hypothesis is confirmed in some of the studies [3], [4], but some of them failed to produce the expected results [5], [6].

Despite the knowledge acquired on neuronal correlates of emotions, only a few studies tried to derive the emotional state of a person from the EEG. As summarized by Chanel et al. [7], most of these studies obtained only moderate results. However, the usability of EEG in emotion recognition was recently demonstrated by the same authors who obtained classification accuracies for two-class problems of around 70%, suggesting that classification of emotion using EEG is possible. Emotions had been elicited by emotional recall and classification was based on time-frequency features and the common information contained in each pair of electrodes.

The goal of this study is to investigate the possibility of formulating a method able to distinguish positive and negative emotions from EEG signals based on asymmetrical cortical activations. We have chosen to elicited emotions using affective pictures. The onset of affective responses in such a setup can be carefully controlled and variations of affective responses during picture presentation can occur only to a small extent.

In the development of the classifier, we applied the Common Spatial Pattern (CSP) algorithm. CSP is well suited for detecting spatial spectral power differences as demonstrated by numerous Brain-Computer-Interface (BCI) approaches focused on motor imaginary phenomena [8], [9]. The classification performance of the CSP algorithm was compared to a simpler one based on training Linear Discriminant Analysis (LDA) on the alpha power measured at several scalp locations. Furthermore, to test the state-of-the-art results in correlating emotions with EEG asymmetry, inter- and intra-subject statistical analysis was performed. Our aim was to show relative left hemispheric activation for positively valenced pictures and relative right hemispheric activation for negatively valenced ones, and to better understand the phenomena of distinct hemispheric activation.

II. Data Acquisition

Nine healthy, right-handed, male subjects with normal or corrected-to-normal vision participated in this study (23-27 years old). All the subjects signed an informed consent before participating. They received a small bonus in the form of a gift certificate for their participation.

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Our method of choice for emotion elicitation was through picture presentation. Because the International Affective Picture System (IAPS) is only available for non-profit research purposes, we selected 48 positive, 48 negative and 16 neutral pictures from a Philips-intern picture database, that contains pictures similar to ones included in the IAPS set. Pictures had been rated on a five-point arousal, pleasant and unpleasant scale by eighty-six subjects. The content of the pictures was similar to the general IAPS picture content, i.e. the pictures depicted among others erotic scenes, happy families, cute animals, sports, objects, mutilated bodies and torture scenes.

The experiment began with a baseline EEG measurement (2 minutes eyes open, 2 minutes eyes closed), followed by picture presentation in a random order. A single experiment trial consisted of the following: A small fixation cross was presented in the middle of the screen for 3s, followed by the presentation of a picture for 6s. After the picture offset, participants were asked to rate the valence and arousal dimensions using computerized self-assessment manikin (SAM) scale [10]. Upon the completion of SAM ratings, the next trial started after a randomly determined interval of 1-3 s.

EEG was recorded continuously from 32 sintered Ag/AgCl electrodes positioned according to the international 10-20-system using a Biosemi Active II system. All channels were recorded using Cz as a reference; impedance was kept below 5kΩ. The actual sampling rate was 2048Hz, decimated off-line to a 200Hz and high-pass filtered at 1Hz.

III. Data analysis

Single 9s long epochs (3s before and 6s after picture onset) were extracted. For artifact reduction, we visually inspected all epochs and manually excluded epochs with excessive eye movements, blinks or muscle artifacts from further analysis. The mean rejection rate was 19%. Spectral power was estimated by Welch's averaged, modified periodogram method. We used FFT windows containing 256 sample points with an overlap of 50%, resulting in a frequency resolution of $\approx$1Hz. Because fixed frequency bands can blur the relationship between cognitive performance and alpha power [11], individual alpha frequency (IAF) was assessed as the peak frequency in the alpha range during the 2-min eyes-closed baseline measurement. The alpha band was defined as 2 Hz on either side of this value ([IAF - 2, IAF + 2]). For maximizing differences in cortical responses to the pictures, we only explored the positive and negative picture category and omitted the neutral category from our analysis.

A. Statistical Analysis

To confirm that the allocation of images to positive, neutral and negative categories was appropriate, SAM ratings for valence and arousal were subjected to repeated-measure analyses of variance (ANOVA). Greenhouse-Geisser Epsilon corrections were applied to correct for unequal covariances when appropriate.

To estimate the degree of asymmetry in brain regions, we analyzed the data in a within-subject design. For each subject, estimates of the alpha power during the 6s picture presentation

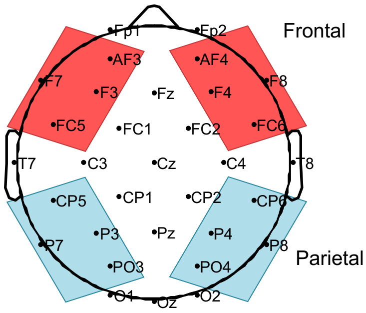

Fig. 1. EEG electrode positions according to the international 10-20-system, including the four clusters depicting hemispheric frontal and parietal brain activity used in computing asymmetry indices.

were computed and averaged across the trials of each stimulus category. Electrodes were collapsed into electrode clusters as shown in Figure 1, resulting in frontal and parietal means for each hemisphere. Alpha asymmetry indices were then computed by subtracting the natural logarithm of left-sided alpha power from the natural logarithm of right-sided alpha power (Asymmetry Index = ln[right alpha] - ln[left alpha]). Assuming an inverse relationship between alpha power and cortical activation, a more positive asymmetry index reflects a greater relative left hemispheric activity. Finally, asymmetry indices for positive vs. negative pictures were subjected to paired t-tests for both the frontal and the parietal region, respectively.

We also examined whether the asymmetry index reflects emotional response on a single-trial basis. We computed the asymmetry index for each trial in the frontal region and tested for differences between the positive and the negative condition with an independent two-sample t-test. We conducted t-tests for each subject separately, as well as over the asymmetry indices from all subjects.

B. Classification

To develop a classifier that is able to distinguish emotional valence on a single-trial basis, we built upon the results from the state-of-the-art research on EEG asymmetry. Initially, we designed a simple linear discriminant analysis (LDA) classifier. We trained the classifier on the log alpha power in the 4 regional means depicted in Figure 1. Classification errors were estimated by repeating a 5-fold cross-validation 5 times.

In the second stage we tried to tailor the classification such that it utilizes the spatial distribution of EEG signals. We focused on designing a linear combination of signals coming from different electrodes, incorporating their relevance for the classification task. In that way we incorporated the modulations of the alpha rhythm originating at different cortical regions of the left or right hemisphere. Hence, we cover the fact that EEG scalp potentials are spatially smeared, i.e., that with increasing distance from the relevant brain areas, the recorded signal will be increasingly contaminated by cortical activity unrelated to the emotional response.

To weight the electrodes in a manner that maximizes the spatial spectral power differences of the classes we decided to use Common Spatial Patterns (CSP) [8], [9]. CSP is a supervised method for the design of specific spatial filters onto which high-dimensional, band-pass filtered EEG data is projected. These filters provide weighting of the electrodes and maximize the variance of the spatially filtered signal in one condition (e.g., positive valence), while minimizing it in the other condition (e.g. negative valence). Since the variance of a band-pass filtered signal is equal to the band-power, the variance of the spatially filtered signal may then give features useful for discrimination. For a mathematical discussion on CSP see Appendix A.

To test the proposed method, the EEG signals were first band-pass filtered to match the individual alpha band. A 5-fold cross-validation was then repeated 5 times. In each run, 4 CSP filters were obtained from the training folds using the whole 6s segments of picture presentation. Classification performance was estimated on the test fold.

IV. Results

A. Statistical Analysis

Behavioral results confirmed that the allocation of images to positive, neutral and negative categories was as expected. The statistical analysis on SAM-ratings for all 3 experimental conditions across subjects revealed a highly significant effect for valence ($F(1.04, 8.27) = 52.9, p < 0.001$) and arousal ($F(2, 16) = 28.4, p < 0.001$). Positive pictures were rated significantly higher on valence than neutral and negative pictures. Valence ratings for neutral pictures were significantly higher than negative pictures. Arousal ratings were significantly higher for both negative and positive as compared to neutral pictures. Negative pictures induced higher arousal than positive pictures (all post-hoc paired t-tests, $p < 0.05$).

The statistical analysis on frontal EEG asymmetry in a within-subject design did not reveal any differences between the affective classes. Asymmetry indices in the parietal and frontal area for positive and negative stimuli are depicted in Figure 2. A paired t-test found significant differences neither in the frontal nor in the parietal region. Independent t-tests over the frontal asymmetry indices calculated per trial revealed significant differences only for subject 1 and subject 4. For subject 1, positive pictures induced a significantly higher left hemispheric activity. The opposite effect was observed for subject 4.

To gain a better understanding on the influence of positive and negative pictures on different brain regions, we visualized signed r^2-values of the alpha power at each electrode for each subject separately. r^2 is the squared version of the point biserial correlation coefficient r. It describes the proportion of the total variance in the class labels that is accounted for by a single feature, e.g., alpha power at one electrode. Scalp topo plots for subject 1 to 4 are shown in Figure 3. However, we could not infer any regular pattern.

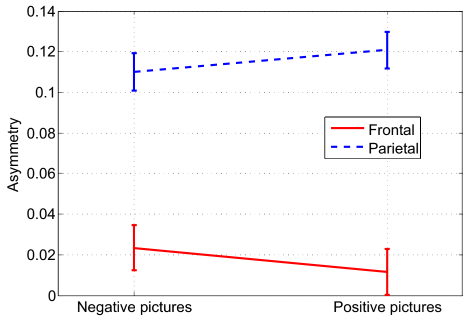

Fig. 2. Means of evoked alpha asymmetries (± within-subject standard errors as proposed by Loftus and Masson [12]). Higher asymmetry scores indicate a greater relative left hemispheric activity.

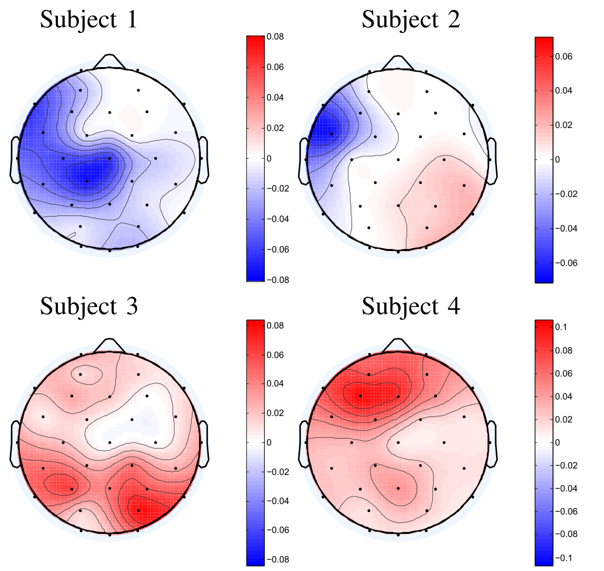

Fig. 3. The signed r^2 -values of the difference in alpha power between the positive and the negative affective condition in subjects 1 - 4. High signed r^2 -values correspond to a higher alpha power for positive pictures compared to negative pictures.

TABLE I
THE CLASSIFICATION ERROR (%) AS CALCULATED BY CROSS-VALIDATION (5 FOLD CROSS-VALIDATION, 5 TIMES REPEATED).

subject	nb trials	Classification error [%]	
		Alpha power	CSP
1	77	40.0 ± 4.4	53.2 ± 8.1
2	86	44.9 ± 2.4	44.0 ± 4.8
3	75	49.0 ± 2.0	55.5 ± 7.7
4	77	39.7 ± 2.0	40.0 ± 7.0
5	56	37.1 ± 2.9	37.9 ± 5.0
6	93	47.7 ± 5.3	35.3 ± 6.0
7	78	42.8 ± 4.9	48.2 ± 4.8
8	82	42.2 ± 3.6	48.5 ± 5.9
9	83	53.7 ± 3.7	43.9 ± 4.2
mean	78.6	44.1 ± 5.2	46.9 ± 6.8

B. Classification

Table I shows the classification errors of both algorithms for each subject as calculated by cross-validation (5 fold cross-validation, repeated 5 times) and the total number of trials available for classification. Note that the cross-validation procedure tends to underestimate the standard deviation of the classification error as the trials are not independent.

Training a LDA on features derived from the alpha power at different electrodes was not successful. An indication for better-than chance performance was only found for two subjects with a classification error below 40% (subjects 4 and 5). CSP did not show significantly better results than when using simpler algorithm based on spectral features. Classification errors below 40% were achieved for only two subjects (subjects 5 and 6). For other subjects the classification rates were very close to chance level.

V. Discussion

The outcome of our study is that the CSP method based on "frontal EEG asymmetry" model is not suitable for classifying the emotional valence elicited by affective pictures. Other studies did not find frontal EEG asymmetry during affective picture presentation [5], [6], suggesting that the correlation of frontal EEG asymmetry with emotional valence is weak.

Inconsistent results for frontal asymmetry have been frequently linked to reliability problems. For estimation of individual asymmetry metrics, resting EEG is typically recorded for at least 4 min. Still, Huster et al. [3] could derive reliable asymmetry indices during the presentation of affective pictures from 60 s of artifact free data. The reliability problem stresses the fact that, even if intra-subject differences in frontal EEG asymmetry can be detected, they may not be detectable on a short-term basis.

Due to the fact that significant differences in asymmetry were not found and scalp maps showed very small differences between classes, the poor classification performance is not very surprising. Relevant question is why CSP, which has been successfully applied to the discrimination of motor imagery tasks for Brain-Computer-Interface systems, did not yield good results in distinguishing emotional valence. Differences between the classes as revealed by r^2 scalp plots are on average slightly higher for motor imagery tasks (see e.g., [13]). These differences follow a physiologically explainable pattern in motor imagery tasks where CSP is used to discern different spatial locations of modulations of the μ-rhythm originating in the somatosensory cortex. In emotion research, the anatomical origin of asymmetrical cortical activation during emotional processing still needs to be unraveled [14], [15].

While CSP can be seen as a tool to localize and detect event-related power changes in localized cortical areas, frontal asymmetry is just the broad manifestation of cortical activation whose origin is not well understood. Thus, CSP might not be the most appropriate tool to detect differences of activation in cortical structures underlying the frontal asymmetry. The complex CSP method depends upon several hyperparameters, (i.e., frequency band, time interval, filters) which can have significant influence on the classification performance. CSP method also requires proper estimation of the covariance matrices, as, e.g., insufficient number of trials can lead to poor covariance estimation. Further optimization of the presented method may improve classification performance.

Another reason for poor classification results might be in the fact that affective pictures fail to evoke emotional or motivational intensity sufficient to engage asymmetrical frontal cortical activations. Recent studies indicate that asymmetrical frontal cortical activity might be more sensitive to motivational direction than affective valence. For example, in a meta-analysis of 106 PET and fMRI studies of human emotions Murphy et al. [16] observed greater-left activity for approach emotions. In contrast, the pattern of neural activity associated with both positive and negative emotions was found to be relatively symmetrical. Furthermore, over a dozen published EEG studies have shown that anger, an approach-oriented negative emotion, relates to relatively greater left frontal cortical activity [17].

Emotional activations in the brain can be detected more readily by using fMRI [18], [19]. Johnson et al. [20] identified the amygdalae (MDL, medial temporal lobe) and insula (VLPFC, ventrolateral prefrontal cortex) areas as the brain structures that predominantly contribute to the processing of emotional content. When affective pictures are used as stimuli, people can up-regulate the activation correlated with negative emotions by self-monitoring the brain activity in these areas through fMRI neurofeedback. Knowing that emotions are mainly processed in deeper brain structures [21], it is reasonable to expect that activations in these structures will contribute far less to the scalp EEG than cortical activations of pyramidal cells uniformly oriented perpendicular to the cortical surface.

VI. Conclusion

The classification of emotional valence from EEG signals utilizing "frontal EEG alpha asymmetry" proved to be difficult. While the frontal EEG asymmetry phenomenon is well documented, we were not able to replicate the predicted asymmetry averaging within subject as well as on a single trial basis. The classification task therefore becomes very hard as reflected by poor classifier performance. We found an indication for better-than-chance performance only for two out of nine subjects.

As a future work we can employ different methods for emotion elicitation, which might lead to more promising results. The results in Chanel et al. [7] obtained by emotional recall show a promising direction. Another option would be to follow the approach of Li and Lu [22] in using gamma band activity in combination with CSP for distinguishing happiness and sadness from pictures showing facial expressions.

Keeping in mind the reliability problem, measuring emotions over a prolonged period of time may facilitate the exploitation of asymmetrical cortical activations. Also monitoring the fMRI activation of the brain having the same experimental design might provide us with more insight in understanding the relation between the frontal EEG asymmetry and the emotional valence.

Appendix A
Common Spatial Patterns

The Common Spatial Patterns (CSP) algorithm can be described as follows. Let $X \in \mathbb{R}^{C \times T}$ denote a band-pass filtered EEG trial, where C is the number of channels and T is the number of sampled time points in a trial. The estimates of covariance matrices of the EEG in the two conditions (e.g. positive vs. negative valence) $\Sigma^{(+)}$ and $\Sigma^{(-)}$ are then obtained by averaging the covariance matrices of each trial XX^T over the trials of each group.

The whitening transformation which converts the composite covariance matrix $\Sigma^{(+)} + \Sigma^{(-)}$ into the identity matrix I is given by

$$P := Q^{1/2} D^T \tag{1}$$

where $\Sigma^{(+)} + \Sigma^{(-)} = QDQ^T$, Q is the matrix of eigenvectors, and D is the diagonal matrix of corresponding eigenvalues.

The covariance matrices of the whitened data $S^{(+)} := P\Sigma^{(+)}P^T$ and $S^{(-)} := P\Sigma^{(-)}P^T$ share the same eigenvectors and their eigenvalues will sum to one, i.e.,

$$S^{(+)} = \Phi\Lambda\Phi^T \Rightarrow S^{(-)} = I - S^{(+)} = \Phi(I - \Lambda)\Phi^T. \tag{2}$$

Here I is the identity matrix, Φ is the matrix of eigenvectors of $S^{(+)}$, and Λ is the diagonal matrix of corresponding eigenvalues.

It follows that

$$\begin{aligned} \Phi^T P\Sigma^{(+)}P^T\Phi &= \Phi^T S^{(+)}\Phi = \Lambda \\ \Phi^T P\Sigma^{(-)}P^T\Phi &= \Phi^T S^{(-)}\Phi = I - \Lambda. \end{aligned} \tag{3}$$

Each row vector $w_j \in \mathbb{R}^C$ of the projection matrix $W := \Phi^T P$ is called a spatial filter. A large eigenvalue (of $S^{(+)}$) indicates that the corresponding spatial filter w_j yields high variance in one condition and low variance in the other condition. Thus the variance of the projection of (band-pass filtered) EEG trials onto $W := \Phi^T P$ gives features that are useful for discrimination. The columns of W^{-1} are called the common spatial patterns.

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