2013
6th International IEEE EMBS Conference on Neural Engineering (NER)

Neural Engineering©

6-8 November 2013 • Sheraton San Diego Hotel • San Diego, California

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IEEE Catalog Number: CFP13CNE-USB
ISBN: 978-1-4673-1968-3

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6th Annual International IEEE EMBS Conference on Neural Engineering
San Diego, California, 6 - 8 November, 2013

Analytic Common Spatial Pattern and Adaptive Classification for Multiclass Motor Imagery-based BCI

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Abstract— **This paper focuses on the classification of motor imagery tasks from electroencephalogram (EEG) for brain computer interfaces (BCI). A new processing algorithm based on filter bank common spatial pattern (FBCSP) is presented. Analytic common spatial pattern (ACSP) and adaptive classification are introduced to investigate whether they can improve the performance. Four versions of FBCSP, namely, common spatial pattern (CSP) and ACSP with static or adaptive classification are studied. The session-to-session performances of the proposed approaches are evaluated on a 4-class problem posed in the BCI Competition IV dataset 2a. Our results demonstrate the effectiveness of the proposed methods in comparison to the winner of the BCI Competition IV Dataset 2a as well as other more recent studies using this dataset. Adaptive classification yields a higher kappa value of 0.61 compared to 0.57 for multiclass FBCSP algorithm. ACSP further improves the performance achieving a mean kappa of 0.63.**

I. Introduction

A brain-computer interface (BCI) based on electroencephalogram (EEG) is a system that enables humans to interact with their surroundings, without the involvement of peripheral nerves and muscles, by using control signals generated from EEG activity [1]. BCIs create an alternative non-muscular pathway for relaying a person's intentions to external devices such as computers, speech synthesizers, assistive appliances, and neural prostheses amongst many others.

One type of BCI is based on the analysis of EEG signals that are dependent on motor imagery. Motor imagery tasks result in modulation of sensorimotor brain signals known as event-related desynchronization/synchronization (ERD/ERS) [2]. Common spatial pattern (CSP) is a successful method for ERD/ERS detection and motor imagery classification [3]. CSP processes multichannel EEG signals to design optimal spatial filters that maximize the variance for one class of data and minimize the variance for the other. The spatial patterns that result from the CSP algorithm highlight the underlying neuronal activity that is most relevant in distinguishing between motor tasks. However, CSP has the limitation that the phase differences between spatial locations are not processed explicitly. Several studies indicate that phase can contain useful information for discerning the types of motor imagery action. High degree of correlation has been demonstrated between ERD/ERS events and phase-based features such as phase locking value (PLV) [4], delta-phase [5], and spectral coherence [4]. Then, we use analytic common spatial pattern (ACSP) that considers an analytic representation of the EEG data. Analytic signal allows the representation of magnitude and phase characteristics. ACSP was firstly used by Falzon et al. [6] for steady state visual evoked potentials (SSVEP) discrimination. In this study, we assess the use of ACSP in multiclass sensorimotor rhythm-based BCIs.

On the other hand, a major challenge for BCI research is the non-stationarity of brain activity. Diverse behavioral and mental states continuously change the statistical properties of brain signals [7]. BCI systems are usually calibrated by users through supervised learning using a labeled dataset. However, patterns observed in the experimental samples during calibration sessions may be different from those recorded during online sessions. Therefore, adaptive algorithms are a very important issue for improving BCI accuracy. Several machine learning techniques have been attempted to address the non-stationarity in BCI. These algorithms can be classified into two main approaches [8]: the methods that improve the model to be robust against the changes [9, 10] and the methods that adapt the models to the changes [8, 11]. In this work, we apply a method that belongs to the second approach. A processing stage that performs adaptation related-tasks is introduced before classification stage. Features extracted are processed before classification in order to reduce the small fluctuations between training and evaluation data. Thereby, the same classification model for training and evaluation sessions can be used reducing the loss of performance as a result of non-stationarity.

The aims of this study are to use the ACSP algorithm and apply an adaptive classification algorithm to investigate whether both of them can improve the performance of multiclass motor imagery-based BCIs. The algorithms are evaluated on the BCI Competition IV dataset 2a [12]. We compare our approaches to the best performing method in BCI Competition IV [13] as well as a number of more recent studies using this dataset [14, 15].

This work was supported in part by the Project Cero 2011 on Ageing from Fundación General CSIC, Obra Social La Caixa and CSIC and a grant by the Ministerio de Economía y Competitividad and FEDER under project TEC2011-22987. L. F. Nicolas-Alonso was in receipt of a PIF-UVa grant from University of Valladolid. R. Corralejo was in receipt of a PIRTU grant from the Consejería de Educación de la Junta de Castilla y León and the European Social Fund (ESF).

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II. BCI COMPETITION IV DATASET 2A DESCRIPTION

The BCI Competition IV dataset 2a challenges the session-to-session transfer. This dataset contains EEG signals from 9 subjects performing 4 classes of motor imagery, namely, left hand, right hand, feet, and tongue [16]. Each subject participated two sessions: one for training and the other for evaluation. 22 EEG channels and 3 monopolar electrooculogram (EOG) channels (with left mastoid serving as reference) were used to record the EEG signals that were sampled at 250 Hz and filtered between 0.5 and 100 Hz. A 50 Hz notch filter was enabled to suppress line noise. For more details refer to Naeem et al. [16].

III. PROPOSED METHOD

The architecture of the proposed algorithm is illustrated in Fig. 1. It is based on filter bank common spatial patterns (FBCSP) [13] and comprises five consecutive stages: multiple bandpass filtering using finite impulse response (FIR) filters, spatial filtering using the ACSP algorithm, feature selection, adaptive processing and classification of the selected ACSP features.

A. *Band-pass filtering*

The first stage employs a filter bank that decomposes the EEG signals into 9 frequency pass bands, namely, 4-8 Hz, 8-12 Hz,…, 36-40 Hz [13]. Every filter has a finite impulse response designed by means of Kaiser Window. The transition bandwidth is set at 1 Hz. We tested others configurations, which are also effective, but this transition bandwidth yields a reasonable order filter and discriminative capacity between frequency bands.

B. *Analytic Common Spatial Patterns*

The second stage of feature extraction performs spatial filtering using ACSP algorithm for each band-pass signal. Similarly to the CSP algorithm, the aim of the ACSP method is to discriminate between two classes of data by determining a set of spatial filters that maximize the variance for one class of data, while minimizing the variance for the other. However, ACSP can deal with the complex-valued variance, which can be more informative than the real-valued counterpart [6]. ACSP has been devised for the analysis of multichannel data belonging to 2-class problems. Consequently, it is necessary to set up ACSP filters based on the trials for each class versus the trials for all other classes.

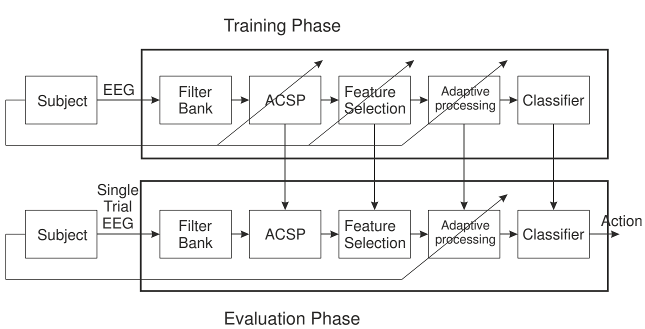

Figure 1. Architecture of the algorithm for the training and evaluation phases. The architecture is based on FBCSP.

1) Analytic signal representation

ACSP involves the computation of the analytic signal representation of the filtered EEG channels [6]. For a real-valued signal *s(t)*, the analytic signal is given by

$$z(t) = s(t) + j\tilde{s}(t) \ , \tag{1}$$

where $\tilde{s}(t)$ is the Hilbert transform of a signal $s(t)$ given by

$$\tilde{s}(t) = \frac{1}{\pi}\, p.v.\!\int \frac{s(\tau)}{t-\tau}\, d\tau \ . \tag{2}$$

p.v. denotes the Cauchy principal value.

2) Spatial filtering

Given the analytic representation of a single trial EEG $Z \in \mathbb{C}^{\mathrm{NxT}}$, where N is the number of channels and T is the number of samples per channel, ACSP calculates the normalized complex-valued covariance matrix C [6]

$$C = \frac{ZZ^{*}}{trace(ZZ^{*})} \tag{3}$$

In the above expression, * represents the hermitian transposition.

ACSP calculates the mean spatial covariances $\overline{C_1}$ and $\overline{C_2}$ for each of the two classes by averaging the spatial covariances over the successive training trials of each class over time. Then, complex-valued spatial filters W can be calculated from class-related mean spatial covariances by solving an eigenvalue decomposition problem [13]

$$\overline{C_1}W = (\overline{C_1} + \overline{C_2})WD \, , \tag{4}$$

where D is the diagonal matrix that contains the eigenvalues of $\overline{C_1}$. The spatial filtered signal Y can be obtained from the analytic representation of EEG trial Z as

$$Y = WZ \, . \tag{5}$$

There are as many spatial filters as EEG channels. All spatial filters of W are not relevant for subsequent classification. The first 2 and the last 2 columns of W are selected [6]. The normalized features for each frequency band are obtained as [13]

$$\boldsymbol{x} = \log\left[\frac{diag(\tilde{W}ZZ^{T}\tilde{W})}{trace(\tilde{W}ZZ^{T}\tilde{W})}\right], \tag{6}$$

where $\tilde{W}$ represents a matrix having the selected spatial filters of W. Finally, the 16 features of the 9 frequency bands for a single-trial are concatenated to form a single feature vector of 144 features [13].

C. Feature selection

After spatial filtering, a feature selection algorithm is employed to select the most discriminative features. Mutual Information-based Best Individual Feature (MIBIF) algorithm is used [13]. MIBIF involves the computation of the mutual information of each feature and class labels. The features with higher mutual information are selected. In this work, the number of selected features is set heuristically to 40.

D. Classification

The classification stage decides the class to which the feature vectors belong. A probabilistic generative model is used [17]. A stage performing adaptation related-processing is introduced before classification in order to reduce the small fluctuations between training and evaluation data. It is important to note that only the adaptive processing stage before classification performs the adaptive-related tasks. The classification model remains unchanged in both training and evaluation sessions.

1) Adaptive processing

The adaptive processing stage centers every incoming data by subtracting the global mean. Firstly, the global mean is estimated from the whole training data. Across the evaluation session, the global mean $\boldsymbol{\mu}_C$ is updated in a casual manner with the following exponential update rule [11]

$$\mu_C(n,t) = (1-\eta)\cdot\mu_1(n-1) + \eta\cdot\boldsymbol{x}(n,t), \tag{7}$$

where $\boldsymbol{x}(n,t)$ is the current input feature vector of the n^{th} evaluation trial at the time t and η is the update coefficient. The update coefficient is fixed to $\eta = 0.05$ for all subjects as was suggested by Vidaurre et al. [11].

2) Probabilistic generative model

We adopt a generative approach to classify each feature vector $\boldsymbol{x}$ into a specific class y. Posterior probabilities $P(y|\boldsymbol{x})$ are computed through the Bayes' rule [17]

$$P(y \mid \boldsymbol{x}) = \frac{P(y)P(\boldsymbol{x} \mid y)}{\sum_y P(y)P(\boldsymbol{x} \mid y)}. \tag{8}$$

In the above expression, it is assumed that the class-conditional densities $P(y|\boldsymbol{x})$ are Gaussian and all classes have the same probability of occurrence, $P(y = 1,2,3,4) = 0.25$. Then, the density for each class is given by

$$P(\boldsymbol{x} \mid y) = \frac{1}{\sqrt{(2\pi)^N |\Sigma|}} \exp[-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu}_y)^T \Sigma^{-1}(\boldsymbol{x}-\boldsymbol{\mu}_y)], \tag{9}$$

where $\boldsymbol{\mu}_i$ is the estimated mean of class i and Σ is the estimated common covariance matrix. Both of them can be computed from the training samples using maximum likelihood [17]. Finally, the feature vector $\boldsymbol{x}$ is assigned to class y with the following maximum a posteriori (MAP) rule [17]

$$y = \underset{y=1,2,3,4}{\arg\max}\; p(y \mid \boldsymbol{x}). \tag{10}$$

IV. Results

The session-to-session transfers of CSP and ACSP algorithms with static and adaptive processing are evaluated on the dataset 2a from BCI Competition 2008 and compared with the winner in this dataset [13] as well as other recently published methods [14, 15]. As the organizers of competition [12], Cohen's kappa coefficient is used to quantify the performance. The results are presented in Table 1. For the purpose of ensuring a fair comparison, we include all possible alternatives. Firstly, it can be observed that the introduction of ACSP yields a higher mean kappa value of 0.59 compared to 0.57 for our baseline CSP algorithm. Compared to CSP, ACSP improves the kappa value for 6 out of the 9 subjects. Secondly, the adaptive processing further increases the mean kappa value of ACSP approach from 0.59 to 0.63. Likewise, it is worth highlighting that the performance also improves using adaptive processing stage without ACSP but it is lower than the one produced using both ACSP and adaptive processing. Regarding other previously published methods, the approaches using adaptive processing stage outperform all of them. As well, ACSP without adaptation produces a higher mean kappa value than FBCSP and Wang et al.

Fig. 2 illustrates the most discriminant spatial filters obtained for the subject A3 using CSP and ACSP. It can be observed that the amplitudes of the coefficients are very similar for both methods. However, the additional phase patterns obtained from the ACSP spatial filter show a gradual change in phase. In contrast to CSP, ACSP can be used to obtain the phase differences between various spatial locations. CSP spatial filters presents only negative and positive coefficients, that is, $-\pi$ and π phases.

V. Discussion and conclusions

This study is concerned about the problem of imaginary motor tasks classification for EEG-based BCI. We considered two issues to increase the performance: (i) the complex-valued spatial filtering in order to combine the amplitude and phase information and (ii) adaptive classification to follow the inherent non-stationarity in brain signals. Four approaches, namely, CSP and ACSP with static or adaptive classification were assessed on a multiclass

TABLE I. PERFORMANCE IN TERMS OF COHEN'S KAPPA COEFFICIENT FOR FBCSP, WANG ET AL., KAM ET AL., CSP, AND ACSP.

Method	Subjects									
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*AVG*
FBCSP [13]	0.68	0.42	0.75	0.48	0.40	0.27	0.77	0.75	0.61	0.57
Wang et al. [14]	0.56	0.41	0.43	0.41	0.68	0.48	0.80	0.72	0.63	0.57
Kam et al. [15]	0.74	0.35	0.76	0.53	0.38	0.31	0.84	0.74	0.74	0.60
CSP	0.69	0.37	0.84	0.57	0.34	0.21	0.71	0.77	0.60	0.57
ACSP	0.75	0.36	0.85	0.58	0.37	0.30	0.69	0.76	0.68	0.59
CSP + Adapt.	0.73	0.41	0.81	0.58	0.42	0.27	0.80	0.79	0.69	0.61
ACSP + Adapt.	0.77	0.39	0.85	0.60	0.43	0.31	0.79	0.77	0.72	0.63

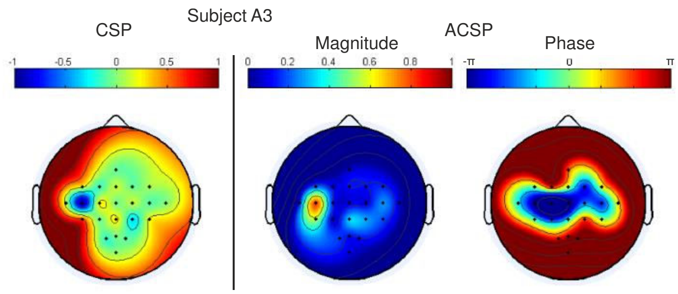

Figure 2. The most discriminant spatial filter obtained for the subject A3 using the CSP and ACSP methods. The complex-valued ACSP spatial filter can be split into a magnitude and a phase component as represented by the spatial map on the right. The phase component is shown in radians from -π to π.

problem posed in the BCI Competition IV dataset 2a. The performances were compared against the winner of the competition as well as other published methods. Our results indicates that the use of the ACSP method and adaptive classification increase the classification accuracy.

The reason behind the improvement produced by the ACSP method is that complex-valued spatial filters are computed. In contrast to CSP, ACSP spatial filtering introduces both a scalar multiplication and a phase shift. It allows processing simultaneously both magnitude and phase EEG characteristics. Therefore, while CSP method overlooks the phase differences between the spatial locations, ACSP captures the amplitude and phase differences across electrodes. This improvement suggests that spatial filters obtained from ACSP can provide additional further insight on phase relationships between various cortical regions during the performance of mental tasks. Effectively, our results suggest that ACSP led to a more robust motor imagery classification than the standard CSP method.

The adaptive processing stage reduces the loss of accuracy in the subsequent classification stage as a result of non-stationarity in brain signals. The adaptive stage reduces the small fluctuations in the global mean throughout the evaluation sessions. These fluctuations are unrelated to task and, accordingly, can be addressed in an unsupervised manner. Adaptive processing before classification enables the use of the same classification model for training and evaluation sessions.

Some limitations of this study have to be considered. Regarding the ACSP method, the analytic signal representation by means of Hilbert transformation is only well-behaved for narrow band signals. Band-pass filtered signals fulfil only partially this requirement. Regarding adaptive classification, exponential update rule requires both classes to be equally likely [11]. Additionally, the exponential rule presents the difficulty of the proper choice of the update coefficient η. Finally, the number of characteristics was set heuristically. Future work should use other methods that provide narrow band signals instead of a band-pass filter bank, explore more sophisticated adaptive procedures than the exponential rule and employ a feature selection method that optimizes the number of selected features for each subject.

In summary, the use of a variant of the CSP method based on the analytic representation of EEG signals and an adaptive classification approach that separates adaptive-related tasks from classification have been tested on BCI Competition IV dataset 2a. Beyond its limitations, this study provides evidences that the ACSP algorithm can improve the performance of sensorimotor rhythms-based BCIs as a result of considering a complex representation of the EEG signals. Likewise, adaptive classification was found to yield a superior performance for features extracted from motor imagery brain signals.

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