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Improving brain–computer interface classification using adaptive common spatial patterns

Xiaomu Song [a,*], Suk-Chung Yoon [b]

[a] Department of Electrical Engineering, School of Engineering, Widener University, Chester, PA 19013, USA
[b] Department of Computer Science, College of Arts and Sciences, Widener University, Chester, PA 19013, USA

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ABSTRACT

Common Spatial Patterns (CSP) is a widely used spatial filtering technique for electroencephalography (EEG)-based brain–computer interface (BCI). It is a two-class supervised technique that needs subject-specific training data. Due to EEG nonstationarity, EEG signal may exhibit significant intra- and inter-subject variation. As a result, spatial filters learned from a subject may not perform well for data acquired from the same subject at a different time or from other subjects performing the same task. Studies have been performed to improve CSP's performance by adding regularization terms into the training. Most of them require target subjects' training data with known class labels. In this work, an adaptive CSP (ACSP) method is proposed to analyze single trial EEG data from single and multiple subjects. The method does not estimate target data's class labels during the adaptive learning and updates spatial filters for both classes simultaneously. The proposed method was evaluated based on a comparison study with the classic CSP and several CSP-based adaptive methods using motor imagery EEG data from BCI competitions. Experimental results indicate that the proposed method can improve the classification performance as compared to the other methods. For circumstances where true class labels of target data are not instantly available, it was examined if adding classified target data to training data would improve the ACSP learning. Experimental results show that it would be better to exclude them from the training data. The proposed ACSP method can be performed in real-time and is potentially applicable to various EEG-based BCI applications.

1. Introduction

Brain–computer interface (BCI) is a communication technique that aims to identify a subject's brain intents and translate them into machine commands to control the operations of electromechanical devices. Electroencephalography (EEG) might be the most widely used noninvasive imaging technique in BCI. Due to the non-stationary nature of EEG, which is usually caused by changes of electrodes impedance or positions, subjects' attention, fatigue, eye movements, or muscular activity, EEG signals exhibit large intra- and inter-subject variation [1]. As a result, an observed EEG pattern from a subject might not be repeatable from the same subject at a different time or from different subjects performing the same task. Various methods have been proposed to address the nonstationarity in EEG-based BCI [1,2]. These methods were focused on either feature extraction process [1,3–16], or feature modelling and classification [16–29]. Some methods adapt to the intra- and/or inter-subject variation through supervised adaptive learning [20,24,30], semi-supervised or unsupervised learning [3,4,7,11,17–19,23,31–34], while others try to identify stationary patterns that are common within a single subject or across multiple subjects [1,5,6,8–10,12,14,13,15,21,22,25–27,35,36]. Among these studies, methods developed based on common spatial patterns (CSP) have been paid special attention. CSP is a two-class spatial filtering technique that maximizes the variance of band-passed EEG signals from one class while minimizing the signal variance from the other [37]. It is efficient in extracting representative features for BCI classification, and can be extended for multi-class BCI applications. The original CSP method is a supervised and subject specific technique that requires training data from a target subject with known class labels. It is typically used on a subject-by-subject basis, and might not perform well for multi-subject BCI.

In order to improve the multi-subject performance of CSP, prior information from different subjects can be added to the CSP learning via regularization. The regularization is typically implemented in two ways [14]. One is to calculate a weighted average of covariance matrices of EEG data from different subjects [3,38,4,6,7,12,39]. Fixed experiential weights are often used [3,4,12,39], but adaptive weights are also proposed to better quantify the similarity between training

* Correspondence to: One University Place, Room 369, Chester, PA 19013. Tel.: +1 610 499 4058.
E-mail address: xmsong@widener.edu (X. Song).

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and testing data [40,41,38,6,7]. The other is to regularize the CSP objective function by adding a penalization term to impose prior information from multiple subjects [5,15,14,10,9]. By incorporating multi-subject information, the regularized CSP methods can outperform the conventional CSP in multi-subject BCI classification tasks. Most of the regularized CSP methods require labelled training data from target subjects. If training data are unlabelled, an estimation of their class labels is performed so that the data can be assigned to a specific class to update the covariance matrix of this class [3,9,7,4]. Erroneous estimations would affect the CSP learning and deteriorate the BCI classification performance.

In this work, a different method to perform adaptive CSP (ACSP) learning is investigated. The method uses unlabelled EEG data from target subjects to learn spatial filters without an estimation of class labels for the target data, and updates spatial filters for both classes simultaneously using adaptive weights. There is no classification needed during the adaptive learning, and spatial filters can be updated in real-time to adapt to intra- and inter-subject variation in EEG. It can be used to classify single trial EEG data from single or multiple subjects. The proposed method was evaluated using multi-subject motor imagery EEG data from BCI competitions III and IV.

The remaining part of the paper is organized as follows. The classic CSP method is introduced in Section 2.1. The proposed ACSP method is described in Sections 2.2, 2.3, and 2.4. Section 2.5 explains the experimental EEG data used in this study, and how the method was evaluated. Experimental results are described and discussed in Section 3. Finally, Section 4 summarizes the paper.

2. Materials and methods

2.1. Common spatial patterns

The proposed adaptive CSP method is developed based on the classic CSP approach [42,43]. CSP is a supervised two-class spatial filtering technique that aims to maximize feature variation for one class and simultaneously minimize feature variation for the other. Given an $M \times N$ matrix $\mathbf{E}_i(y)$ that represents the ith trial of EEG data collected under a brain task with class label y, $y \in \{1,2\}$, the normalized class-specific spatial covariance matrix $\mathbf{C}_y$ is computed as:

$$\mathbf{C}_y = \frac{1}{n_y} \sum_{i=1}^{n_y} \frac{\mathbf{E}_i(y)\mathbf{E}_i^T(y)}{\mathrm{tr}(\mathbf{E}_i(y)\mathbf{E}_i^T(y))}, \tag{1}$$

where $\mathbf{E}_i(y)$ is mean-centered, M is the number of channels, N is the number of time points, n_y is the number of EEG trials in class y, and T is the matrix transpose operator. Based on the covariance matrix, the CSP training is to maximize the following Rayleigh coefficient:

$$\frac{\mathbf{W}\mathbf{C}_y\mathbf{W}^T}{\mathbf{W}\sum_y \mathbf{C}_y \mathbf{W}^T}, \tag{2}$$

which is equivalent to solve the generalized eigenvalue problem [40,14,37]:

$$\mathbf{C}_1\mathbf{W}^T = \mathbf{C}_2\mathbf{W}^T\Lambda, \tag{3}$$

where the matrix $\mathbf{W}$ consists of spatial filters in rows, and $\mathbf{\Lambda}$ is a diagonal matrix assorted in descending order of eigenvalues of $\mathbf{C}_2^{-1}\mathbf{C}_1$ that measure the variance ratio between the two classes. With the projection matrix $\mathbf{W}$, the spatial filtering of a trial $\mathbf{E}_i(y)$ is computed as:

$$\mathbf{Z}_i = \mathbf{W}\mathbf{E}_i(y). \tag{4}$$

The columns of $\mathbf{W}^{-1}$ are the common spatial patterns that are considered as time-invariant EEG source distribution vectors. The discrimination is based on the feature projections on $\mathbf{W}$ with maximal variations, which are the first and last m rows of $\mathbf{Z}_i$. Based on $\mathbf{Z}_i$, a feature vector is constructed for the ith trial with the rth spatial filter:

$$x_r = \log\left[\frac{\mathrm{Var}(z_r)}{\sum_{j=1}^{2m}\mathrm{Var}(z_j)}\right], \tag{5}$$

where Var() is the variance calculator, and z_r is the rth row of $\mathbf{Z}_i$. The logarithmic transformation is applied to make the distribution of x_r more close to Gaussian.

2.2. Adaptive common spatial patterns

In CSP and some of its extensions for multi-subject analysis, the spatial filter $\mathbf{W}$ is calculated and then fixed for the processing of new data [6,12,15]. When there is no or unlabelled training data from target subjects, fixed spatial filters are usually not sufficient to characterize spatial covariance structures of new data. CSP extensions have been proposed to adapt to unlabelled data [3,38,9,7,4]. For example, in an adaptive method proposed in [3], the class label of each testing trial is first estimated. Then the trial is assigned to the estimated class to update its covariance matrix with a fixed weight, and CSP features are updated and reclassified. In a parametric model-based adaptive method [4], CSP features extracted from a testing trial are modelled by a two-component Gaussian mixture model (GMM). The expectation maximization (EM) algorithm is used to estimate class labels for testing trials. The classified trials showing high posterior class probabilities are added to the estimated class to update its covariance matrix and CSP features. This process is repeated multiple times until the overall change of class labels between two contiguous iterations is below a predefined threshold. In another adaptive method [7], an initial classification is first performed on a testing trial, and then the covariance matrix of the estimated class is updated based upon a weight calculated using the Kullback–Leibler divergence (KLD) between the training and testing trials. After updating the covariance matrix, CSP features are updated and reclassified. This process can be repeated multiple times. An initial classification is required in these methods to assign a testing trial to a class to update the class spatial covariance matrix. Ideally, if the new trial is from class y, then it should be similar to training trials from y in terms of feature variation, data distribution, or normalized spatial covariance matrix, and be correctly classified by a classifier. Due to EEG nonstationarity, however, the expected similarity may not be apparent, and it is possible that the new data is more similar to training data of the opposite class. If the new trial is mis-classified, the spatial filters updated based on the erroneous classification could affect the BCI classification. In this work, a different way to perform the ACSP learning is proposed. Instead of estimating class labels for new EEG trials, a similarity measure between new and training data in each class is calculated, and spatial filters of both classes are simultaneously updated based on the similarity measure. Three different similarity measures are used based upon which the ACSP method is developed. The details of the proposed method are described as follows.

Given a new EEG trial from a target subject with an unknown class label and a normalized spatial covariance matrix $\mathbf{C}_{new}$, the following method is proposed to calculate the new class covariance matrices:

$$\overline{\mathbf{C}}_1 = \frac{\phi_1}{n_1+\mathrm{sgn}(\phi_1)}\mathbf{C}_{new} + \frac{n_1}{n_1+\mathrm{sgn}(\phi_1)}\mathbf{C}_1,$$
$$\overline{\mathbf{C}}_2 = \frac{\phi_2}{n_2+\mathrm{sgn}(\phi_2)}\mathbf{C}_{new} + \frac{n_2}{n_2+\mathrm{sgn}(\phi_2)}\mathbf{C}_2, \tag{6}$$