Adaptive CSP with subspace alignment for subject-to-subject transfer in motor imagery brain-computer interfaces

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***Abstract*—In brain-computer interfaces, adapting a classifier from one user to another is challenging but essential to reduce training time for new users. Common Spatial Patterns (CSP) is a widely used method for learning spatial filters for user specific feature extraction but the performance is degraded when applied to a different user. This paper proposes a novel Adaptive Selective Common Spatial Pattern (ASCSP) method to update the covariance matrix using selected candidates. Subspace alignment is then applied to the extracted features before classification. The proposed method outperforms the standard CSP and adaptive CSP algorithms previously proposed. Visualization of extracted features is provided to demonstrate how subspace alignment contributes to reduce the domain variance between source and target domains.**

***Keywords*—BCI, motor imagery, transfer learning, CSP, subspace alignment**

I. Introduction

A brain-computer interface (BCI) is a platform that can interpret a user's brain signals, such as those reflected in electroencephalogram (EEG) signals, and send commands to the external world. Performing real or imagined movements will elicit different neural patterns which can be detected by BCI. BCI-based user specific motor imagery has been widely investigated and common spatial patterns (CSP) has been successfully applied to this problem [1].

However, due to the distortion of temporal and local information of brain signals and variance between subjects, it is difficult to classify EEG patterns in one user using a classifier trained in another user. To overcome these drawbacks, various modified CSP methods have been proposed to obtain more robust filters (see e.g. [2]). There are two main ways to approach the problem: One is to regularize the objective function by adding a penalty term. Such regularization uses priors to guide the optimization process toward robust spatial filters. The other is to incorporate a weighted average of covariance matrices from other subjects to regularize the current covariance matrix [3], [4].

Inspired by adaptive learning, spatial filters learned by CSP can be adapted recursively by new incoming unlabeled EEG signals [5], [6]. Previous adaptive CSP methods rarely check the distribution of extracted features after updating the covariance matrix. A subtle change in the covariance matrix may lead to significant difference between source and target data filtered by CSP. To reduce domain variance of output data, we propose a novel Adaptive Selective Common Spatial Pattern (ASCSP) method that selects the most appropriate candidates to update the covariance matrix without resulting in a great change to the distribution of extracted features. Subspace alignment [7] is then applied to the extracted features before final classification to further reduce the domain variance.

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II. Dataset and Method

A. Dataset

To test our methodology, we used data from 6 participants from the study previously published in [8]. In this study, participants were instructed to perform kinesthetic motor imagery of their left or right hand to control a cursor to hit a target on a screen in front of them. In each trial, a cursor was presented at the center of the monitor and the target at either end - the center was three cursor steps away from each end. After 1.5 seconds the target would vanish to reduce distraction and then the cursor began to move at the speed of one step per second. Participants were led to believe that they controlled the cursor; however, the cursor moved based on a pre-determined order for the purposes of the original study [8].

Data were collected using a 64-channel BrainAmp system (Brain Products GmbH). The electrodes were distributed on the cap based on the International 10-20 system. Data were collected at 5000 Hz sampling rate but were downsampled to 500 Hz for further analysis. Data were analyzed offline in MATLAB and EEGLAB [9]. For further details on the pre-processing of the data please refer to [8]. In this study, we use data 150 ms to 950 ms after the cursor movements towards the target and only consider the frequency band of 7-12 Hz as this covers the mu band for motor imagery. Since in the pre-processing phase for each participant up to five channels contaminated with muscle and other artifacts were removed, the common channels shared by all participants were selected, as the same channels are required for subject-to-subject transfer.

B. Common Spatial Patterns

The common spatial pattern (CSP) algorithm was suggested for motor imagery classification by Ramoser *et al.* [1]. CSP learns optimal spatial filters that maximize filtered variance for one class and simultaneously minimize filtered variance for the other class. The *i*th trial of the pre-processed EEG data for each class is denoted as an $M \times N$ matrix $\boldsymbol{X}_i(y)$ with class label $y \in \{1, 2\}$, where M is the number of channels and N is the number of samples. The averaged normalized spatial covariance matrix C_y is computed for each class as:

$$\boldsymbol{C}_y = \frac{1}{n_y} \sum_{i=1}^{n_y} \frac{\boldsymbol{X}_i(y)\boldsymbol{X}_i^T(y)}{trace(\boldsymbol{X}_i(y)\boldsymbol{X}_i^T(y))}, \tag{1}$$

where n_y is the number of EEG trials in class y and T represents the matrix transpose operator. The optimal set of CSP filters can be found to maximize the following Rayleigh quotient:

$$max \frac{\boldsymbol{W}\boldsymbol{C}_y\boldsymbol{W}^T}{\boldsymbol{W}(\boldsymbol{C}_1 + \boldsymbol{C}_2)\boldsymbol{W}^T}. \tag{2}$$

This problem can be solved by the generalized eigenvalue problem in the form: $\boldsymbol{W}\boldsymbol{C}_1 = \boldsymbol{\Lambda}\boldsymbol{W}\boldsymbol{C}_2$, where $\boldsymbol{\Lambda}$ is a diagonal matrix containing eigenvalues of $\boldsymbol{C}_2^{-1}\boldsymbol{C}_1$ sorted in descending order and the matrix $\boldsymbol{W}$ consists of corresponding eigenvectors. With the transformation matrix $\boldsymbol{W}$, $\boldsymbol{X}(y)$ is spatially filtered to obtain: $\boldsymbol{Z} = \boldsymbol{W}\boldsymbol{X}(y)$. First and last m rows of $\boldsymbol{Z}$ are selected to discriminate the two classes. Feature vector of *r*th spatial filter is constructed as:

$$f_r = log \frac{var(z_r)}{\sum_{j=1}^{2m} var(z_j)}, \tag{3}$$

where $var()$ is the variance calculator and z_r (r=1,..,2m) is the *r*th row of $\boldsymbol{Z}$. The logarithmic transformation makes the distribution of f_r more similar to Gaussian.

C. Subspace Alignment

Fernando *et al.* [7] proposed a domain adaptation algorithm based on unsupervised subspace alignment (SA). This algorithm is part of our proposed method to reduce the variance between source and target domains. Given source data $\boldsymbol{y_S}$ and target data $\boldsymbol{y_T}$, source subspace X_S and target subspace X_T are generated from the eigenvectors of these input data by PCA. Then the given data are projected to the subspaces by the operations $\boldsymbol{y_S}X_S$ and $\boldsymbol{y_T}X_T$. A linear transformation M is learned to map the source subspace to the target subspace by minimizing a Bregman matrix divergence:

$$M^* = argmin_M ||X_S M - X_T||_F^2, \tag{4}$$

where $|| \cdot ||_F^2$ is the Frobenius norm. Because the Frobenius norm is invariant to orthonormal operations, the objective function can be rewritten as:

$$\begin{aligned} M^* &= argmin_M ||X_S^{'} X_S M - X_S^{'} X_T||_F^2 \\ &= argmin_M ||M - X_S^{'} X_T||_F^2. \end{aligned} \tag{5}$$

Based on this equation, the optimal M^* is obtained as $M^* = X_S^{'} X_T$. This implies that the new coordinate system is equivalent to $X_a = X_S X_S^{'} X_T$. Subspace alignment domain adaptation algorithm [7] is presented in Algorithm 1.

Algorithm 1: Subspace Alignment [7]

Input: Source data S, target data T, reduced dimension d
Output: Subspace aligned data S_a, T_T

```
1 X_S ← PCA(S, d)
2 X_T ← PCA(T, d)
3 X_a ← X_S X'_S X_T
4 S_a = S X_a
5 T_T = T X_T
6 return S_a, T_T
```

D. Adaptive Selective CSP

With the help of CSP and SA, a novel adaptive selective CSP (ASCSP) is proposed. Current adaptive CSP methods ignore the change of the distribution of the CSP filtered features extracted after updating the covariance matrices. ASCSP checks the variance of CSP filtered data before updating the covariance matrix and selects the probable candidate trials from target data that maintain the similarity of source and target distribution.

Given EEG trials $X^s = \{X^{s_1} \cup X^{s_2}\}$ from source subject labeled with left (class 1) and right (class 2) respectively and unlabeled trials X^t from target subject, C_1 and C_2 are initialized as averaged normalized covariance matrices from X^{s_1} and X^{s_2} using Eq. (1).

The first step of ASCSP is to select candidate trial x_i from X^t for class 1. CSP filters are trained from source labeled data and applied to both source (X^s) and target (X^t) data to extract logarithmic features. Subspace alignment is then applied to the logarithmic features to reduce domain discrepancy. Linear Discriminant Analysis (LDA) is trained upon the extracted features in source aligned subspace and then predicts the label in the target aligned subspace. If the prediction is class 1 then this trial is selected as the candidate to update the covariance matrix later, otherwise another trial is picked and tested sequentially until a label of class 1 is obtained.

After selecting the candidate x_i for class 1, candidate x_j for class 2 is chosen from remaining X^t. New covariance matrices $\tilde{C_1}$ and $\tilde{C_2}$ are obtained from:

$$\begin{aligned} C_1^{new} &\leftarrow \frac{C_1 n_1}{n_1 + 1} + \frac{cov(x_i)}{trace(cov(x_i))(n_1 + 1)}, \\ C_2^{new} &\leftarrow \frac{C_2 n_2}{n_2 + 1} + \frac{cov(x_j)}{trace(cov(x_j))(n_2 + 1)}, \end{aligned} \tag{6}$$

where $cov()$ calculates the covariance matrix. CSP is trained with $\tilde{C_1}$ and $\tilde{C_2}$ and applied to both source X^s and target X^t data. The logarithmic features $\tilde{f}_s$ in source domain and $\tilde{f}_t$ in target domain are obtained and the difference of their means $|mean(\tilde{f}_s - \tilde{f}_t)|$ is calculated. If this value is too large, the selected trial for class 2 should be discarded, because the extracted features differ too much between source and target subjects and a classifier trained on the source domain is unable to distinguish the patterns in target domain. The remaining trials of the target subject that satisfy the previous condition are all considered. Since CSP learns a projection matrix with filters that maximize the projected variance of the signals from each class [1], the trial that results in a modified covariance matrix that leads to CSP extracted features with the highest variance is chosen as the final candidate for class 2.

After selecting the trial for class 2 resulting in highest filtered variance, covariance matrices C_1 and C_2 are updated by Eq. (6) using the candidates for class 1 and class 2. Then CSP is calculated to extract logarithmic features and a new aligned subspace is constructed. LDA is then trained upon these features. In the next iteration, LDA can be used to select trials of class 1 and repeat previous steps. The whole algorithm is shown in Algorithm 2.

Algorithm 2: ASCSP

Input: Source domain data set $X^s = \{X^{s_1} \cup X^{s_2}\}$ and target domain data set X^t
Output: Transform matrix W

Initialize C_1, C_2 as the average covariance matrix of X^{s_1} and X^{s_2}
Initialize both X^{t_1} and X^{t_2} with the value of X^t
$W = CSP(C_1, C_2)$
Calculate features f^s and f^t using Eq. (3)
Construct aligned subspace X^s_{sa} and X^t_{sa}
Train LDA on X^s_{sa}
while there exists a trial $x_i \in X^{t_1}$ whose subspace aligned features are classified as class 1 by LDA **do**
    x_j = *Empty*
    $m = -INF$
    while *pick* $\tilde{x}_j$ *in* X^{t_2} ***and*** $x_i \neq \tilde{x}_j$ **do**
        Calculate $\tilde{C}_1, \tilde{C}_2$ using $x_i, \tilde{x}_j$ based on Eq. (6)
        $W = CSP(\tilde{C}_1, \tilde{C}_2)$
        Calculate features $\tilde{f}^s$ and $\tilde{f}^t$ using Eq. (3)
        Construct aligned subspace $\tilde{X}^t_{sa}$
        if $|mean(\tilde{f}^s - \tilde{f}^t)| < Thresh$ ***and*** $var(W\tilde{X}^t_{sa}) > m$ **then**
            $m \leftarrow var(W\tilde{X}^t_{sa})$
            $x_j \leftarrow \tilde{x}_j$

    if $x_j \neq$ *Empty* **then**
        Update C_1, C_2 using x_i, x_j using Eq. (6)
        $X^{t_1} \leftarrow X^{t_1} - \{x_i, x_j\}$
        $X^{t_2} \leftarrow X^{t_2} - \{x_i, x_j\}$
        $W = CSP(C_1, C_2)$
        Calculate features f^s and f^t using Eq. (3)
        Construct aligned subspace X^s_{sa} and X^t_{sa}
        Train LDA on X^s_{sa}
return W

III. RESULTS

The classification accuracies on the 6 participants are reported in Table I. Each pair of two participants is evaluated twice with each of them used as the training data (source data) and the other as testing data (target data). CSP is adopted as baseline method. The previously proposed Adaptive CSP method (ACSP) by Song *et al.* [5] using Frobenius norm is evaluated for comparison. ASCSP is our proposed method for feature extraction. The threshold is set to 6 after searching values from 1 to 10 on subject 2 as source domain and subject 5 as target domain (The ASCSP and ASCSP_SA data for this pair is marked by * in Table I to indicate potential overfitting on this pair only). The threshold is fixed for all other source-target combinations. Subspace alignment is then adopted for the features extracted by ASCSP. This method is called ASCSP_SA. The LDA algorithm is used to classify the features extracted by these four methods. As Table I presents, ASCSP outperforms the previous ACSP and baseline method. ASCSP with subspace alignment further improves the accuracy and performs best in nearly all cases.

TABLE I
ACCURACIES OF FOUR DIFFERENT METHODS. SEE TEXT FOR DESCRIPTION OF *.

Test Subj	Train Subj	Acc			
		CSP	*ACSP*	*ASCSP*	*ASCSP_SA*
S1	S2	**0.5586**	0.5154	0.5247	0.5370
	S3	0.4938	0.5123	0.4877	**0.5340**
	S4	0.4784	0.5093	**0.5802**	0.5556
	S5	0.5000	0.4969	**0.6019**	0.5988
	S6	0.4969	0.4969	0.5617	**0.5648**
	Mean	0.5055	0.5062	0.5512	**0.5580**
S2	S1	0.5216	0.4846	0.4722	**0.6790**
	S3	0.4938	0.4969	0.5278	**0.6327**
	S4	0.4321	0.5031	0.5926	**0.6975**
	S5	0.4969	0.5123	0.5340	**0.6204**
	S6	0.5309	0.4815	**0.5864**	0.5710
	Mean	0.4951	0.4957	0.5426	**0.6401**
S3	S1	0.4907	0.5278	0.5154	**0.5525**
	S2	0.4938	0.5031	0.4815	**0.5679**
	S4	0.4969	0.5093	0.5309	**0.5710**
	S5	0.4969	0.5556	**0.5617**	0.5432
	S6	0.5062	0.4938	0.5494	**0.5926**
	Mean	0.4969	0.5179	0.5278	**0.5654**
S4	S1	0.4383	0.5000	**0.6451**	0.5957
	S2	0.4691	0.4907	0.5154	**0.6574**
	S3	0.4784	0.5093	0.5278	**0.6327**
	S5	0.5000	0.5000	0.5154	**0.6080**
	S6	0.4815	0.5031	0.5123	**0.5864**
	Mean	0.4734	0.5006	0.5432	**0.6160**
S5	S1	0.4599	0.4722	0.5123	**0.5802**
	S2	0.4815	0.5031	0.5216*	**0.6080***
	S3	0.4753	0.5031	0.5000	**0.5895**
	S4	0.4753	0.5062	0.5154	**0.5895**
	S6	0.4599	0.5247	0.5741	**0.6173**
	Mean	0.4704	0.5019	0.5247	**0.5969**
S6	S1	0.5000	0.5000	0.5957	**0.6358**
	S2	0.5309	0.5093	0.5093	**0.6574**
	S3	0.5000	0.5000	0.6019	**0.6080**
	S4	0.4907	0.5000	0.5556	**0.6852**
	S5	0.5000	0.5000	0.5988	**0.6944**
	Mean	0.5043	0.5019	0.5722	**0.6562**

Fig. 1 demonstrates the reason why our proposed methods outperform previous ACSP. Previous Adaptive CSP ignores the domain variance after updating the covariance matrix. In Fig. 1(a), source and target domain features differ from each other and thus the decision boundary learned in the source domain cannot successfully be applied in the target domain. ASCSP reduces the domain variance according to Fig. 1(b) but still the features are not adaptive enough for the target domain. By adding subspace alignment to the ASCSP filtered features, domain variance can be further reduced and the classifier learned in the source domain can be applied directly in the target domain. In Fig. 1(c), the two decision boundaries are close enough and the source domain classifier can discern most of the labels in the target domain better than the methods without subspace alignment.

IV. Conclusion

Small perturbations of the covariance matrix will lead to large discrepancy in features extracted by CSP between source and target domain. Thus the classifier trained on data from the source subject is unable to classify the target subject data reliably. The proposed ASCSP can reduce domain variance by selecting trials to update the covariance matrix; moreover, applying subspace alignment before classification can further reduce the difference in the distributions between source and target domain. Visualization of features filtered by three methods (ACSP, ASCSP and ASCSP_SA) is shown to demonstrate how ASCSP together with subspace alignment reduces the domain variance.

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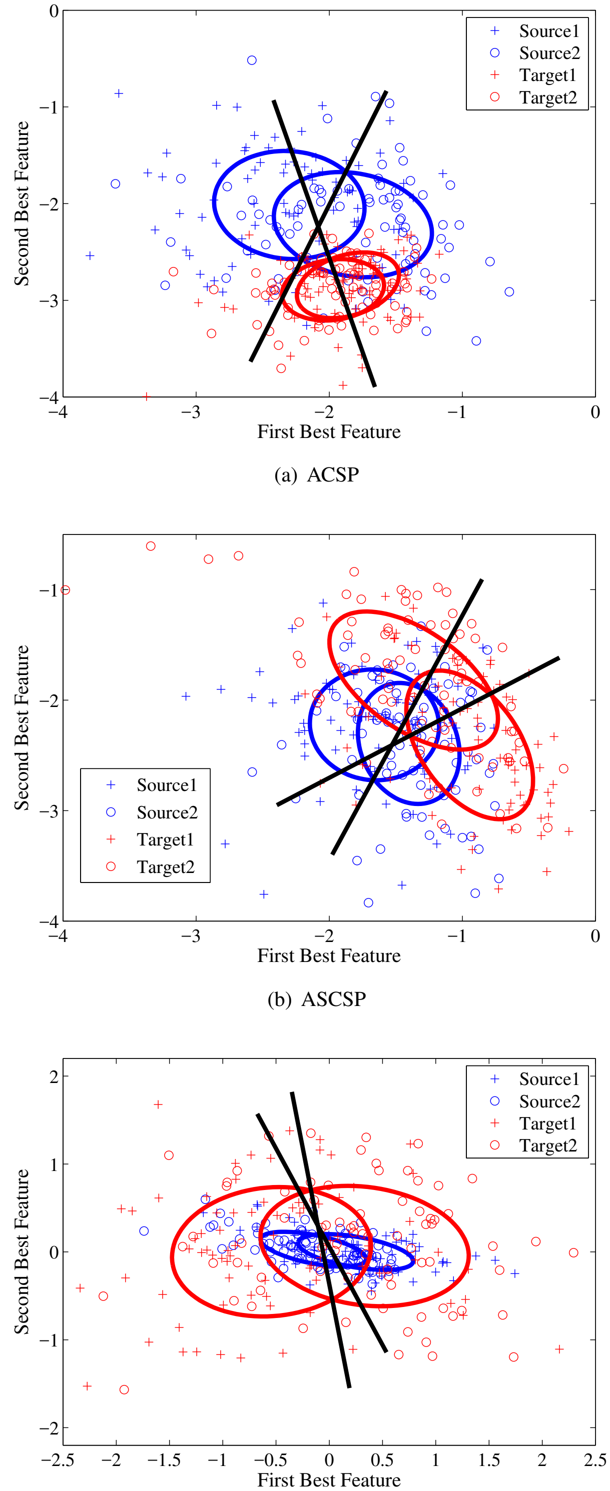

(a) ACSP

(b) ASCSP

(c) ASCSP_SA

Fig. 1. Visualization of domain variance and the effect of subspace alignment. The black lines represent optimal linear decision boundaries for the training and testing data set. First and second rows of the extracted features are plotted in the above figures. Subject 4 and 6 are the source and target subjects respectively. Fig. 1(a), 1(b), 1(c) are ACSP, proposed ASCSP and ASCSP with subspace alignment respectively.