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Optimizing spatial patterns with sparse filter bands for motor-imagery based brain–computer interface

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HIGHLIGHTS

• This study proposes a sparse filter band common spatial pattern (SFBCSP) for optimizing the spatial patterns.
• Experimental results on two public EEG datasets (BCI Competition III dataset IVa and BCI Competition IV Iib) confirm the effectiveness of SFBCSP.
• The optimized spatial patterns by SFBCSP give overall better MI classification accuracy in comparison with several competing methods.
• Our study suggests that the proposed SFBCSP is a potential method for improving the performance of MI-based BCI.

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ABSTRACT

Background: Common spatial pattern (CSP) has been most popularly applied to motor-imagery (MI) feature extraction for classification in brain–computer interface (BCI) application. Successful application of CSP depends on the filter band selection to a large degree. However, the most proper band is typically subject-specific and can hardly be determined manually.

New method: This study proposes a sparse filter band common spatial pattern (SFBCSP) for optimizing the spatial patterns. SFBCSP estimates CSP features on multiple signals that are filtered from raw EEG data at a set of overlapping bands. The filter bands that result in significant CSP features are then selected in a supervised way by exploiting sparse regression. A support vector machine (SVM) is implemented on the selected features for MI classification.

Results: Two public EEG datasets (BCI Competition III dataset IVa and BCI Competition IV Iib) are used to validate the proposed SFBCSP method. Experimental results demonstrate that SFBCSP help improve the classification performance of MI.

Comparison with existing methods: The optimized spatial patterns by SFBCSP give overall better MI classification accuracy in comparison with several competing methods.

Conclusions: The proposed SFBCSP is a potential method for improving the performance of MI-based BCI.

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1. Introduction

A brain–computer interface (BCI) is an advanced communication approach that assists to establish the capabilities of environmental control for severely disabled people (Wolpaw et al., 2002; Gao et al., 2014; Hoffmann et al., 2008; Jin et al., 2015; Zhang et al., 2012; Rutkowski and Mori, 2015; Chen et al., 2015). BCI can translate a specific brain activity into computer command, thereby building a direct connection between human brain and external device. One of the most popularly adopted brain activities is event-related (de)synchronization (ERD/ERS) ( Pfurtscheller and Neuper, 2001; Li et al., 2013), and can be typically measured by electroencephalogram (EEG). ERD/ERS can be quantified by band-power changes occurring when subjects do motor-imagery (MI) tasks, i.e., imagine their limbs (left hand, right hand and foot) ( Pfurtscheller et al., 2006; Li and Zhang, 2010; Koo et al., 2015).

So far, a large number of methods have been introduced to EEG analysis for various applications (Li et al., 2015, 2008; Arvaneth et al., 2013; Zhang et al., 2012, 2014; Cong et al., 2010; Jin et al., 2013; Zhang et al., 2015b). Common spatial pattern (CSP) is a very efficient method and has been mostly applied to MI feature extraction (Ramoser et al., 2000; Higashi et al., 2012). The variance of

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Fig. 1. Illustration of the proposed sparse filter band common spatial pattern (SFBCSP) algorithm for motor-imagery classification.

Table 1

<table>
<thead>
<tr>
<th>Subject</th>
<th>CSP</th>
<th>FBCSP</th>
<th>DFBCSP</th>
<th>SFBCSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>aa</td>
<td>20.11 ± 3.82</td>
<td>9.61 ± 2.14</td>
<td>9.68 ± 2.36</td>
<td>8.46 ± 2.10</td>
</tr>
<tr>
<td>al</td>
<td>2.11 ± 1.45</td>
<td>2.18 ± 1.72</td>
<td>1.54 ± 1.21</td>
<td>1.43 ± 1.09</td>
</tr>
<tr>
<td>av</td>
<td>29.61 ± 4.16</td>
<td>27.46 ± 6.67</td>
<td>24.86 ± 3.22</td>
<td>22.57 ± 4.87</td>
</tr>
<tr>
<td>aw</td>
<td>6.96 ± 2.32</td>
<td>2.79 ± 1.53</td>
<td>2.18 ± 1.38</td>
<td>1.97 ± 1.24</td>
</tr>
<tr>
<td>ay</td>
<td>7.86 ± 2.86</td>
<td>5.46 ± 2.88</td>
<td>4.71 ± 2.35</td>
<td>5.31 ± 2.96</td>
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<td>9.50 ± 2.99</td>
<td>8.59 ± 2.10</td>
<td>7.95 ± 2.45</td>
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<td>p = 0.14</td>
<td>p = 0.27</td>
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</tr>
</tbody>
</table>

Table 2

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<th>FBCSP</th>
<th>DFBCSP</th>
<th>SFBCSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>B0103T</td>
<td>23.44 ± 5.88</td>
<td>22.50 ± 4.61</td>
<td>22.06 ± 4.48</td>
<td>21.85 ± 4.79</td>
</tr>
<tr>
<td>B0203T</td>
<td>44.44 ± 6.97</td>
<td>44.06 ± 6.05</td>
<td>42.75 ± 5.89</td>
<td>41.25 ± 5.84</td>
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<td>B0303T</td>
<td>47.38 ± 8.10</td>
<td>46.25 ± 6.95</td>
<td>44.81 ± 6.50</td>
<td>44.19 ± 6.09</td>
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<tr>
<td>B0403T</td>
<td>1.94 ± 1.50</td>
<td>1.13 ± 1.13</td>
<td>1.19 ± 1.43</td>
<td>1.15 ± 1.23</td>
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<td>B0503T</td>
<td>11.81 ± 4.77</td>
<td>9.56 ± 2.42</td>
<td>7.56 ± 2.14</td>
<td>7.94 ± 2.35</td>
</tr>
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<td>B0603T</td>
<td>30.63 ± 5.60</td>
<td>21.94 ± 3.44</td>
<td>18.31 ± 3.17</td>
<td>17.68 ± 3.62</td>
</tr>
<tr>
<td>B0703T</td>
<td>16.56 ± 4.85</td>
<td>13.50 ± 2.90</td>
<td>10.50 ± 1.83</td>
<td>9.75 ± 1.25</td>
</tr>
<tr>
<td>B0803T</td>
<td>13.44 ± 3.02</td>
<td>11.25 ± 2.78</td>
<td>11.38 ± 2.93</td>
<td>11.13 ± 3.21</td>
</tr>
<tr>
<td>Average</td>
<td>23.10 ± 5.04</td>
<td>20.70 ± 3.74</td>
<td>19.31 ± 3.52</td>
<td>18.83 ± 3.55</td>
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<td>p &lt; 0.01</td>
<td>p &lt; 0.01</td>
<td>p &lt; 0.01</td>
<td>-</td>
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</table>

Band-pass filtered signals has been known to be equal to the band-power. Since CSP finds spatial filters to maximize the variance of the projected signal from one class while minimizing it for another class, it provides a natural approach to effectively estimate the discriminant information of MI (Blankertz et al., 2008). However, to guarantee the successful application of CSP to MI classification, a pre-specified filter band is required to accurately capture the band-power changes resulting from ERD/ERS (Ang et al., 2008). Unfortunately, the most proper filter band is typically subject-specific and can hardly be determined in a manual way. A poor selection of the filter band may result in low effectiveness of CSP (Sun et al., 2010).

Although a wide filter band (i.e., 8–30 Hz) was usually adopted for CSP in MI classification, an increasing number of studies suggested that the optimization of filter band could significantly improve classification accuracy (Ang et al., 2008; Sun et al., 2010; Lemm et al., 2005; Dornhege et al., 2006; Novi et al., 2007). So far, two types of approaches have been mainly proposed to fix the problem of filter band selection. One is simultaneous optimization of spectral filters within the CSP (Lemm et al., 2005; Dornhege et al., 2006; Higashihara and Tanaka, 2013) while another one is selection of significant CSP features from multiple frequency bands (Ang et al., 2008; Novi et al., 2007, Thomas et al., 2009).

By extending CSP to state space, common spatio-spectral pattern (CSSP) (Lemm et al., 2005) was proposed to optimize a simple FIR filter by employing a temporal delay within CSP. A further extension of CSSP is called common sparse spectral spatial pattern (CSSSP) (Dornhege et al., 2006), which optimizes an adaptive FIR filter simultaneously with CSP. More recently, (Higashihara and Tanaka, 2013) proposed to simultaneously learn multiple FIR filters and the associated spatial weights by maximizing a cost function extended from CSP.

On the other hand, an alternative approach is sub-band common spatial spatial pattern (SBSCSP) (Novi et al., 2007). Instead of simultaneously optimizing a spectral filter within CSP, SBSCSP filtered EEG signals using multiple filter bands and extracted the sub-band CSP features for classification with score fusion. Although SBSCSP achieved superior classification accuracy over both CSP and CSSSP.
(Novi et al., 2007), it ignored the correlation among CSP features from different filter bands. (Ang et al., 2008) introduced a filter bank common spatial pattern (FBCSP) to select the optimal filter bands through estimating the mutual information among CSP features at several fixed filter bands. Higher classification accuracy was achieved by FBCSP over SCSP. Subsequently, Thomas et al. (2009) proposed a discriminant FBCSP (DFBCSP) using Fisher ratio to select subject-specific filter bands instead of fixed ones, which enhanced accuracy of the FBCSP.

In this study, we will focus on further improving the second type of approaches, i.e., CSP feature selection from multiple frequency bands. To this end, we propose a sparse filter band common spatial pattern (SFBSP) by exploiting sparse regression for automatic band selection. Recently, sparse regression has been increasingly applied to BCI and shown its efficiency in ERP feature extraction to alleviate overfitting (Zhang et al., 2014). In the proposed method, CSP features are estimated on multiple signals that are filtered from raw EEG data at a set of overlapping filter bands. Sparse regression is implemented to supervisedly select the significant CSP features with class labels. A support vector machine (SVM) with linear kernel is then trained on the selected features to classify MI tasks. The proposed SFBSP is validated on two public EEG datasets (BCI Competition III dataset IVA and BCI Competition IV dataset IIb), and compared with CSP, FBCSP and DFBCSP. Experimental results show SFBSP achieves superior classification accuracy.

2. SFBSP for MI classification

2.1. Feature extraction by CSP

Common spatial pattern (CSP) is an effective method for feature extraction in discriminating two classes of data. In recent years, CSP has become greatly popular for the extraction of EEG features related to motor imagery. Consider two classes of EEG samples \(X_{i,1}\) and \(X_{i,2}\) \(\in \mathbb{R}^{C \times p}\) recorded from \(i\)-th trial, where \(C\) is the number of channels, and \(p\) denotes the number of samples. Both EEG samples are bandpass filtered within a specified frequency band. Without loss of generality, we assume \(X_{i,1}\) and \(X_{i,2}\) have been centered. Spatial covariance matrix \(\Sigma\) of the class \(l (l = 1, 2)\) is then computed by

\[
\Sigma_l = \frac{1}{N_l} \sum_{i=1}^{N_l} X_{i,l} X_{i,l}^T.
\]

where \(N_l\) is the number of trials in class \(l\). CSP is aimed at learning linear transforms (also called spatial filters) to maximize the ratio of transformed data variance between the two classes:

\[
\max_{\mathbf{w}} \frac{\mathbf{w}^T \Sigma_1 \mathbf{w}}{\mathbf{w}^T \Sigma_2 \mathbf{w}} \quad \text{s.t.} \quad \|\mathbf{w}\|_2 = 1,
\]

where \(\|\cdot\|_2\) denotes the \(l_2\)-norm, and \(\mathbf{w} \in \mathbb{R}^C\) is a spatial filter. The maximization of Rayleigh quotient \(J(\mathbf{w})\) can be achieved by solving the following generalized eigenvalue problem:

\[
\Sigma_1 \mathbf{w} = \lambda \Sigma_2 \mathbf{w}.
\]

The eigenvectors are then obtained to form the learned spatial filters matrix \(\mathbf{W}\). The projection \(\mathbf{Z}\) of a given EEG sample \(\mathbf{X}\) is then given by

\[
\mathbf{Z} = \mathbf{W}^T \mathbf{X}.
\]
Generally, only a small number $M$ of projected signals are used for feature computation. With the $M$ first and last rows of $Z$, i.e., $Z_m, m \in \{1, \ldots, 2M\}$, the feature vector is then formed as $g = [g_1, \ldots, g_{2M}]^T$ with entries

$$g_m = \log \left( \frac{\text{var}(Z_m)}{\sum_{h=1}^{2M} \text{var}(Z_h)} \right),$$

where $\text{var}(Z)$ denotes the variance of each row of $Z$.

### 2.2. Sparse filter band CSP

The successful application of CSP to MI classification largely depends on the frequency band selection for bandpass filtering of EEG (Blankertz et al., 2008). A good selection of filter bands can considerably improve the MI classification accuracy, whereas a poor one will result in low effectiveness of CSP (Ang et al., 2008; Thomas et al., 2009). The optimal filter band is typically subject-specific and can hardly be determined in a manual way. To solve the problem, this study proposes a sparse filter band common spatial pattern (SFBCSP) for automatic selection of filter bands.

Instead of directly using a wide filter band, we perform bandpass filtering on raw EEG by using a set of overlapping subbands $[f_b \pm \Delta f, f_b + \Delta f]$. These subbands are chosen from the frequency range 4–40 Hz with bandwidth of 4 Hz and overlapping rate of 2 Hz, i.e., $f_b = 4–8$ Hz, $f_b = 6–10$ Hz, ..., $f_b = 36–40$ Hz where $K = 17$. The adopted settings of bandwidth and overlapping rate are consistent with those in literature (Thomas et al., 2009). CSP is then implemented on the filtered signals at each sub-band to calculate the corresponding features by (5). As a result, $2MK$ features are extracted from each EEG sample. With the extracted CSP features, we can construct the following feature set:

$$G = \begin{bmatrix} g_{1,1} & \cdots & g_{1,2MK} \\ \vdots & \ddots & \vdots \\ g_{N,1} & \cdots & g_{N,2MK} \end{bmatrix},$$

where $g_{j,i}$ denotes the $j$-th feature extracted from EEG sample at $i$-th trial, and $N = N_1 + N_2$.

Here, we propose to use the following sparse regression model (i.e., the well-known Lasso estimate (Tibshirani, 1996)) for significant CSP feature selection

$$u = \arg \min_u \frac{1}{2} \|Gu - y\|_2^2 + \lambda \|u\|_1,$$

where $\| \cdot \|_1$ denotes the $l_1$-norm of $y \in \mathbb{R}^N$ is a vector containing class labels $\{1, 2\}$, $u$ is a sparse vector to be learned, $\lambda$ is a positive regularization parameter for controlling the sparsity of $u$, and larger $\lambda$ could result in more sparse $u$. The coordinate descent algorithm (Friedman et al., 2010) is adopted to solve the optimization problem in (7). The coordinate-wise update form for $u$ is given by:

$$u_j \leftarrow S \left( \sum_{i=1}^{N} g_{i,j} (y_i - \hat{y}_i^{(j)}), \lambda \right),$$

where $\hat{y}_i^{(j)} = \sum_{d \neq j} g_{i,d} u_d$ is the fitted value excluding the contribution from $g_{i,j}$, and $S(a, \lambda)$ is a shrinkage-thresholding operator:

$$\text{sign}(a|a| - \lambda)_+ = \begin{cases} a - \lambda & \text{if } a > \lambda \\ 0 & \text{if } |a| \leq \lambda \\ a + \lambda & \text{if } a < -\lambda. \end{cases}$$

We can obtain the optimized sparse vector $\tilde{u}$ satisfying (7) through repeating the update form in (9) for $j = 1, 2, \ldots, D, 1, 2, \ldots$ until convergence. The column vectors in $G$ corresponding to those zero entries in $\tilde{u}$ are excluded to form an optimized feature set $\hat{G}$ that is of lower dimensionality in comparison with $G$. The given $\lambda$ determines the sparsity degree of $\tilde{u}$, and hence the selection of CSP features.

Support vector machine (SVM) is adopted and implemented on the optimized feature set $\hat{G}$ to train the classifier. For a new test sample $X \in \mathbb{R}^{C \times p}$, the corresponding subband feature vector $\tilde{g} \in \mathbb{R}^{2MK}$ is estimated by CSP. The optimal features are selected according to the sparse vector $\tilde{u}$ and then fed into the trained SVM for MI classification. A simple linear kernel is adopted for the SVM training. Fig. 1 illustrates the proposed SFBCSP algorithm for MI classification.

### 3. Experimental study

#### 3.1. Public BCI Competition datasets

##### 3.1.1. BCI Competition III dataset IVA

This dataset is recorded for five subjects (named “aa”, “al”, “av”, “aw”, and “ay”) at 118 electrodes during right hand and foot MI tasks. For each subject, a total of 280 trials of EEG measurements are available (half for each class of MI). The visual cue indicating the MI task at each trial lasted for 3.5 s. The sampling rate was 100 Hz. More details about the dataset can be found at website [http://www.bbci.de/competition/ibci/](http://www.bbci.de/competition/ibci/).

##### 3.1.2. BCI Competition IV dataset IIb

This dataset is recorded from nine subjects at electrodes C3, Cz and C4 with sampling rate of 250 Hz, during right hand and left hand MI tasks. For comparison with the results reported in literature (Thomas et al., 2009), this study only uses the third training sessions of the dataset, i.e., “B0103T”, “B0203T”, “B0303T”, “B0403T”. For each subject, a total 160 trials of EEG measurements are available (half for each class of MI). In each trial, the subject was indicated by a visual cue to perform MI task for 4.5 s. See website [http://www.bbci.de/competition/iv/](http://www.bbci.de/competition/iv/) for more details about the dataset.

#### 3.2. Evaluation scheme

The effectiveness of the proposed SFBCSP method is tested on the two above-mentioned datasets, in comparison with the CSP, SFBCSP (Ang et al., 2008) and DFBCSP methods (Thomas et al., 2009). On each trial, a segment is extracted starting from 0.5 to 2.5 s after the visual cue. A wide filter band 4–40 Hz is adopted for CSP while 17 overlapping subbands as mentioned in section 2.2 are chosen for SFBCSP, DFBCSP and SFBCSP. For each of the two datasets, a 10 × 10-fold cross-validation is implemented to evaluate the classification performance. After the optimal CSP features are selected, SVM is trained to classify the MI tasks. The regularization parameters $\lambda$ in SFBCSP and $C$ in SVM are determined by cross-validation on training data. The number of CSP filters is set to 2 (i.e., $M = 1$).

#### 3.3. Experimental results

##### 3.3.1. BCI Competition III dataset IVA

Table 1 presents classification errors derived by the CSP, FBCSP, DFBCSP and SFBCSP methods, respectively, for the five subjects. All of the three modified CSP algorithms outperformed the standard CSP. The proposed SFBCSP method further yielded lower average errors than those of the FBCSP and DFBCSP methods. The average error rate reductions achieved by SFBCSP were 40.36%, 16.32% and 7.45% in comparison with the CSP, FBCSP and DFBCSP methods, respectively. The SFBCSP method obtained significant improvement on classification accuracy compared to CSP ($p < 0.05$).
3.3.2. BCI Competition IV dataset IIb

Table 2 summarizes classification errors for the nine subjects. The SFBCSP method yielded lower classification errors for most subjects than those of the other three methods. The classification performance of SFBCSP was significantly better than those of CSP ($p<0.01$), FBCSP ($p<0.01$) and DFBCSP ($p<0.05$). The average error reductions achieved by the SFBCSP method were 18.48%, 9.03% and 2.49% in comparison with the CSP, FBCSP and DFBCSP methods, respectively.

Additionally, the classification accuracies for all subjects from both the aforementioned datasets are depicted in Fig. 2. In summary, the proposed SFBCSP method yielded higher overall accuracy over the CSP, FBCSP and DFBCSP methods for MI classification.

4. Discussion

In the proposed SFBCSP method, the regularization parameter $\lambda$ required by sparse regression played an important role in CSP feature selection. A too large $\lambda$ may exclude useful features from the model while a too small one could not eliminate redundancy effectively. In this study, the optimal subject-specific $\lambda$ was determined by cross-validation on training data. Fig. 3 presents an example to see the effects of varying $\lambda$ on the classification accuracy for subject “B0103T”. The optimal validation accuracy was achieved at $\lambda=0.14$ that was chosen for the subsequent test procedure. A potential problem for the proposed method is that the cross-validation procedure is usually time-consuming and is not applicable for small sample size datasets (Lu et al., 2010). Instead of cross-validation, Bayesian inference provides an effective approach to automatically and quickly estimate the model parameters under the so-called evidence framework (MacKay, 1992; Bishop, 2006). Recently, sparse Bayesian learning (Tipping, 2001) has been increasingly applied to the automatic determination regularization in EEG analysis (Wu et al., 2011, 2014, 2014; Zhang et al., 2015a; Zhang and Rao, 2011). In fact, Bayesian estimation of the optimal $\lambda$ may further improve the efficiency of SFBCSP, which will be investigated in our future study.

Moreover, sparse regularization has been increasingly applied to EEG analysis, such as feature reduction (Zhang et al., 2014; Blankertz et al., 2002), channel optimization (Arvaneh et al., 2011)
and trial selection (Zhang et al., 2013). This study exploited sparse regression for filter band optimization to further improving the MI classification accuracy. With a properly determined regularization parameter $\lambda$, the optimal sparse vector $\mathbf{u}$ can be learned from (7) to effectively select the significant CSP features extracted from multiple filter subbands. Fig. 4 presents the sparse vectors and the most significant spatial filters learned by SFBCSP for each subject in BCI Competition III dataset IVa. Fig. 5 shows the sparse vectors learned by SFBCSP for each subject in BCI Competition IV dataset IIb. It can be seen that the distribution of significant filter bands is sparse and subject-specific. The spatial filter corresponding to the most significant band accurately captured the features in the sensorimotor areas. The significant feature appeared at multiple subbands for some subjects but at an exact subband for some other subjects (e.g., “B0403T” and “B0903T”). This indicates that an effective optimization of filter band for CSP is necessary to improve the MI classification accuracy. Fig. 6 depicts distributions of the most significant two features derived by CSP, FB, DCSP and SFBCSP, respectively, from subject B0703T. All of the three modified CSP algorithms provided more separable feature distributions in comparison with the standard CSP. The highest discriminability of features was achieved by SFBCSP.

In recent years, multilayer learning algorithms have shown their promising potentials for the collaborative optimization in the spatial, temporal and spectral dimensions of brain signals (Cong et al., 2013, 2015; Zhang et al., 2013, 2014; Cichocki et al., 2008; Wu et al., 2014; Zhou et al., 2013; Zhao et al., 2015). A combination of collaborative multilayer optimization and regularization for filter band selection could further benefit to improve the effectiveness of CSP for MI-based BCI.

5. Conclusions

In this study, we introduced a sparse filter band common spatial pattern (SFBCSP) algorithm to automatically select the significant filter bands for improving MI task classification performance in BCI. In the proposed method, CSP features were first estimated on multiple signals filtered from raw EEG data at a set of overlapping filter bands. Significant CSP features were then selected by exploiting sparse regression and were used in SVM to classify MI tasks. Experimental studies on two public EEG datasets (BCI Competition III dataset IVa and BCI Competition IV dataset IIb) indicated that the proposed SFBCSP yielded higher overall classification accuracy in comparison with several other competing methods.

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