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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.

1. Introduction

A brain–computer interface (BCI) is an advanced communication approach that assists to establish the capabilities of environmental control for severally 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; Arvaneh 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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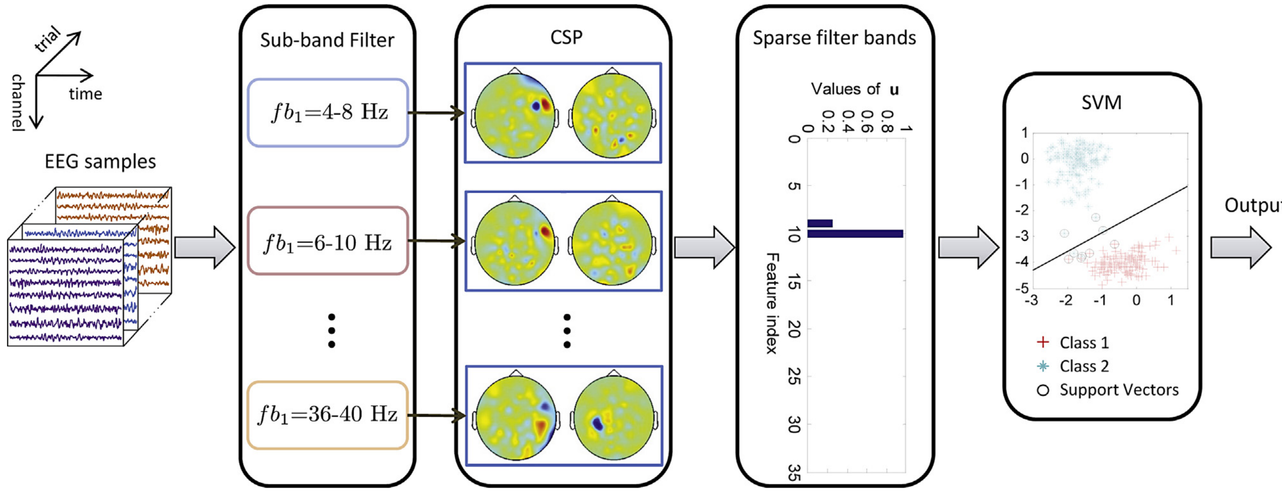

Fig. 1. Illustration of the proposed sparse filter band common spatial pattern (SFBCSP) algorithm for motor-imagery classification.

Table 1
Classification errors (%) obtained by the CSP, FBCSP, DFBCSP, and SFBCSP methods, respectively, for BCI Competition III dataset IVa. For each subject, the lowest error is marked in boldface.

Subject	CSP	FBCSP	DFBCSP	SFBCSP
aa	20.11 ± 3.82	9.61 ± 2.14	9.68 ± 2.36	**8.46** ± 2.10
al	2.11 ± 1.45	2.18 ± 1.72	1.54 ± 1.21	**1.43** ± 1.09
av	29.61 ± 4.16	27.46 ± 6.67	24.86 ± 3.22	**22.57** ± 4.87
aw	6.96 ± 2.32	2.79 ± 1.53	2.18 ± 1.38	**1.97** ± 1.24
ay	7.86 ± 2.86	5.46 ± 2.88	**4.71** ± 2.35	5.31 ± 2.96
Average	13.33 ± 2.92	9.50 ± 2.99	8.59 ± 2.10	**7.95** ± 2.45
p-value	$p < 0.05$	$p = 0.14$	$p = 0.27$	–

Table 2
Classification errors (%) obtained by the CSP, FBCSP, DFBCSP, and SFBCSP methods, respectively, for BCI Competition IV dataset IIb. For each subject, the lowest error is marked in boldface.

Subject	CSP	FBCSP	DFBCSP	SFBCSP
B0103T	23.44 ± 5.88	22.50 ± 4.61	22.06 ± 4.48	**21.85** ± 4.79
B0203T	44.44 ± 6.97	44.06 ± 6.05	42.75 ± 5.89	**41.25** ± 5.84
B0303T	47.38 ± 8.10	46.25 ± 6.95	44.81 ± 6.50	**44.19** ± 6.09
B0403T	1.94 ± 1.50	**1.13** ± 1.13	1.19 ± 1.43	1.15 ± 1.23
B0503T	11.81 ± 4.77	9.56 ± 2.42	**7.56** ± 2.14	7.94 ± 2.35
B0603T	30.63 ± 5.60	21.94 ± 3.44	18.31 ± 3.17	**17.68** ± 3.62
B0703T	16.56 ± 4.85	13.50 ± 2.90	10.50 ± 1.83	**9.75** ± 1.25
B0803T	13.44 ± 3.02	11.25 ± 2.78	11.38 ± 2.93	**11.13** ± 3.21
B0903T	18.25 ± 4.63	16.12 ± 3.39	15.25 ± 3.33	**14.50** ± 3.61
Average	23.10 ± 5.04	20.70 ± 3.74	19.31 ± 3.52	**18.83** ± 3.55
p-value	$p < 0.01$	$p < 0.01$	$p < 0.05$	–

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; Higashi 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, (Higashi 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 pattern (SBCSP) (Novi et al., 2007). Instead of simultaneously optimizing a spectral filter within CSP, SBCSP filtered EEG signals using multiple filter bands and extracted the sub-band CSP features for classification with score fusion. Although SBCSP achieved superior classification accuracy over both CSSP and CSSSP