Increasing the Spectral Signal-To-Noise Ratio of Common Spatial Patterns

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Abstract. Common Spatial Patterns (CSP) is a popular method for extracting class-discriminative oscillatory neural signals in Brain-Computer Interface (BCI) studies. Here we suggest a mechanism to increase the spectral signal-to-noise ratio of CSP by way of regularizing the CSP objective. The approach is evaluated on a data set containing $N = 80$ subjects and a significant increase of classification performance is observed.

Keywords: EEG, SMR-BCI, CSP, SSD, Regularization, cwSSD

1. Introduction

Brain-Computer Interfaces (BCI) rely on the extraction of a class-discriminative and possibly low-dimensional representation of neural sources from high dimensional and noisy data. In the case of motor imagery (MI) driven BCI, a widely used method for obtaining such a representation is the Common Spatial Patterns Algorithm [Blankertz et al., 2008]. CSP optimizes spatial filters such that the contrast of spectral power (approximated by variance of the band-pass filtered signal) between two MI classes is maximized. Recently and in a non-BCI context, a novel spatial filtering method was suggested which decomposes oscillatory EEG/MEG data such that the extracted components have a maximized signal-to-noise ratio (SNR) in the frequency band of interest. This method is called Spatio-Spectral Decomposition (SSD) [Nikulin et al., 2011] and was shown to outperform independent component analysis (ICA) in the extraction of components with pronounced spectral peaks. In this contribution, we propose a fusion of CSP and SSD in order to obtain higher classification performance in a BCI setting by combining the positive aspects of both algorithms (between-class contrast and optimized SNR in the spectral domain). We refer to this methods as *class-wise Spatio-Spectral Decomposition* (cwSSD).

2. Material and Methods

The objective function of cwSSD encodes the core ideas of CSP and SSD and is given below:

$$f(\mathbf{w}) = \frac{\mathbf{w}^\top \mathbf{C}_i \mathbf{w}}{\mathbf{w}^\top \left(\alpha \mathbf{C}_{1+2} + (1-\alpha)\mathbf{C}_n\right)\mathbf{w}}, \tag{1}$$

where $\mathbf{C}_i$ denotes the covariance matrix of class $i \in \{1,2\}$, $\mathbf{C}_{1+2}$ denotes the covariance matrix of both classes together and $\mathbf{C}_n$ denotes the covariance matrix of noise. For $\mathbf{C}_i$ and $\mathbf{C}_{1+2}$ the data is band-pass filtered in the frequency band of interest (e.g. 8 to 12 Hz). However, $\mathbf{C}_n$ is obtained by taking the covariance of data that is filtered in bands that are neighboring to the band of interest (e.g. 6 to 8 and 12 to 14). $\mathbf{C}_{1+2}$ and $\mathbf{C}_n$ are normalized using the trace norm. The parameter α allows to interpolate between standard CSP ($\alpha = 1$) and SSD ($\alpha = 0$).

The performance of cwSSD is evaluated by re-analyzing a MI BCI data set consisting of N=80 subjects [Blankertz et al., 2010]. For each subject, calibration (75 trials per class) and online (150 trials per class) BCI data was collected. A subject-specific frequency band and time interval was used for both CSP and cwSSD, and 3 components per class were selected each. Linear discriminant analysis (LDA) was employed as a classifier, acting on log-var features of the spatially filtered data. CSP/cwSSD as well as subsequent LDA were trained on the calibration data and applied to the online data. A subject-specific α was obtained by cross-validation on the calibration data.

3. Results

Fig. 1 (**A**) shows the classification accuracy on the online data in a scatter plot. cwSSD achieves higher accuracy than CSP for 55 % of the subjects while the performance is worse for 29 % of the subjects. The mean accuracy

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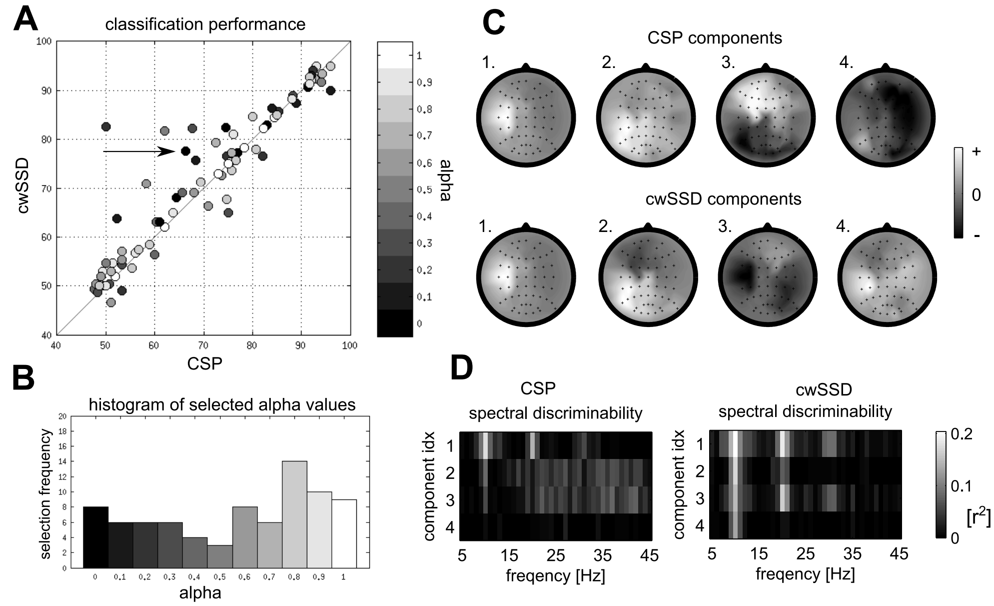

Figure 1: *Results of comparing CSP and cwSSD on data from N=80 subjects. (**A**) Scatter plot that shows the classification performance obtained on the online data for CSP (x-axes) and cwSSD (y-axes). Each point corresponds to a subject and the color of the point indicates the selected α value for cwSSD. (**B**) Histogram of selected α values. (**C**) CSP and cwSSD components of a representative subject (indicated by the arrow in **A**) with improved performance. (**D**) R-square values for 1 Hz frequency bins (5 Hz to 45 Hz), computed for the components displayed in (**C**).*

of cwSSD is 71.72 % ($\pm$15.08) while that of CSP is 70.07 % ($\pm$ 15.6), with the improvement being statistically significant ($p = 0.011$, paired-sample t-test). The histogram of chosen α values is depicted in part (**B**) of the figure. Spatial patterns of the 4 most class-discriminative components of a representative subject are shown in Fig. 1 (**C**). The spectral SNR of the CSP/cwSSD components is assessed by way of computing r-square values for 1 Hz frequency bins of the spatially filtered signal. For the subject depicted in Fig. 1 (**D**), one can observe pronounced peaks at 10 Hz, as well as at the harmonics (20 and 30 Hz).

4. Discussion

The presented method (cwSSD) can be regarded as a special case of the general framework for regularization of CSP, described in [Lotte and Guan, 2010]. Thus, the combination of the objective functions of CSP and SSD represents an effective regularization of the original objective of CSP. The highest gain in performance was achieved for subjects who had less than 80 % accuracy with CSP, rendering our approach a suitable alternative in BCI settings where users have difficulties in controlling the application. Ongoing research effort is focused on further exploitation of the increased spectral SNR, for example by using narrower frequency bands or by taking the increased harmonic spectral peaks into account as well.

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