An Iterative Algorithm for Spatio-Temporal Filter Optimization

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SUMMARY: We propose a simultaneous spatio-temporal filter optimization algorithm for the single trial ElectroEncephaloGraphy (EEG) classification problem. The algorithm is a generalization of the Common Spatial Pattern (CSP) algorithm, which incorporates non-homogeneous weighting of the cross-spectrum matrices. The spectral weighting coefficients and the spatial filter are alternately updated. The validation results on 162 motor-imagery BCI datasets show that the proposed method outperforms wide-band filtered CSP in most datasets and gives comparable accuracy to Common Sparse Spectral Spatial Pattern (CSSSP) with far less computational cost. The proposed method is highly interpretable and modular at the same time because the temporal filter is parameterized in the spectral domain.

INTRODUCTION

A Common Spatial Pattern (CSP) [1] based classifiers for the motor-imagery BCI system has been successful in extracting subject specific discriminative spatial patterns. However, the problem of choosing the temporal filter or the spectral band on which CSP works has not been fully investigated in spite of recent efforts [2, 3].

We propose a novel simultaneous spatio-spectral filter optimization technique and compare the classification accuracy on 162 motor-imagery BCI datasets with three conventional techniques, namely, Common Spatial Pattern (CSP) [1], Common Spatio Spectral Pattern (CSSP) [2], Common Sparse Spectral Spatial Pattern (CSSSP) [3].

MATERIALS

We use 162 datasets of motor-imagery BCI experiment from 29 healthy subjects. Each dataset contains EEG signal recorded during 200-400 trials of one of the pairwise combinations of three motor imagination tasks, namely right hand (R), left hand (L) or foot (F) (see [3] for the detail).

METHODS

PREPROCESSING

We band-pass filter the signal from 7-30Hz and cut out the interval of 500-3500ms after the appearance of the visual cue on the screen from the continuous EEG signal for each trial of imaginary movement.

SPATIO-SPECTRAL FILTER

Let us denote by $X \in \mathbb{R}^{d\times T}$ the EEG signal of a single trial of imaginary motor movement, where d is the number of electrodes and T is the number of sampled time-points in a trial. We consider a binary classification problem where each class, e.g. right or left hand imaginary movement, is called positive $(+)$ or negative $(-)$ class. The task is to predict the class label for a single trial X.

In this paper, we use a feature vector, namely *log-variance feature*, defined as follows:

$$\phi_j(X;\boldsymbol{w}_j,\boldsymbol{\alpha}^{(j)}) = \log\sum_{k=1}^{T}\alpha_k^{(j)}\boldsymbol{w}_j^{\mathrm{T}}V_k\boldsymbol{w}_j \qquad (j=1,\ldots,J), \tag{1}$$

where $\boldsymbol{w}_j \in \mathbb{R}^d$ is a spatial projection that projects the signal into a single dimension, $\boldsymbol{\alpha}^{(j)} = \{\alpha_k^{(j)}\}_{k=1}^T$ is the spectrum of the temporal filter, which is homogeneous ($\alpha_k = 1\,\forall k$) in the case of conventional CSP algorithm, and $V_k := \hat{\boldsymbol{x}}_k\hat{\boldsymbol{x}}_k^{\dagger} \in \mathbb{C}^{d\times d}\,(k=1,\ldots,T)$ are the cross-spectrum matrices. The training of a classifier is composed of two steps. In the first step, the coefficients $\boldsymbol{w}_j$ and $\boldsymbol{\alpha}^{(j)}$ are optimized. In the second step, the Linear Discriminant Analysis (LDA) classifier is trained on the feature vector.

Since the covariance matrix of the temporally filtered signal can be written as $V(\boldsymbol{\alpha}) := \sum_{k=1}^T \alpha_k V_k$, we solve the following problem for the optimization of the spatial projection[1]:

$$\max_{\boldsymbol{w}\in\mathbb{R}^d} \quad \frac{\boldsymbol{w}^{\mathrm{T}}\langle V(\boldsymbol{\alpha})\rangle^{+}\boldsymbol{w}}{\boldsymbol{w}^{\mathrm{T}}\langle V(\boldsymbol{\alpha})\rangle^{-}\boldsymbol{w}}.$$

Writing the spectrum of the spatially projected signal as $\{s_k(\boldsymbol{w})\}_{k=1}^T$, we set the spectral coefficients $\boldsymbol{\alpha} = \{\alpha_k\}_{k=1}^T$ as follows:

$$\alpha_k \propto \begin{cases} \frac{\left(s_k^{(+)}-s_k^{(-)}\right)\left(s_k^{(+)}+s_k^{(-)}\right)}{v_k^{(+)}+v_k^{(-)}} & \text{if } s_k^{(+)}-s_k^{(-)}>0 \\ & \text{and } k\in I_{[7,30]}, \\ 0 & \text{otherwise,} \end{cases}$$

where $I_{[7,30]}$ is the set of DFT indices corresponding to 7-30Hz, and the following short hands are used: $s_k^{(c)} := \langle s_k(\boldsymbol{w})\rangle^c$ and $v_k^{(c)} := \mathrm{Var}\left[s_k(\boldsymbol{w})\right]^c$.

[1] Angled brackets $\langle\cdot\rangle^c$ denote expectation within a class $c \in \{+,-\}$.

Since both the spatial projection and the spectral coefficients depend on the other, we alternately update them starting from a CSP with homogeneous spectral filter. The process is illustrated in Fig. 1.

RESULTS

Figure 2 shows the improvements in the 10×10 cross-validation error by iteratively updating spatio spectral filter for six subjects. We use the log-variance feature (Eq. (1)) with $n_{\text{of}} = 3$ features for each class and LDA as a classifier. The odd steps correspond to the spatial projection updates; the even steps are spectral updates. Although major improvements were often observed at the second step (spectral update), further improvements were also observed after the third step (CSP recalculation). For some subjects (e.g., in subject F) systematic increases in the cross-validation errors were observed.

Table 1 shows the comparison of test errors of four algorithms, namely CSP[1], CSSP [2], CSSSP [3], and the proposed method. Here, the validation was done in the chronological manner, i.e., all methods were trained on the first half of the samples and applied on the remaining half. The time-lag parameter τ for CSSP and the regularization constant C for CSSSP were chosen by cross validation on the training set (see [2, 3]).

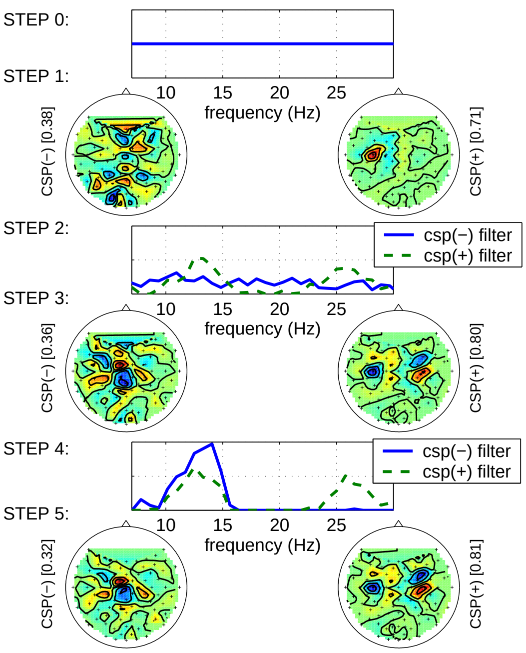

Figure 1: The topographical pattern of the CSP projection and the spectrum of the filter are shown for each step of iteration for a Left (−) vs. Foot (+) dataset. The iteration starts from a homogeneous spectral filter (step 0) and the spatial projection and spectral filter are updated alternately (step 1-5). Note that although we use $n_{\text{of}} = 3$ features for each class, only the top patterns are shown here for the visualization purpose.

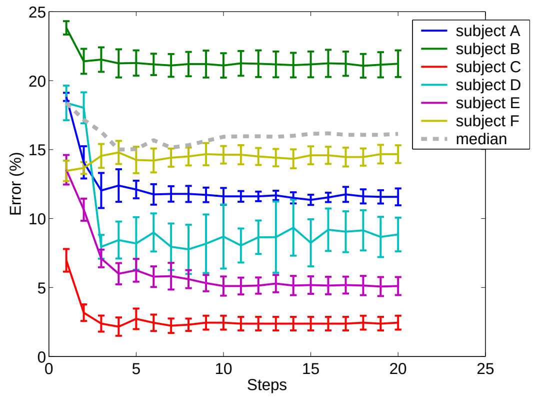

Figure 2: The cross-validation error at each step of iteration is shown for six subjects. The median over 162 datasets is also shown (dashed line). The odd steps and the even steps correspond to spatial projection updates and the spectral filter updates, respectively. Note that the first step is the CSP with white spectral filter over 7-30Hz.

	CSP (7-30Hz)	CSSP	CSSSP	proposed (20 steps)
25%-tile	10.6	6.67	7.00	8.00
median	23.8	21.1	21.0	19.7
75%-tile	35.8	33.6	36.4	35.3

Table 1: The 25%-tile point, the median, and the 75%-tile point of chronological test errors over 162 datasets are shown for CSP, CSSP, CSSSP, and the proposed method.

CONCLUSION

We have proposed a spatio-spectral filter optimization algorithm for the single trial EEG classification problem; the method is based on iterative updates of spectrally weighted CSP and the spectral coefficients. The validation results on 162 BCI datasets show that the proposed method outperforms wide-band filtered CSP [1] and gives comparable results with CSSP [2] and CSSSP [3] with far less computational cost.

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