Common Spatial Pattern Patches - an Optimized Filter Ensemble for Adaptive BCIs

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Abstract. The use of an ensemble of local Common Spatial Patterns (CSP) patches (CSPP) is proposed, which can be considered as a compromise between Laplacians and CSP: CSPP reaches a robust performance with less training data than CSP, while being superior to Laplacian filtering. This property is shown to be particularly useful for the co-adaptive calibration design and is demonstrated in combination with on-line adaptation, on off-line calibration data of 80 naïve users.

Keywords: Spatial Filtering; Common Spatial Patterns; Robust systems; On-Line Adaptation.

1. Introduction

Laplacian filters are commonly used in Brain Computer Interfacing (BCI). Especially when data from few channels are available, or when, like at the beginning of an experiment, no previous data from the same user are available to train more complex algorithms, the band power calculated on Laplacian filtered channels represents an easy, robust and general feature to control a BCI, since its calculation does not involve any class information. Due to practical constraints, long multi-channel recordings might be difficult to realize and researchers have investigated ways to allow good performance with just a little amount of calibration data [Lotte and Guan, 2010] or with subject-independent spatial filters and classifier. Usually, the performance obtained with Laplacian features is poor in comparison to subject-specific optimized spatial filters, such as Common Spatial Patterns (CSP) analysis, which, on the other hand, can only be used just in a later phase of the experiment, since they require a considerable amount of training data in order to enroll a stable and good performance. Therefore, Laplacian filtering is preferred to CSP [Blankertz et al., 2008], e.g., in the initial period of co-adaptive calibration [Vidaurre et al., 2010], a novel BCI paradigm designed to alleviate the problem of BCI inefficiency. Here, we propose a novel spatial filter that can be considered as a compromise between Laplacian and CSP filters. Since it consists of an ensemble of local “CSP patches” the method is called CSPP. The performance of CSPP in combination with online-adaptation is validated and compared with Laplacian filters and standard CSP. CSPP results in a significantly better performance.

2. Material and Methods

2.1. Experimental Setup

We used 80 BCI motor imagery data sets. All experiments belong to the study described in [Blankertz et al., 2010], each data set was acquired in one single session and all users were BCI novices. To obtain a fair comparison among the three investigated spatial filters, just the calibration data are used in this study.

2.2. Common Spatial Patterns Patches (CSPP)

CSPP is the application of CSP analysis to small sets of channels (patches), and the combination of the resulting features. CSPP can be thought as a Laplacian filter, where the weights assigned to each involved channel are optimized instead of being fixed. The application of CSP on groups of few channels reduces the risk of over-fitting in comparison to a CSP computed in all channels, because the number of parameters to fit for each patch is less. The patches can include a different number of
surrounding channels and also the position of the patches can be chosen. A preliminary study [Sannelli et al., 2010] showed that a patch containing 18 channels results to be very robust with very little training set. Here, we use that configuration and center each patch on 18 different locations on the scalp (with a total number of 73 channels). A Laplacian filter is calculated using the same channels as the corresponding CSP patch, and CSP is calculated using all the channels of the different patches together. At the beginning of the experiment no subject-specific parameters can be calculated, therefore a broad frequency band which includes both \( \mu \) and \( \beta \) bands (8-35 Hz) and a fixed time interval (750-3750 ms after stimulus presentation) were used. Starting from 20 trials, an online simulation was carried out, where spatial filters and a shrink Linear Discriminant Analysis (shrinkLDA) classifier were re-trained after each trial. In particular, for CSPP, one filter per class and patch is calculated choosing the extreme eigenvalues, i.e. two filters per patch are obtained. Then, the six most informative features are chosen. Six features are also selected for CSP and Laplacians.

3. Results

Results are shown in Fig. 1. It can be observed that CSPP performs significantly better than Laplacian filters and CSP, \( p=10^{-11} \) against Laplacians, \( p = 0.03 \) against CSP using a Wilcoxon signed rank tests for equality of medians). Also the percentage of users where each method performs better is shown.

![Figure 1. Comparison of CSPP performance against Laplacian and CSP filters. Each point is the performance for one user, for each point above the line CSPP performs better than Laplacian resp. CSP.](image)

4. Discussion

The classical BCI machine learning approach requires a calibration session where data are acquired in order to train complex algorithms that can then decode the brain activity during the feedback application Here we have shown that CSPP is a data-driven approach that, unlike CSP, only needs very few data to be tuned. Moreover, in the context of co-adaptive calibration, CSPP can be used in combination with on-line adaptation, to allow local spatial flexibility to adjust the system to possibly changing SMR modulations.

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References


