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Slow Feature Analysis as a Potential Preprocessing Tool in BCI

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Abstract. Here we present initial results of the unsupervised preprocessing method Slow Feature Analysis (SFA) for a BCI data set. It is the first time SFA is applied to EEG. SFA optimizes the signal representation with respect to temporal slowness. Its objective as well as its computational properties render it a possibly useful candidate for the preprocessing of BCI EEG data in order to detect task relevant components as well as components that represent artifacts or non-stationarities of the background brain activity or external sources.

Keywords: Brain-Computer Interface, BCI, SFA, slow feature analysis, slowness, unsupervised preprocessing

1. Introduction

In order to robustly classify single-trial EEG data in Brain-Computer Interface (BCI) applications, the data is often projected (e.g. by PCA or CSP) into a new data space before it is classified. The recently developed Slow Feature Analysis (SFA) [Wiskott and Sejnowski, 2002] decomposes the recorded signal according to the temporal variability of the assumed sources. Undesirable EEG components can be either slower (e.g. non-stationarities reflecting changes in the level of attention) or faster (e.g. eye artifacts) than task related components. Given that relevant signal components act on different time scales, it is likely that incorporating an SFA step in the data analysis to project out undesired components proves beneficial. Yet, to our knowledge, SFA has neither been applied in the BCI context nor for the analysis of EEG data.

2. Material and Methods

2.1. Slow Feature Analysis

SFA is an unsupervised learning algorithm that finds a set of scalar functions of the data whose outputs vary slowly in time (slowness objective) and are mutually uncorrelated. SFA was first presented in [Wiskott and Sejnowski, 2002] and we refer to this publication for further details on the algorithm. It is important to note that the objective is not achieved by low-pass filtering in the time domain, the obtained functions are instantaneous in time. The close relationship between linear SFA and a specific type of ICA is discussed in [Blaschke et al., 2006].

2.2. EEG Data

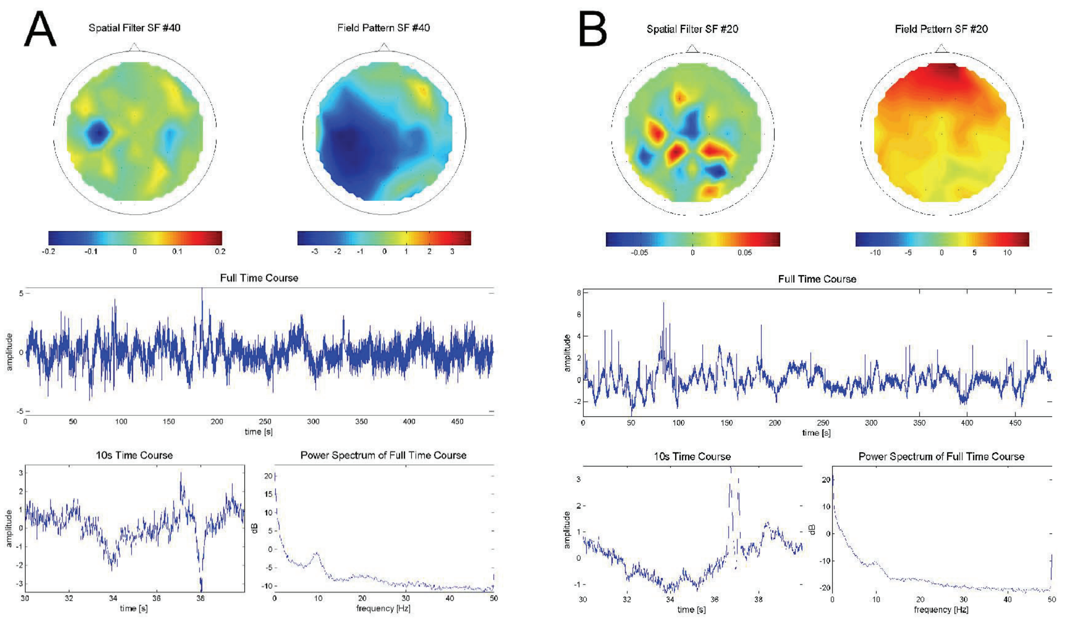
The EEG data consisted of about 20 minutes of continuous 62 channel recordings, acquired from one BCI-naive subject during 160 randomized executions of two motor imagery tasks. The subject was instructed to imagine movements of the right hand in one condition and movement of both feet in the other condition.

3. Results

Fig. 1 shows two example components found by SFA, which lend themselves well to interpretation. Component **A** corresponds to an assumed source over the left motor cortex, which was activated for the right hand motor imagery. Its spectrum indicates rhythmic activity in the alpha band, which – given the spatial distribution of **A** – can be interpreted as a mu rhythm of the motor cortex. However, the time series of A represents a mixture of mu and slower activity. Component **B** is a nice example of a strong eye artifact source. If clean data is necessary, it can be projected out by linearly reconstructing the original data without

component **B**. A thorough screening of the 62 SFA components shows, that a considerable number of them contains mixtures of typical EEG sources instead of single sources. For example, alpha activity is contained in several components besides component **A**, and eye artifacts are found also in a few other components, even though with smaller energy than in component **B**.
Projecting the data on a suitable subset of the SFA components can improve classification performance. The offline analysis of the presented data set revealed, that the error of a CSP-based regularized LDA classifier [Blankertz et al., 2008] could be reduced from 25.2% to 20.7% MSE (estimated

Figure 1. *Two example SFA components.* ***A*** *and* ***B****: Spatial filter and corresponding scalp pattern (top row), full 8*



minute time course of the projected signal (second row), 10 second excerpt of the full time course (third row, left), and power spectrum of the full time course (third row, right). The polarity of the filters and field patterns is arbitrary.

by random 5 shuffles of a 15-fold cross-validation). The error decrease was gained by discarding the 20 slowest SFA components and using only the remaining components for CSP calculation.

4. Discussion

The presented single-case analysis is promising but the generalization of these results of course has to be tested for larger data collections. For SFA to become a useful tool in the context of BCI data analysis a number of issues have yet to be resolved: First of all an automated component-selection mechanism is needed. Only after the components can be reliably separated into task related and artifact related, SFA can become useful for classification as well as artifact removal. In both domains, however, SFA would have to withstand extensive comparisons with already established methods such as CSP and ICA based methods. Non-linear and therefore potentially more powerful extensions of SFA exist. The results obtained here justify further investigation into the applicability of SFA and its variants to BCI EEG data.

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