Removal of muscular artefacts for the analysis of brain oscillations: Comparison between ICA and SSD

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Abstract

The electroencephalogram (EEG) is contaminated by undesired signals of non-neural origin, such as movements of the eyes and muscles. The most common approach for muscle artefact reduction is the linear transformation of EEG signals into source components using Blind Source Separation (BSS) techniques, to separate artefactual and neuronal sources.

Here we present a case study in which we are interested in clean oscillatory EEG activity. We compare the frequently used Independent Component Analysis (ICA) approach with the recently proposed spatio-spectral decomposition (SSD) method. SSD is designed to extract components that explain oscillations-related variance, and is several orders of magnitude faster than ICA. We investigate EEG data from 18 subjects performing self-paced foot movements with respect to event-related desynchronisation (ERD) in the beta band. Results indicate that SSD recovers cleaner signals than ICA on this data set.

1. Introduction

As the interpretation of electroencephalographic (EEG) signals depends on relatively clean recordings, artefact reduction is an important step in EEG signal processing. These artefacts are caused by non-neural physiological activities of the subject, such as movements of the eyes and muscles, heart beat and pulse, or by external technical sources.

The most common approach for muscle artefact reduction is the linear transformation of EEG signals into source components with techniques of Blind Source Separation (BSS), the most frequently used being Independent Component Analysis (ICA). If artefactual and neural activity are contained in separate components, artefactual components can be identified and a cleaner EEG can be reconstructed.

The assumptions for the application of ICA methods are only approximately met in practice (linear mixture of independent components, stationarity of the sources and the mixture, no systematic co-activiation of artefacts and neuronal signals). Nevertheless, their application usually leads to a good separation (Crespo-Garcia et al., 2008; McMenamin et al., 2010). However, separation is usually not perfect and a number of mixed components contain both neural and artefactual activity. While several methods try to alleviate this issue, ICA remains the state-of-the-art (see e.g. (Vigario & Oja, 2008; Urigüen & Garcia-Zapirain, 2015) for a review).

In this paper, we are interested in obtaining clean *oscillatory* EEG activity. We present evidence that in some cases, the recently developed spatio-spectral decomposition (SSD) method (Nikulin et al., 2011), which extracts components explaining oscillations-related variance, may achieve better artefact reduction than ICA.

We investigate Event-Related Desychronisation (ERD), that is, the suppression of brain rhythms in response to an event, in a data set that is heavily contaminated by mus-

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cle artefacts. 18 subjects performed self-paced foot movements, which are well known to be preceded by an ERD of 8-13 Hz (mu band) and 15-30 Hz (beta band) rhythms over corresponding sensorimotor areas (Neuper & Pfurtscheller, 2001). Here we focus on beta ERD, which is thought to be related to movement preparation and execution (Kilavik et al., 2013).

2. Methods

2.1. Data

Data stem from a pre-measurement of a simulated driving experiment described in (Haufe et al., 2011). 18 healthy participants were instructed to perform self-paced right foot movements (i.e. to press the brake pedal) once per second for five minutes. EEG data were recorded with 64 Ag/AgCl electrodes at 1000 Hz. Furthermore, an electromyographic (EMG) signal was recorded using a bipolar montage at the tibialis anterior muscle and the knee of the right leg. For the presented offline-analysis, EEG data were decimated to 200 Hz, broad-band filtered between 2 and 45 Hz, and artefactual electrodes were rejected using a variance criterion.

2.2. Compared methods

We compare two methods of blind source separation (BSS) for artefact reduction. BSS is the task of recovering underlying signals $S \in \mathbb{R}^{K\times T}$ from multivariate recordings $X \in \mathbb{R}^{M\times T}$ generated from the linear model $X = AS$, with very little information about the underlying source signals S or the mixing process $A \in \mathbb{R}^{M\times K}$. The problem is underdetermined and can only be solved using assumptions about the signals to be recovered. A demixing matrix $\hat{W} \in \mathbb{R}^{K\times M}$ is estimated such that the estimated sources

$$\hat{S} = \hat{W}X \tag{1}$$

best fulfil pre-defined assumptions.

In BSS-based artefact reduction we then hope that artefactual and neuronal activity are contained in different source components, so that cleaner EEG signals can be reconstructed by omitting the artefactual signals.

2.2.1. ICA

The most common approach for artefact reduction is Independent Component Analysis (ICA), which solves the BSS problem under the assumption of mutually statistically independent sources.

Here we applied FastICA (Hyvärinen & Oja, 1997) to EEG signals whose dimensionality was reduced with Principal Component Analysis (PCA) to 99.9% explained variance. We then manually selected artefactual components, based on the pattern, spectrum and time course of each component. On average per subject, 14 components were identified as artefacts, and cleaner EEG signals were reconstructed with the remaining 17 components. For a description of typical artefact components we refer the reader to (Chaumon et al., 2015).

2.2.2. SSD

The purpose of spatio-spectral decomposition (SSD) (Nikulin et al., 2011) is to extract brain oscillations in a frequency band of interest. It maximizes the signal power in a frequency band of interest (here: 15 - 30 Hz) while simultaneously minimizing it at the neighbouring frequency bins (here: 13-14 Hz, 31-32 Hz). SSD seeks spatial filters $\mathbf{w} \in \mathbb{R}^k$ which maximize

$$\text{SNR}(\mathbf{w}) = \frac{\mathbf{w}^\top \Sigma_{\text{sig}} \mathbf{w}}{\mathbf{w}^\top \Sigma_{\text{noise}} \mathbf{w}} \tag{2}$$

where Σ_{sig} is the covariance of the data filtered in the frequency band of interest and Σ_{noise} is the covariance of the data filtered in the sidebands. The entire SSD demixing matrix can be computed by solving a generalised eigenvalue problem in a matter of seconds (Nikulin et al., 2011; Haufe et al., 2014).

For the subsequent analysis, we retained the 10 components with the highest SNR, as in (Dähne et al., 2014; Winkler et al., 2015). This choice of 10 SSD components was based on prior experience.

2.3. Event-Related Desynchronisation

SSD and ICA were independently applied to the continuous EEG data. To compare the methods, we plot grand-average Event-related (de-)synchronisation (ERD/ERS) in the beta band (15 - 30 Hz), aligned to EMG peak activity.

ERD is computed as the relative difference in signal power of a certain frequency band compared to a reference period (Pfurtscheller & Aranibar, 1979; Blankertz et al., 2008):

$$\text{ERD}(t) = \frac{\text{Power}(t) - \text{Reference power}}{\text{Reference power}} \tag{3}$$

We use the interval of [-1200 -800 ms] prior to EMG peak activity as the reference interval.

3. Results

Grand-average ERDs for the three different preprocessing variants (Nothing, SSD and ICA) are depicted in Fig. 1. Prior to foot movement, we see a typical foot ERD over central sensorimotor areas as expected (cf. (Neuper & Pfurtscheller, 2001)). During movement, the ERD is contaminated by a muscular artefact which spans the whole

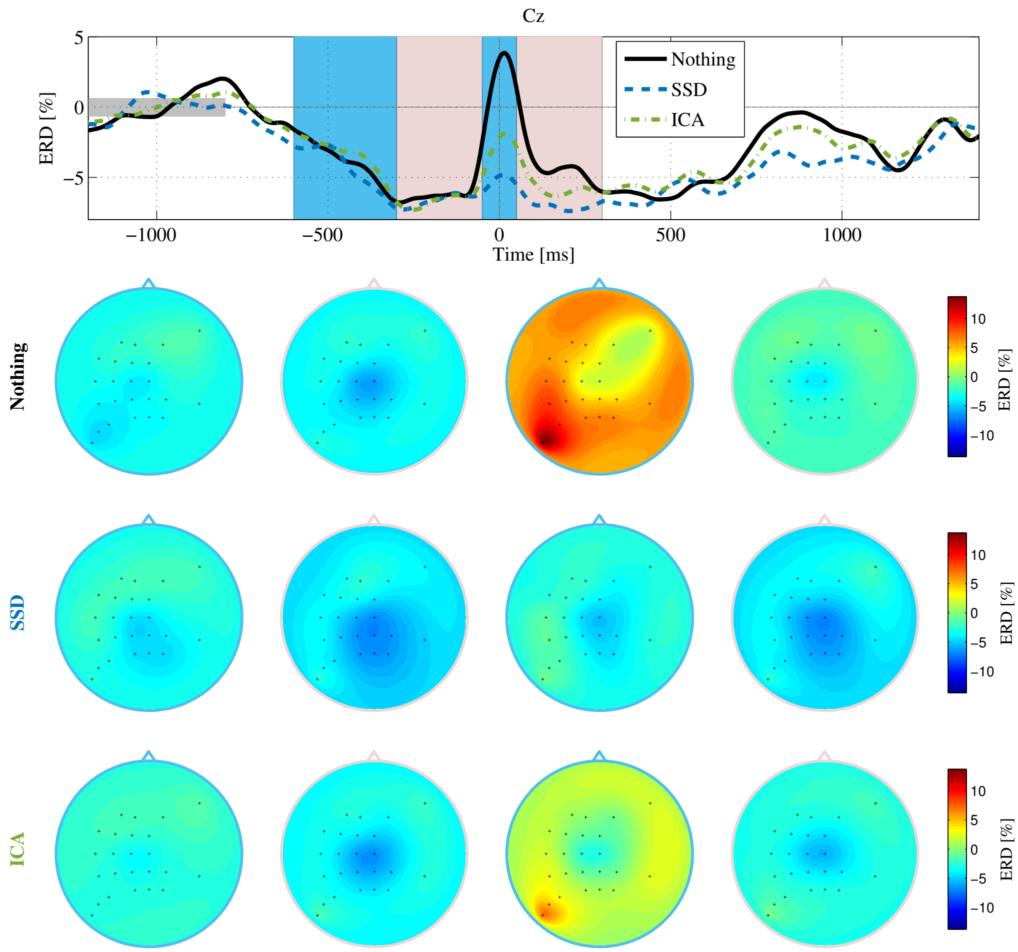

Figure 1. Grand-average ERD/ERS for 18 subjects recorded during self-paced foot movements in the beta band (15-30 Hz), aligned to EMG peak activity. The plots show time courses at channel Cz and series of ERD maps for three conditions: No pre-processing, SSD pre-processing (10 components with highest SNR as defined in Eq. (2) were retained) and ICA-based artefact removal (manually selected neural components were retained).

scalp. This is probably due to subjects moving their heads along with the fairly rhythmical foot movement once per second.

This muscle artefact is reduced after a preceding ICA-based artefact removal step. ERD is even cleaner when SSD was applied. SSD is able to almost completely eliminate the artefact, without removing neural beta activity.

4. Discussion

We presented preliminary evidence that SSD may be a powerful tool for the removal of artefacts in EEG data, when the neural signals of interest are of oscillatory nature. Compared to ICA, SSD is much faster to compute (seconds vs. minutes), and recovered a cleaner grand-average ERD on the self-paced movement data set we analysed here.

Our findings are in line with findings in Motor Imagery based Brain-Computer-Interfaces (BCI), where SSD improved classification performance (Haufe et al., 2014). In contrast, applying two different ICA methods (Bell & Sejnowski, 1995; Ziehe et al., 2004) in combination with two different automatic artefactual component classifiers (Frøhlich et al., 2015; Winkler et al., 2014) on the same data set, did not (Winkler et al., 2014; Frølich et al., 2015).

SSD is especially designed to increase the signal-to-noise ratio of oscillatory sources, and it is therefore not surprising that it can be more suitable to separate artefacts (=noise) from oscillatory neuronal signals. In the EEG data presented here, the observed muscle artefacts are also not occurring independently from motor planning neuronal activity, which violates ICA's assumptions. However, the coactiviation of artefacts and neuronal activity is quite common, and often poses the most serious problems in practice. In those cases, ICA is often applied anyway, due to lack of better alternatives and/or satisfactory performance. SSD also assumes uncorrelated sources, but seemed to be able to better separate correlated artefacts by using information about the neuronal sources' expected frequency content.

The findings presented here are subject to future research. Interestingly, while SSD outperforms ICA in terms of identifying the subspace that contains the relevant neural activity, ICA was better at extracting a single motor preparatory source component on the same data set (cf. (Winkler et al., 2015)). Another point is that ICA separation quality depends on pre-processing steps such as high-pass filtering. It remains to be seen whether stronger high-pass filtering would improve ICA's performance. An open question is also how many components to choose for SSD.

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