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Artifact-Insensitivity of CSP in Motor Imagery BCI

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Abstract. While Brain-Computer Interfaces (BCIs) should generate control commands based on neural activity only, the electroencephalogram contains artifacts such as eye-or muscle activity, and healthy subjects might use those (sub-)consciously for BCI-control. We analyze the influence of an automatic, subject independent artifact reduction step on the performance of a motor imagery setup that uses Common Spatial Patterns. The offline test conducted on data from 80 subjects revealed no performance drop of the Berlin Brain-Computer-Interface after rigorous artifact reduction based on Independent Component Analysis (ICA).

Keywords: Artifact Removal, EEG, Brain-Computer Interface (BCI), Independent Component Analysis (ICA), Motor Imagery, Common Spatial Patterns (CSP)

1. Introduction

Brain Computer Interfaces (BCIs) are devices which translate brain signals directly into control commands. For motor imagery BCI paradigms, the method of Common Spatial Patterns (CSP) for spatial filtering is a widely used preprocessing step. While neurological phenomena should be the only source of control in BCI systems, signals of the electroencephalogram (EEG) also contain artifacts such as eye blinks, eye movements and muscle activity in the vicinity of the head (e.g. of face muscles, jaws, tongue). High sensitivity of a BCI system for artifacts is considered problematic as BCI systems are typically developed for people with severe motor disabilities, but are usually tested on healthy subjects, who might intentionally or unconsciously use artifacts for BCI control.

One common approach for EEG artifact reduction uses Independent Component Analysis (ICA). Based on the idea that artifactual signal components and neural activity are generated independently, EEG signals are linearly transformed into a space of independent source components. After neural sources are selected, the EEG is reconstructed ideally without the artifactual sources.

While the problems artifacts can cause in BCI systems are widely recognized, most BCI papers do not report on if or not they consider muscle and eye artifacts in their analysis [Fatourechi, et al., 2007]. Here we compare the standard Berlin Brain Computer Interface procedure for motor imagery paradigms [Blankertz et al., 2009] with an ICA-based artifact reduction preceding the procedure.

2. Material and Methods

Eighty healthy BCI-novices performed motor imagery first in a calibration measurement (i.e. without feedback). During the experiment, a classifier was trained using CSP analysis. While subjects could control a 1D cursor application during a feedback measurement [Blankertz et al., 2009], the present study is based on an offline re-analysis of the data only, and the original classifier was not used.

The parameters for the artifact reduction were determined on the calibration data as described in the following. To avoid the artificial split of signal components due to the high dimensionality of the data, the separation of the EEG signals by ICA was preceded by a dimensionality reduction from about 90 EEG channels in the sensor space into k=30 PCA components. This choice of k was based on previous experience, but was probably not the optimal choice. We used the TDSEP algorithm [Ziehe and Müller 1998] to transform the 30 PCA components into 30 independent source components. An automatic, subject-independent method to classify the 30 independent source components as artifactual or neural sources was applied [Tangermann et al., 2009], where a classifier **A** had been trained on EEG data collected during a completely different study to discriminate artifacts from neural sources. Based on **A**'s output, which was used as a surrogate for the probability of being an artifact, the components were ranked. Retaining a smaller or larger number of sources corresponds to an either very strict or soft policy for the removal of potential artifactual sources. We retained 6 to 30 source components which most probably were true neural sources, and removed the others. Based on the remaining (band-pass filtered) sources, spatial CSP filters were determined and the log-variance of the spatially filtered signals were exploited to train a regularized linear classifier **B**, as it is typically used for BCI.

The application to the feedback measurement in a manner that allows for real-time BCI applications is straightforward: After un-mixing the original data according to the ICA filters determined on the calibration measurement, the previously determined 6 to 30 sources were selected for band-pass and CSP filtering and log-variance determination in order to form the test data features. To estimate the influence of the artifact reduction step on BCI performance, we compared the performance of classifier **B** (depending on the number of selected sources) with the standard CSP procedure using no artifact reduction.

3. Results

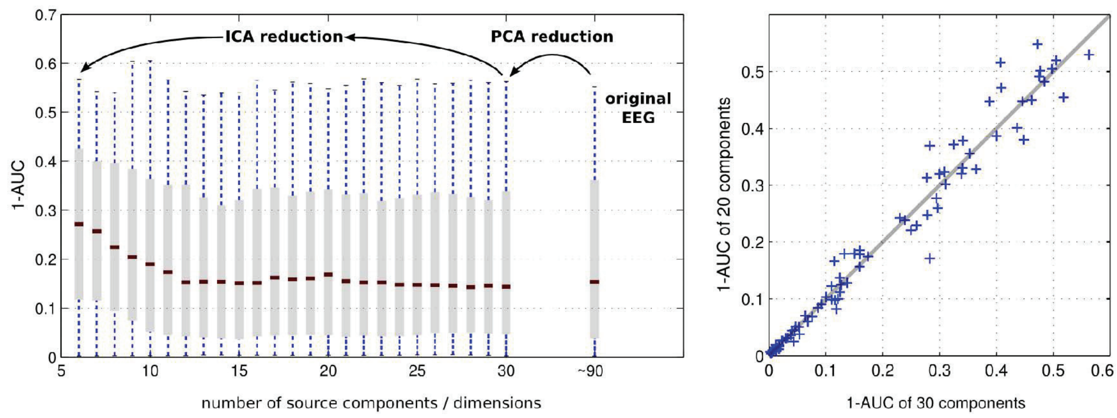

Figure 1. *Influence of ICA-based artifact reduction in a motor imagery BCI tested with 80 subjects. Left: box plot of classification errors (1-AUC) against the number of remaining independent sources compared with no artifact reduction. Right: scatter plot of classification errors (1-AUC) of each subject when removing 10 source components vs. using all 30 source components.*

Visual analysis of the ranking of source components revealed a high accuracy of classifier **A**. Following the ranking of very probable artifacts to less probable artifacts, the inspection resulted in clear artifactual components to components that contained mixtures of neural and artifactual activity. Figure 1 (left) plots 1-AUC (as a measure of the classification error) against the number of remaining independent components, including one entry for the standard procedure without artifact reduction. It can be observed, that reducing the dimensionality of the data to 30 dimensions by PCA does not affect BCI performance. Moreover, consecutively removing components does not impair BCI performance at first, as these are artifactual components according to the classifier. Performance breaks down only when a strict removing policy is applied and less than about 12 sources (out of 90 original channels) are retained, which have been ranked as neural sources by classifier **A**.

4. Discussion

The present results can only be interpreted carefully, as the performance of the artifact classifier used is a crucial factor. Assuming that the artifact classifier shows a performance comparable to [Tangermann et al., 2009], it can be stated, that the removal of artifactual sources did not impair the overall classification performance of the Berlin Brain-Computer Interface during the motor imagery task for 80 subjects. Interpreting Fig. 1 (right) features the explanation, that for subjects with very good classification rates, artifacts did not play any role, whereas in other subjects, artifacts either obstruct the relevant neural activity or improve performance. However, as the performance changes induced by artifact removal are very small, CSP seems to use very few information from artifactual signal components in general.

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