

Slow Sphering to Suppress Non-Stationarities in the EEG

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Abstract. Non-stationary signals are ubiquitous in electroencephalogram (EEG) signals and pose a problem for robust application of brain-computer interfaces (BCIs). These non-stationarities can be caused by changes in neural background activity. We present a dynamic spatial filter based on time local whitening that significantly reduces the detrimental influence of covariance changes during event-related desynchronization classification of an imaginary movement task.

Keywords: brain-computer interface, non-stationarities, electroencephalogram, common spatial patterns.

1 Introduction

A big challenge for current brain-computer interfaces (BCIs) is the non-stationary nature of electroencephalogram (EEG) signals. The machine learning methods used to train the BCI often assume that the training data is sampled from the same distribution as the data that will be observed during online application which can result in a degradation in the performance of the BCI during online sessions, and prevents the effective use of a single BCI model for different sessions. These non-stationarities are often attributed to differences in the mental state of the subject [Blankertz et al., 2007, Shenoy et al., 2006].

Shenoy et al. [2006] demonstrated that the distribution of task-relevant features change during the transition from off-line to online operation due to differences in background activity. The main result of these changes is that the class distributions shift in feature space; supervised adaptation of the bias at the beginning of the feedback session significantly reduced the error rate in the feedback session. Vidaurre et al. [2008] explored different online adaptation schemes for a linear discriminant analysis (LDA) classifiers. Among the unsupervised options were recursive tracking of the shared covariance and tracking of the means of the EEG features (unsupervised bias adaptation). Unsupervised adaptation of the means outperformed a static classifier, but between the two methods there was no significant difference.

In the above studies the classifier is adapted to the non-stationarities but the feature extraction remains fixed. The spatial filters used to extract features — such as common spatial patterns (CSP) — can be adapted to varying sources as well. Tomioka et al. [2006] propose to adapt spatial filters based on the assumption that the spatially whitened features remain stationary from session to session: the spatial filter is separated in a whitening transformation P and a projection transformation B :

$$W = BP, \quad P = U\Lambda^{-\frac{1}{2}}U^T \quad (1)$$

with eigenvectors U and eigenvalues Λ of the channel covariance matrix. After training the classifier on a training block, a new spatial filter is constructed by replacing the whitening transformation by a new whitening transformation that is learned from the test set in an unsupervised manner. This adaptation is equivalent to block-wise whitening of the data.

2 Slow sphering

In this article, we propose the slow sphering (SS) transform, which combines the continuous, causal updating of Vidaurre et al. [2008] with the filter adaptation of Tomioka et al. [2006]: a locally estimated covariance matrix is used to whiten the data locally based on only past observations. We categorise non-stationarities in two distinct groups: natural fluctuations in the task-relevant neural sources, and fluctuations in non task-related sources (background activity). Power fluctuation in the target sources can be reduced by bias adaptation if the fluctuations drift slowly over time, or equivalently by scaling the spatial filters. The second type of non-stationarities is caused by changes in the synchrony of background activity. While changes in the magnitudes of the noise sources are filtered out to some extent, changes in the synchrony of noise sources can severely affect the filtered signals:

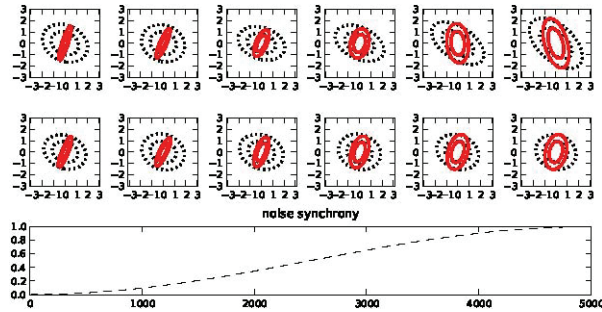


Figure 1: The effect of the simulated synchronization of two noise sources on two normal distributions fitted to the whitened class distributions (first row) and to the class distributions after slow sphering (second row) as observed by two sensors (x-and y-axis respectively). The density of the first class is indicated with dashed contour lines, the second with red lines. The last row displays the synchrony of the two noise sources.

Consider two artificial unsynchronized noise sources and target source whose power correlates with the task, positioned on a straight line below two sensors. Over time, the noise sources synchronize, resulting in a changing covariance in the recorded signal. When a whitening transform is trained on the first half of the data, the changing covariance caused by the synchronizing sources results in both a change in scale and orientation of the class distributions (first row of Fig. 1). If a single CSP spatial filter is trained on this whitened distribution, bias adaptation is not sufficient to recover from this change; the direction of the spatial filter needs to be adapted as well.

The effect of the non-stationarity described in the previous section can be reduced by using a locally estimated whitening transform W_t that varies slightly slower than the features of interest. We use regularized covariance estimates for blocks of one second to estimate W_t , and use an exponential moving average with a forgetting factor of 0.95 to remove fast fluctuations that might contain class-relevant information. In contrast to static whitening, the SS transformed distribution remains spherical when the noise sources synchronize (second row of Fig. 1), and the optimal projection direction remains approximately constant in this specific example.

We applied the SS method to dataset 4a of the BCI competition III in a standard event-related desynchronization (ERD) pipeline: bandpass 8–30 Hz, slow sphering, CSP, log-variance features and followed by a linear support vector machine (SVM), and evaluated both a pipeline with SS enabled and SS disabled with chronological 2-fold cross-validation. The slow-sphering transform reduced the mean error rate by a factor of 11% (from 13.2% to 11.7%) which is statistically significant ($p=0.03$ with a one-sided Wilcoxon signed-rank test). Because the second (static) whitening transform is redundant when SS is enabled, we can conclude that there is a non-stationarity in the data that SS attenuates.

3 Conclusions

We presented an adaptive spatial filtering approach to suppress non-stationarities that can both adapt to bias changes, as well to some directional changes in filter space, and have shown that adaptive filtering improves the performance on a real BCI dataset. In contrast to approaches that adapt the classifiers, the slow sphering can be used with different types of classifiers and can even be used for traditional analyses, e.g. ERP plots and spectral analyses.

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