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Prediction of cognitive states using MEG and Blind Source Separation

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Abstract. The present study investigates the predictability of a subject's state based on the classification of the underlying brain activity recorded via magnetoencephalography (MEG). We use Second Order Blind Identification (SOBI) to reduce the high dimensionality of MEG sensors into a smaller number of task-related components. A classification of distinct cognitive states is then achieved by feeding the spectral power of these components into a Support Vector Machine (SVM). We tested this approach on data from one subject during a visuomotor control experiment and found that our method outperforms classification based on the spectral powers computed directly from the MEG sensor array. Our findings suggest that combining SOBI and SVM may provide a reliable classifier for the prediction of cognitive states in MEG. © 2007 Elsevier B.V. All rights reserved.

Keywords: Magnetoencephalography (MEG); Blind Source Separation (BSS); Second Order Blind Identification (SOBI); Support Vector Machine (SVM); Visuomotor control

1. Introduction

The prediction of cognitive states is crucial to applications such as Brain Computer Interfaces (BCI). We investigated this problem using magnetoencephalography (MEG) for the classification of continuous cognitive tasks.

Computing the power spectral densities of MEG sensors in selected frequency bands is a straightforward method to extract task relevant parameters for classification, but the high number of sensors leads to a high number of features that impairs classification accuracy. We

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solved this problem by applying a Blind Source Separation (BSS) technique to represent MEG sensor data as an instantaneous linear mixing of a restricted number of task relevant components. Second Order Blind Identification (SOBI) is a BSS technique particularly suitable to our problem since it allows retrieving uncorrelated components relying on their spectral properties [1,2]. Once a reduced number of task-related components had been determined using SOBI, the next step was to estimate the power spectral density of each one of these relevant components. The power values averaged over specific frequency bands were then processed by a classifier in order to differentiate between two cognitive tasks based on MEG recordings of the ongoing neural activity. To achieve good classification accuracy, we used the linear Support Vector Machine (SVM) classifier combined with variable selection.

2. Materials and methods

2.1. SOBI algorithm

We assumed that the vector of observed MEG signals $\mathbf{x}(t)$ (which is supposed centered to simplify notations) is an instantaneous linear mixing of a vector of uncorrelated components with unit variance $\mathbf{s}(t)$ such that $\mathbf{x}(t)=\mathbf{Ms}(t)$, where $\mathbf{M}$ is the mixing matrix. SOBI only uses MEG signals to compute both an estimated unmixing matrix $\mathbf{U}\approx\mathbf{M}^{-1}$ and the estimated time course of the components, $\hat{\mathrm{s}}(t)=\mathbf{Ux}(t)$. This estimate is achieved using information on temporal coherence of the wide-band (0–100 Hz in our case) MEG signals contained in the empirical delayed correlation matrices $\mathbf{R_x}(\tau_i)$ defined at many time delays $(\tau_i)_{i=1..D}$ such that:

$$\mathbf{R_x}(\tau_i)=\frac{1}{N-1}\sum_{n=0}^{N-1}\mathbf{x}(n)\mathbf{x}^T(n-\tau_i).$$

The algorithm we used proceeds in two steps:

- Whitening: the original MEG signals are transformed into whitened signals $\mathbf{z}(t)$ (uncorrelated components of unit variance) which are the first principal components of $\mathbf{x}(t)$ representing 99% of the total variance. This is achieved with a whitening matrix $\mathbf{Q}$ such that $\mathbf{z}=\mathbf{Qx}$.
- Approximate joint diagonalization of the delayed correlation matrices $\mathbf{R}_z(\tau_i)$ that aims at finding an orthogonal matrix $\mathbf{W}$ that jointly minimizes the magnitude of the off-diagonal terms of all the matrices $\mathbf{WR}_z(\tau_i)\mathbf{W}^T$. For our specific classification purposes we computed separately delayed correlation matrices for the signals corresponding to the cognitive state 1, $\mathbf{R}_z^1(\tau_i)$, and the cognitive state 2, $\mathbf{R}_z^2(\tau_i)$(τ_i ranging from 0 to 300 ms by steps of 2 ms), and included both matrix sets in the joint diagonalization.

2.2. Classification

The resulting estimated unmixing matrix $\mathbf{U}=\mathbf{WQ}$ was used to estimate the time course of the SOBI components and the distribution of each component on the scalp was given by each column of the estimated mixing matrix $\widehat{\mathrm{M}}\approx\mathbf{U}^+$ (the Moore–Penrose pseudo-inverse). The power spectra of these signals were then computed using the Welch periodogram on each