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 Published by Elsevier B.V.

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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...
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 \( x(t) \) (which is supposed centered to simplify notations) is an instantaneous linear mixing of a vector of uncorrelated components with unit variance \( s(t) \) such that \( x(t) = Ms(t) \), where \( M \) is the mixing matrix. SOBI only uses MEG signals to compute both an estimated unmixing matrix \( U \approx M^{-1} \) and the estimated time course of the components, \( \hat{s}(t) = Ux(t) \). 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 \( R_x(\tau_i) \) defined at many time delays \( \tau_i = \tau_1, \tau_2, \ldots, \tau_D \) such that:

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

The algorithm we used proceeds in two steps:

- Whitening: the original MEG signals are transformed into whitened signals \( z(t) \) (uncorrelated components of unit variance) which are the first principal components of \( x(t) \) representing 99% of the total variance. This is achieved with a whitening matrix \( Q \) such that \( z = Qx \).
- Approximate joint diagonalization of the delayed correlation matrices \( R_x(\tau_i) \) that aims at finding an orthogonal matrix \( W \) that jointly minimizes the magnitude of the off-diagonal terms of all the matrices \( WR_x(\tau_i)W^T \). For our specific classification purposes we computed separately delayed correlation matrices for the signals corresponding to the cognitive state 1, \( R_x^1(\tau_i) \), and the cognitive state 2, \( R_x^2(\tau_i) \) (\( \tau_i \) 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 \( U = WQ \) 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 \( \hat{M} = U^+ \) (the Moore–Penrose pseudo-inverse). The power spectra of these signals were then computed using the Welch periodogram on each

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successive 1-s time windows of the MEG recordings. The average power obtained for each one of six distinct frequency bands (δ: 2–4 Hz, θ: 5–7 Hz, α: 8–12 Hz, β: 13–30 Hz, γ₁: 30–60 Hz, γ₂: 60–90 Hz) provided the final quantification associated with each time window. A learning set made up of quantified time windows corresponding to each of the two cognitive states was used to train a SVM classifier. Although restricting the analysis to the SOBI components reduced the number of variables, the quantification described here still yielded a high dimensional feature space (six times the number of components) and severely impaired the classification accuracy due to overfitting of the learning set. We therefore further reduced the dimensionality via variable selection: i.e. only the most discriminant features (according to a Student’s t-test) among the spectral powers were fed into the SVM.

3. Results

We applied this novel approach to MEG data recorded with a whole scalp (151 channels) CTF neuromagnometer during a continuous visuomotor coordination experiment which required subjects to continuously manipulate a track-ball to compensate the random rotations of a cube projected on a display screen [3]. The MEG recording sessions were split into 1-s time windows and separated in two classes: the first corresponding to rest periods (Rest) while
the second contained the epochs of sustained visuomotor control (VM). Each session contained approximately 2 min of rest periods and 4 min of VM activity. We computed classification accuracy with a cross-validation across two experimental sessions of one subject with two quantification methods using the multi-frequency signal power of either a) the SOBI components or b) the whole sensor data directly. The resulting classification accuracies of the two methods are plotted in Fig. 1 for various numbers of preselected variables. Moreover, Fig. 2 shows the scalp topographies (see Section 2.2) and the power spectra of the two SOBI components for which power spectral density features were the most discriminant for classification.

4. Discussion

The classification results show that the use of SOBI allows for a better prediction of the MEG states than the one achieved with sensor quantification, and with fewer selected variables. This highlights the ability of SOBI to extract task relevant components giving more information on the cognitive state than direct MEG sensor measurements. The physiological relevance of MEG components is also supported by the topographies of the two most discriminant SOBI components (Fig. 2). These spatial maps of the scalp amplitude of each component correspond most likely to primary sensorimotor cortex (S1–M1) and the supplementary motor area (SMA) both known to be involved in sensorimotor behavior. In accordance with the literature, the power spectra of these components reveal event-related desynchronization (ERD) in α and β bands during VM activity compared to the resting state. Moreover, the classifier accuracy reached 93% reflecting the high separability of short periods of VM activity and rest using MEG.

5. Conclusion

Our study shows that SOBI can be successfully applied to ongoing MEG signals to extract oscillatory activities involved in a continuous cognitive task. The SOBI-based methodology described in this paper transforms the MEG sensor space to a lower dimensional space that provides a highly interpretable representation of MEG signal and thereby improves the performance of the classifier. More generally, our results also indicate that MEG imaging might be particularly useful to classify mental states. Further work will include other subjects and task specificity of the SOBI components will be studied under more control conditions (e.g. pure motor activity).

References