SINGLE-TRIAL CLASSIFICATION OF ERPS USING SECOND-ORDER BLIND IDENTIFICATION (SOBI)

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Abstract:

Single-trial classification of EEG signals has received increasing attention in both basic research and for the development of EEG based Brain Computer Interfaces (BCI). Typically, such classification has been performed using signals from a set of selected EEG sensors. Because EEG sensor signals are mixtures of signals from multiple intra- and extra-cranial sources, single-trial sensory and motor evoked potentials can be difficult to detect and classify. In this paper, Second-order blind identification (SOBI) was used to preprocess EEG data and extract activity from the left and right primary somatosensory (SI) cortices. Subsequently, classification of event-related potentials (ERPs) evoked by a sequence of randomly mixed left, right, and bilateral median nerve stimulations was performed by back-propagation neural networks, using as inputs the two SOBI-recovered SI components or the two "best sensors". Results from four subjects showed that classification accuracy was significantly higher when SOBI-recovered left and right SI components were used for classification than when the EEG sensor signals were used directly.

Keywords:

Electroencephalography (EEG), single-trial classification, brain computer interface (BCI), event-related potential (ERP), neural networks

1. Introduction

The ability to perform single-trial classification of EEG data is an area of research that has recently received much attention. For example, single-trial classification techniques have allowed for the development of Brain Computer Interfaces (BCI) which can support communication abilities for physical disabled patients (for reviews see e.g. [1,2]). In basic research the ability to assess the trial-to-trial variability in event-related potentials (ERPs) could provide new insights into brain function. Identical stimuli do not necessarily evoke identical responses and substantial trial-to-trial variability is often the rule rather than the exception. Averaging EEG signals across multiple identical stimulation trials discards information about such trial-to-trial variations. Furthermore, the ability to assess EEG data at the level of single-trial would allow for the analysis of transient psychological phenomenon that cannot be repeated over a large number of trials.

Generally, single-trail classification is difficult due to the unfavorable signal-to-noise ratio (SNR) of any evoked response embedded within ongoing background activity. To distinguish signals of interest from the background activity different feature extraction methods have been applied, including band power calculations [3], adaptive autoregressive models (AAR) [4,5], common spatial filters (CSP) [6] and recently wavelet transforms [7]. Using the extracted features of interest, two main classification methods have been used, linear and nonlinear classification. Linear discrimination analysis (LDA) [8,9] is a commonly used method for classification. Neural networks [10] and support vector machines [8,9] are two main nonlinear classification methods. Regardless of the specific methods employed for feature extraction or classification, substantial between-subject variability in classification accuracy is often observed, e.g. [5,11].

In this paper, we applied second-order blind identification (SOBI) [12-14], a blind source separation (BSS) algorithm to EEG data collected during median nerve stimulation with the goal of performing classification of ERPs elicited under different stimulation conditions. For reviews of various BSS algorithms that have been applied to MEG or EEG data, see [15,16]. Previously, we have shown that when applied to MEG data, SOBI can separate functionally distinct neuronal signals from each other and from other extra-cranial noise sources under conditions of poor SNR [17,18]. SOBI was able to recover components that were physiologically and neuroanatomically interpretable [17,18]. These advantages motivated us to explore the utility of SOBI for the preprocessing of EEG data for the purpose of single-trial classification.

Here, we applied SOBI to EEG data collected during a sequence of mixed left (L), right (R), and bilateral (B) median nerve stimulations which was designed to induce overlapping activation in the primary somatosensory cortices (SI) of the left and right hemispheres. Back-Propagation Neural Networks (BPNN), one of the most widely used neural networks for pattern classification, were then used to classify these three types of stimulation based on the SOBI-recovered left and right SI sources. Classification performance based on the SOBI-recovered sources was compared to that based on the two EEG sensors with the largest amplitudes in their ERPs.

To evaluate the feasibility of SOBI processing EEG data in real time, we also examined how quickly SOBI could converge. We show that stable separation of the SOBI-recovered SI sources can be achieved after only a few tens of iterations, thus making real time application a future possibility. In Part 2, we describe the EEG data; Part 3 the SOBI algorithm; Part 4 the BPNN; Part 5 gives performance comparisons; Part 6 demonstrates SOBI rapid convergence; Part 7 discusses the results.

2. EEG Data

Four right-handed subjects (2 males), aged between 20 and 25 years volunteered to participate in this experiment. All subjects were free of a history of neurological or psychological disorders. The experimental procedures were conducted in accordance with the Human Research Review Committee at the University of New Mexico.

Unilateral (L: left; R: right) and bilateral (B) stimuli were delivered intermixed and pseudo-randomly with no more than three consecutive identical stimulations. Bilateral stimulation was used to generate simultaneous neuronal activation in the left and right hemispheres in comparison to activation of only one hemisphere by L or R stimulation alone, thus providing a challenge for the decomposition of separate, individual components for left and right SI activations. The number of stimuli per condition was 400 for two subjects, 200 and 150 for the remaining two.

EEG signals were recorded with 128 channels continuously sampled at 1000Hz and bandpass filtered between 0.1-200Hz. In conventional data analysis, the continuous EEG data are typically epoched, baseline corrected, possibly filtered, and averaged. Data length is typically reduced after rejecting epochs containing visually identified artifacts. Here, the SOBI BSS algorithm was applied directly to the continuous EEG data as it had been collected (sensor data) without epoching, artifact rejection, baseline correction, filtering, removal of bad channels or signal averaging, similar to previous applications of SOBI to MEG data [17,18].

3. SOBI Analysis

Let $\mathbf{x}(t)$ represent n-dimensional vectors which correspond to the n continuous time series from the n EEG channels. Then $\mathbf{x}_i(t)$ corresponds to the continuous sensor readings from the i^{th} EEG channel. Because various underlying sources are summed via volume conduction to give rise to the scalp EEG, each of the $\mathbf{x}_i(t)$ are assumed to be an instantaneous linear mixture of n unknown components or sources $\mathbf{s}_i(\mathrm{t})$, via the unknown mixing matrix $\mathbf{A}$.

$$\mathbf{x}(\mathrm{t}) = \mathbf{A}\,\mathbf{s}(\mathrm{t}) \tag{1}$$

SOBI uses the EEG measurement $\mathbf{x}(\mathrm{t})$ and nothing else to generate an unmixing matrix $\mathbf{W}$ that approximates $\mathbf{A}^{-1}$, and the vector of the estimated component values, $\hat{\mathbf{s}}(t)$,

$$\hat{\mathbf{s}}(t) = \mathbf{W}\,\mathbf{x}(t), \tag{2}$$

where $\hat{\mathbf{s}}(t)$ is the continuous time series of the components or recovered sources. Sensor space projections, which indicate the effect of a given component, in isolation, on all sensors are given by the estimated mixing matrix,

$$\hat{\mathbf{A}} = \mathbf{W}^{-1}. \tag{3}$$

The SOBI algorithm [12-14] proceeds in two stages. First, the sensor signals are zero-meaned and presphered as follows:

$$\mathbf{y}(\mathrm{t}) = \mathbf{B}(\mathbf{x}(\mathrm{t})-\langle \mathbf{x}(t)\rangle). \tag{4}$$

The angle brackets $\langle\cdot\rangle$ denote an average over time, so the subtraction guarantees that $\mathbf{y}$ will have a mean of zero. The matrix $\mathbf{B}$ is chosen so that the correlation matrix of $\mathbf{y}$, $\langle \mathbf{y}(t)\mathbf{y}(t)^T \rangle$, becomes the identity matrix. This is accomplished by moving to the PCA basis using,

$$\mathbf{B} = \mathrm{diag}(\lambda_i^{-1/2})\mathbf{U}^T, \tag{5}$$

where λ_i are the eigenvalues of the correlation matrix,

$$\langle (\mathbf{x}(t) - \langle \mathbf{x}(t)\rangle)\,(\mathbf{x}(t) - \langle \mathbf{x}(t)\rangle)^T \rangle, \tag{6}$$

and $\mathbf{U}$ is the matrix whose columns are the corresponding eigenvectors, that is, the "PCA components" of $\mathbf{x}$.

For the second stage, one constructs a set of matrices that, in the correct separated basis, should be diagonal. We chose a set of time delay values, τs to compute symmetrized correlation matrices between the signal **y**(t) and a temporally shifted version of itself:

$$\mathbf{R}_\tau = \text{sym}\left(\langle \mathbf{y}(t)\mathbf{y}(t+\tau)^T \rangle \right). \qquad (7)$$

Where,

$$\text{sym}(\mathbf{M}) = (\mathbf{M} + \mathbf{M}^T)/2, \qquad (8)$$

is a function that takes an asymmetric matrix and returns a closely related symmetric one. This symmetrization discards some information, but the problem is already highly overconstrained, and the symmetrized matrices provide valid, albeit slightly weaker, constraints on the solution.

After calculating the $\mathbf{R}_\tau$, we look for a rotation **V** that jointly diagonalizes all of them by minimizing,

$$\Sigma_\tau \Sigma_{i \neq j} (\mathbf{V}^T \mathbf{R}_\tau \mathbf{V})^2_{ij}, \qquad (9)$$

the sum of the squares of the off-diagonal entries of the matrix products $\mathbf{V}^T\mathbf{R}_\tau\mathbf{V}$, via an iterative process ([13]; using MATLAB code available on-line at http://sig.enst.fr/~cardoso/). Users can set a threshold parameter for the *sin* of the angle of rotation V. When the *sin* of the angle of rotation V is smaller than a chosen threshold, the iterative process ends. The final estimate of the separation matrix is:

$$\mathbf{W} = \mathbf{V}^T\mathbf{B}, \qquad (10)$$

which is used to derive the separated components in Eq. 2.

A wide range of time delays, τs were chosen to generate multiple covariance matrices for source separation. Similar to previous studies where SOBI was applied to MEG data [17,18], the following τs were used:

$$\tau \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 14, 16, 18, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 120, 140, 160, 180, 200, 220, 240, 260, 280, 300\}.$$

Using the above parameters, SOBI-recovered components corresponding to left and right SI activation were identified. The identity of the corresponding SOBI components was established using both spatial and temporal constraints. Temporally, somatosensory evoked potentials (SEPs) averaged around median nerve stimulation must have shown characteristic SI responses and spatially, the scalp current source density maps and the equivalent current dipole (ECD) locations, obtained using BESA 5.0 (Brain Electrical Source Analysis; MEGIS Software, Munich, Germany), must have been in the vicinity of the hand region of SI to be considered SI sources. For more details, see companion paper in this volume by Sutherland et al.

4. Back-Propagation Neural Networks

To determine whether SOBI source separation offered any advantage in regards to single-trial classification of SEPs, single epochs (trials) from the SOBI-recovered left and right SI components were used as inputs to BPNN. Alternatively, the two sensors over the regions of interest (above SI) with the largest SEP amplitudes were also used as inputs. Figure 1A displays images of single-trial ERPs for the SOBI-recovered L (C-012) and R SI (C-016) and Figure 1B for the L and R "best sensors". Each row of colored pixels represents a single epoch and epochs are stacked vertically with earlier trials displayed at the bottom (images were generated using EEGLAB [20]). The labels, L, R, and B, on the left side of each image, indicate left, right, or bilateral stimulation conditions. It is apparent (when viewed in color) that the recovered left (C-012) and right SI(C-016) sources showed selective responses to contralateral (left SI = R stimulation, Right SI = L) and bilateral (B) stimulation. Note, although the trials are shown grouped by (C-016)

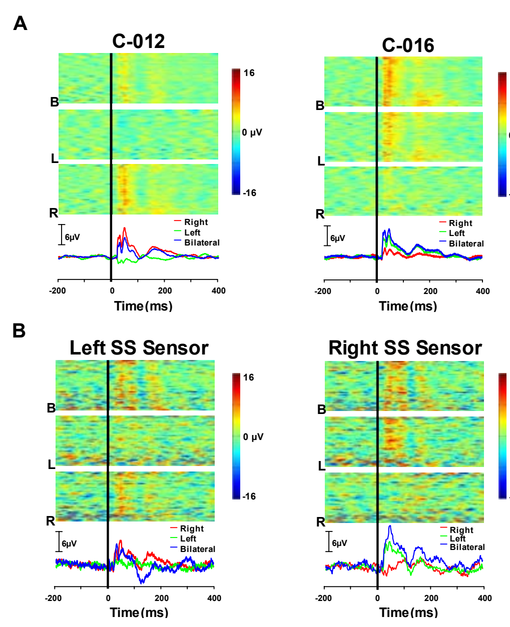

Figure 1. Single-trial and averaged SEPs

sources showed selective responses to contralateral (left SI = R stimulation, Right SI = L) and bilateral (B) stimulation. Note, although the trials are shown grouped by stimulation type, L, R, and B stimulation trials were intermixed randomly throughout the experiment. In the images from both the left and right SOBI-recovered SIs, single-trial SEPs were clearly visible. In contrast, SEPs from the best sensors were noisier and the single-trial SEPs were not as clearly visible as those from the recovered sources.

Multilayer back-propagation neural networks were trained to classify single-trial ERPs into three stimulus classes: left, right, and bilateral stimulation. The three classes were coded by 3 output units, one representing each of the three types of stimulation (L, R, or B). The hidden layer consisted of 20 units. The input layer had 20 units, 10 representing left SI activation and 10 for the right SI. Each input unit represented an average of 10 ms of data, covering a time window between 20-120ms post-stimulus onset.

To train the network, we used the traingdx learning algorithm (provided by Matlab Neural Network Toolbox, MathWorks, Inc., Natick, MA) which uses gradient descend with momentum and variable learning rate in batch learning mode [21]. Gradient descend with momentum can avoid a shallow local minimum and a variable learning rate can make the learning as fast as possible while maintaining stability. The batch learning was used to update the network weights after all training data was presented.

For each of the four subjects, a series of neural networks were trained to 90% classification accuracy using 50% of the trials randomly selected (training set). Different initial random weights were used for each training set. After reaching the 90% training criterion, the trained network was used to classify the remaining 50% of trials (testing set). The classification accuracy obtained for the testing set was used to evaluate performance. This two-step process was repeated 100 times with different sets of initial weights and different training sets for the data from each subject.

5. SOBI Improved Single-Trial ERP Classification

To examine whether SOBI preprocessing offered any advantage in single-trial classification, we compared single-trial response classification accuracy using the SOBI-recovered SI components to classification accuracy using the two "best" EEG sensors.

When using the two SOBI-recovered SI sources as inputs, the neural networks trained on 50% of the trials led to a classification accuracy of 83.3% ± 5.6% (N = 4) on the remaining 50% of the trials. In contrast, when using single-trial SEPs from the "best sensors", similarly trained neural networks only reached a classification accuracy of 64.1% ± 2.3% (N = 4), which was significantly lower than that obtained from the SOBI-recovered left and right SIs (Wilcoxon test, N = 4, $p < .05$, one tailed, Figure 2). Chance level performance was 33.3% given three classes. Thus, generalization from the training to testing sets was significantly improved by SOBI preprocessing.

The range in classification accuracy across subjects (51.7% to 79.7%) was relatively large (~30%) when the "best sensor" data was used. In contrast, when the SOBI-recovered SI components were used, the range in accuracy (79.2% to 88.9%) was decreased substantially (<10%) (Figure 2). A test for heterogeneity of non-independent samples [22, 23] revealed that the variance in classification accuracy was significantly greater when the "best sensor" data was used than when the SOBI-recovered SIs were used ($t(2)$= 33.0, $p < .01$). Therefore, generalization of single-trial classification from the training to testing sets demonstrated lower between-subject variability when the SOBI-recovered SIs were used than when the "best sensor" data was used.

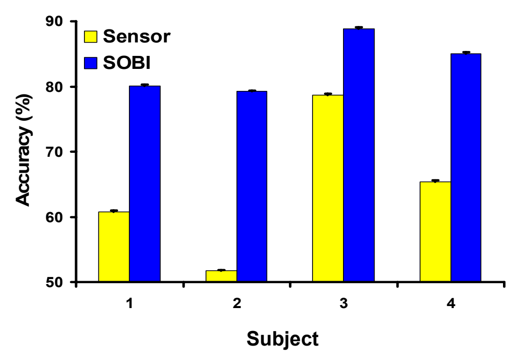

Figure 2. Single-trial ERP classification accuracy.

6. Efficiency of SOBI Algorithm

Because SOBI is an iterative algorithm, the feasibility of SOBI real-time application depends partially on how quickly SOBI converges. We empirically determined the number of iterations needed to obtain adequate source separation by examining the SOBI-recovered left and right SI components. Figure 3 shows for the 4 subjects, the *sin* of the angle of rotation **V** as a function of number of iterations. The arrows and the numbers above them indicate the number of iterations where the *sin* angle of rotation **V** reached a threshold of 10^{-3} and 10^{-9}. The SOBI source separation process appeared to reach asymptote after less than 40 iterations.

To determine an appropriate threshold level where the iterative process should end, we examined the relationship between the *sin* angle of rotation **V** and the quality of the recovered left and right SI sources. Using the unmixing matrices, **W**s, obtained at multiple threshold values ranging from 10^{-1} to 10^{-9} by increments of 10^{-1}, we extracted the recovered left and right SIs and estimated their spatial locations for all 4 subjects.

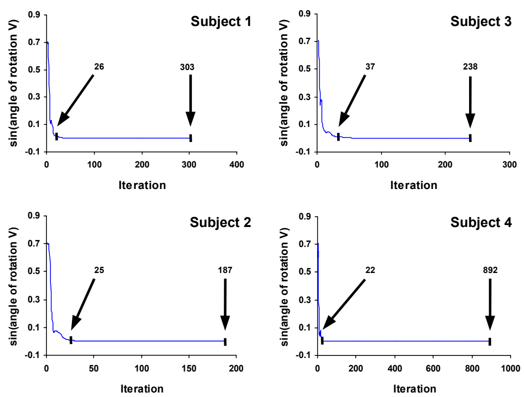

Figure 3. Rapid convergence of SOBI

The ECD locations for the recovered left and right SIs were virtually identical at threshold levels of 10^{-3} and 10^{-9} (compare the xyz coordinates and the goodness of fit, *g*, obtained at the two threshold levels (Table 1). The maximum distance between the estimated SI dipole locations at the two threshold levels was 1 mm and the maximum difference between the goodness of fit values was 0.7%. Thus, a rather small number of iterations (maximum = 37) were needed to reach stable separation results. At threshold levels greater than $10e^{-3}$ (i.e., fewer numbers of iterations), the source separation results were not optimal (data not shown).

Table 1. Stability of dipole locations at two threshold levels.

		SOBI Recovered SI							
		Left				Right			
Subject	sin(angle of rotation V)	X	Y	Z	*g*	X	Y	Z	*g*
1	1e-3	-37	5	91	95.1	37	9	93	98.1
	1e-9	-37	5	91	95.1	37	9	93	98.1
2	1e-3	-35	4	84	98.4	35	8	90	97.1
	1e-9	-35	4	84	98.4	35	8	90	97.1
3	1e-3	-32	12	95	97.7	32	6	87	97.3
	1e-9	-32	12	95	97.6	32	6	88	97.7
4	1e-3	-43	4	83	99.1	35	5	93	97.0
	1e-9	-43	4	83	99.2	35	5	93	96.3

7. Conclusion

The ability to measure and classify single-trial responses from specific brain regions has important theoretical and practical implications for both basic and applied research. For brain research, the ability to measure single-trial ERPs is one important step toward understanding how the relative timing of neuronal activity can affect learning and how memory of a particular experience can be encoded rapidly with a single or very few exposures. In clinical applications, the ability to obtain such measures in a computationally efficient manner could allow functionally meaningful brain signals to be extracted and used to generate better input and feedback signals for brain computer interfaces.

The results presented here show that single-trial ERPs from specific brain regions can be extracted using SOBI and that these extracted neuronal sources offer clear advantages over sensor data for single-trial ERP classification. With SOBI, an average of 83% classification accuracy was achieved with less than 10% between-subject variability. In contrast, when using the “best sensors”, average classification accuracy was only 64% with nearly 30% between-subject variability.

These results were obtained using a challenging data set which consisted of highly overlapped responses across the three stimulation classes, specifically created by the inclusion of bilateral stimulation. For example, responses to unilateral and bilateral stimulation have 50% overlap because both activate the same cerebral hemisphere. These findings were also demonstrated for data with relatively high SNR because median nerve stimulation is known to generate highly reliable ERPs. Thus, SOBI’s advantage is not limited to poor SNR situations.

Finally, we believe that the current discrimination performance could be further improved because a rather crude 10 ms time scale was used to derive the inputs for the neural network. Some useful information may be lost due to the averaging over this 10 ms window. In future work, we plan to further improve single-trial ERP classification performance by combining the SOBI-based approach with our recently developed multi-resolution method for single-trial ERP detection (see see companion paper in this volume by Loring et al.) and by using SOBI for harder classification problems, such as those described in [24].

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