# Blind Source Separation can Recover Systematically Distributed Neuronal Sources from "Resting" EEG

Matthew T. Sutherland, and Akaysha C. Tang

*Abstract*—**Blind source separation algorithms have been increasingly applied to electroencephalographic (EEG) and magnetoencephalographic (MEG) signals from the human brain. Second-order blind identification (SOBI) [1] is one of the emerging algorithms which enable the extraction of functionally distinct, neuro-physiologically, and anatomically meaningful components. SOBI's ability to extract activity associated with a variety of brain sources during visual, auditory, and somatosensory stimulation has been well documented [2]-[6] . Here we demonstrate that SOBI is able to extract a set of neuronal components distributed within the visual, and somatosensory systems, as well as the frontal cortices, from resting EEG data obtained in the absence of explicit sensory stimulation or overt behavioral responses.**

## I. Introduction

Blind source separation (BSS) is a signal processing technique which aims to recover unobservable source signals from their observed mixtures. One of its many applications is to recover neuronal activity arising from multiple brain regions from their mixtures recorded by sensors outside of the head by EEG or MEG [7], [8]. In the past decade, this application has offered neuroscientists new ways of formulating questions concerning brain function [9], improved single-trial assessment capabilities [3], [6], [10], and has allowed for more effective artifact removal, thus improving signal quality [11]-[13].

In cognitive neuroscience research, scientists are interested in recovering signals associated with neuronal activity from specific brain regions. Typically, BSS algorithms are applied to averaged EEG/MEG waveforms obtained from repeated trials of sensory stimulations or behavioral response generations. The presumed need for signal averaging under controlled and identical conditions requires the subject to attend to the stimulation or task, often for extended periods of time, hence making the study of clinical populations and children particularly difficult.

Here we explore the possibility of recovering neuro-anatomically meaningful brain sources from continuous non-averaged electrical signals obtained in the absence of explicit sensory stimulation or behavioral responses. Such a demonstration may not only improve clinical and developmental assessment but also lead to new way of studying the dynamics of the brain at "rest".

Manuscript received December 20, 2005. This work was supported by a DARPA grant from the Augmented Cognition Program (ONR: N00014-02-1-0348) and the MIND institute (#2021) to ACT.

M. T. Sutherland is with the University of New Mexico, Department of Psychology, Albuquerque, NM 87131 USA (email: msuther@unm.edu).

A. C. Tang is with the University of New Mexico, Departments of Psychology, and Neurosciences, Albuquerque, NM 87131 USA (phone: 505-610-9077; fax: 505-277-1394; email: akaysha@unm.edu).

## II. EEG Data

Five minutes of 128-channel EEG data was collected from 9 right-handed subjects while they sat quietly with eyes closed in a relaxed position following an experiment involving somatosensory stimulation (sampling rate: 2000 Hz; bandpass filter: 0.1-200 Hz). All channels were referenced to the nose and impedances were maintained below 10 kΩ. The continuous-resting EEG data were used as input to the SOBI algorithm.

## III. SOBI

SOBI [1] decomposes $n$-channel continuous EEG into $n$ SOBI components, each of which corresponds to a recovered putative source that contributes to the scalp EEG signal. Each SOBI component has a time course of activation and an associated sensor space projection that specifies the effect of that putative source on each of the $n$ electrodes.

Let $\mathbf{x}(t)$ represent the $n$ continuous time series from the $n$ EEG channels and $\mathbf{x}_i(t)$ the 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 to obtain the estimated component values, $\hat{\mathbf{s}}(t)$,

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

The continuous time course of the $i^{\mathrm{th}}$ component is given by $\hat{\mathbf{s}}_i(t)$. Sensor weights, which indicate the effect of a given component, in isolation, across all sensors are given by the estimated mixing matrix,

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

The sensor weights for the $i^{th}$ component are given by the $i^{th}$ column of $\hat{\mathbf{A}}$.

SOBI proceeds in two stages. First, the sensor signals are zero-meaned and presphered as follows:

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

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 $\lambda_i$ 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, $\tau$s to compute symmetrized correlation matrices between the signal $\mathbf{y}(t)$ and a temporally shifted version of itself:

$$\mathbf{R}_\tau = \mathrm{sym}(\langle \mathbf{y}(t)\mathbf{y}(t+\tau)^T \rangle). \tag{7}$$

Where,

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

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 $\mathbf{V}$ that jointly diagonalizes all of them by minimizing,

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

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 ([14]using MATLAB code available on-line at http://sig.enst.fr/~cardoso/). The final estimate of the separation matrix is:

$$\mathbf{W} = \mathbf{V}^T\mathbf{B}, \tag{10}$$

which is used to derive the separated components as in (2).

The sensor signals (sensor space projection) resulting from just one of the components can be computed as,

$$\hat{\mathbf{x}}(t) = \hat{\mathbf{A}}\mathbf{D}\mathbf{W}\mathbf{x}(t) = \hat{\mathbf{A}}\mathbf{D}\hat{\mathbf{s}}(t), \tag{11}$$

where $\mathbf{D}$ is a matrix of zeros except for ones on the diagonal entries corresponding to each component that is to be retained.

To determine the spatial origin of a single component, one computes this component's sensor space projection, $\hat{\mathbf{x}}^{(i)}(t)$:

$$\hat{\mathbf{x}}^{(i)}(t) = \hat{\mathbf{s}}_i(t)\hat{\mathbf{a}}^{(i)} \tag{12}$$

where $\hat{\mathbf{a}}^{(i)}$ is the $i^{th}$ column of $\hat{\mathbf{A}}$. Note, as $\hat{\mathbf{x}}^{(i)}(t)$ is at each point in time equal to the unchanging vector $\hat{\mathbf{a}}^{(i)}$, scaled by the time course of interest $\hat{\mathbf{s}}_i(t)$, dipole fitting algorithms will localize $\hat{\mathbf{x}}^{(i)}(t)$ to the same location no matter what window in time is chosen. To determine the spatial location of the generator for a component, $\hat{\mathbf{x}}^{(i)}(t)$ can be given as input to any source modeling algorithm. Here, we used BESA 5.0, a commercially available package to fit equivalent current dipoles (ECDs) to each component.

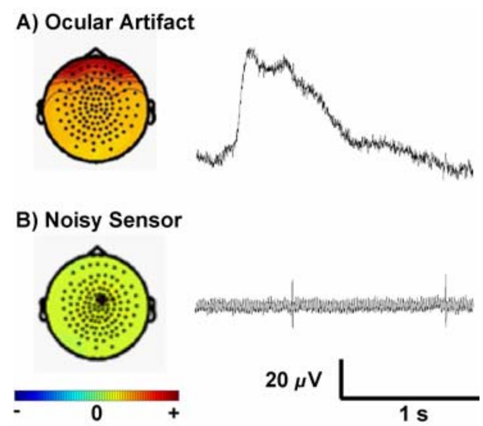


Fig. 1. Known types of artifactual components recovered from resting EEG.

## IV. SOBI-Recovered Artifact Components

Under resting conditions where neither stimuli nor responses are controlled for, the functional state of the brain is "undefined". However, it is reasonable to expect the presence of certain artifacts in the resting EEG. Here we first address the question of whether such artifactual sources can be recovered from the resting EEG using SOBI. Figure 1A shows an ocular component whose time course (right) reveals a slow large-amplitude deflection predominately at sensor locations near the eyes (left). Figure 1B shows a noise component whose time course reveals clear 60Hz noise and whose scalp projection map indicates activation at a single sensor. Both types of components were found across all subjects studied.

These findings demonstrate that ocular and sensor artifacts routinely recovered by applying SOBI to EEG data collected during sensory stimulation or behavioral responses can be recovered from 5 minutes of resting EEG data in the absence of controlled stimulation or response generation. For detailed criteria used in the identification of ocular or noise sources, see [4].

## V. SOBI-Recovered Neuronal Components

Even though subjects were at "rest" during EEG data collection, this does not mean that the brain was at rest. It is known that certain ongoing rhythmic activity (e.g., posterior alpha activity) is prominent particularly when subjects are at rest with eyes closed. It is possible that SOBI may recover neuronal components corresponding to neuro-anatomically distinct brain regions using only the detailed temporal information contained in the ongoing activity that is unique to specific brain regions.

Figure 2 presents SOBI neuronal components recovered from continuous-resting EEG data. Detailed criteria for identifying neural components can be found elsewhere [4]. The scalp projection maps (Fig. 2, left) reveal systematic spatial patterns of sensor activation. The sequence of six occipital-parietal components has a pattern of bi- or unilateral focal activation with increasing distance between the underlying source location (Fig. 2, right) and the midline. These components possibly capture neuronal generators correspond to different visual processing areas along the visual pathways. The pair of somatosensory components, most likely reflect ongoing (mu rhythm) activity from the left and right primary somatosensory (SI) cortices as indicated by the ECD locations, see [4]-[6] for further discussion of these somatosensory sources. The last group of components shows symmetry along the midline, with varying underlying source locations along the anterior-posterior axis and varying distances from the scalp. The ECD locations indicate that the origins of these components are in the frontal cortices, and may reflect activity associated with self-referential thought during the resting period [15].

To offer a preliminary assessment of cross-subject reliability in extracting neuronal components, we show scalp projection maps and the corresponding dipole locations for two of the above described components across all 9 subjects studied (Fig. 3). Notice the remarkable similarity across different subjects between the ECD locations within each of the two component types. Note that two components with similar dipole locations can have different scalp projection maps due to differences in how the underlying signal generators are situated across subjects. In all aforementioned source solutions goodness-of-fit values of the ECD models were greater than 90% indicating that the underlying sources of brain activity can be well approximated by point sources.

## VI. Conclusion

We applied SOBI to continuous high-density EEG data collected during a brief resting period without controlled, repeated sensory stimulation or explicit tasks, and thereby imposing little demand for subject cooperation. We found that SOBI-recovered sources show systematic spatial distributions within the visual, somatosensory, and frontal cortices. This result indicates that perturbation of the neuronal system by stimulation or task performance is unnecessary for the recovery of neuro-anatomically

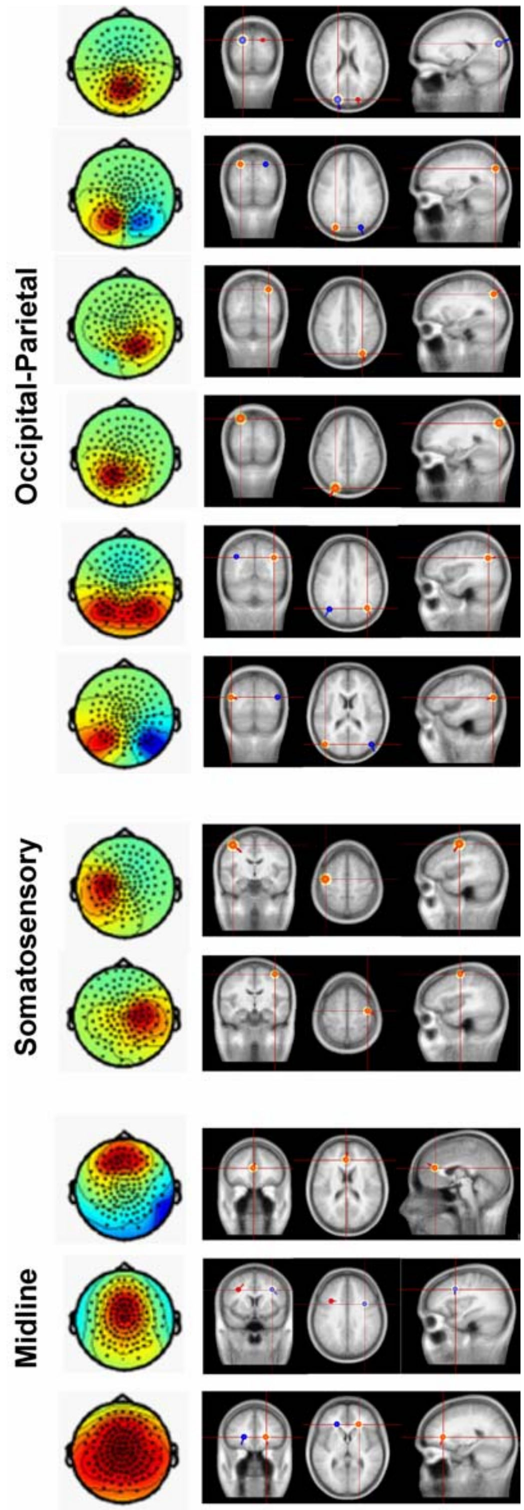


Fig.2. SOBI-recovered neuronal sources. Scalp maps (left) and ECD locations (right).

meaningful components. Therefore, SOBI must achieve successful decomposition by using information contained in the temporal structures embedded in ongoing brain activity. The spatial localization and further characterization of the temporal dynamics among these distinct components may together offer novel matrices for monitoring changes in dynamic functional brain organization as a result of learning, development, disease, and pharmacological influence. Furthermore, this approach may be potentially usefully for assessing the dynamics of the resting brain, an area of inquiry that has so far been mainly confined to neuroimaging modalities with poor temporal resolution, such as positron emission tomography and functional magnetic resonance imaging [16], [17].

## ACKNOWLEDGMENT

We thank B.C. Reeb and C.J. McKinney for assistance during data collection.

## REFERENCES

[1] A. Belouchrani, K. Abed-Meraim, J.-F. Cardoso, E. Moulines, "A blind source separation technique using second-order statistics," *IEEE. Trans. on Signal Processing,* vol. 45, no. 2, pp. 434-444, Feb. 1997.

[2] A.C. Tang, B.A. Pearlmutter, N.A. Malaszenko, D.B. Phung, and B.C. Reeb, "Independent components of magnetoencephalography: Localization," *Neural Computation*, vol. 14, pp. 1827-1858, 2002.

[3] A.C. Tang, B.A. Pearlmutter, N.A. Malaszenko, and D.D. Phung, "Independent components of magnetoencephalography: Single-trial response onset times," *NeuroImage*, vol. 17, pp. 1773-1789, 2002.

[4] A.C. Tang, M.T. Sutherland, and C.J. McKinney, "Validation of SOBI-components from high-density EEG," *NeuroImage*, vol. 25, pp. 539-553, 2005.

[5] A.C. Tang, J.-Y. Liu, and M.T. Sutherland, "Recovery of correlated neuronal sources from EEG: The good and bad ways of using SOBI," *NeuroImage*, vol. 28, pp. 507-519, 2005.

[6] A.C. Tang, M.T. Sutherland, and Y. Wang, "Contrasting single-trial ERPs between experimental manipulations: Improving differentiability by blind source separation," *NeuroImage*, vol. 29, pp.335-346, 2006.

[7] R. N. Vigario, J. Sarela, V. Jousmaki, M. Hamalainen, and E. Oja, "Independent component approach to the analysis of EEG and MEG recordings," *IEEE Trans. Biomed. Eng.*, vol. 47, pp. 589-593, 2000.

[8] K.R. Muller, R. Vigario, F. Meinecke, and A. Ziehe, "Blind source separation techniques for decomposing event-related brain signals," *Int. J. Bifurc. Chaos*, vol. 14, pp. 773-791, 2004.

[9] S. Makeig, S. Debener, J. Onton, and A. Delorme, "Mining event-related brain dynamics," *Trends in Cogn. Sci.*, vol. 8, no. 5, pp.204-210, 2004.

[10] T.P. Jung, S. Makeig, M. Westerfield, J. Townsend, E. Courchesne, and T.J. Sejnowski, "Analysis and visualization of single-trial event-related potentials," *Human Brain Map.*, vol. 14, no. 3, pp. 166-185, 2001.

[11] R.N. Vigario, "Extraction of ocular artifacts from EEG using independent component analysis," *Electroenceph. and Clin. Neurophysiol.,* vol. 103, pp. 395-404, 1997.

[12] T.-P. Jung, C. Humphries, T.-W. Lee, M.J. McKeown, V. Iragui, S. Makeig, and T.J. Sejnowski, "Removing electroencephalographic artifacts by blind source separation," *Psychophysiol.*, vol. 37, pp. 163-178, 2000.

[13] C.A. Joyce, I.F. Gorodnitsky, and M. Kutas, "Automatic removal of eye movement and blink artifacts from EEG using blind component separation," *Psychophysiol.*, vol. 41, pp. 313-325, 2004.

[14] J.-F. Cardoso, and A. Souloumiac, "Jacobi angles for simultaneous diagonalization," SIAM J. of Matrix Analysis and Applications, vol. 17, no.1, pp.161-164, Jan. 1996.

[15] G. Northoff, and F. Bermpohl, "Cortical midline structures and the self," *Trends in Cogn. Sci.*, vol. 8, no. 3, pp. 102-107, 2004.

[16] D.A. Gusnard, and M.E. Raichle, "Searching for a baseline: Functional imaging and the resting human brain," Nature Rev. Neurosci., vol. 2, pp. 685-694, 2001

[17] M.D. Fox, A.Z. Synder, J. L. Vincent, M. Corbetta, D.C. Van Essen, and M.E. Raichle, "The human brain is intrinsically organized into dynamic, anticorrelated functional networks," *Proc. Nat. Acad. of Sci.*, vol. 102, no. 27, pp. 9673-9678, 2005.

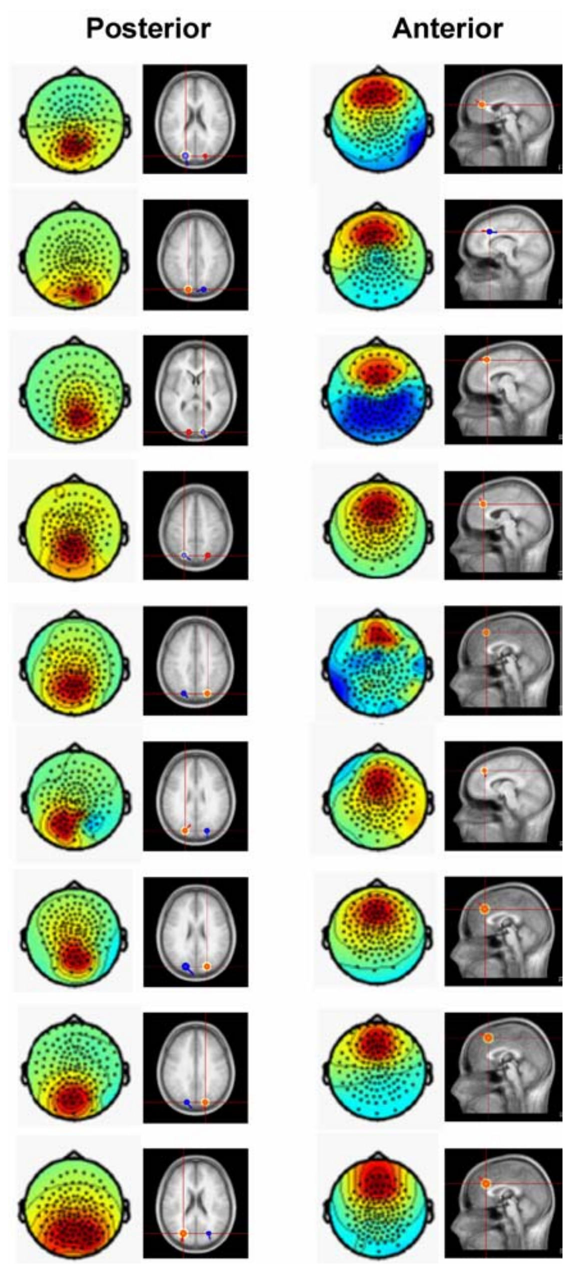


Fig. 3. Corss-subject consistency in SOBI-recovered neuronal sources.