Applications of Second Order Blind Identification to High-Density EEG-Based Brain Imaging: A Review

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Abstract. In the context of relating specific brain functions to specific brain structures, second-order blind identification (SOBI) is one of the blind source separation algorithms that have been validated extensively in the data domain of human high-density EEG. Here we provide a review of empirical data that (1) validate the claim that SOBI is capable of separating correlated neuronal sources from each other and from typical noise sources present during an EEG experiment; (2) demonstrating the range of experimental conditions under which SOBI is able to recover functionally and neuroanatomically meaningful sources; (3) demonstrating cross- as well as within-subjects (cross-time) reliability of SOBI-recovered sources; (4) demonstrating efficiency of SOBI separation of neuronal sources. We conclude that SOBI may offer neuroscientists as well as clinicians a cost-effective way to image the dynamics of brain activity in terms of signals originating from specific brain regions using the widely available EEG recording technique.

Keywords: BSS, ICA, SOBI, Source modeling, Source localization, Single-trial analysis, human EEG, Multichannel.

1 Introduction

Relating specific brain functions to specific brain structures is a fundamental problem in neuroscience. Of many sensor modalities that offer measurement of brain signals, EEG is one that is mobile and relatively inexpensive and has high temporal resolution of millisecond. Thus, EEG potentially has the widest applications in both research and clinical settings. However, until recently, EEG data are typically expressed as signals read at particular sensor locations outside of the head, and thus do not readily provide direct answers to the question of structure-function relationship.

To investigate structure-function relations, one needs to separate the mixture of signals recorded at each EEG sensor into signals from functionally and neuroanatomically specific brain sources. InfoMax ICA [1] and SOBI [2, 3] are two frequently used blind source separation algorithms in relating specific brain structures to specific brain functions [4-9]. Since many original and review papers were written solely on the topic of ocular artifact removal, here I present a review of SOBI applications with an exclusive focus on separation of neuronal sources from high-density EEG data.

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2 Validation

From its birth to its wide application, an algorithm may take a long time, or never, reach a wide range of users. In the case of the application of blind source separation (BSS) in general this seems to be the case. One of the reasons for this slow translation may have to do with how the algorithm is validated.

In the field of engineering or mathematics, a source separation algorithm is typically validated initially using simulated data with certain characteristics. As the algorithm is applied to one specific signal domain (e.g. acoustic versus neuroelectrical), the simulated data may or may not capture the critical features that enable the source separation within that specific signal domain. Hence, the ultimate validation that is meaningful and convincing to the end user has to be validations using data from that specific signal domain. Two examples of such domain-specific validations are presented below.

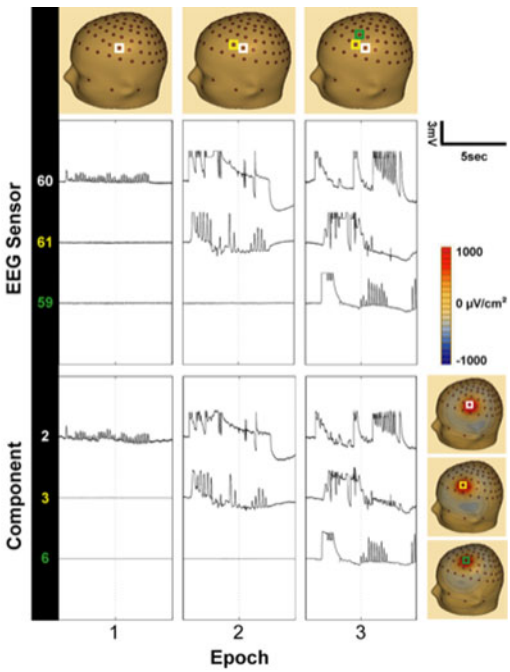

Fig. 1. SOBI recovery of artificially created known noise sources

2.1 Validation via “Bad” EEG Sensors

To validate, one needs the source signals to be separated to be somehow already known. How could one find such known sources when one is trying to separate the mixture of EEG signals? We took advantage of the so-called bed sensors to show that temporally overlapping transient noises injected into adjacent EEG sensors can be recovered as separate sources, the recovered source locations and source time courses match the known source locations and time courses [10].

Shown in Fig. 1, three arbitrarily chosen EEG sensors (59, 60, 61) were touched, one, two, or all three simultaneously during Epoch 1, 2 and 3 to injected noise into specific sensors. Since we know which sensors were touched, these sources are known. We were able to find three SOBI components (6, 2, and 3 respectively) with time courses match that of the sensors (59, 60, and 61) and with spatial maps with peak activity centered at the correct sensor locations (59, 60, and 61).

Note that these touch-induced noise sources represents a class of commonly present unknown and unpredictable noise sources associated with minor head movement and other changes in the physical and electrical contact between the EEG sensor and the scalp. The ability to isolate them from the neuronal sources is critical for correct separation of neuronal sources.

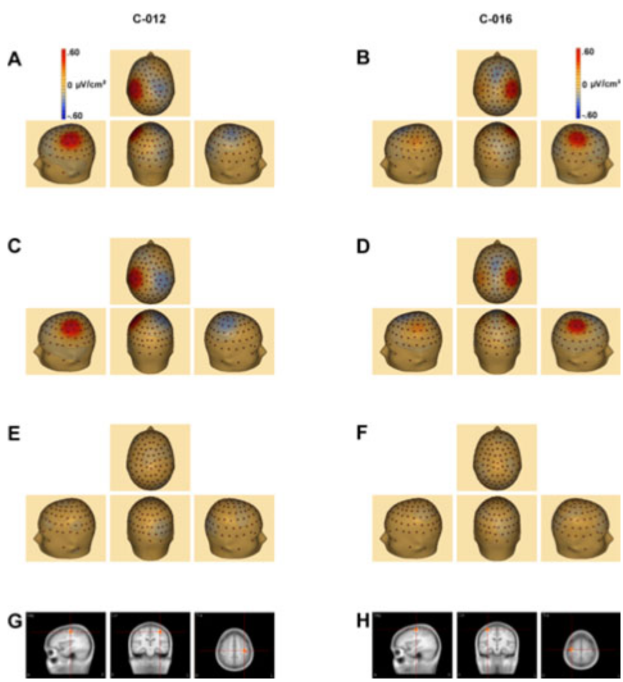

Fig. 2. SOBI recovery of correlated neuronal sources

2.2 Validation via Bench-Mark Neuronal Sources

The ability to separate overlapping noise sources in the presence of neuronal sources, does not guarantee that the algorithm will be able to separate neuronal sources among themselves, particularly when the neuronal sources are activated in a correlated fashion as in the case of simultaneous electrical stimulation of the left (L) and right (R) median nerve. Here we show that the latter can be achieved with SOBI [8, 10].

EEG data were recorded during mixed trials of simultaneous L and R stimulation and unilateral L or R stimulation to generate correlated but "known" activation of the L and R primary somatosensory cortices (SI). If SOBI works well with correlated neuronal sources, at least two SOBI components should have spatial maps of activation that can be well explained by the known extremely focal and superficially located dipole sources at the expected SI locations.

Shown in Fig. 2 are two such component sensor space projections (A,B) and the projections of two dipole sources placed at the typical locations of the L and R SIs (C, D). Notice how similar they are and how little residual is left (E,F) if one subtracts the maps of the dipole models (C,D) from the maps of the components (A,B). The locations of the dipoles with the least square fit are typical of SI as established by converging imaging modalities.

3 Robustness and Versatility

The usefulness of a source separation algorithm for basic neuroscience research and clinical diagnosis and monitoring, to a large extent, depends on the robustness of the algorithm across a wide range of data-acquisition conditions. Variations in such conditions may arise from differences in noise present in the recording environment. Variations may also be associated with the specific brain functions one attempts to study that require the use of different activation tasks or a lack of any tasks (e.g. in sleep and meditation studies or study of coma patients). Here we show two examples that expand the limit of what one typically considers as possible to obtain from scalp recorded EEG.

3.1 Separation of Neuronal Sources from Resting EEG

Separation of scalp EEG signals into source signals, if done at all, are typically done for EEG data collected using ERP paradigms, where an average waveform of repeated presentation of a stimulus or repetition of a response were generated and used in the process of dipole or other type of model fitting. Sources are fitted for different temporal components of a characteristic waveform. Such an approach excludes the possibility of source modeling when the EEG data were collected without ERPs (e.g. during sleep or meditation).

As SOBI uses temporal delays computed over continuous data, there is no reason for the requirement of an ERP paradigm. We have shown that SOBI can decompose the scalp-recorded mixed signals into components whose sensor space projections are characteristic of those found to be neuronal sources and that these projections can be well accounted for by dipoles at known neuroanatomically meaningful locations [11].

Shown in Fig. 3 are typical examples of neuronal sources recovered from approximately 10 min resting EEG. On the left are sources believed to correspond to neuronal sources along the ventral visual processing streams and on the right-top are sources of L and R primary somatosensory cortices and on the right-bottom are multiple frontal sources. This example suggests that with SOBI, one can monitor fast neuroelectrical activity at specific brain regions without having to make the subjects to perform any specific task, thus enabling investigation of brain function during sleep, meditation, coma, and other disorders that render subjects incapable of performing a task.

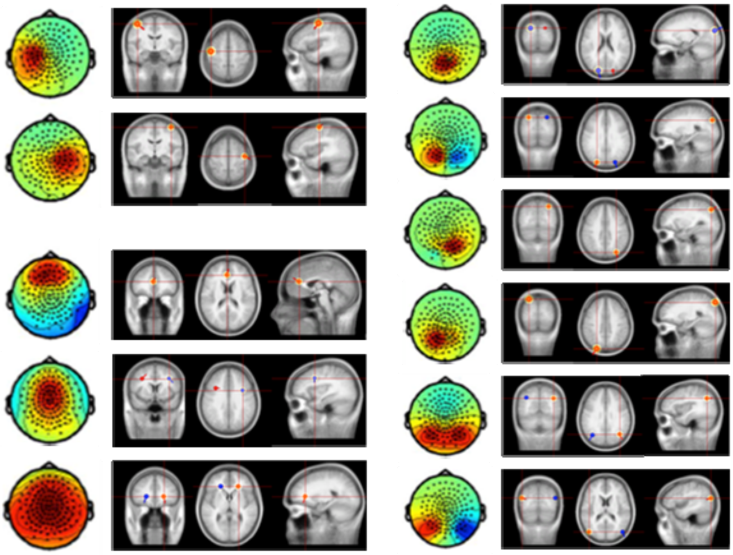

Fig. 3. SOBI recovery of neuronal sources from resting EEG

3.2 Separating Neuronal Sources from EEG Recorded during Free and Continuous Eye Movement

As the electrical signals associated with eye movement can be 1-2 orders of magnitude of neuronal signals, it has become an accepted practice to manually review the entire EEG record channel by channel to identify specific time windows where eye blinks and eye movement have occurred. Subsequently, data from these time windows are "chopped" for the purpose of "artifact removal". This approach would fail completely if one's goal is to investigate brain function while the subject is engaging in activity requiring normal free and continuous eye movement. Here we show examples of a neuronal source posterior visual cortex and an ocular source, recovered by SOBI from EEG data collected when the subject was playing a video game in front of a computer screen for less than 20 minutes [9]. The sensor space projections of both SOBI-recovered sources (Fig. 4 top row) are characteristic of those found from EEG recordings of an ERP experiment and their respective spatial origins are provided by the dipoles models (Fig. 4 middle row).

Most importantly, when an average waveform is generated by averaging signals from multiple epochs surrounding a button press, a waveform resembling the visual evoked potentials (VEPs) emerged for the posterior visual source (Fig. 4, right-bottom). Furthermore, the similarly generated average waveform for the ocular source showed large amplitude variations associated with eye movement even though it overlaps in time with the VEPs of visual source (Fig. 4, left-bottom). This experiment demonstrates the possibility that with SOBI, neuronal sources can be recovered even in the presence of continuous eye movement that generate large amplitude signals

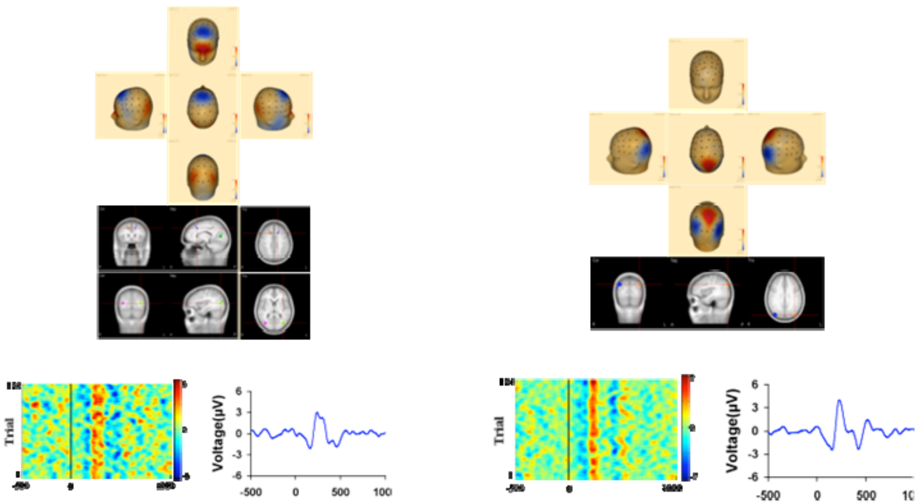

Fig. 4. SOBI recovery of neuronal and ocular sources from data obtained during continuous eye movement

overlapping with all neuronal activity. This capability offers neuroscientists and clinician a new opportunity to study their chosen phenomena within the normal real-world context.

4 Reliability

The usefulness of a source separation algorithm also depends on the reliability of the algorithm in findings similar neuronal sources across different subjects (cross-subject reliability) and the reliability in finding similar neuronal sources across repeated recording sessions (within-subject reliability), particularly across long time delays (days and weeks). Within-subject reliability across longer time delays is particularly critical for addressing questions in developmental neuroscience and in monitoring progression, treatment, and recovery from brain pathology. Here we present descriptive data pertaining to these two forms of reliability [7].

4.1 Cross-Subject Reliability

To evaluate cross-subject reliability in identifying sources corresponding to the same architetonically defined brain regions from multiple subjects, ideally one needs the structural MRI images of the individual subjects as large variations in individual brain structures exist. Here the structural MRI of a standard brain is used. With this limitation in mind, we show two typical sources: the top row is for a frontal source and the bottom is for a visual source.

These two sources are used as benchmark sources because they are always found from all EEG recordings regardless of what the subjects are doing. Be it eye-closed resting, eyes-closed imagining, eye-open resting, or search eye-open actively view, be it during a visual or somatosensory activation paradigm. The variations in scalp maps across different subjects (columns) is reasonable because the activation across the map (Fig. 5 top row: voltage map; middle row: current source density) is both a function of brain activity and relative position of the EEG cap on the head.

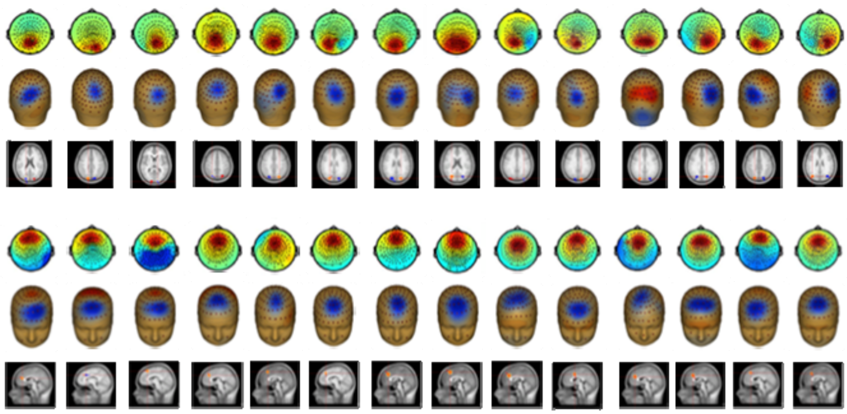

Fig. 5. Frontal and posterior sources from 14 subjects: cross-subject variations

4.2 Within-Subject Reliability (Cross-Time)

Variations in source identification from different recording sessions across days or weeks may arise from multiple sources. These include changes in the EEG cap placement over the head, changes in the subject's state of mind, changes in maturation if the delay is sufficiently long to cover a window of developmental change, or changes associated with health status and medical treatment. It is important to maintain the ability to separate neuronal sources and match one set of sources at one time to that of another and simultaneously retain the ability to compare *temporal dynamic changes* reflecting the differing circumstances.

Shown in Fig. 6 are dipole locations for the two typical sources (left: posterior visual; right: fonrtal cortex) [7]. The three rows correspond to three sessions of recordings of the same groups of subjects (Week 0, Week 1, and Week 3 or longer). The multiple overlapping dipoles are from different subjects. First the tight clustering of dipoles within each sub-panels further support cross-subject reliability No statistically significant differences in source locations were found across weeks and neither were there visible differences in dipole clustering. This level of within-subject reliability means that with SOBI, one can investigate long-term changes of a given brain region.

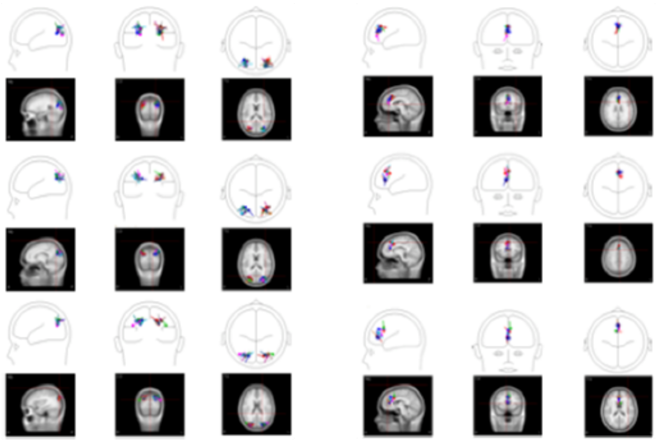

Fig. 6. Frontal and visual sources recovered from 3 sessions up-to one month apart (cross time within-subject reliability)

5 Efficiency

There are two contrasting types of applied problems. The first deals with only one set of enormously complex data where special handling is needed as well as possible and efficiency is not a primary concern. The other deals with large number of data sets whose processing is time-sensitive and efficiency is critical. Brain imaging data in the context of clinical diagnosis and monitoring belongs to the latter category. Here using the separation of the L and R SIs as benchmark neuronal sources, we show how quickly SOBI can reach a stable solution.

Shown in Fig. 7 are results from EEG data collected during median nerve electrical stimulation from four subjects. SOBI is an iterative algorithm and the separation matrix produced by SOBI is modified with each iteration. The *sin* (angle of rotation) is used as an indicator of whether one should continue the iterative process. We examined how the spatial location of the SOBI recovered L and R SI sources change as a function of the number of iterations as well as the ERP waveforms (not shown here) after each iteration.

We found that after less than 40 iterations, the resulting SOBI-recovered L and R SI sources for all subjects showed essentially no differences. Though the number of iterations required to reach the stable solution differs across subjects, possibly due to the quality of data as well as individual differences in the neuronal sources themselves, this experiment showed that as few as 22 iterations could be enough for SOBI to reach stable solutions for certain neuronal sources.

This suggests that SOBI process for all practical purposes might be surprisingly fast, particularly in comparison to other algorithms that require randomly-set initial conditions and averaging of multiple sets of solutions across a large number of random initial conditions (e.g. as in the case of InfoMax ICA).

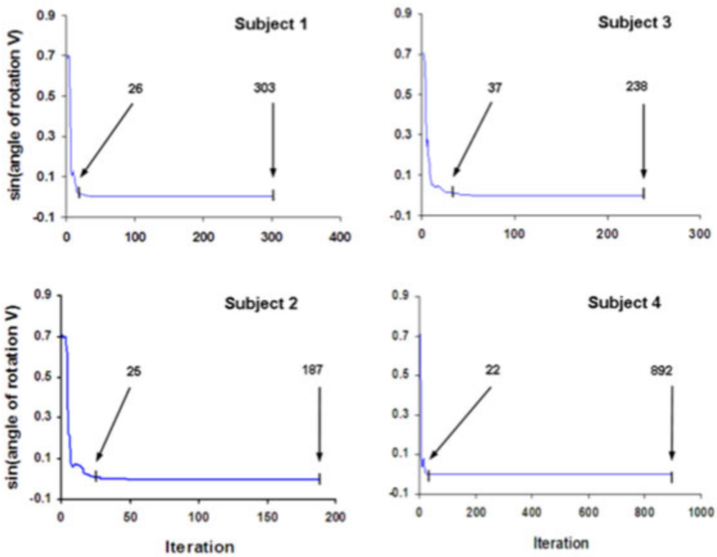

Fig. 7. SOBI process can reach stable source solution in as few as 22 iterations

6 Conclusions

We presented a mini-review of SOBI applications for addressing the problem of structure-function relations using high-density EEG. This presentation is not a comprehensive review of all works of SOBI application to EEG data and neither was it a general review of different BSS algorithms' application to brain imaging data. We specifically left out works exclusively focused on artifacts removal, a topic for which many excellent reviews existed. The work reviewed here is exclusively empirical and selective for the purpose of focusing on (1) signal-domain-specific validations, (2) robustness across varying experimental conditions; (3) reliability of source identification across repeated measures; and (4) efficiency. I believe that this review fills a particular gap of knowledge about SOBI that is worth sharing with both the signal processing as well the neuroscience community.

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