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Combining the extremities on the basis of separation: a new approach to EEG/ERP source localization

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Abstract. Current methods for the localization of EEG and event-related potentials (ERP) sources assume that sources are either discrete (dipole-like) or distributed. While both types of sources are likely to contribute significantly to EEG and ERP signals, each method adopts only one of these models and thus may localize the sources of other type incorrectly or not find them at all. Recently introduced Independent Component Analysis (ICA) and more general approach, Blind Source Separation (BSS), make possible the separation of signals from various brain and extra-brain (related to artifacts) sources and can be used as preprocessing technique before applying the localizing algorithms. We suggest using this preprocessing step for combining different localization methods. A brain source, if extracted correctly, can be analyzed separately from the other sources, and thus, the most appropriate localization technique can be chosen for each source. Distributed sources are likely to be localized more precisely without detailed separation but after BSS "cleaning" data from strong localized sources. © 2004 Published by Elsevier B.V.

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1. The two extreme approaches to brain source localization

Spatial localization of the signal sources remains one of the most difficult methodological problems in the analysis of EEG and ERP. While numerous techniques aimed at solving this problem have been developed up to date (see Ref. [1] for review), each of them, at best, can only provide correct localization of some types of the sources.

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The type of the sources which are most efficiently localized by a specific method depends on the source model which is assumed. Typically, sources are supposed to be discrete (the signal is produced by a few dipoles) or distributed (in this case, thousands of points are considered as possible location of a current source). It is quite evident that the discrete source model often can be inadequate in describing widely distributed activation, especially when its spatial pattern is complicated. On the other hand, the localization results obtained with the distributed source models can be evidently biased by various strong a priori assumptions required when these models are used. For example, the Laplacian Weighted Minimum Norm Algorithm implemented in the popular LORETA software [2] generally provides a rather blurred solution, which is the result of the assumption of smoothness of the spatial distribution of the sources [1]. Intuitively, it seems that any possible type of distributed source model will lead to less exact localization of the strong localized sources than discrete models can provide for the same sources.

Both discrete and distributed types of sources, however, can participate in the generation of EEG and ERP signal.

2. Blind source separation (BSS) as a tool for prelocalization separating EEG and ERP components related to different sources

The EEG and ERP signal always include mixed activity from many brain sources, which makes the task of source localization especially difficult. It seems to be reasonable to suggest that signal components from distinct sources should exhibit relatively low correlation or statistical dependency and can be separated (although not yet localized) without any a priori assumptions by finding most uncorrelated or most independent components. Many techniques for such “blind” source separation (BSS) have been developed recently and received growing interest not only in the analysis of EEG or MEG signals but also in many other areas of application [3]. The localization algorithm can be then applied to each of the separated sources. This approach is especially attractive for the application of discrete source model because only one or, in the case of bilateral symmetry, two dipoles should be fitted to each separated component, while the presence of noise (including activities of brain sources which do not fit the model) is minimized.

To date, many simulation and real data studies demonstrated the usefulness of Principal Component Analysis (PCA) followed by rotation, BSS based on Second Order Statistics (such as implemented in SOBI algorithm), and Independent Component Analysis (ICA) for improving source localization [4–13]. All these BSS techniques, theoretically, may help to localize even very weak and strongly overlapped sources, and to locate much higher number of dipole-like sources than can be localized without such preprocessing because the number of the dipoles which can be fitted is limited, in the case that separation is performed perfectly, only by the number of separated sources, which is, in the case of ICA and many other BSS techniques, usually equal to the number of electrodes.

3. BSS as a tool for combining discrete and distributed source modeling

To the best of our knowledge, no algorithm combining both discrete and distributed source modeling has been proposed yet. Moreover, it seems that no model exists which could be in between these two extreme approaches and combine their advantages. The two models could be easily used in parallel, however, if both types of the sources which best fit each of them are correctly separated in preprocessing. After separating the sources with some of BSS algorithms, one can select the most appropriate model for each source.

The performance of BSS algorithms on such complicated signals like EEG or ERP cannot be perfect. Application of distributed source model to the components separated with BSS has been studied too little yet to decide if BSS is really helpful in this case. Analysis of separated sources can be more problematic with distributed source modeling than with discrete source modeling. For example, a spatially extended source, which is formed by long-distance neuronal interactions, can be probably less homogenous and coherent than a strong local source and can be more easily split by the separating algorithm into several subsources.

However, one simple solution can help in combined use of both models.

Consider the procedure of cleaning ERP or EEG data from artifacts (e.g., eye blinking) using BSS, which is shown to be rather efficient [14,15]. In this procedure, the sources which can prevent correct estimation of the target activity are separated, identified, and then removed from the data; in other words, the ERP or EEG signal is reconstructed using only nonartificial components. Strong local brain sources can also significantly interfere with the modeling of distributed sources, and removing them from the data before distributed source analysis could be desirable. Therefore, for improving distributed source modeling, we can apply essentially the same procedure as in the case of removing artifacts: separate, identify, and remove strong local sources with BSS. The data “cleaned” from such sources can be then analyzed with distributed source modeling. Unlike in the artifact removing procedure, we can also analyze these sources which are to be removed before distributed source analysis; of course, we can analyze them with discrete source modeling.

One may hypothesize that spatially distributed sources are statistically more dependent or correlated than localized sources because the large neural networks may be more often driven by the input which is common with other large networks or even be directly connected to each other than distinct localized networks. If this is true, one should avoid the use of typical BSS technologies (based on decorrelation or independence criteria) for separating of distributed brain sources; the approach described above is in accordance with this understanding of the relations between brain sources.

The sources separated by BSS have one attribute whose negative effect on EEG and ERP analysis is often underestimated: their spatial pattern does not change in time. However, after removing the discrete sources, the temporal variations of the data spatial pattern do not disappear, and the spatial dynamics of distributed sources can be studied as usual.

Combination of BSS and discrete source modeling has already been proven to be, in general, practically efficient, but more studies are needed to choose the criteria for determining whether a component separated by BSS can be correctly modeled as a discrete source or should it be kept in the data for distributed source analysis.

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