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Frequency Domain Identification of Interacting Systems in the Brain

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Abstract. In order to understand interference among brain areas, it is fundamental to separate true source interaction from noise and to identify independent subsystems composed of interacting sources. Here, a frequency domain approach is proposed which, first, separates true source interaction from noise by considering only the imaginary part of the data cross-spectra; then, decomposes the interaction phenomenon into uncorrelated subsystems by applying the source Principal Component Analysis (sPCA) that exploits the assumption of spatial orthogonality of sources rather than signals. Finally, the contribution of correlated sources within each subsystem is disentangled by means of the Minimum Overlap Component Analysis (MOCA) by using a pure spatial criterion to unmix pairs of correlates sources.

Keywords: Electroencephalography, Magnetoencephalography, Coherency, Source Interaction, Inverse Problem.

1. Introduction

In understanding and modeling brain functioning, it is not only important to be able to identify active areas but also to understand interference among different areas. To this end, it is fundamental to separate true interaction from noise and to unmix the contribution of different subsystems composed of interacting sources. To isolate true interactions we focus on the imaginary part of the data cross-spectra that reflects true non zero-lagged interactions in the brain [Nolte et al., 2004; Marzetti et al., 2007]. In order to separate the contribution of various subsystems, a PCA/sPCA decomposition of the imaginary part of the cross-spectra is applied which necessarily results in complex eigenvectors. The respective real and imaginary parts span the two-dimensional subspaces in a signal-space that is identical to the subspace spanned by pairs of interacting sources. In order to split the contribution of these two interacting sources, a purely spatial criterion: Minimum Overlap Component Analysis (MOCA), is employed. MOCA also localizes the respective sources related to each eigenvector with a weighted minimum norm method combining geometry and amplitude information to avoid bias towards superficial sources. The approach is here tested in simulations.

2. Material and Methods

A straightforward way to study interaction between sources is to decompose imaginary parts of cross-spectra into eigenvectors and then interpreting these eigenvectors. For the sPCA decomposition, we assume that the sources are temporarily uncorrelated and spatially orthogonal in source space rather than in signal space as in PCA where, for a given spatial pattern in signal space, a source is estimated with a convenient linear inverse method. The real and imaginary parts of the eigenvectors are a linear combination of the fields of the sources in the brain. When solving the inverse problem, for these eigenvectors a mixture of the sources is localized. To demix the source contributions the MOCA method was developed. Here, one first solves the inverse problem for the real and imaginary parts by a weighted minimum norm solution. Then, it is assumed that the sources are orthogonal to each other, which, however, does not allow for a unique decomposition. As an additional criterion, we assume that the two source distributions have a minimum overlap defined for as a fourth order measure for vector fields, namely

$$\sum_x \left(\vec{J}_1(x) \cdot \vec{J}_2(x)\right)^2 = \min$$

for $\vec{J}_1(x)$ and $\vec{J}_2(x)$ being two orthogonal (in source space) and normalized source distributions defined on voxels at locations x.

This approach was tested in Monte Carlo simulations consisting of 5000 runs in the presence of 2 or more dipoles as uncorrelated sources. Spatially correlated, uncorrelated or realistic noise has been added in order to evaluate the robustness of the sPCA approach. Similarly, for pairs of correlated sources, noise free Monte Carlo simulations have been carried out in order to assess the robustness of the MOCA method.

3. Results

In Fig.1 we show an example of sPCA decomposition as opposed to classical PCA for one pair of uncorrelated dipoles. The patterns extracted by applying sPCA to the global field pattern are almost identical to the true field patterns. In contrast, classical PCA identifies two patterns, which are clearly a mixture of the fields of the single dipoles as a result of the wrong assumption of orthogonality in the signal space made by PCA.

In Fig.2 left, we show the error distribution between true fields and resolved dipole fields by means of PCA and sPCA for 2, 3 and 4 uncorrelated dipoles in the noise free case as well as in the presence of noise. The distributions show that, when no noise is added to the simulated data, sPCA is far superior to PCA in disentangling the field patterns generated by uncorrelated dipoles regardless of their number. The median values of the error distributions for sPCA are at least 15 times smaller than the corresponding median value for PCA. Similar results were obtained also when spatially correlated noise is added to the signals. This type of noise is typically the case for spontaneous brain activity not related to the neural activity under study [Sekihara and Scholz, 1996]. In this case, the sPCA model is able to account for this kind of noise, which is correctly disentangled from the true fields. In contrast, classical PCA slightly degrades its performances with respect to the noise free case. Furthermore, if the noise model is constituted by realistic noise, the sPCA model is also able to explain such noise in terms of a field pattern orthogonal to the true fields, thereby succeeding in recovering the original field patterns. In the presence of uncorrelated noise among all channels, we do not observe a strong advantage of sPCA over PCA because brain sources can hardly explain uncorrelated channel noise. In principle, it is possible to consider regularized inverse operators. However, uncorrelated channel noise is an unrealistic event that would mean that internal noise in the electronics of the measurement equipment is dominating the signal. Nevertheless, in this limiting case, sPCA performances become comparable to the PCA performances.

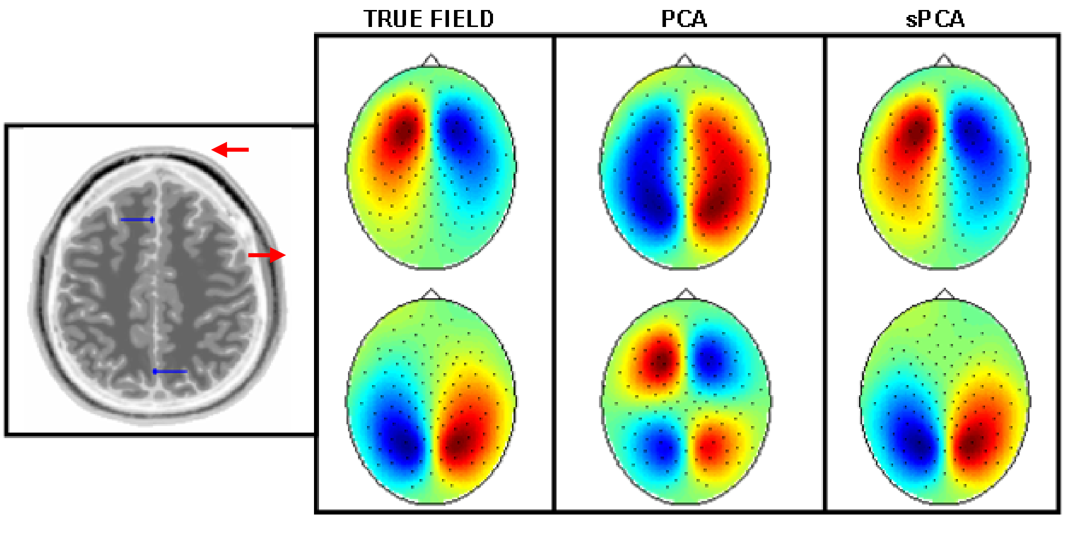

Figure 1. *Left: simulated dipole positions and orientations. Right:true dipole field, patterns resulting from PCA decomposition of the global field , patterns resulting from sPCA decomposition of the global field. The source space orthogonality assumption results in a sPCA decomposition which is almost identical to the true field patterns.*

For the separation of coherent or correlated sources (Fig.2 right), the error distribution shows that neither PCA nor sPCA achieve a good separation whereas MOCA does. For almost all of the simulated pairs of dipoles, in fact, MOCA strongly succeeds in the decomposition. Although the MOCA method does not make any assumption on the dynamical properties of the sources, it also succeeds in separating the contribution of uncorrelated sources with results as good as sPCA. This result is surprising as sPCA makes a dynamical assumption (in place of a stronger spatial one) that is exactly fulfilled. In any case, both sPCA and MOCA are clearly far superior in comparison to PCA.

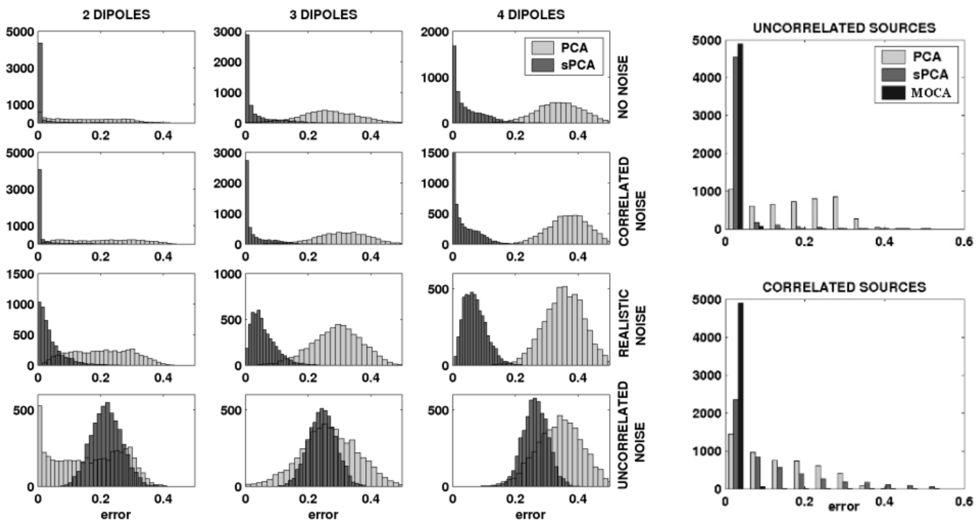

Figure 2. *Left: PCA and sPCA error distributions between the true fields and the disentangled ones for various number of uncorrelated dipoles. Right: PCA, sPCA and MOCA error distributions between the true fields and the disentangled ones for 2 uncorrelated or correlated dipoles.*

4. Discussion and Conclusions

We propose a method for identifying systems composed by interacting sources in the brain and disentangling the contribution of the various sources within each system. As a prerequisite, we developed the sPCA method for the decomposition of temporally uncorrelated or non-interacting sources or systems. This method is more effective than classical PCA in separating the contribution of various brain sources to a measured field, due to the assumption of spatial orthogonality of the sources rather than fields, as assumed by classical PCA. A second method, MOCA, is designed for the study of correlated source pairs and aims at disentangling the contribution of each source within a system by exploiting a purely spatial criterion. Nevertheless, although MOCA does not make any explicit dynamical assumption, for uncorrelated sources it performs as well as sPCA and far better than PCA. The MOCA approach provides also a weighted minimum norm localization of the decomposed source patterns, which is able to estimate focal as well as extended and distributed sources in contrast to methods that assume dipolar sources.

We believe this approach can help improving understanding brain interference phenomena by revealing networks composed of systems of sources interacting at a specific frequency or in a given frequency band. Therefore, we expect this method to be particularly effective in identifying interference among brain regions involved in the generation and keeping of human brain rhythms such as alpha rhythm for resting state activity or mu rhythm for somato-motor activity. We also believe that in all cases of pathologies in which an alteration of the power or frequency of such rhythms has been observed (e.g Alzheimer disease), the method could contribute to the investigation of a possible alteration of the interaction mechanism as well.

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