Journal of Neuroscience Methods 223 (2014) 40–49

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Computational Neuroscience

Second order blind identification on the cerebral cortex

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HIGHLIGHTS

- We extend the SOBI blind source separation method to data on the cerebral cortex.
- We compare this extension to the FastICA and original SOBI methods.
- The extended SOBI method outperforms the other methods in simulations.
- Application to structural data on the cortex reveals original networks.

ARTICLE INFO

Article history:
Received 11 July 2013
Received in revised form 2 November 2013
Accepted 26 November 2013

Keywords:
Blind source separation (BSS)
Independent component analysis (ICA)
Second order blind identification (SOBI)
Cerebral cortex
Sulcal folding pattern
Gray matter thickness

ABSTRACT

Blind source separation (BSS) methods have become standard brain imaging tools and are routinely used for noise and artifact removal, as well as for extracting related spatial and temporal components from brain signals. Despite their popularity, BSS methods have rarely been used to explore maps of cortical thickness and sulcal folding patterns. Our limited knowledge of the relationship between cortical morphometry, brain development and pathologies of the central nervous system makes BSS methods ideal investigative tools. We propose a novel spatial BSS method tailored for application to the cerebral cortex based on the second order blind identification (SOBI) method. Our method outperforms the regular SOBI and popular FastICA BSS methods on simulations. Application to maps of cortical thickness and curvature from normal controls reveals original structural networks.

1. Introduction

With the advent of modern brain imaging methods, researchers now have a wealth of data to explore brain networks. In this pursuit, blind source separation (BSS) methods have become increasingly popular to identify, separate, and denoise brain signals (Makeig et al., 1997; Damoiseaux et al., 2006; Jung et al., 2000). BSS methods, such as second order blind identification (SOBI; Belouchrani et al., 1997) and FastICA (Hyvärinen and Köster, 1997), decompose a dataset into a linear mixture of sources that best match some target property with typically little or no other prior knowledge of the sources or mixture model. For example, independent component analysis (ICA) is a very popular subset of BSS that relies on independence to separate and identify sources. Performance can vary greatly among different methods depending on how well the data satisfies each method's assumptions, and therefore selecting a proper BSS method is critical. In general, most BSS methods fall into or are a hybrid of one of the three following categories:

ICA methods using higher-order statistics (HOS): Sources are assumed to lack temporal, spatial, or other structure, requiring the use of HOS (often indirectly) to maximize source independence. Common methods include maximization of non-Gaussianity using kurtosis or negentropy, maximum likelihood estimation, minimization of mutual information, and tensorial methods. In almost all cases these methods optimize different measures of the same criterion (Hyvärinen et al., 2001), and as such, they all suffer from the same inability to separate more than one Gaussian source. The FastICA method is a widely-used member of this group.

BSS methods using second-order statistics (SOS): Sources have an underlying structure, allowing separation of merely uncorrelated (not necessarily independent) sources using SOS, such as shifted autocovariance matrices. SOS are more robust than HOS and allow Gaussian sources to be separated; however, SOBI and other methods in this

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http://dx.doi.org/10.1016/j.jneumeth.2013.11.023

category are unable to separate sources with identical power spectral densities (see Section 2.2).

BSS methods using nonstationarity: These methods require the data be nonstationary and often employ SOS to decorrelate the data at all data points (Matsuoka et al., 1995). Aside from nonstationarity, no other common requirements are placed on the data.

Most BSS applications in brain imaging have been to fMRI (Calhoun et al., 2003; McKeown et al., 1998), EEG (Vigário et al., 2000; Onton et al., 2006), and MEG (Vigário et al., 1998; Ikeda and Toyama, 2000) data. As a multivariate approach that makes minimal assumptions on the underlying model, BSS is a natural choice for exploring brain signals, which often have a complex structure with no clear best model (Zhukov et al., 2000; Sato et al., 2001; Jung et al., 2001). The independence forced upon ICA sources and the decorrelation forced upon BSS sources using SOS make these methods ideal for noise and artifact removal (Callan et al., 2001; Vorobyov and Cichocki, 2002) and separating functional brain networks (Calhoun et al., 2008) into subnetworks, such as the resting state networks (van de Ven et al., 2004; Beckmann et al., 2005). In applying these methods, one must choose the dimension(s) over which to optimize source independence or decorrelation with different applications favoring different dimensions. For example, temporal BSS is often used on EEG data to remove heart beat artifacts. Similarly, spatial BSS is often used on fMRI data to identify and remove head movement artifacts. In fact, BSS can be performed on any dataset dimension(s), not just space or time, and extensions to multiple dimensions, such as spatiotemporal ICA (Stone et al., 2002), exist. Many other modifications to basic BSS have been proposed; one notable example fuses EEG and fMRI data (Moosmann et al., 2008).

One drawback of BSS is that analyses procedures do not readily generalize to group studies. This is in contrast to many univariate methods which provide a direct one-to-one correspondence between results across subjects. Many methods have been proposed to circumvent this problem, and for fMRI data alone these methods fall into at least 5 categories (Calhoun et al., 2009): combining single subject BSS's (Esposito et al., 2005), temporally concatenating (Schmithorst and Holland, 2004), spatially concatenating (Svensén et al., 2002), pre-averaging (Schmithorst and Holland, 2004), and using a tensorial framework (Beckmann and Smith, 2005). Similar to temporal concatenation, concatenating data from subjects that have been registered to a common anatomical space allows for BSS analysis of any multi-subject dataset.

SOBI is frequently used on brain data (Tang et al., 2005; Joyce et al., 2004; Theis et al., 2004) for its ability to incorporate the correlation structure of the data and separate multiple Gaussian sources, which is not possible with ICA methods using HOS. Hyvärinen points out that ignoring such structural information may lead other methods to be substantially suboptimal (Hyvärinen et al., 2001), which was recently corroborated by one study comparing the performance of 22 different BSS methods on simulated EEG data (Klemm et al., 2009). Source separation is achieved by joint diagonalization of a set of shifted/lagged autocovariance matrices computed across a single dimension, typically time. Although application of SOBI to one-dimensional data is straightforward, the computation of shifted covariance matrices on the two-dimensional cortical manifold is not. In this paper we extend SOBI to data on the cerebral cortex using a two-dimensional analog of the one-dimensional shift to construct the covariance matrices.

We further propose a new way to study cortical brain networks using BSS: structural networks of gray matter thickness, gray matter thickness variance, and cortical curvature variance. Unlike functional networks and diffusion anatomical networks, little attention has been given to such networks based on the general physical structure of the cortical surface. Thickness changes have been implicated in brain development and aging (Sowell et al., 2003), and pathologies of the central nervous system, such as schizophrenia (Narr et al., 2005) and Alzheimer's disease (Lerch et al., 2005). Furthermore, brain networks constructed from interregional gray matter thickness correlations share many pathways in common with diffusion tensor images and manifest small-world and modular properties consistent with functional studies (He et al., 2007; Chen et al., 2008). Cortical folding patterns, whose shape can be locally quantified by the curvature metric (Luders et al., 2006), have also been associated with autism (Hardan et al., 2004), schizophrenia (Sallet et al., 2003), and sex differences (Zilles et al., 1997). In one recent study, cortical shape was represented by estimates of regional joint probability density functions of an orthogonal reparameterization of the principal curvatures (Awate et al., 2009). Differences in these joint densities were then connected to differences in type of congenital heart disease in neonates. To our knowledge, thickness and curvature relationships have not been previously studied with BSS, yet BSS is ideal for structural studies because they lack prior information about the signal topographies. Here we validate our BSS method using simulation and identify significant structural networks in thickness and curvature.

2. Materials and methods

In this section we provide a background on BSS, ICA, and the regular SOBI approach, and then introduce our SOBI method for the cerebral cortex.

2.1. Blind source separation (BSS)

Assume a number of source signals, denoted by $s_i(t)$, $i\epsilon\{1, \ldots, N\}$, that cannot be recorded directly and instead must be estimated from observed signals $x_i(t)$, $i\epsilon\{1, \ldots, N\}$. In the context of brain imaging, $s_i(t)$ could be electrical signals produced from different brain areas, and $x_i(t)$ the recordings from sensor electrodes surrounding the head. BSS assumes that the source signals are linearly combined by an unknown mixing matrix $\boldsymbol{A}$:

$$x(t) = \boldsymbol{A}s(t) \tag{1}$$

where $x(t) = [x_1(t)x_2(t)\ldots x_N(t)]^T$, $s(t) = [s_1(t)s_2(t)\ldots s_N(t)]^T$, and $(.)^T$ denotes the transpose operator. BSS then poses a target source property that constrains the solution of this underdetermined problem and allows for estimation of sources $s_i(t)$, with the exclusion of possible permutations and scalings of sources that cannot be recovered. For example, in the case of ICA the target source property is independence of all sources $s_i(t)$. It should also be noted that even though signals here are functions of time, the same analysis directly extends to signals parameterized by space or another index.

Most BSS methods begin by prewhitening the observed data $x_i(t)$, which simplifies the estimation of the sources. Define the source time-lagged covariance matrix as $\boldsymbol{C}_s(\tau) = \mathrm{E}\{s(t)s^*(t-\tau)\}$ with $(.)^*$ indicating the conjugate transpose operator. Sources $s_i(t)$ are uncorrelated and, without loss of generality, can be assumed to have zero mean and unit variance. Therefore, $\boldsymbol{C}_s(0) = \boldsymbol{I}$ and $\boldsymbol{C}_s(\tau) = \boldsymbol{D}_{\boldsymbol{\tau}}$, where $\boldsymbol{I}$ is the $N \times N$ identity matrix and $\boldsymbol{D}_{\boldsymbol{\tau}}$ is a diagonal matrix. In the whitened space, the model in Eq. (1) becomes

$$z(t) = \boldsymbol{WA}s(t) \tag{2}$$

where the whitened signals $z_i(t)$ compose $z(t)$, $\boldsymbol{W}$ is the whitening operator, and $\boldsymbol{C}_z(0) = \boldsymbol{I}$. Computing the 0-lagged covariance from Eq. (2) gives

$$\boldsymbol{I} = \boldsymbol{WAA}^*\boldsymbol{W}^* \tag{3}$$