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Source-space ICA for EEG source separation, localization, and time-course reconstruction

Yaqub Jonmohamadi [a,b,*], Govinda Poudel [b,c,d], Carrie Innes [b,e,f], Richard Jones [a,b,e,f]

[a] Department of Medicine, University of Otago, Christchurch, New Zealand
[b] New Zealand Brain Research Institute, Christchurch, New Zealand
[c] Monash Biomedical Imaging, Monash University, Melbourne, Australia
[d] School of Psychological Sciences, Monash University, Clayton, Victoria, Australia
[e] Department of Electrical and Computer Engineering, University of Canterbury, Christchurch, New Zealand
[f] Department of Medical Physics and Bioengineering, Christchurch Hospital, Christchurch, New Zealand

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ABSTRACT

We propose source-space independent component analysis (ICA) for separation, tomography, and time-course reconstruction of EEG and MEG source signals. Source-space ICA is based on the application of singular value decomposition and ICA on the neuroelectrical signals from all brain voxels obtained post minimum-variance beamforming of sensor-space EEG or MEG. We describe the theoretical background and equations, then evaluate the performance of this technique in several different situations, including weak sources, bilateral correlated sources, multiple sources, and cluster sources. In this approach, tomographic maps of sources are obtained by back-projection of the ICA mixing coefficients into the source-space (3-D brain template). The advantages of source-space ICA over the popular alternative approaches of sensor-space ICA together with dipole fitting and power mapping via minimum-variance beamforming are demonstrated. Simulated EEG data were produced by forward head modeling to project the simulated sources onto scalp sensors, then superimposed on real EEG background. To illustrate the application of source-space ICA to real EEG source reconstruction, we show the localization and time-course reconstruction of visual evoked potentials. Source-space ICA is superior to the minimum-variance beamforming in the reconstruction of multiple weak and strong sources, as ICA allows weak sources to be identified and reconstructed in the presence of stronger sources. Source-space ICA is also superior to sensor-space ICA on accuracy of localization of sources, as source-space ICA applies ICA to the time-courses of voxels reconstructed from minimum-variance beamforming on a 3D scanning grid and these time-courses are optimally unmixed via the beamformer. Each component identified by source-space ICA has its own tomographic map which shows the extent to which each voxel has contributed to that component.

Introduction

A substantial advantage of electroencephalography (EEG) and magnetoencephalography (MEG), over other noninvasive functional imaging of the brain, such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET), is their millisecond temporal resolution. This high temporal resolution provides the opportunity for the study of highly transient brain source activities.

In EEG and MEG, the inverse solution is used to estimate the location of sources and corresponding time-courses. The inverse problem in EEG and MEG, however, is ill-posed as the EEG/MEG scalp sensors are highly outnumbered by the brain source signals.

Several approaches have been proposed for solving the inverse problem including dipole fitting (Mosher et al., 1992; Sarvas, 1987; Uutela et al., 1983), minimum-norm spatial filters (Dale et al., 2000; Hämäläinen and Ilmoniemi, 1994; Pascual-Marqui, 2002), and minimum-variance spatial filters (Greenblatt et al., 2005; Robinson and Vrba, 1998; Sekihara et al., 2001; Van Veen et al., 1997). Dipole fitting is a popular technique which assumes that a predefined number of dipoles have generated the given EEG/MEG segment. The main limitation of this technique is that an arbitrary number of sources must be specified in advance. In addition, dipole fitting finds a single point for each brain source and is unable to produce a tomographic map. Minimum-norm based spatial filters, such as the original minimum-norm filter (Hämäläinen and Ilmoniemi, 1994) and standardized low resolution brain electromagnetic tomography (sLORETA) (Pascual-Marqui, 2002), produce a tomographic map for the whole brain for a given MEG/EEG epoch and do not require prior knowledge of the number of brain sources. Minimum-variance spatial filters, such as the

* Corresponding author at: New Zealand Brain Research Institute, 66 Stewart Street, Christchurch 8011, New Zealand.
E-mail address: jonya247@student.otago.ac.nz (Y. Jonmohamadi).

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adaptive minimum variance beamformers (Robinson and Vrba, 1998; Sekihara et al., 2001; Van Veen et al., 1997), scan the whole brain (source-space) voxel by voxel and estimate the power of each voxel for a given epoch to produce a tomographic map. Minimum-variance beamformers have been shown to have a higher spatial resolution than minimum-norm based filters and can reconstruct signal sources with a small signal-to-noise-ratio (SNR) (Jonmohamadi et al., 2014a; Sekihara et al., 2005).

The recently proposed Champagne algorithm (Owen et al., 2012; Wipf et al., 2009, 2010) has shown improvement over other popular source localization algorithms in terms of accuracy, robustness to correlated sources, and computational efficiency. However, in the performance evaluation of Champagne (Owen et al., 2012), there is no example of the reconstruction of weak sources, e.g., SNR < 1. Champagne is dependent on segmentation of the EEG/MEG to pre- and post-stimulus epochs, and performance of Champagne is partly dependent on the orientation of the sources as the performance drops when the orientation of the sources is not known (Owen et al., 2012).

The above-mentioned techniques are based on detecting sources based on measuring the power and, therefore, these techniques may not be able to detect weak sources in the presence of stronger interfering sources. Besides measuring the power of the signals for source localization, the statistical properties of the signals, such as entropy and non-Gaussianity, can be estimated and used as a means to detect and separate source signal time-courses. Independent component analysis (ICA) is a blind source separation (BSS) technique which aims to separate P mutually statistically independent, zero mean, sources from M linearly combined signal mixtures (Sanei and Chambers, 2007). In EEG and MEG, ICA has been extensively used for component extraction of event related potentials (ERPs) (Jervis et al., 2007; La Foresta et al., 2009; Makeig et al., 2004; Onton et al., 2006; Ventouras et al., 2010) and for artifact removal (Fatima et al., 2013; Jung et al., 1998, 2000).

In the case of source localization, ICA accompanied with dipole fitting (Makeig et al., 2004) has been applied to localize and reconstruct the time-course of the sources. In this approach, after applying ICA on EEG (sensor-space ICA), dipole fitting is used to localize the identified sensor-space components in the source-space (brain). The limitation of this approach is that dipole fitting does not provide a tomographic map and shows a single point as the location of the generator of the identified sensor-space independent component. In another approach (Ventouras et al., 2010), sLORETA has been applied instead of dipole fitting for the components of sensor-space ICA which can provide the tomographic maps. As a minimum-norm spatial filter, sLORETA has been shown to have low spatial resolution compared to minimum-variance beamformers (Sekihara et al., 2005) and, as will be demonstrated, dipole fitting of sensor-space independent components is not accurate in localization of sources.

We propose source-space ICA for separation, tomography and time-course reconstruction of EEG and MEG source signals (Jonmohamadi et al., 2013), which, similar to minimum-variance beamformers, has a high spatial resolution and, similar to ICA, can separate weak and strong sources and provide a unique spatial signature for every separated source. Source-space ICA applies a vector minimum-variance spatial filter to reconstruct the time-series of the source-space (brain volume) on a 3D scanning grid and then applies singular value decomposition and ICA to separate the sources. This approach does not rely on a known number of sources and their orientations, or pre- and post-stimulus segmentation, but also estimates the orientations of the separated sources. The difference between the popular sensor-space ICA and the proposed source-space ICA is that, in sensor-space ICA, the ICA is applied to the time-courses of the data from actual sensors (scalp EEG/MEG sensors), whereas, in source-space ICA, the ICA is applied to the time-courses of a 3D grid of virtual sensors in the brain (as reconstructed via beamforming). Consequently, the independent components of sensor-space signals have corresponding topographic maps, whereas the independent components of the source-space signals have corresponding tomographic maps.

In this paper, the performance of source-space ICA in several simulated situations, including single and multiple weak sources, bilateral correlated sources, and cluster sources is evaluated and compared with the beamforming technique and sensor-space ICA/dipole fitting (Makeig et al., 2004). Finally, we demonstrate the source-space ICA approach for source reconstruction of real visual evoked potentials (VEPs). Throughout this paper, plain italics indicate scalars, lower-case boldface italics indicate vectors, and upper-case boldface italics indicate matrices.

Methods

Problem formulation

The EEG signal for K time samples $\boldsymbol{B}(t) = [\boldsymbol{b}(t_1), b(t_2), \ldots, \boldsymbol{b}(t_K)]^T$, on M sensors, at time point t is

$$\boldsymbol{b}(t) = \int \boldsymbol{L}(\boldsymbol{r})\boldsymbol{q}(\boldsymbol{r})s(t,\boldsymbol{r})d(\boldsymbol{r}) + \boldsymbol{\eta}(t), \tag{1}$$

and $\boldsymbol{L}(\boldsymbol{r}) = [\boldsymbol{l}_x(\boldsymbol{r}), \boldsymbol{l}_y(\boldsymbol{r}), \boldsymbol{l}_z(\boldsymbol{r})]$ is a $M \times 3$ lead-field matrix which shows the sensitivity of scalp sensors in three orthogonal directions (x,y,z) to the source signal $s(t, \boldsymbol{r})$ located at $\boldsymbol{r} = [r_x, r_y, r_z]^T$ (mm) with a moment of $\boldsymbol{q}(\boldsymbol{r}) = [q_x(\boldsymbol{r}), q_y(\boldsymbol{r}), q_z(\boldsymbol{r})]^T$ (A·m), and $\boldsymbol{\eta}(t)$ is the additive noise.

The reconstructed time-course, $\hat{\boldsymbol{s}}(t,\boldsymbol{r}) = [\hat{s}_x(t,\boldsymbol{r}), \hat{s}_y(t,\boldsymbol{r}), \hat{s}_z(t,\boldsymbol{r})]^T$, for a given location $\boldsymbol{r}$ to the vector spatial filter can be written as

$$\hat{\boldsymbol{s}}(t,\boldsymbol{r}) = \boldsymbol{W}^T(\boldsymbol{r})\boldsymbol{b}(t), \tag{2}$$

where $\boldsymbol{W}(\boldsymbol{r}) = [\boldsymbol{w}_x(\boldsymbol{r}), \boldsymbol{w}_y(\boldsymbol{r}), \boldsymbol{w}_z(\boldsymbol{r})]$ is a $M \times 3$ matrix of the vector spatial filter coefficients. One way to obtain a tomographic map for all the brain locations (voxels) for a given EEG/MEG segment, is to measure the power for each voxel

$$\boldsymbol{p}_\xi(\boldsymbol{r}) = \boldsymbol{w}_\xi^T(\boldsymbol{r})\boldsymbol{C}\boldsymbol{w}_\xi(\boldsymbol{r}) = \left\langle \hat{\boldsymbol{s}}_\xi(t,\boldsymbol{r})^2 \right\rangle, \quad \xi \in x, y, z; \boldsymbol{r} \in \Omega, \tag{3}$$

where $\langle \cdots \rangle$ is the ensemble average, and Ω is the different location on the scanning grid which covers the whole brain (source-space), and $\boldsymbol{C}$ is the covariance matrix

$$\boldsymbol{C} = \left\langle \boldsymbol{b}(t)\boldsymbol{b}^T(t) \right\rangle. \tag{4}$$

In Eq. (3), only the dominant sources will be identified for the period that $\boldsymbol{C}$ is measured but weaker sources may not be identified due to their small power.

Beamformer

Beamforming, as a form of spatial filtering, is a popular technique for localization and signal reconstruction of brain sources in EEG and MEG and has been successfully applied (Robinson and Vrba, 1998; Sekihara et al., 2001; Van Veen et al., 1997) and the performances of different beamformers have been evaluated (Greenblatt et al., 2005; Huang et al., 2004; Sekihara et al., 2005). Of the several beamformers, we chose the vector weight-normalized minimum-variance (WNMV) beamformer, also known as Borgiotti–Kaplan (Sekihara et al., 2001), as it has normalized weight vectors which results in unit noise gain and, hence, the time-courses of all voxels have the same gain. The weight matrix of the vector WNMV beamformer is

$$\boldsymbol{W}_{WNMV}(\boldsymbol{r}) = \frac{\boldsymbol{C}^{-1}\boldsymbol{L}(\boldsymbol{r})\boldsymbol{P}^{-1}(\boldsymbol{r})}{\sqrt{\boldsymbol{P}^{-1}(\boldsymbol{r})\boldsymbol{Q}(\boldsymbol{r})\boldsymbol{P}^{-1}(\boldsymbol{r})}}$$