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Bayesian model selection of template forward models for EEG source reconstruction

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ABSTRACT

Several EEG source reconstruction techniques have been proposed to identify the generating neuronal sources of electrical activity measured on the scalp. The solution of these techniques depends directly on the accuracy of the forward model that is inverted. Recently, a parametric empirical Bayesian (PEB) framework for distributed source reconstruction in EEG/MEG was introduced and implemented in the Statistical Parametric Mapping (SPM) software. The framework allows us to compare different forward modeling approaches, using real data, instead of using more traditional simulated data from an assumed true forward model. In the absence of a subject specific MR image, a 3-layered boundary element method (BEM) template head model is currently used including a scalp, skull and brain compartment. In this study, we introduced volumetric template head models based on the finite difference method (FDM). We constructed a FDM head model equivalent to the BEM model and an extended FDM model including CSF. These models were compared within the context of three different types of source priors related to the type of inversion used in the PEB framework: independent and identically distributed (IID) sources, equivalent to classical minimum norm approaches, coherence (COH) priors similar to methods such as LORETA, and multiple sparse priors (MSP). The resulting models were compared based on ERP data of 20 subjects using Bayesian model selection for group studies. The reconstructed activity was also compared with the findings of previous studies using functional magnetic resonance imaging. We found very strong evidence in favor of the extended FDM head model with CSF and assuming MSP. These results suggest that the use of realistic volumetric forward models can improve PEB EEG source reconstruction.

Introduction

The aim of EEG source reconstruction is to estimate the generating neuronal sources of electrical activity measured on the scalp, within the brain. In general, three components can be distinguished. The first component is associated with the definition of the solution space and a parametric representation of the sources (e.g., the electrical current dipole). The second component contains the information about the physical and geometrical properties of the head. These two components comprise a forward model of the EEG data that describes the electromagnetic field propagation of the sources through the various tissues. The third component is an inverse technique that, according to a certain criterion and the given forward model, defines a unique source distribution (Phillips et al., 2005).

There exist several different forward modeling approaches depending on how the head is modeled and which source space is chosen. An analytical solution is only possible for a highly symmetrical geometry and homogeneous isotropic electrical conductivity. For other more general cases, numerical methods are required. These methods include the finite element method (FEM) (Wolters et al., 2002), the finite difference method (FDM) (Hallez et al., 2005; Vanrumste et al., 2001) and the boundary element method (BEM) (Mosher et al., 1999). The FEM and the FDM make no assumptions about the shape of the head model

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and allow the estimation of the electrical potentials at any location in the volume. The BEM is based on the hypothesis that the volume is divided into subvolumes of homogeneous and isotropic conductivity and the potentials are estimated only on the surfaces separating these subvolumes. As a consequence the FEM and the FDM offer a more general solution of the forward problem at the expense of the computation time (Phillips et al., 2007).

In recent years, the inverse techniques have evolved from single dipole iterative searching methods to comprehensive distributed source estimations for distributed source models (Michel and Murray, 2012; Pascual-Marqui et al., 2009). In distributed models, the solution space typically contains a large number of current dipoles at discrete points within the brain, which leads to a largely underdetermined EEG inverse problem. Bayesian approaches offer a natural way to introduce multiple constraints, or priors, to regularize the solution (Baillet and Garnero, 1997; Grech et al., 2008; Henson et al., 2011; Lucka et al., 2012; Michel et al., 2004; Wipf and Nagarajan, 2009). They allow a more detailed description of the anatomical and functional a priori information compared to the classical methods (Daunizeau et al., 2007; Luessi et al., 2011; Ou et al., 2010).

A parametric empirical Bayesian (PEB) framework for distributed sources was recently introduced and implemented in the widely used Statistical Parametric Mapping (SPM) software package (http://www.fil.ion.ucl.ac.uk/spm) (Henson et al., 2011). The framework allows integration of multiple constraints in the distributed source reconstruction problem for EEG and MEG (Henson et al., 2009b, 2010). Furthermore, the PEB framework allows us to compare forward models based on the negative variational free energy bound on the Bayesian log evidence. It provides an alternative way of testing forward models, using (though conditional on) real data, rather than the more traditional simulated data from an assumed true forward model. Only a few forward modeling approaches have been compared within the PEB framework for MEG source reconstruction. Based on event related fields (ERF) for visual processing of faces and scrambled faces, Henson et al. (2009a) recommend to use a 3-layered Boundary Element Method (BEM) approximation of the head containing 3 homogeneous isotropic conducting compartments corresponding with the scalp, skull and brain tissue.

To our knowledge, no prior studies have been published that used the PEB framework to compare forward modeling approaches for EEG source reconstruction. The forward model is however more crucial for EEG source reconstruction than for MEG source reconstruction (Lew et al., 2013). In this study we therefore extended the Henson et al. (2009a) study to EEG forward modeling approaches. In the context of group studies, we used an anatomical template MR image (i.e. the Colin27 template (Mazziotta et al., 2001)) to construct the head models. In addition to the currently used 3-layered BEM approach we introduced models based on the finite difference reciprocity method (Hallez et al., 2005; Vanrumste et al., 2001). As such we were able to construct a head model including cerebrospinal fluid (CSF) segmented from the template MRI.

In previous studies, EEG and MRI experiments in supine and prone subject position experimentally proved how important the effect of CSF on the EEG is (Rice et al., 2013). Also simulation studies showed that it is crucial to model the CSF (Ramon et al., 2004, 2006; Vanrumste et al., 2000), and it was recently shown that the CSF effect is far bigger than differences in numerical errors between state-of-the-art forward modeling approaches (Vorwerk et al., 2012). This study is complementary to these studies by comparing different head models with and without CSF using realistic EEG data.

Based on 96-channels ERP datasets of 20 subjects in 4 stimulus conditions and using Bayesian model selection for group studies (Rigoux et al., 2013; Stephan et al., 2009), we investigated the effect of using three different template head models and three different types of source priors related to the type of inversion used in the PEB framework. We considered the default BEM model used in the SPM software, a FDM model equivalent to the 3-layered BEM model and a FDM model extended with CSF compartments segmented from the template. Three different types of source priors were compared for each of these head models: independent and identically distributed (IID) sources, which is equivalent to classical minimum norm approaches (Hämäläinen and Ilmoniemi, 1994), coherence (COH) priors or smoothness priors similar to methods such as LORETA (Pascual-Marqui et al., 1994) and multiple sparse priors (MSP) (Friston et al., 2008). In addition, the reconstructed activity was also compared with the findings of previous studies using functional magnetic resonance imaging (fMRI) in similar stimulus conditions.

In the next section we will present a general introduction to Bayesian approaches to solve the EEG inverse problem for distributed sources, followed by a short description of the source priors and the free energy optimization approach in the PEB framework. Next, we introduce the FDM forward modeling approach. For numerical validation, we first compare the FDM approach numerically to a state-of-the-art BEM approach based on an analytical spherical reference model. In the following subsections we will describe how we constructed the different head models based on the anatomical template MR image. We explain how we compared the models numerically and how we compared the models for each of the assumed source priors using Bayesian model selection based on free energy.

Methods

Bayesian framework for distributed EEG source reconstruction

We can represent the EEG measurements as a multivariate linear model involving a distributed source model with fixed positions and orientations (Dale and Sereno, 1992):

$$V = L_m J_m + \epsilon \tag{1}$$

where $V \in \mathbb{R}^{N_c \times N_t}$ is the EEG dataset of N_c channels and N_t time samples, $J_m \in \mathbb{R}^{N_d \times N_t}$ is the amplitude of N_d current dipoles located on the cortical surface with fixed orientations perpendicular to it, $\epsilon \in \mathbb{R}^{N_c \times N_t}$ is zero mean additive Gaussian noise and $L_m \in \mathbb{R}^{N_c \times N_d}$ is a lead field matrix linking the source amplitudes in J_m to the electrical scalp potentials in V. The lead field matrix represents the forward model m and embodies the assumptions about the head model and which forward modeling technique is used. We can write the likelihood associated with Eq. (1) as (López et al., 2012):

$$p(V|J_m, m) = \mathcal{N}(L_m J_m, R) \tag{2}$$

with $\mathcal{N}(\cdot)$ the multivariate normal probability density function and $R \in \mathbb{R}^{N_c \times N_c}$ the channel noise covariance. This leads to a posterior distribution of the source activity via Bayes' rule:

$$p(J_m|V, m) = \frac{p(V|J_m, m)p(J_m)}{p(V|m)} \tag{3}$$

where $p\ (J_m)$ represents the prior assumptions about the source activity and $p(V|m)$ is the model evidence. Because the number of sources (N_d) is much higher than the number of channels (N_c) this is an ill-posed problem. To solve the problem it is necessary to find an inverse operator $M_m \in \mathbb{R}^{N_d \times N_c} \approx L_m^{-1}$:

$$\widehat{J_m} = M_m V. \tag{4}$$

This can be solved within the Bayesian framework by assuming that both J_m and ϵ are zero mean Gaussian distributed:

$$p(J_m) = \mathcal{N}(0, Q) \quad , \quad p(\epsilon) = \mathcal{N}(0, R) \tag{5}$$