Volumetric sparse priors for the EEG inverse problem

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Introduction:

A parametric empirical Bayesian (PEB) framework for distributed sources is recently introduced in the widely used neuroimaging package SPM (Henson, 2011). The framework offers multi-modal and multi-subject integration and the ability to test forward models using real data in Bayesian model comparison based on free energy. Within the PEB approach, the multiple sparse priors (MSP) algorithm is the state-of-the-art technique in which multiple cortical sources with compact spatial support, specified in terms of empirical priors, are automatically selected (Friston, 2008).

More realistic forward modeling can be introduced in the MSP approach to further increase the precision of source estimation. In the current implementation, the source-space is divided into a number of small cortical patches calculated based on dipoles distributed on a cortical mesh. The field propagation of the surface patches is calculated based on solutions for a 3-layered, scalp-skull-brain Boundary Element Method (BEM) approximation to the head, see figure 1A. In reality, dipoles can also be located inside gray matter. More realistic volume-conductor models including gray matter can be modeled based on a high resolution anatomical MR image and finite difference method (FDM) forward modeling (Hallez, 2007), see figure 1B. As such and in analogy with the MSP algorithm based on cortical patches, the source-space can be divided into a number of small volumetric regions in gray matter.

Methods:

A Finite Difference Method forward solver based on reciprocity (van Rumste, 2000) was introduced in the parametric empirical Bayesian framework of SPM. This allowed us to model dipoles inside gray matter and therefore we could generalize the surface patch generation process to the construction of multiple volumetric sparse regions. We used volume-conductor models based on the MNI template which is used by default in SPM. A 2D cortical mesh was constructed including 7006 dipoles to use with BEM forward modeling, see figure 1A. This mesh was extended to dipoles located inside gray matter with an inter-dipole distance of 2mm, based on a head model including gray matter and CSF, see figure 1C. This new volumetric forward modeling approach was compared with the standard MSP forward modeling in terms of free energy and the plausibility of source reconstructions with previously published real data (De Vos, 2012). In brief, twenty healthy individuals (12 females, age 20–28 years) participated in a visual detection paradigm in which face, house, inverted face and words stimuli were presented. We used 83 channels grand averaged datasets over subjects for each task.

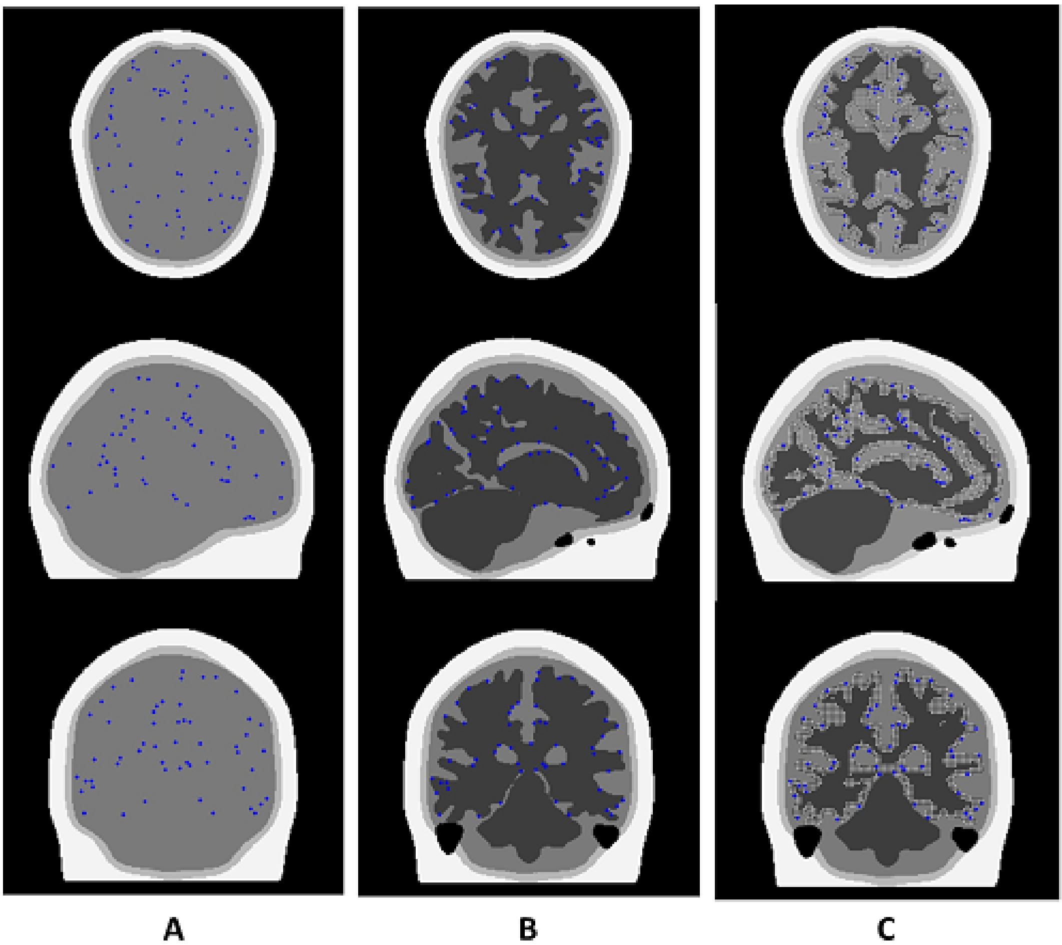

Figure 1: Slices in orthogonal directions of the volume-conductor models based on the MNI template. Column **A:** 3-layered BEM approximation to the head. The blue spots are dipoles located on a 3D cortical mesh. Column **B**: extension of the volume-conductor model with CSF and air cavities. Column **C**: Volumetric dipolar grid extension based on dipoles inside gray matter with an inter-dipole distance of 2mm represented by the white spots.

Results:

In figure 2, the reconstructions for the different tasks based on the default BEM forward modeling and volumetric FDM extension are compared based on their free energy. For each task there is very strong evidence in favor of the volumetric FDM extension. For the faces task, we expected activation of the fusiform face area between 150 and 200 ms after stimulus. Figure 3 corresponds with the evoked energy of the reconstructed activity in this time window. For the words task, we also expected activation of the fusiform face area but more expressed in the left hemisphere between 150 and 200 ms after stimuli. Figure 4 corresponds with the evoked energy of the reconstructed activity in this time window. Both figure 3 and 4 show that the reconstructed activity based on the volumetric FDM extension is more plausible compared to the default BEM forward modeling.

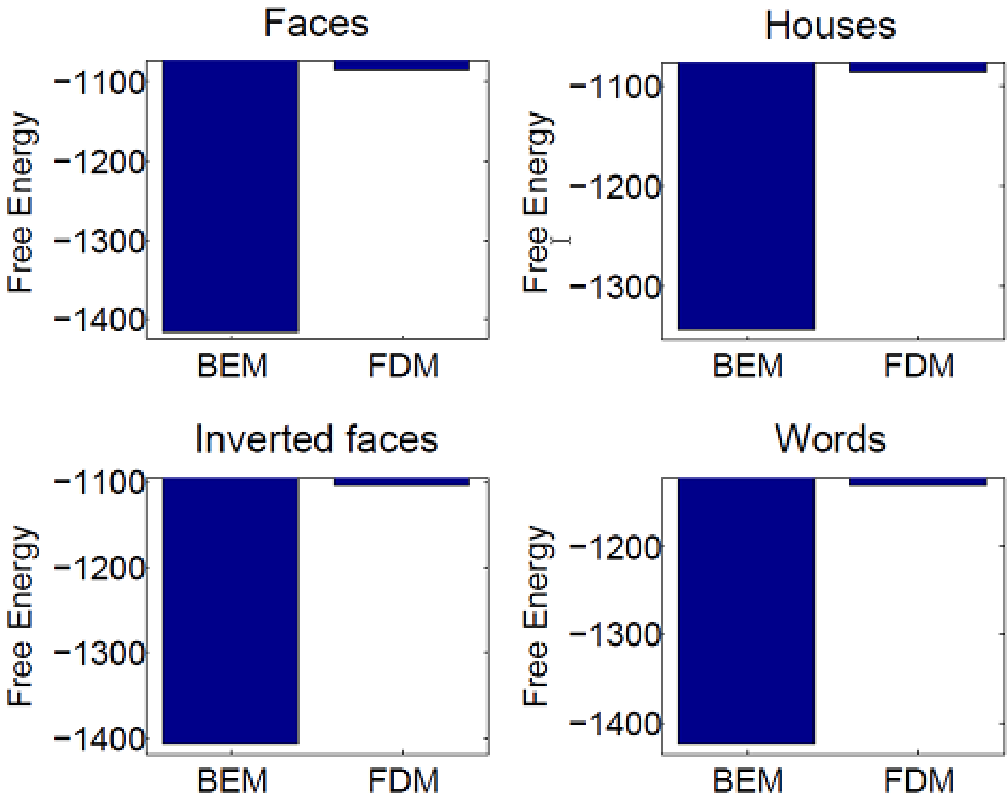

Figure 2: Free energy comparison for the different tasks, Faces, Houses, Inverted faces and Words. The x-axis describes whether the default BEM forward modeling with surface patches is used or the volumetric extension based on FDM forward modeling.

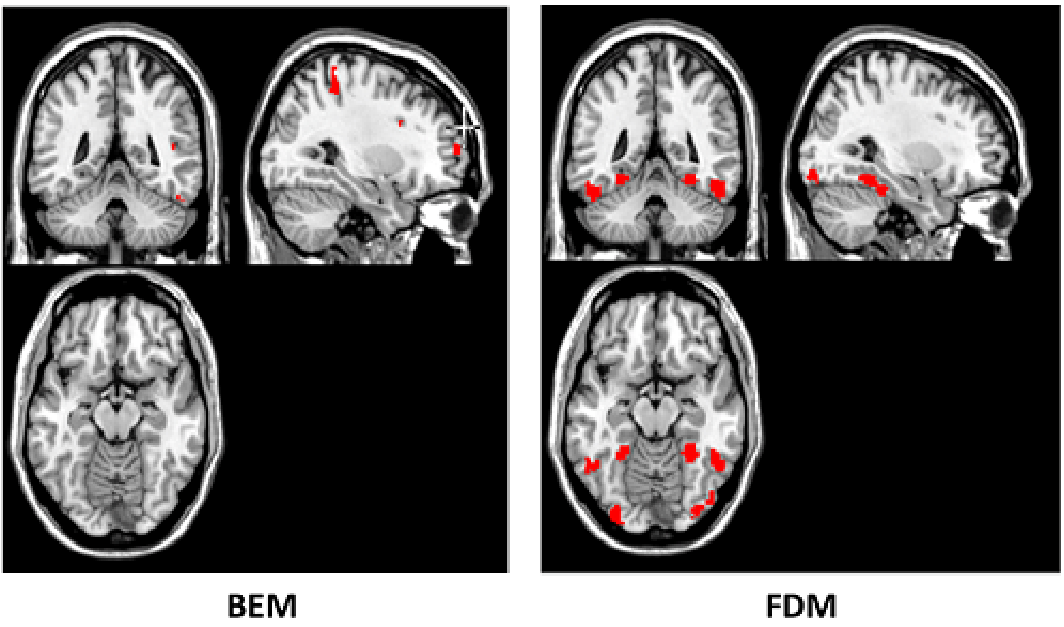

Figure 3: Comparison of the evoked energy between 150 and 200 ms after stimulus for the Faces task. On the left the BEM based reconstruction is shown, on the right the FDM based reconstruction. Activity is expected in the fusiform face areas which is the case for the FDM extension.

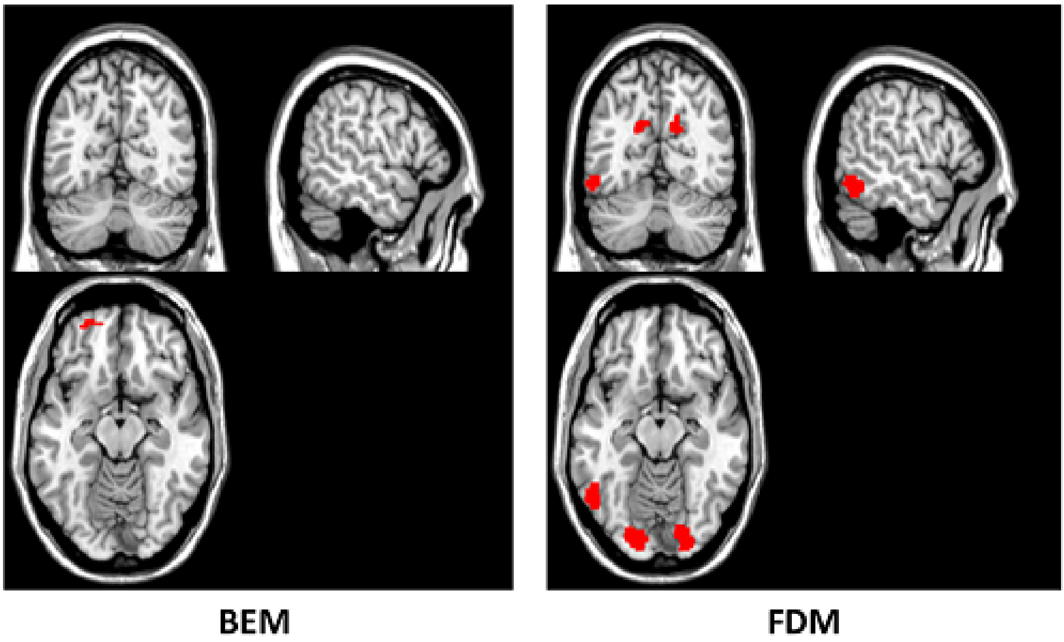

Figure 4: Comparison of the evoked energy between 150 and 200 ms after stimulus for the Words task. On the left the BEM based reconstruction is showed, on the right the FDM based reconstruction. Activity is expected in the fusiform face area, more expressed in the left hemisphere, which is nicely expressed in the reconstruction for the FDM extension.

Conclusions:

In this study we prove that the extension of the default forward modeling in the MSP algorithm to volumetric regions and FDM forward modeling improves the estimation of the underlying sources significantly both in terms of free energy and the plausibility of the reconstructed activity. The ability to use volumetric regions as empirical priors has therefore much potential for further studies, for example using subject specific volume-conductor models.

Modeling and Analysis Methods:

EEG/MEG Modeling and Analysis

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