Westfälische Wilhelms-Universität Münster

IBB Institute for Biomagnetism and Biosignalanalysis

Fachbereich 10 Mathematik und Informatik

Hierarchical Fully-Bayesian Inference for EEG/MEG Combination: Examination of Depth Localization and Source Separation using Realistic FE Head Models

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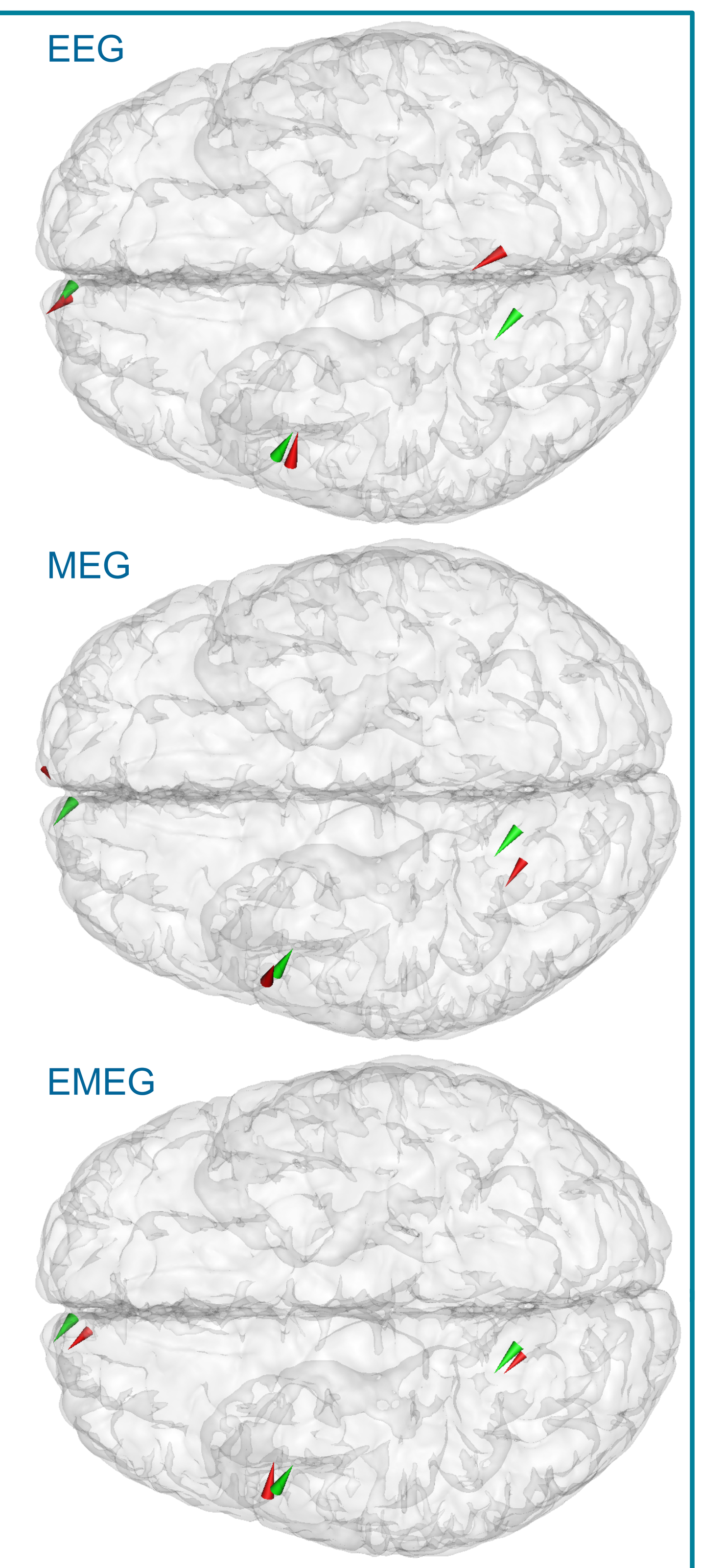
Background

In Lucka et al., 2012, we compared *fully-Bayesian inference* methods *for hierarchical Bayesian modeling* (*HBM*) for EEG source reconstruction to established *current density reconstruction* (*CDR*) methods like the *minimum norm estimate* (*MNE*, Hämäläinen and Ilmoniemi, 1994) or *sLORETA* (Pascual-Marqui, 2002). For multiple focal source scenarios, fully-Bayesian inference methods for HBM improved upon established CDR in many aspects. In particular, they showed good localization properties for single dipoles and did not suffer from systematic depth mis-localization (*depth bias*). In contrast to the established inverse methods, HBM-based methods were less likely to miss single sources in multiple source scenarios (*masking*) and were often able to reconstruct the correct number of sources.

Motivation

In this work, we addressed two questions that were posed in the outlook of Lucka et al., 2012:

- EEG vs. MEG and EEG/MEG combination (*EMEG*): Do our findings also apply for MEG? The differences between EEG and MEG have mainly been examined by established inverse methods up to date (e.g., Molins et al., 2007). How are things for fully-Bayesian inference for HBM? What is the profit of EMEG over the single modalities? Which source configurations benefit?
- To facilitate the interpretation of our results, we formerly used a simplified head model with a homogenous inner brain. Especially for EEG/MEG combination, the use of a realistic, individual and anisotropic head model is mandatory.



Model Setup

For our studies, we use a realistic, anisotropic *finite element* (*FE*) head model. The model generation is sketched in Figure 3. A realistic EEG cap with 63 electrodes is used. For a fair comparison, 63 magnetometers positioned 3 cm away from the electrodes are used as MEG sensors (see Figure 5). A regular grid is used to discretize the complete volume of the cerebral gray matter for a CDR (grid size: 6 mm).

Inverse Methods

Our focus is on three fully-Bayesian HBM methods: Full-MAP, Full-CM and Full-NM (*Near-Mean*) estimates (see Lucka et al., 2012). Their results will be compared to MNS with different weightings (*WMNS*, see, e.g., Fuchs et al., 1998) and sLORETA.

Numerical Studies

In two extensive simulation studies source configurations were reconstructed using (a) EEG, (b) MEG and (c) EMEG data. SNR: 20.

(1) Single dipole recovery: 1000 single dipoles were randomly placed in the gray matter. Validation measures: *Dipole localization error* (*DLE*), *earth mover's distance* (*EMD*, see Lucka et al., 2012) and depth of reference and estimated source.

(2) Two dipole recovery: 500 two-dipole configurations were randomly chosen. Validation measures: EMD.

In addition, exemplary three dipole scenarios were computed.

Results

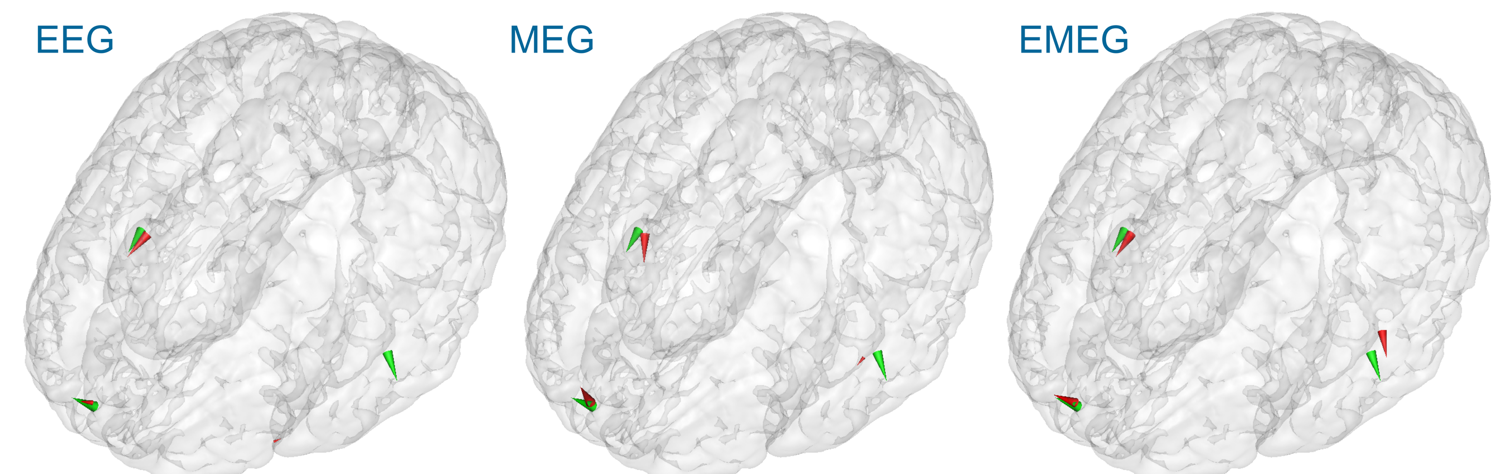
EEG vs. MEG

- HBM methods and sLORETA do not show a depth bias in any modality.
- Weighting of MNS to avoid depth bias in all modalities is difficult and comes at the cost of other draw-backs.
- The average localization performance (mean DLE) of HBM methods is equal for EEG and MEG. For WMNS variants and sLORETA, it is better for MEG.
- The mean EMD (localization + spatial extend) is better for EEG than MEG for all methods, although the differences are differently pronounced.

EEG/MEG combination

- The combination improves the average performance of all methods (measured in EMD and DLE).
- The improvement of the EMD of HBM methods for multiple source scenarios is larger than for established methods (see Figures 1 and 2).
- The combination reduces variance and outliers in the error statistics.
- The correct depth localization does not always profit from EEG/MEG combination, especially if one of the single modalities is very weak in that aspect.

Figure 1 (right) and 2 (bottom): Two different three-dipole source configurations (green cones) and HBM-NM source reconstructions (red cones) for simulated EEG, MEG and EMEG data.



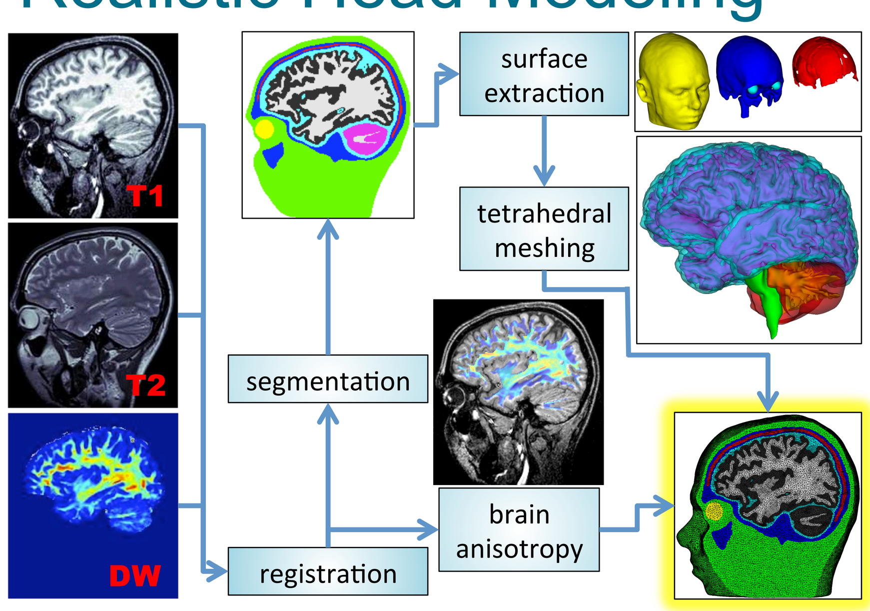
Conclusions

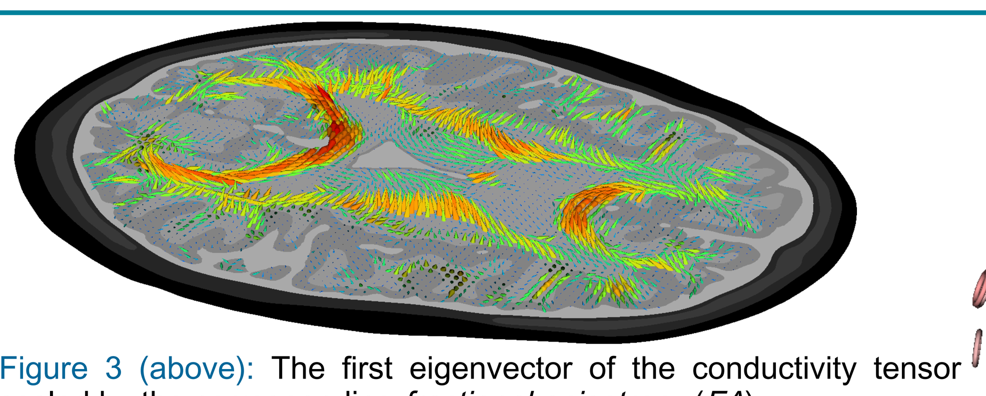
- Statements about localization properties of single modalities cannot be made without a reference to the inverse method used. This is a feature of the ill-posed nature of the EEG/MEG inverse problem.
- EEG/MEG combination stabilizes and improves source reconstruction to a considerable amount.
- Fully-Bayesian HBM methods profit from EEG/MEG combination especially for source separation in multiple source scenarios. This further underlines the potential of these methods for complex sources scenarios in real applications.
- For all MNS variants and sLORETA, MEG offers a better localization (DLE) of single dipoles while having a lower EMD. In total this means that in this source scenario, the better localization comes at the costs of a larger spatial blurring for these methods.

Outlook

- Preliminary results for combined AEP/AEF data can be found on Poster **Mo-70**. A detailed, extensive group study of AEP/AEF and SEF/SEP data sets will follow.
- Practical aspects of EEG/MEG combination: Noise rescaling (see, e.g., Henson et al., 2011), volume conductor calibration and sensor weighting.
- Theoretical aspects of EEG/MEG combination: Source and recovery conditions and information gain.
- Exact impact of the head model on EEG/MEG combination: Which of the differences between EEG and MEG are due to volume conduction?
- Comparison of HBM methods and EEG and MEG for extended source configurations.

Realistic Head Modeling





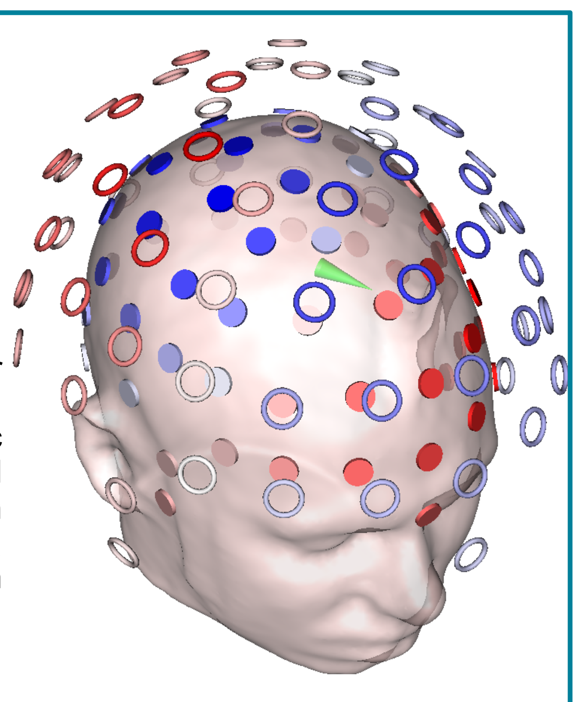


Figure 3 (above): The first eigenvector of the conductivity tensor scaled by the corresponding *fractional anisotropy* (*FA*).
Figure 4 (left): Procedure to build an individual, realistic, anisotropic *finite element* (*FE*) head model. Compartments: Skin, eyes, skull compacta, skull spongiosa, csf, gray and white matter of both cerebrum and cerebellum and brain stem. For gray and white matter, anisotropic conductivities are used, which have been computed from *diffusion weighted MRI* (*DW-MRI*) scans.
Figure 5 (right): Sensor configuration used in the simulation studies. Shown with the topography of a single dipole (green cone).

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Cells in Motion Cluster of Excellence

volume visualization was done with: SCIRun 4.6 with BioMesh3D

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