Hierarchical Bayesian Estimation for the EEG Inverse Problem using Realistic FE Head Models: Depth Localization and Source Separation for Focal Primary Currents

Felix Lucka[1,2], Sampsa Pursiainen[3], Martin Burger[1], Carsten H. Wolters[2]

(1) Institute for Computational and Applied Mathematics, University of Muenster, Germany. (2) Institute for Biomagnetism and Biosignalanalysis, University of Muenster, Germany. (3) Institute of Mathematics, Aalto University, Finland.

Introduction and Motivation

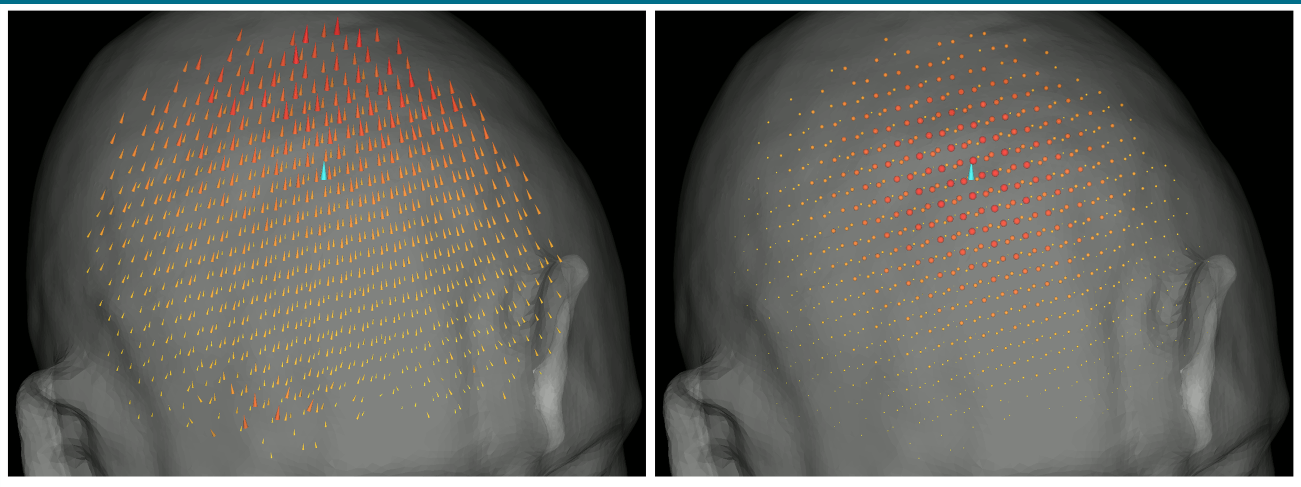

Figure 1: Depth-bias illustration. Measurement data for a focal, deep-lying, current dipole (blue cone) is simulated and reconstructed with the *minimum norm estimate* (*MNE*, left figure, yellow-red cones, Hämäläinen and Ilmoniemi, 1994) and with sLORETA (right figure, yellow-red spheres, Pascual-Marqui, 2002). The MNE suffers from depth-bias, whereas sLORETA does not.

Focal epilepsy is believed to originate from brain networks of focal sources. They are active during *inter-ictal spiking activity*, which can be recorded by EEG/MEG. The *epileptic focus localization* by means of this data has to solve two main tasks:

Task 1: Determine number of focal sources (*multi focal epilepsy?*).

Task 2: Determine location and extend of sources.

Since number and spatial extend of the sources are unknown, we use *current density reconstruction* (*CDR*) approaches to solve the inverse problem. Established CDR methods face two problems:

Depth-Bias: Reconstruction of deeper sources too close to the surface. An illustration can be found in Figure 1 (left).

Masking: In multiple source scenarios, near-surface sources ``mask`` deep-lying ones. An illustration can be found in Figure 2 (right).

Apparently, masking is a problem for task 1, while depth-bias concerns task 2.

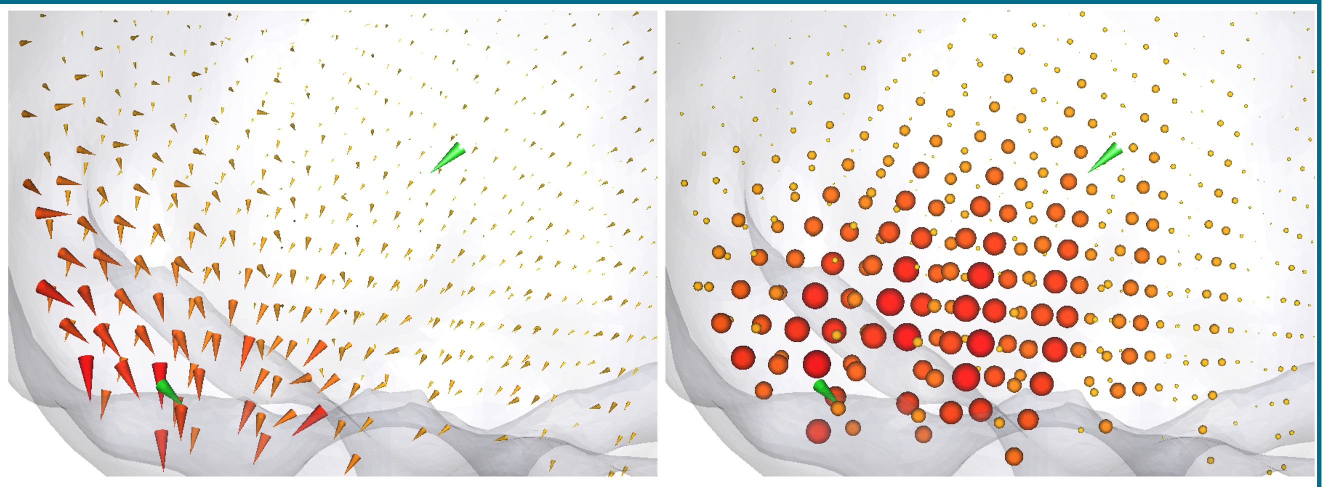

Figure 2: Masking illustration. Measurement data for a network of a deep-lying (top right green cone) and a near-surface (bottom left green cone) current dipole is simulated and reconstructed with the MNE (left) and sLORETA (right). Both reconstructions have only one local source amplitude maximum and thus indicate only one active source. While MNE seems to only recover the near-surface source, sLORETA peaks in-between the real sources.

Hierarchical Bayesian Modeling

Hierarchical Bayesian modeling (*HBM*) is a recent development for CDR. The aim of this poster is to show some results attained with methods based on HBM for the challenges depth-bias and masking. Unfortunately, a proper introduction of the theory behind it is beyond the scope of this poster. We refer to Wipf and Nagarajan, 2009 and Lucka, 2011 for a comprehensive introduction.
We can only highlight some features here:

- Stochastic model based on the *Bayesian perception* of the inverse problem.
- Further development of *weighted minimum norm estimation* (*WMNE*) schemes.
- Flexible framework for the construction of complex models.
- Adds an adaptive, data-driven element into the estimation (*empirical Bayesian inference*) which automatically reduces the complex models (*automatic relevance determination*).
- Different levels for the embedding of quantitative or qualitative a-priori information (*prior* and *hyperprior*).
- Comprises former methods like MNE, WMNE, LORETA, sLORETA, FOCUSS...
- Offers new ways of inference: ***Full-MAP***, ***Full-CM***, *γ-MAP*, *S-MAP*, *VB*

Key Issue

Starting point for our work: Sato et al., 2004 introduced a specific hierarchical Bayesian model into EEG/MEG inversion to recover source configurations consisting of few, focal sources. For this model, Calvetti et al., 2009 examined Full-MAP and Full-CM estimation and found promising results for Full-CM estimation with respect to depth-bias and masking. However, their study had some limitations:

- The Full-MAP results were not convincing and the reason for this remained unclear.
- The focus was not on an systematic examination of depth-bias and masking but rather on an introduction of the methods.
- In particular; only two source scenarios were considered; One of them in a very simplified head model.

Based on these first results, the key question for us was:

Can Full-MAP and Full-CM estimation for hierarchical Bayesian modeling overcome the limitations (depth-bias, masking) of established CDR methods and become a valuable tool for epileptic focus localization in presurgical epilepsy diagnosis?

Contributions

- Implementation of Full-MAP and Full-CM estimation methods for HBM with in combination with realistic, high resolution *finite element* (*FE*) head models (see bottom left box on this poster).
- Development of own algorithms for Full-MAP estimation.
- Examination of general properties, parameter choices, etc.
- Introduction of new performance measures for the validation of inverse methods through simulation studies: The *earth mover's distance* (*EMD*) is sensitive to various aspects of the reconstruction (e.g., localization, spatial extend, relative weighting) and can be computed in arbitrary source scenarios for arbitrary inverse methods.
- In the first study, 1000 single current dipoles with random location and orientation were reconstructed. The reconstructions were compared using different performance measures. The depth-bias was examined in detail.
- In the second study, 1000 source configurations consisting of one near-surface and one deep-lying dipole. Reconstructions were compared with respect to the EMD.

Results

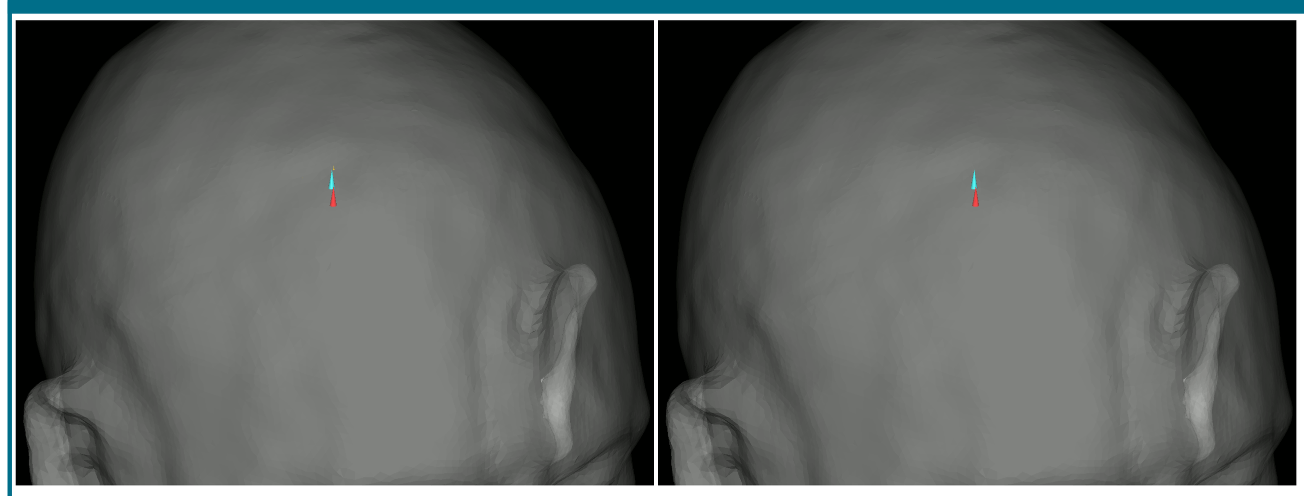

Figure 3: HBM-Results for a single source. Left: Full-CM result. Right: Full-MAP result. Note that the reference source (blue cone) is NOT located on one of the source grid nodes, thus exact recovery is not possible.

The results of Full-CM and Full-MAP estimation for a single, deep-lying source are depicted in Figure 3 (left, cf. Figure 1). Both methods yield reconstructions that are focal and are able to localize the reference source well. The results for a two source scenario are depicted in Figure 4 (cf. Figure 2). While the Full-CM result can not convince in every aspect, the Full-MAP estimate yields a good reconstruction of both sources. The results of the systematic studies confirm this impression:

- Good performance in all validation measures. In total superior to established CDR methods like MNE, sLORETA, WMNE.
- No depth bias.
- Good results w.r.t. orientation, amplitude and spatial extend.
- Full-MAP estimate (by our algorithm): Best results in every aspect examined; superior to Full-CM estimate.

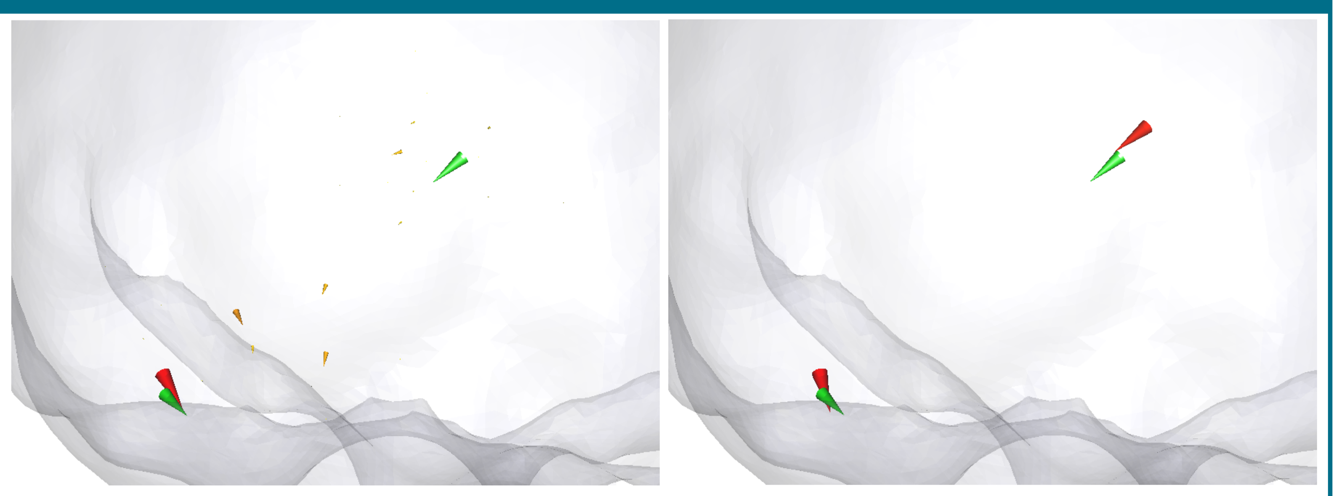

Figure 4: HBM-Results for a masking scenario. Left: Full-CM result. Right: Full-MAP result. Note that the reference sources (green cones) are NOT located on one of the source grid nodes, thus exact recovery is not possible.

More Results

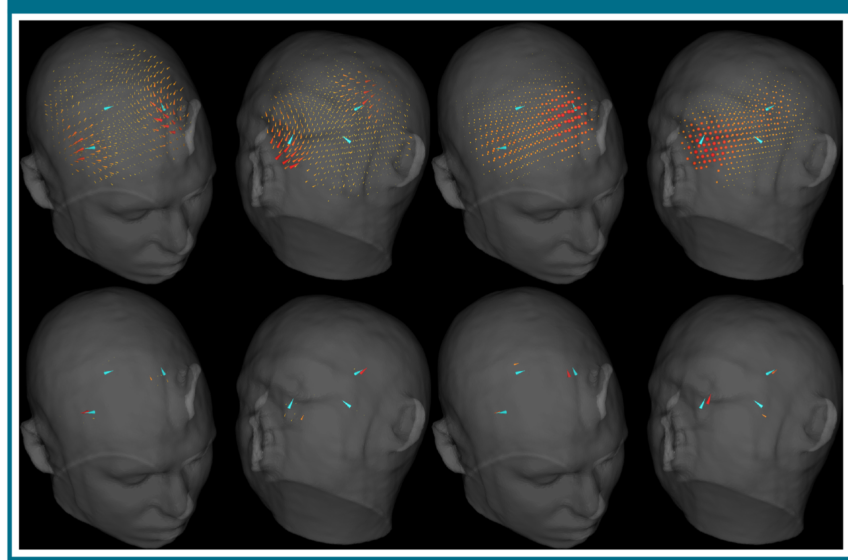

Figure 5: Recovery of three focal sources (blue cones). MNE (top left), sLORETA (top right), Full-CM (bottom left), Full-MAP (bottom right). Note that the reference sources are NOT located on one of the source grid nodes, thus exact recovery is not possible. Masking effects are even more pronounced in this scenario: MNE and sLORETA show serious limitations. Full-CM is not convincing either while Full-MAP is able to recover all sources.

Conclusion

- **Hierarchical Bayesian modeling used with realistic head modeling is a promising framework for EEG/MEG current density reconstruction.**
- **Promising results for deep sources (no depth bias).**
- **Promising results for challenging multiple source scenarios (no masking).**

For the important source scenarios we examined, Full-CM and Full-MAP estimation methods for HBM are able to improve upon established CDR methods like minimum norm estimation and sLORETA in many aspects. In particular, they show good localization properties for single current dipoles and do not suffer from depth bias.
Our studies also show that small localization errors for single source scenarios are not sufficient to judge about the quality of an inverse method for EEG or MEG source analysis in general. However, in contrast to established inverse methods like MNE and sLORETA, HBM based methods are able to maintain good reconstructions in the presence of two or three focal sources.

Outlook

- Confirm results with real data from early components of evoked responses and presurgical epilepsy diagnosis.
- Extend the focal HBM used here to recover spatially extended sources as well. This might be of more interest for research in the area of cognitive neuroscience.
- Compare Full-CM and Full-MAP estimates to other methods that rely on HBM, e.g., to *Variational Bayesian inference* (see Sato et al, 2004; Wipf and Nagarajan, 2009).
- For this first, elementary study, we simplified the brain volume conduction properties as homogeneous and isotropic, as it is often done in source analysis. In future, we will investigate the interplay of HBM and more realistic head modeling, e.g., by incorporating the inner brain compartments and the white matter anisotropy.
- Comparison to *dipole fitting* and *scanning/beamforming* methods.

Realistic Head Modeling

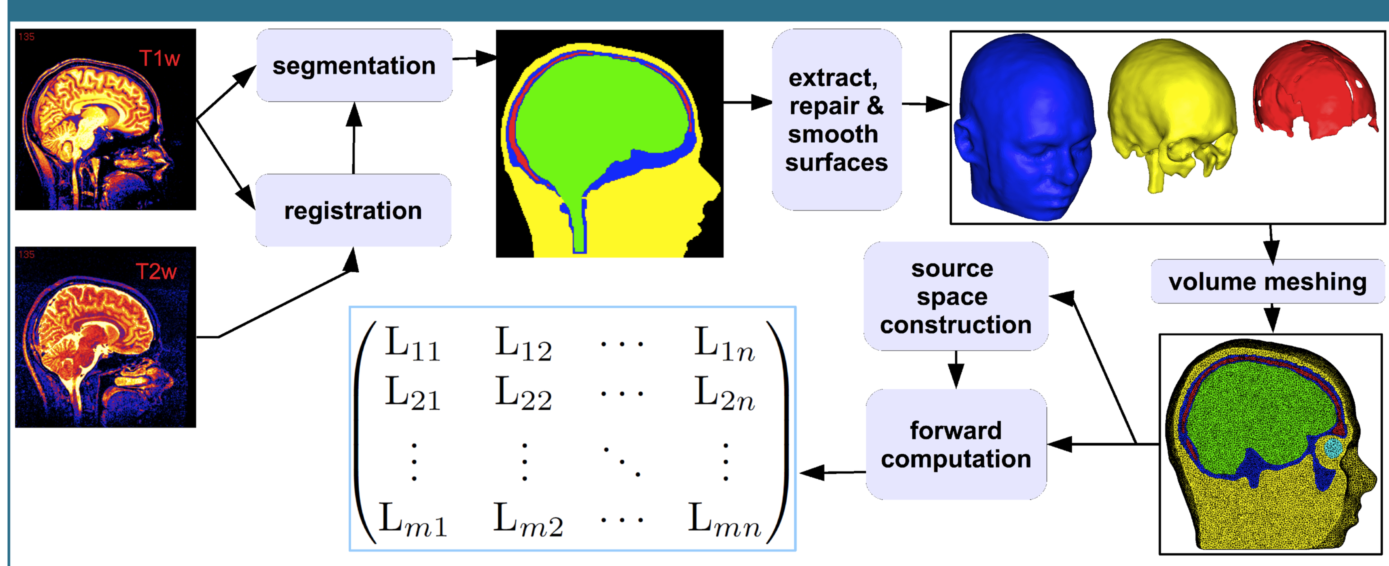

Figure 6: The different steps to attain a realistic, high resolution *finite element* (*FE*) head model are sketched. The inner brain tissues (csf, gray and white matter) have been merged, because we wanted to focus on the effects of depth bias and masking separate from others, e.g., from the effects caused by the anisotropy of the white matter. In addition, to facilitate the interpretation of the results, we need a homogeneous innermost compartment without holes and enclosures.

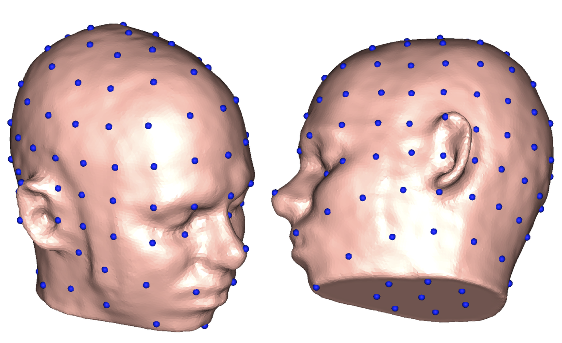

Figure 7: Artificial EEG sensor configuration used to separate the effect of depth-bias from the effect of *insufficient sensor coverage* in these first, basic studies: The semi shell like sensor distribution of realistic caps (caused by the neck) is not able to record fields in the direction of the feet. Especially deep sources suffer from this insufficiency.

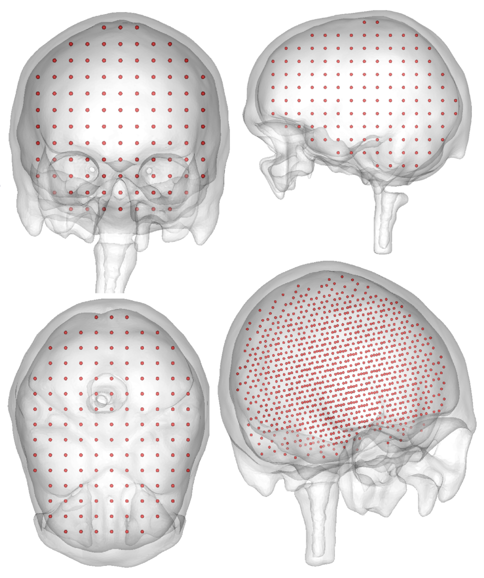

Figure 8: Source space consisting of 1000 nodes based on a regular grid.

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All visualization was done with:

Corresponding author:

Felix Lucka

✉ felix.lucka@uni-muenster.de