WESTFÄLISCHE
WILHELMS-UNIVERSITÄT
MÜNSTER

Hierarchical Fully-Bayesian Inference for EEG and MEG

"Matti Hämäläinen is visiting us - Workshop"

wissen.leben
WWU Münster

Felix Lucka

12.10.2012

Background

WESTFÄLISCHE
WILHELMS-UNIVERSITÄT
MÜNSTER

Diplomarbeit in Mathematik

Hierarchical Bayesian Approaches to the Inverse Problem of EEG/MEG Current Density Reconstruction

eingereicht von
Felix Lucka

Münster, 10. März, 2011

FACHBEREICH 10
MATHEMATIK UND
INFORMATIK

IBB
Institute for
Biomagnetism and
Biosignalanalysis

Gutachter:
Prof. Dr. Martin Burger
Institut für Numerische und Angewandte Mathematik
Priv.-Doz. Dr. Carsten Wolters
Institut für Biomagnetismus und Biosignalanalyse

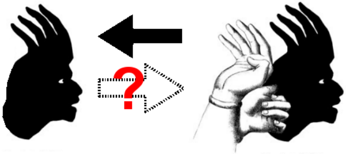
ELSEVIER
Contents lists available at SciVerse ScienceDirect
NeuroImage
journal homepage: www.elsevier.com/locate/ynimg

Hierarchical Bayesian inference for the EEG inverse problem using realistic FE head models: Depth localization and source separation for focal primary currents

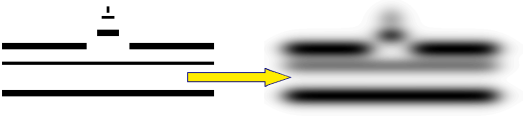
Felix Lucka[a,b,*], Sampsa Pursiainen[c], Martin Burger[a], Carsten H. Wolters[b]

[a] Institute for Computational and Applied Mathematics, University of Muenster, Germany
[b] Institute for Biomagnetism and Biosignalanalysis, University of Muenster, Germany
[c] Department of Mathematics, Tampere University of Technology, Finland

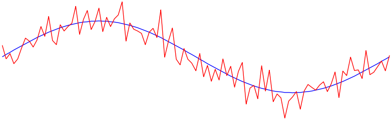
Reconstruction of brain activity by non-invasive measurement of induced electromagnetic fields?



- (Presumably) under-determined



- Severely ill-conditioned



- Low SNRs

Summary: The inverse problem is severely ill-posed.

Measurements alone are insufficient and unsuitable to determine solution.

$\Longrightarrow$ Incorporation of a-priori information about the solution in an explicit or implicit way:

- Knowledge about general/specific brain activity?
- Integration of multimodal information (fMRI, DW-MRI, PET, NIRS)?
- Mathematical formulation?
- Computational implementation?

$\Longrightarrow$ Variety of inverse methods for EEG/MEG

My focus: Hierarchical Bayesian inference for current density reconstruction (CDR).

Current Density Reconstruction

Lead-field matrix concept:

- $L \in \mathbb{R}^{m \times n}$; columns represent measurements at m sensors caused by the n single current dipoles.
- Linear combination of the dipoles is represented by source vector $s \in \mathbb{R}^{n}$.
- Measurements $b \in \mathbb{R}^{m}$ caused by s can then be calculated via:

$$b = L\, s$$

Current Density Reconstruction

Lead-field matrix concept:

- $L \in \mathbb{R}^{m \times n}$; columns represent measurements at m sensors caused by the n single current dipoles.
- Linear combination of the dipoles is represented by source vector $s \in \mathbb{R}^n$.
- Measurements $b \in \mathbb{R}^m$ caused by s can then be calculated via:

$$b = L\,s$$

Infer s from b? Apparently ill-posed problem:

- $n \gg m. \implies b = L\,s$ is under-determined.
- L inherits the bad condition of the continuous problem.
- Noise $\mathcal{E} \sim \mathcal{N}(0, \sigma^2 \mathrm{Id})$ is added to signal.

Common approaches:

- Variational regularization
- (Hierarchical) Bayesian inference
- Spatial scanning methods/beamforming

Strategy of Bayesian Inference

1. Make stochastic model for the relation between parameters, data and noise.

- $B = L\,s + \mathcal{E}$ $\quad$ b is now random vaiable B
- Compute probability density of B given s: $p_{like}(b|s)$ (likelihood)

Strategy of Bayesian Inference

1. Make stochastic model for the relation between parameters, data and noise: $p_{like}(b|s)$.

2. Supplement information given by the data by a-priori information about the parameters of interest. $\longrightarrow$ Bayesian modeling:

- s is considered to be a random variable itself ($s \rightarrow S$).
- Its distribution $p_{prior}(s)$ reflects a-priori assumptions/knowledge.
- Task of the prior: Render the estimation problem well-posed.

Strategy of Bayesian Inference

1. Make stochastic model for the relation between parameters, data and noise: $p_{like}(b|s)$.

2. Supplement information given by the data by a-priori information about the parameters of interest: $p_{prior}(s)$

3. Merge information **before** the measurement (prior) with the information gained **after** performing the measurement (likelihood) by **Bayes rule**:

$$p_{post}(s|b) = \frac{p_{like}(b|s)p_{prior}(s)}{p(b)}$$

- Conditional distribution of S given B is called **posterior distribution**.
- Represents all information on S given the realization of $B = b$.
- **Complete solution** to the inverse problem in Bayesian Inference

Strategy of Bayesian Inference

1. Make stochastic model for the relation between parameters, data and noise: $p_{like}(b|s)$.

2. Supplement information given by the data by a-priori information about the parameters of interest: $p_{prior}(s)$

3. Merge information before the measurement (prior) with the information gained after performing the measurement (likelihood) by Bayes rule: $p_{post}(s|b)$

4. Exploit a-posteriori information by infering point estimates:
   1. *Maximum a-posteriori-estimate (MAP)*: $\hat{s}_{\text{MAP}} := \text{argmax}_{s \in \mathbb{R}^n} \; p_{post}(s|b)$.
      Practically: High-dimensional optimization problem.
   2. *Conditional mean-estimate (CM)*: $\hat{s}_{\text{CM}} := \mathbb{E}\left[s|b\right] = \int_{\mathbb{R}^n} s \; p_{post}(s|b) ds$.
      Practically: High-dimensional integration problem.

Empirical Bayesian Inference

Problem: Brain activity is too complex (or our knowledge is too limited) to be captured in a fixed but sufficiently informative prior.

Empirical Bayesian Inference

Problem: Brain activity is too complex (or our knowledge is too limited) to be captured in a fixed but sufficiently informative prior.

Solution: Let the same data determine the prior used for the inference based on this data!

Empirical Bayesian Inference

Problem: Brain activity is too complex (or our knowledge is too limited) to be captured in a fixed but sufficiently informative prior.

Solution: Let the same data determine the prior used for the inference based on this data!

Sounds like...

Empirical Bayesian Inference

Problem: Brain activity is too complex (or our knowledge is too limited) to be captured in a fixed but sufficiently informative prior.

Solution: Let the same data determine the prior used for the inference based on this data!

Sounds like...

...but can be formulated into a consistent, statistical reasoning by adding a new dimension of inference: Hyperparameters and hyperpriors.

→ Parametric Empirical Bayesian inference

Top-down construction scheme → Hierarchical Bayesian modeling (HBM).

Hierarchical Bayesian Modeling (HBM) for CDR: Overview

- Current trend in all areas of Bayesian inference.
- Further development weighted minimum norm schemes.
- Flexible framework for the construction of complex models with different levels for the embedding of different qualitative and quantitative a-priori information: *Spatial, temporal, multimodal, functional, anatomical, neuro-physiological...*
- Adds an adaptive, data-driven model redcution element into the estimation.
- Embeds several heuristic approaches into sound mathematical framework.
- Comprises many former EEG/MEG methods like MNE, WMNE, LORETA, sLORETA, FOCUSS, MCE,...
- Offers various new ways of inference: Full-MAP, Full-CM, γ-MAP, S-MAP, VB

David Wipf and Srikantan Nagarajan.
A unified Bayesian framework for MEG/EEG source imaging.
Neuroimage, 44(3):947-66, February 2009

Example: Hierarchical Bayesian Modeling of Focal Activity

Wanted: A prior promoting focal source activity.

First try:

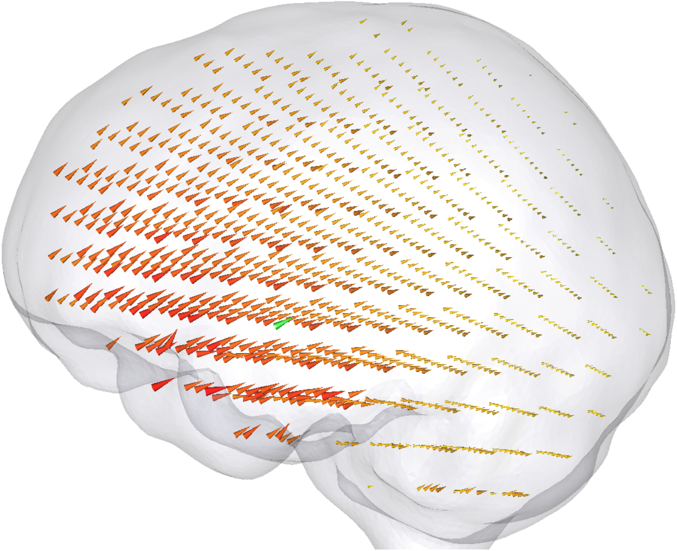
- Take Gaussian prior with zero mean and covariance $\Sigma_s = \gamma \cdot \mathrm{Id}, \quad \gamma > 0$ (*Minimum norm estimation*).
- Compute MAP or CM estimate (equal)!

$$\hat{s}_{\text{MAP}} := \underset{s \in \mathbb{R}^n}{\operatorname{argmax}} \left\{ \exp\left(-\frac{1}{2\,\sigma^2} \|b - \mathrm{L}\, s\|_2^2 - \frac{1}{2\gamma} \|s\|_2^2 \right) \right\}$$
$$= \underset{s \in \mathbb{R}^n}{\operatorname{argmin}} \left\{ \|b - \mathrm{L}\, s\|_2^2 + \frac{\sigma^2}{\gamma} \|s\|_2^2 \right\}$$

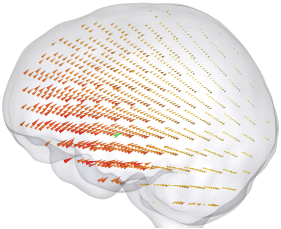
Felix Lucka (*felix.lucka@wwu.de*)

Example: Hierarchical Bayesian Modeling of Focal Activity

First try: NOT a focal reconstruction.



Example: Hierarchical Bayesian Model for Focal Activity



What went wrong?

- Gaussian variables = characteristic scale given by variance. (not *scale invariant*)
- All sources have variance $\gamma \Longrightarrow$ Similar amplitudes are likely.

$\Longrightarrow$ Focal activity is very unlikely.

Example: Hierarchical Bayesian Model for Focal Activity

Idea:

- Let sources at single locations i, $i = 1, \dots, k$ have different variances γ_i.
- Let the data determine $\gamma_i \Longrightarrow$ New level of inference!
  - $\boldsymbol{\gamma} = (\gamma_i)_{i=1,\dots,k}$ are called hyperparameters.
  - Bayesian inference: $\boldsymbol{\gamma}$ are random variables as well.
  - Their prior distribution $p_{hyper}(\boldsymbol{\gamma})$ is called hyperprior.

Example: Hierarchical Bayesian Model for Focal Activity

Idea:

- Let sources at single locations i, $i = 1, \ldots, k$ have different variances γ_i.
- Let the data determine $\gamma_i \Longrightarrow$ New level of inference!
  - $\boldsymbol{\gamma} = (\gamma_i)_{i=1,\ldots,k}$ are called hyperparameters.
  - Bayesian inference: $\boldsymbol{\gamma}$ are random variables as well.
  - Their prior distribution $p_{hyper}(\boldsymbol{\gamma})$ is called hyperprior.
- Encode focality assumption into hyperprior:
  - Focality: Nearby sources should a-priori not be mutually dependent.
  - Focality: Most sources silent, few with large amplitude;
  - No location preference for activity should be given a priori.

Example: Hierarchical Bayesian Model for Focal Activity

Idea:

- Let sources at single locations i, $i = 1, \dots, k$ have different variances γ_i.
- Let the data determine $\gamma_i \Longrightarrow$ New level of inference!
  - $\boldsymbol{\gamma} = (\gamma_i)_{i=1,\dots,k}$ are called hyperparameters.
  - Bayesian inference: $\boldsymbol{\gamma}$ are random variables as well.
  - Their prior distribution $p_{hyper}(\boldsymbol{\gamma})$ is called hyperprior.
- Encode focality assumption into hyperprior:
  - γ_i should be stochastically independent.
  - Focality: Most sources silent, few with large amplitude;
  - No location preference for activity should be given a priori.

Example: Hierarchical Bayesian Model for Focal Activity

Idea:

- Let sources at single locations i, $i = 1, \dots, k$ have different variances γ_i.
- Let the data determine $\gamma_i \Longrightarrow$ New level of inference!
  - $\boldsymbol{\gamma} = (\gamma_i)_{i=1,\dots,k}$ are called hyperparameters.
  - Bayesian inference: $\boldsymbol{\gamma}$ are random variables as well.
  - Their prior distribution $p_{hyper}(\boldsymbol{\gamma})$ is called hyperprior.
- Encode focality assumption into hyperprior:
  - γ_i should be stochastically independent.
  - Sparsity inducing hyperprior, e.g., inverse gamma distribution.
  - No location preference for activity should be given a priori.

Example: Hierarchical Bayesian Model for Focal Activity

Idea:

- Let sources at single locations i, $i = 1, \dots, k$ have different variances γ_i.
- Let the data determine $\gamma_i \Longrightarrow$ New level of inference!
  - $\boldsymbol{\gamma} = (\gamma_i)_{i=1,\dots,k}$ are called hyperparameters.
  - Bayesian inference: $\boldsymbol{\gamma}$ are random variables as well.
  - Their prior distribution $p_{hyper}(\boldsymbol{\gamma})$ is called hyperprior.
- Encode focality assumption into hyperprior:
  - γ_i should be stochastically independent.
  - Sparsity inducing hyperprior, e.g., inverse gamma distribution.
  - γ_i should be equally distributed.

Example: Hierarchical Bayesian Model for Focal Activity

In formulas:

$$p_{prior}(s|\gamma) \sim \mathcal{N}(0, \Sigma_s(\gamma)), \quad \text{where} \quad \Sigma_s(\gamma) = \mathrm{diag}(\gamma_i \cdot Id_3, i = 1, \dots, k)$$

$$p_{hyper}(\gamma) = \prod_{i=1}^{k} p^i_{hyper}(\gamma_i) = \prod_{i=1}^{k} p_{hyper}(\gamma_i) = \prod_{i=1}^{k} \frac{\beta^\alpha}{\Gamma(\alpha)} \gamma_i^{-\alpha-1} \exp\left(-\frac{\beta}{\gamma_i}\right)$$

$\alpha > 0$ and $\beta > 0$ determine *shape* and *scale*, $\Gamma(x)$ denotes the Gamma function.

Joint prior: $$p_{pr}(s, \gamma) = p_{prior}(s|\gamma)\, p_{hyper}(\gamma)$$

Implicit prior: $$p_{pr}(s) = \int p_{prior}(s|\gamma)\, p_{hyper}(\gamma) d\gamma$$

$$= \int \mathcal{N}(0, \Sigma_s(\gamma))\, p_{hyper}(\gamma) d\gamma \quad \rightsquigarrow \text{“Gaussian scale mixture”}$$

(actually a Student's t-distribution with $2(\alpha + 1)$ degrees of freedom)

Example: Hierarchical Bayesian Model for Focal Activity

Posterior, general:

$$p_{post}(s, \gamma | b) \propto p_{like}(b|s)\; p_{prior}(s|\gamma)\; p_{hyper}(\gamma)$$

Comparison: $p_{post}(s|b) \propto p_{like}(b|s)\; p_{prior}(s)$

Posterior, concrete:

$$p_{post}(s, \gamma | b) \propto$$

$$\exp\left(-\frac{1}{2\sigma^2} \| b - L\, s \|_2^2 - \sum_{i=1}^{k} \left(\frac{\frac{1}{2} \| s_{i*} \|^2 + \beta}{\gamma_i} + \left(\alpha + \tfrac{5}{2}\right) \ln \gamma_i \right) \right)$$

Analytical advantages...

- Energy is quadratic with respect to s
- Factorizes over γ_i's.

and disadvantages...

- Energy is non-convex w.r.t. (s, γ) (posterior is multimodal)

Excursus: Full-, Semi-, and Approximate Inversion

Two types of parameters $\longrightarrow$ more possible ways of inference.

Full-MAP: Maximize $p_{post}(s, \gamma | b)$ w.r.t. s and γ.

Full-CM: Integrate $p_{post}(s, \gamma | b)$ w.r.t. s and γ.

γ-MAP: Integrate $p_{post}(s, \gamma | b)$ w.r.t. s, and maximize over γ, first. Then use $p_{post}(s, \hat{\gamma}(b) | b)$ to infer s. (*Hyperparameter MAP/Empirical Bayes*)

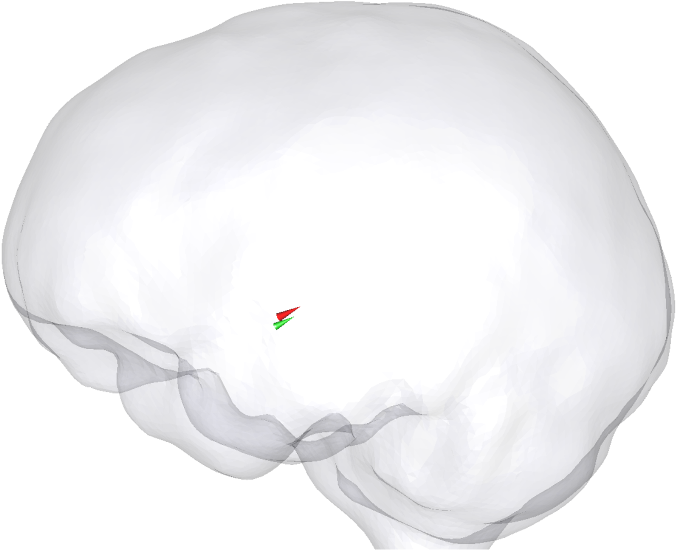
S-MAP: Integrate $p_{post}(s, \gamma | b)$ w.r.t. γ, and maximize over s.

VB: Assume approximative factorization $p_{post}(s, \gamma | b) \approx \hat{p}_{post}(s|b)\, \hat{p}_{post}(\gamma|b)$; Approximate both with distributions that are analytically tractable.

Focus of our work: Fully Bayesian inference.

Example: Hierarchical Bayesian Modeling of Focal Activity

Full-MAP estimate



Starting Point for our Studies

- A specific HBM aims to recover source configurations consisting of few, focal sources (introduced in Sato et al., 2004; further examined in Nummenmaa et al., 2007; Wipf and Nagarajan, 2009; Calvetti et al., 2009)
- Calvetti et al., 2009 found promising first results for certain inference strategies for deep-lying sources and the separation of multiple (focal) sources.

Limitations of Calvetti et al., 2009 :

- Specific results were not convincing; reason unclear.
- No systematic examination; only two source scenarios.
- Head models insufficient.

Starting Point for our Studies

- A specific HBM aims to recover source configurations consisting of few, focal sources (introduced in Sato et al., 2004; further examined in Nummenmaa et al., 2007; Wipf and Nagarajan, 2009; Calvetti et al., 2009)
- Calvetti et al., 2009 found promising first results for certain inference strategies for deep-lying sources and the separation of multiple (focal) sources.

Limitations of Calvetti et al., 2009 :

- Specific results were not convincing; reason unclear.
- No systematic examination; only two source scenarios.
- Head models insufficient.

Why are we interested in that?

(*rhetorical question to switch to another talk in an elegant way...*)

Tasks and Problems for EEG/MEG in Presurgical Epilepsy Diagnosis

EEG/MEG in epileptic focus localization:

- *Focal epilepsy* is believed to originate from networks of focal sources.
- Active in inter-ictal spikes.
- Task 1: Determine number of focal sources (*multi focal epilepsy*?).
- Task 2: Determine location and extend of sources.

Unknown number and spatial extend of sources?

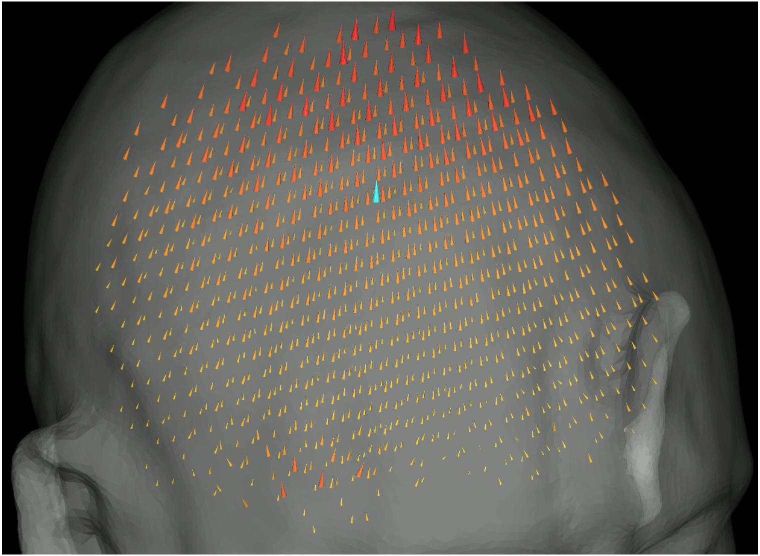
$\longrightarrow$ Current density reconstruction (CDR).

Problems of established CDR methods:

- Depth-Bias: Reconstruction of deeper sources too close to the surface.
- Masking: Near-surface sources “mask“ deep-lying ones.

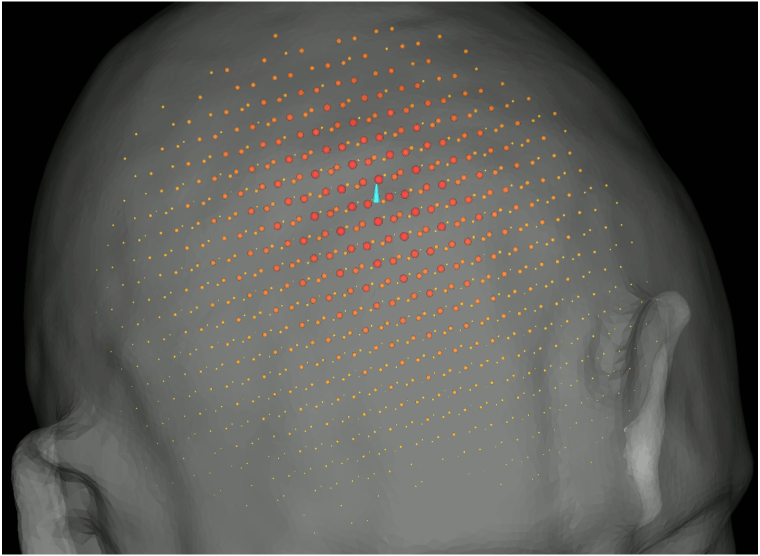
Depth Bias: Illustration

One deep-lying reference source (blue cone) and minimum norm estimate (MNE, Hämäläinen and Ilmoniemi, 1994).



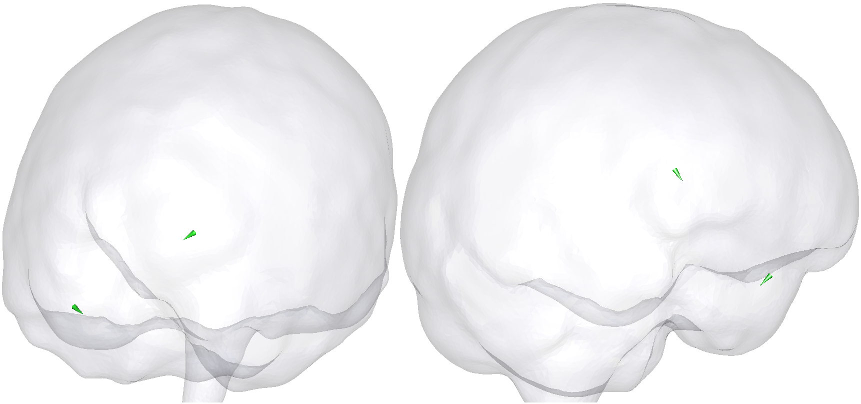
Depth Bias: Illustration

One deep-lying reference source (blue cone) and sLORETA result (Pascual-Marqui, 2002).



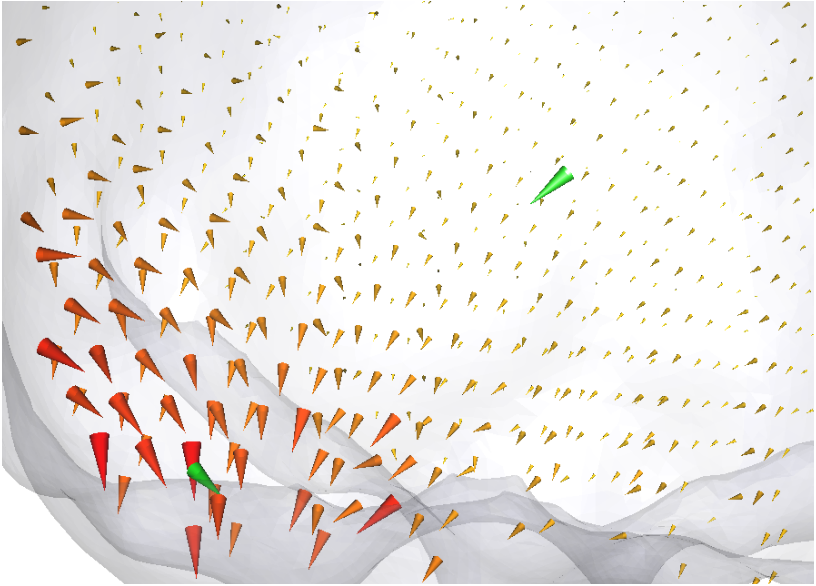
Masking: Illustration

Reference sources.



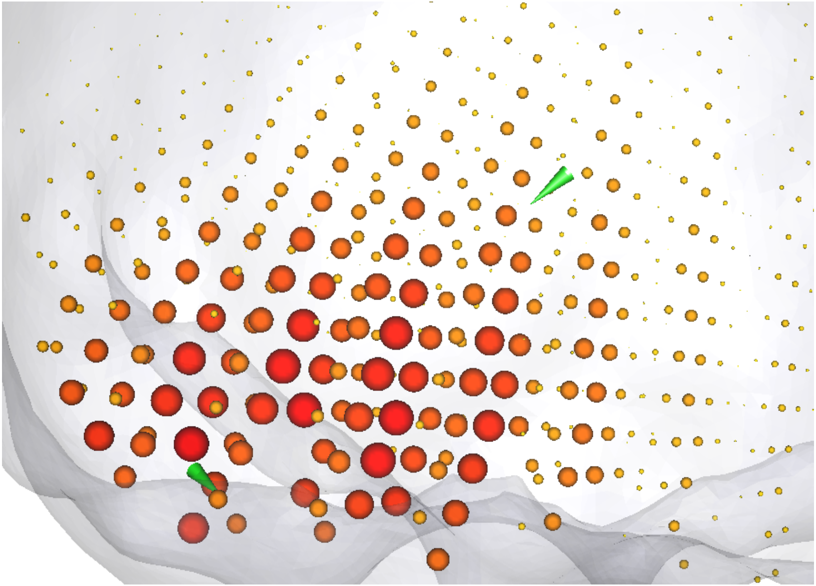
Masking: Illustration

MNE result and reference sources (green cones).



Masking: Illustration

sLORETA result and reference sources (green cones).



Diploma Thesis and Neuroimage Paper (EEG only!)

Key question

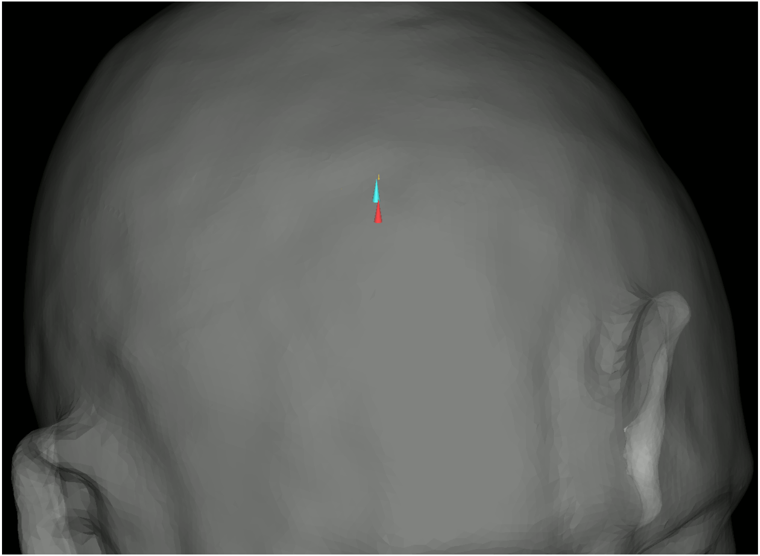
Can Full-MAP and Full-CM for HBM overcome the limitations (depth-bias, masking) of established CDR methods?

Work program:

- Implementation of Full-MAP and Full-CM inference for HBM with realistic, high resolution Finite Element (FE) head models.
- Propose own algorithms for Full-MAP estimation.
- Introduction of suitable performance measures for validation of simulation studies.
- Systematic examination of performance concerning depth-bias and masking in simulation studies.

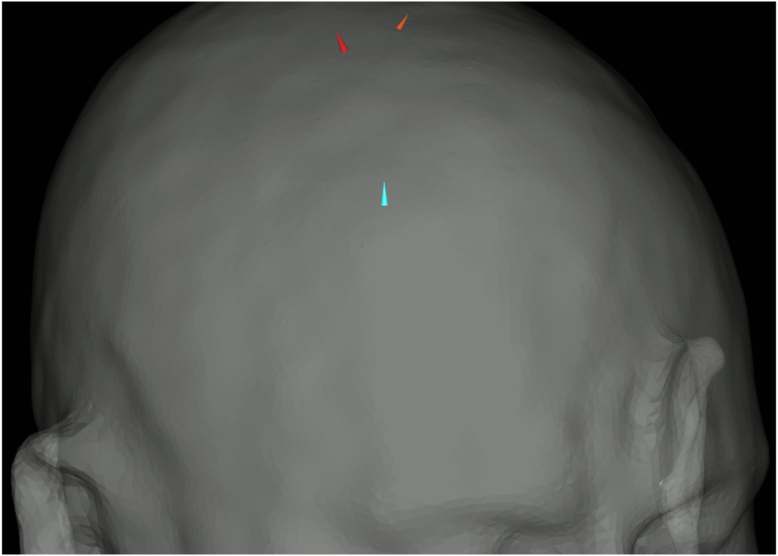
Results Depth Bias: Illustration

One deep-lying reference source (blue cone) and Full-CM result.



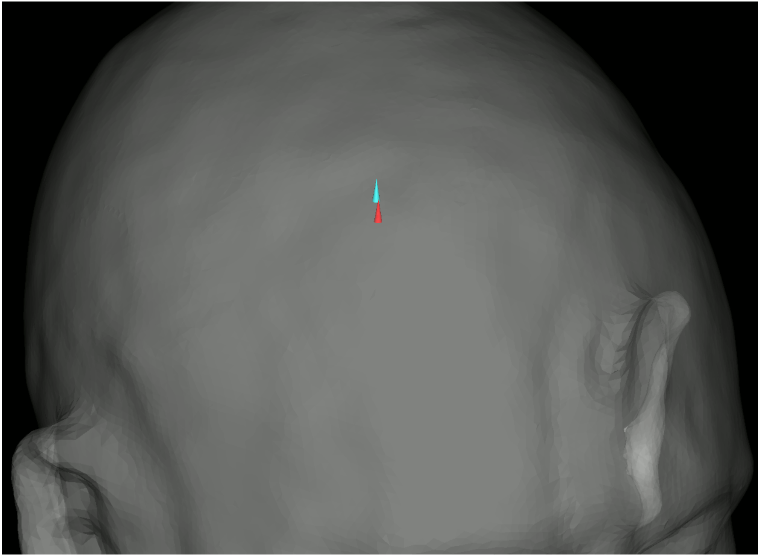
Results Depth Bias: Illustration

One deep-lying reference source (blue cone) and Full-MAP result proposed by Calvetti et al., 2009.



Results Depth Bias: Illustration

One deep-lying reference source (blue cone) and Full-MAP result proposed by us.

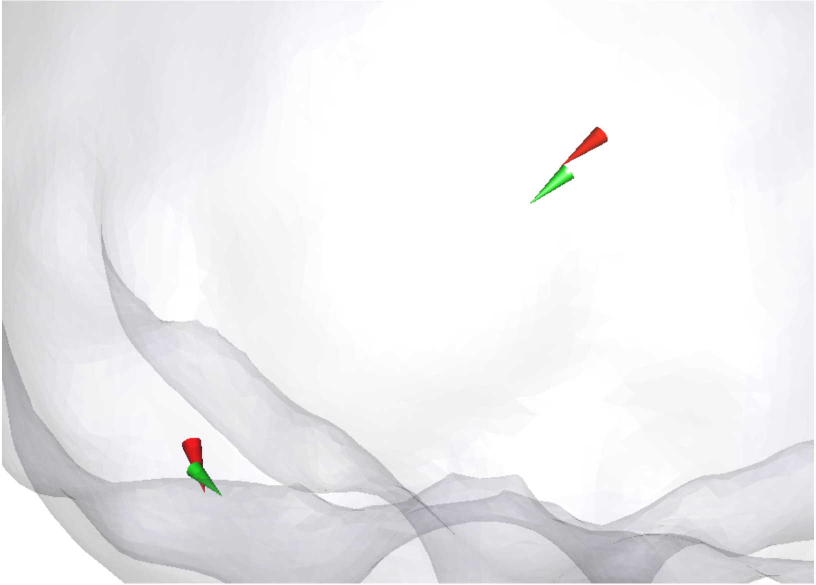


Results Masking: Illustration

Full-CM result and reference sources (green cones).

Results Masking: Illustration

Full-MAP result (by our algorithm) and reference sources (green cones).



Systematic Studies: Summary

Study 1 (depth-bias):

- Reconstruction of single 1000 dipoles; random location and orientation.
- Reconstructions were compared using different performance measures.
- Specific examination of depth bias.

Study 2 (masking):

- Reconstruction of 1000 source configurations consisting of one near-surface and one deep-lying dipole.
- Reconstructions were compared using a performance measure based on *optimal transport* (called *earth mover's distance*, a *Wasserstein metric*).

Systematic Studies: Summary

Results for Full-MAP and Full-CM estimation:

- Good performance in all validation measures.
- 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.

Full results:

Felix Lucka., Sampsa Pursiainen, Martin Burger,Carsten H. Wolters. 2012.
Hierarchical Bayesian Inference for the EEG Inverse Problem using Realistic FE Head Models: Depth Localization and Source Separation for Focal Primary Currents.
Neuroimage 61(4), 1364-1382.

Conclusions, Diploma Thesis and Neuroimage paper

Key question

Can Full-MAP and Full-CM for HBM overcome the limitations (depth-bias, masking) of established CDR methods?

Conclusions, Diploma Thesis and Neuroimage paper

Key question

Can Full-MAP and Full-CM for HBM overcome the limitations (depth-bias, masking) of established CDR methods?

Results

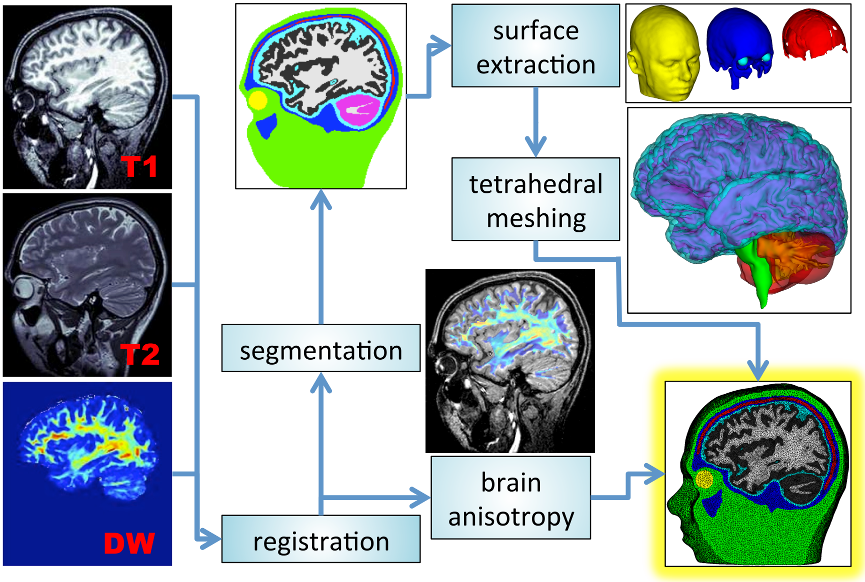
- Hierarchical Bayesian modeling used with realistic head modeling is a promising framework for EEG CDR.
- Promising results for deep sources (no depth bias).
- Promising results for challenging multiple source scenarios (no masking).

★ A promising tool for the analysis of neurophysiological data. ★

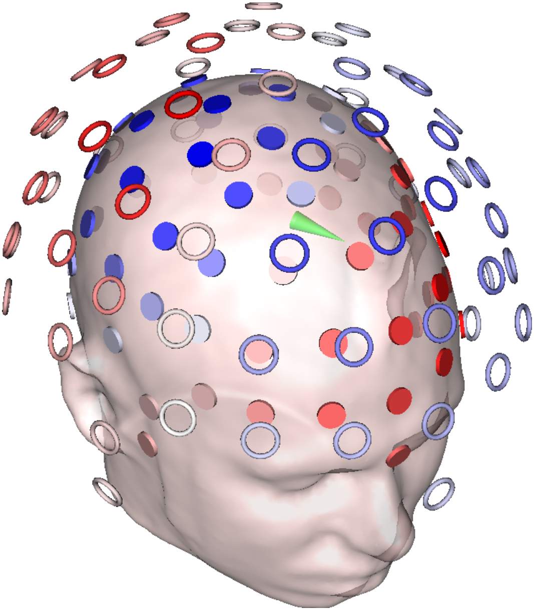
We addressed two questions that were posed in the outlook of the paper:

- EEG vs. MEG and EEG/MEG combination (EMEG):
  - Do our findings also apply for MEG?
  - Previously (e.g., Molins et al., 2008), the differences between EEG and MEG have mainly been examined by established inverse methods. How are things for fully-Bayesian inference for HBM?
- Realistic Head Model: Formerly, we used a simplified head model with a homogenous inner brain (to facilitate the interpretation of the results). Especially for EEG/MEG combination, the use of a realistic, individual and anisotropic head model is mandatory.

Model Setup: Modeling Pipeline



Model Setup: Sensor Configuration



Simulation Studies

Inverse Methods:

- Three fully-Bayesian HBM methods:
  - Full-MAP estimates
  - Full-CM estimates
  - Full-NM (Near-Mean) estimates
- Minimum norm estimates (MNE) with different weightings (WMNE).
- sLORETA

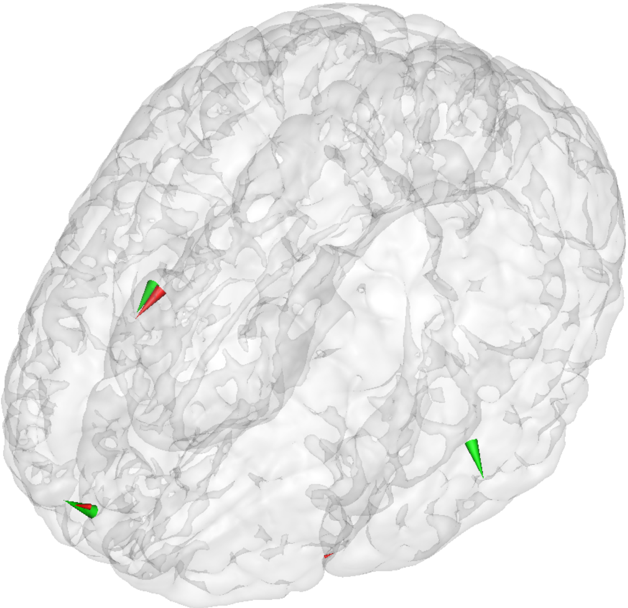
Simulation studies (similar to Neuroimage paper):

1. Single dipole recovery ⟶ localization, focality, depth-bias.
2. Two dipole recovery ⟶ source separation.

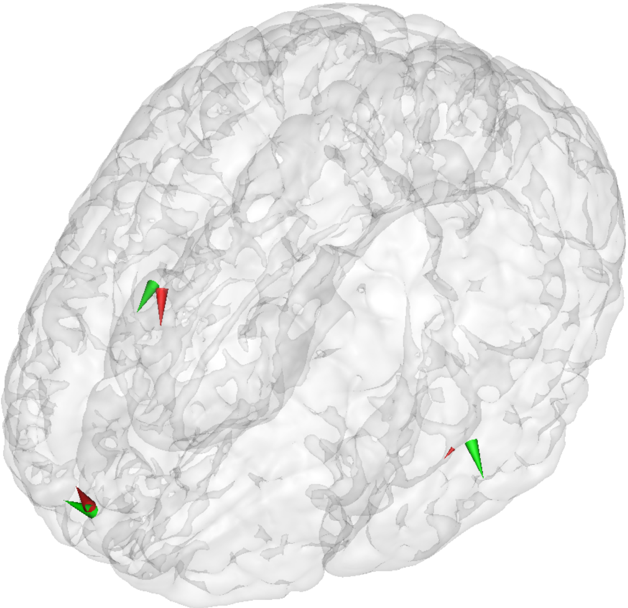
Source configurations were reconstructed using

(a) EEG alone (b) MEG alone (c) EMEG data

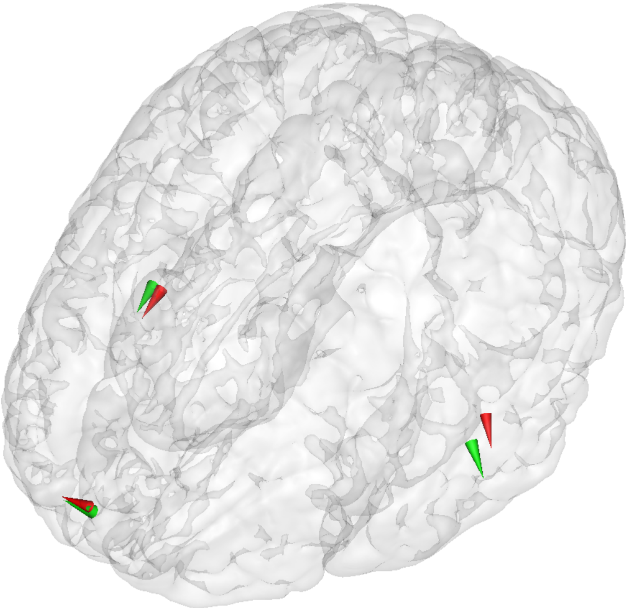
Exemplary Three Dipole Scenarios 1: HBM-NM Estimate, EEG alone



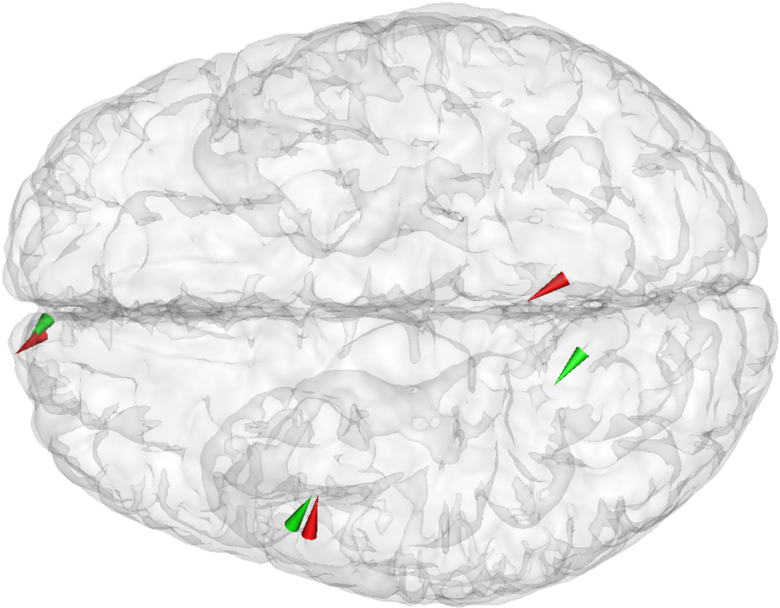
Exemplary Three Dipole Scenarios 1: HBM-NM Estimate, MEG alone



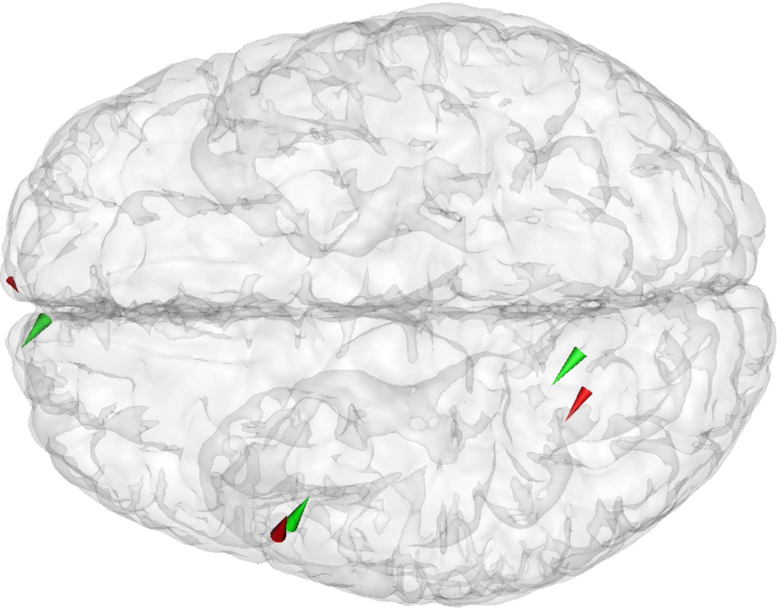
Exemplary Three Dipole Scenarios 1: HBM-NM Estimate, EMEG



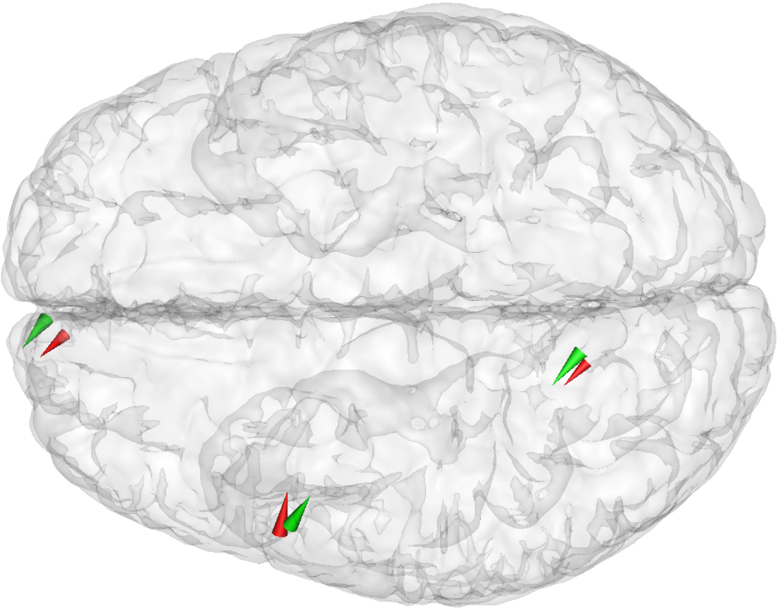
Exemplary Three Dipole Scenarios 2: HBM-NM Estimate, EEG alone



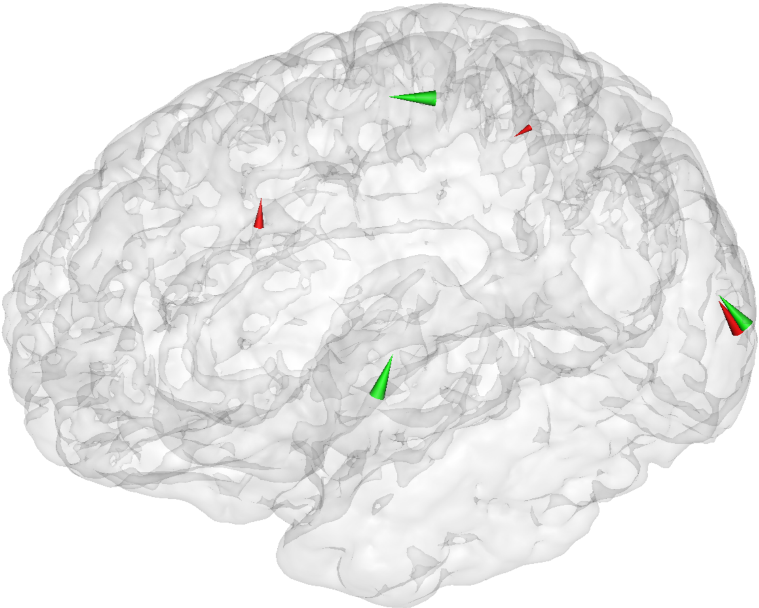
Exemplary Three Dipole Scenarios 2: HBM-NM Estimate, MEG alone



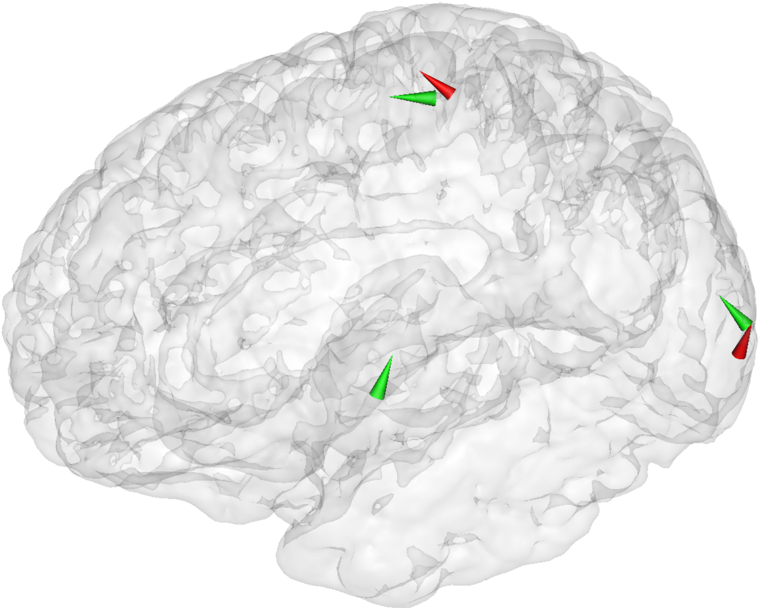
Exemplary Three Dipole Scenarios 2: HBM-NM Estimate, EMEG



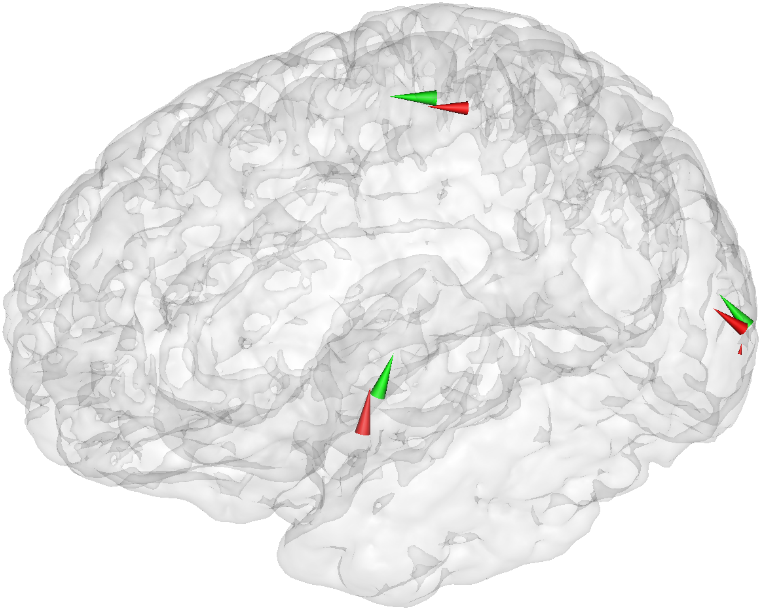
Exemplary Three Dipole Scenarios 3: HBM-NM Estimate, EEG alone



Exemplary Three Dipole Scenarios 3: HBM-NM Estimate, MEG alone



Exemplary Three Dipole Scenarios 3: HBM-NM Estimate, EMEG



Biomag Results and Conclusions, EEG vs. MEG

Results:

- HBM methods and sLORETA do not show a depth bias in any modality.
- Weighting of MNE 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 WMNE 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.

Biomag Results and Conclusions, EEG vs. MEG

Results:

- HBM methods and sLORETA do not show a depth bias in any modality.
- Weighting of MNE 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 WMNE 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.

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.
- For all MNE variants and sLORETA, MEG offers a better localization (DLE) of single dipoles while having a higher EMD $\Longrightarrow$ better localization comes at the costs of a larger blurring.

Biomag Results and Conclusions, EEG/MEG Combination

Results:

- 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.
- The combination reduces variance and outliers in the error statistics.
- The depth localization does not always profit from combination, especially if a single modality is very weak in that aspect.

Biomag Results and Conclusions, EEG/MEG Combination

Results:

- 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.
- The combination reduces variance and outliers in the error statistics.
- The depth localization does not always profit from combination, especially if a single modality is very weak in that aspect.

Conclusions:

- 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.

Outlook & Future Work

- Current focus: Processing of real data:
  - combined AEP/AEF and SEF/SEP data;
  - interictal epileptic activity;
- Practical aspects of EEG/MEG combination: Noise rescaling, volume conductor calibration and sensor weighting.
- Temporal extension of our HBM methods.
- Generalization of the specific HBM
  - to also recover more extented source scenarios;
  - to model inhibintion, excitation and syncrony between brain areas;
  - to incorporate mulitmodal information from, e.g., DW-MRI, PET, SPECT, fMRI, NIRS;
- Comparison of HBM methods and EEG and MEG for extended source configurations.
- Comparison to other HBM-based methods like variational Bayesian approaches.

Thank you for your attention!

Software used by our group:

- Registration: FSL,FAIR;
- Segmentation: FSL, CURRY;
- FEM Meshing: Tetgen, vgrid, iso2mesh;
- FEM Computation: SimBio;
- Data Preprocessing: CURRY, BESA;
- Inverse computation: Matlab;
- Volume Visualization: SCIRun;
- Everything else & software integration: Matlab;