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Hierarchical Bayesian Modeling for EEG/MEG: From Simulated to Experimental Data

Mini-Symposium "Inverse Problems with Experimental Data"

Applied Inverse Problem Conference 2013 in Daejeon, Korea

wissen.leben
WWU Münster

Felix Lucka

02.07.2013

Preamble...

Warning

This is not a talk about success!

Preamble...

Warning

This is not a talk about *direct* success!

Outline

Hierarchical Bayesian Modeling in EEG/MEG Source Reconstruction

First Results for Experimental Data

Sensitivity Studies

Current Results for Experimental Data

Conclusion & Next Steps

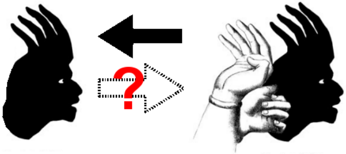
Source Reconstruction by Electroencephalography (EEG) and Magnetoencephalography (MEG)

Aim: Reconstruction of brain activity by non-invasive measurement of induced electromagnetic fields (bioelectromagnetism) outside of the skull.

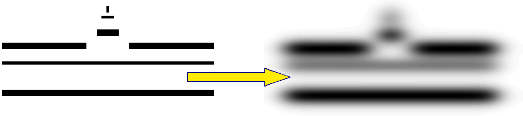
source: Wikimedia Commons

source: Wikimedia Commons

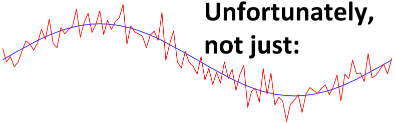
One Challenge of Source Reconstruction: The Inverse Problem



- Under-determined



- Severely ill-conditioned, special spatial characteristics.



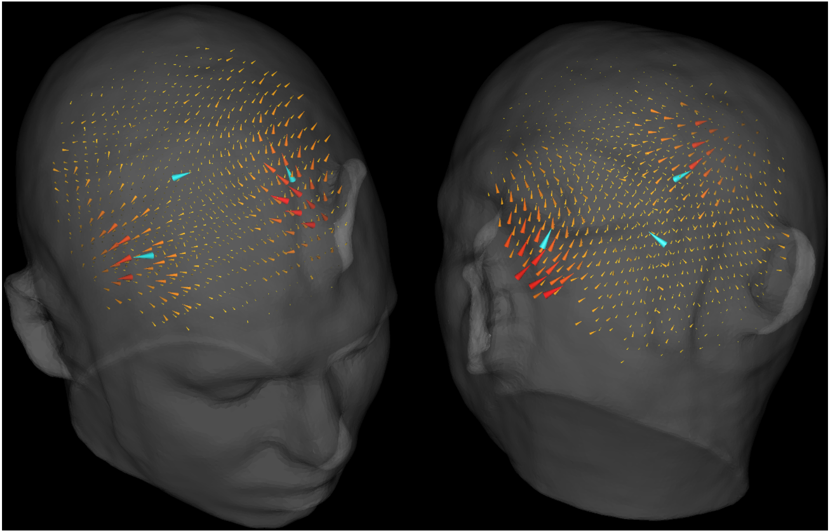
Unfortunately, not just:

- Signal is contaminated by a complex spatio-temporal mixture of external and internal noise and nuisance sources.

Discretization Approach: Current Density Reconstruction (CDR)

Continuous (ion current) vector field $\approx$ grid with 3 orthogonal elementary sources at each node.

$$f = K\,u, \qquad \Longrightarrow \qquad p_{li}(f|u) \propto \exp(-\tfrac{1}{2}\|\Sigma_\varepsilon^{-1/2}(f - K\,u)\|_2^2)$$



Cooperation with...

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School of Science

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Department of Mathematics and Systems Analysis,
Aalto University, Finland

Applied Mathematics Münster

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IBB
Institute for Biomagnetism and Biosignalanalysis

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Institute for Biomagnetism and Biosignalanalysis,
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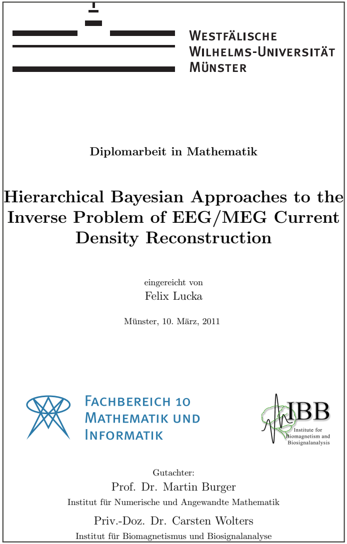
Hierarchical Bayesian Modeling for Source Reconstruction

- Extend Gaussian prior model by flexible, individual source variances γ_i.
- Let the data determine γ_i (hyperparameters).
- Use sparsity constraints on hyperprior $\rightsquigarrow$ by direct correspondence, we might get sparsity over the primary unknowns u as well.
- Resulting regularization functional is non-convex / Posterior is multimodal.
- Compute Full-Conditional Mean (CM) or Full-Maximum A-Posteriori (MAP) estimates.

Our starting point:

Daniela Calvetti, Harri Hakula, Sampsa Pursiainen, Erkki Somersalo, 2009.
Conditionally Gaussian hypermodels for cerebral source localization

Summary of Simulation Results


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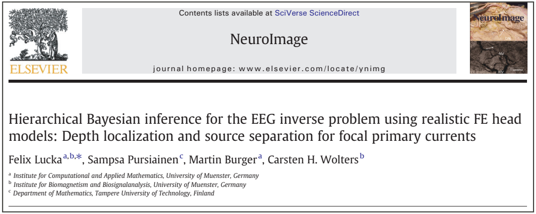
Institut für Numerische und Angewandte Mathematik
Priv.-Doz. Dr. Carsten Wolters
Institut für Biomagnetismus und Biosignalanalyse


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

- Implementation of HBM with realistic, high resolution Finite Element (FE) head models.
- Improve Full-MAP estimation by utilizing MCMC.
- Systematic examination of different aspects in extensive simulation studies.
- EEG vs. MEG and EEG/MEG combination (EMEG)

From Simulated to Real Data...

Partial results in:

Felix Lucka., Sampsa Pursiainen, Martin Burger,Carsten H. Wolters.
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), 2012.

- Summary: Excellent results for sparse source configurations! Overcomes deficiencies of established inverse methods.
- Proceed to experimental data as soon as possible!
- Start with evoked responses, e.g. simple auditory activity.
- Proceed to interictal epileptic activity.
- Extend simple HBM in every possible way (spatio-temporal, multimodal, multi-resolution...).

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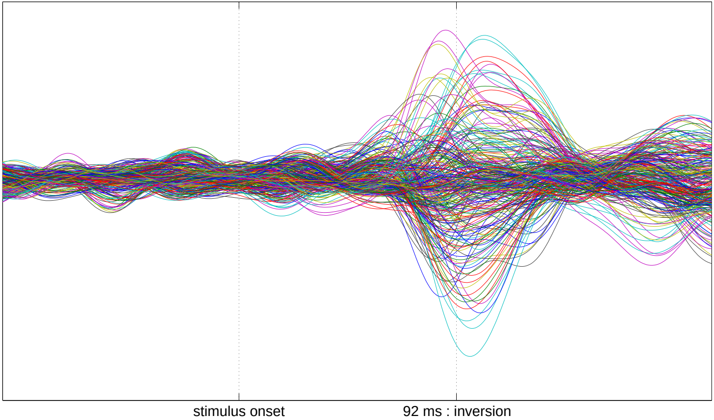
Auditory Data I: MEG Butterfly Plot

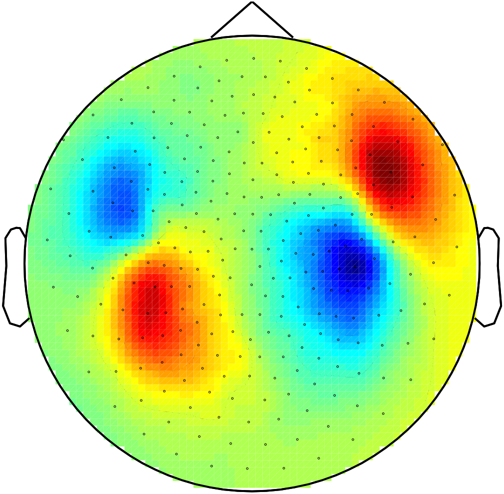
Aim: Fast results for Biomag 2012 conference.

1. Record resonses to many simuli.
2. Conservative bandpass filtering: 1-30 Hz.
3. Average responses of 109 simuli.



Warning: Only illustration, different data set!

Auditory Data I: MEG Topographic Field Distribution



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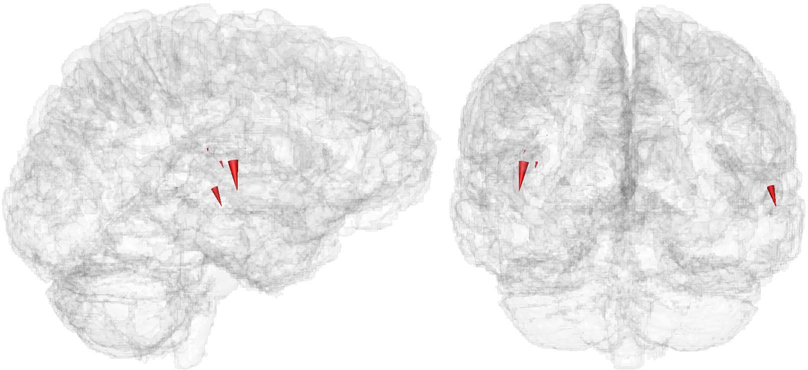
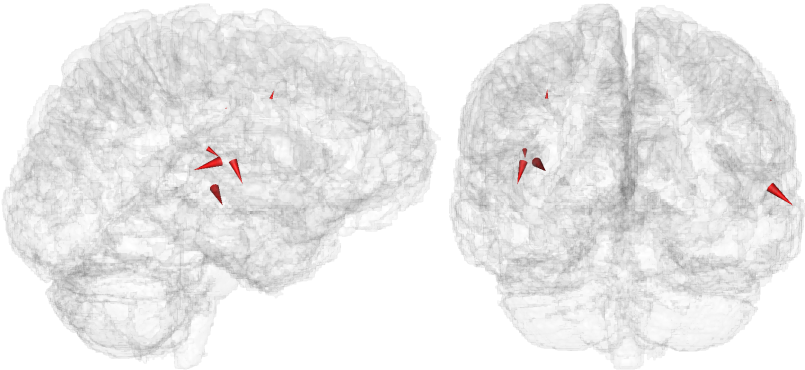
Auditory Data I: Some Images



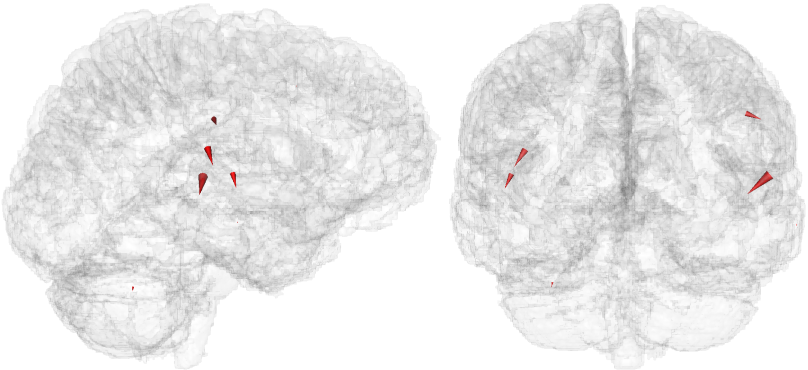
Full CM estimate for MEG data

Auditory Data I: Some Images



Full MAP estimate I for MEG data

Auditory Data I: Some Images



Full MAP estimate II for MEG data

Auditory Data I: Summary of Observations

- Full-MAP estimates are unstable and sometimes totally senseless.
- Not robust to parameter choice?!
- CM estimate seem more robust, but could also be better.
- Others report similar results:
  - "*...these fancy non-linear, non-convex methods...good in simulations* @#+! *in practice*"
  - "*...too sensitive and not robust enough...*"

and give a lot of advice what to do better...

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What Shall We Do?

- Naive inverse problem guy's view: $f = Ku$.
  - Give me K
  - Give me f (and Σ_ε)
  - I'll return u
  - Tell me if it is good.
- Works until you face a problem

Ümit Aydin

Johannes Vorwerk

What Shall We Do?

- Naive inverse problem guy's view: $f = Ku$.
  - Give me K $\rightsquigarrow$ forward modeling, sensor registration
  - Give me f (and Σ_ε) $\rightsquigarrow$ preprocessing
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- Works until you face a problem
- HBM more sensitive to errors/uncertainties?

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- Works until you face a problem
- HBM more sensitive to errors/uncertainties?

I have control the whole pipeline to find out!

$\rightarrow$ Replace commercial software by own pipeline: Extremely time consuming!

Ümit Aydin

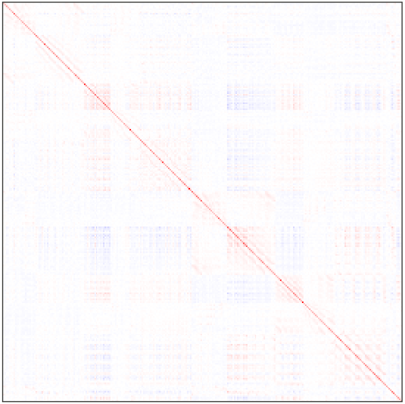
Johannes Vorwerk

Example of What Might Go Wrong: Noise Modeling

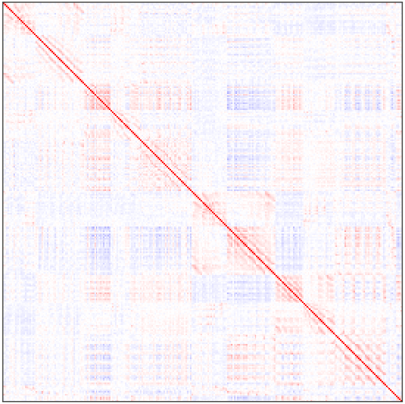
Naive approach: $f = K\,u + \varepsilon$

- Simulation studies: $\varepsilon \sim \mathcal{N}(0, \sigma^2)$ (iid).
- Reality: $\varepsilon = \delta + \eta + \kappa$
  - δ: Sensor noise and external nuisance fields $\rightarrow$ Empty room recordings
  - η: Averaged internal nuisance fields $\rightarrow$ highly correlated.
  - κ: Averaged background brain activity $\rightarrow$ highly correlated, in range of forward operator.
- Static temporal filtering?
- Blind unmixing? PCA, ICA?
- Model-based unmixing?

Example of What Might Go Wrong: Empty Room Recordings



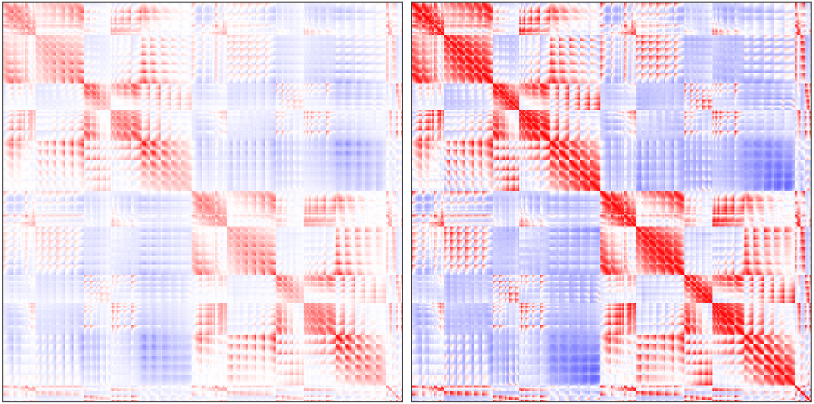
(a) Covariance



(b) Correlation

Condition number of covariance matrix: 50
Largest ratio of variance: = 5.1

Example of What Might Go Wrong: Prestimulus Data



(a) Covariance (b) Correlation

Condition number of covariance matrix: 6839
Largest ratio of variance: = 5.3

Example of What Might Go Wrong: Preprocessing and Noise Estimation

1. Static temporal bandpass (1-30 Hz) filtering: $\rightarrow$ temporal correlation.
2. Average data of 109 epochs to improve SNR.
3. Estimate the channel variances σ_i^2 from this data based on pre-stimulus interval ($\sim$ 300 avg. sample).
4. Use $\Sigma_\varepsilon = \mathrm{diag}(\sigma_i^2)$ (like CURRY does).

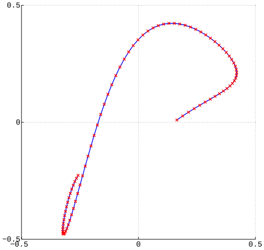


Abbildung: Timecourses of EEG channels 1 and 2 (left) and 20 and 50 (right).

Simulation Studies for Noise Sensitivity

Observations:

- Degenerate covariance structure, correlated noise components dominate.
- Preprocessing renders estimation of residual noise difficult.

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Is HBM sensitive to these issues?

Examine by simulation studies.:

- Reconstruct 1000 single sources from noisy measurements (SNR $= 20$).
- Use different noise covariance for noise simulation and reconstruction
- Use average localization error of reconstruction for validation.

Simulation Studies for Noise Sensitivity: Minimum Norm Solution

$$u_{\text{MNE}} = \operatorname{argmin}\{\|\Sigma_\varepsilon^{-1/2}(f - K\,u)\|_2^2 + \lambda\|u\|_2^2\}$$

		Data Cov			
		$\bar{\sigma}^2 \cdot I_m$	$\mathrm{diag}(\Sigma)$	Σ	Σ_{perm}
Model Cov	$\bar{\sigma}^2 \cdot I_m$	17.54	17.52	18.08	17.73
	$\mathrm{diag}(\Sigma)$	x	17.39	17.98	17.58
	Σ	x	x	17.51	34.87
	Σ_{perm}	x	x	x	17.38

Abbildung: Localization error for minimum norm solution

Σ is given by empty room data.

Simulation Studies for Noise Sensitivity: HBM CM

		Data Cov			
		$\bar{\sigma}^2 \cdot I_m$	$\mathrm{diag}(\Sigma)$	Σ	Σ_{perm}
Model Cov	$\bar{\sigma}^2 \cdot I_m$	5.49	5.68	5.88	5.57
	$\mathrm{diag}(\Sigma)$	x	5.57	5.77	5.74
	Σ	x	x	5.65	5.89
	Σ_{perm}	x	x	x	5.48

Abbildung: Localization error for CM estimate

Σ is given by empty room data.

Simulation Studies for Noise Sensitivity: HBM MAP

		Data Cov			
		$\bar{\sigma}^2 \cdot I_m$	$\mathrm{diag}(\Sigma)$	Σ	Σ_{perm}
Model Cov	$\bar{\sigma}^2 \cdot I_m$	5.47	5.64	5.87	5.56
	$\mathrm{diag}(\Sigma)$	x	5.59	5.76	5.71
	Σ	x	x	5.57	5.73
	Σ_{perm}	x	x	x	5.52

Abbildung: Localization error for MAP estimate

Σ is given by empty room data.

Simulation Studies for Noise Sensitivity: Summary Noise

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(a) CM

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(b) MAP

Result: HBM estimates are surprisingly robust against noise miss-specification!

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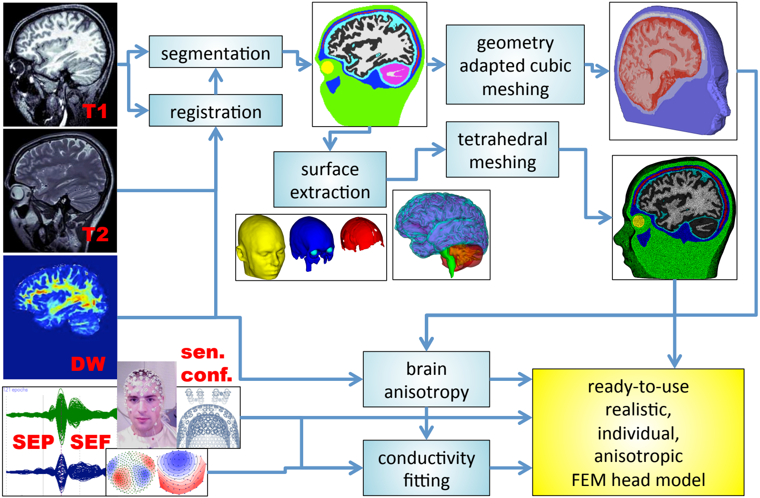
(b) MAP

Result: HBM estimates are surprisingly robust against noise miss-specification!

Good to know, but we still don't know what is going on.

What Else Might Go Wrong: Forward Modeling



- Approximation error modeling for EEG/MEG?
- Better model calibration?

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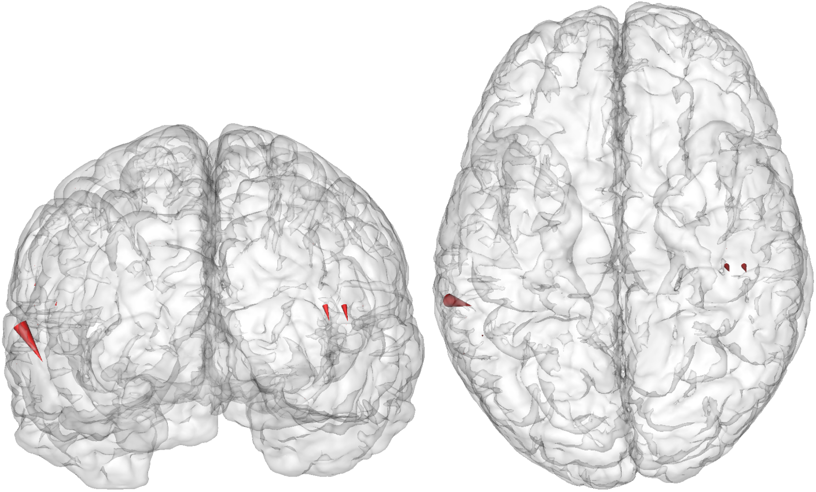
In the meantime...Auditory Data II

- Rebuild of own pipeline complete
- Aim: Use the same inversion procedure to reproduce the bad results
- Examine how change in pipeline affect results
- Different subject (no particular reason)

Auditory Data II: Full CM Estimate for MEG



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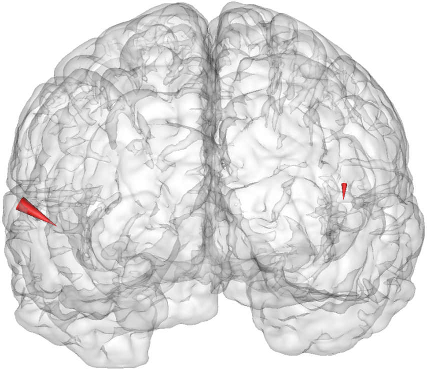
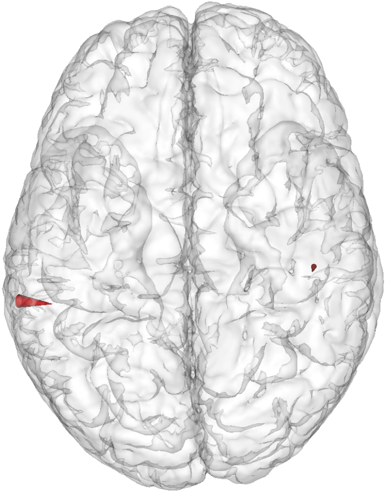
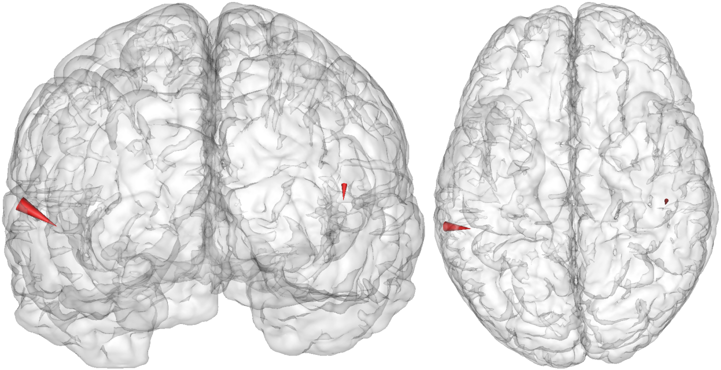




Auditory Data II: Summary



- Not able to reproduce bad results!
- Only able to produce good results!
- Very robust to parameter changes!?

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Summary and conclusions:

- Don't decide to do too much work to soon...take a different data set first.
- However, leaving the "only the inverse problem" comfort zone pays off:
  - I learned a lot about EEG/MEG as a whole.
  - I have my own complete processing pipeline.
- HBM estimates are surprisingly robust.
- HBM can also give good results in practice.

Next steps:

- Reexamine first data set with own pipeline.
- Examine more data sets from different activity.

Thank you for your attention!

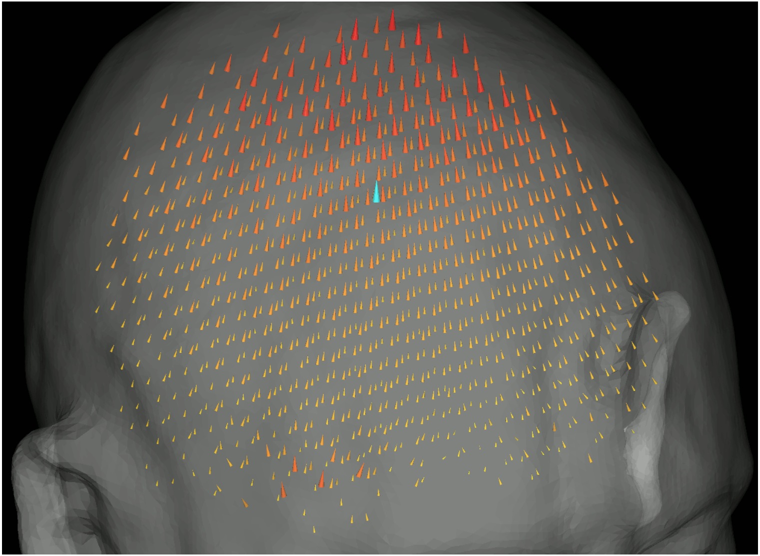
and thanks to:

- ★ *Institute for Biomagnetism and Biosignalanalysis (WWU, Münster)*:
  Carsten Wolters, **Ümit Aydin**, **Johannes Vorwerk**,
  Benjamin Lanfer & Andreas Wollbrink
- ★ *Institute for Applied Mathematics (WWU Münster)*:
  Martin Burger
- ★ *Donders Institute, Nijmegen:*
  Arno M. Janssen, Sumientra M. Rampersad & Dick F. Stegeman
- ★ *Martinos Center, Boston*:
  Seok Lew

Depth Bias: Illustration

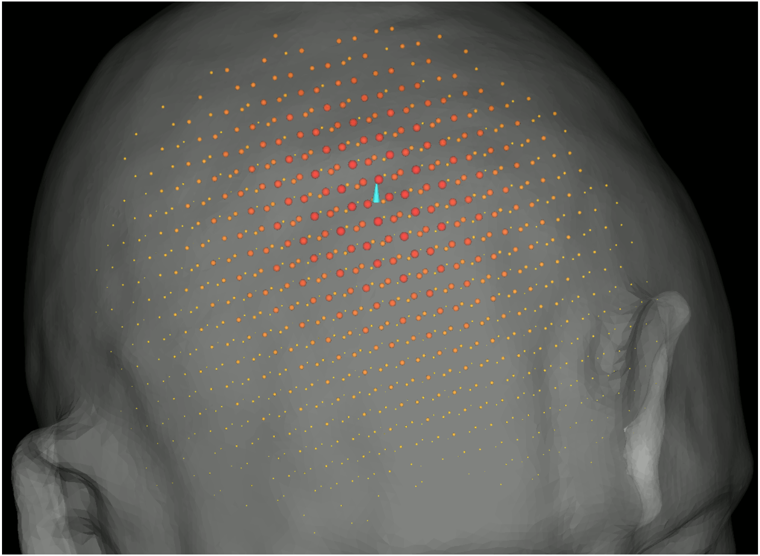
One deep-lying reference source (blue cone) and minimum norm estimate:

$u_{\mathrm{MNE}} = \operatorname{argmin}\{\|\Sigma_\varepsilon^{-1/2}(f - K\,u)\|_2^2 + \lambda\|u\|_2^2\}$



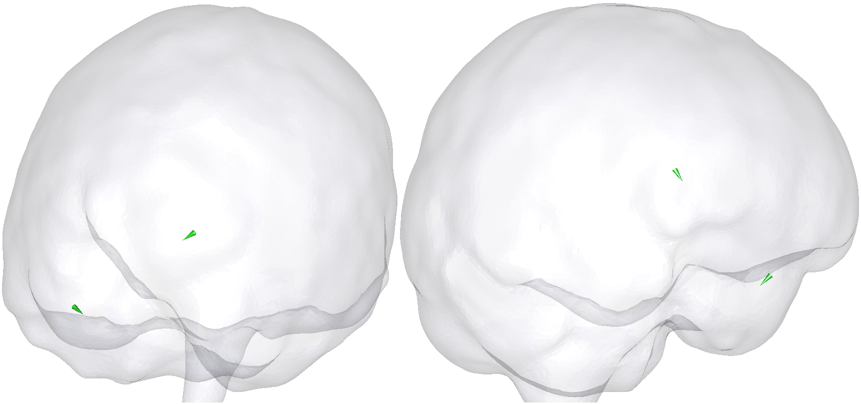
Depth Bias: Illustration

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



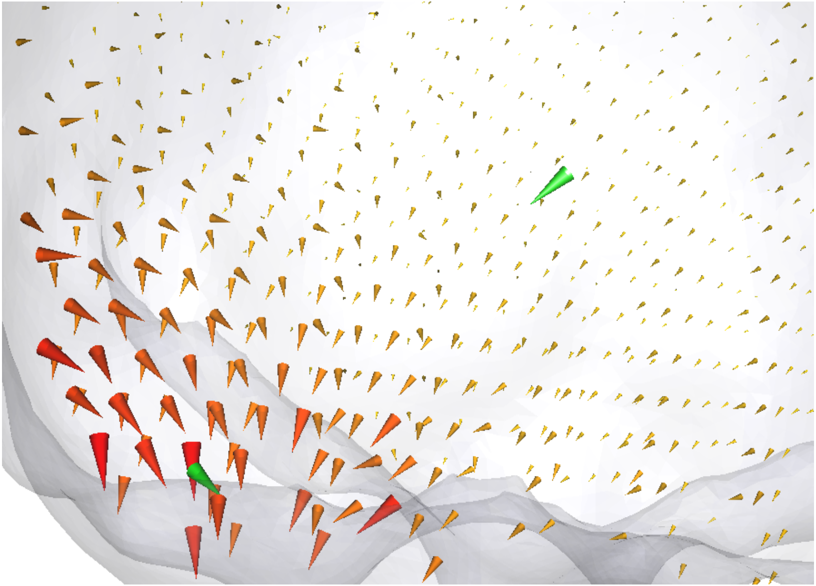
Masking: Illustration

Reference sources.



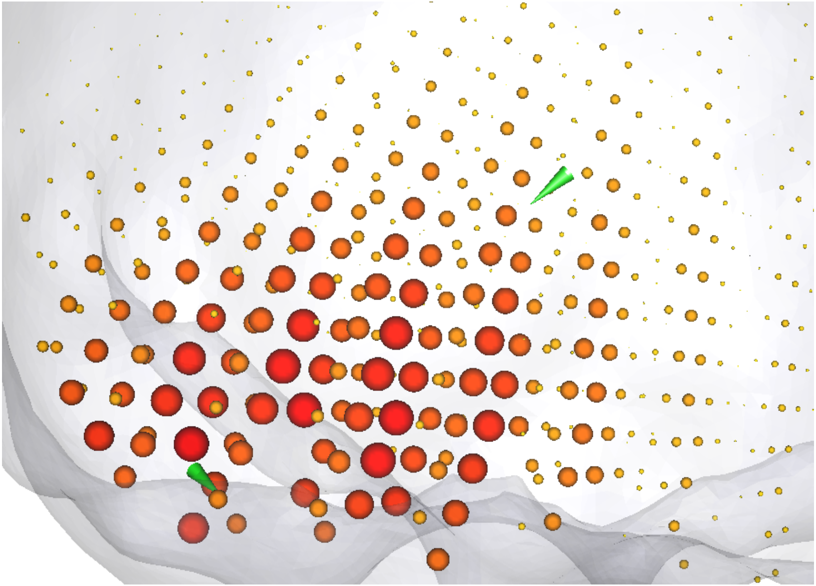
Masking: Illustration

MNE result and reference sources (green cones).



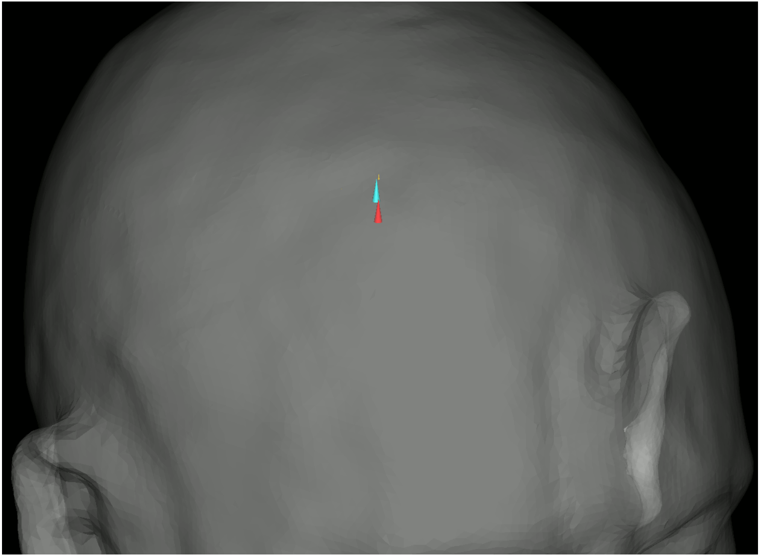
Masking: Illustration

sLORETA result and reference sources (green cones).



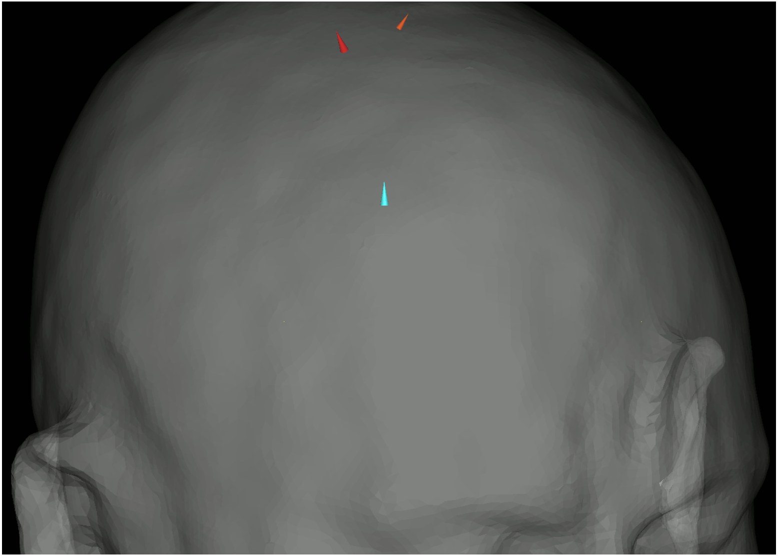
Depth Bias: Full-Conditional Mean Estimate (CM)

Computed by blocked Gibbs MCMC sampler.



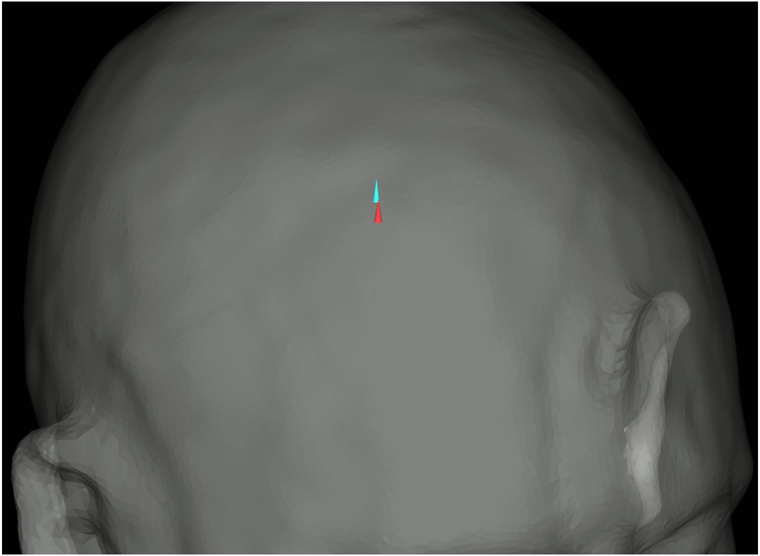
Depth Bias: Full-Maximum A-Posteriori Estimate (MAP), Algorithm I

Computed by alternating optimization, uniform initialization.



Depth Bias: Full-MAP, Algorithm II

Computed by alternating optimization initialized at the CM estimate.

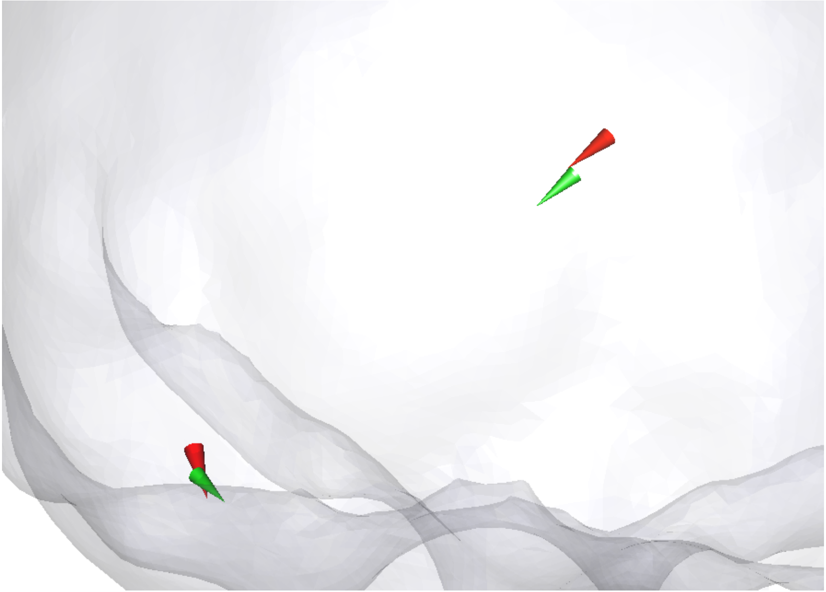


Masking: Result Full-CM

Computed by blocked Gibbs MCMC sampler.

Masking: Result Full-MAP

Computed by alternating optimization initialized at the CM estimate.



Basics of Hierarchical Bayesian Modeling

Full Posterior:

$$p_{post}(u, \gamma | f) \propto$$

$$\exp\left(-\left(\frac{1}{2}\|\Sigma_\varepsilon^{-1/2}(f - K\,u)\|_2^2 + \sum_{i=1}^{k}\left(\frac{\frac{1}{2}\|u_i^{\text{amp}}\|_2^2 + \beta}{\gamma_i} + \left(\alpha + \tfrac{5}{2}\right)\ln\gamma_i\right)\right)\right)$$

- Quadratic/Gaussian with respect to u.
- Factorizes over γ_i's.
- (Regularization) energy is non-convex w.r.t. (u, γ) / Posterior is multimodal.

Simulation Studies for Background Sensitivity

- EEG/MEG is severely ill-conditioned and underdetermined.
- Inverse Solutions for EEG/MEG are prior dominated.
- Sensitive to miss-specification of prior?

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- EEG/MEG is severely ill-conditioned and underdetermined.
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- Sensitive to miss-specification of prior?

A : Add signal of two focal sources with 10% / 20% main signal strength.
B : Add signal of Gaussian sources with 10% / 20% main signal strength.

Method	Pure	**A, 10%**	**A, 20%**	**B, 10%**	**B, 20%**
MNE	17.54	17.58	17.60	17.55	17.68
sLORETA	5.20	5.29	5.57	5.26	5.59
HBM CM	5.55	5.90	6.12	5.72	6.62
HBM MAP	5.58	5.81	6.23	5.69	6.80

Tabelle: Localization errors for background activity, Σ : Empty room data.