Direct cortical localization of the MEG auditory temporal response function: a non-convex optimization approach

Proloy Das*[1], Christian Brodbeck[2], Jonathan Z. Simon[1 2 3], Behtash Babadi[1 2] *proloy@umd.edu

[1]Department of Electrical and Computer Engineering, [2]Institute for Systems Research, [3]Department of Biology, University of Maryland, College Park, Maryland

Computational Sensorimotor Systems Lab

Introduction

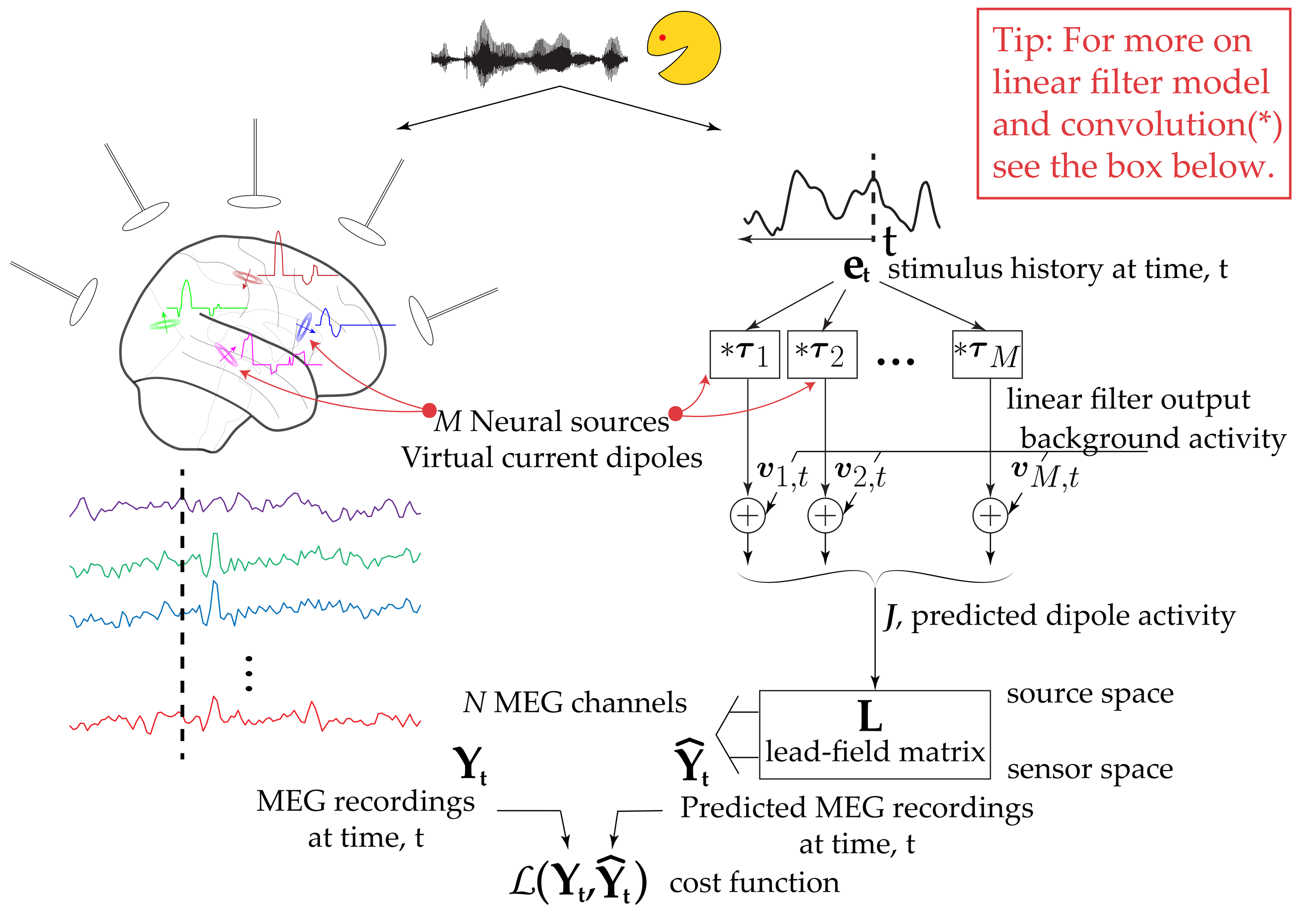
The magnetoencephalography (MEG) response to continuous speech is often modeled as generated by a linear filter, the auditory temporal response function (TRF). Functional roles of sensor-space estimated TRFs have been well characterized, but less so for neural-source estimated TRFs, which are problematic to compute. Existing methods employ two stages: a distinct TRF estimate for each potential location, only after mapping the response to neural sources. This separation fails to exploit MEG's full source localization power.

Here we provide a novel framework for simultaneously determining the TRFs and their cortical distribution, by integrating the TRF and distributed forward source models into a unified model, and casting the estimation task as a Bayesian optimization problem. TRF and source estimations now compete with each other to explain observed responses, which restricts spatial leakage (spread).

We demonstrate that our proposed algorithm shows significant improvements over other methods, including better effective spatial resolution, and reduced reliance on fine-tuned coordinate co-registration.

Model Schematic

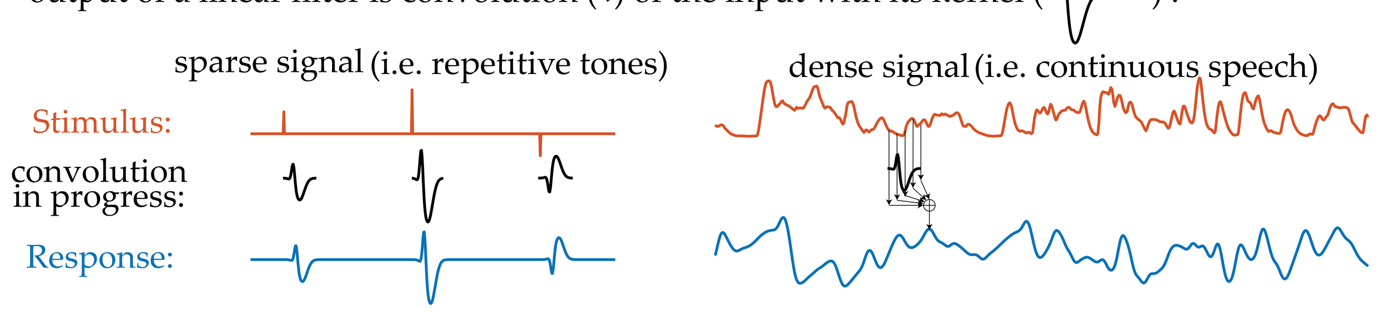
Tip: For more on linear filter model and convolution(*) see the box below.



Aim: minimize the cost function w.r.t. to the filters to find the ones making best prediction.

Linear filter model and kernels:

output of a linear filter is convolution (*) of the input with its kernel :



References:

Brodbeck, C., Presacco, A., & Simon, J. Z. (2018). Neural source dynamics of brain responses to continuous stimuli: speech processing from acoustics to comprehension. NeuroImage, 172, 162-174.

Wipf, D. P., Owen, J. P., Attias, H. T., Sekihara, K., & Nagarajan, S. S. (2010). Robust Bayesian estimation of the location, orientation, and time course of multiple correlated neural sources using MEG. NeuroImage, 49(1), 641-655.

Goldstein, T., Studer, C., & Baraniuk, R. (2014). A field guide to forward-backward splitting with a FASTA implementation. arXiv preprint arXiv:1411.3406.1.

Yang, X., Wang, K., & Shamma, S. A. (1991). Auditory representations of acoustic signals. IEEE Transactions on Information Theory, 38(2), 824–839.

Mardia, K. V., & Jupp, P. E. (2009). Directional statistics (Vol. 494). John Wiley & Sons.

Supported by:

–National Science Foundation Award No. 1552946

–National Science Foundation Award No. 1734892

Some of this work has been invited for publication in 2018 Asilomar Conference on Signals, Systems, and Computers, Oct 28 - Oct 31, Pacific Grove, CA

Computational Model

- MEG sensor measurements, $\mathbf{Y}$ arise from neural currents, J:

$$\mathbf{Y} = \mathbf{L}\,J + \mathbf{W},$$

$\mathbf{L}$, the lead-field ($N \times 3M$) matrix (i.e., Maxwell's equations)
$\mathbf{W}$, measurement noise ~ Gaussian (measured covariance, Σ_w)

- model assumes linear stimulus processing, so the neural currents, J due to stimulus history, $\mathbf{S}$ are:

$$J = \Phi\mathbf{S} + \mathbf{V}$$

Φ, matrix of 3D vector TRFs per neural source
$\mathbf{V}$, background activity

- background activity at each source ~ Gaussian, independent of other sources.
  - variance of m^{th} source, Γ_m 3×3 matrix
  - source variance, Γ $3M \times 3M$ block diagonal matrix

- Eliminate J to get the likelihood of observed MEG data, as a function of TRF matrix, Φ and source covariance, Γ:

$$p(\mathbf{Y}|\Phi,\Gamma) \propto |\Sigma_w + \mathbf{L}\Gamma\mathbf{L}^\top|^{-T/2} \times \exp\left(-\frac{1}{2}\|\mathbf{Y}-\mathbf{L}\Phi\mathbf{S}\|^2_{(\Sigma_w+\mathbf{L}\Gamma\mathbf{L}^\top)^{-1}}\right)$$

Problem Formulation:

$$\underset{\Phi}{\text{minimize}}\ \underbrace{\frac{1}{2}\|\mathbf{Y}-\mathbf{L}\Phi\mathbf{S}\|^2_{(\Sigma_w+\mathbf{L}\Gamma\mathbf{L}^\top)^{-1}}}_{\text{Data fidelity term}} + \underbrace{\eta\|\Phi\|_{2,1,1}}_{\text{Regularization term}}$$

Data fidelity term minimizes error in prediction. Regularization term guards against overfitting.

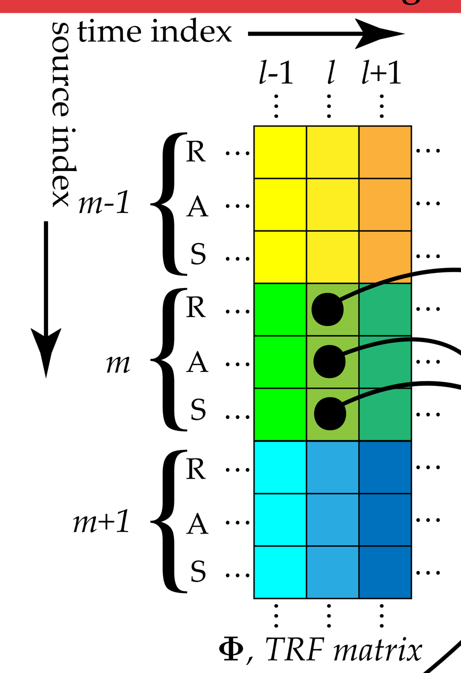
But, Γ, source variance is not known. Need a suitable approximation!

Idea: Solve for both TRF matrix, Φ and source variance, Γ !!

$$\underset{\Phi\ \Gamma}{\text{minimize}}\ \frac{T}{2}\log\left(\Sigma_w + \mathbf{L}\Gamma\mathbf{L}^\top\right) + \frac{1}{2}\|\mathbf{Y}-\mathbf{L}\Phi\mathbf{S}\|^2_{(\Sigma_w+\mathbf{L}\Gamma\mathbf{L}^\top)^{-1}} + \eta\|\Phi\|_{2,1,1}$$

Cost function is not convex anymore ⟶ hard to reach the optimal solution
Direct optimization w.r.t. both Φ, Γ difficult ⟶ Update Φ and Γ alternatingly

Mixed-norm Regularization



$$\|\Phi\|_{2,1,1} = \sum_{m=1}^{M}\sum_{l=1}^{L}\left(\tau^2_{m,R,l}+\tau^2_{m,A,l}+\tau^2_{m,S,l}\right)^{1/2}$$

– Promotes sparse solution.
– co-registration coordinate invariant

Regularization parameter: controls the importance of the regularization term.
bigger η ⟶ sparser (simple) solution
smaller η ⟶ denser (complex) solution
selected by cross-validation or estimation stability

Proposed Algorithm

– input: MEG matrix, $\mathbf{Y}$; Stimulus matrix, $\mathbf{S}$; Lead-field matrix, $\mathbf{L}$; regularizing parameter, η
– initialize $\Phi^{(0)} = \mathbf{0}$
– repeat
1. compute $\mathbf{C}_v = \frac{1}{T}(\mathbf{Y}-\mathbf{L}\Phi^{(r)}\mathbf{S})(\mathbf{Y}-\mathbf{L}\Phi^{(r)}\mathbf{S})^\top$
2. $\Gamma^{(r+1)} = \arg\min_{\Gamma} \mathrm{tr}\left(\Sigma_v^{-1}\mathbf{C}_v{}^{(r)}\right) + \log|\Sigma_v|$ s.t. $\Sigma_v = \Sigma_w + \mathbf{L}^\top\Gamma\mathbf{L}$
3. compute $\Sigma_v^{(r+1)} = \Sigma_w + \mathbf{L}\Gamma^{(r+1)}\mathbf{L}^\top$
4. $\Phi^{(r+1)} = \arg\min_{\Phi} \frac{1}{2}\|\mathbf{L}\Phi\mathbf{S}-\mathbf{Y}\|^2_{\Sigma_v^{(r+1)^{-1}}} + \eta\|\Phi\|_{2,1,1}$
5. **until** $\frac{\|\Phi^{(r+1)}-\Phi^{(r)}\|_2}{\|\Phi^{(r)}\|_2} <$ tol or $r = R_{\max}$
6. set $r \leftarrow r+1$

– output: $\Phi^{(R)}$, where R is the index of the last iteration.

Γ update:
- adaptively changes the definition of 'best' kernels by noise normalization.
- non-convex problem
- hard to get the optimal solution
- we used Champagne (Wipf et al., 2010)
- each pass is guaranteed to reduce cost function

Φ update:
- assigns sparse kernels to each neural sources to make 'best' prediction
- convex (easy) problem.
- smooth + non-smooth
- forward-backward splitting
- we employ 'FASTA' (Goldstein et al., 2014)

Comments:
- kernels are allowed to compete with each other, unlike independent analysis methods (Brodbeck et al., 2018).
- No assumptions for orientation of the source activity or the 3D vector TRFs.

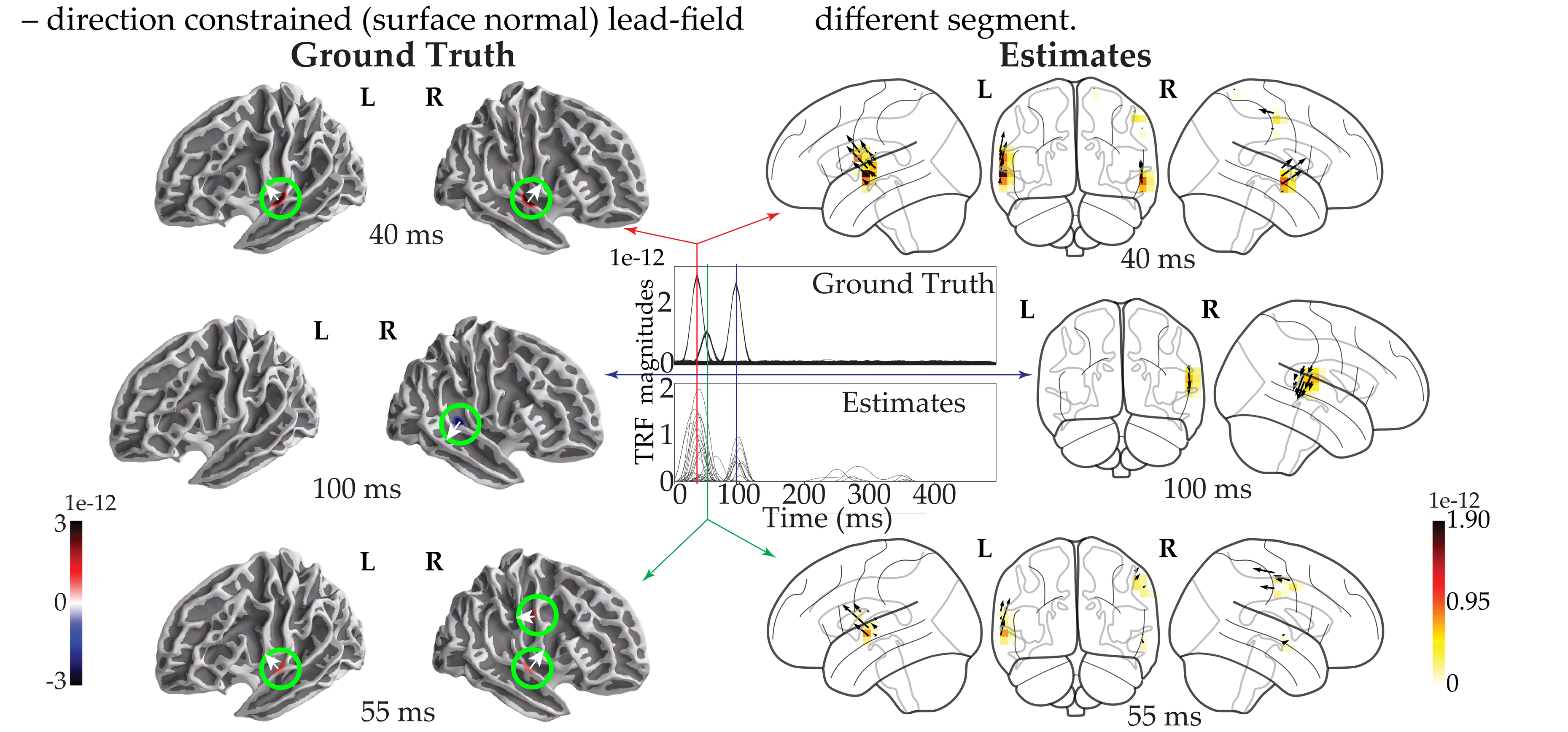
python implementations available at:

Dataset

- **MEG Data**
  – 17 participants.
  – Two 60-second segments from 'The Legend of Sleepy Hollow' by Washington Irving.
  – 3 repetitions for each segment.
- **An average "brain model"**
  – "fsaverage", FreeSurfer.
  – scaled and coregistered to each subject's head.
  – volume source space on regular grid.
  – resolution ~ 7mm.
  – virtual dipoles on 3322 grid points.
  – free orientation lead-field matrix.
- **Stimulus representation:**
  – acoustic envelope, average over frequency band of an auditory spectrogram representation (Yang et al., 1991).

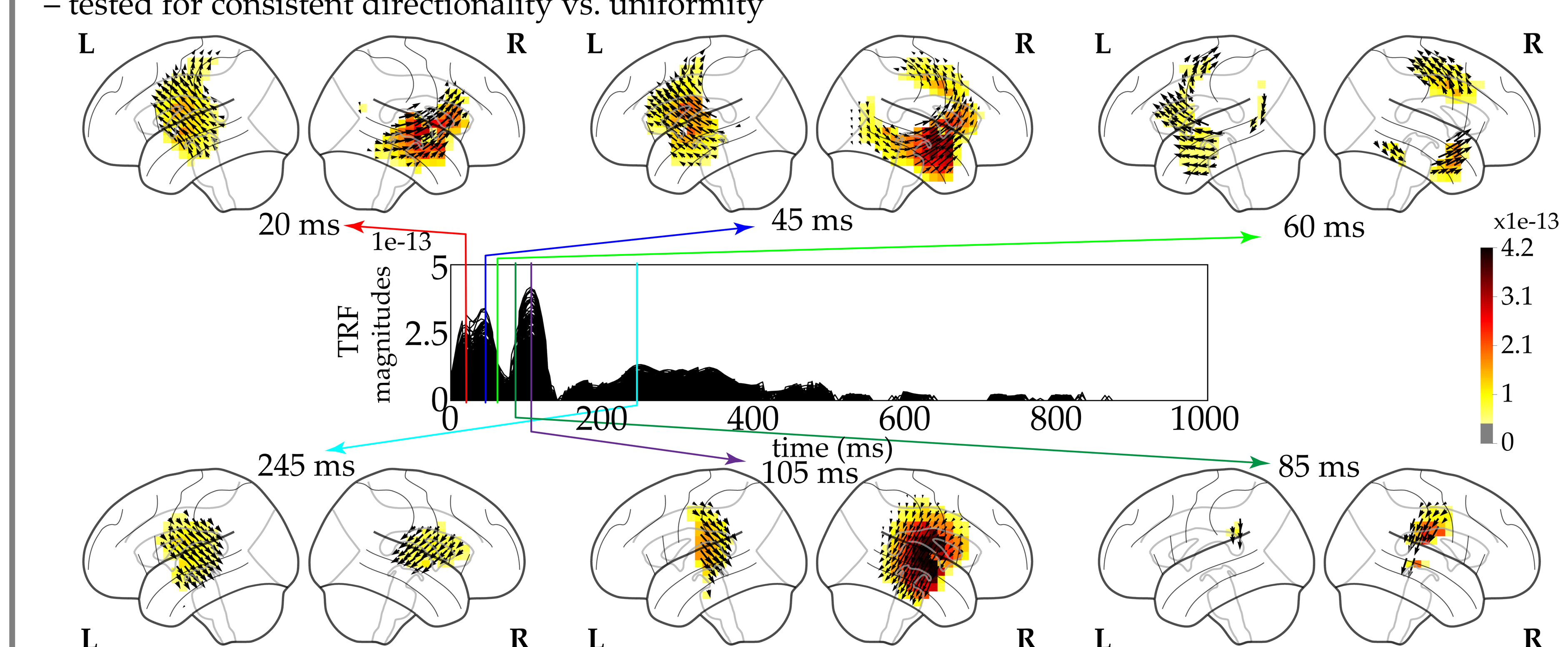
Results

- **Simulated MEG data**:
  – finer source space, resolution ~ 3.1 mm (ico-5).
  – direction constrained (surface normal) lead-field matrix.
  – background noise = unaltered MEG recording of different segment.



- **Observations:**
  – recovers TRF time-courses faithfully.
  – the spatial extent of the active dipole sources closely resembles the simulated active region.
  – estimated 3D vector TRFs align well with direction normal to cortical surface without requiring it as assumption.
  – spurious peaks are weaker and more variable.

- **Experimental MEG data:**
  – 3-fold cross-validation for each subject.
  – spatial smoothing w/ Gaussian kernel (10 mm).
  – tested for consistent directionality vs. uniformity (Mardia, 2009) using permutation test.
  – average response functions across subject. only significant values displayed (p < .05).



- **Acoustic envelope response functions:**
  – peaks at 20 ms, 45 ms and 105 ms.
  – bilaterally centered on auditory cortex.
  – increased activity in inferior frontal, sensorimotor cortices at 45 ms over 20 ms.
  – 100 ms peak right hemisphere dominant.
  – current dipole reverses direction in sensorimotor cortex at 85 ms.