



MRC Cognition
and Brain
Sciences Unit



UNIVERSITY OF
CAMBRIDGE

EEG/MEG 2: Spatial Resolution and Nonlinear Methods

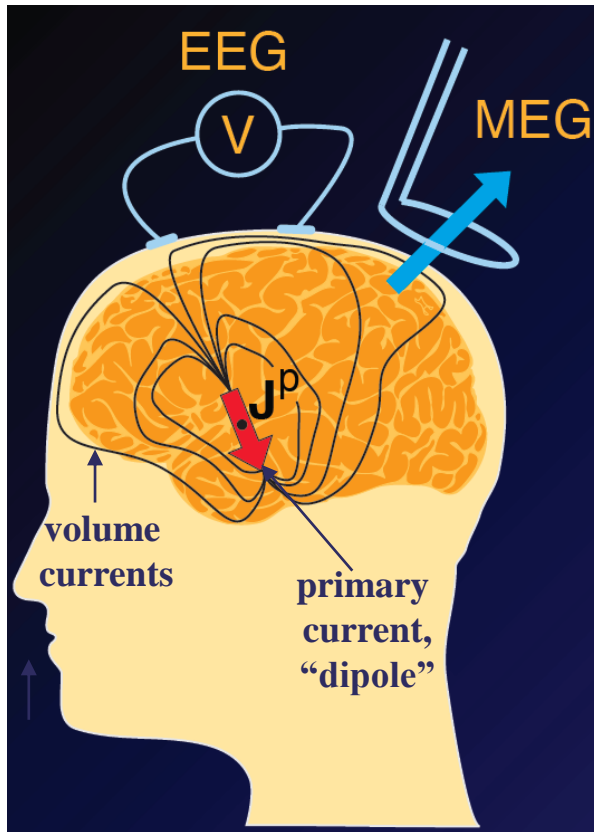
Olaf Hauk

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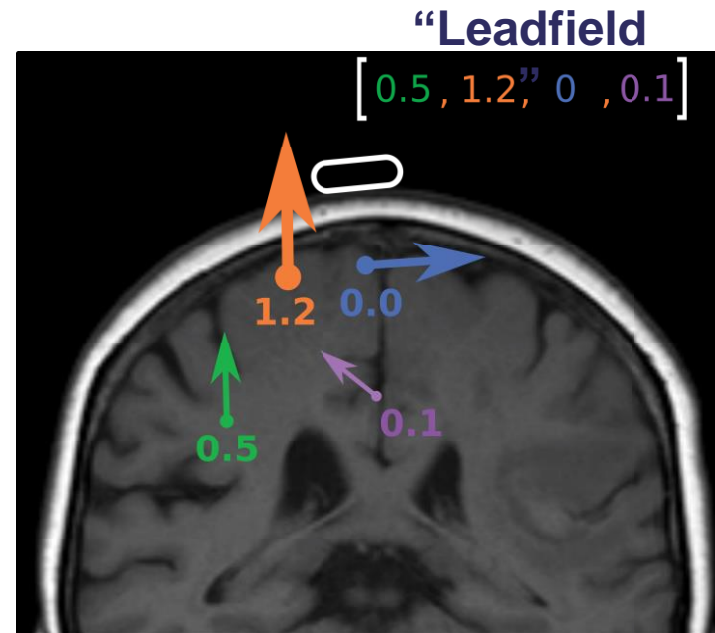
COGNESTIC 2023

The EEG/MEG Forward Problem

EEG/MEG measure the primary sources indirectly

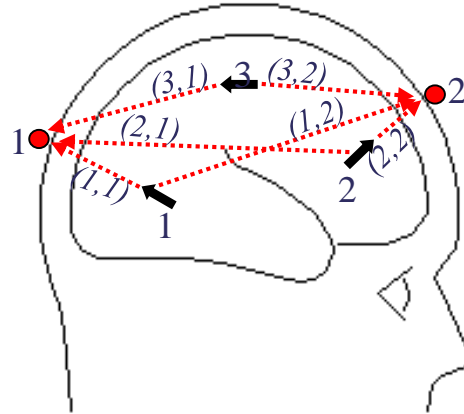


Sensors are differently sensitive to different sources



Hauk, Stenroos, Tieder. In: Supek S, Aine C (eds), "Magnetoencephalography: From Signals to Dynamic Cortical Networks, 2nd Ed."

We Have To First State The Forward Problem In Order To Solve The Inverse Problem



Inverse Operator

data	“leadfield”	dipoles		dipoles	inverse	data
$\begin{matrix} \bullet \\ 1 \\ \bullet \\ 2 \end{matrix} \begin{pmatrix} d_1 \\ d_2 \end{pmatrix}$	$= \begin{pmatrix} 0.5 & 0 & 0.3 \\ 0 & 1 & -0.3 \end{pmatrix}$	$\begin{pmatrix} j_1 \\ j_2 \\ j_3 \end{pmatrix}$?	$\begin{matrix} \bullet \\ 1 \\ \bullet \\ 2 \\ \bullet \\ 3 \end{matrix} \begin{pmatrix} j_1 \\ j_2 \\ j_3 \end{pmatrix}$	$= \begin{pmatrix} 1.5034 & 0.1241 \\ 0.2483 & 0.9379 \\ 0.8276 & -0.2069 \end{pmatrix}$	$* \begin{pmatrix} d_1 \\ d_2 \end{pmatrix}$
			inversion			

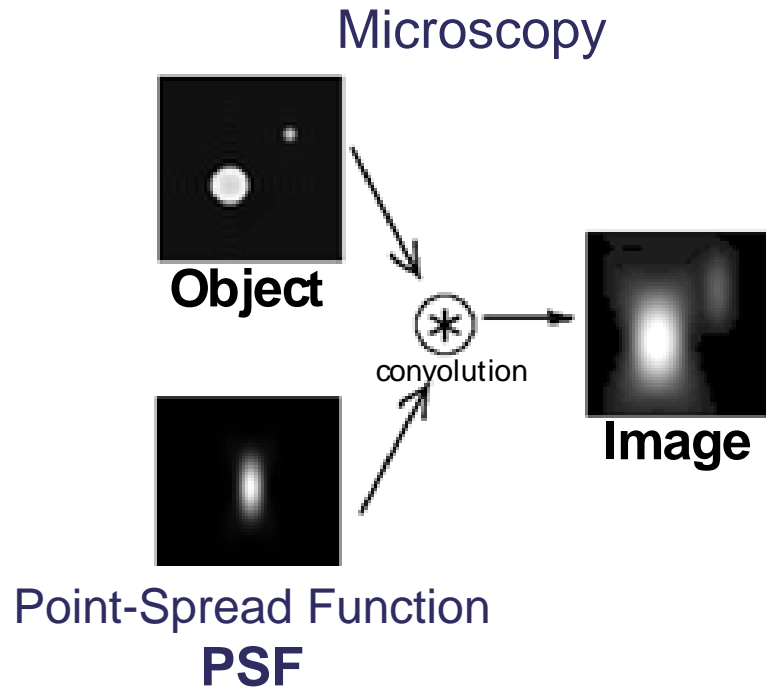
Let's Start Again: The “Blurry Image” Analogy

Just because the brain is complicated doesn't mean source estimation has to be complicated

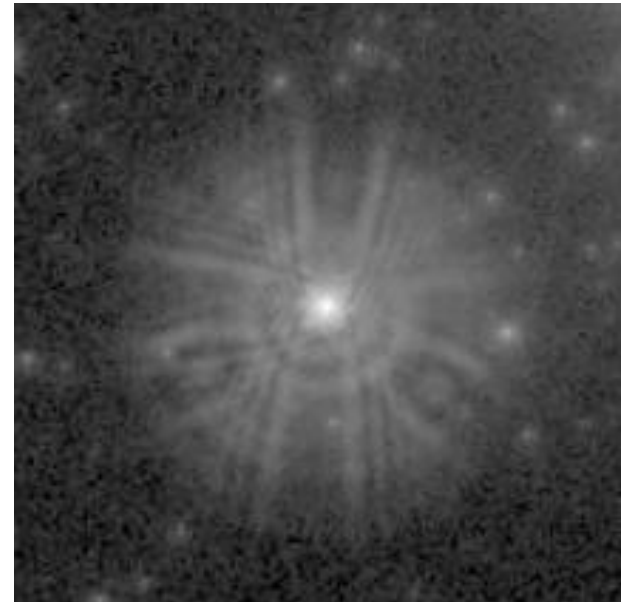


The Superposition Principle

A “Constraint-Free” Interpretation of Linear Methods

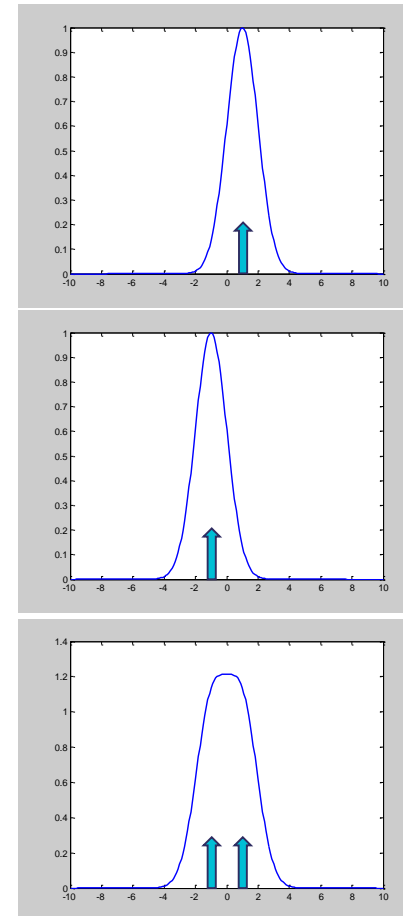
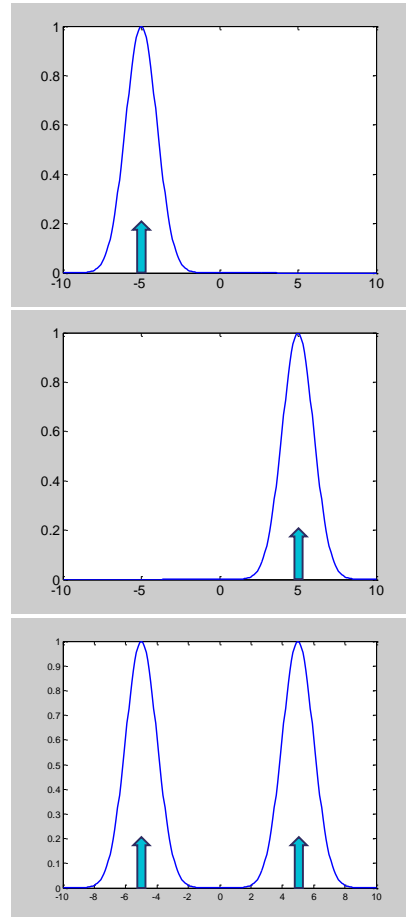


Astronomy



Linear Methods Can Easily Tell Us If They Do What We Want

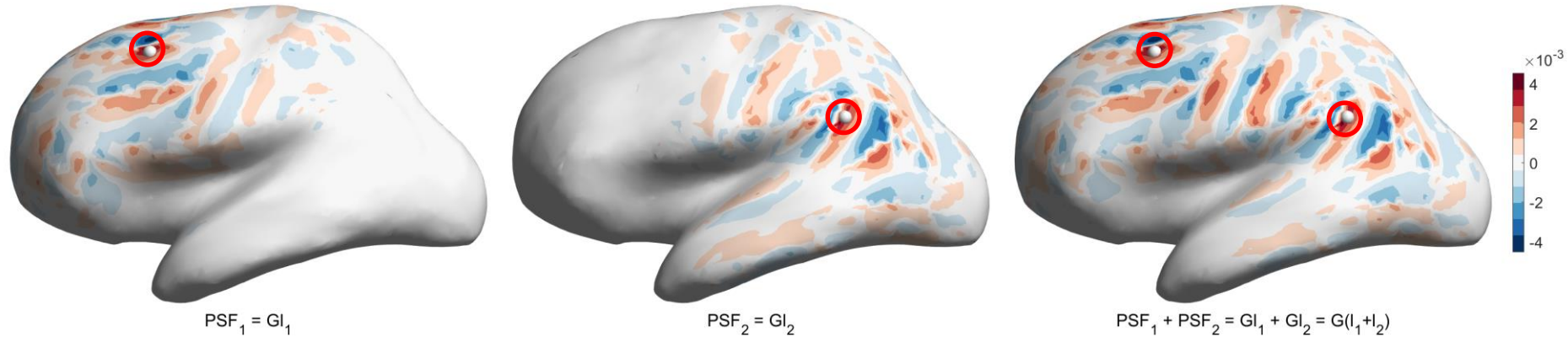
Superposition Principle



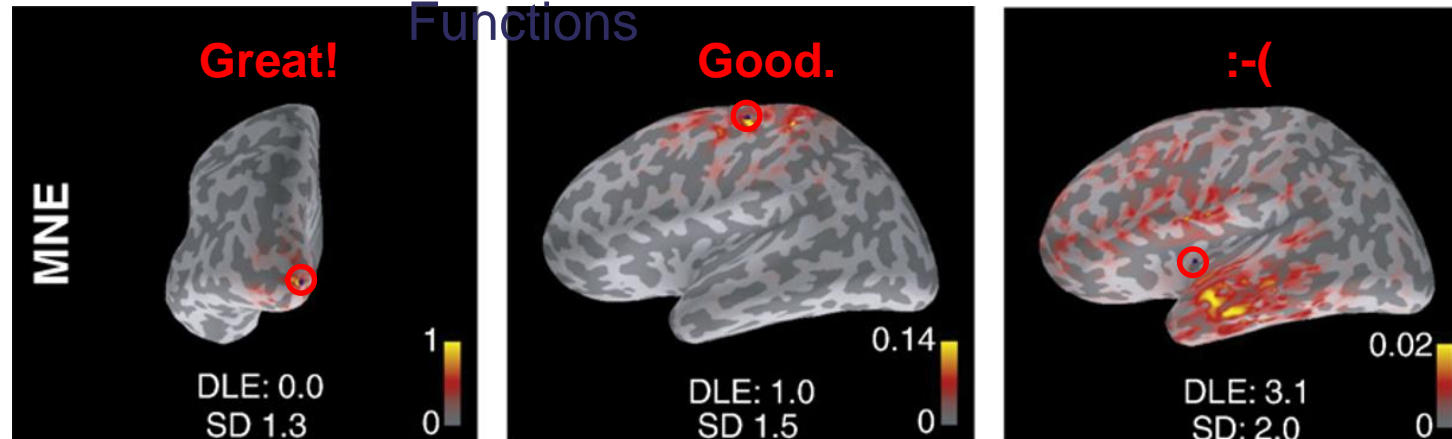
If you know the behaviour for point sources,
you can predict the behaviour for complex sources

Linear Methods – Superposition Principle

Superposition In Source Space



Example Point-Spread Functions



Spatial Resolution of Source Estimation Is Complex

Spatial resolution depends on:

number of sensors (EEG/MEG or both)

source location

source orientation

signal-to-noise ratio

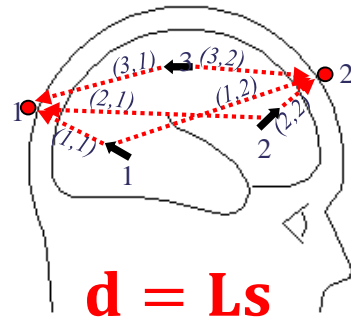
head modelling

assumptions about the sources

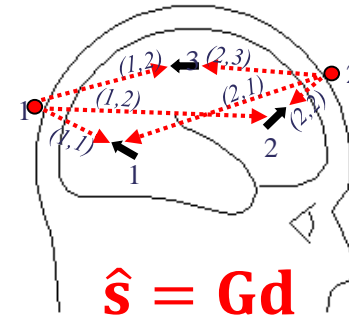
=> difficult to make general statement

Resolution Matrix

Forward Problem



Linear Inverse Problem



$$\hat{\mathbf{s}} = \mathbf{G}\mathbf{L}\mathbf{s} \stackrel{\text{def}}{=} \mathbf{R}\mathbf{s}$$

Relationship between estimated and true source distribution.

Creating an Optimal Resolution Matrix

$$\hat{\mathbf{s}} = \mathbf{R}\mathbf{s}$$

The closer \mathbf{R} is to the identity matrix, the closer our estimate is to the true source.

Therefore, let us minimise the difference between \mathbf{R} and the identity matrix in the least-squares sense:

$$\|\mathbf{R} - \mathbf{I}\|_2 = \min$$

This leads to the **Minimum Norm Estimator (MNE)**:

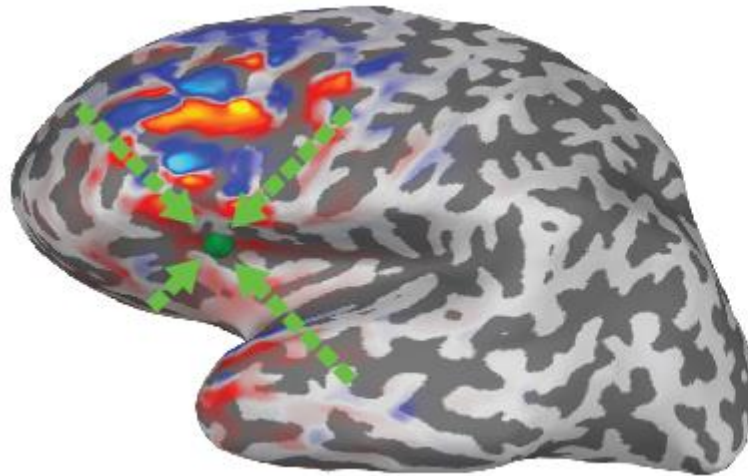
$$\mathbf{G}_{MN} = \mathbf{L}^T (\mathbf{L}\mathbf{L}^T)^{-1}$$

Its resolution matrix $\mathbf{R}_{MN} = \mathbf{L}^T (\mathbf{L}\mathbf{L}^T)^{-1} \mathbf{L}$ is symmetric.

Spatial Resolution / Leakage:

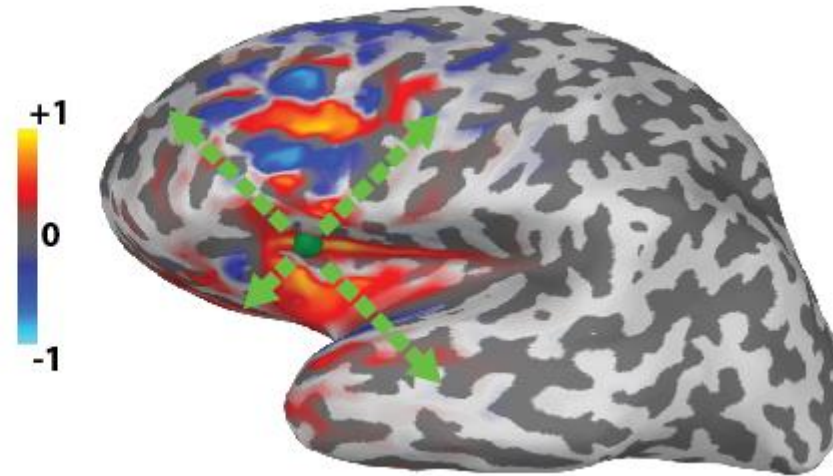
Point-Spread and Cross-Talk

Cross-Talk Function
(CTF)



How other sources may affect the estimate for this source

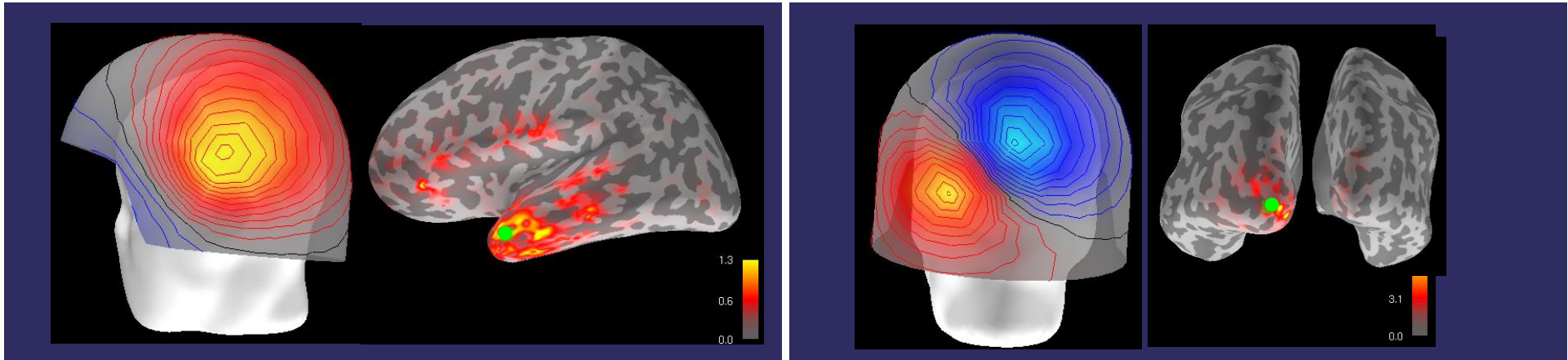
Point-Spread Function
(PSF)



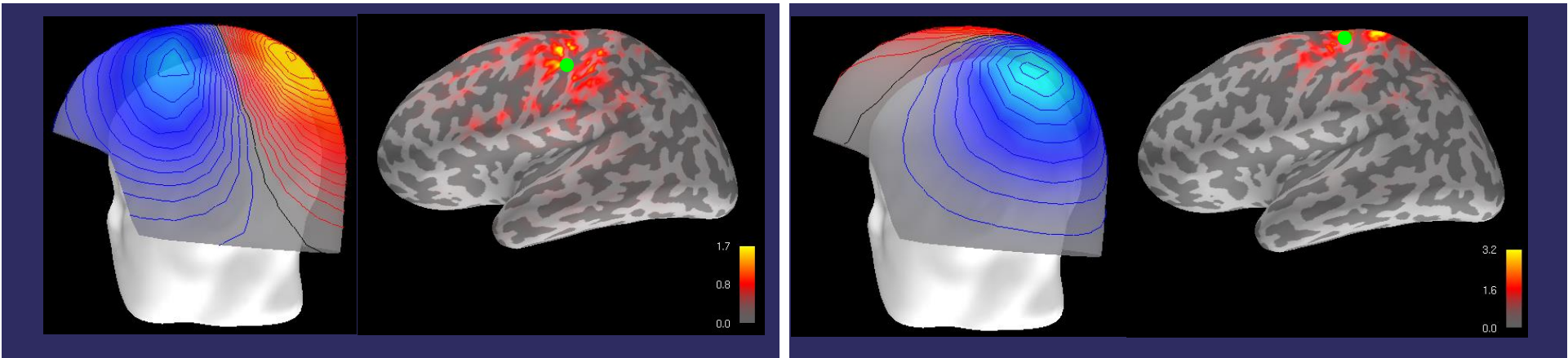
How this source affects estimates for other sources

PSFs and CTFs for Some ROIs

For MNE, PSFs and CTFs turn out to be the same

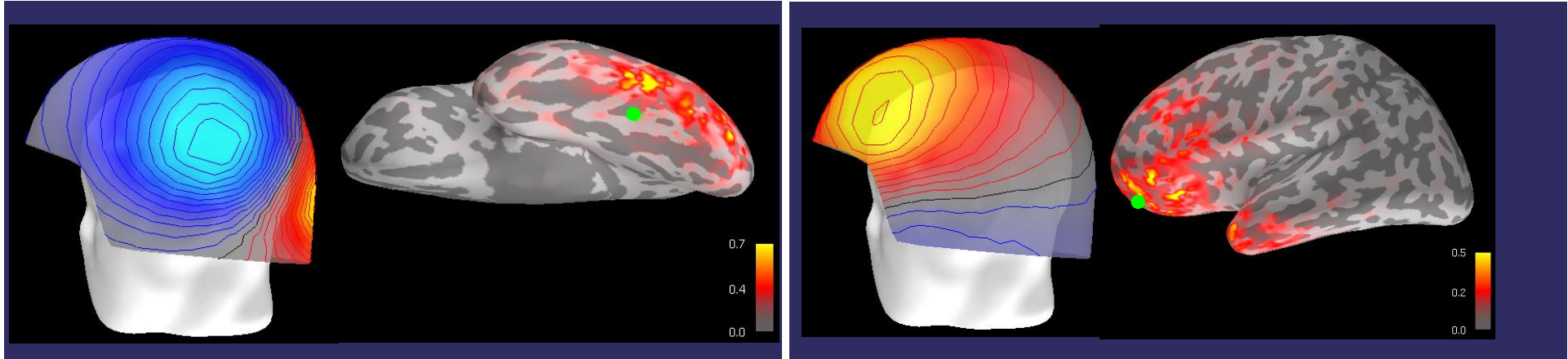


Good

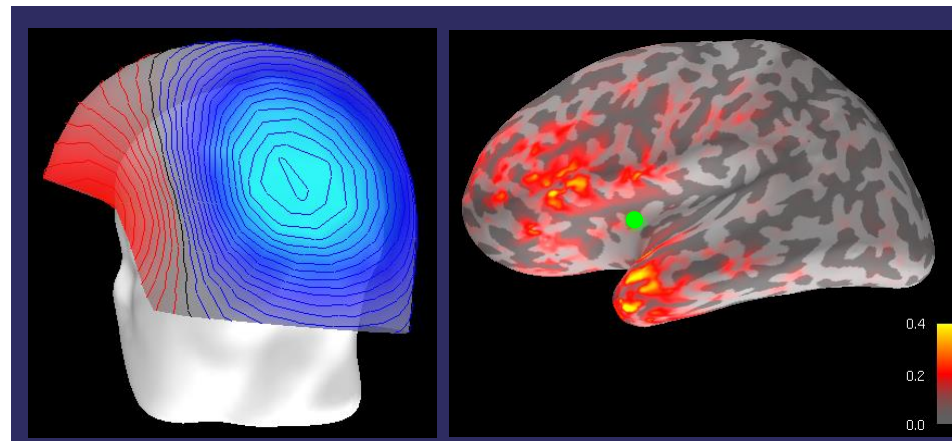


PSFs and CTFs for Some ROIs

For MNE, PSFs and CTFs turn out to be the same

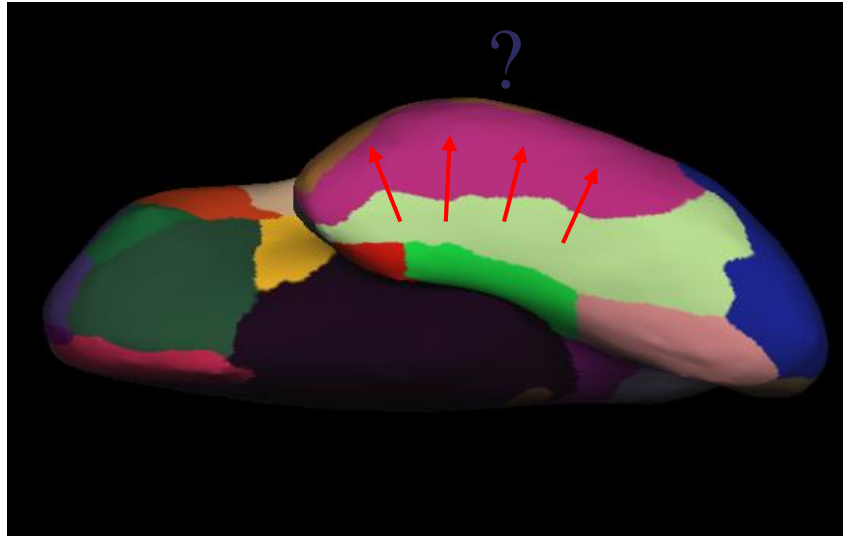


Less good

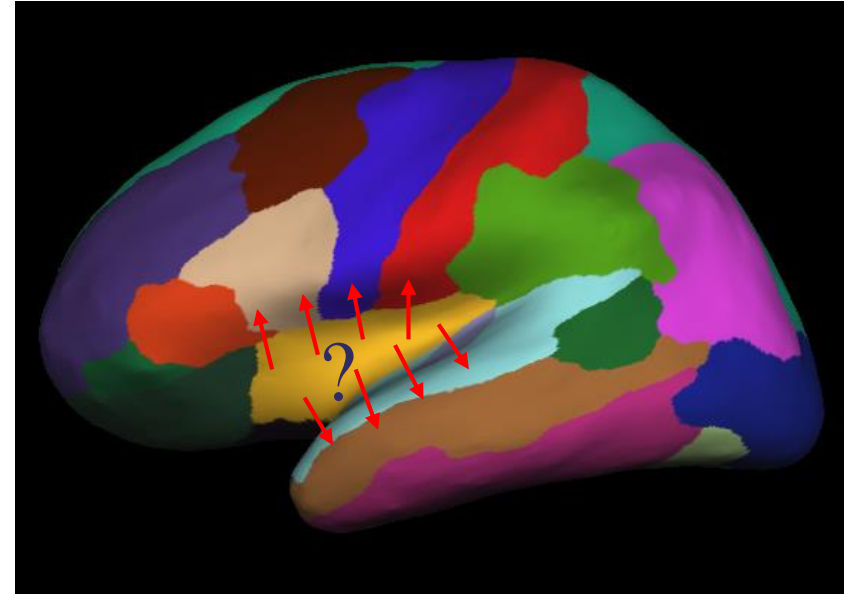


Localisation Bias Has Consequences for ROI analysis

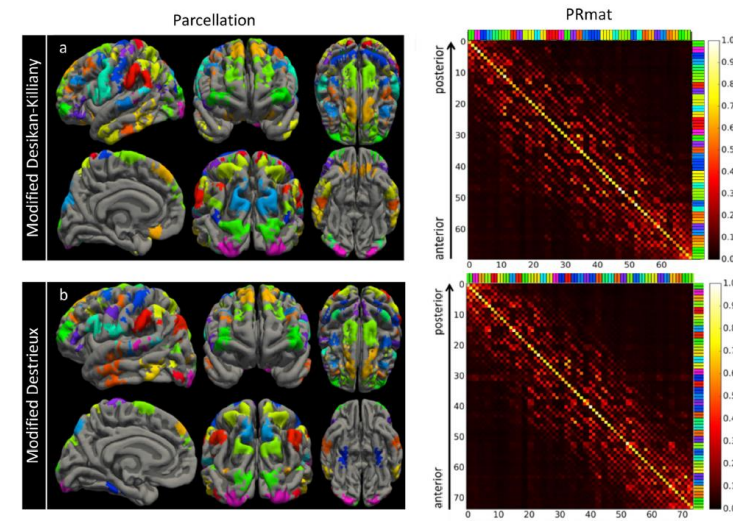
PSFs/CTFs Can Tell You How It Looks Like



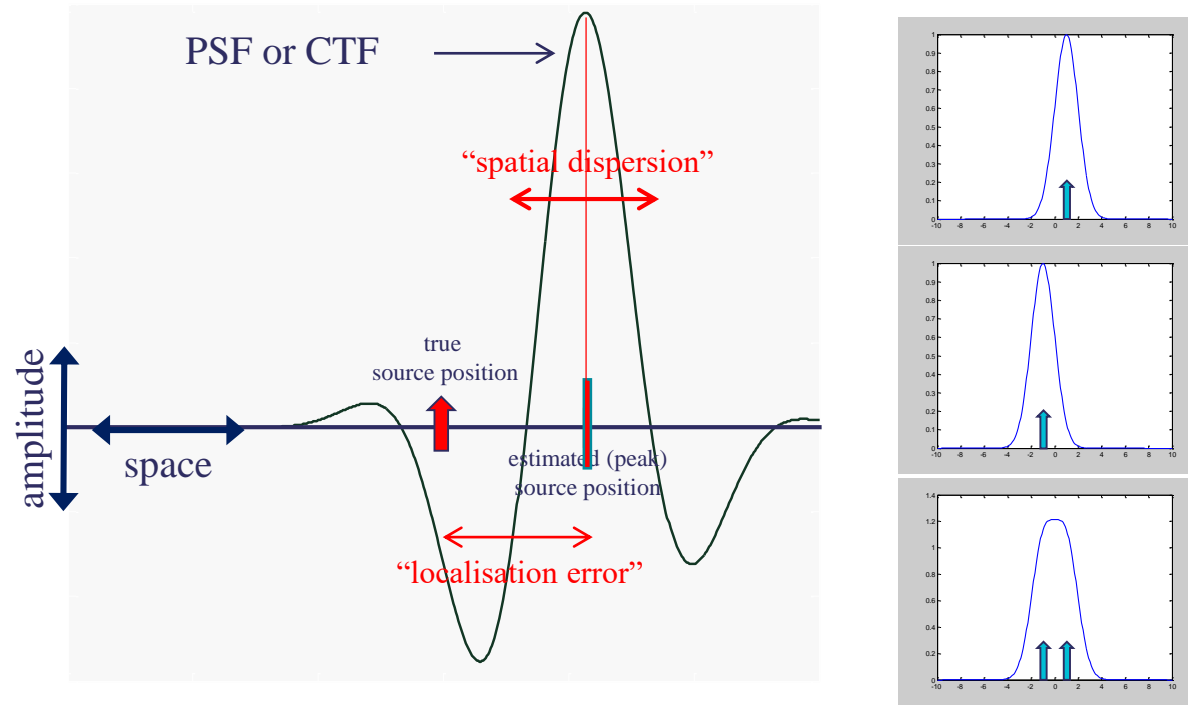
Desikan-Killiany Atlas parcellation



Adaptive cortical parcellation based on resolution matrix are possible: Farahibozorg/Henson/Hauk NI 2018
<https://pubmed.ncbi.nlm.nih.gov/28893608/>

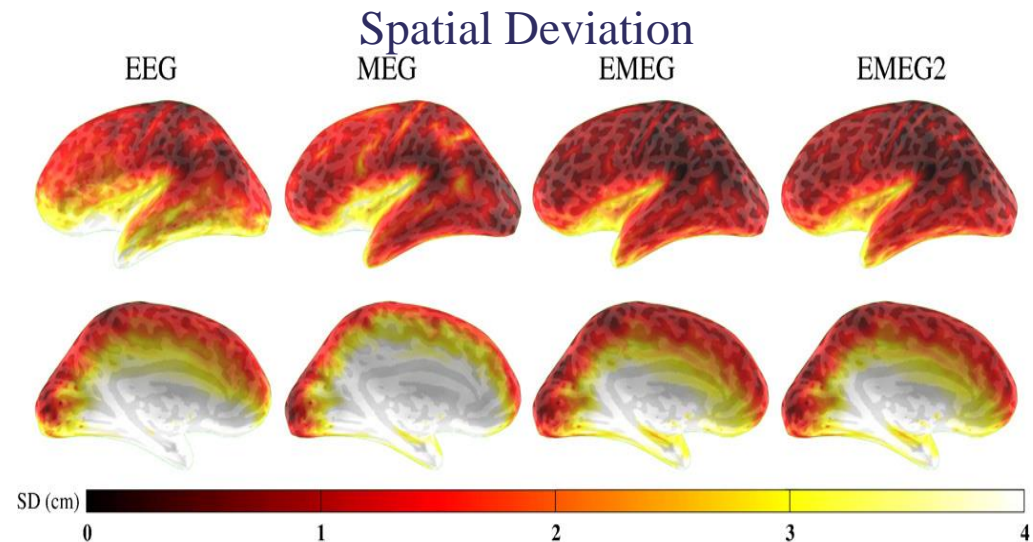
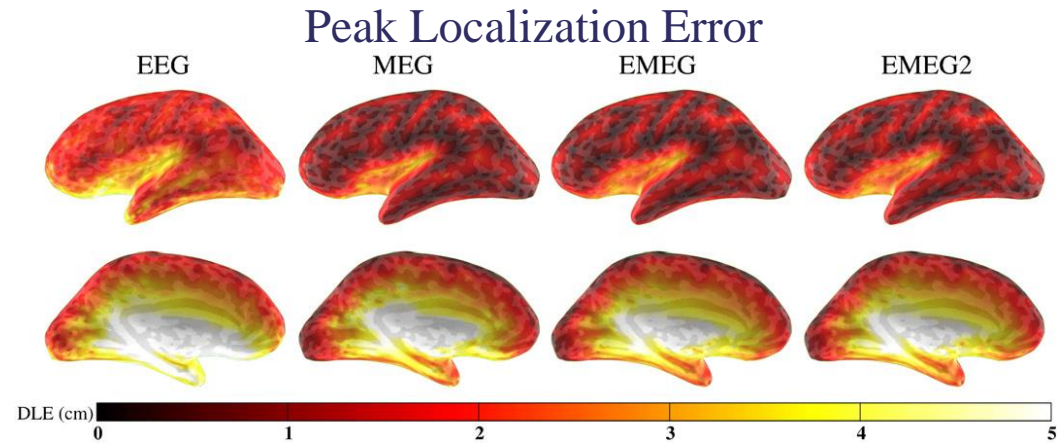


Quantifying Resolution From PSFs and CTFs



It's not just peak localisation that counts,
but also spatial extent of the distribution.

Whole-Brain Maps of Resolution Metrics

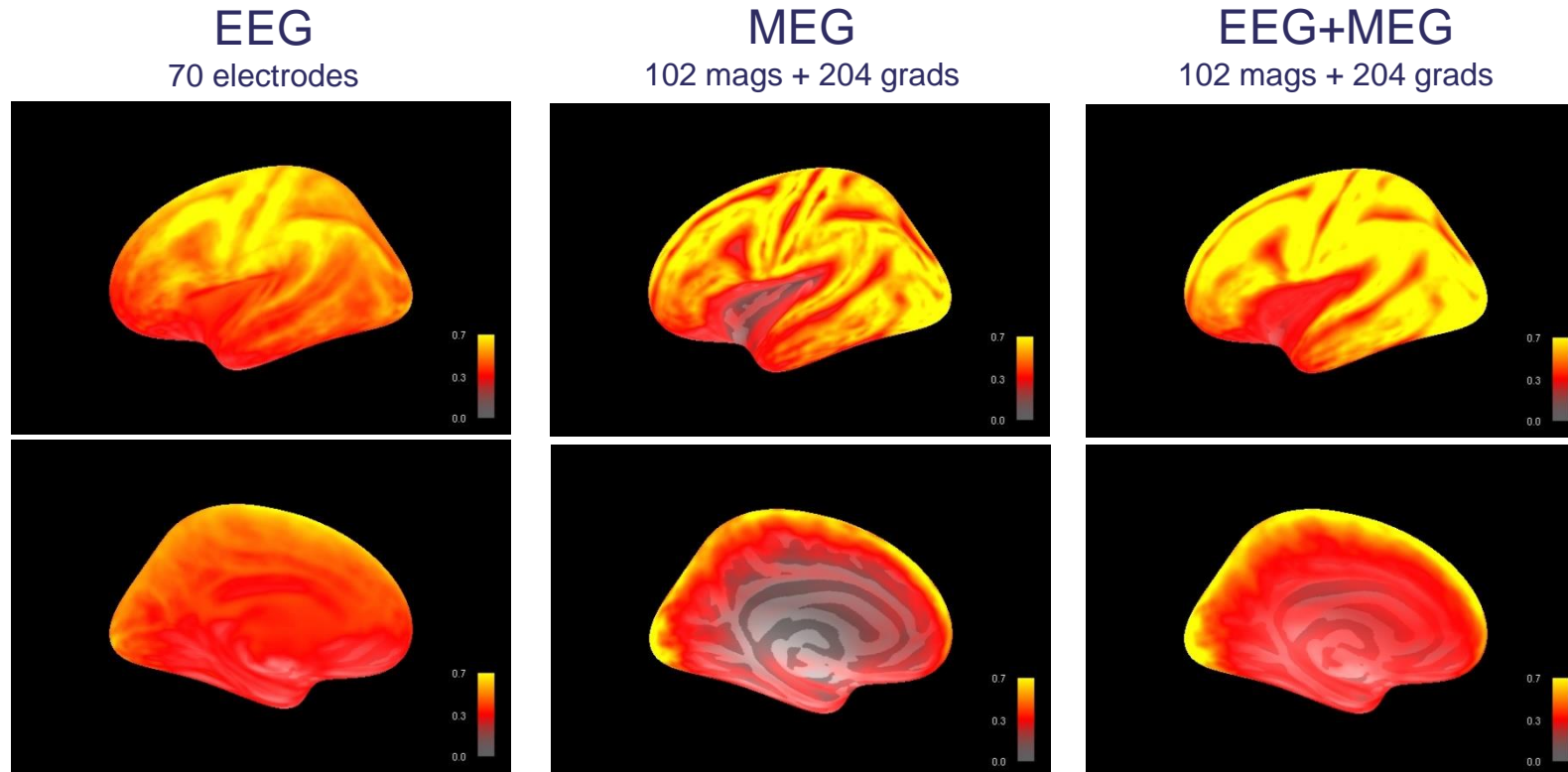


Molins et al., Neuroimage 2008

Combining EEG and MEG improves spatial resolution.

Sensitivity Maps

RMS of Leadfield Columns



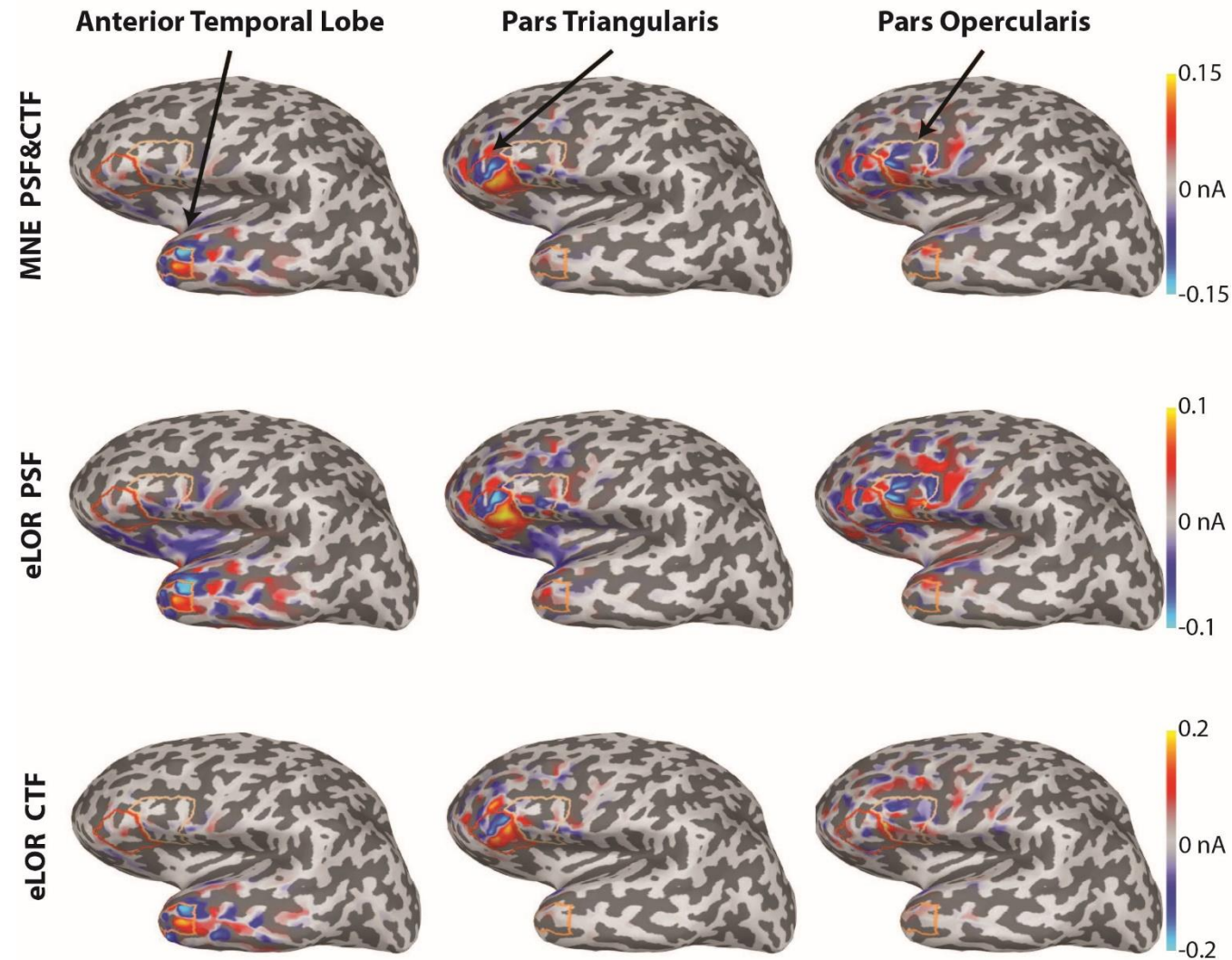
Combining EEG and MEG improves sensitivity.

Methods Comparison

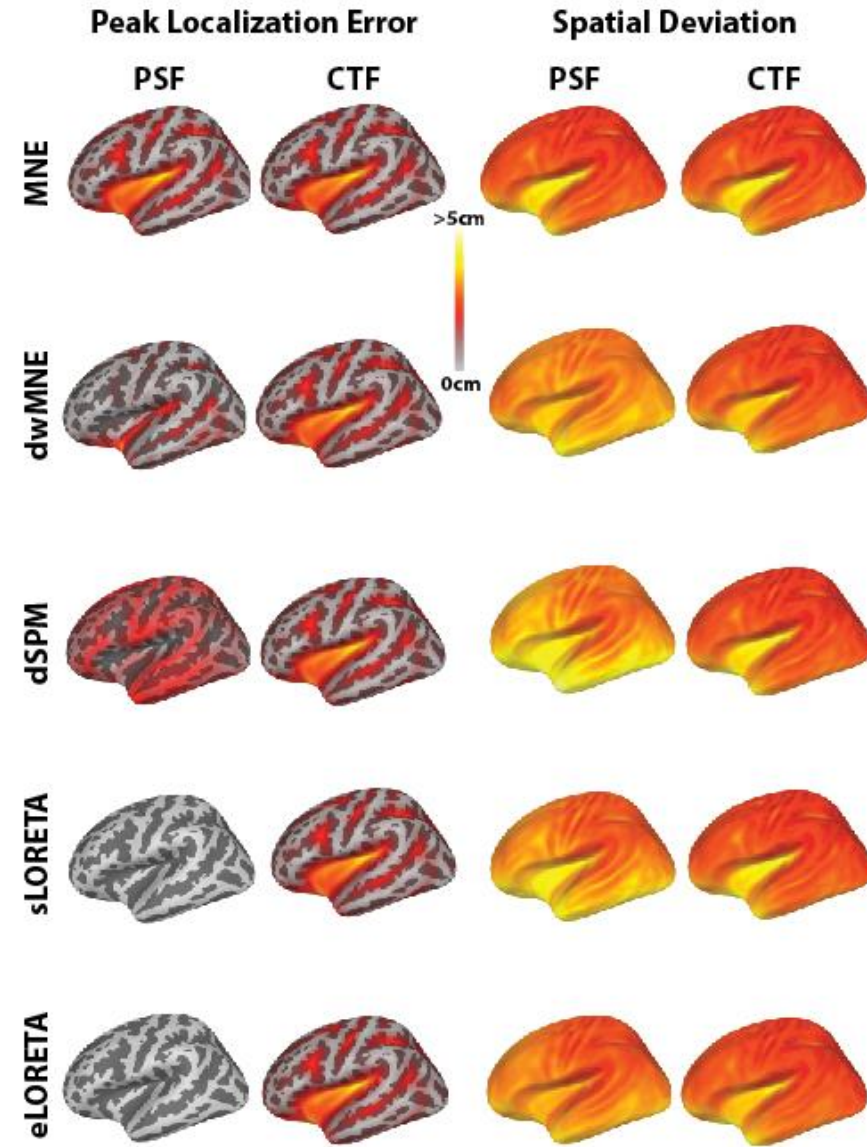
- **MEG+EEG:** Elekta Vectorview (360+70 channels), Wakeman & Henson open data set
- **Methods:**
 - L2-MNE
 - depth-weighted L2-MNE
 - dSPM
 - sLORETA
 - 2 LCMV beamformers (pre- and post-stimulus covariance matrices)
- **Resolution Metrics:**
 - Peak Localisation Error
 - Spatial Deviation (extent)

Example PSFs and CTFs for MNE and eLORETA

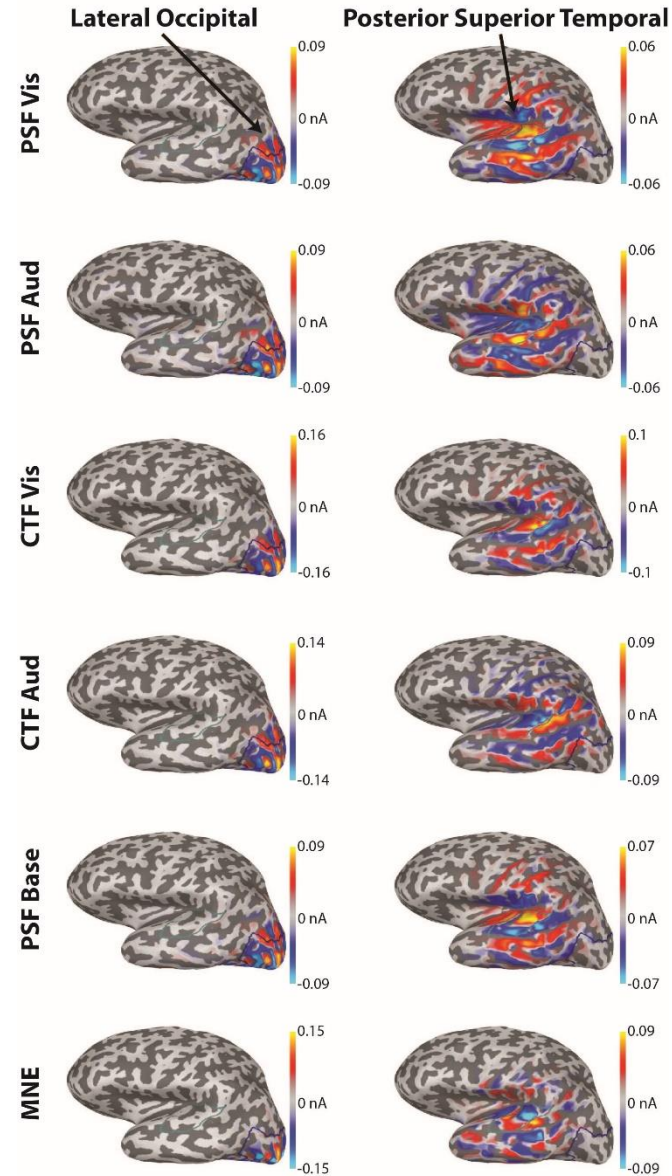
Note: For MNE PSFs and CTFs are the same



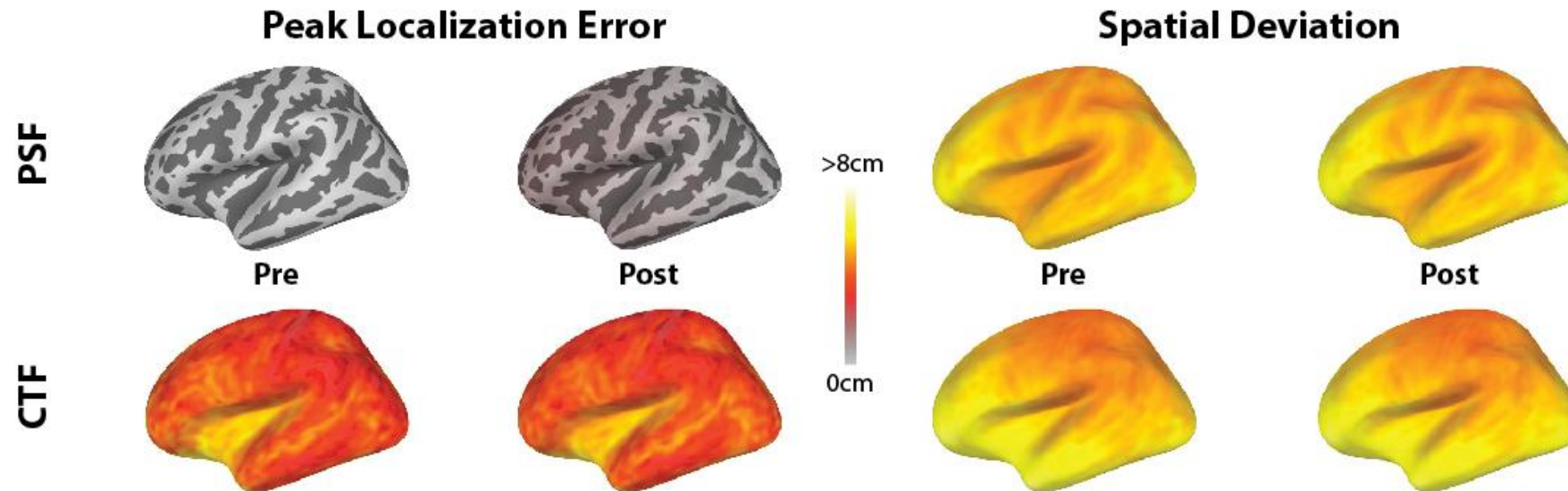
Comparing Estimators – MNE-type



Example PSFs and CTFs for Beamformers



Comparing Estimators – Beamformers



Conclusion From Methods Comparison

- Methods vary with respect to localisation error and spatial deviation.
- Improvements in localization error are accompanied by increases in spatial deviation.
- Localisation error for PSFs can be minimised (even to zero), but not for CTFs.
- Spatial deviation for PSFs and CTFs cannot be minimised beyond a certain limit.
- Localisation error for beamformers is low (even zero), but spatial deviation higher than for MNE-type methods.
- Performance of beamformers similar for different covariance matrices.

⇒ There is no obvious “best method”.

⇒ In this analysis, MNE and eLORETA seem to offer the best compromise between localisation and spatial deviation.

⇒ The tools (PSFs/CTFs, resolution metrics) can be applied to individual datasets – try it yourself!

Thank you

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