EEG/MEG 2:

Spatial Resolution and Nonlinear Methods

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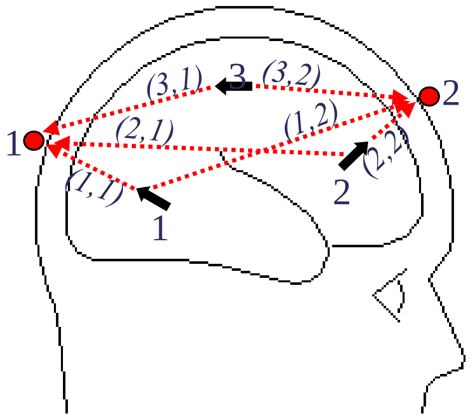
Spatial Resolution of EEG/MEG – Basic Concepts

Resolution Matrix, Point-Spread and Cross-Talk Functions (PSFs and CTFs)

The EEG/MEG Forward Problem



data “leadfield” dipoles

$$\begin{pmatrix} d_1 \\ d_2 \end{pmatrix} = \begin{pmatrix} 0.5 & 0 & 0.3 \\ 0 & 1 & -0.3 \end{pmatrix} \begin{pmatrix} j_1 \\ j_2 \\ j_3 \end{pmatrix}$$

?

inversion

dipoles inverse data

$$\begin{pmatrix} j_1 \\ j_2 \\ j_3 \end{pmatrix} = \begin{pmatrix} 1.5034 & 0.1241 \\ 0.2483 & 0.9379 \\ 0.8276 & -0.2069 \end{pmatrix} * \begin{pmatrix} d_1 \\ d_2 \end{pmatrix}$$

$j_1 + j_2 = 1$

under-determined problem, no unique solution

d=Lj

d: data (n_sensors x 1) **L**: “leadfield” (n_sensors x n_dipoles), **j**: dipoles (n_dipoles x 1)

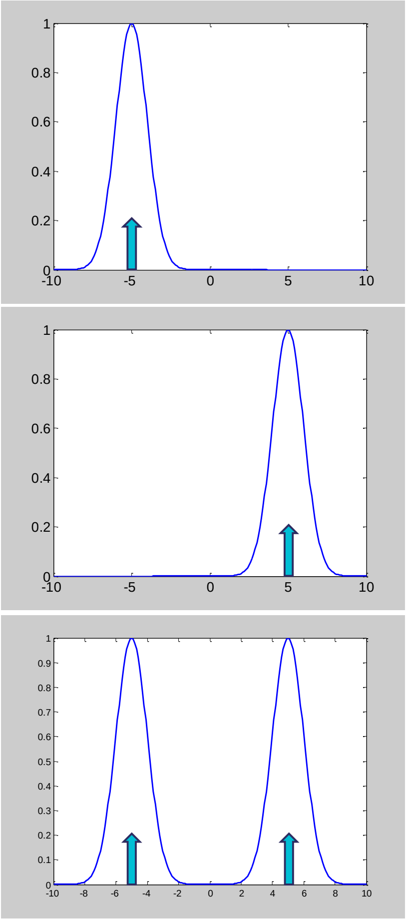
Usually n_dipoles >> n_sensors.

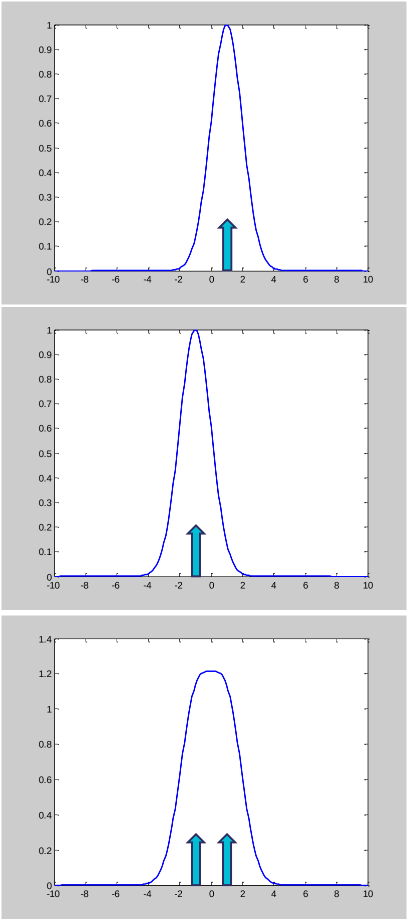
Let’s Start Again:
The “Blurry Image” Analogy

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

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

Superposition Principle

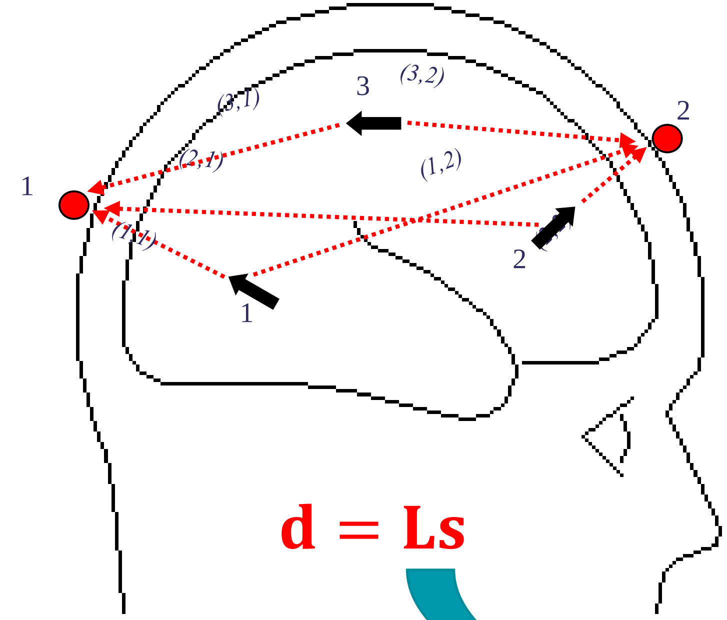




If you know the behaviour for point sources,
you can predict the behaviour for complex sources.

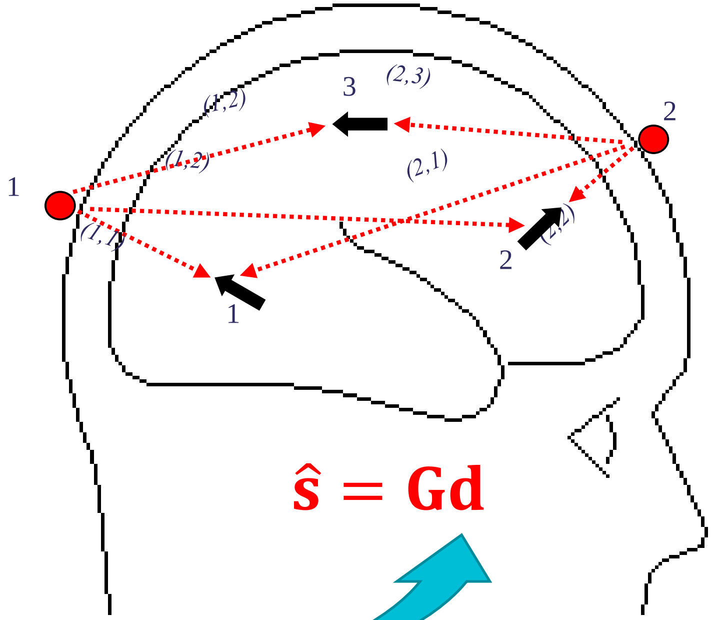
The Resolution Matrix

Forward Problem



$$\mathbf{d} = \mathbf{L}\mathbf{s}$$

Linear Inverse Problem



$$\hat{\mathbf{s}} = \mathbf{G}\mathbf{d}$$

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

Relationship between estimated and true source distribution.

e.g. Hauk/Stenroos/Treder, bioRxiv 2019
https://www.biorxiv.org/content/10.1101/672956v1

Creating an Optimal Resolution Matrix

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

The closer **R** is to the identity matrix, the closer our estimate is to the true source.

Therefore, let us minimise the difference between **R** and the identity matrix in the least-squares sense:

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

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

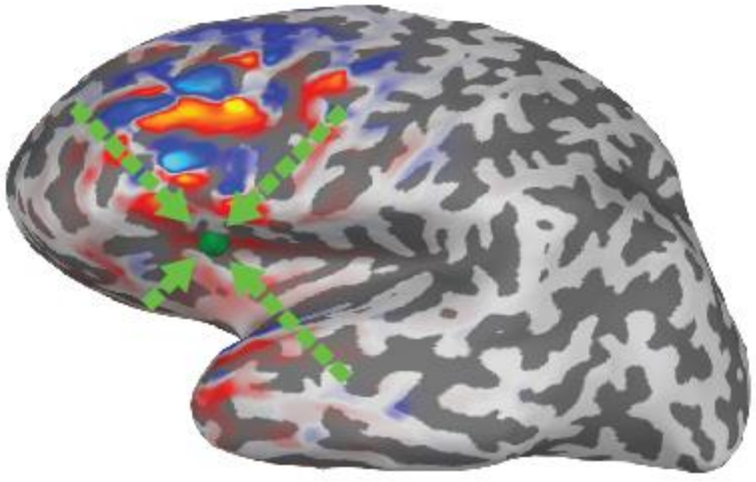
$$\boldsymbol{G}_{\boldsymbol{MN}} = \mathbf{L}^T(\mathbf{L}\mathbf{L}^T)^{-1}$$

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

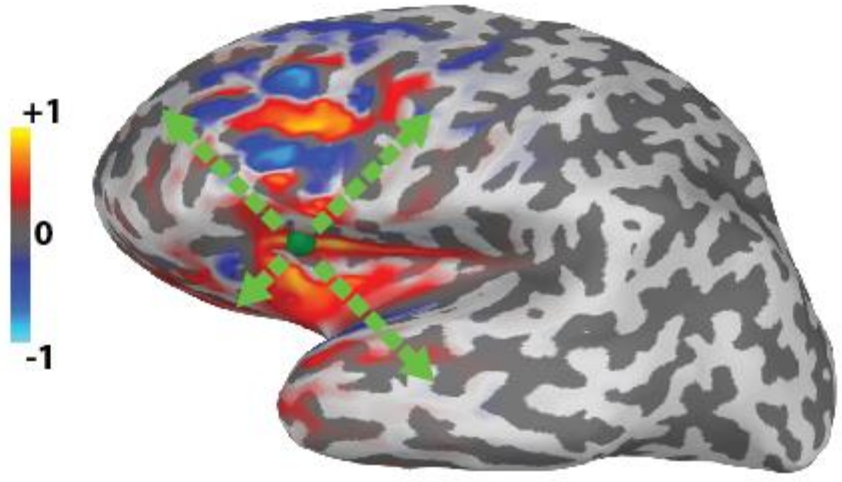
e.g. Hauk/Stenroos/Treder, bioRxiv 2019
https://www.biorxiv.org/content/10.1101/672956v1

Spatial Resolution / Leakage:
Point-Spread and Cross-Talk

Cross-Talk Function
(CTF)



How other sources may affect the estimate for this source



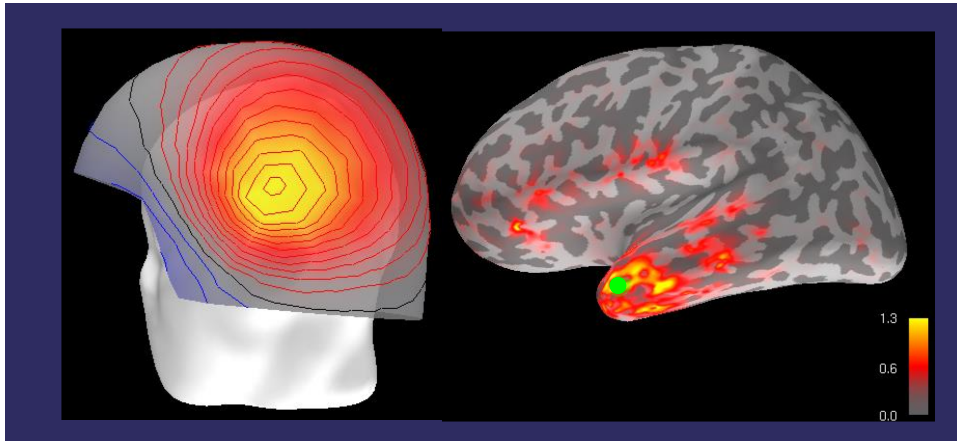
Point-Spread Function
(PSF)

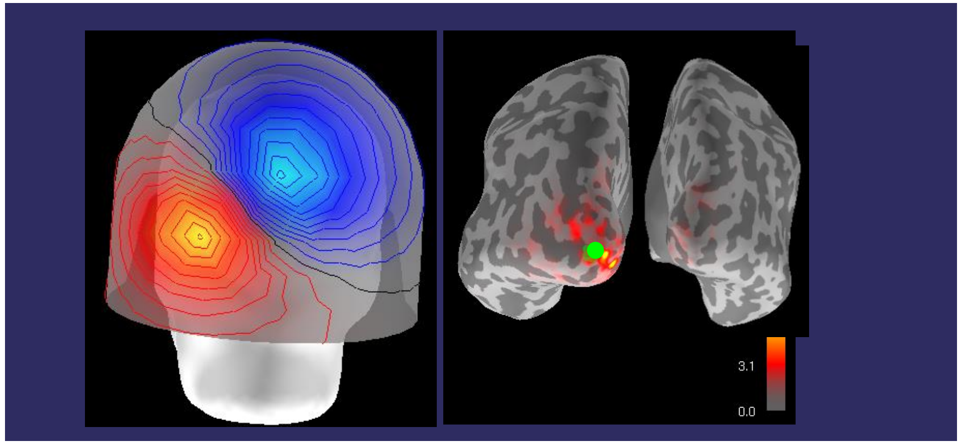
How this source affects estimates for other sources

e.g. Hauk, Stenroos, Treder, Neuroimage 2022
https://www.sciencedirect.com/science/article/pii/S1053811922002993

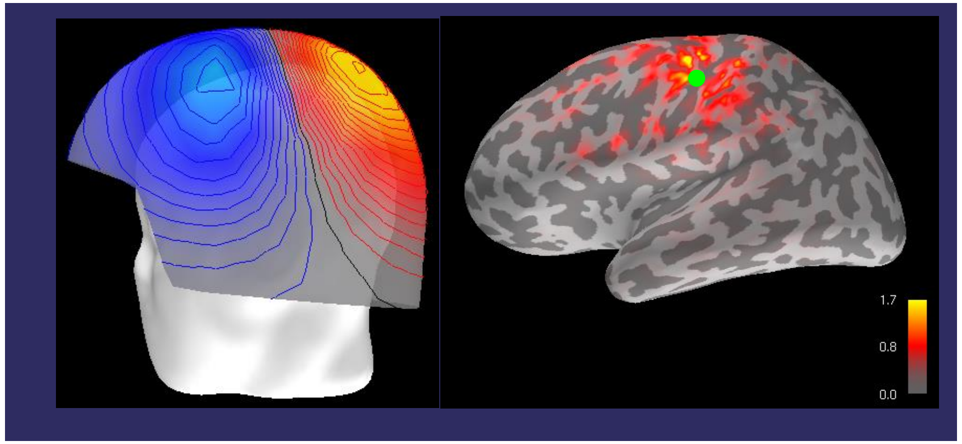
PSFs and CTFs for Some ROIs

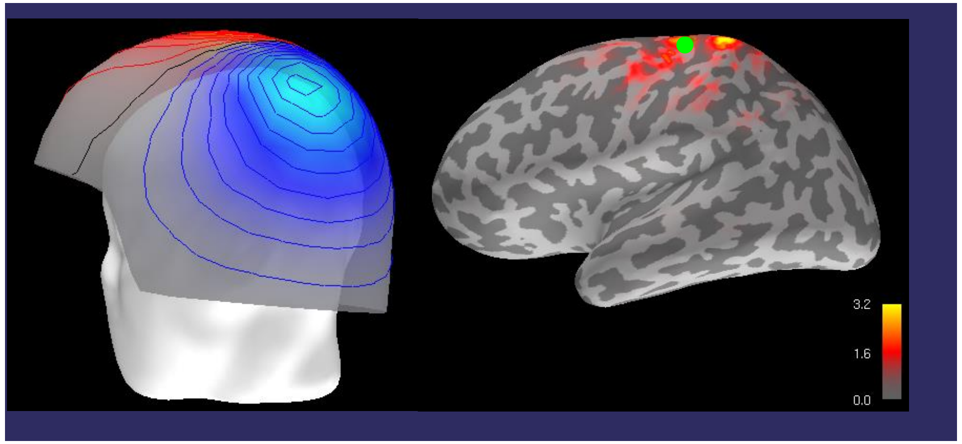
For MNE, PSFs and CTFs turn out to be the same





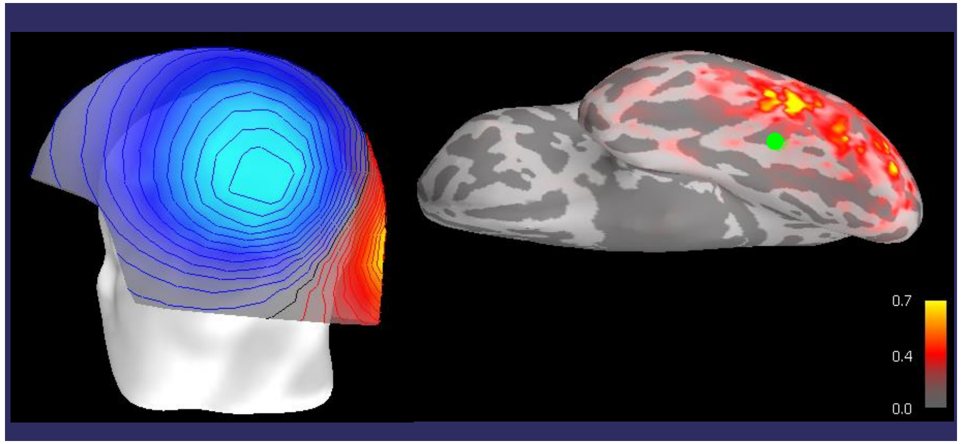
Good

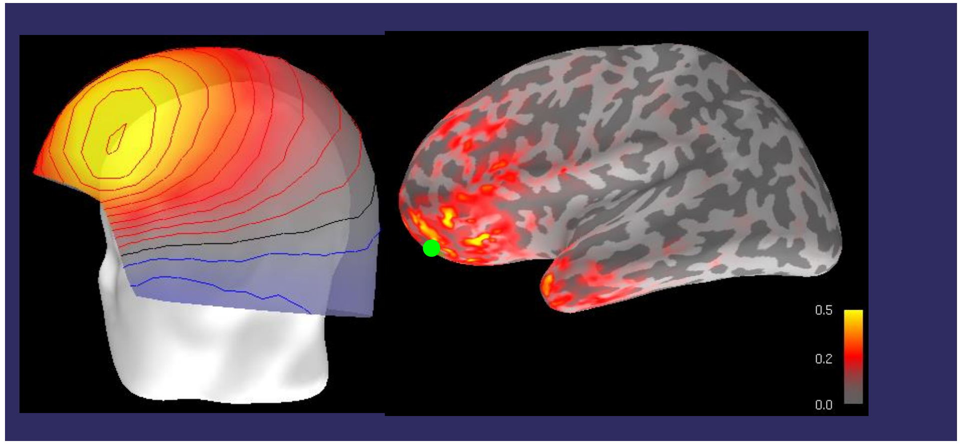




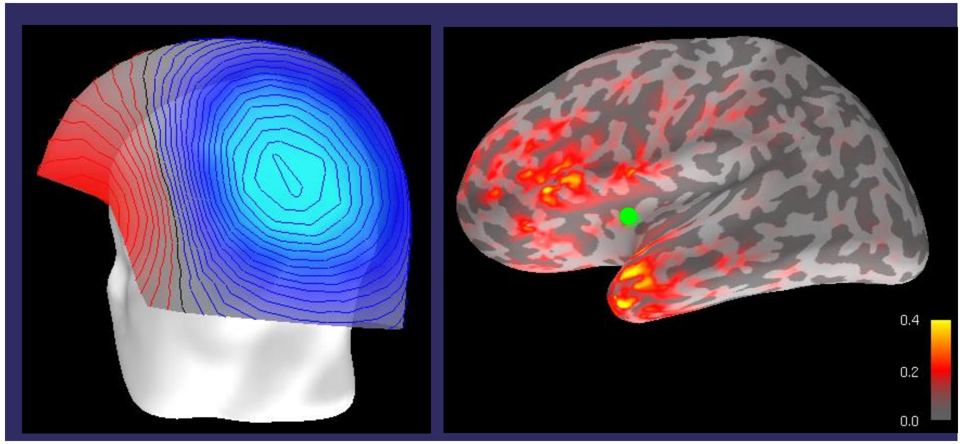
PSFs and CTFs for Some ROIs

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



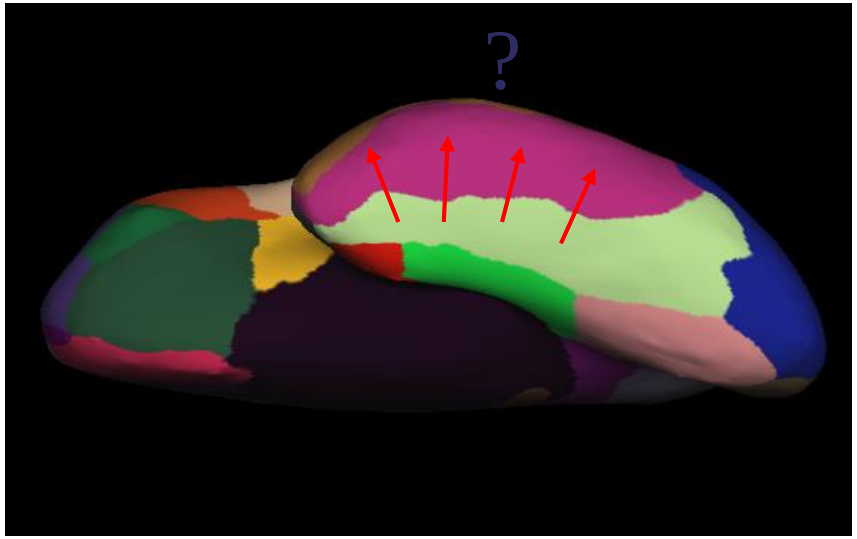


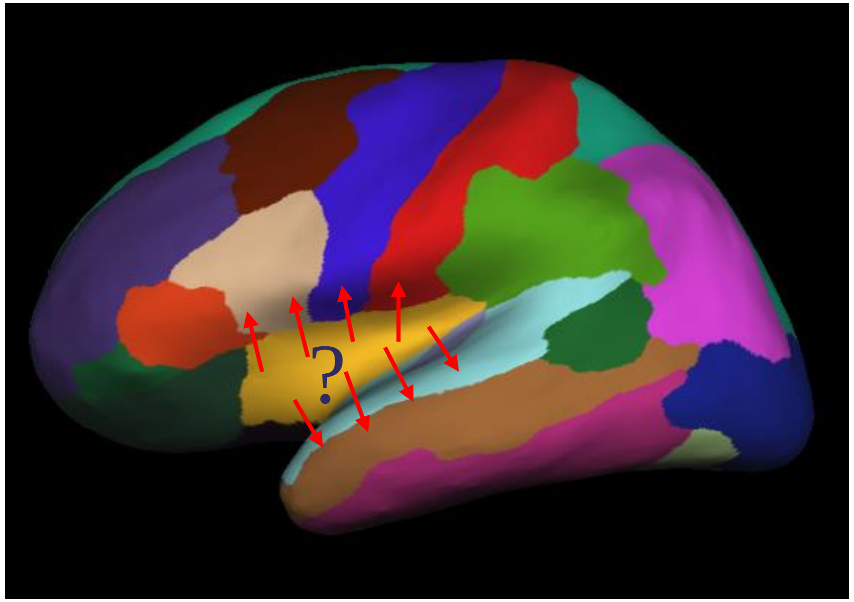
Less good



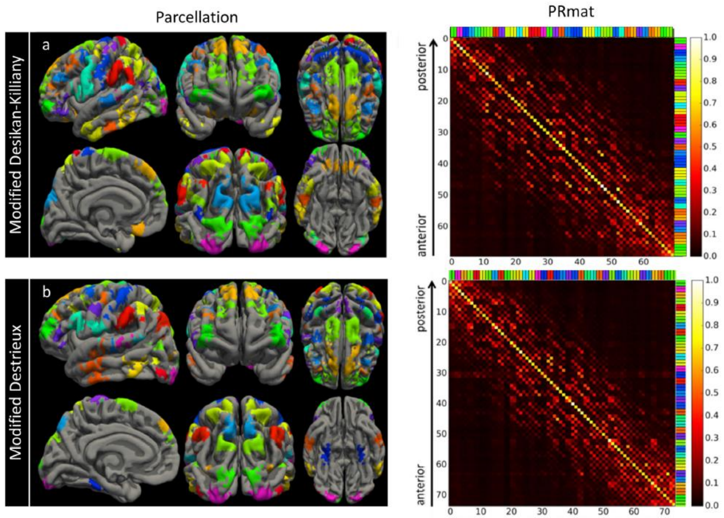
Localisation Bias Has Consequences for ROI analysis

PSFs/CTFs Can Tell You How It Looks Like



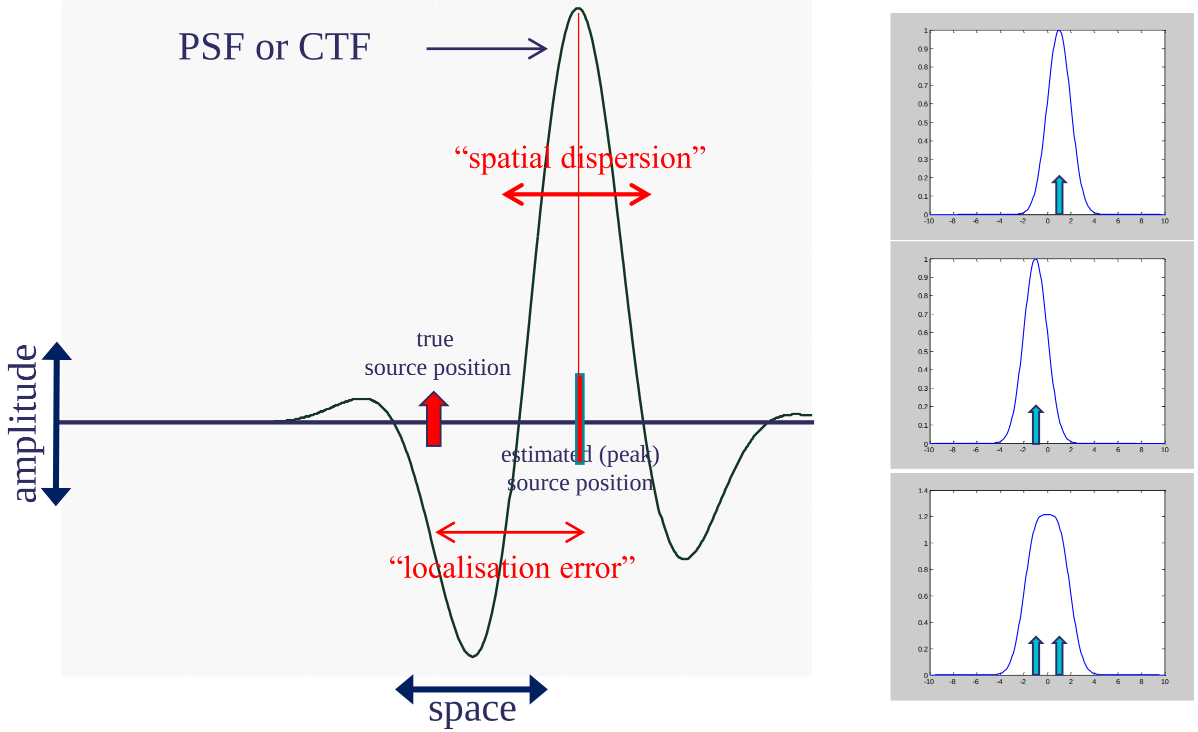


Desikan-Killiany Atlas parcellation



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

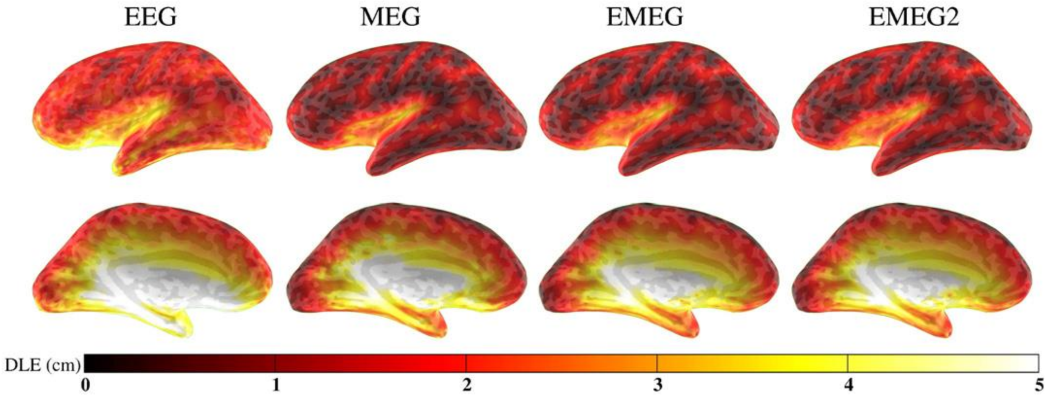
Quantifying Resolution From PSFs and CTFs



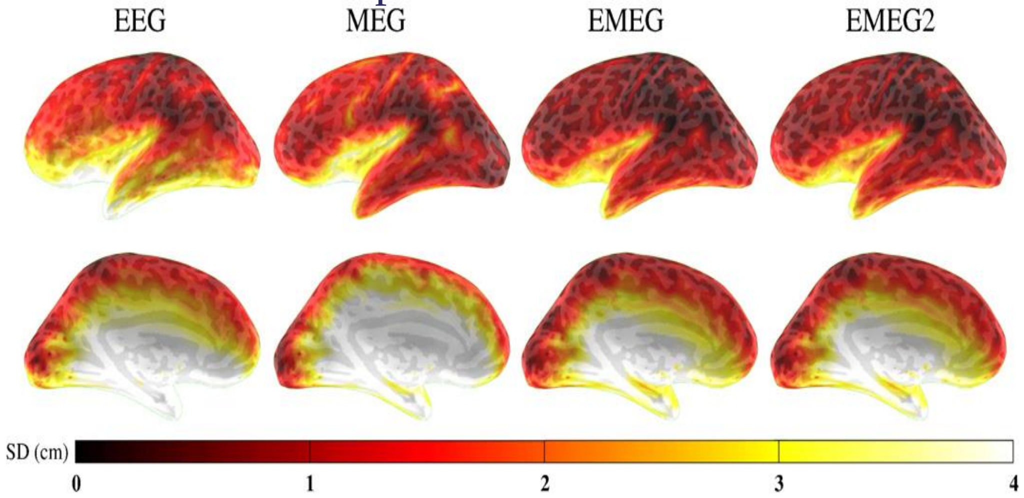
It’s not just peak localisation that counts,
but also spatial extent of the distribution.

Whole-Brain Maps of Resolution Metrics

Peak Localization Error



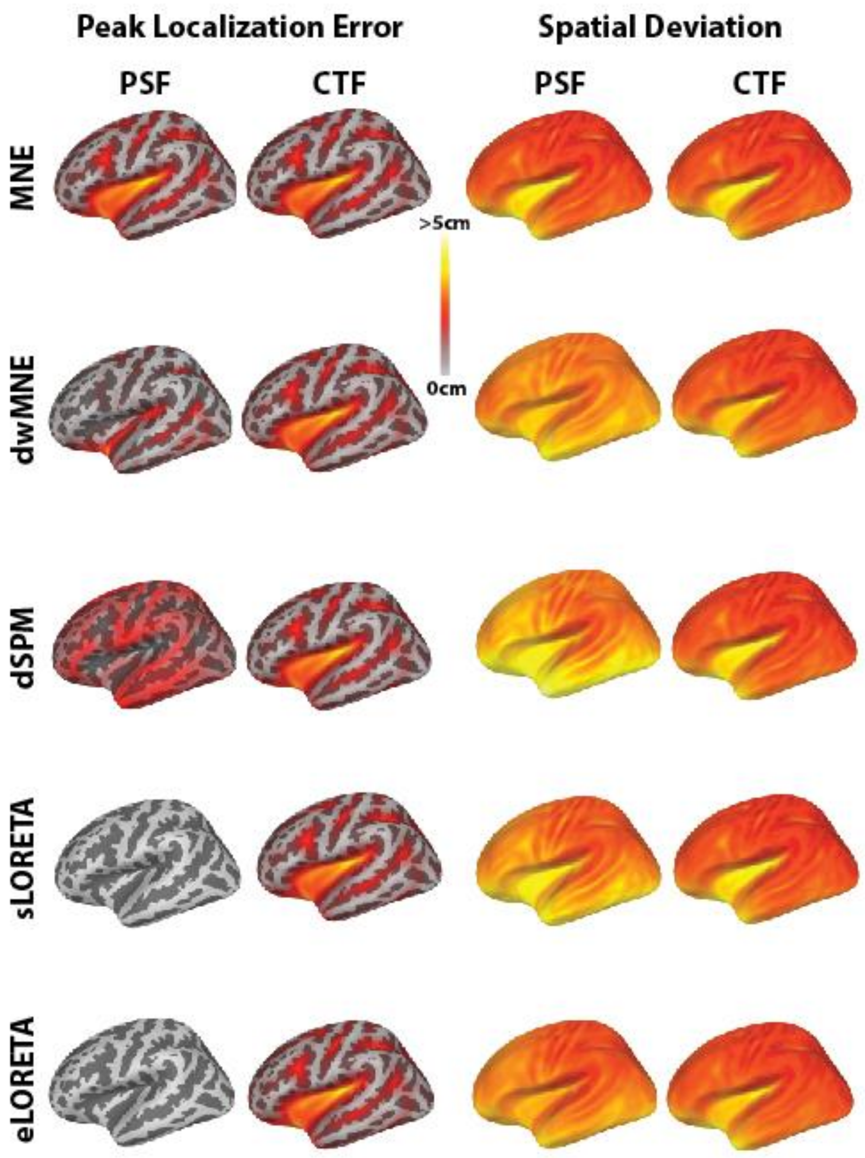
Spatial Deviation



Combining EEG and MEG improves spatial resolution.

Molins et al., Neuroimage 2008
https://pubmed.ncbi.nlm.nih.gov/18602485/

Comparing Estimators – MNE-type methods



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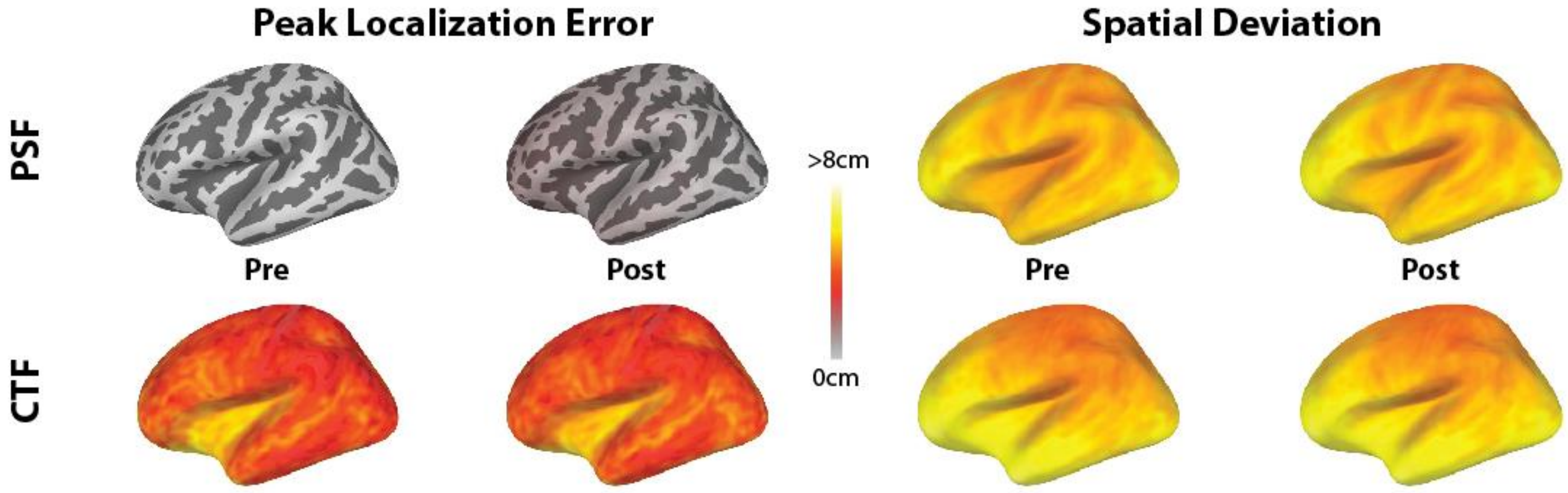
https://www.sciencedirect.com/science/article/pii/S1053811922002993

Comparing Estimators – Beamformers



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Thank you