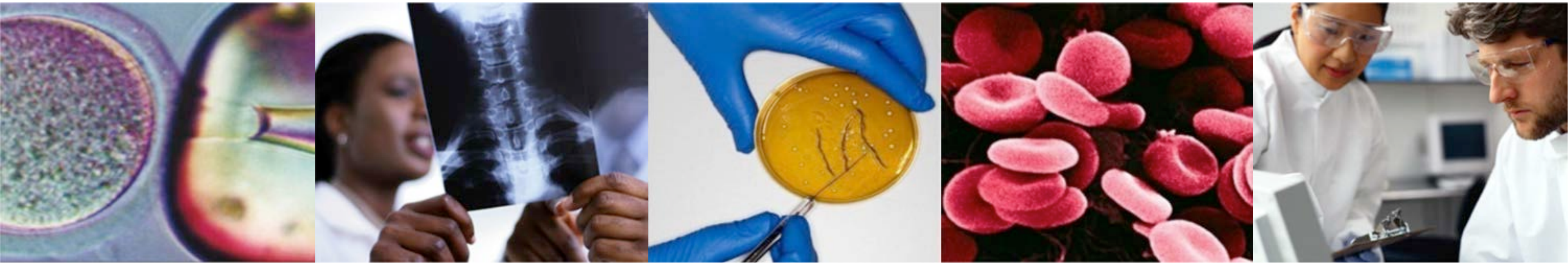

EEG/MEG 2:

Head Modelling and Source Estimation

Olaf Hauk

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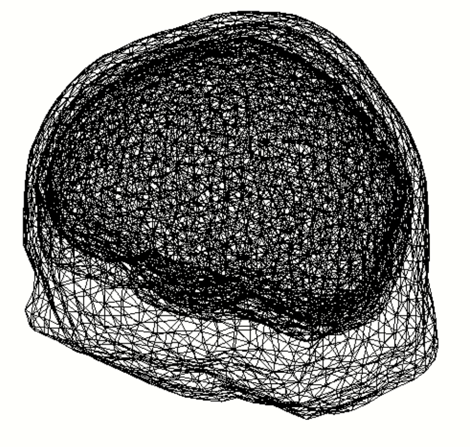
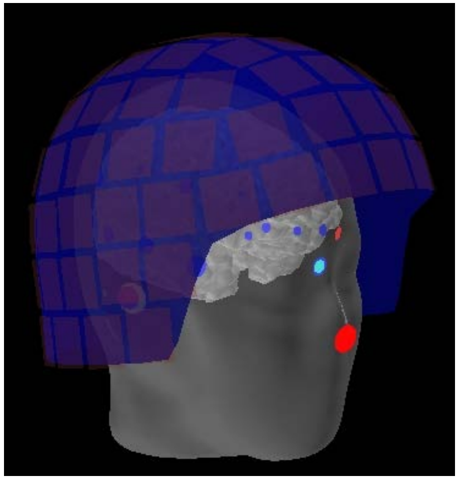
Introduction to Neuroimaging Methods, 20.2.2018

Ingredients for Source Estimation

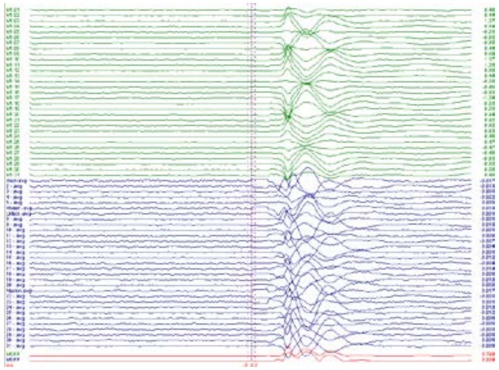
Volume Conductor/
Head Model



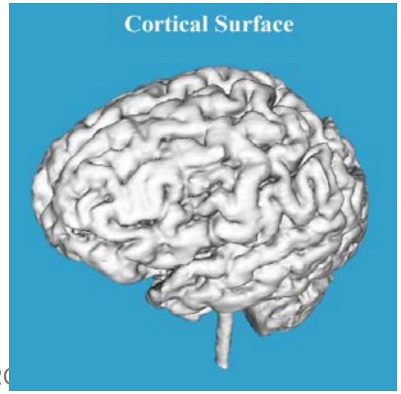
Coordinate
Transformation



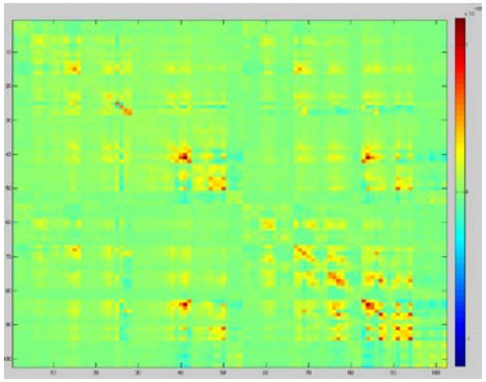
MEG data



Source Space

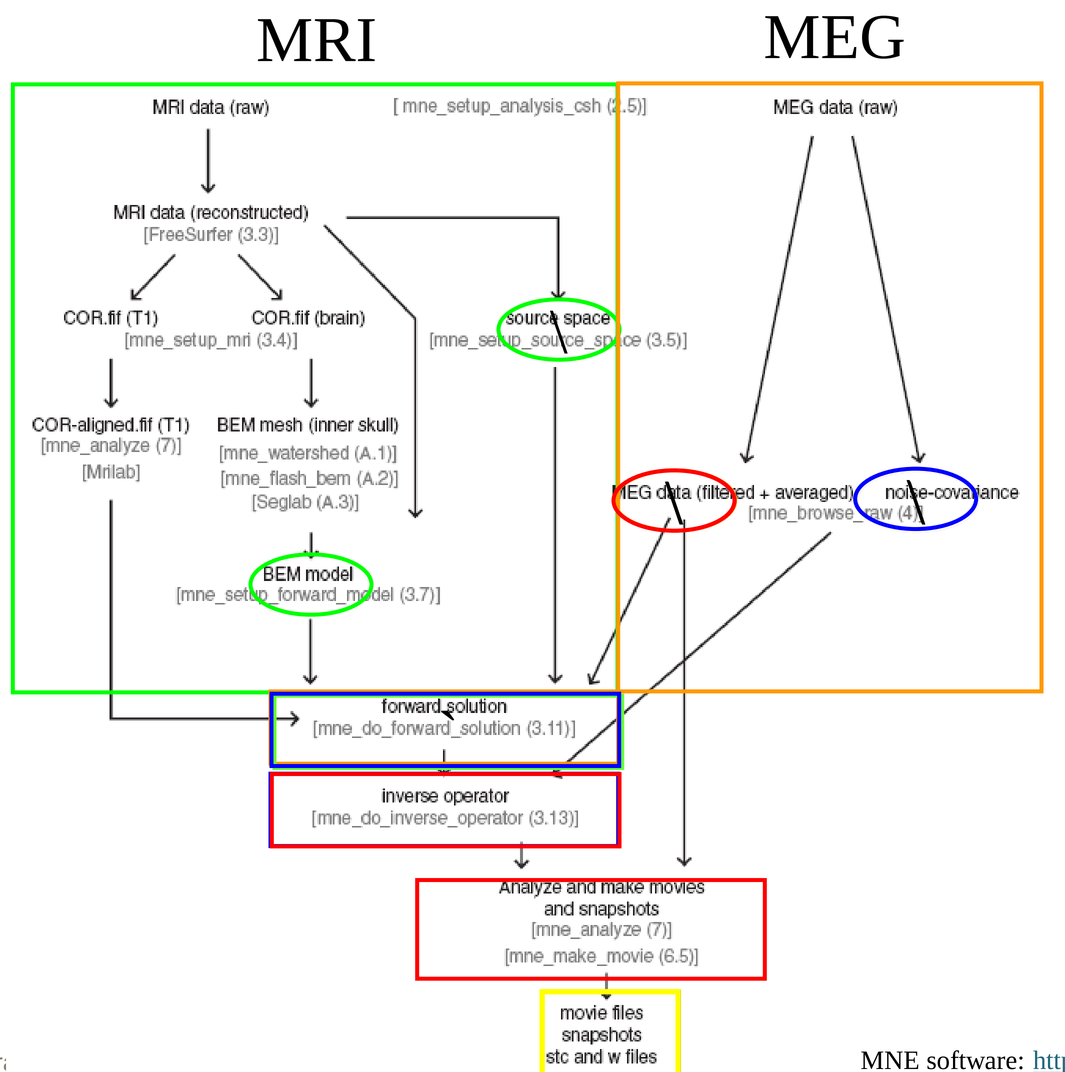


Noise/Covariance Matrix



MRC

The Path to the Source



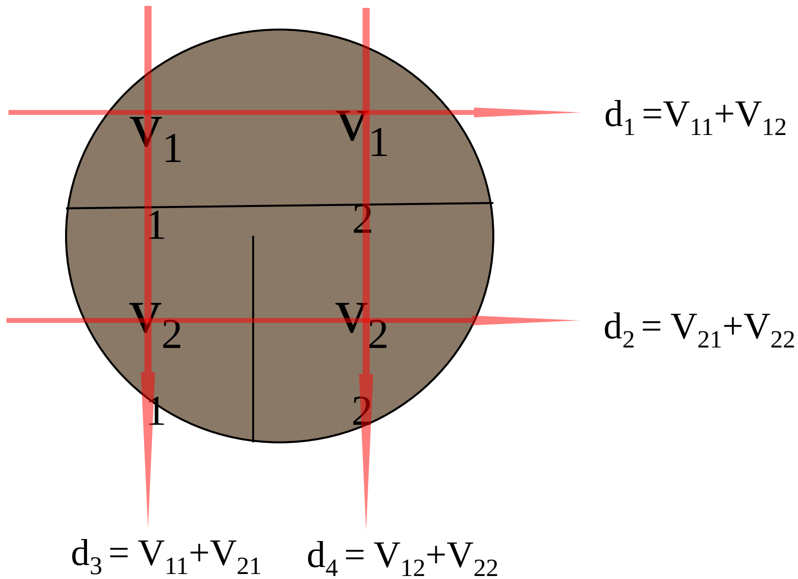
MNE software: http://www.martinos.org/mne/

See also: http://www.mrc-cbu.cam.ac.uk/methods-and-resources/imaginganalysis/

Practice

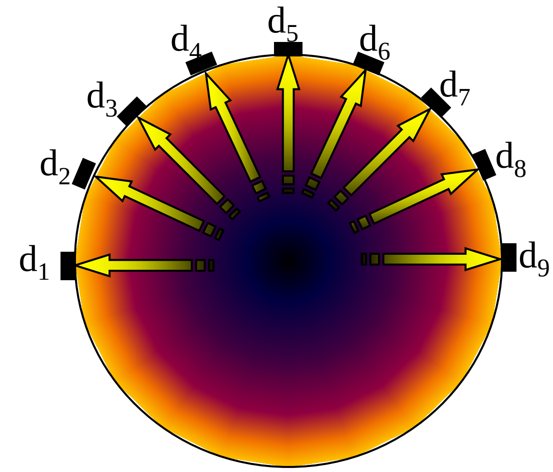
Why Inverse "Problem"?

Tomography (CT, fMRI…)



$$d_1 = V_{11}+V_{12}$$
$$d_2 = V_{21}+V_{22}$$
$$d_3 = V_{11}+V_{21}$$
$$d_4 = V_{12}+V_{22}$$

EEG/MEG



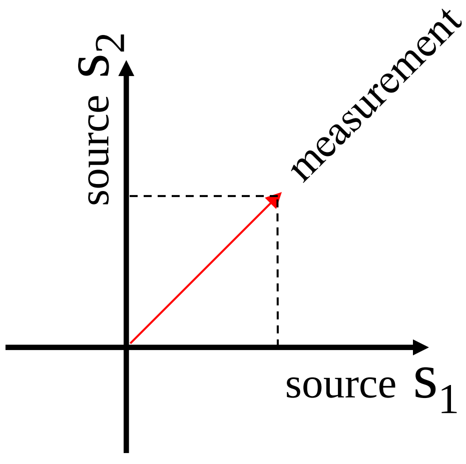
$$d_1 = V_{11}+V_{12}+V_{13}+V_{14} \ldots$$
$$d_2 = V_{21}+V_{22}+V_{23}+V_{24} \ldots$$

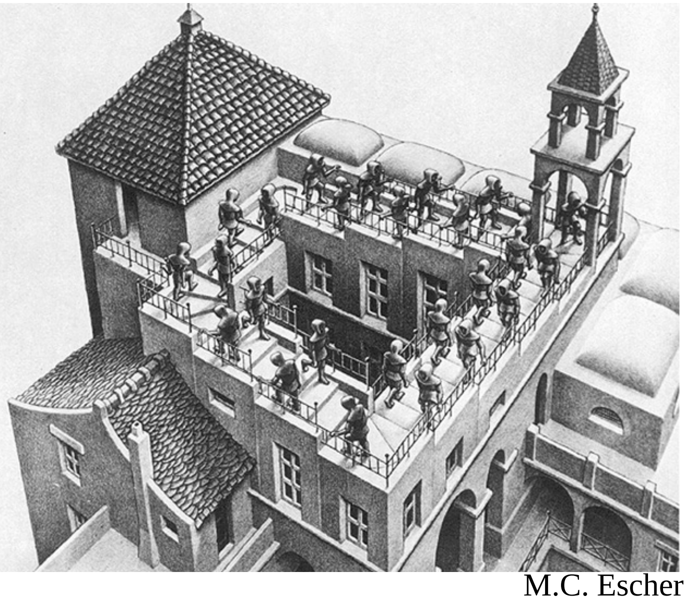
Information is lost during measurement

Cannot be retrieved by mathematics

Inherently limits spatial resolution

Why Inverse "Problem"?





M.C. Escher

In "signal space", we see a faint shadow of activity in "source space".

If you are not shocked by the EEG/MEG inverse problem…

… then you haven't understood it yet.

(freely adapted from Niels Bohr)

Non-Uniquely Solvable Problem

What is the solution to

$$x_1 + x_2 = 1$$

Maybe

$x_1 = 0 ; x_2 = 1$?

$x_1 = 1 ; x_2 = 0$?

$x_1 = 1000 ; x_2 = -999$?

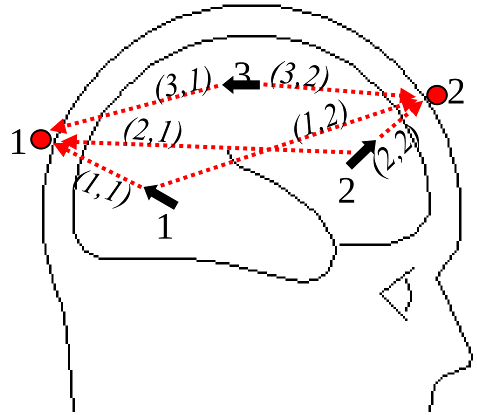
$x_1 = \pi ; x_2 = (1-\pi)$?

The minimum norm solution is:

$$x_1 = 0.5 ; x_2 = 0.5$$

with $(0.5^2 + 0.5^2)=0.5$ the minimum norm among all possible solutions

Non-Uniquely Solvable Problem



"Minimum Norm Solution"

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

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

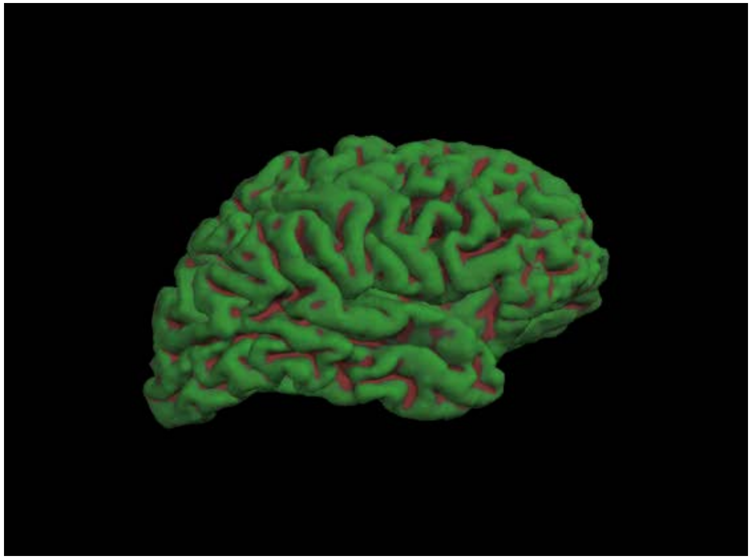
MNE produces solution with minimal power or "norm":

$$\left(j_1^2 + j_2^2 + j_3^2\right)$$

Practice

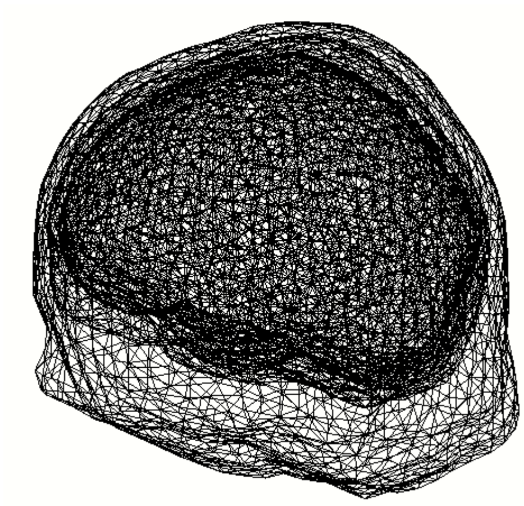
MRI Preprocessing: Source Space and Head Model

Source Space,
e.g. grey matter, 3D volume



http://www.cogsci.ucsd.edu/~sereno/movies.html

Volume Conductor/Head Model
e.g. sphere, 1- or 3-compartments from MRI

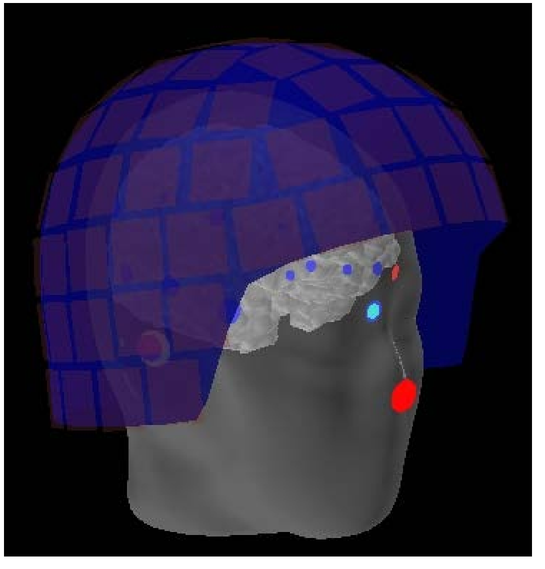


Sometimes “standard head models” are used, when no individual MRIs available.

SPM uses the same “canonical mesh” as source space for every subjects, but adjusts it individually.

Coregistration of EEG/MEG and MRI Spaces

Coordinate
Transformation



Practice

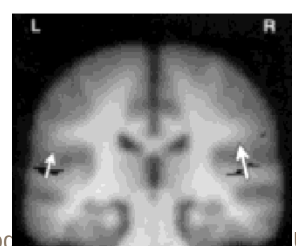
Source Estimation Approaches

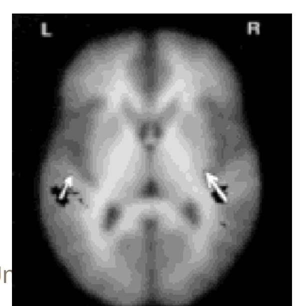
"Dipole Fitting"

1. Assume there are only a few distinct sources

2. Iteratively adjust the location, orientation and strength of a few dipoles…

3. …until the result best fits the data



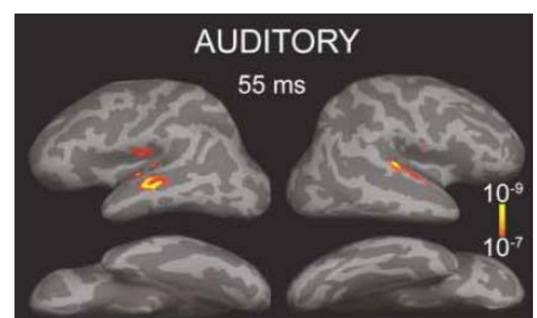


"Distributed Sources"

1. Assume sources are everywhere (e.g. distributed across the whole cortex)

2. Find the distribution of source strengths that explains the data…

3. …AND fulfils other constraints



Minimum Norm Estimation: Minimal Modelling Assumptions

"No frills" solution (Minimum Norm)

$$(\hat{\mathbf{s}}-\hat{\mathbf{s}}_0)^T \mathbf{C}_s (\hat{\mathbf{s}}-\hat{\mathbf{s}}_0) = \min$$

$$(\mathbf{L}\hat{\mathbf{s}}-\mathbf{d})^T \mathbf{C}_d (\mathbf{L}\hat{\mathbf{s}}-\mathbf{d}) = \varepsilon > 0$$

$$\Rightarrow \quad \hat{\mathbf{s}} = \hat{\mathbf{s}}_0 + \mathbf{C}_s^{-1}\mathbf{L}^T \left(\mathbf{L}\mathbf{C}_s^{-1}\mathbf{L}^T + \lambda\, \mathbf{C}_d^{-1}\right)^{-1} (\mathbf{d}-\mathbf{L}\hat{\mathbf{s}}_0) \quad \Rightarrow \quad \hat{\mathbf{s}} = \mathbf{L}^T \left(\mathbf{L}\mathbf{L}^T + \lambda\, \mathbf{I}\right)^{-1} \mathbf{d}$$

"Most likely" solution (Maximum Likelihood)

$$\mathbf{P}\ (\mathbf{s}) \sim \exp\{-(\hat{\mathbf{s}}-[\mathbf{s}])^T \mathbf{C}_s (\hat{\mathbf{s}}-[\mathbf{s}])\}$$

$$\mathbf{P}\ (\mathbf{d},\hat{\mathbf{s}}) \sim \exp\{-(\mathbf{d}-\mathbf{L}\hat{\mathbf{s}})^T \mathbf{C}_d^{'} (\mathbf{d}-\mathbf{L}\hat{\mathbf{s}})\}$$

$$\Rightarrow \quad \hat{\mathbf{s}} = [\mathbf{s}] + \mathbf{C}_s^{-1}\mathbf{L}^T (\mathbf{L}\mathbf{C}_s^{-1}\mathbf{L}^T + \lambda \mathbf{C}_d^{-1})^{-} (\mathbf{d}-\mathbf{L}[\mathbf{s}]) \quad \Rightarrow \quad \hat{\mathbf{s}} = \mathbf{L}^T \left(\mathbf{L}\mathbf{L}^T + \lambda\, \mathbf{I}\right)^{-1} \mathbf{d}$$

"Best focussing" solution (Beamformer)

$$Min\,(\mathbf{W}(\mathbf{r}_i - \mathbf{t}_i))^2$$

$$Min([\mathbf{G}_{i.}\mathbf{n}]^2) \Rightarrow Min(\mathbf{G}_{i.}\mathbf{C}_n\mathbf{G}_{i.}^T)$$

$$\Rightarrow \quad \mathbf{G}_{i.} = (\mathbf{S} + \lambda \mathbf{C}_n)^{-1}\mathbf{u} \qquad \mathbf{S} = \mathbf{L}\mathbf{L}^T \quad \mathbf{u} = \mathbf{L}_{.i}$$

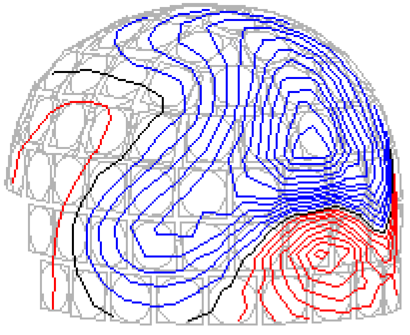
$$\mathbf{G}_{i.} = (\mathbf{L}\mathbf{L}^T + \lambda \mathbf{I})^{-1}\mathbf{L}_{.i} \quad \Rightarrow \quad \hat{\mathbf{s}} = \mathbf{L}^T \left(\mathbf{L}\mathbf{L}^T + \lambda\, \mathbf{I}\right)^{-1} \mathbf{d}$$

"Minimum Least-Squares Solution"

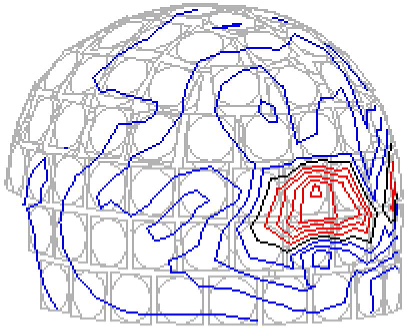
All approaches converge to the same solution if no a priori information is available.

There are many possible assumptions, and therefore many different methods – but unfortunately no gold standard to properly compare them.

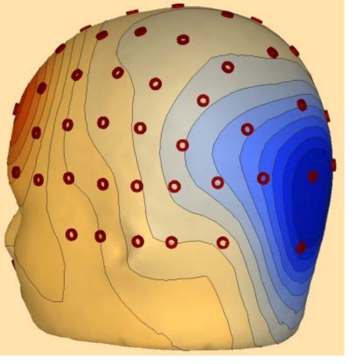
Visually Evoked Activity ~100 ms



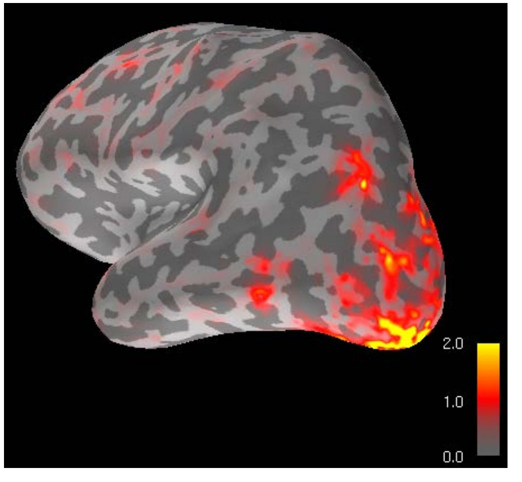
Magnetometers



Gradiometers

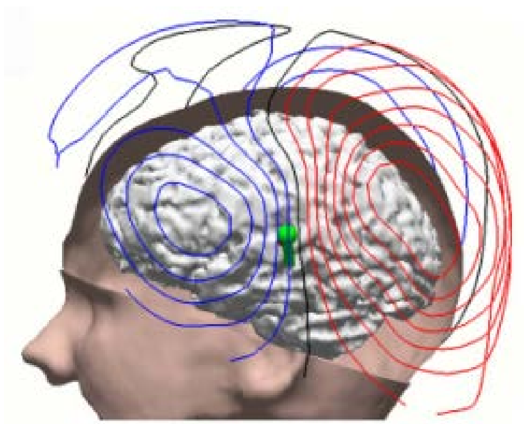


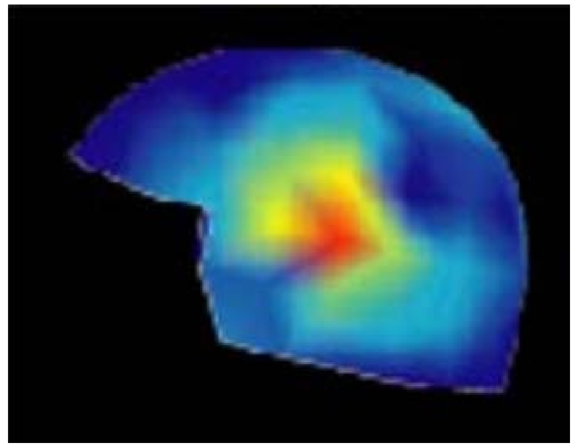
EEG

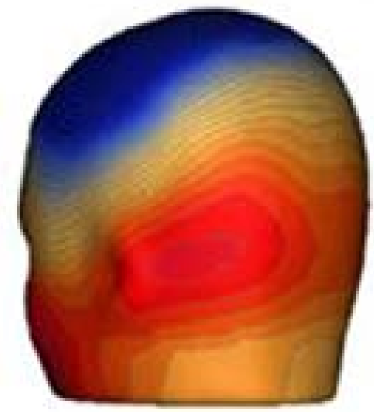


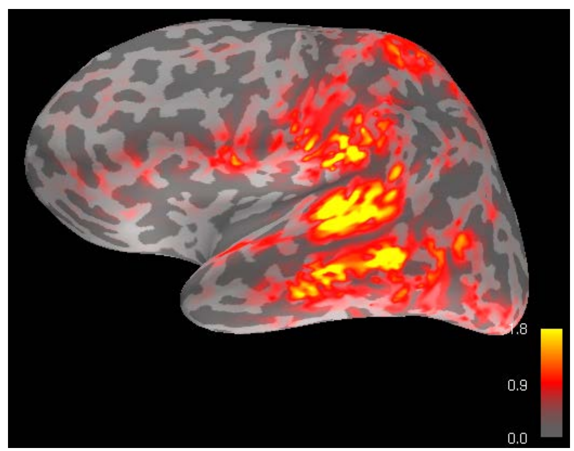
Minimum Norm Estimate

Auditorily Evoked Activity



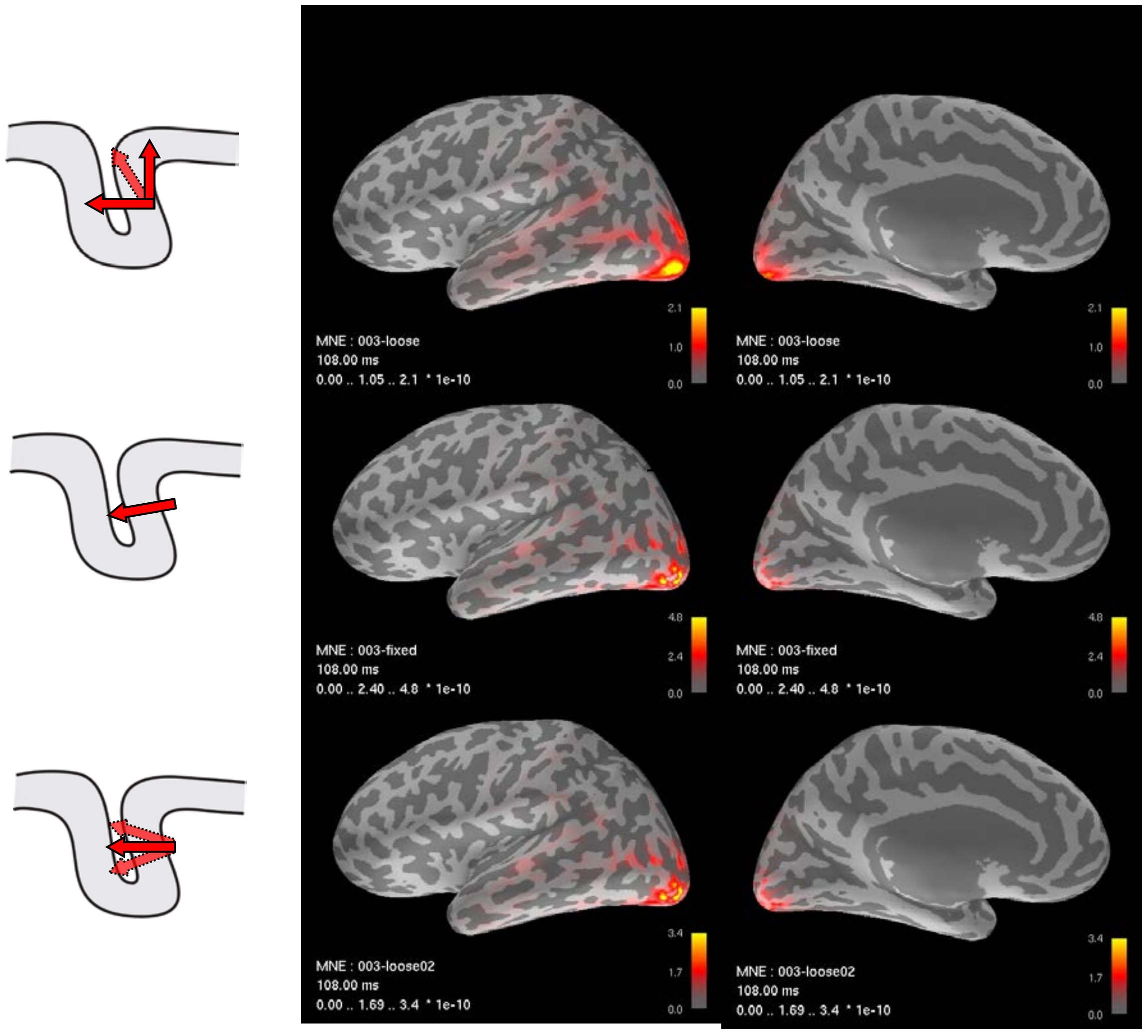






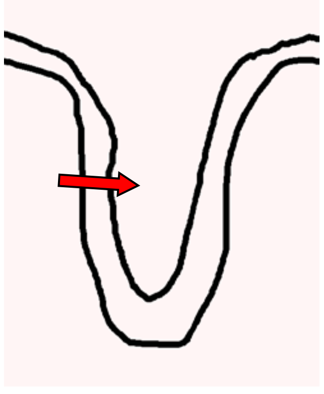
Minimum Norm Estimate

Source Orientation Constraints

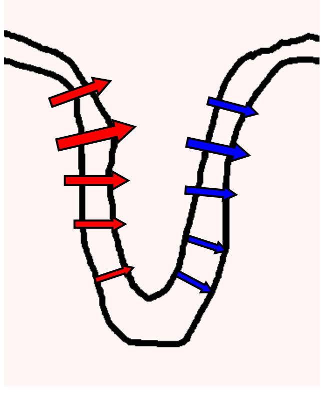


Direction of Current Flow

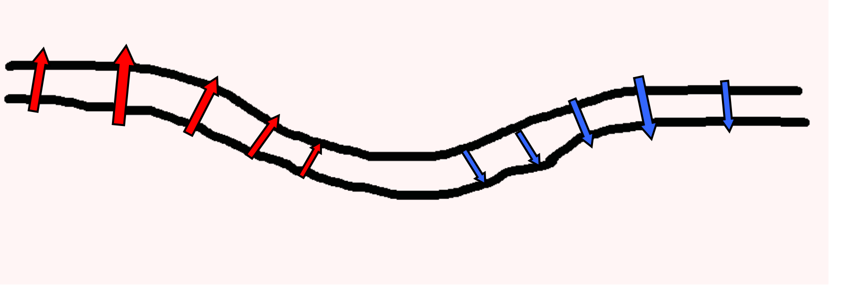
Dipole Source



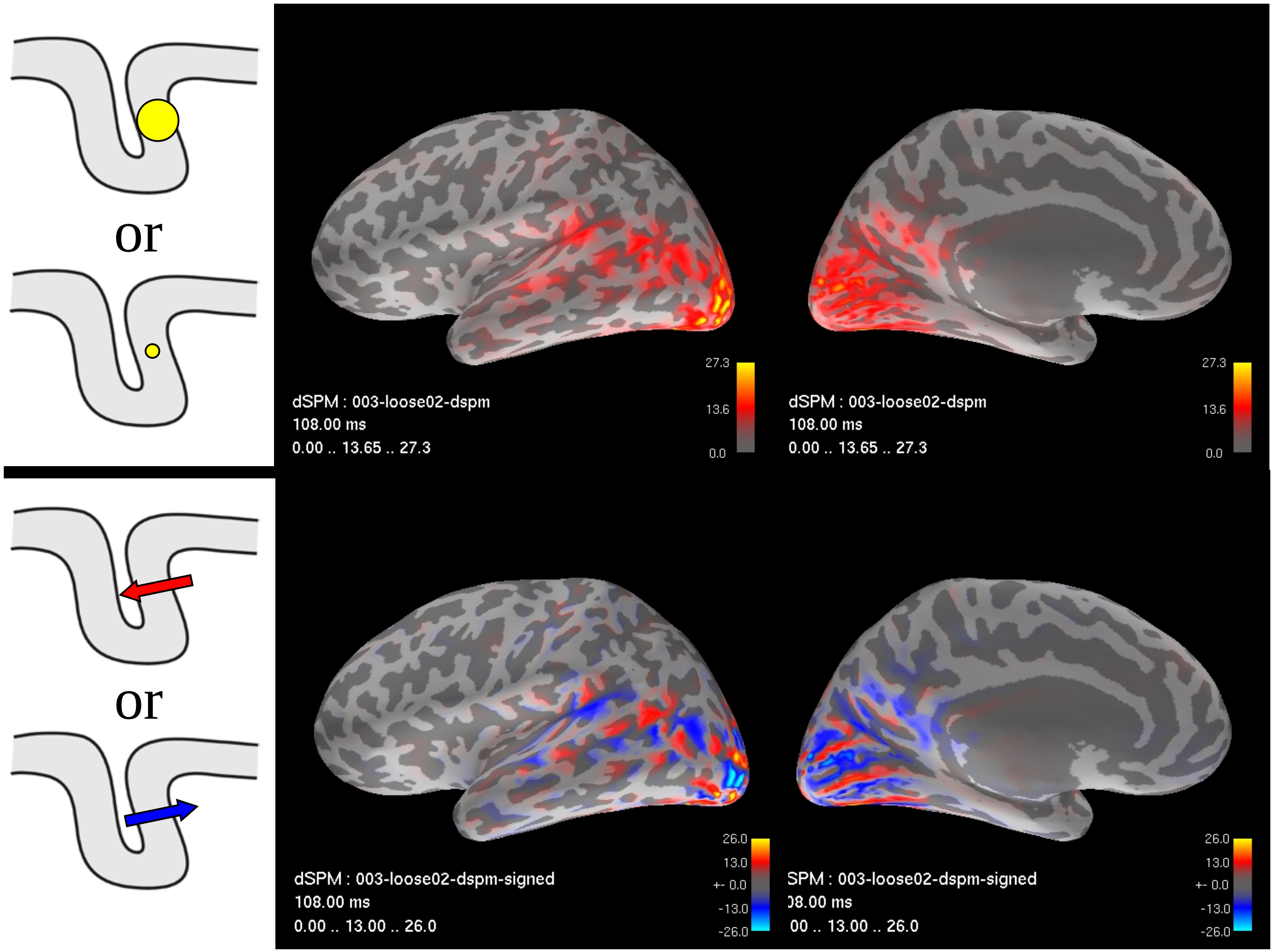
Distributed Source



Distributed Source, Inflated Surface



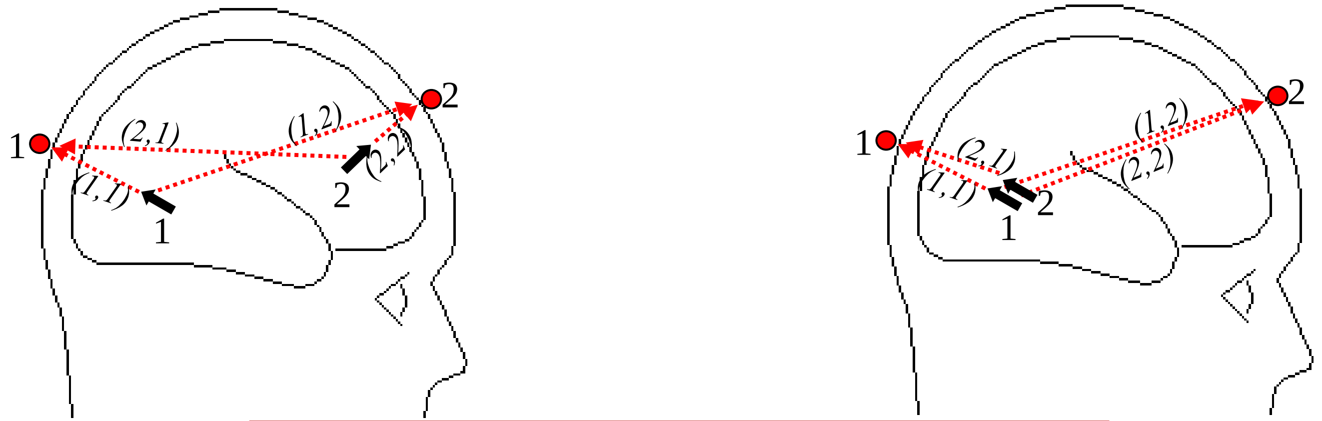
Direction of Current Flow

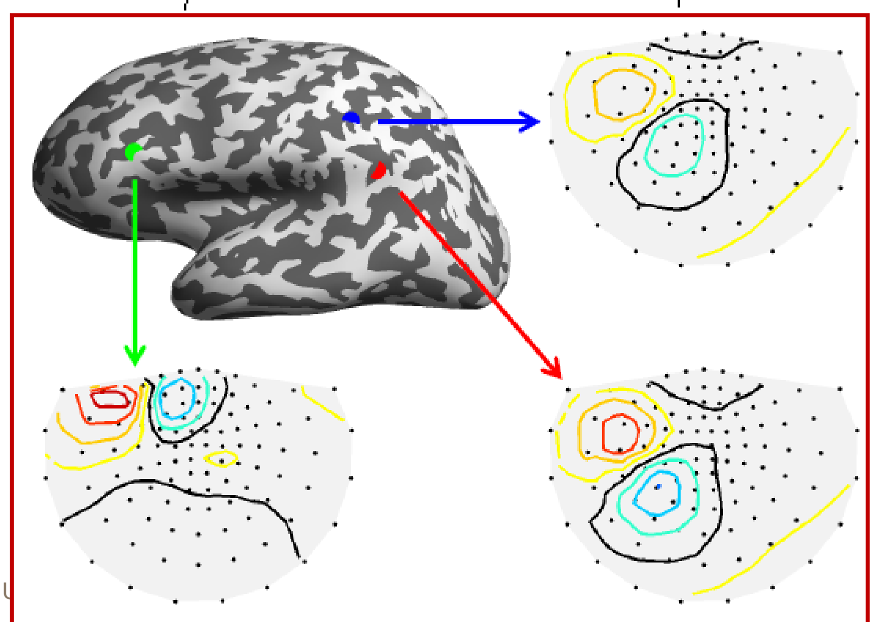


Practice

(In)Stability – Sensitivity to Noise

Stable | Instable





Similar topographies are difficult to distinguish, especially in the presence of noise.

Practice

Noise covariance

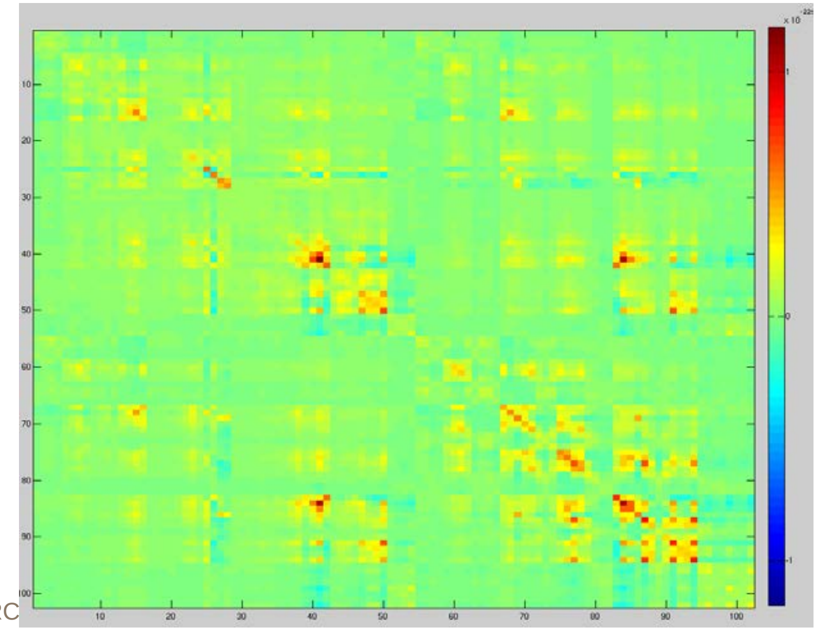
Some channels are noisier than others

⇒They should get different weights in your analysis

Sensors are not independent

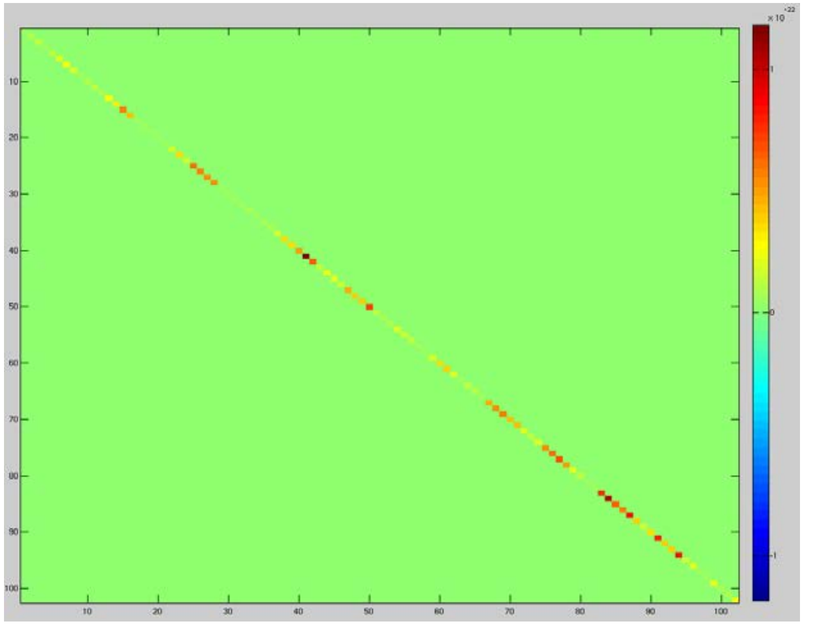
=> Sensors that carry the same information should be downweighted relative to more independent sensors

(Full) Noise Covariance Matrix



(Diagonal) Noise Covariance Matrix

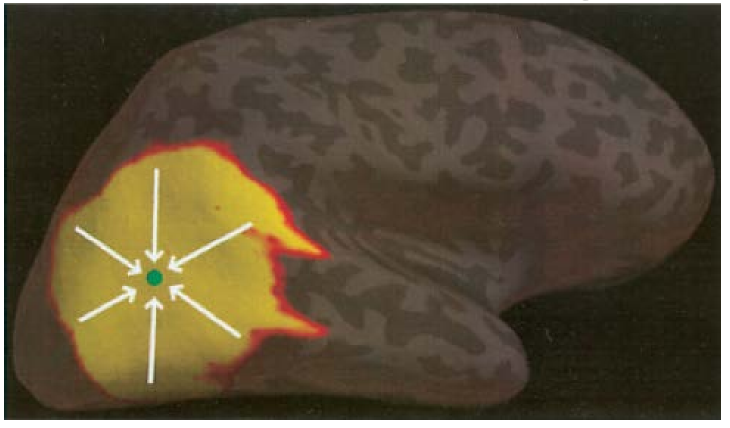
(contains only variance for sensors)



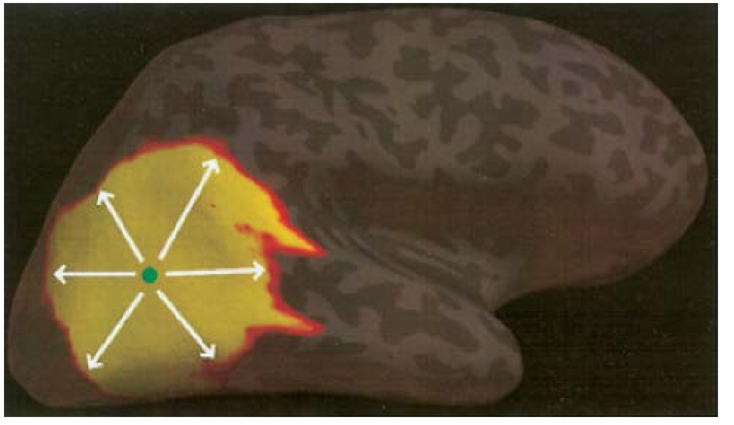
Practice

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

Cross-Talk/Leakage



Point-Spread



Liu et al., HBM 2002

"How other sources may affect the spatial filter for this source"

"How this source affects other spatial filters"

Spatial Resolution of Source Estimation

Spatial resolution depends on:

modeling assumptions
number of sensors (EEG/MEG or both)
source location
source orientation
signal-to-noise ratio
head modeling

=> difficult to make general statement

Spatial Resolution – A Naïve Estimate

With *n* sensors:

-> *n* independent measurements

-> *n* independent parameters estimable

-> at best separate activity from *n* brain regions

Sensors are not independent -> ~ 50 degrees of freedom

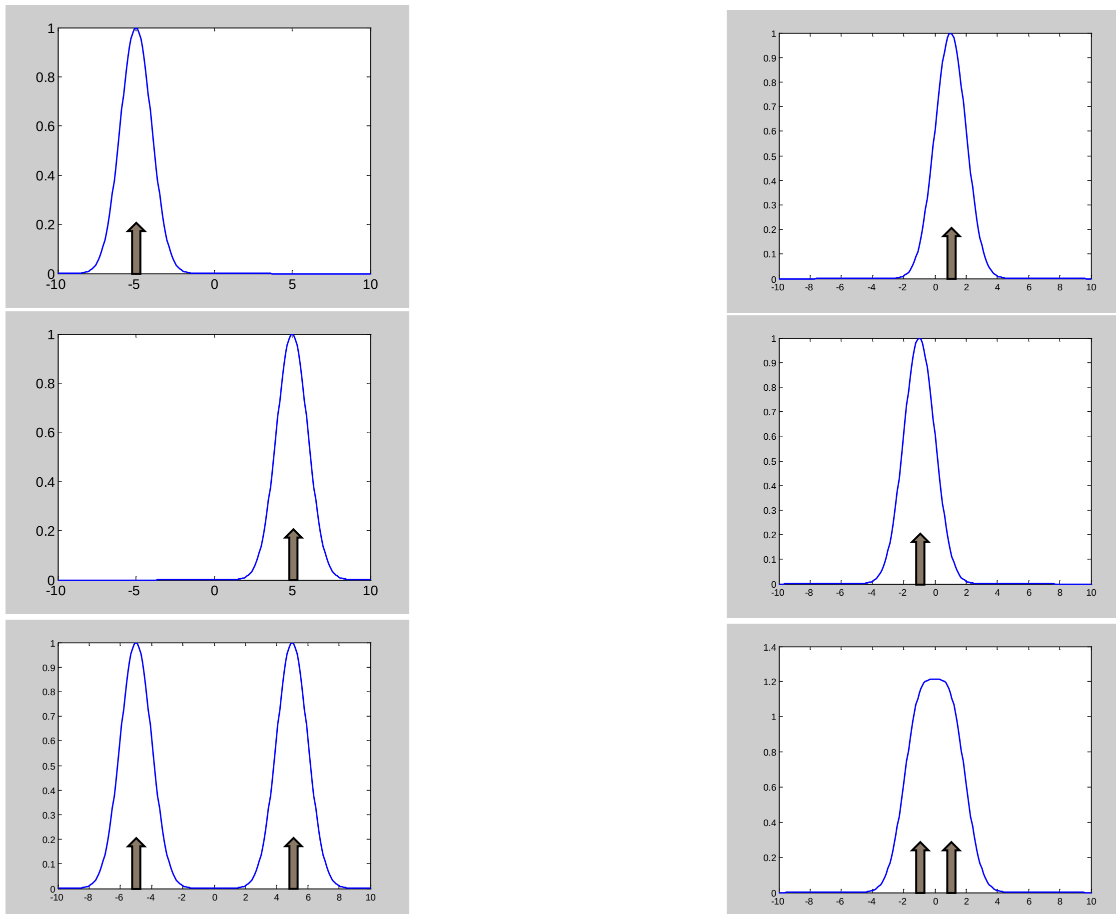
Volume of source space:

Sphere 8cm minus sphere 4 cm: volume ~1877 cm^3

"Resel": 38 cm^3 -> $\underline{3.4}^3$ cm^3

The spatial resolution of the measurement is inherently limited!

Linear Methods – Superposition Principle

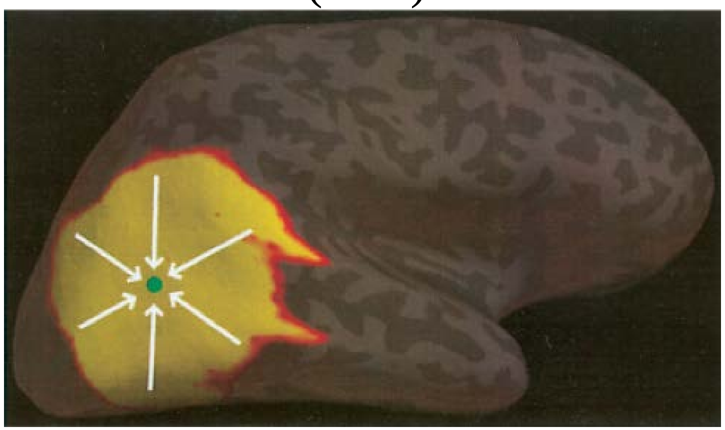


If you know the behaviour for point sources,
you can predict the behaviour for complex sources

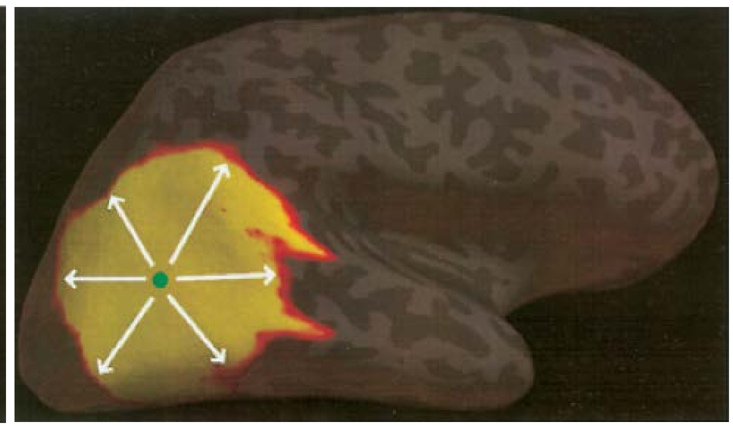
Practice

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

Cross-Talk Function
(CTF)



Point-Spread Function
(PSF)

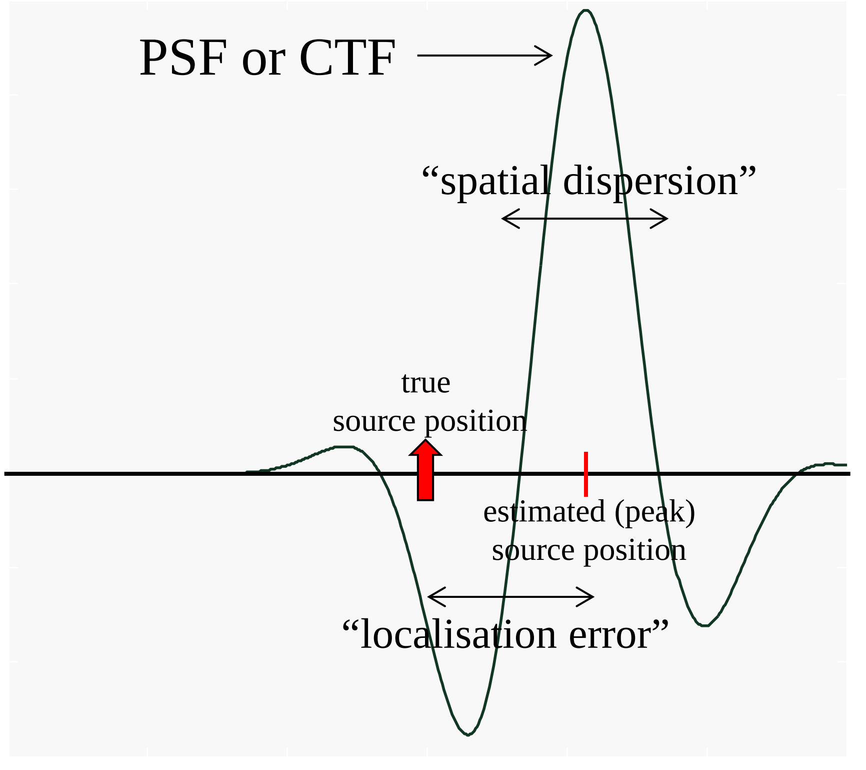


Liu et al., HBM 2002

How other sources may affect the estimate for this source

How this source affects estimates for other sources

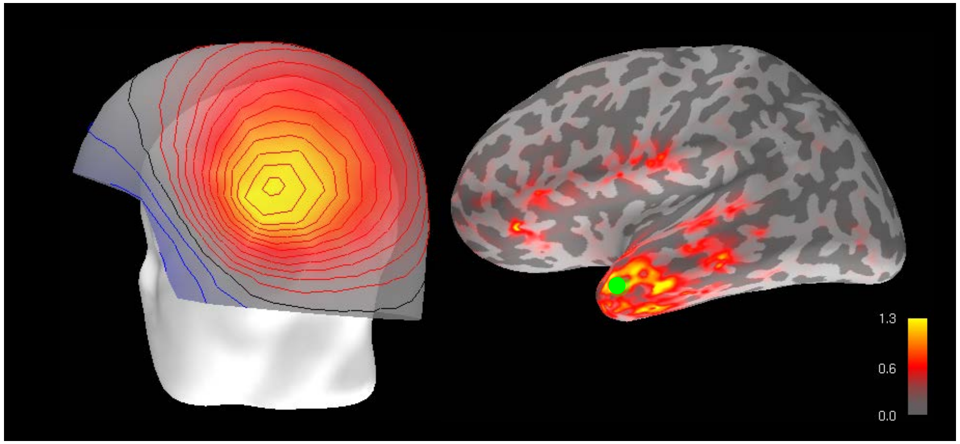
Quantifying "Resolution"

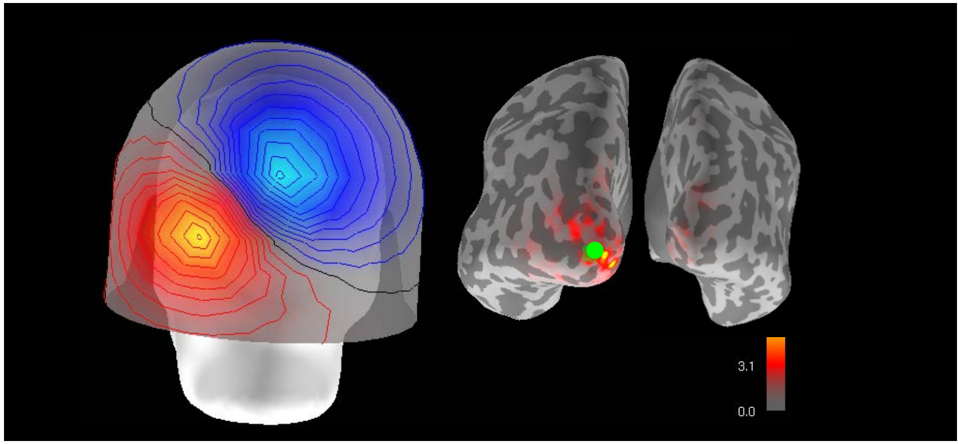


It's not just "peak localisation" that counts,
but also spatial extent of the distribution ("resolution")

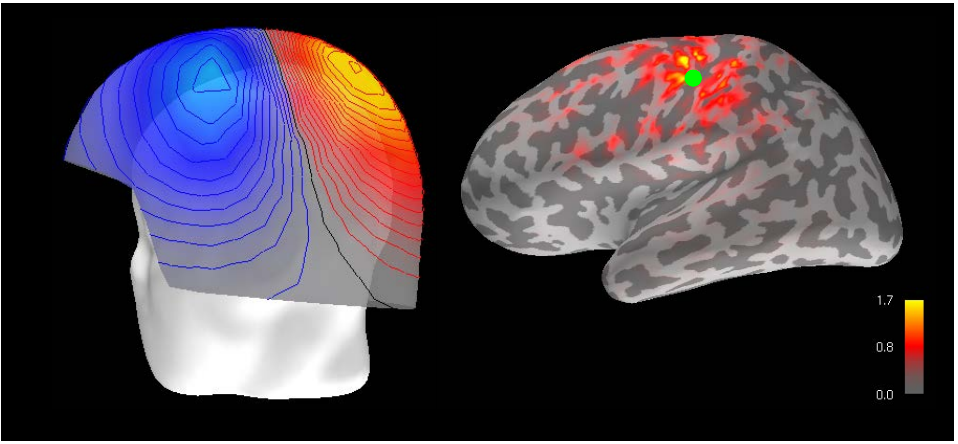
PSFs and CTFs for Some ROIs

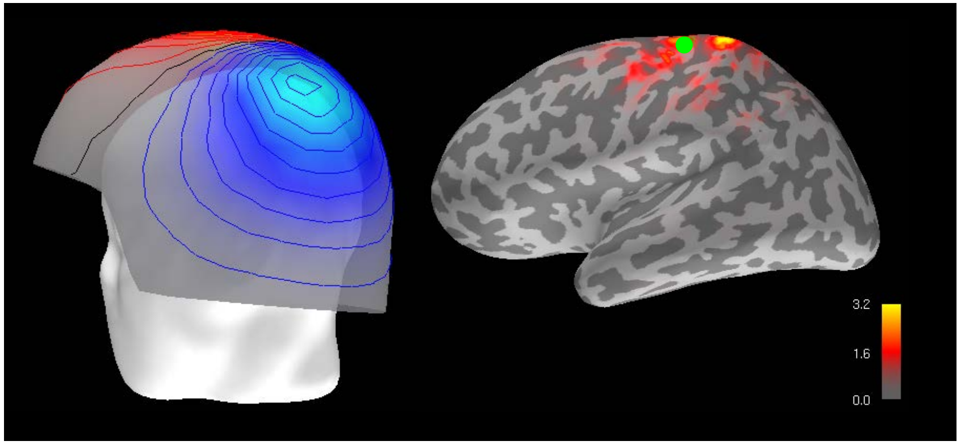
For MNE, PSFs and CTFs turn out to be the same





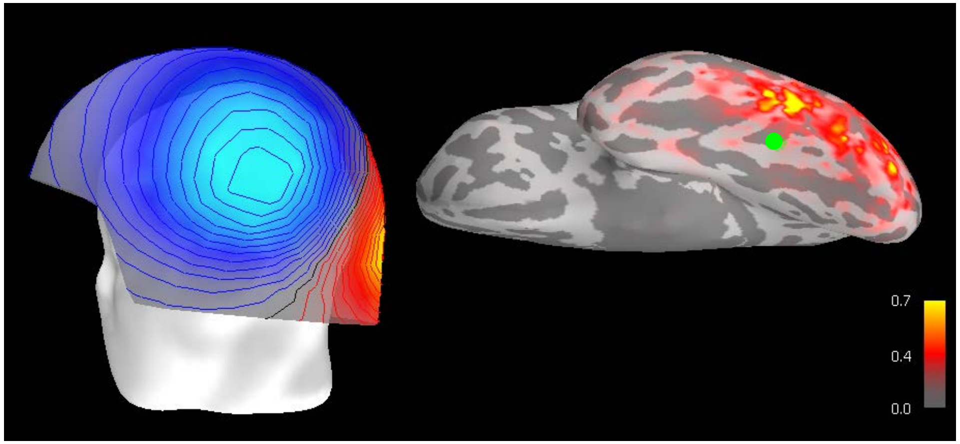
Good

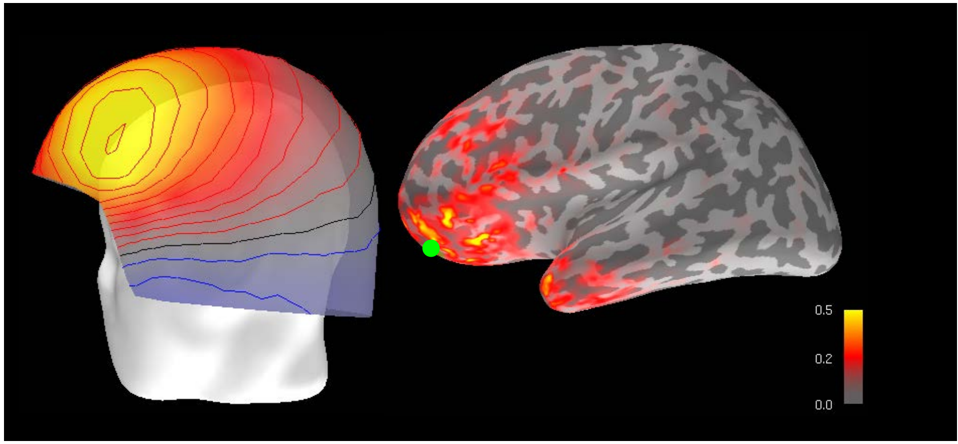




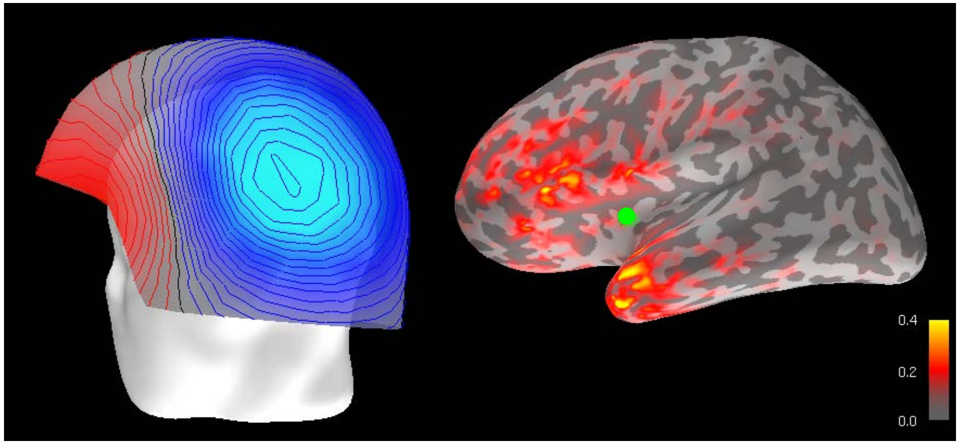
PSFs and CTFs for Some ROIs

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





Less good



Comparing Methods

Different methods make different compromises.

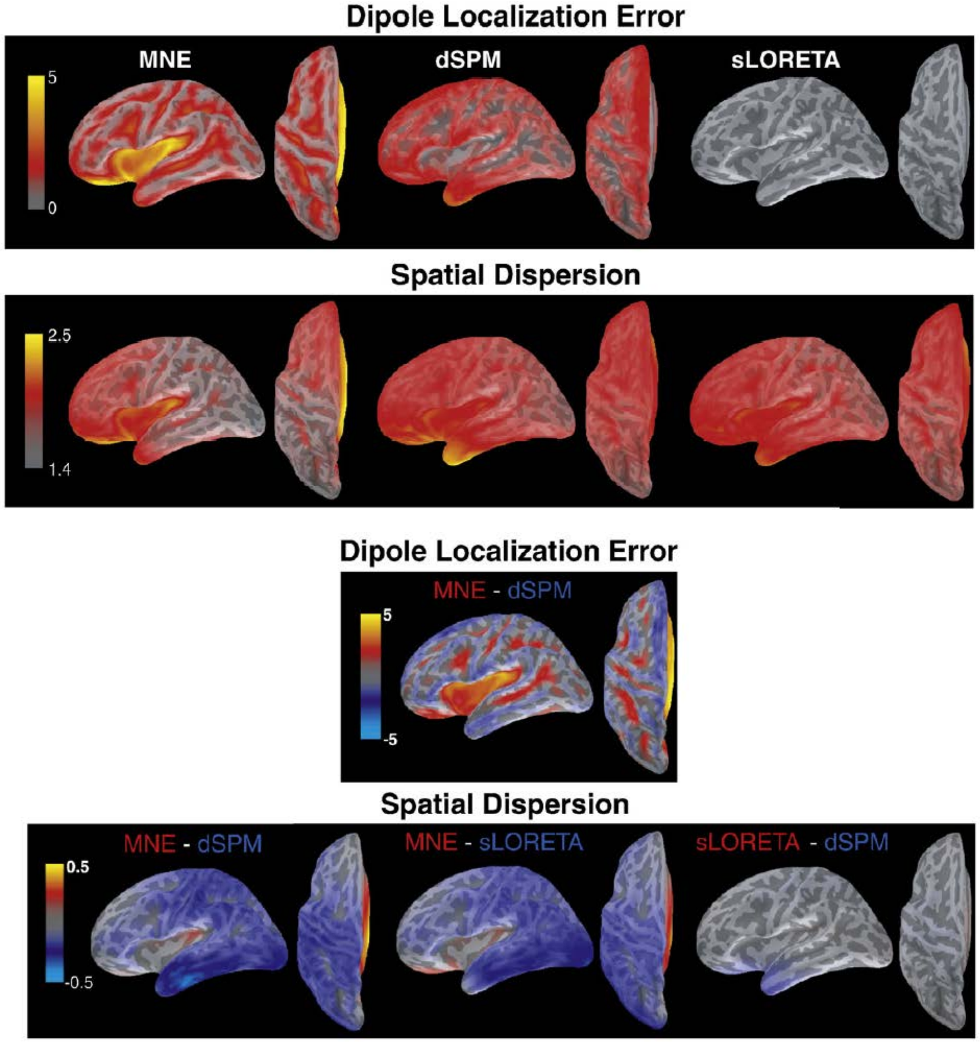
There is no "best" method – best for what?

One should compare methods for the same purpose and under the same assumptions.

Difficult to generalize results from one example or data set

=> Important to understand the principles

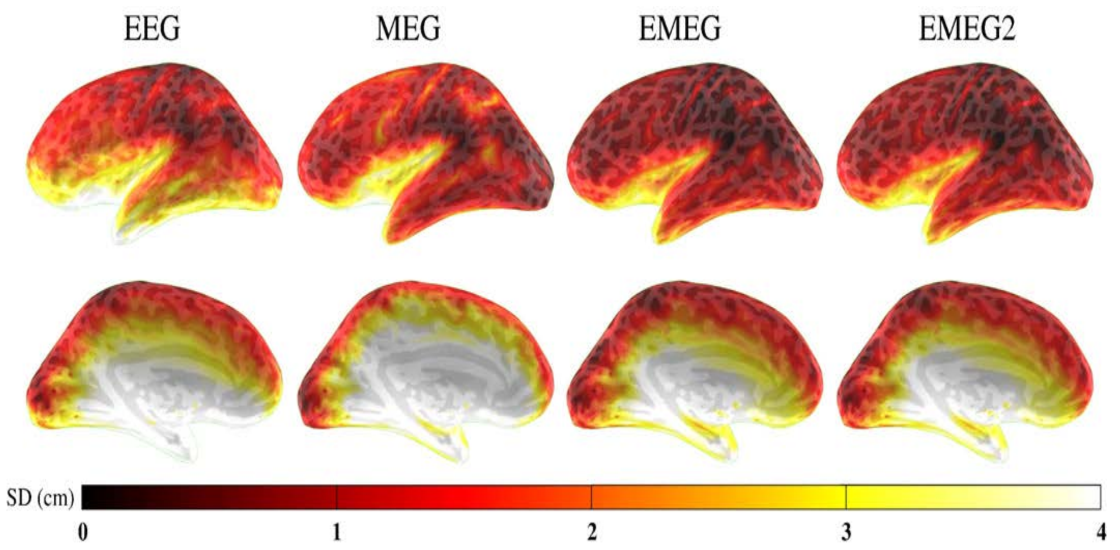
Method Comparison



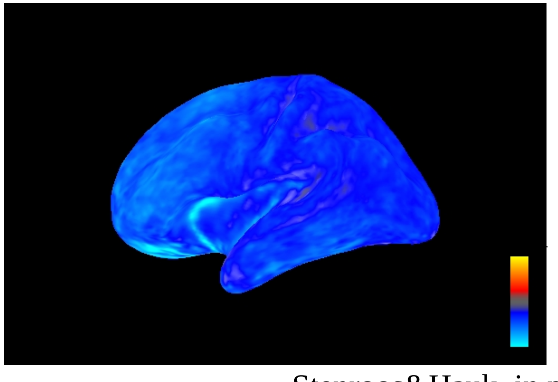
Hauk/Wakeman/Henson, Neuroimage 2011

Combining EEG and MEG Increases Resolution

Spatial Extent



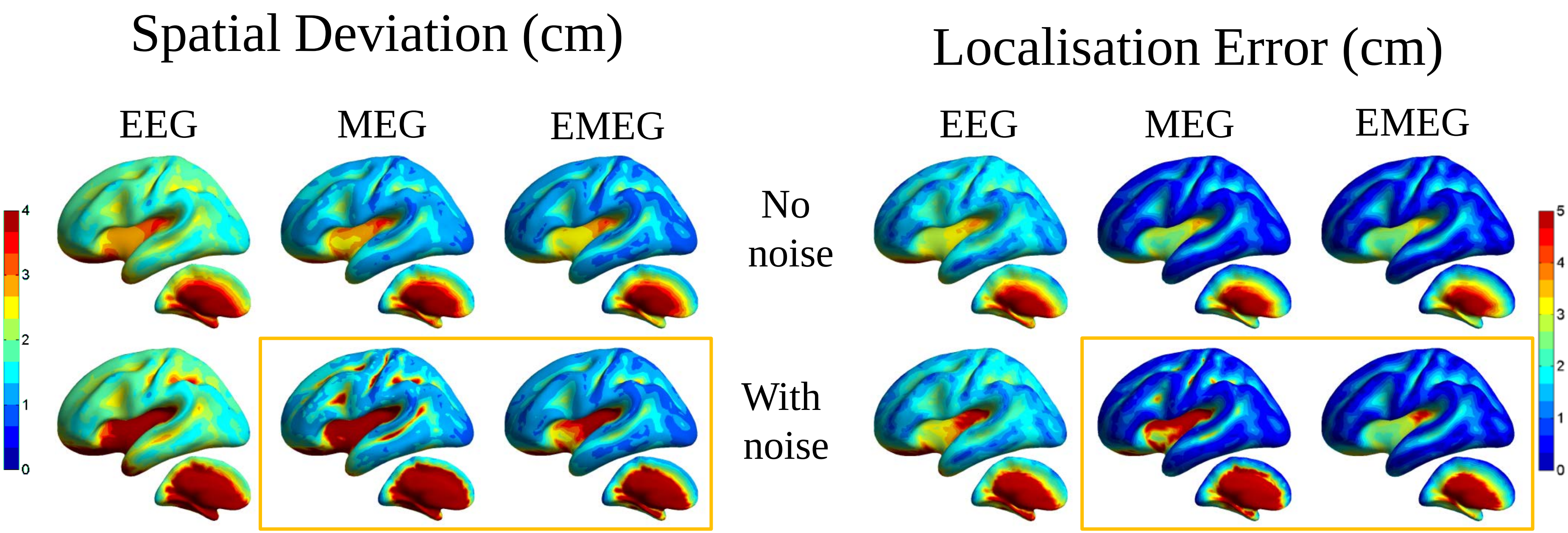
Molins et al., Neuroimage 2008



Stenroos&Hauk, in prep

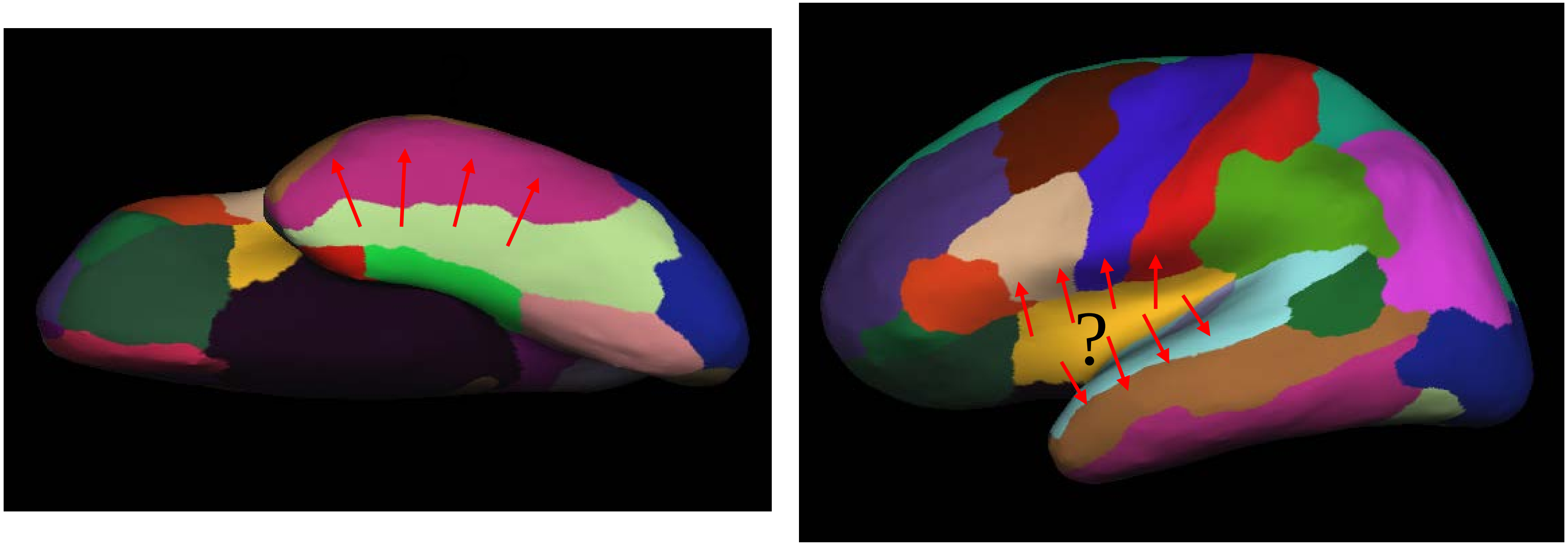
Combining EEG and MEG Improves Resolution

…especially in the presence of (correlated) noise



Stenroos&Hauk, in prep

Localisation Bias Has Consequences for ROI analysis



Desikan-Killiany Atlas parcellation

The End Of #2

Please leave your feedback.