EEG/MEG 4:

Multimodal Integration and Prior Information

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COGNESTIC 2023

Multimodal Dataset

A multi-subject, multi-modal human neuroimaging dataset

Daniel G Wakeman & Richard N Henson

Scientific Data **2**, Article number: 150001 (2015) | Cite this article

https://www.nature.com/articles/sdata20151

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From raw MEG/EEG to publication: how to perform MEG/EEG group analysis with free academic software

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METHODS article

Front. Neurosci., 06 August 2018
Sec. Brain Imaging Methods
Volume 12 - 2018 | https://doi.org/10.3389/fnins.2018.00530

This article is part of the Research Topic
From raw MEG/EEG to publication: how to perform MEG/EEG group analysis with free academic software
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A Reproducible MEG/EEG Group Study With the MNE Software: Recommendations, Quality Assessments, and Good Practices

Mainak Jas[1] Eric Larson[2] Denis A. Engemann[3,4] Jaakko Leppäkangas[1] Samu Taulu[2,5] Matti Hämäläinen[6] Alexandre Gramfort[1,3,4*]

https://www.frontiersin.org/articles/10.3389/fnins.2018.00530/full

METHODS article

Front. Neurosci., 24 April 2019
Sec. Brain Imaging Methods
Volume 13 - 2019 | https://doi.org/10.3389/fnins.2019.00300

This article is part of the Research Topic
From raw MEG/EEG to publication: how to perform MEG/EEG group analysis with free academic software
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Multimodal Integration of M/EEG and f/MRI Data in SPM12

Richard N. Henson[1*] Hunar Abdulrahman[1] Guillaume Flandin[2] Vladimir Litvak[2]

https://www.frontiersin.org/articles/10.3389/fnins.2019.00300/full

How Can We Combine Measurement Modalities?

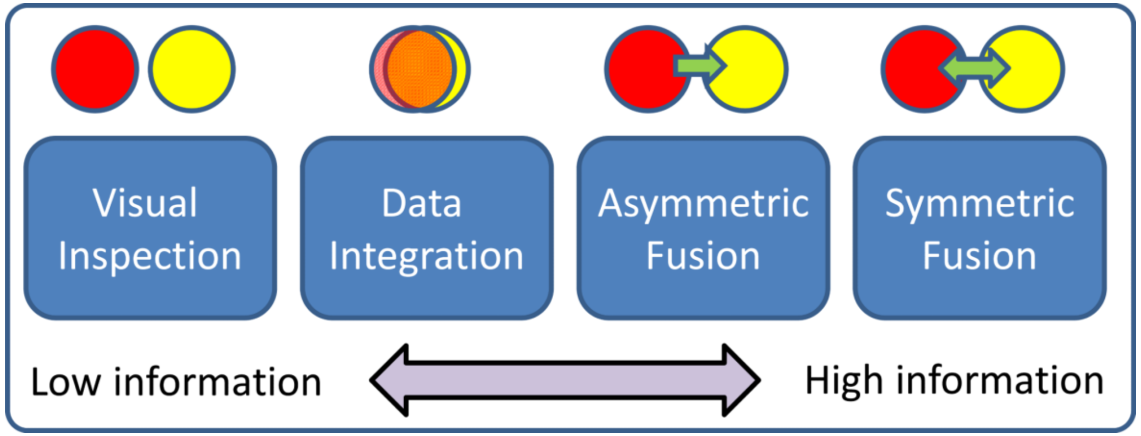
“Converging Evidence”:
Compare results from different modalities, determine commonalities and differences.

“(Asymmetric) Fusion”:
Use one modality as a constraint for another.
(e.g. EEG->fMRI, fMRI->EEG/MEG)

“Neural Modelling” (“Symmetric Fusion”):
Use of a common neural model that accounts for signals in all modalities.
(e.g. EEG<->MEG)

e.g. Horwitz&Poeppel, HBM 2002; Henson et al., HBM 2010

Each of these options poses different challenges with respect to modelling assumptions and complexity.



Calhoun & Sui, Biol Psych Cogn Nsc 2017

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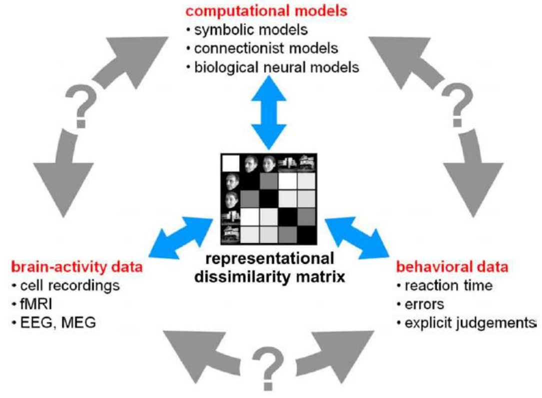
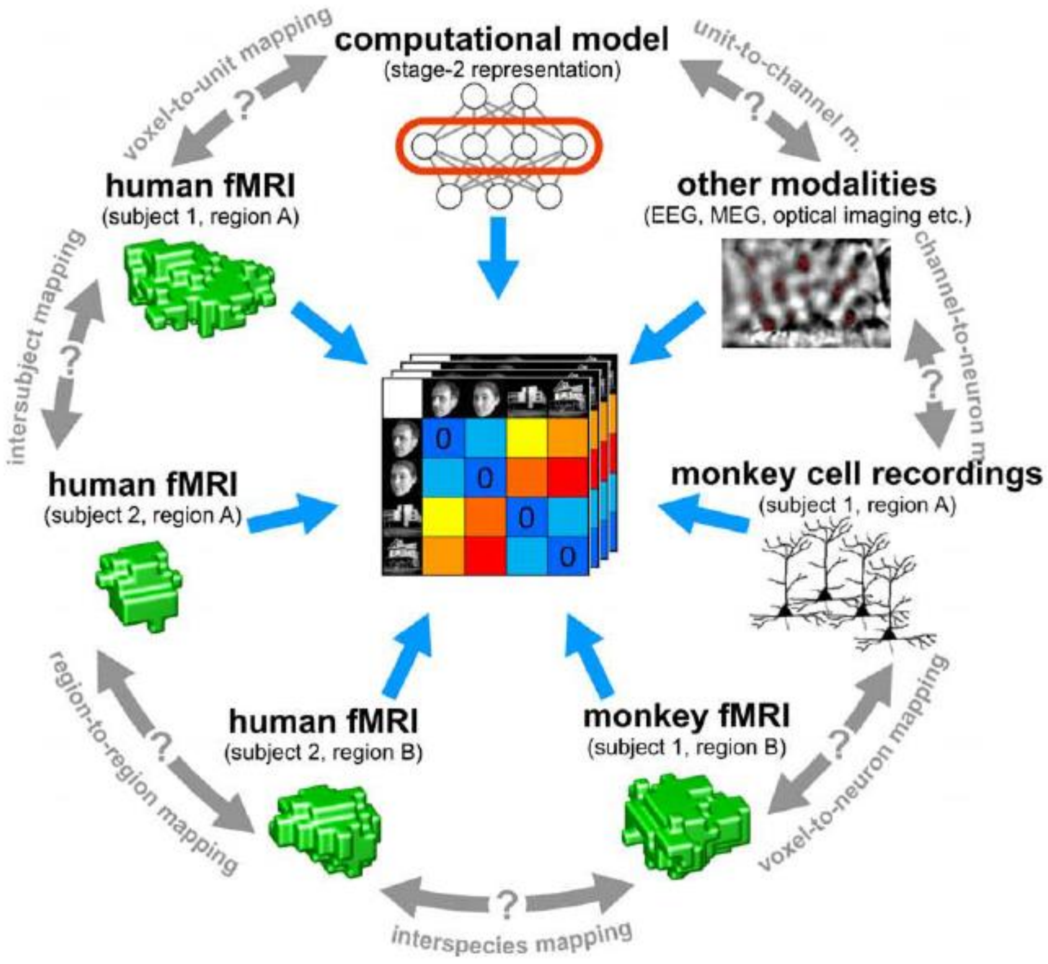
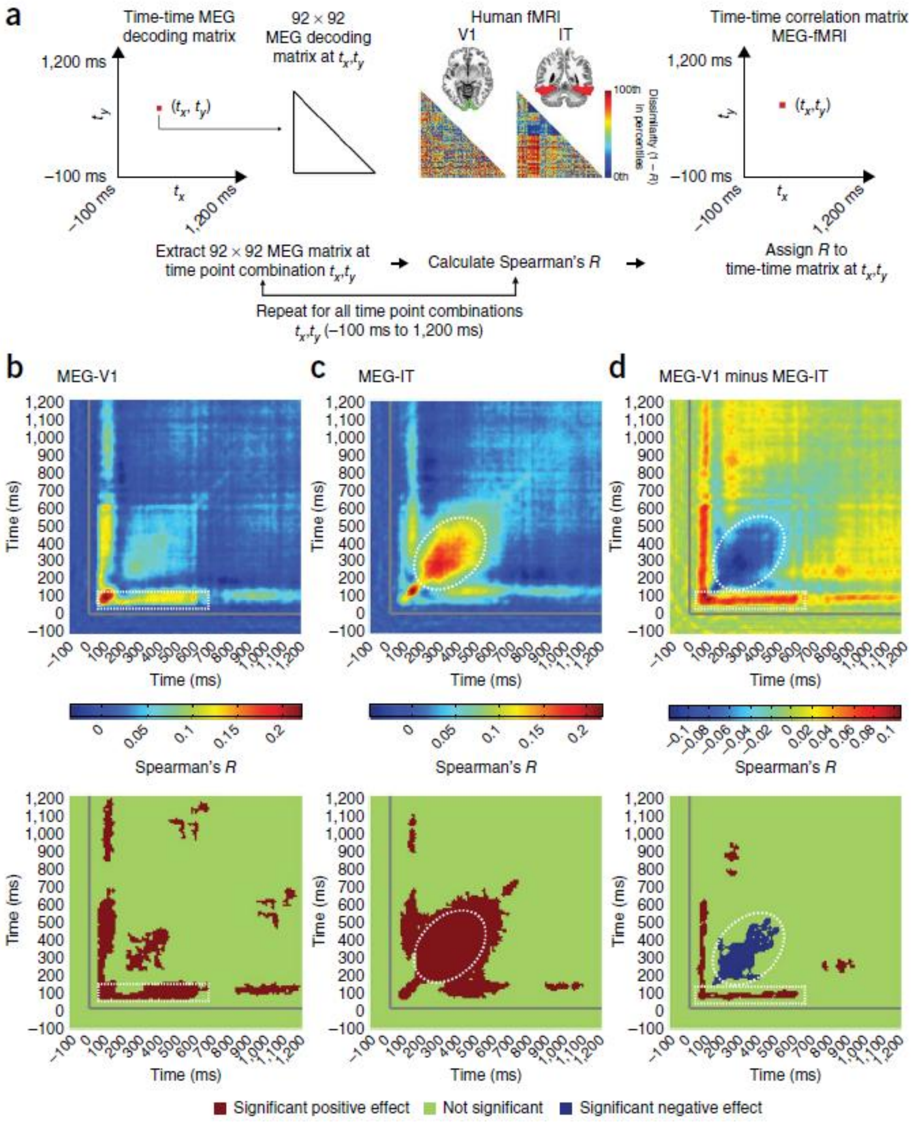
Comparing Representational Dissimilarity Across Neuroimaging Methods





Kriegeskorte et al., Front Syst Nsc 2008

Comparing Representational Dissimilarity Across Neuroimaging Methods



Cichy et al., Nat Nsc 2014

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Problems Integrating EEG/MEG And fMRI

1. Metabolic activity can occur without EEG/MEG activity.
2. EEG/MEG activity can occur without BOLD activity.
3. EEG/MEG and metabolic activity may have common sources, but are not fully spatially overlapping.
4. EEG/MEG and metabolic activity have different time courses.

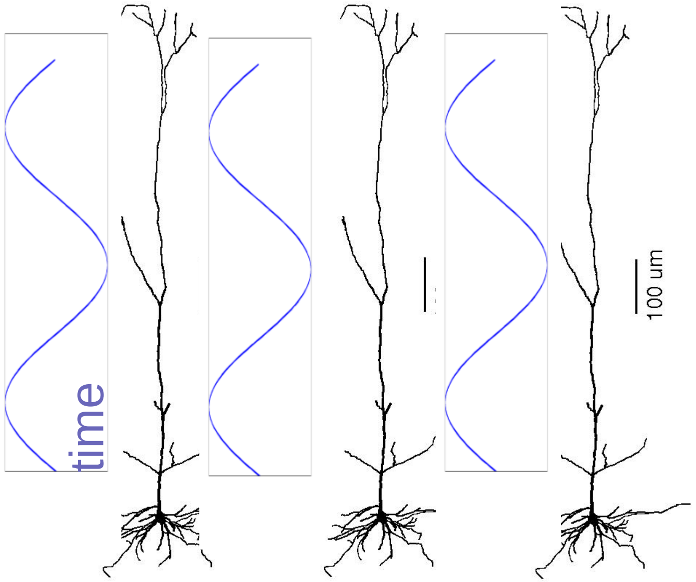
Note: Usually EEG/MEG and fMRI are acquired in different sessions, causing:

a) inter- and intra-subject variability (same or different subjects in different sessions)
b) differences in scanning position (supine, seated)
c) differences in scanning environment (e.g. scanner noise)

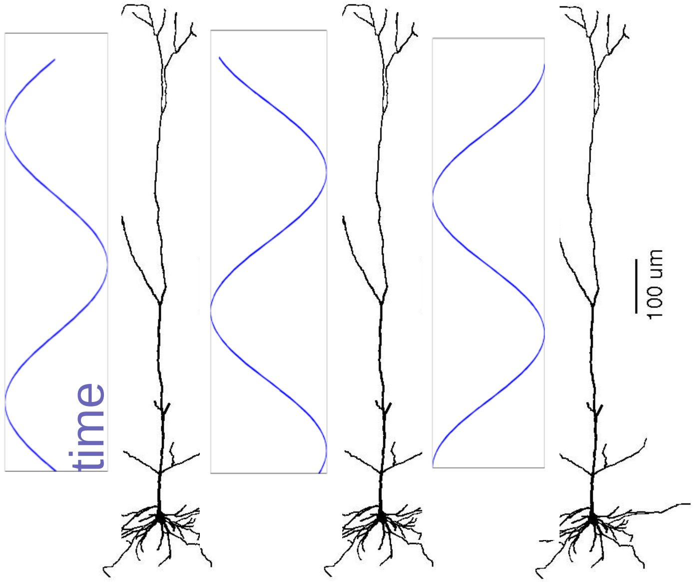
e.g. Poline et al., in "MEG – An Introduction to Methods"

Problems Integrating EEG/MEG And fMRI

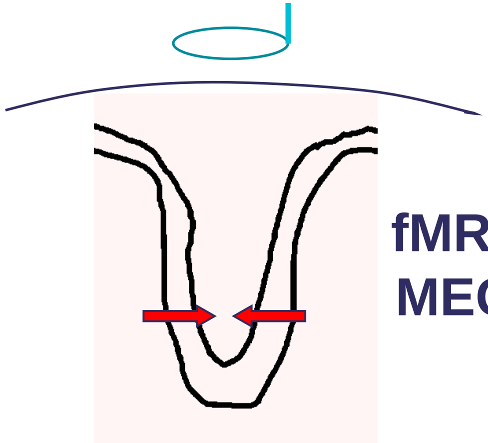
Synchronous: fMRI↑ MEG↑



Asynchronous: fMRI↑ MEG↓

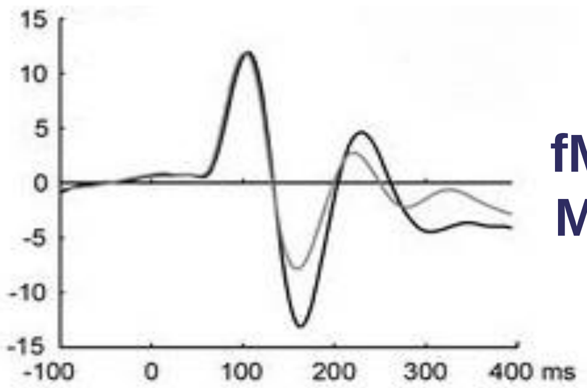


Source Configuration



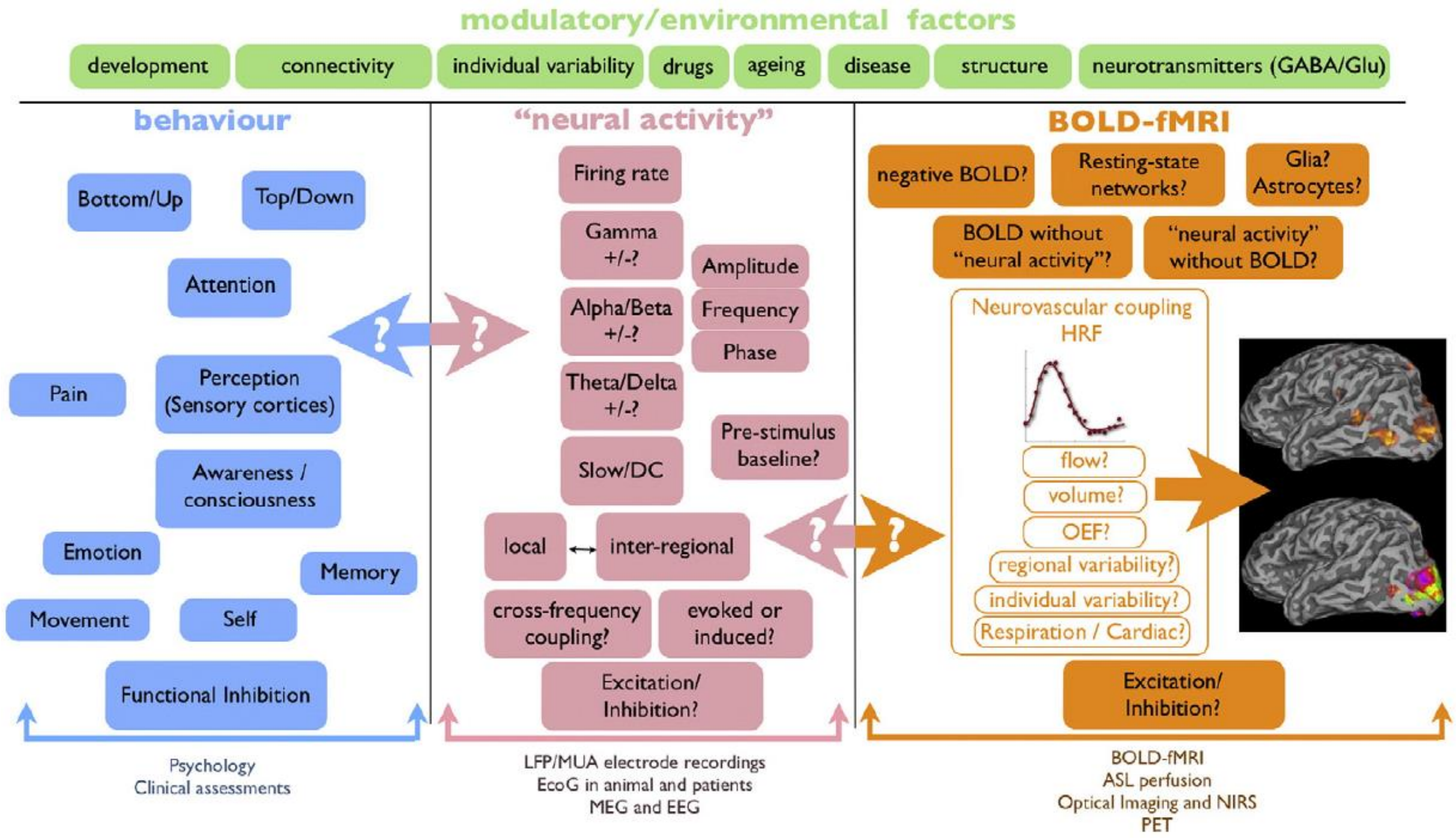
fMRI↑
MEG↓

Time Scale



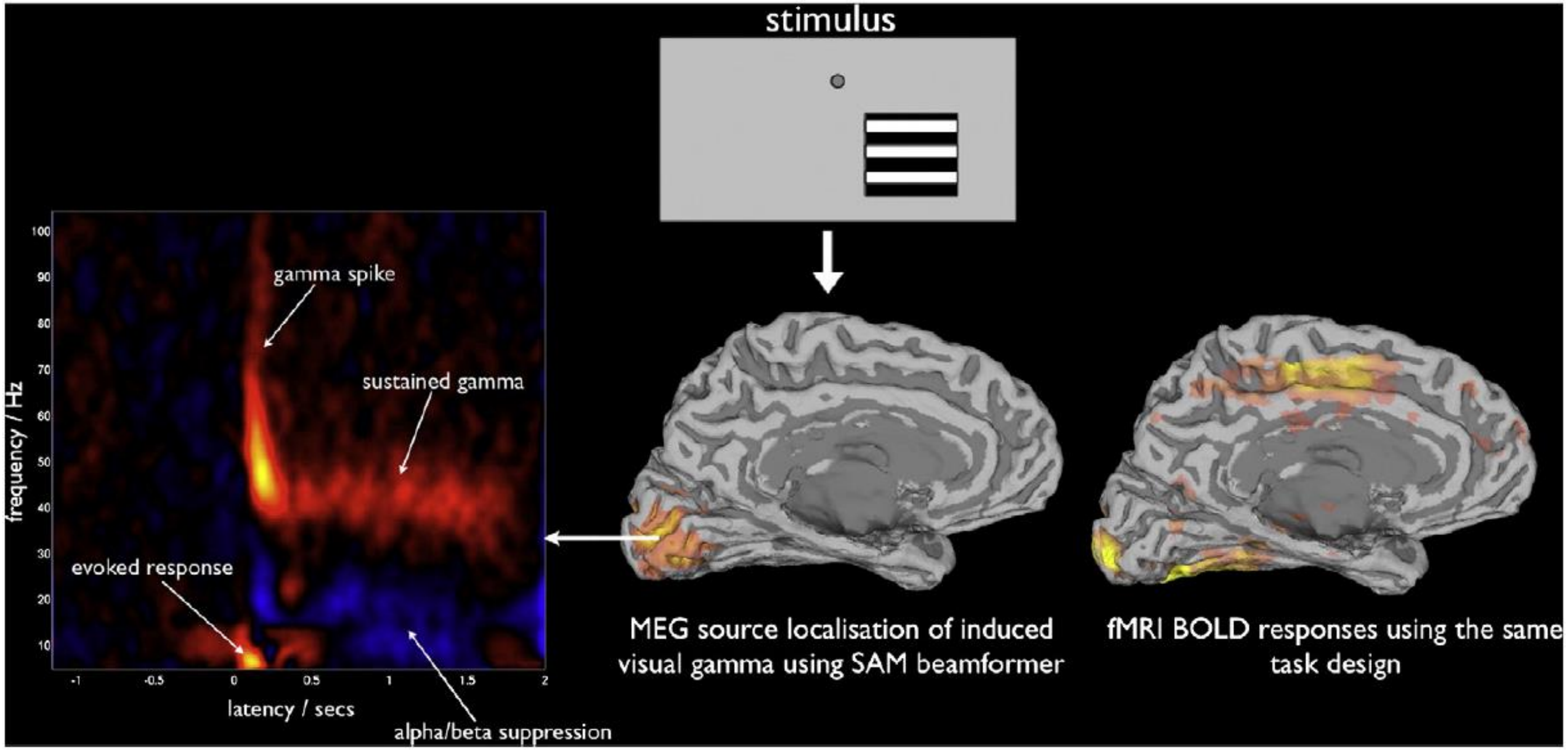
fMRI↓
MEG↑

Which "Neural Activity" Do You Mean?



Singh, NI 2012

Which “Neural Activity” Do You Mean?



Singh, NI 2012

Problems Integrating EEG/MEG And fMRI

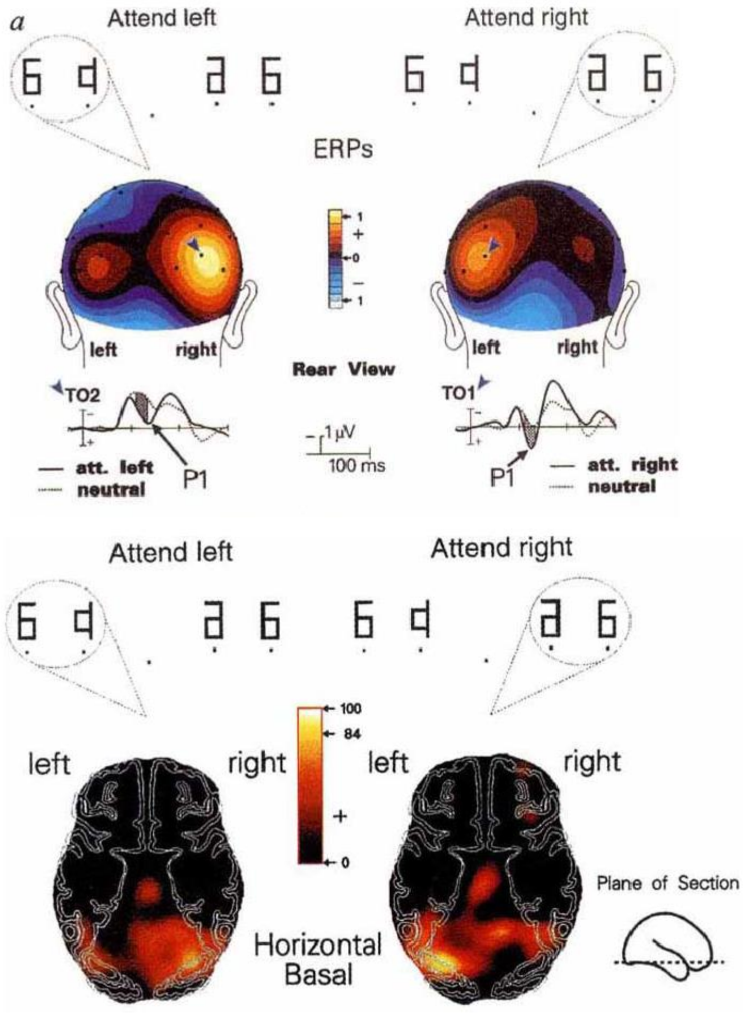
Liu et al., PNAS 1998:

1) “**Fundamental mis-specifications** can arise because EEG and MEG and fMRI measure physically different aspects of brain function.”
2) “**Experimental mis-specifications** refer to measurement or estimation errors that can be corrected, at least in theory”.

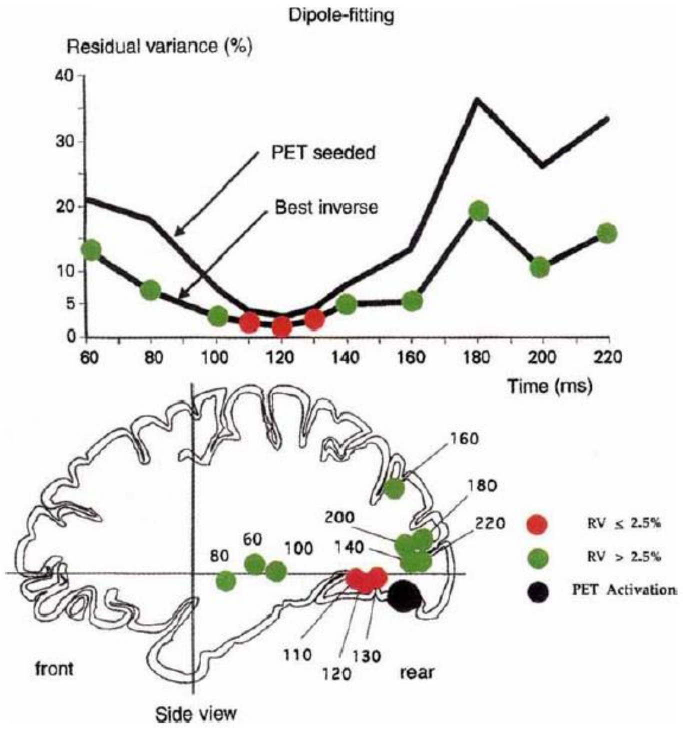
Multimodal Integration
Hypothesis-Guided Dipole Modelling

ERPs

PET



PET-constrained
Dipole Modelling



Heinze et al., Nature 1994

“Weighting” and “Priors”

$$P(\mathbf{j}(\mathbf{r},t)|\mathbf{x}(t)\ \&\ f(\mathbf{r},t)) = \frac{P(\mathbf{x}(t)|\mathbf{j}(\mathbf{r},t))\,P(f(\mathbf{r},t)|\mathbf{j}(\mathbf{r},t))\,P(\mathbf{j}(\mathbf{r},t))}{P(\mathbf{x}(t)\ \&\ f(\mathbf{r},t))}$$

If source strengths and priors can be modelled as multivariate Gaussian distributions, then the maximum a posteriori probability (MAP) estimate is the minimum norm estimate:

$$\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t), \text{ where } \mathbf{W} = \mathbf{R}\mathbf{A}^T(\mathbf{A}\mathbf{R}\mathbf{A}^T + \mathbf{C})^{-1}$$

A: Leadfield
R/C: Source/noise covariance

$0<\mathbf{R}_{ii}<1$
depending on fMRI

Dale et al., Neuron 2000, also Liu et al., PNAS 1998

Relative Weighting of fMRI

Ideally, this requires knowledge about “fMRI visible” and “fMRI invisible” sources –
if we knew those, we wouldn’t need source estimation anymore.

“The optimal fMRI weighting, which depends on the confidence in the hypothesis that neuronal and hemodynamic activity are tightly coupled, currently cannot be determined *a priori*.”
Liu et al., PNAS 1998

Relative Weighting of fMRI

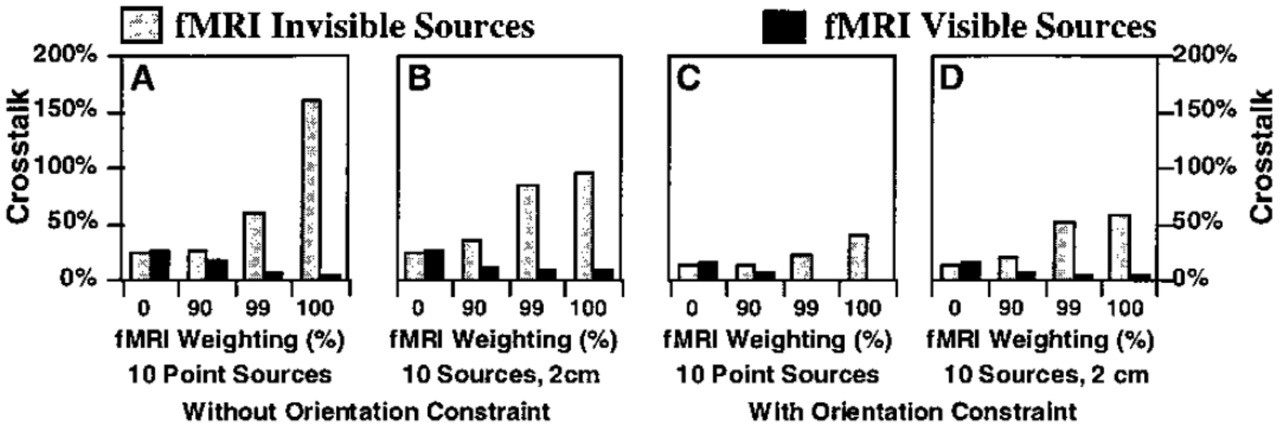


FIG. 3. Crosstalk versus relative fMRI weighting. Crosstalk is shown for 10 sources (point and 2 cm in diameter), with and without orientation constraint. The relative fMRI weighting was either 0%, 90%, 99%, or 100%. The optimal fMRI weighting requires a compromise between resolving fMRI visible sources (i.e., higher fMRI weighting) and minimizing distortion from fMRI invisible sources (i.e., lower fMRI weighting). The results indicate that a 90% fMRI weighting greatly reduces the crosstalk from fMRI visible sources, while only slightly increasing the crosstalk from fMRI invisible sources.

Liu et al., PNAS 1998

Relative Weighting of fMRI

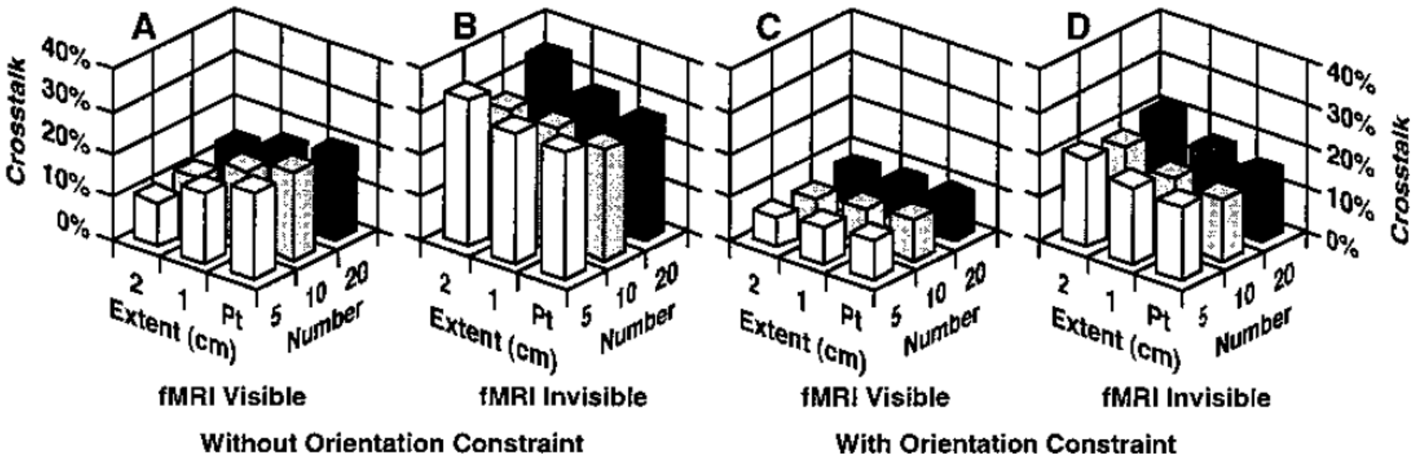
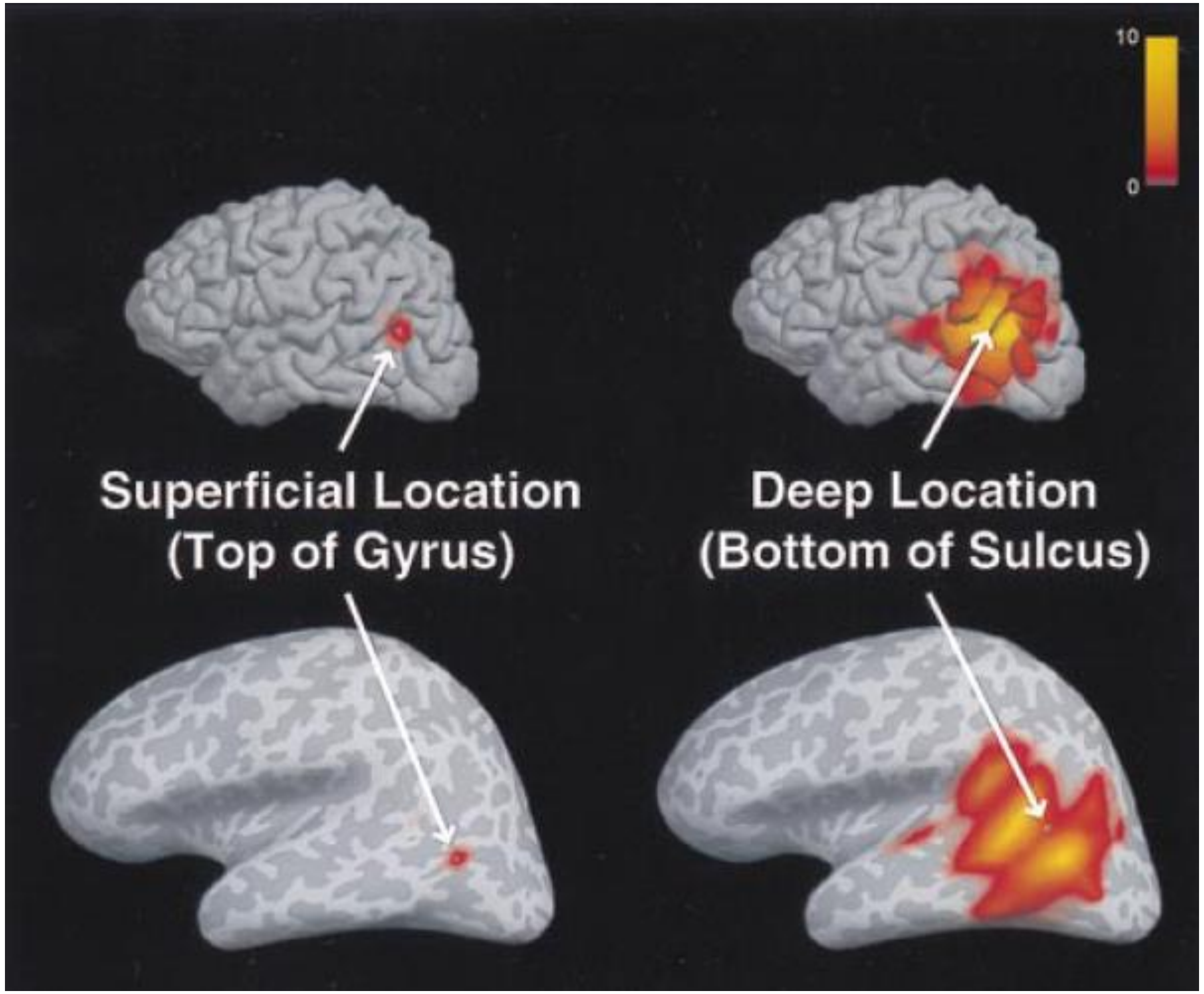


FIG. 4. Crosstalk versus extent and number of sources. Crosstalk is shown for a variety of extents and numbers of sources. The extent of sources was either point, 1 cm or 2 cm in diameter, and the number of sources was 5, 10, or 20 (indicated by different gray scale). A partial fMRI weighting of 90% was used in these simulations. The results indicate that the crosstalk is relatively independent of source extent and number. This demonstrates that the proposed linear estimation method is appropriate for modeling multiple, extended areas of activation, as typically encountered in functional neuroimaging studies.

Liu et al., PNAS 1998

(How) Can We Estimate Deep Sources?



Liu et al., PNAS 1998

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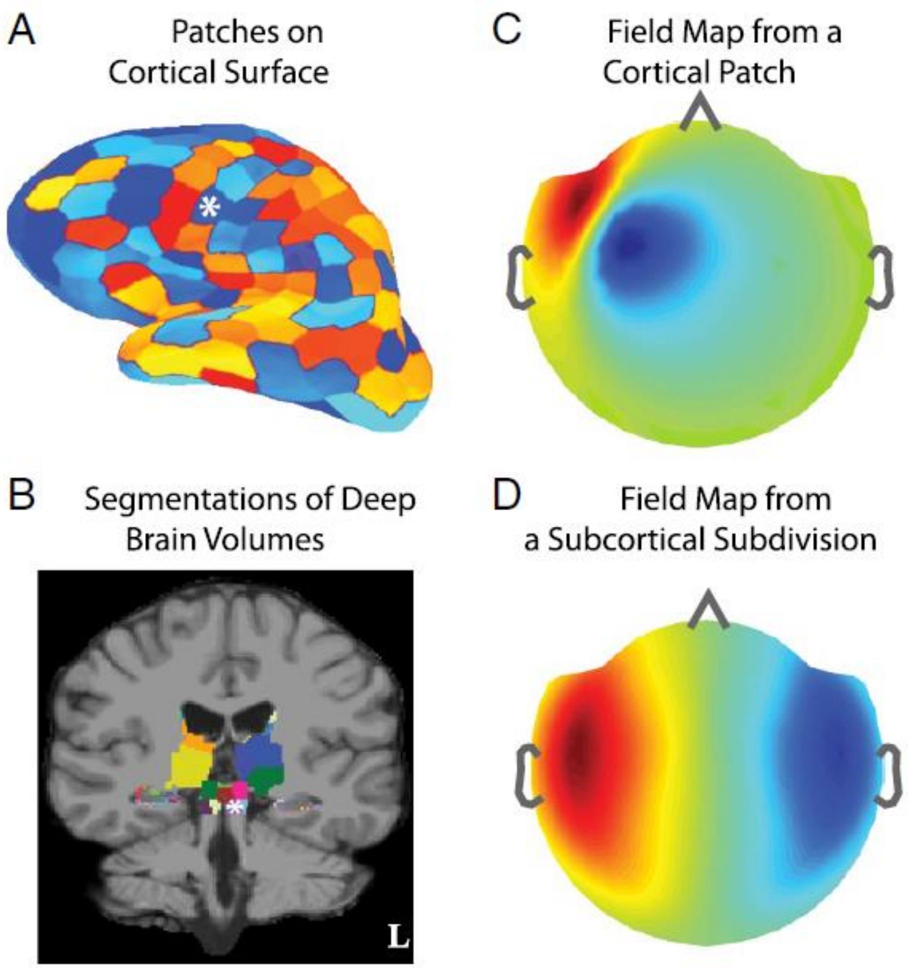

Krishnaswami et al., PNAS 2017
https://www.pnas.org/doi/10.1073/pnas.1705414114

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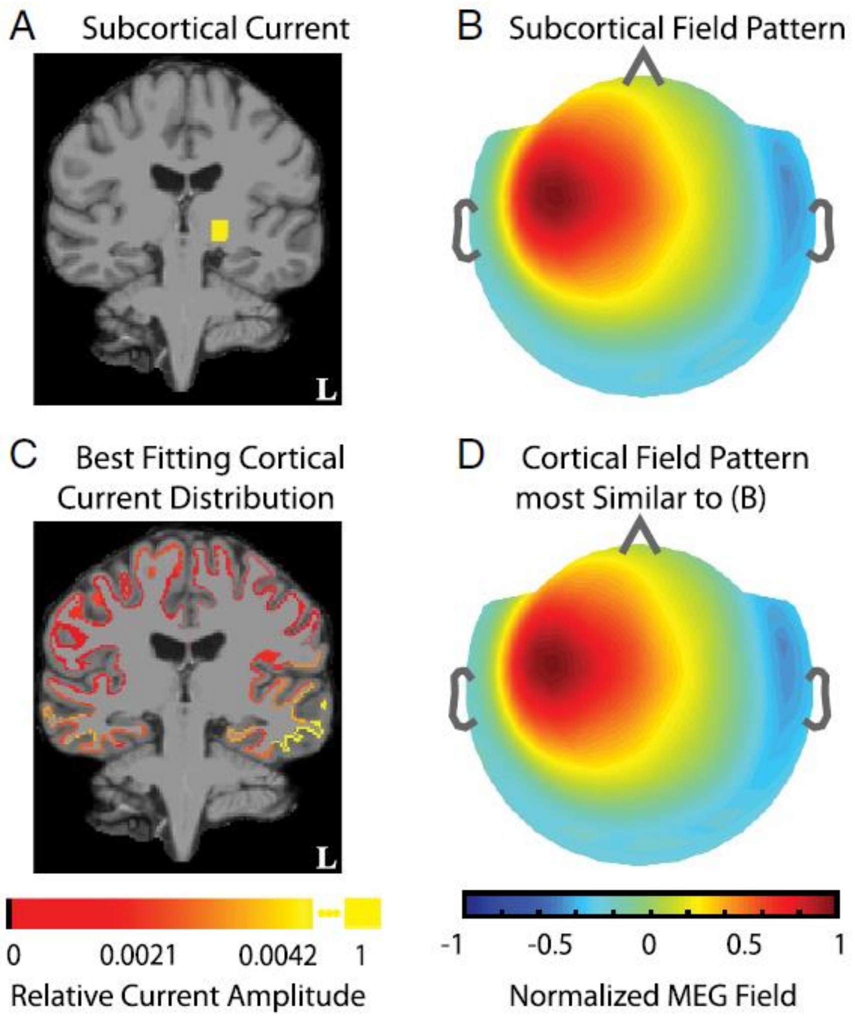

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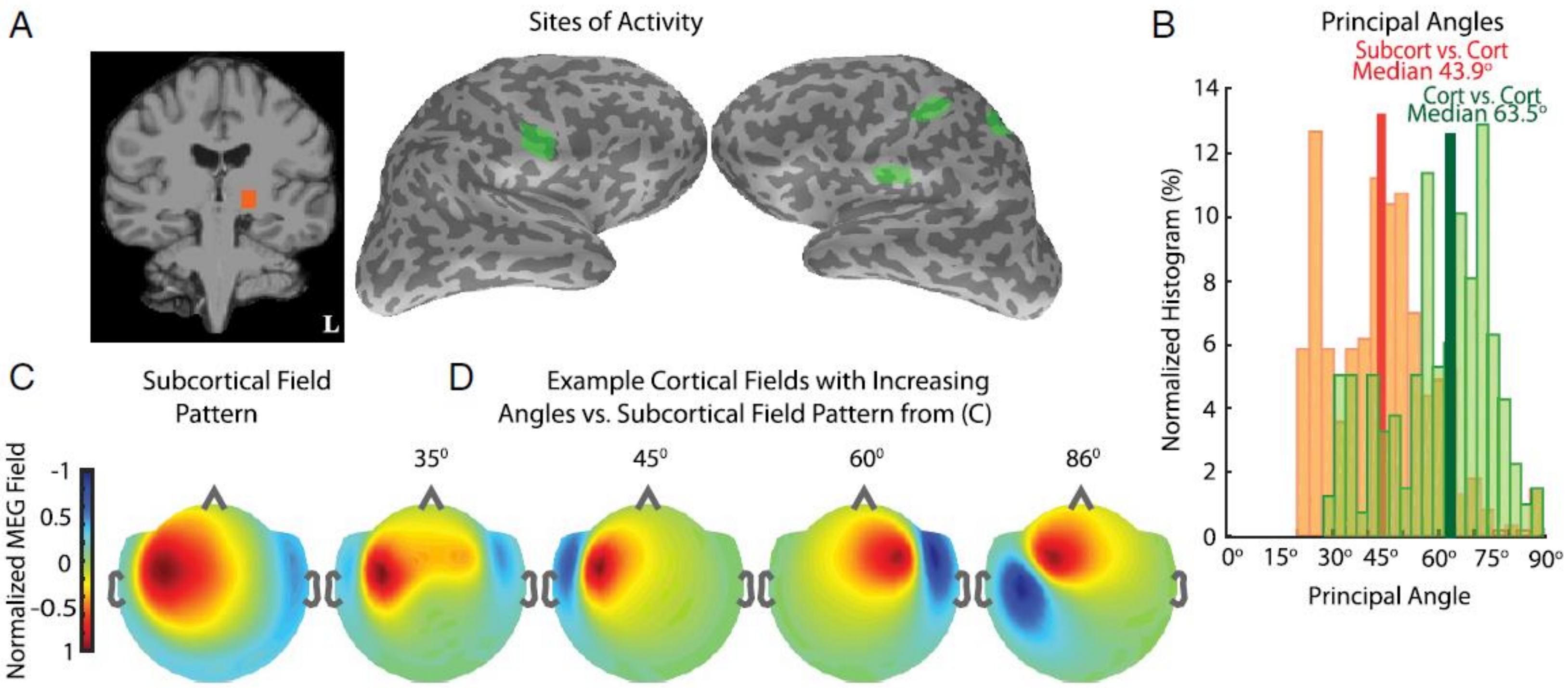

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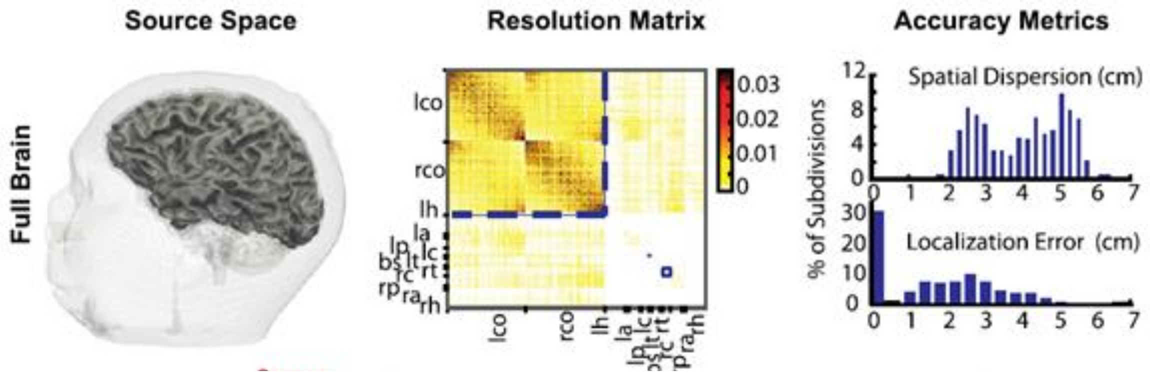
The Importance Of Sparsity



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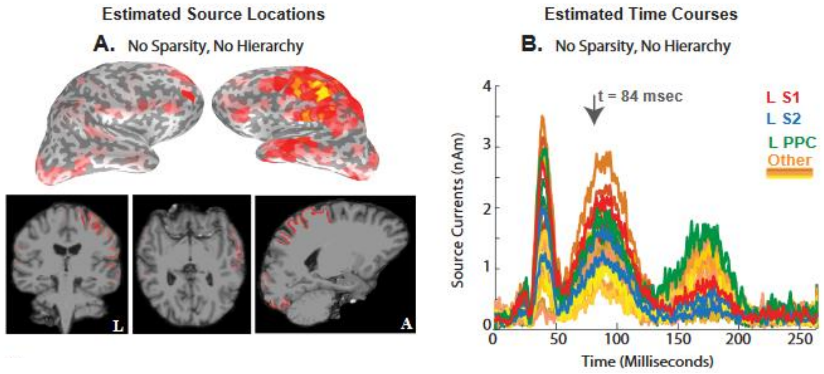
(How) How Can We Estimate Deep Sources?

Sparsity And Hierarchy Are Key



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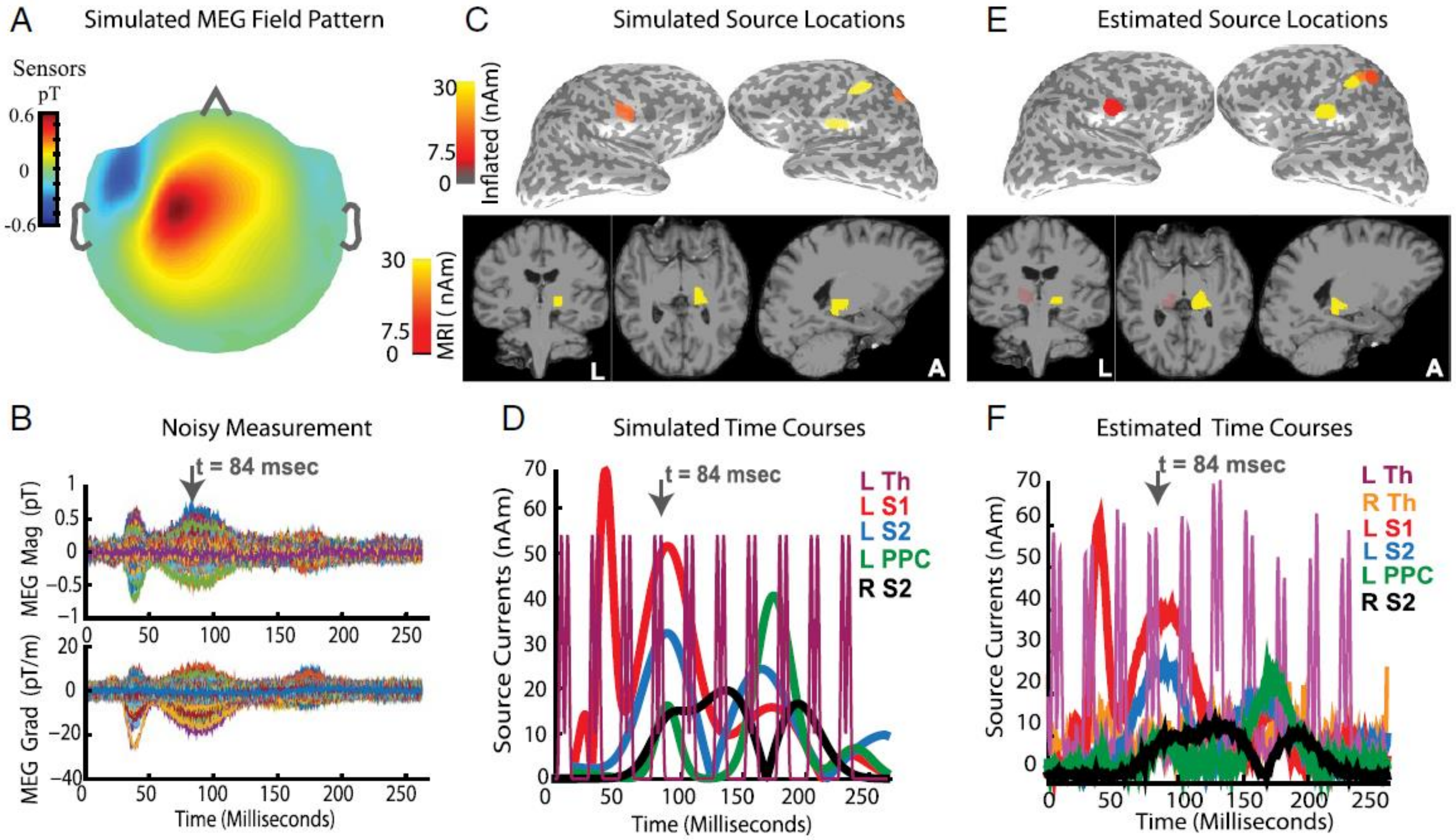

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Conclusions

- Priors lead to a bias of your solution towards what you already know.
- The link between the physiology of EEG/MEG and fMRI is not well understood.

  The usefulness of priors depends on the individual case.
- Priors can be implemented as weightings or source covariance matrices in the (Bayesian) minimum-norm framework.
- Prior information on the location and sparsity of sources is particularly useful (required) for deep sources.

Thank you