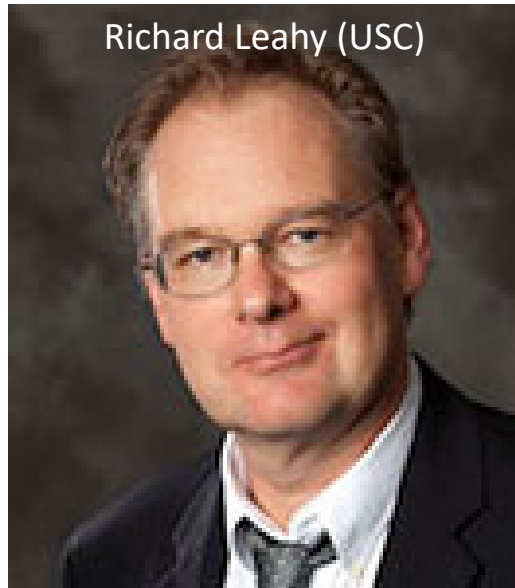




Sylvain Baillet (McGill)



Richard Leahy (USC)



Francois Tadel



John Mosher
(U Texas, Houston)



Brainstorm: MEG/EEG software since 2000

- Current team: Sylvain Baillet, John Mosher, Raymondo Cassani Gonzalez, Takfarinas Medani, Anand Joshi, Dimitrios Pantazis, Marc Lalancette, Chinmay Chinara, Anshul Gupta, Richard Leahy

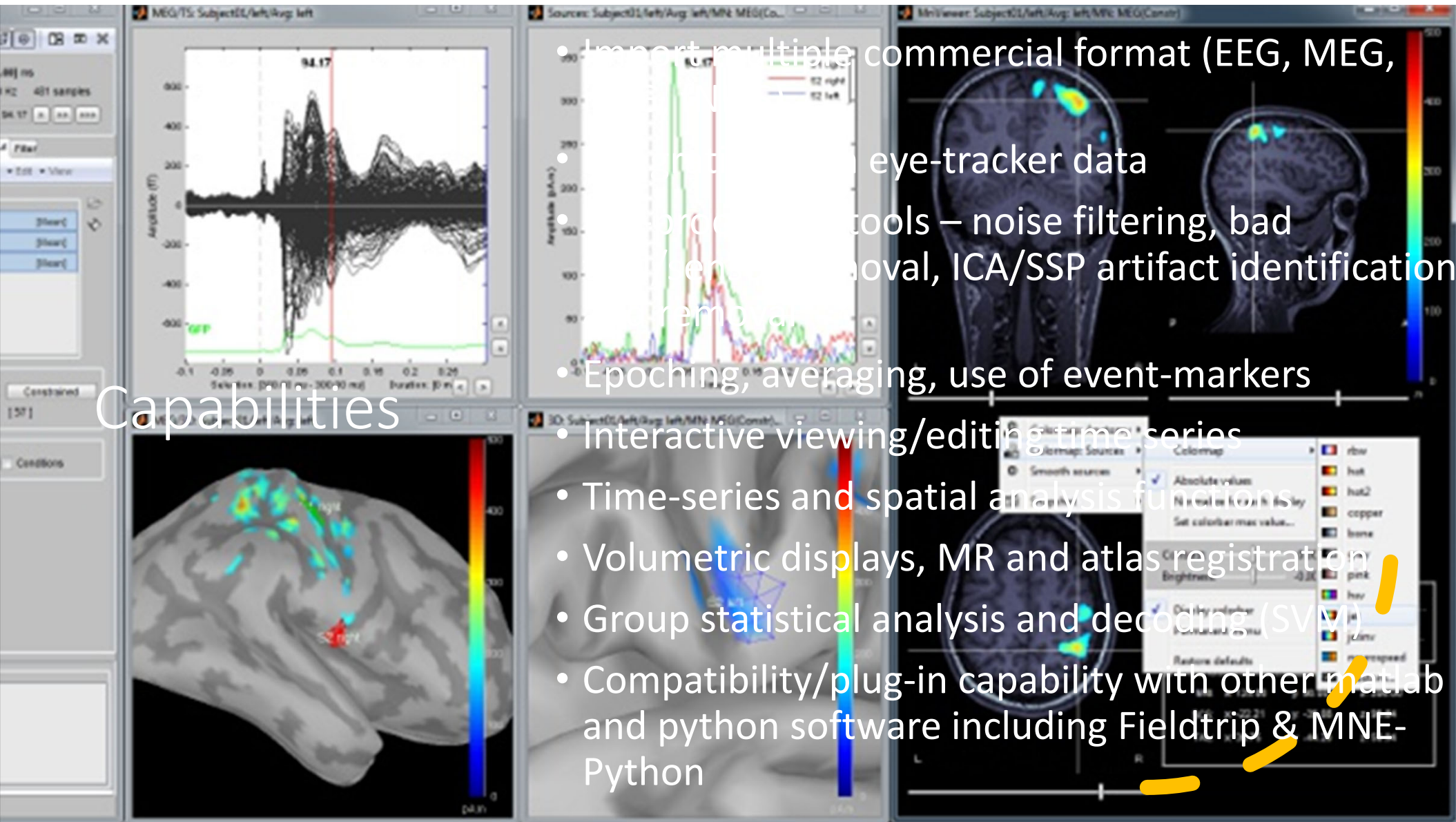
Brainstorm Overview

- Matlab/Java software – highly interactive GUI environment & scripting capabilities
- Copious documentation through a large series of on-line tutorials:
 - <https://neuroimage.usc.edu/brainstorm/Tutorials>
- On-line video introductions
 - <https://neuroimage.usc.edu/brainstorm/Introduction>
- Tutorial publications
 1. F Tadel, S Baillet, JC Mosher, D Pantazis, RM Leahy (2011) Brainstorm: a user-friendly application for MEG/EEG analysis. Computational intelligence and neuroscience, 1-13
 2. S Baillet, JC Mosher, RM Leahy, Electromagnetic brain mapping (2001) IEEE Signal processing magazine 18 (6), 14-30
 3. F Tadel, E Bock, G Niso, JC Mosher, M Cousineau, D Pantazis, RM Leahy, S Baillet (2019) MEG/EEG group analysis with brainstorm, Frontiers in neuroscience, 76

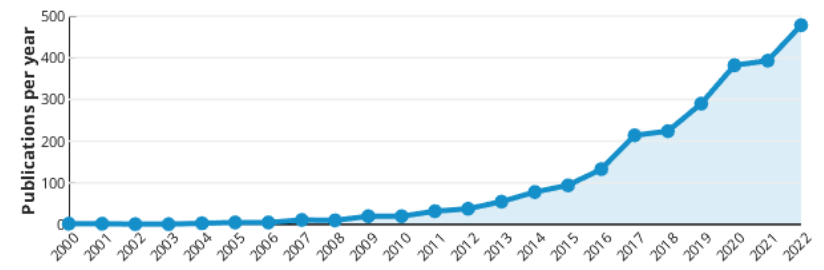
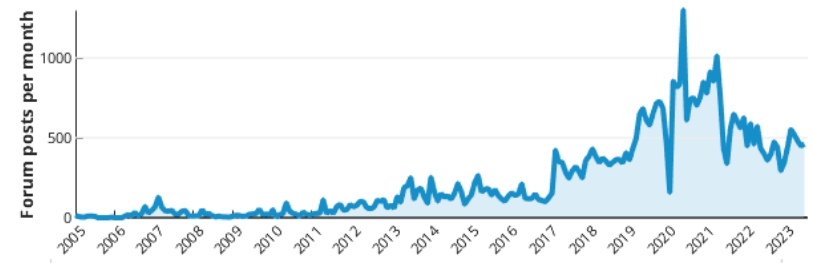
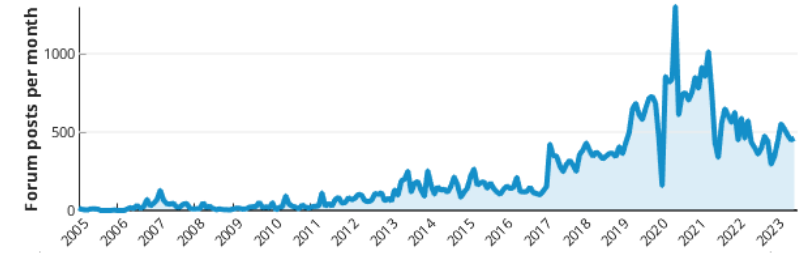
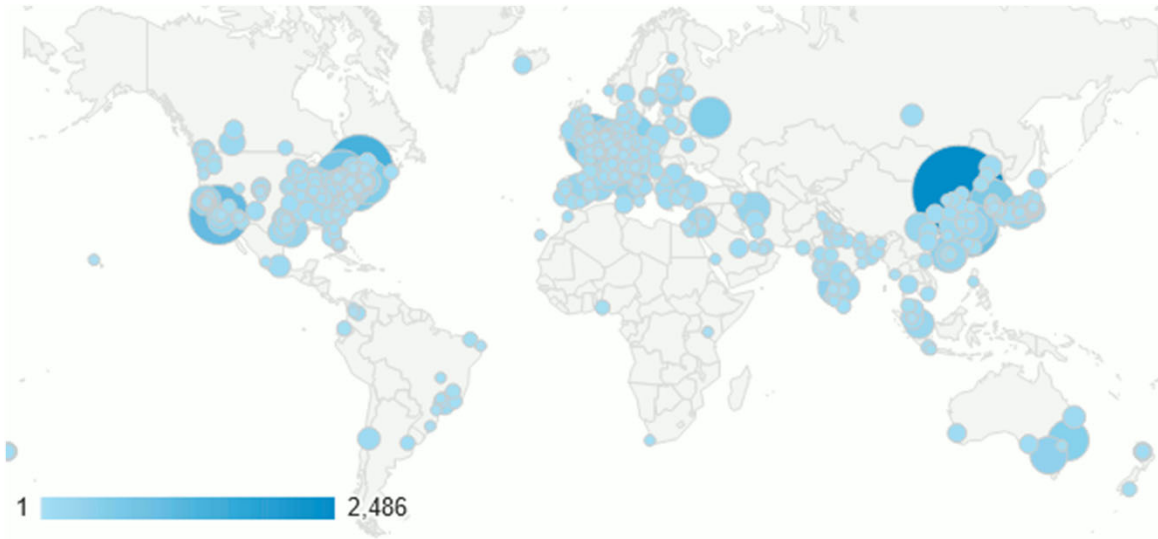
With the generous support of National Institute of Biomedical Imaging and Bioengineering: R01 EB026299, R01EB009048, R01 EB002010

Capabilities

- Import multiple commercial format (EEG, MEG, eye-tracker data)
- Processing tools – noise filtering, bad channel removal, ICA/SSP artifact identification
- Epoching, averaging, use of event-markers
- Interactive viewing/editing time series
- Time-series and spatial analysis functions
- Volumetric displays, MR and atlas registration
- Group statistical analysis and decoding (SVM)
- Compatibility/plug-in capability with other matlab and python software including Fieldtrip & MNE-Python

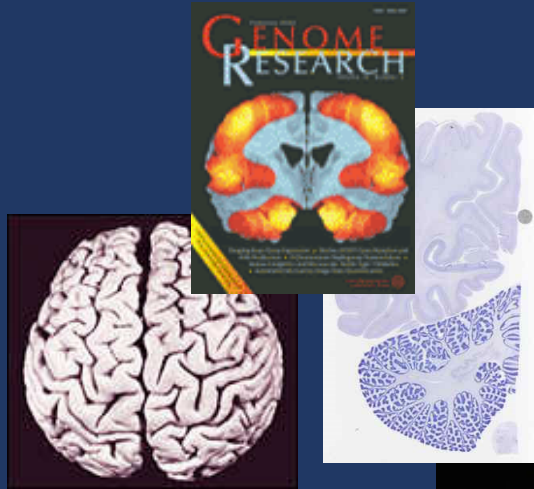


The Brainstorm Community



Data

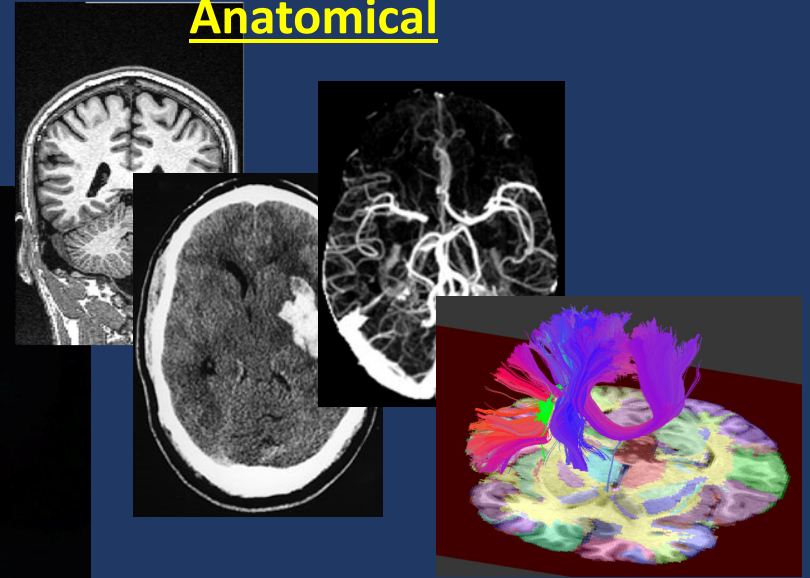
Post Mortem



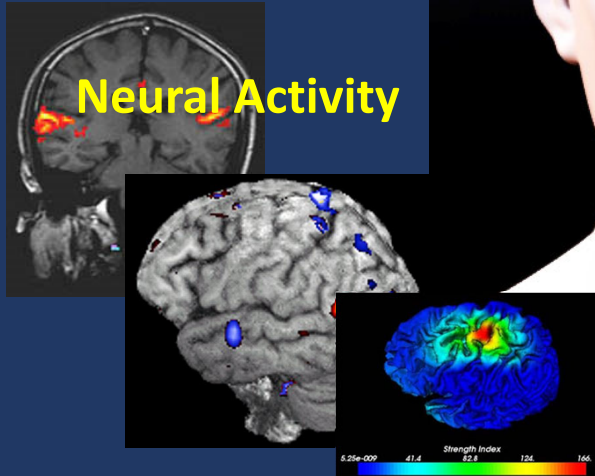
Imaging the Human brain



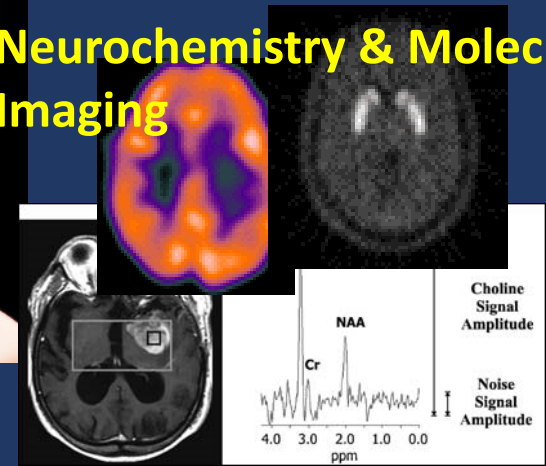
Anatomical



Neural Activity



Neurochemistry & Molecular Imaging



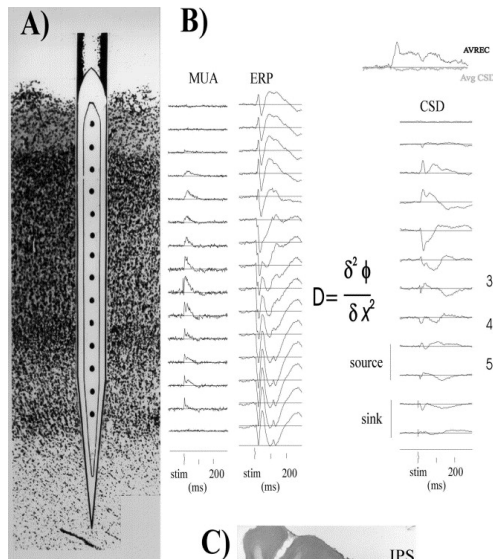
Electromagnetic recordings

100-1000micron

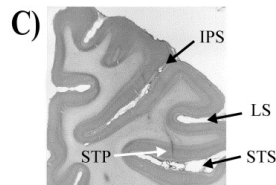
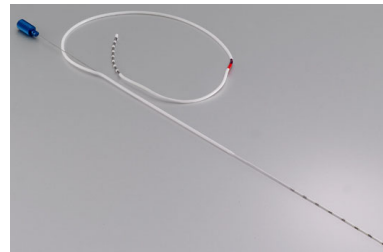
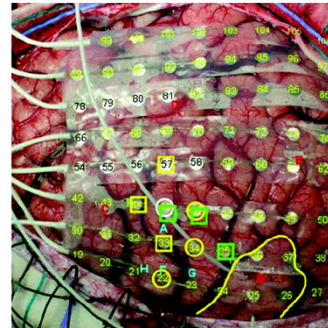
1-10mm

1cm-10cm

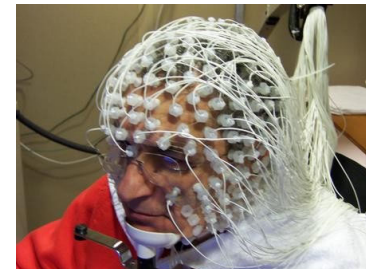
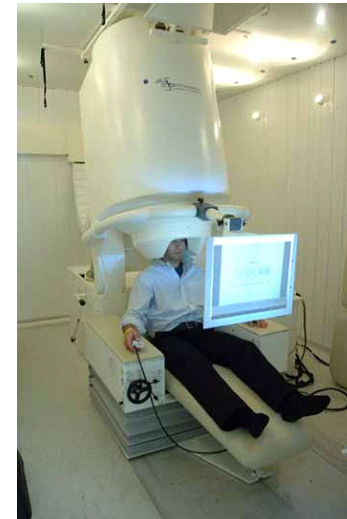
Micro electrodes



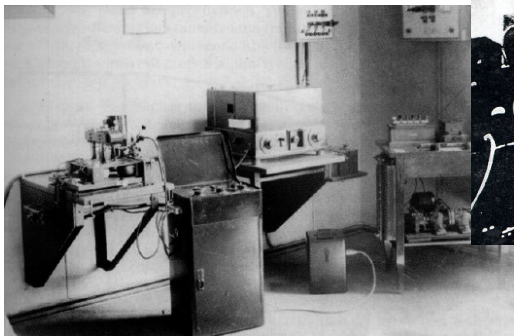
Depth Electrode



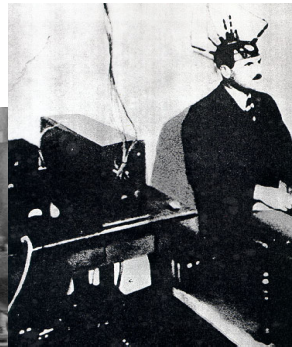
MEG EEG



Electroencephalography (EEG)



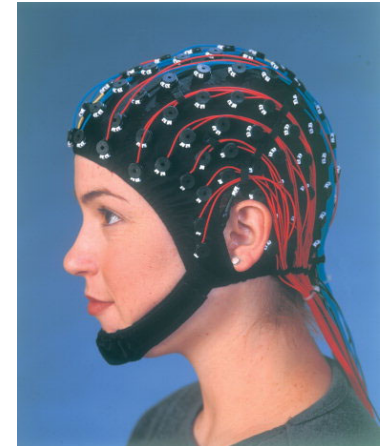
Hans Berger (1929)



Wearable Sensing

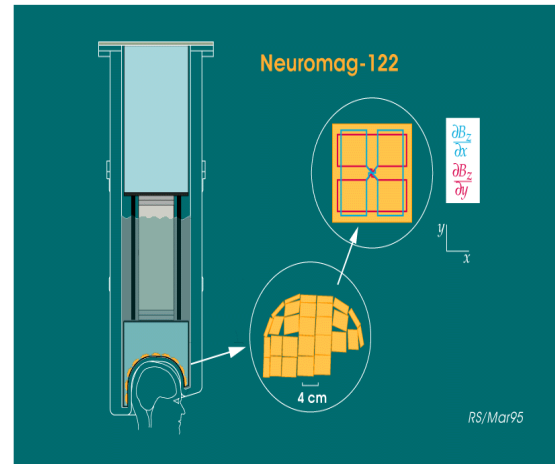
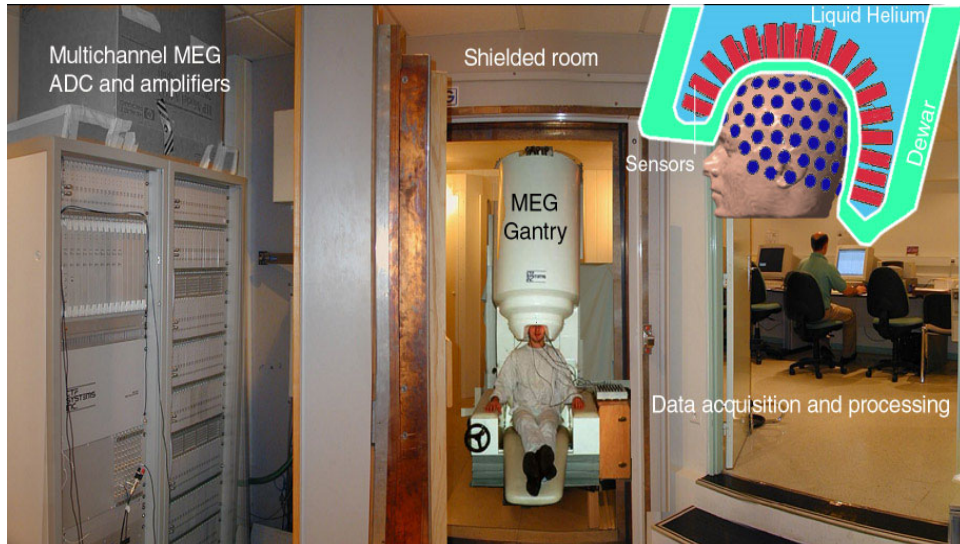


Electrical Geodesics



NeuroScan

Magnetoencephalography (MEG)



- MEG signals \sim 50-500fT (Earth's magnetic field \sim 50mT)
- Detected using SQUID magnetometers
- Gradiometers and magnetic screening reduce interference

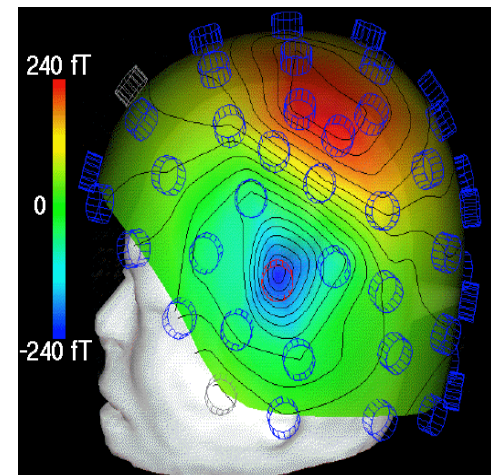
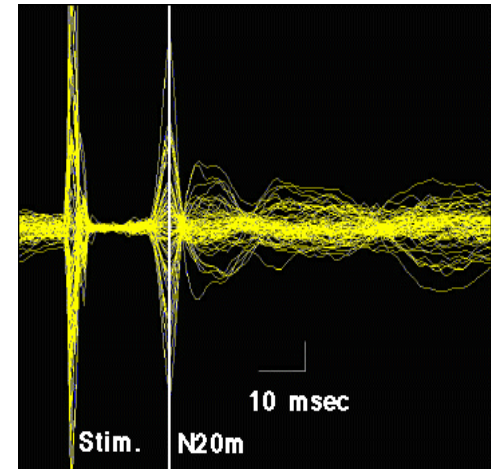
Magnetic Fields

B (Teslas)

10^{-4}	Earth's Field
10^{-5}	
10^{-6}	
10^{-7}	Urban Noise
10^{-8}	
10^{-9}	Lung Particles
10^{-10}	Human Heart
	Skeletal Muscles
10^{-11}	Human Eye
10^{-12}	Human Brain (α)
10^{-13}	Human Brain (evoked response)
10^{-14}	SQUID System
10^{-15}	Noise

Data

- **Temporal:** Averaged event-related signals - high temporal resolution monitoring of neural activation
- **Spatial:** Snap-shot topographic maps of external magnetic fields
- **Problem:** Explore relationship between neuronal sources in space and time and task or mental/neurological disorder
 - Evoked or event related studies
 - Naturalistic stimuli
 - Resting-state
 - Hyper-scanning



Median nerve stimulation
(MEG)

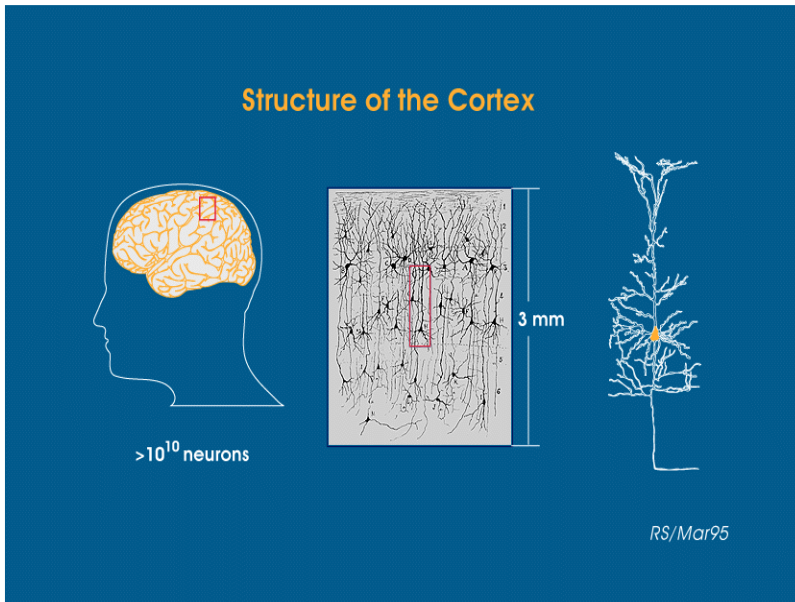
Challenges

- High temporal-resolution low spatial-resolution data
- Extraction of time-series features
 - Evoked potentials
 - Time-frequency analysis
 - Connectivity analysis
- Spatial localization
 - Lead-field sensitivity and forward models
 - Inverse solutions
 - Identifying regional sources
- Statistical Analysis
 - Individual vs. group analysis
 - Parametric vs. nonparametric methods
 - ANOVA and GLMs
 - Machine Learning for regression, classification and prediction (tomorrow!)

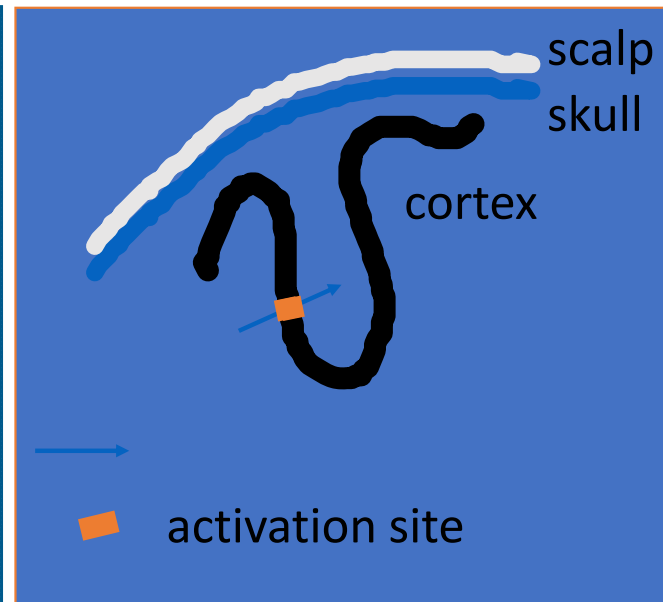
Source Estimation

Sources of the EEG and MEG Signal

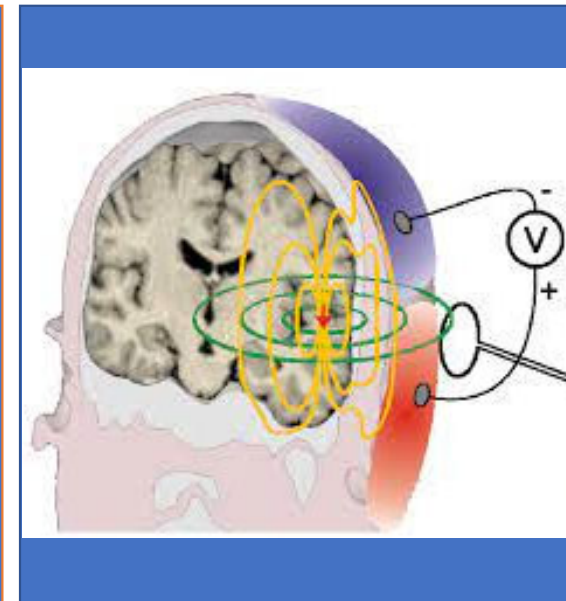
Scalp potentials and extra-cranial magnetic fields are produced by current flow in apical dendrites in cortical pyramidal neurons



from Ritta Salmelin, low temperature lab, Helsinki university of Technology

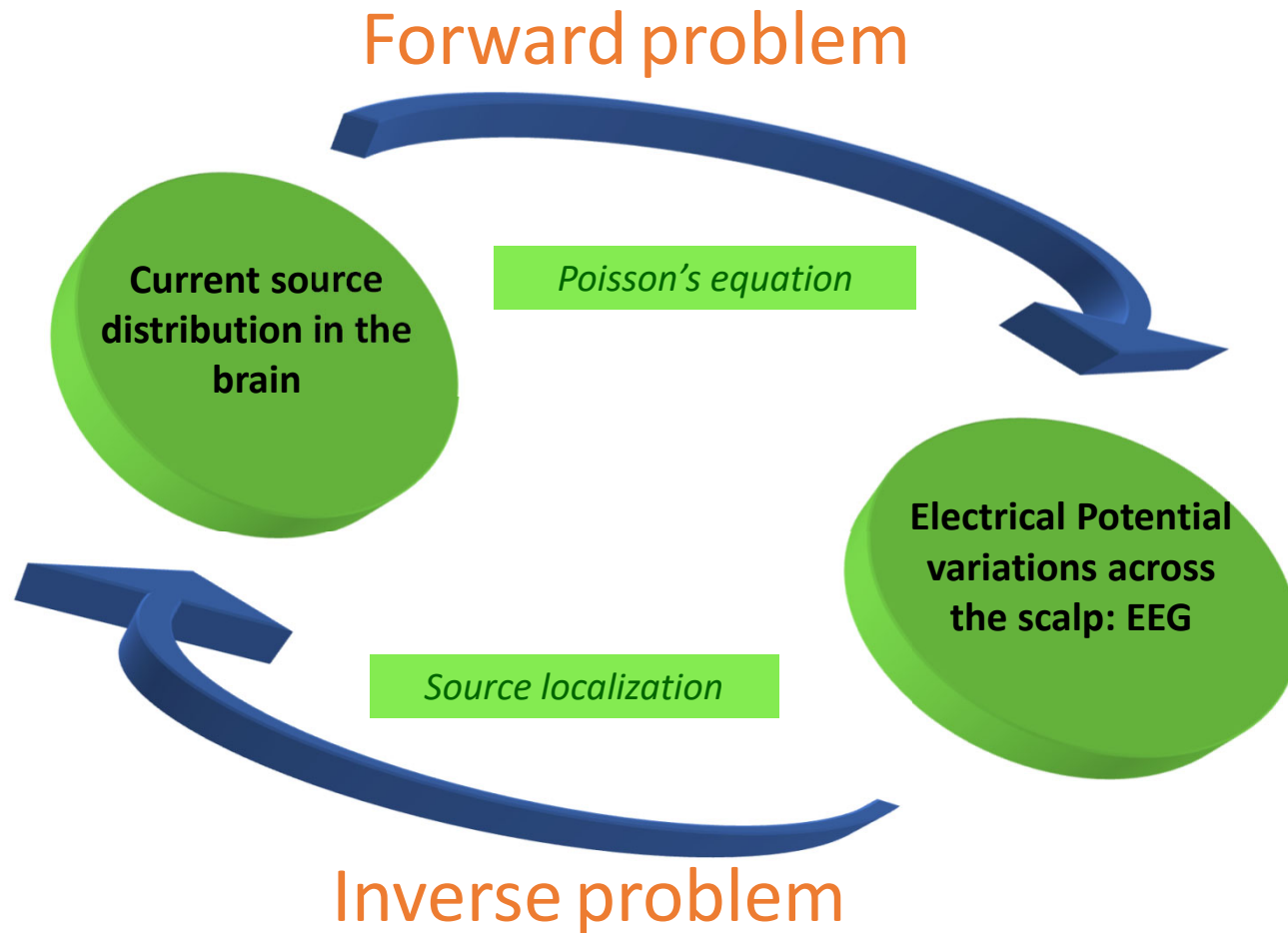


Columnar organization of cortex and spatial functional specialization on cortical surface lead to **current dipole model** for focal regions of activation



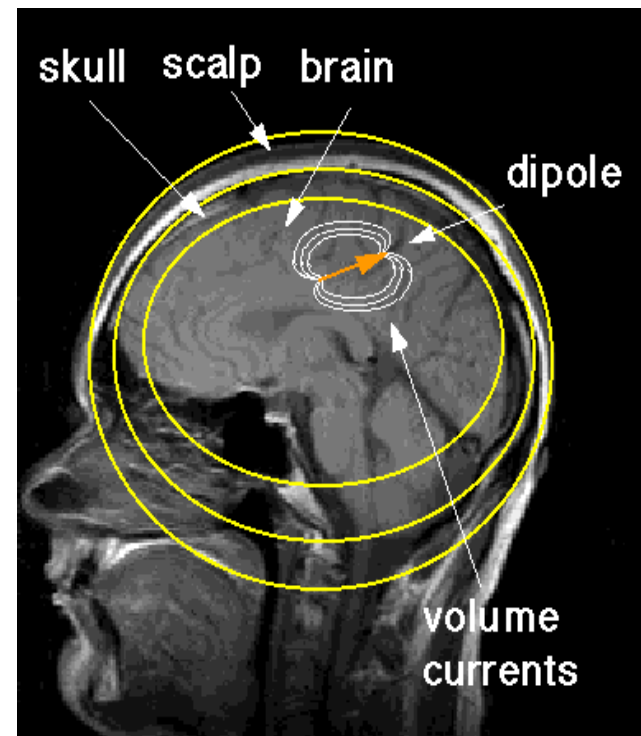
Volume currents from dipole pass through the skull to produce spatially varying potentials on the scalp and the EEG

Forward and Inverse Problems

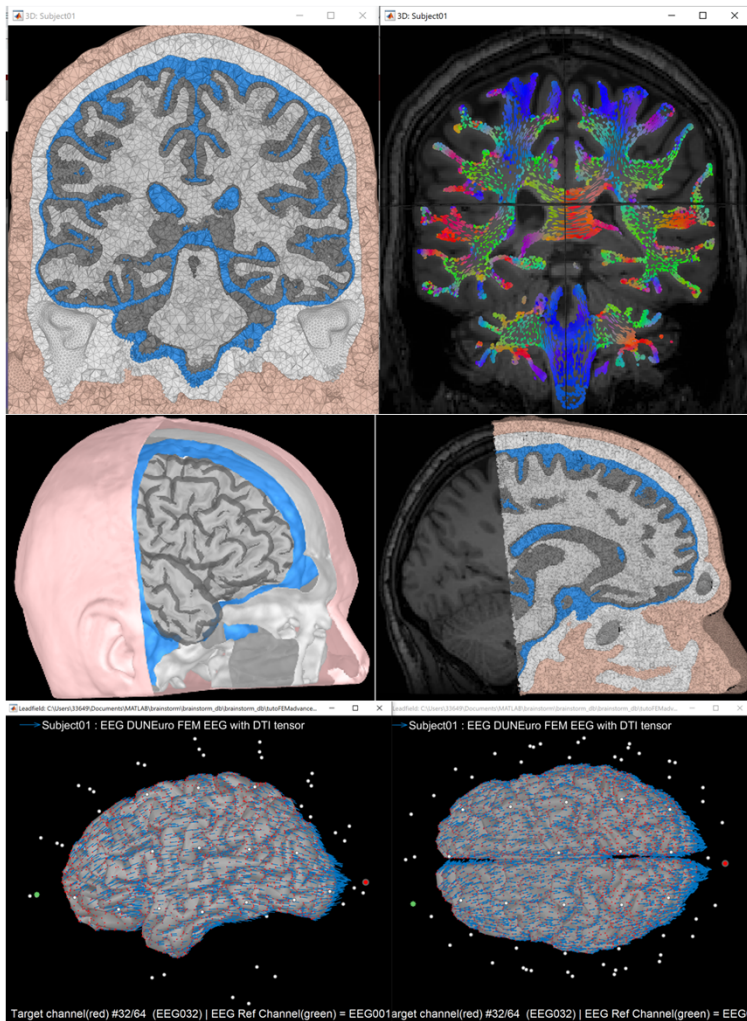


Forward Models

- Use quasistatic EM model to map from current source to measured fields
- Interested in “primary” rather than “volume” currents
- Spherical head: closed form
- Real head shape & conductivity from MR: use BEM or FEM



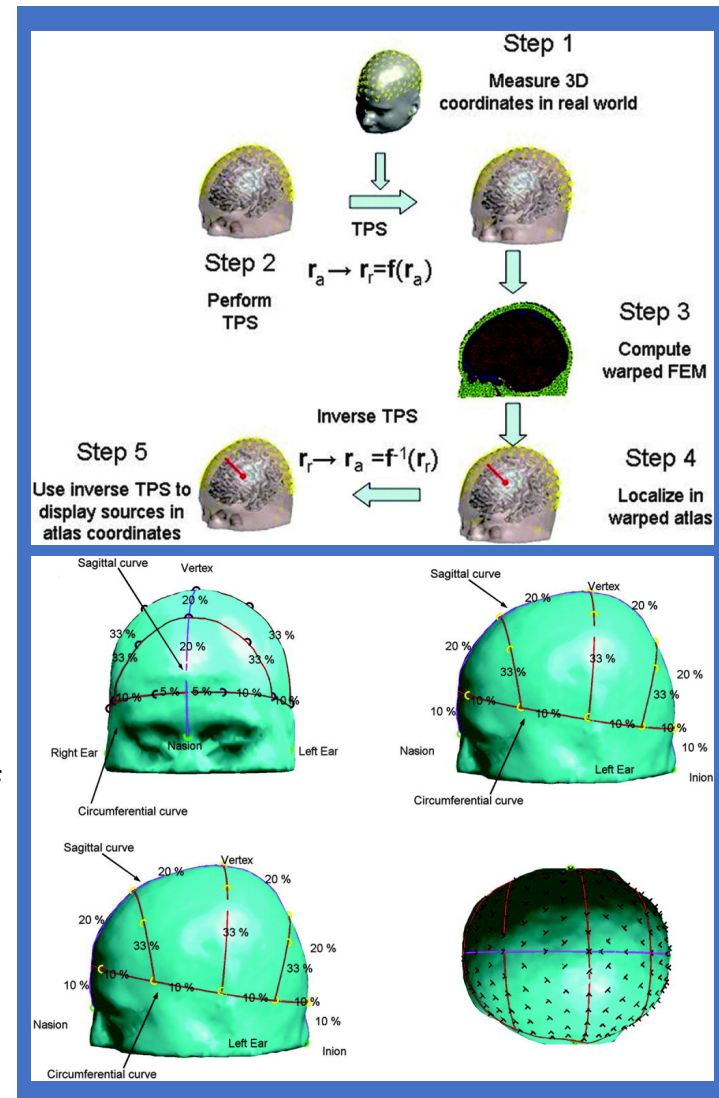
Individualized Forward Models



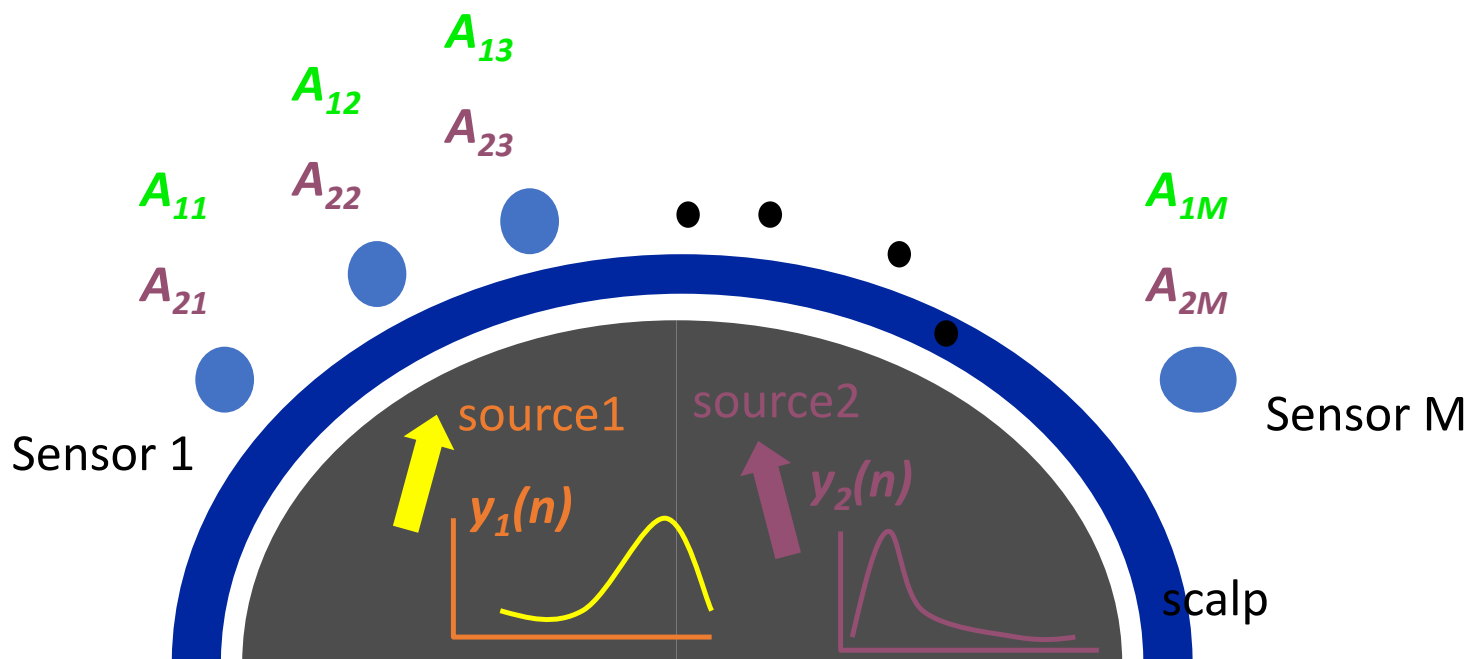
Detailed forward model based on segmented MRI with anisotropic diffusion from DW-MRI

Lower panel shows lead-field sensitivity for a pair of electrodes

In absence of individual MRI, use Polhemus localized to map scalp coordinates and warp atlas to individual subject

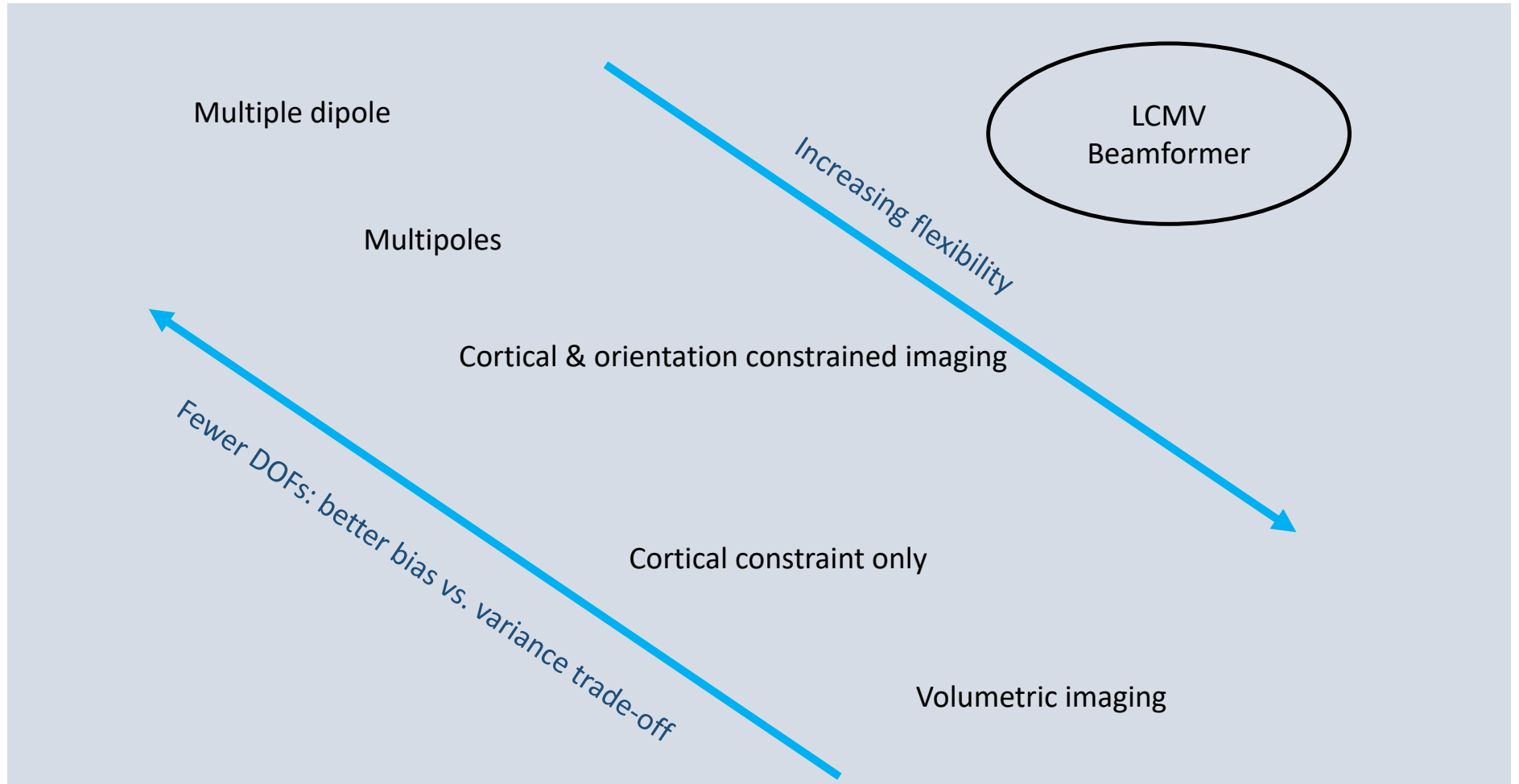


The inverse problem for multiple sources

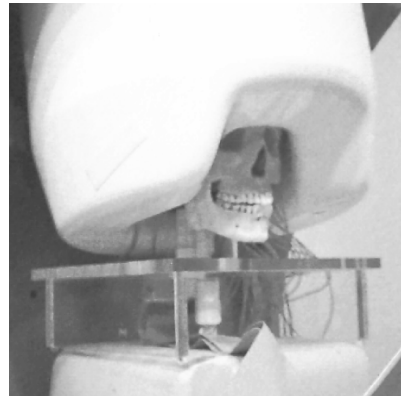
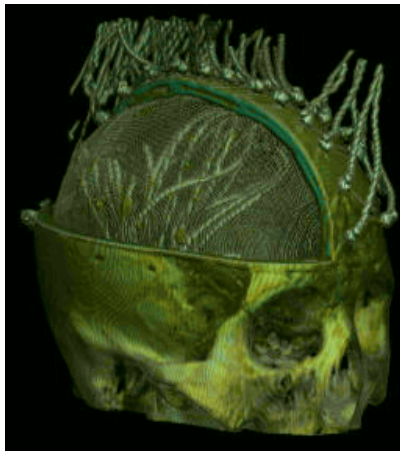


$$\begin{bmatrix} \mathbf{b}_1(\mathbf{n}) \\ \vdots \\ \mathbf{b}_M(\mathbf{n}) \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{21} \\ \vdots & \vdots \\ \mathbf{A}_{1M} & \mathbf{A}_{2M} \end{bmatrix} \begin{bmatrix} \mathbf{y}_1(\mathbf{n}) \\ \mathbf{y}_2(\mathbf{n}) \end{bmatrix} \quad n = 1, \dots, N$$

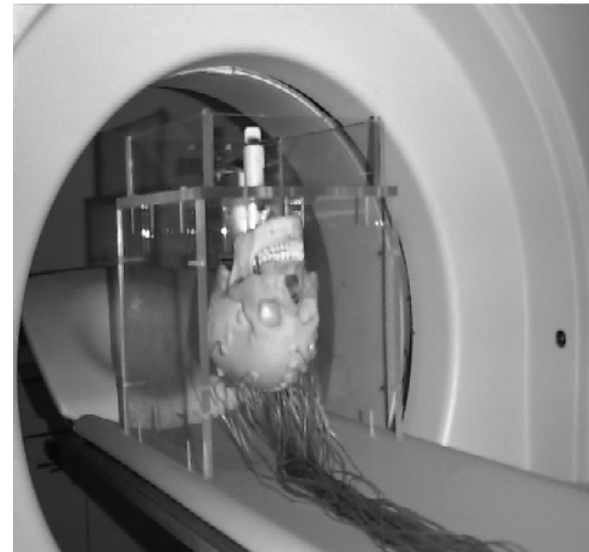
Explicit & Implicit Models



Phantom Study

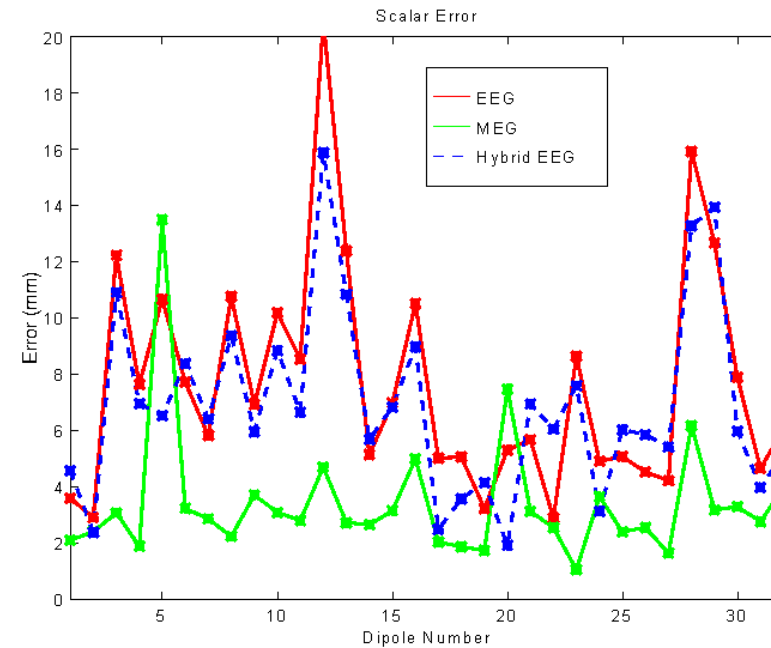
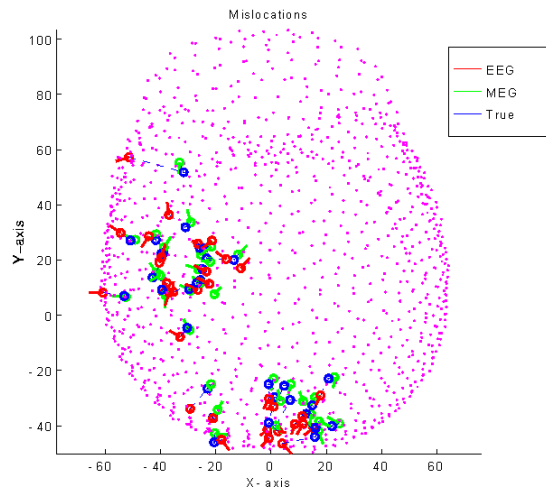


- 32 current dipoles in human skull phantom
- Ground truth from CT scan
- MEG data from Neuromag-22
- Sources fit using R-MUSIC, spherical and realistic BEM forward models

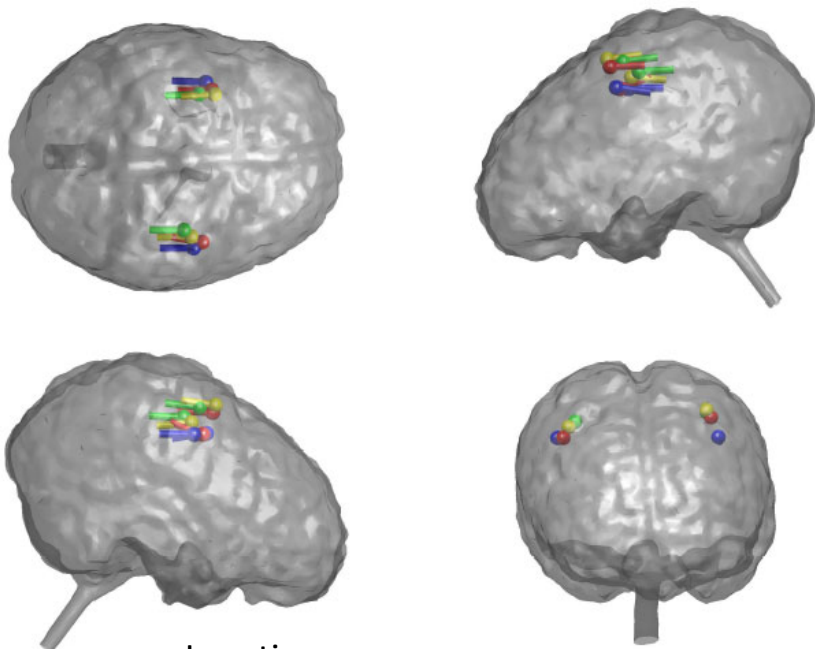


Phantom Localization Errors

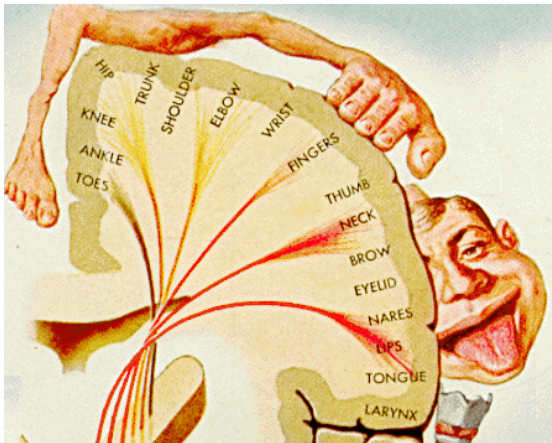
- Average error for 32 dipoles using spherical head model: 4.1mm
- Average error for 32 dipoles using BEM head model: 3.4mm



RM Leahy, JC Mosher, ME Spencer, MX Huang, JD Lewine (1998) A study of dipole localization accuracy for MEG and EEG using a human skull phantom, *Electroencephalography and clinical neurophysiology* 107 (2), 159-173

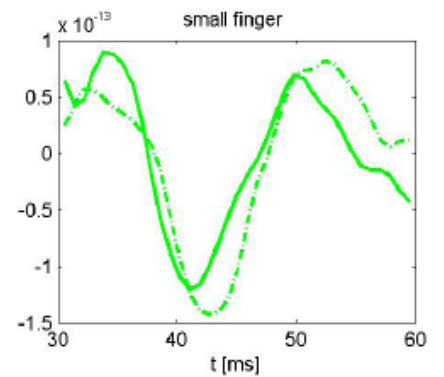
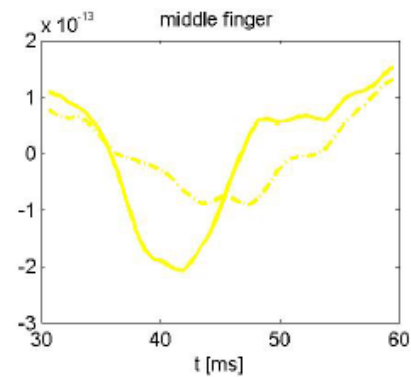
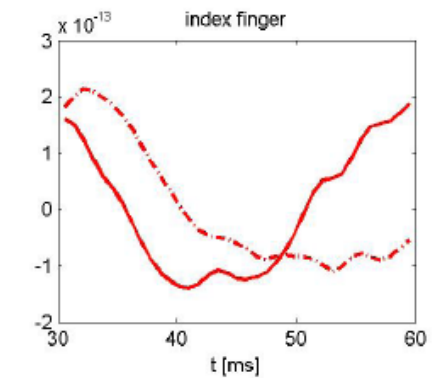
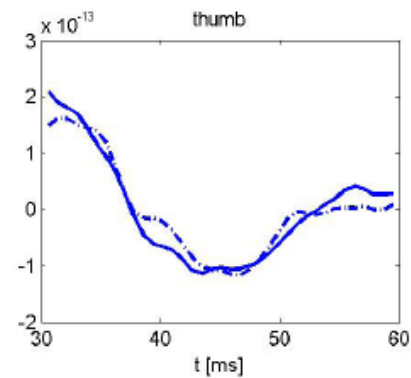


Locations



Somatosensory Stimulation & Localization

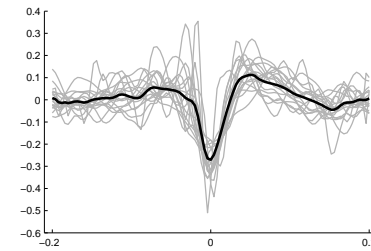
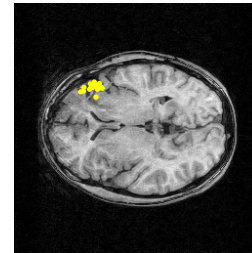
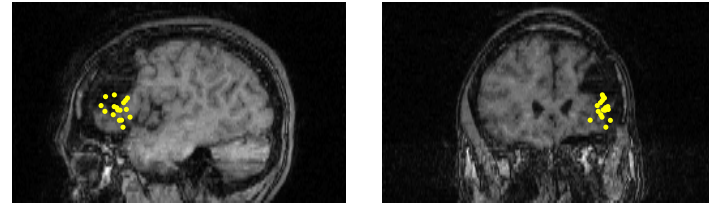
Electric stimulation of 4 digits of left and right hand



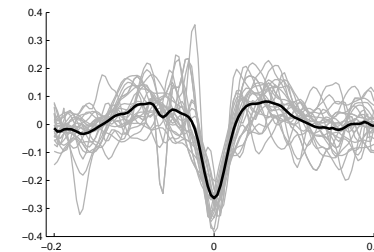
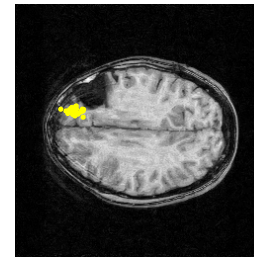
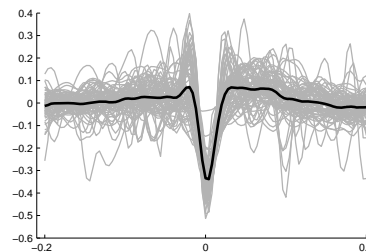
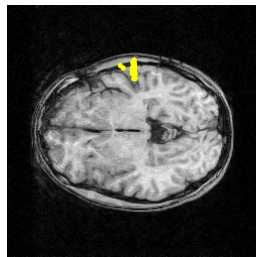
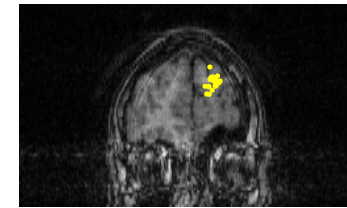
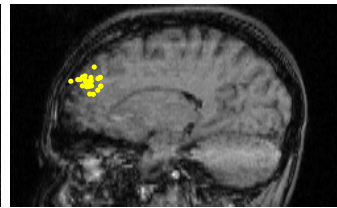
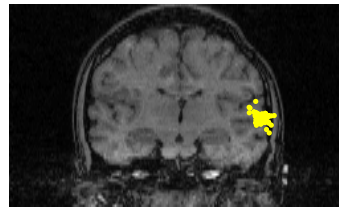
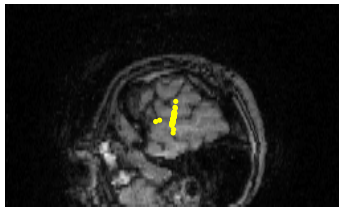
Time series

Source localization in Epilepsy

Automated noninvasive spike detection,
localization and clustering from spontaneous
interictal spikes



Cluster 2



Cluster 1

Cluster 3

Distributed solutions: Minimum Norm Imaging

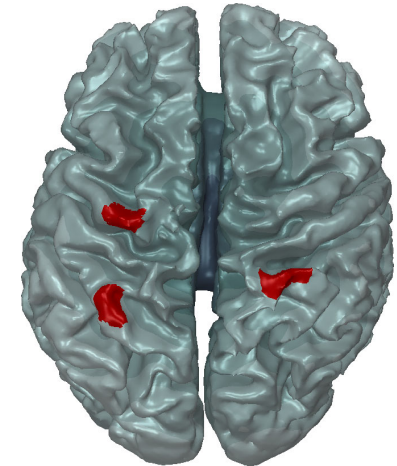
Inverse solutions based on regularized least-squares

$$\min \|\mathbf{b} - \mathbf{A}\mathbf{y}\|_2^2 + \lambda \|\mathbf{W}\mathbf{y}\|_2^2$$

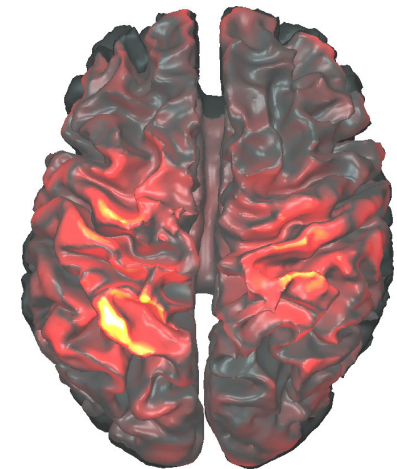
Possible regularizers

$$\left\{ \begin{array}{l} \mathbf{W} = \mathbf{I} \\ \mathbf{W} = \mathbf{W}_{\text{norm}} = \text{diag}[1/\|a_1\|, \dots, 1/\|a_N\|] \\ \mathbf{W} = \mathbf{W}_{\text{norm}}\mathbf{B} \end{array} \right.$$

- Problem is highly ill-posed (relative to CT/MRI)
- Alternatives use non-quadratic regularizers, sparse and Bayesian formulations....
- Data-fit error often weighted by inverse noise-covariance



Simulated

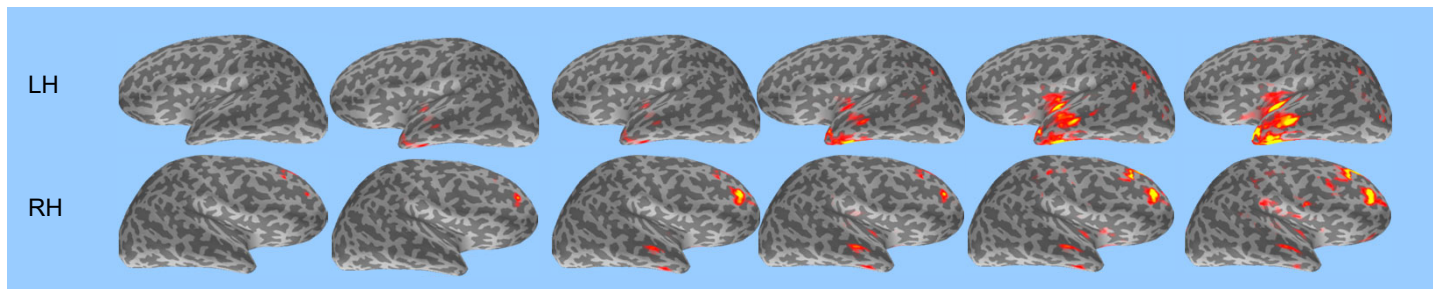


Estimated

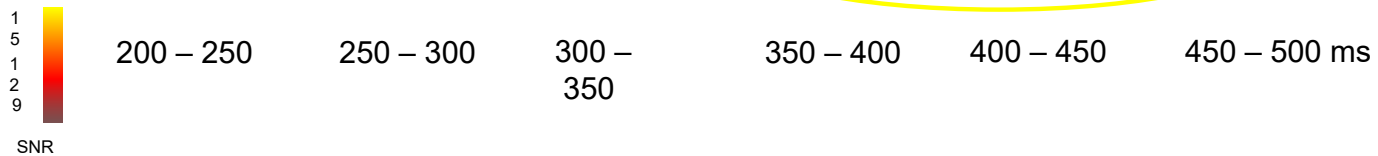
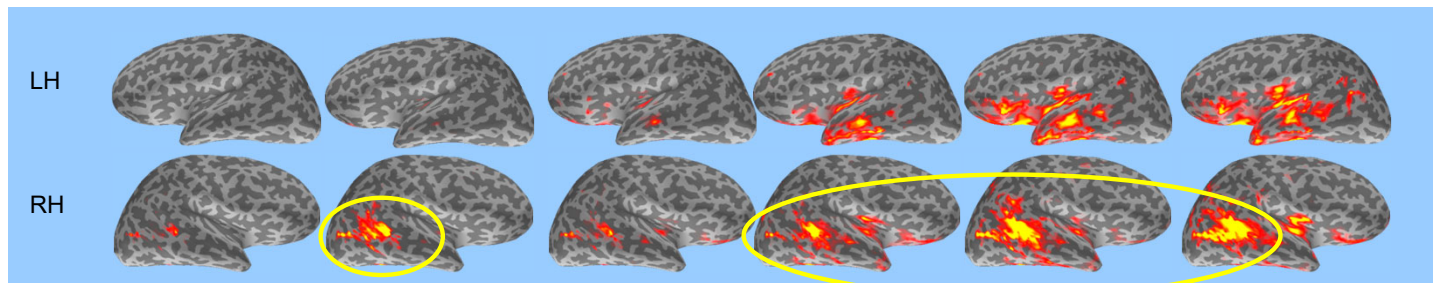
MEG in an auditory oddball task

**Phonologically similar words (|bøt| vs. |pøt|)
Group analysis of the rare |pøt| in 7 – 13 year olds**

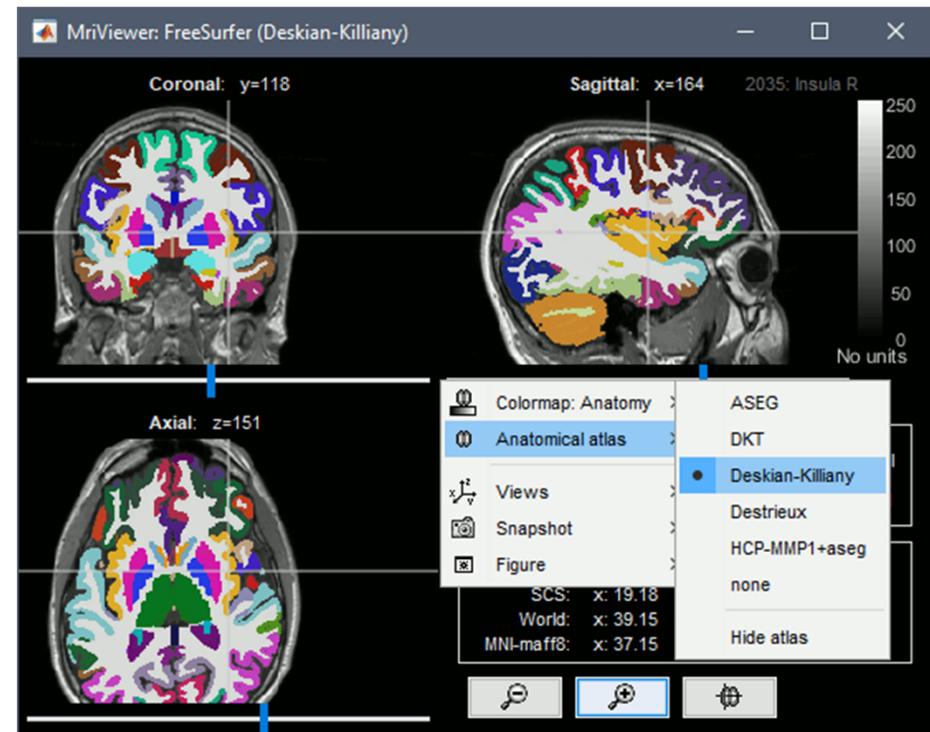
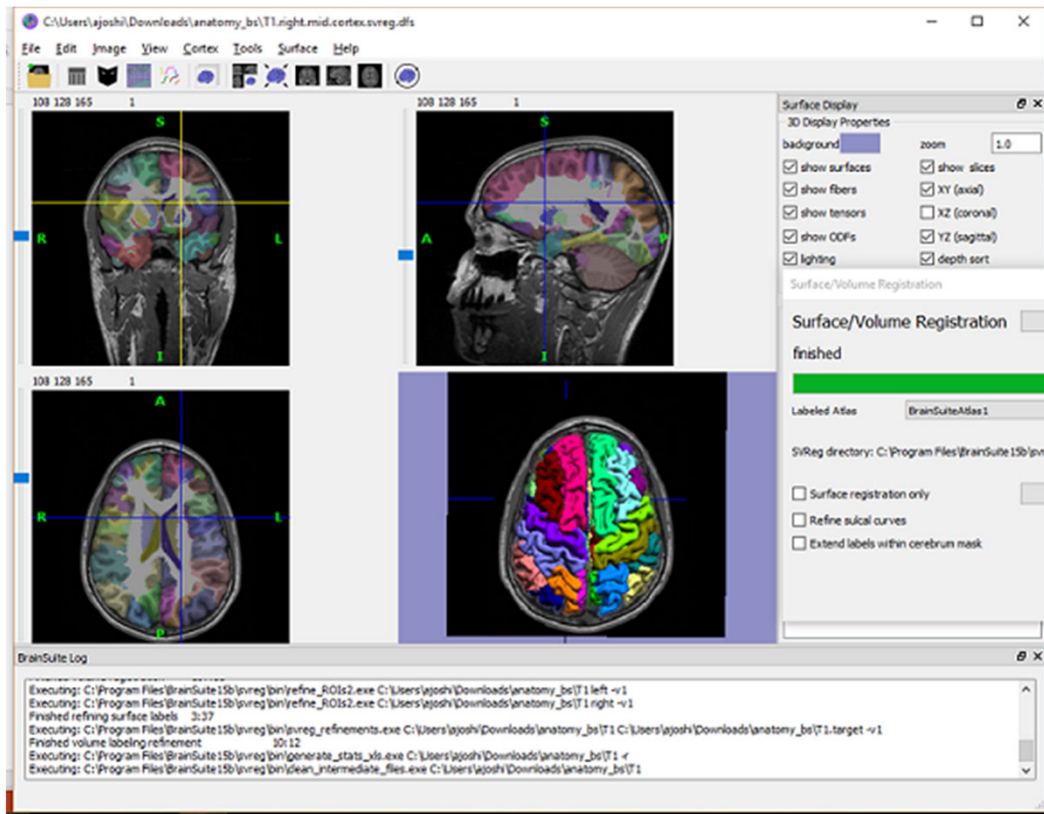
Normal readers



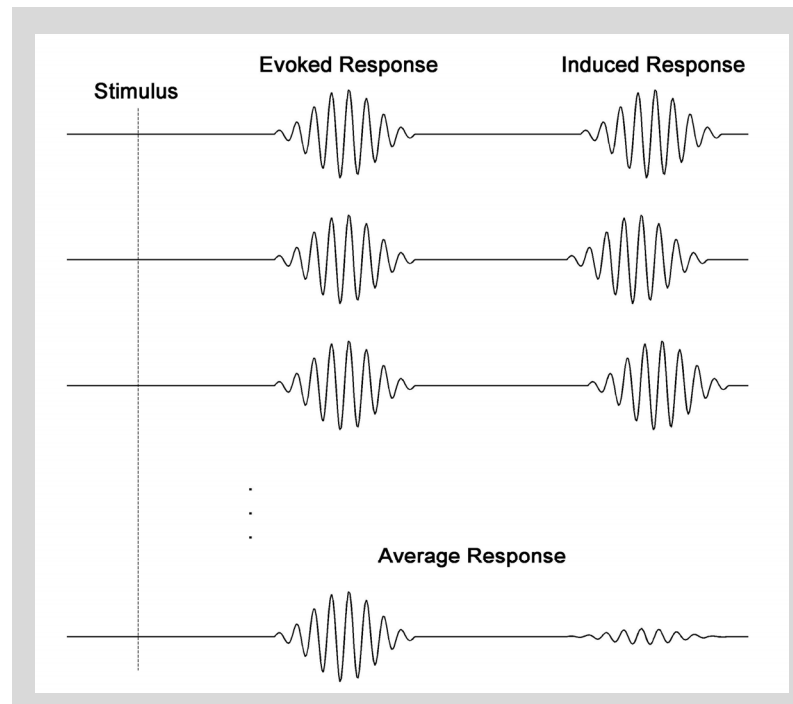
Impaired readers



We can quantify neuronal activity over ROIs in parcellated atlas

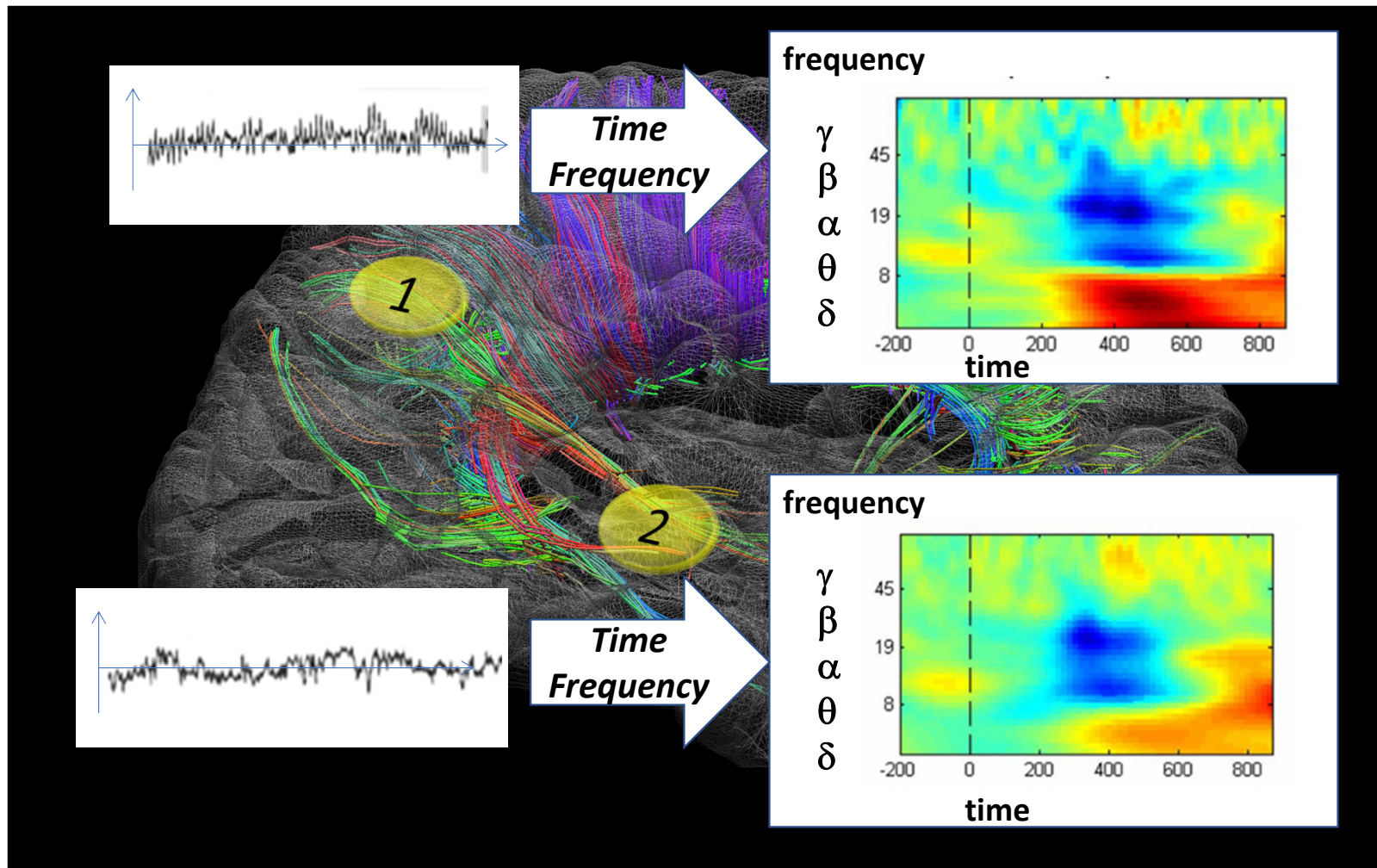


Evoked vs. Induced Response



- **Evoked response:** Precisely phase locked to the stimulus, averaging increases signal
- **Induced response:** Variable latency, averaging leads to signal cancellation – instead we average over the time-frequency magnitude

Spatio-temporal complexity



EEG analysis using TF data

Energy Statistic

$$E^{stf} = |C^{stf}|^2$$

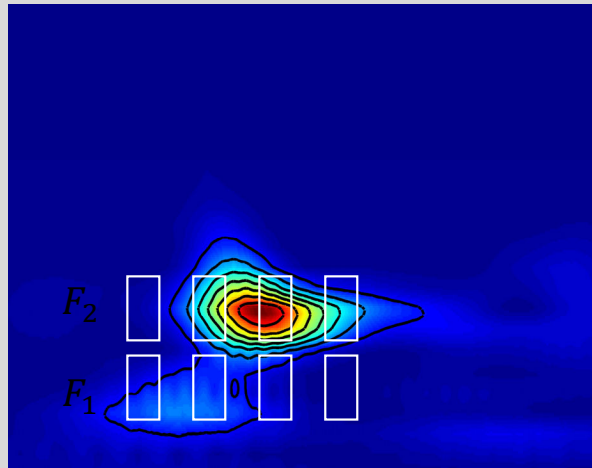
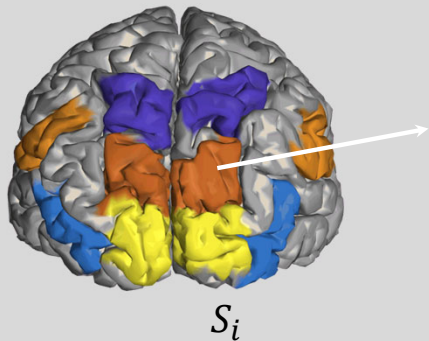
$$E^{STF} = \iiint_{(s,t,f) \in (S,T,F)} |C^{stf}|^2 ds dt df$$

$$T = [t_1, t_2]$$

$$F = [f_1, f_2]$$

S = cortical ROI

Regions of Interest (ROIs)



T_1 T_2 T_3 T_4

Time-Frequency

Space

ANCOVA Model

$$E_{ijl}^{STF,k} = \mu_{ij}^{STF,k} + \beta_j^{STF,k} c_{ijl}^{STF,k} + \rho_{il}^{STF,k} + \varepsilon_{ijl}^{STF,k}$$

Energy Observations Cue/Hem main effect Baseline Covariate Within trial Correlation i.i.d. Error
 $\mu_{ij}^{STF,k}$ Subject index
 $c_{ijl}^{STF,k}$ Cue R/L Repetition index
 $\rho_{il}^{STF,k}$ Hemisphere R/L

Matrix Form

$$\mathbf{E}^{STF,k} = \mathbf{X}\mathbf{b}^{STF,k} + \boldsymbol{\varepsilon}^{STF,k}$$

	μ_{11}	μ_{12}	μ_{21}	μ_{22}	β_1	β_2	ρ_{11}	ρ_{21}	ρ_{12}	ρ_{22}
Hem R	1						1			
Hem L		1						1		
Hem R			1						1	
Hem L				1						1
	1									1
		1								1
			1							1
				1						1

Hem R } Trial 1, cue right
 Hem L }
 Hem R } Trial 2, cue left
 Hem L }

Shift vs. sustain in visual attention task – effects on alpha power

SPL: Superior Parietal Lobe

TPJ: Temporal Parietal Junction

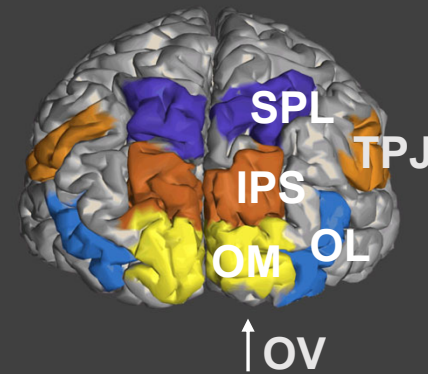
IPS: Intra-Parietal Sulcus

OL: Occipital Lateral

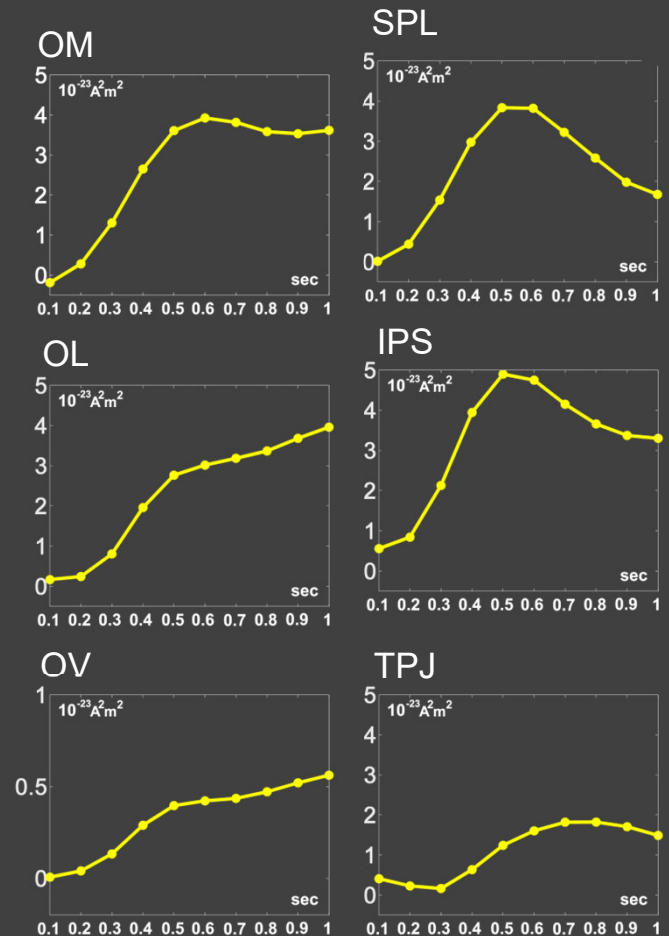
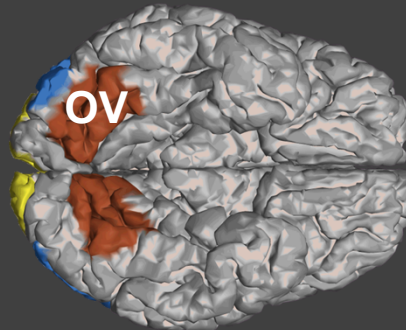
OM: Occipital Middle

OV: Occipital Ventral

Caudal

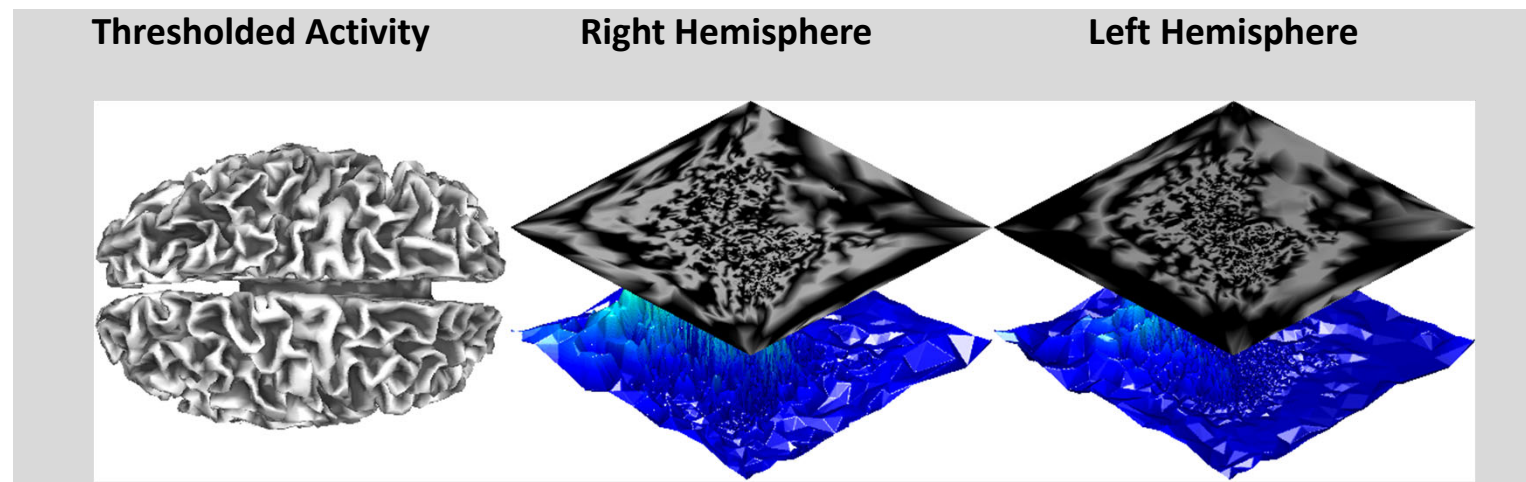
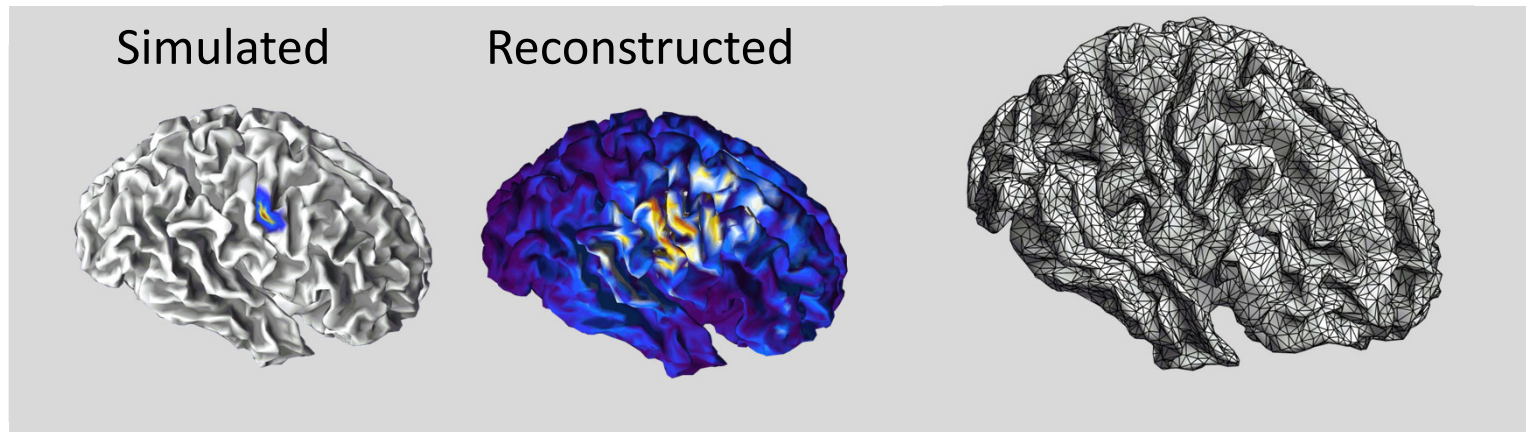


Ventral



D Pantazis, G Simpson, D. Weber, CL Dale, TE Nichols, RM Leahy (2009) A novel ANCOVA design for analysis of MEG data with application to a visual attention study, Neuroimage. 44(1): 164–174.

Detecting Statistically Significant Activation: Thresholding



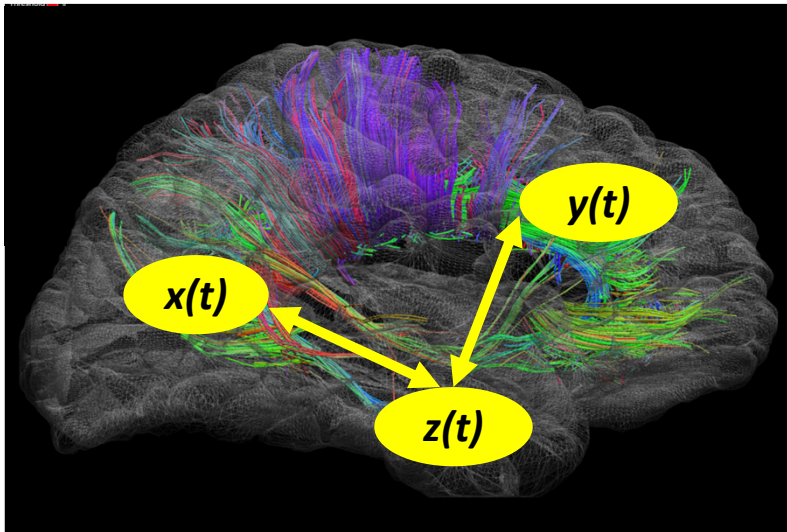
Multiple comparisons

- Control of False Discovery Rate
- Control of Familywise Error Rate

Assumptions

- Parametric model – p-values from distribution
- Nonparametric model: p-values from permutations

Connectivity Analysis



Computer interactions between two or more regions in the brain

PAIRWISE MEASURES	NETWORK MODELS
Correlation	Partial correlation
Coherence	Partial coherence
Phase coupling	Partial phase coupling
Phase/ampl. coupling	???
Canonical correlation	Partial canonical correlation
Granger causality	Directed transfer function
	Independent Components Analysis
	Dynamic causal modeling
	Bayesian networks

Summary

- EEG/MEG can provide unique insights into human brain function through studies of fast temporal dynamics, focal and regional activation, studies of oscillatory activity and connectivity
- Cautionary factors:
 - Limited spatial resolution
 - EEG/MEG signals are complex – mix of event-related and un-related activity
 - Noise: environmental, cardiac, eye-blink, EMG
 - Inter-trial variability