

Functional High-Definition Imaging of EEG Brain Dynamics



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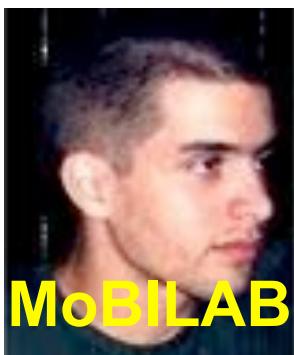
13th EEGLAB Workshop
Aspet, France
June 2011



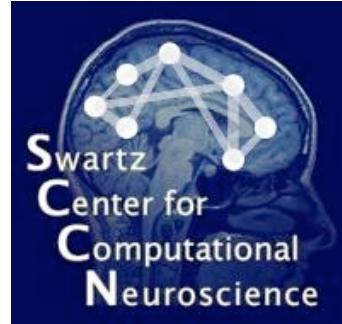
Arnaud Delorme



Jason Palmer



Alejandro Ojeda



EEGLAB



TEACH

Julie Onton



Tony Bell



Christian Kothe



Tim Mullen



Zeynep
Akalin Acar



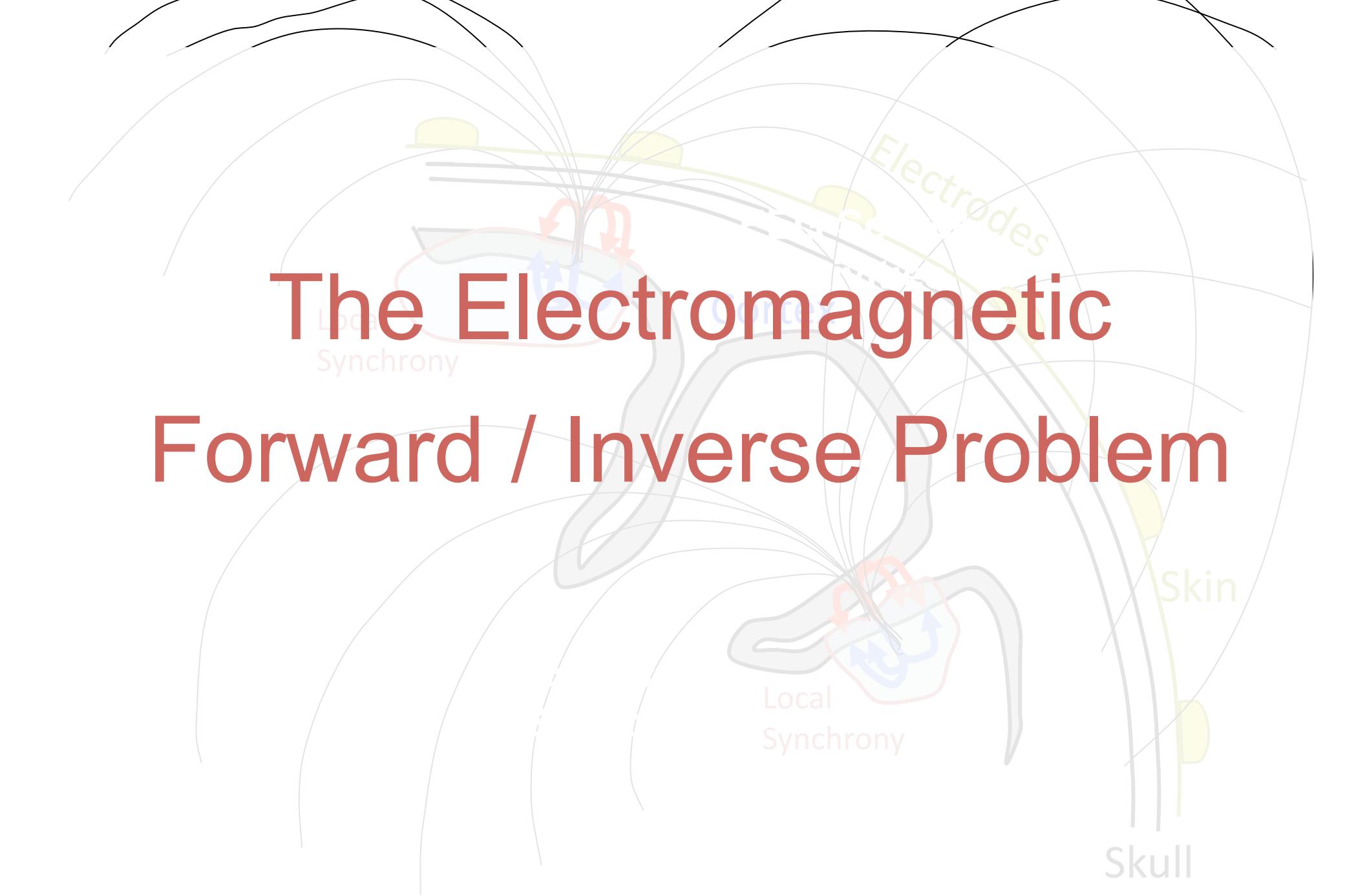
MUET
David Groppe



DRY EEG
Tzzy-Ping Jung



MPT
Nima Bigdely
Shamlo



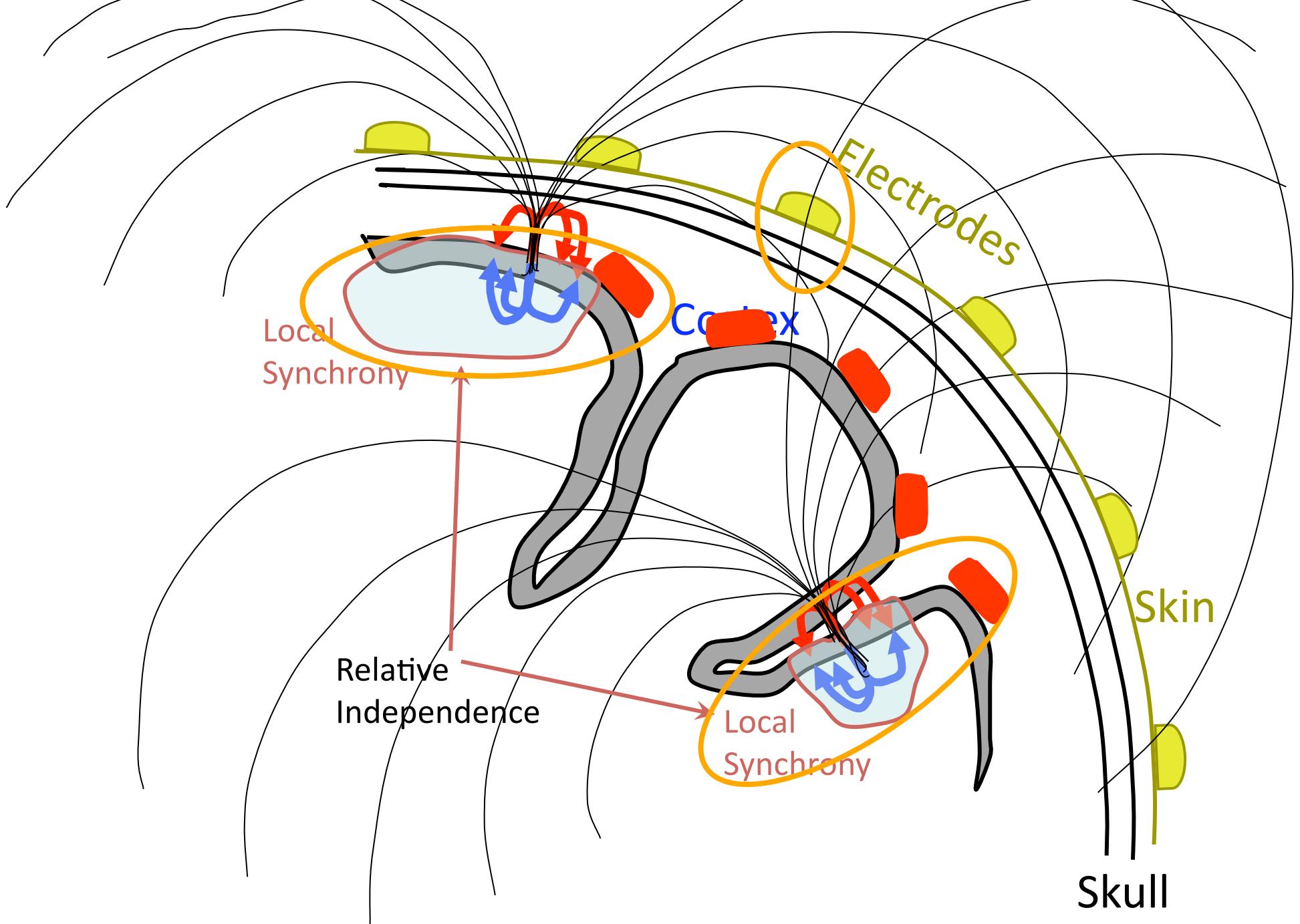
The Electromagnetic Forward / Inverse Problem

Phase cones (Freeman)

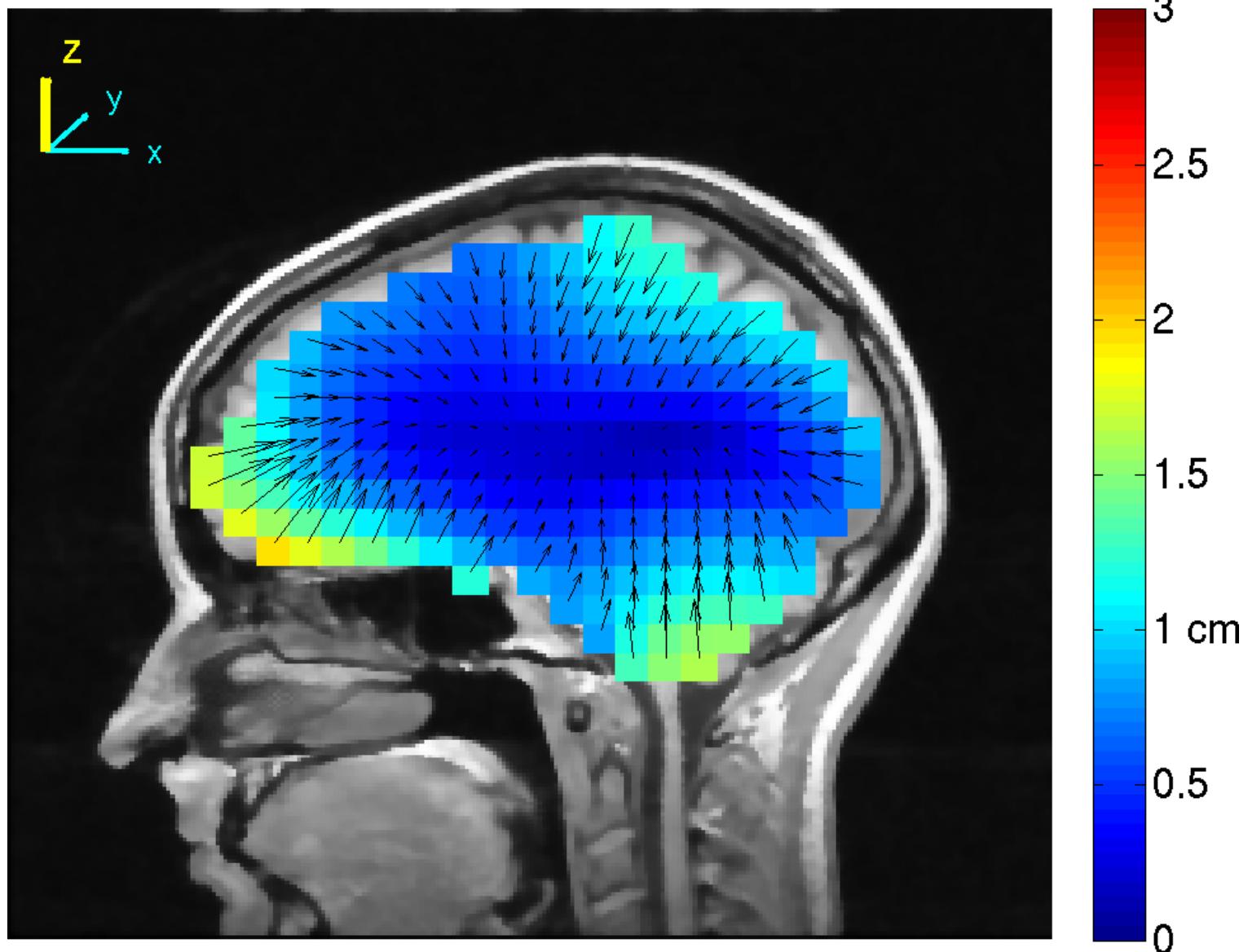
Avalanches (Plenz)



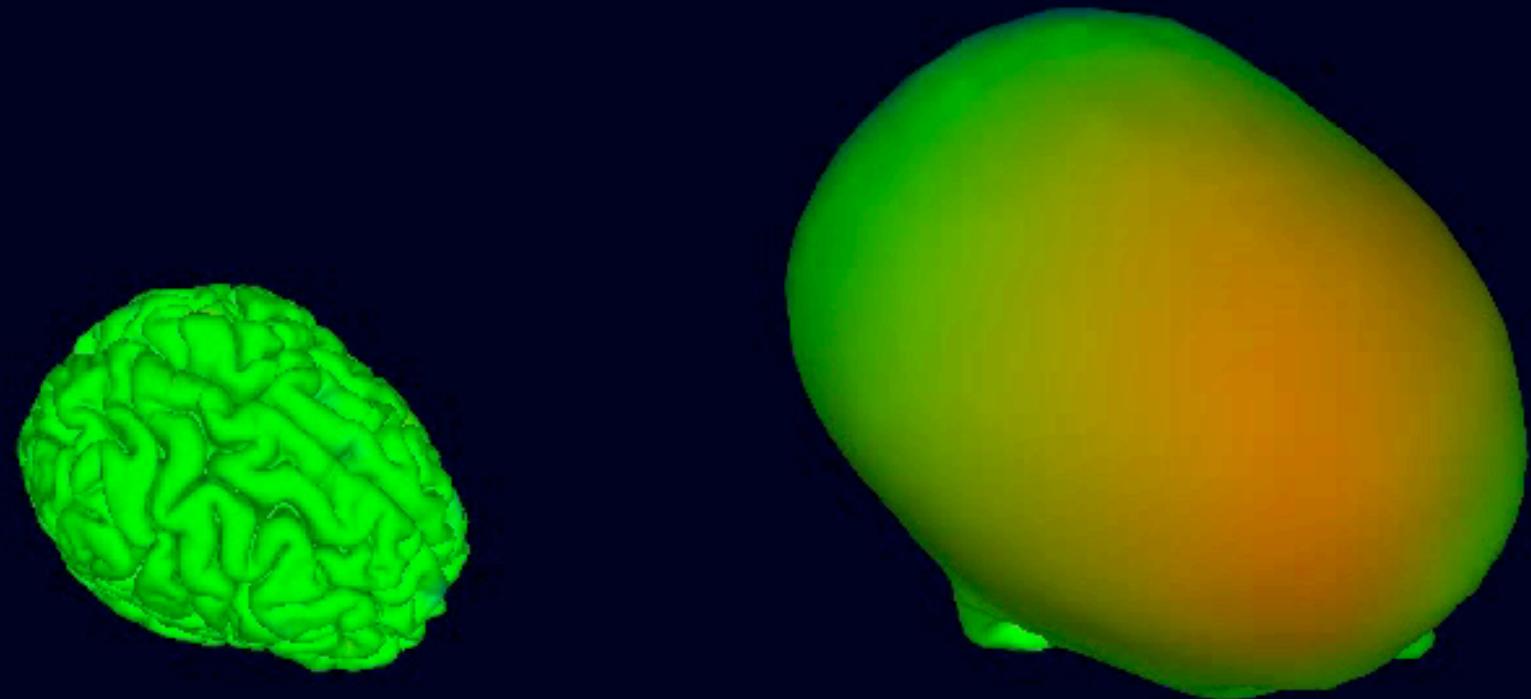
S. Makeig 2007



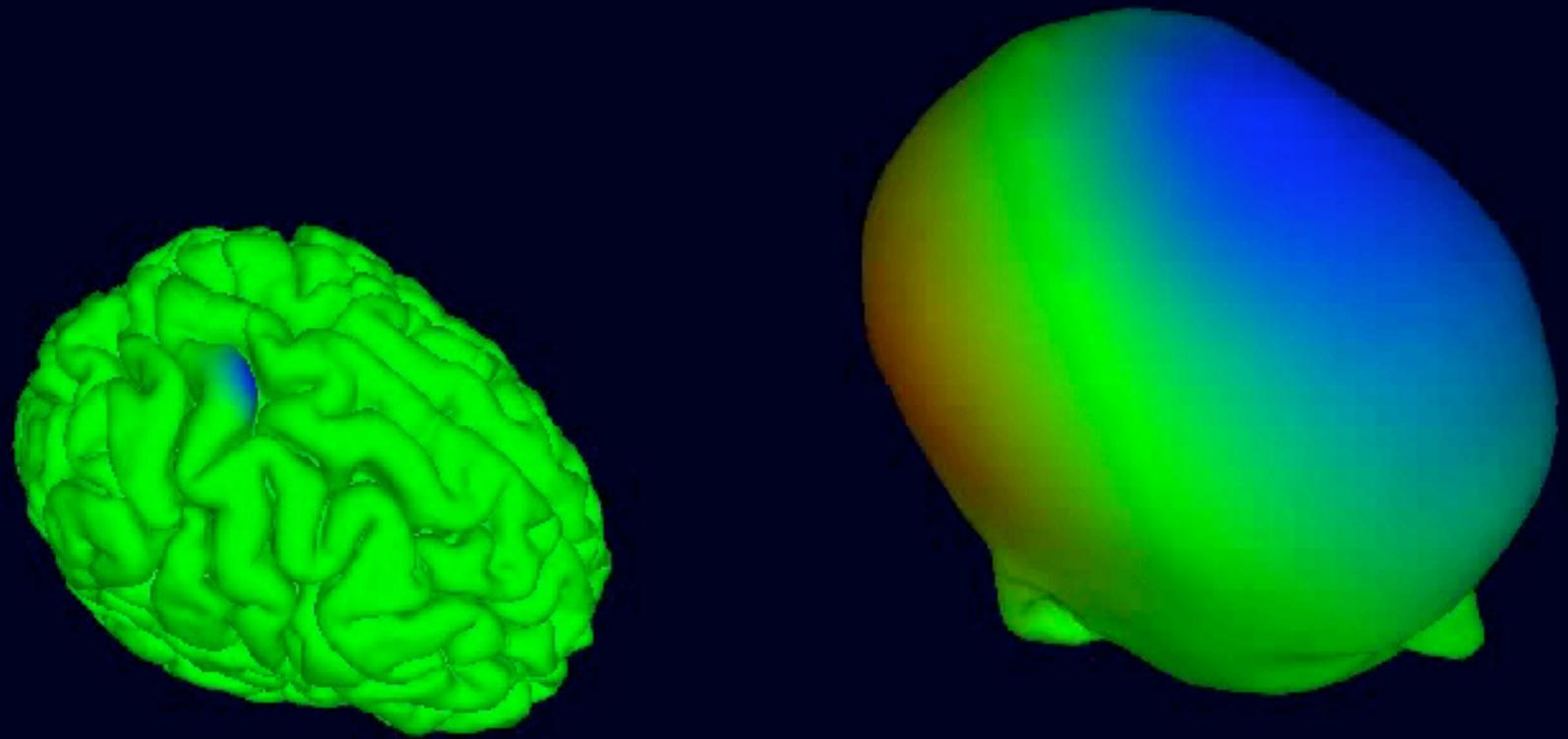
Electromagnetic source localization using realistic head models → The NFT toolbox



The very broad EEG point-spread function



The very broad EEG point-spread function

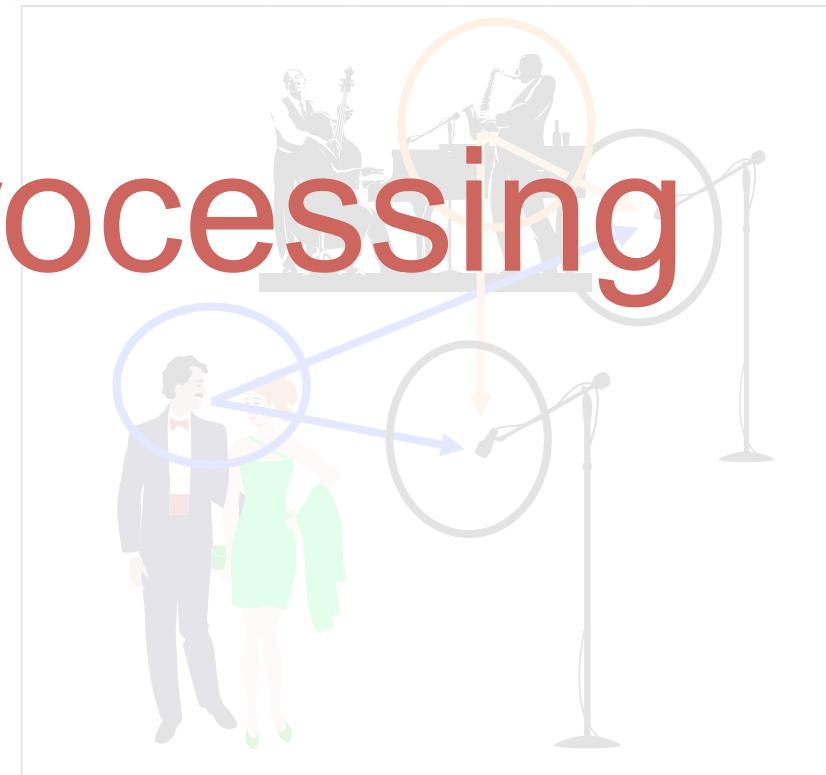
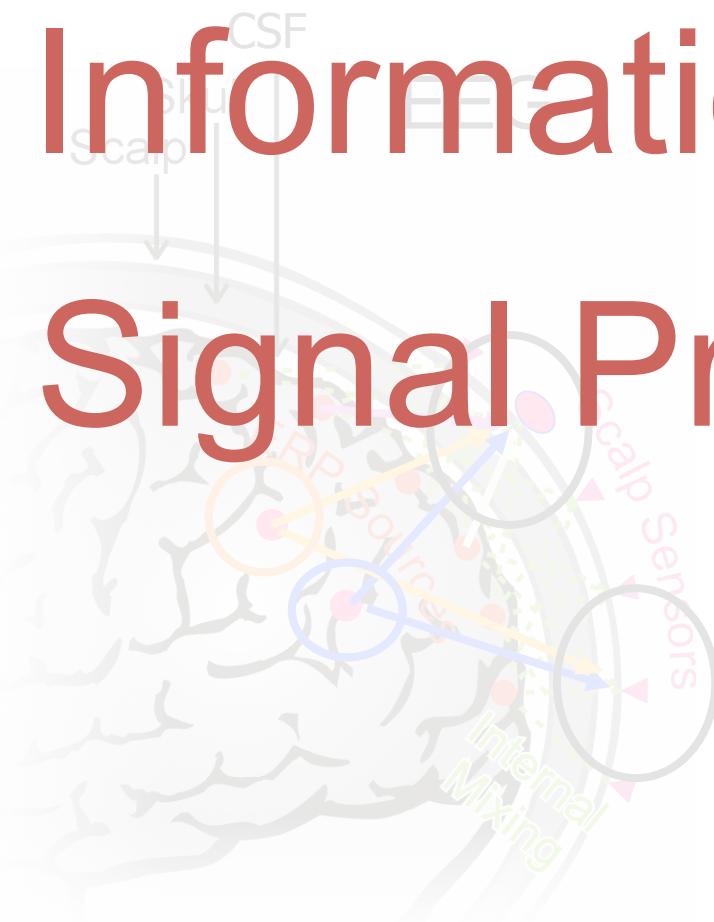


Simulated spatially labile (traveling wave) parietal source activity

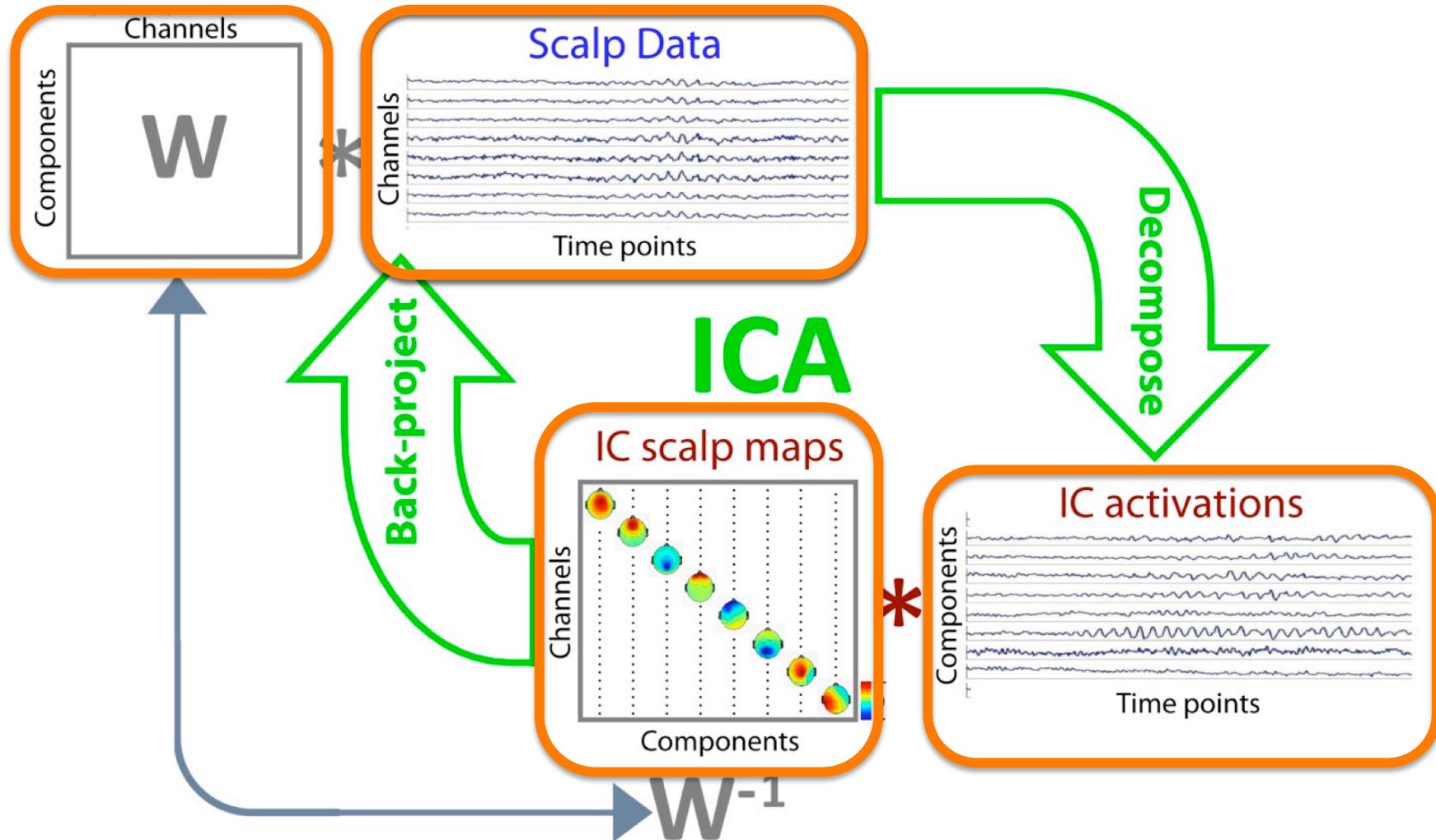
Akalin Acar & Makeig 2010

Blind EEG Source Separation by ICA

Information-based Signal Processing



ICA is a linear decomposition



Independent Component Analysis of Electroencephalographic Data



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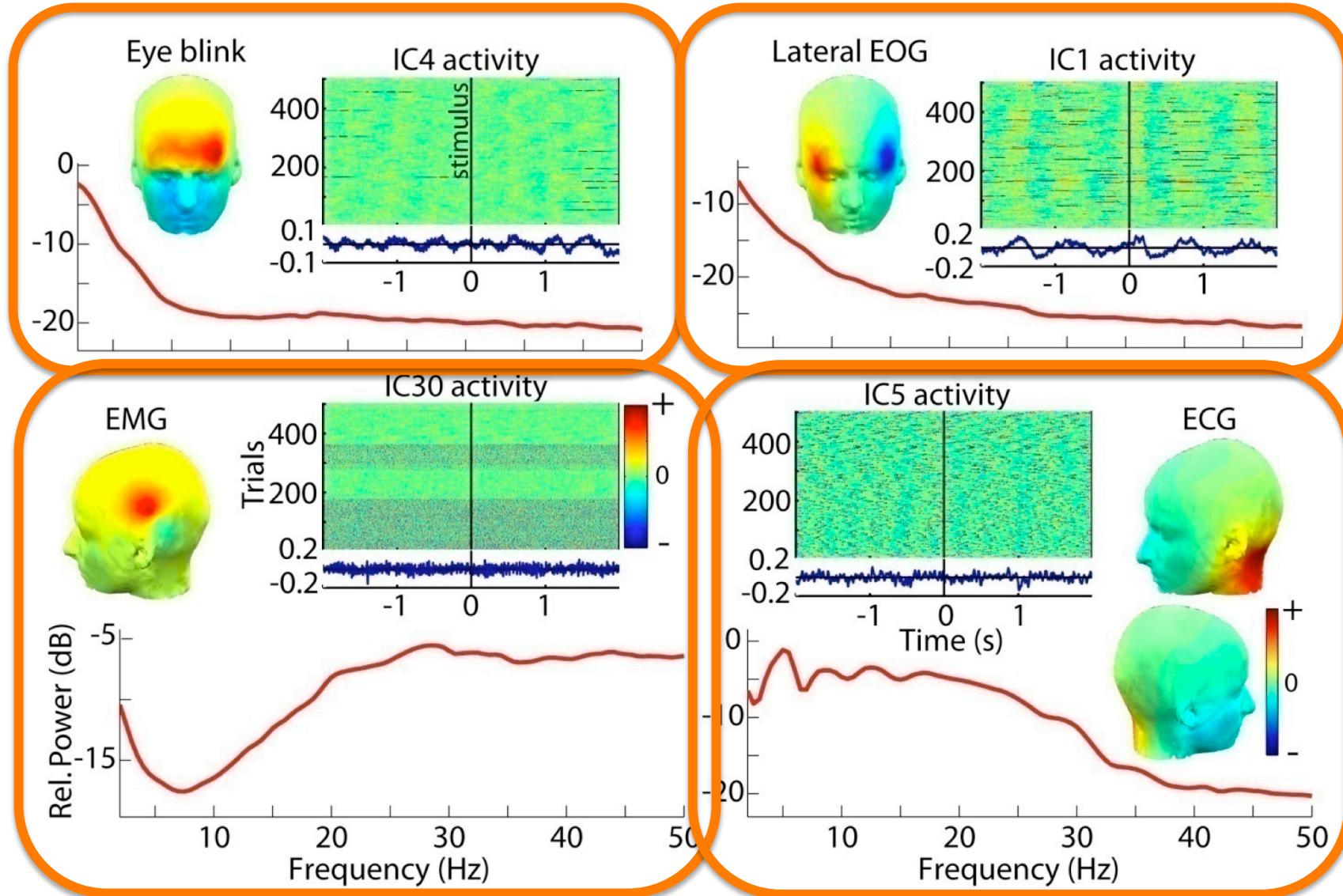
Abstract

Because of the distance between the skull and brain and their different resistivities, electroencephalographic (EEG) data collected from any point on the human scalp includes activity generated within a large brain area. This spatial smearing of EEG data by volume conduction does not involve significant time delay, however, suggesting that the Independent Component Analysis (ICA) algorithm of Bell and Sejnowski [1] is suitable for performing blind source separation on EEG data. The ICA algorithm separates the problem of source identification from that of source localization. First results of applying the ICA algorithm to EEG and event-related potential (ERP) data collected during a sustained auditory detection task show: (1) ICA training is insensitive to different random seeds. (2) ICA may be used to segregate obvious artifactual ERP components (eye and muscle noise, eye movements) from other sources. (3) ICA is capable of isolating overlapping ERP phenomena, including alpha and theta bands and spatially-reproducible ERP components, to separate ICA channels. (4) Nonstationarities in EEG and behavioral state can be tracked using ICA via changes in the amount of residual correlation between ICA-filtered output channels.

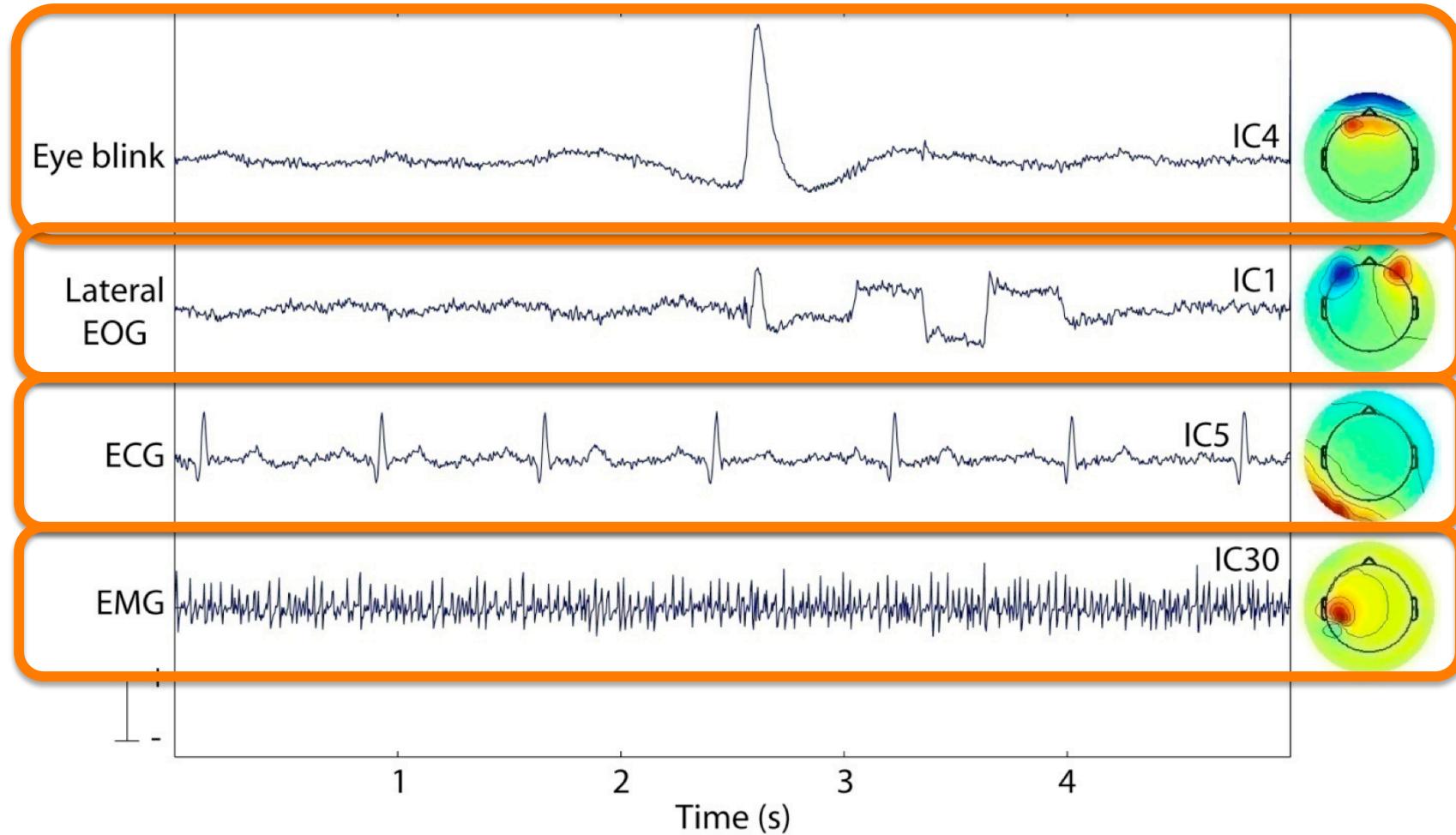
1

“ICA may be used to segregate obvious artificial EEG component (line and muscle noise, eye movements) from other sources.”

- Makeig et al., 1996



IC activation time courses



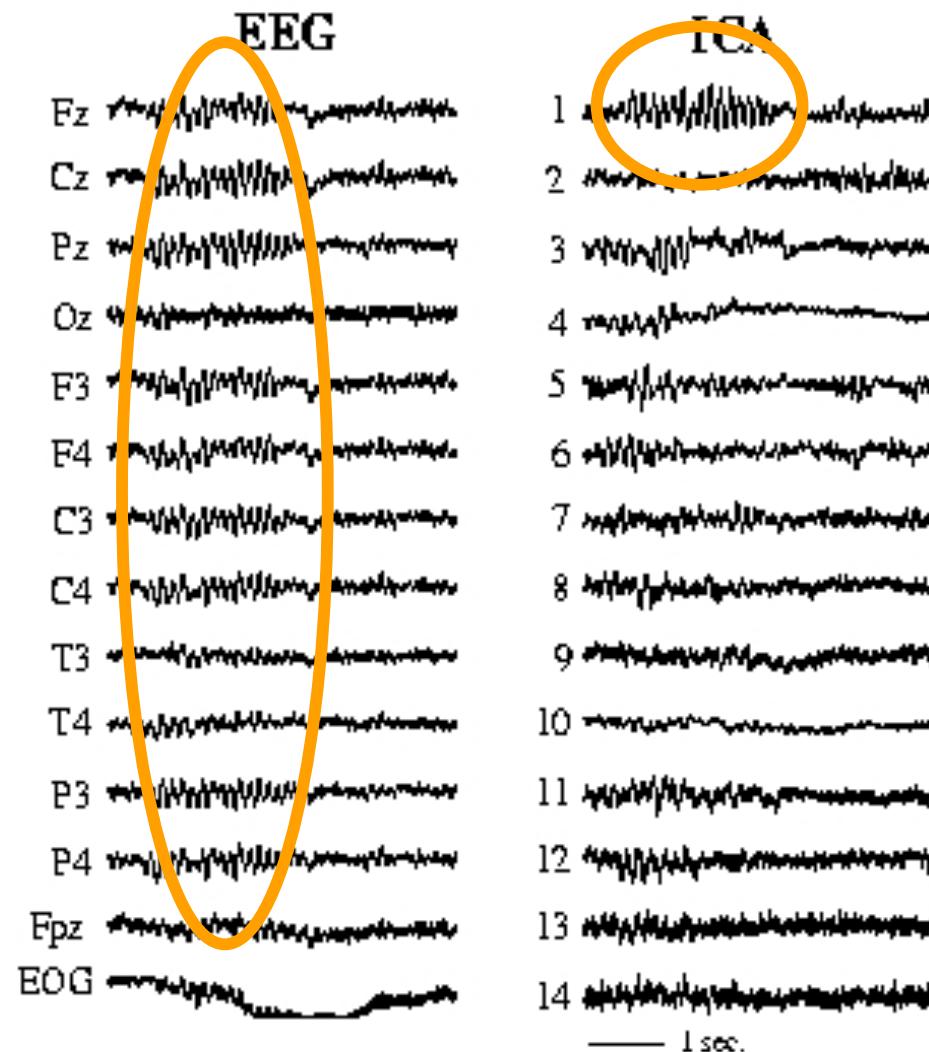


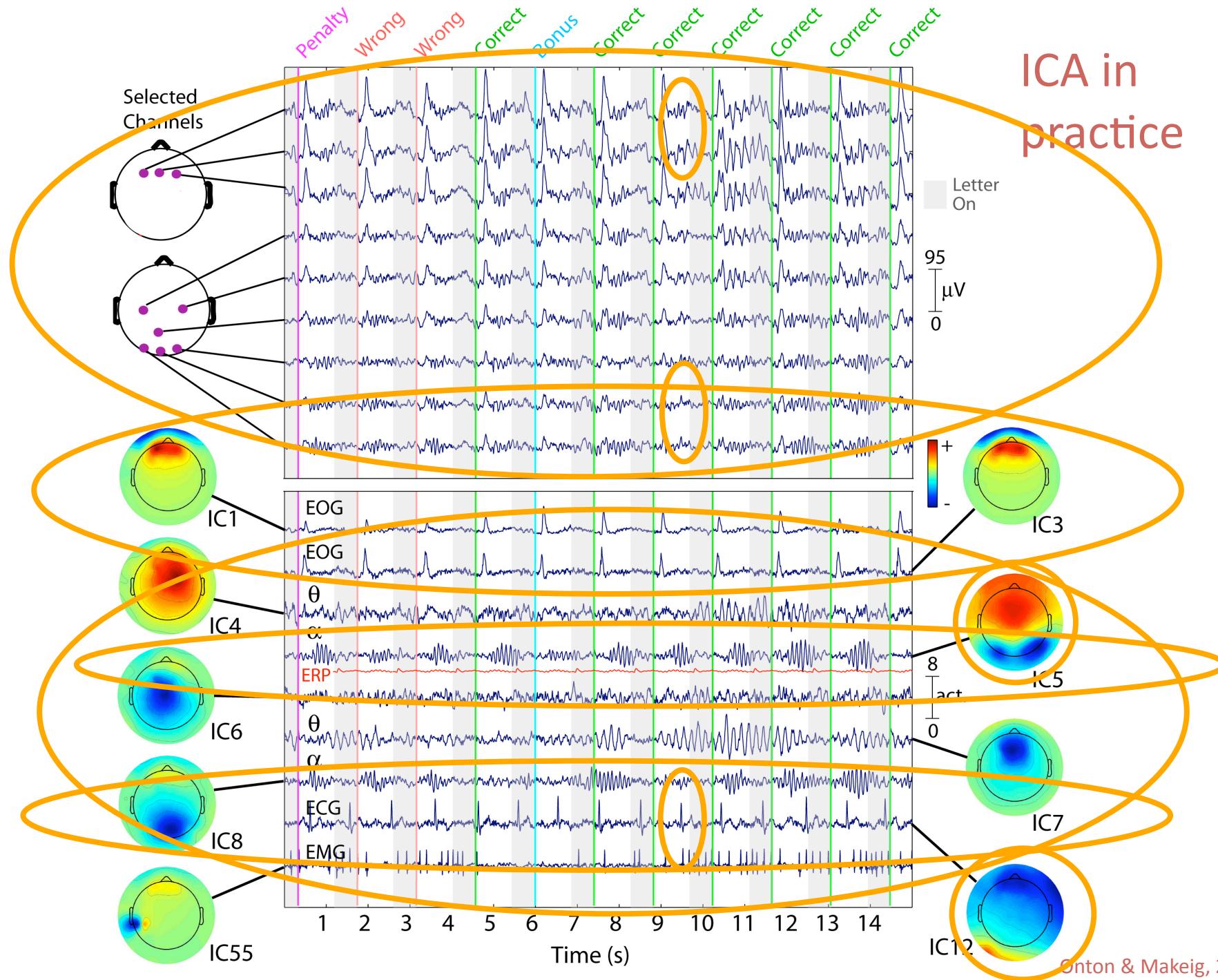
Figure 1: Left: 4.5 seconds of 14-channel ERVA data. Right: an ICA transform of the same data, using weights trained on 6.5 minutes of similar data from the same session.

2

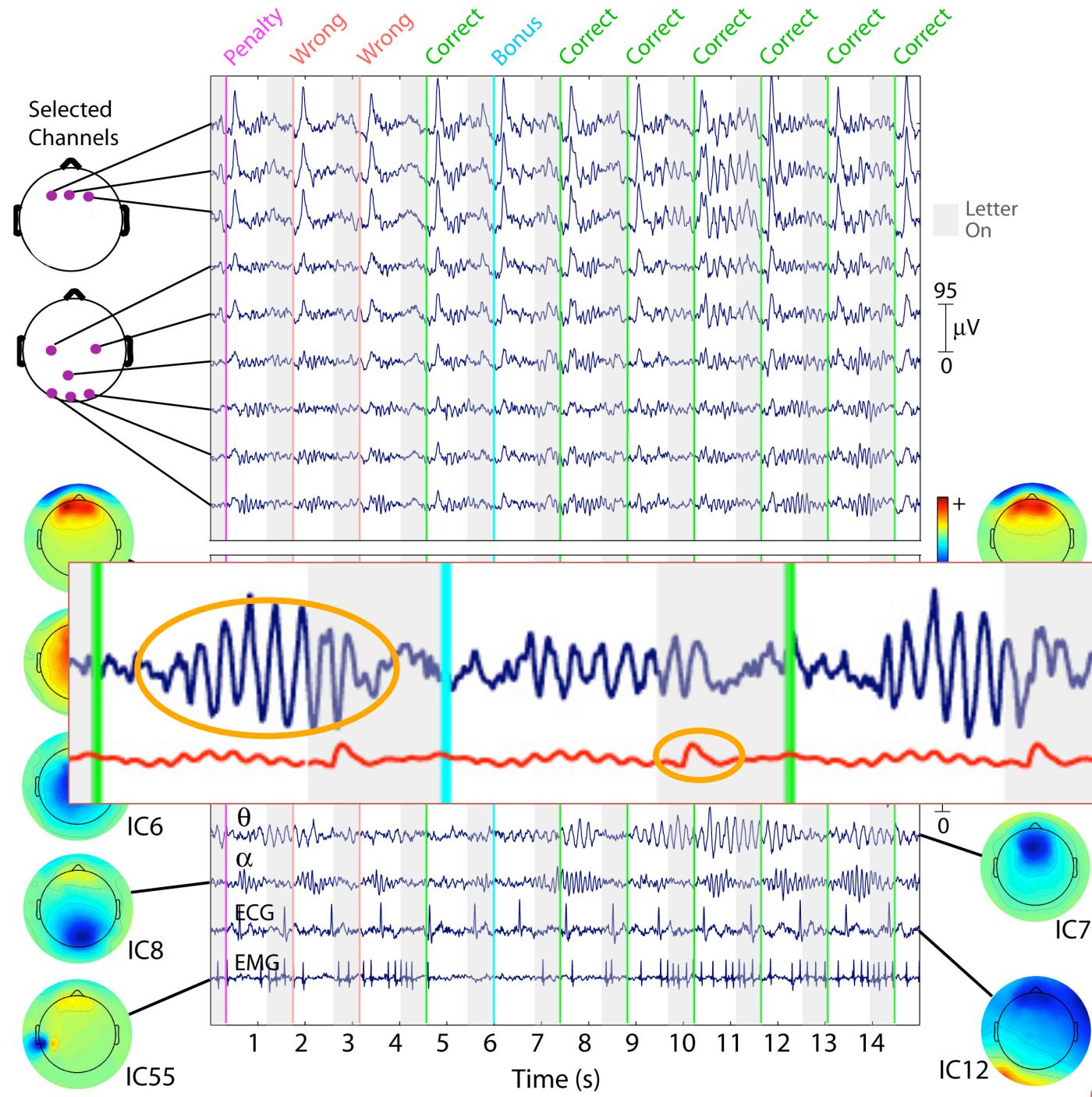
“ICA is capable of isolating overlapping EEG phenomena including alpha and theta bursts and spatially separable ERP components, to separate [ICs].”

- Makeig et al., 1996

ICA in practice



Onton & Makeig, 2006



3

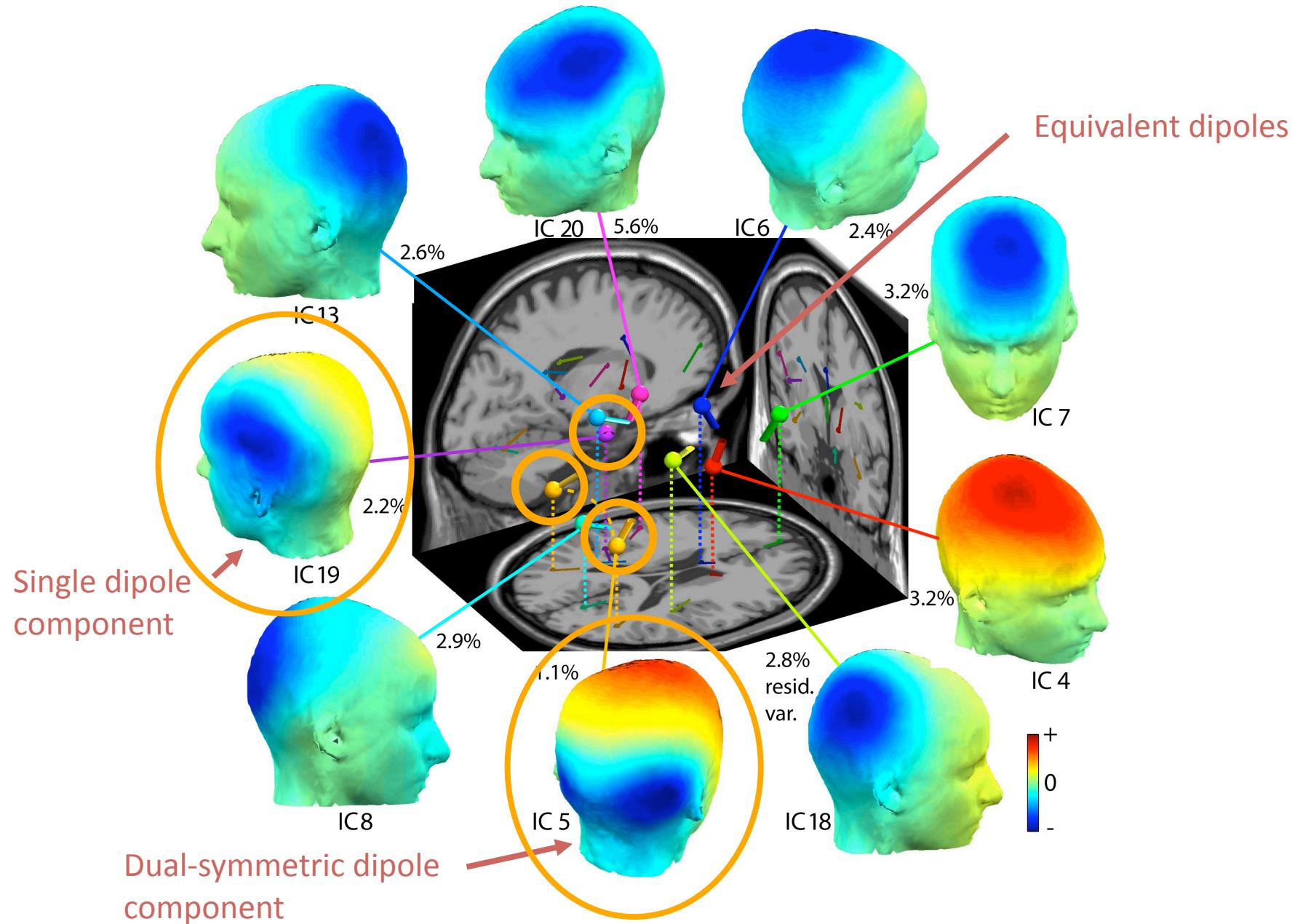
“ICA training is insensitive to
different random seeds,”
[... and can separate out
independent components of data
with hundreds of channels].

- Makeig et al., 1996

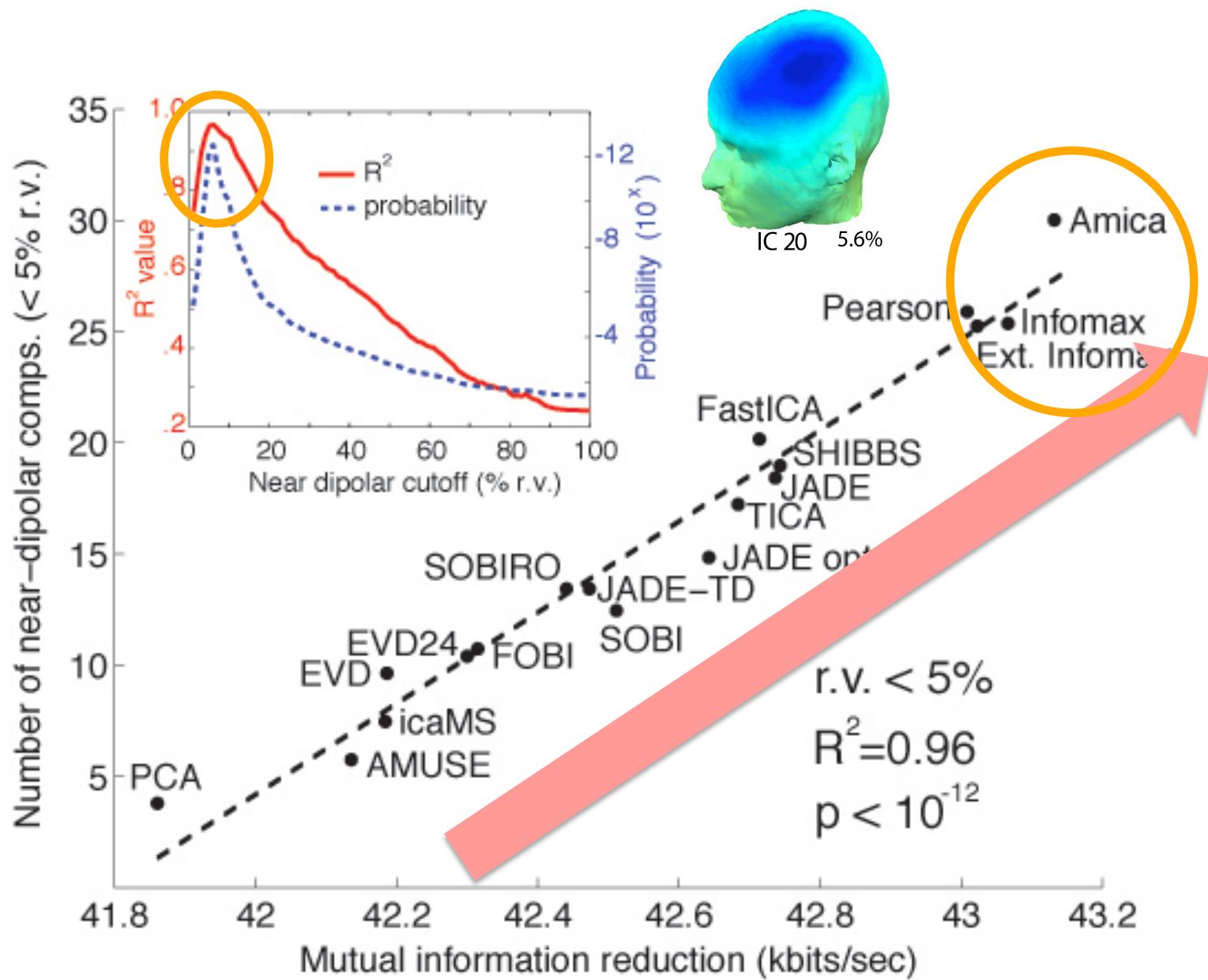
4

Brain-based, ‘dipolar’
independent components of
EEG data are projections of
single (dual) cortical patches.

Independent cortical components



Julie Onton & S. Makeig (2006)

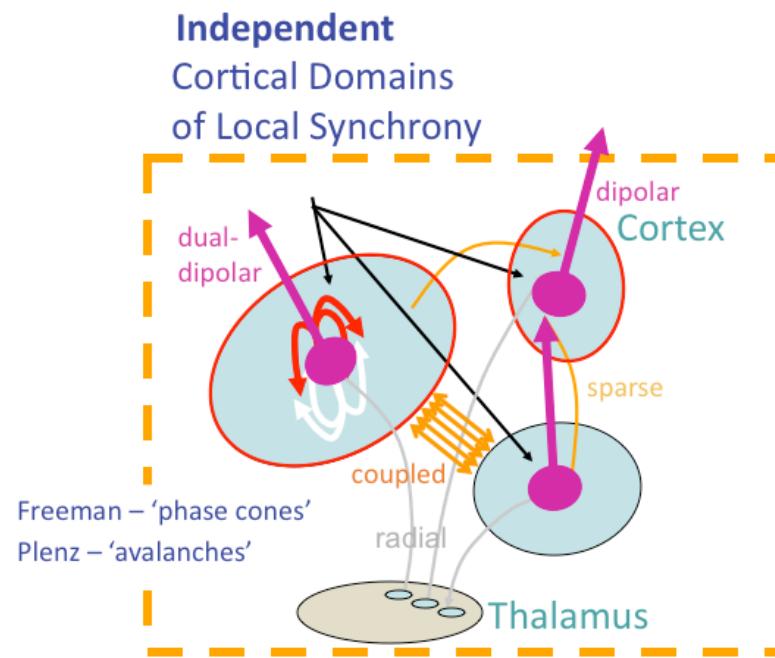
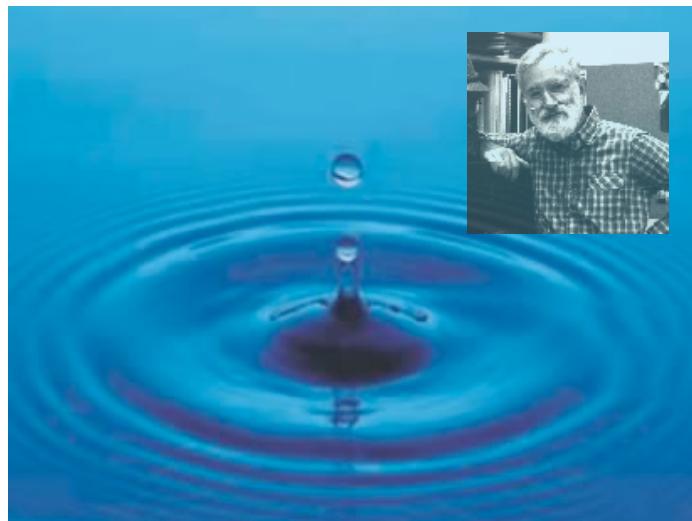


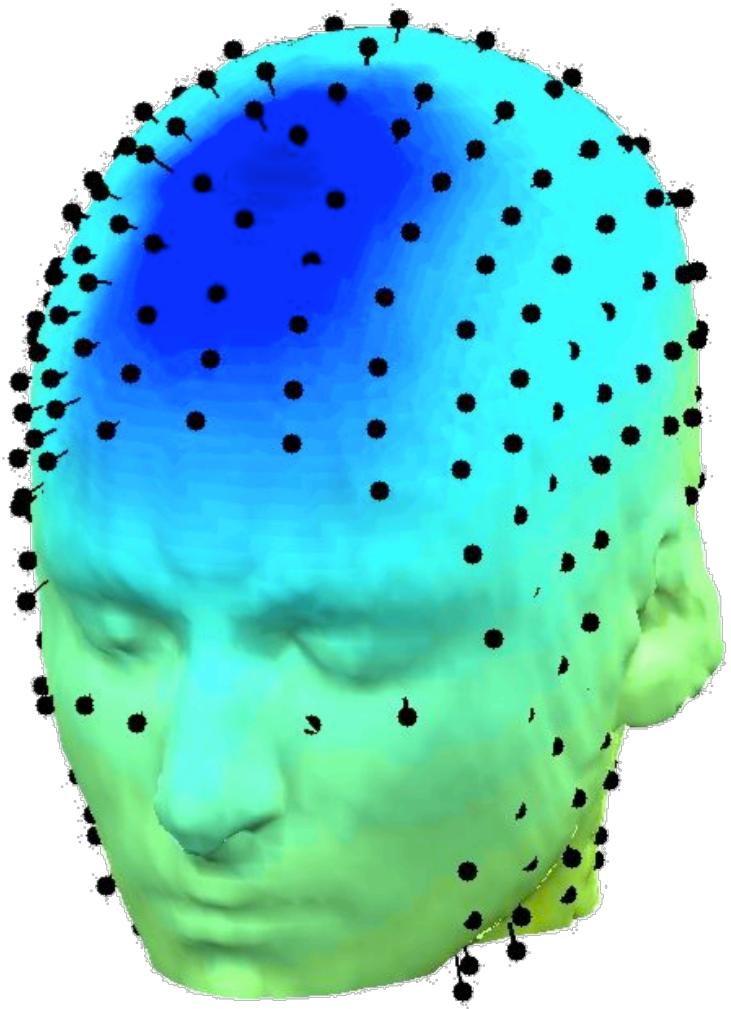
THUS → ICA (BSS) decompositions that
find components whose time courses are **more**
independent
→ also find **more** components whose scalp maps
are '**dipolar**'!

Thus, the two approaches to
constraining the EEG inverse problem,
biophysical and ***statistical***,
are directly interlinked.

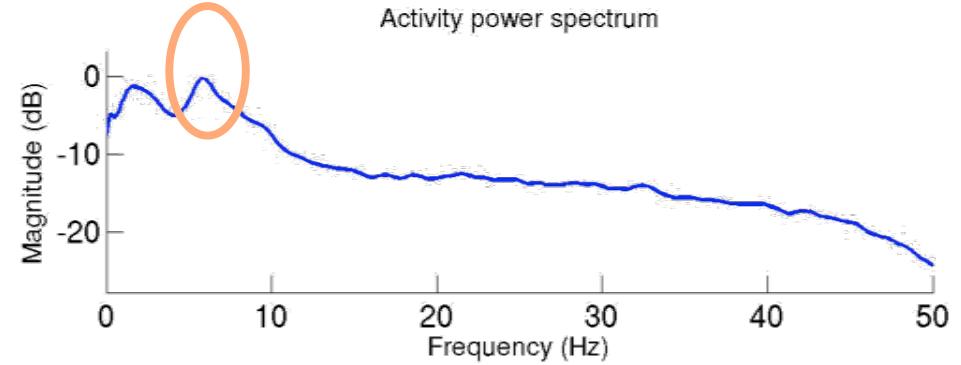
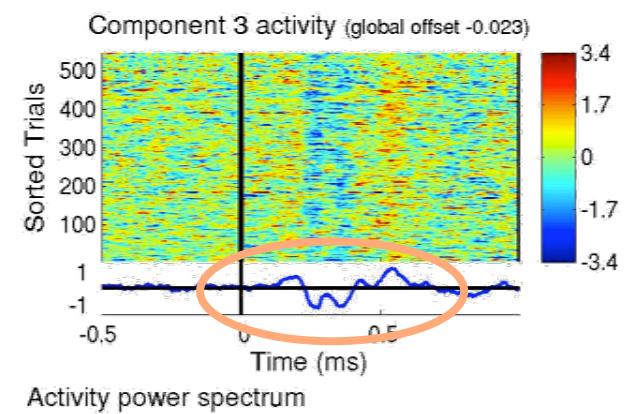
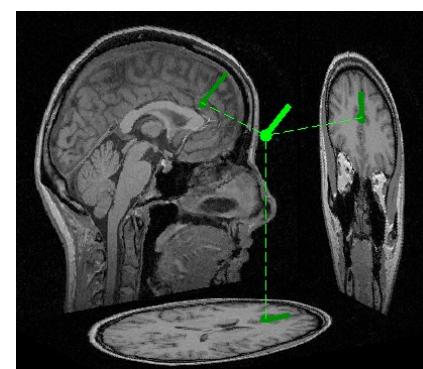
Why?

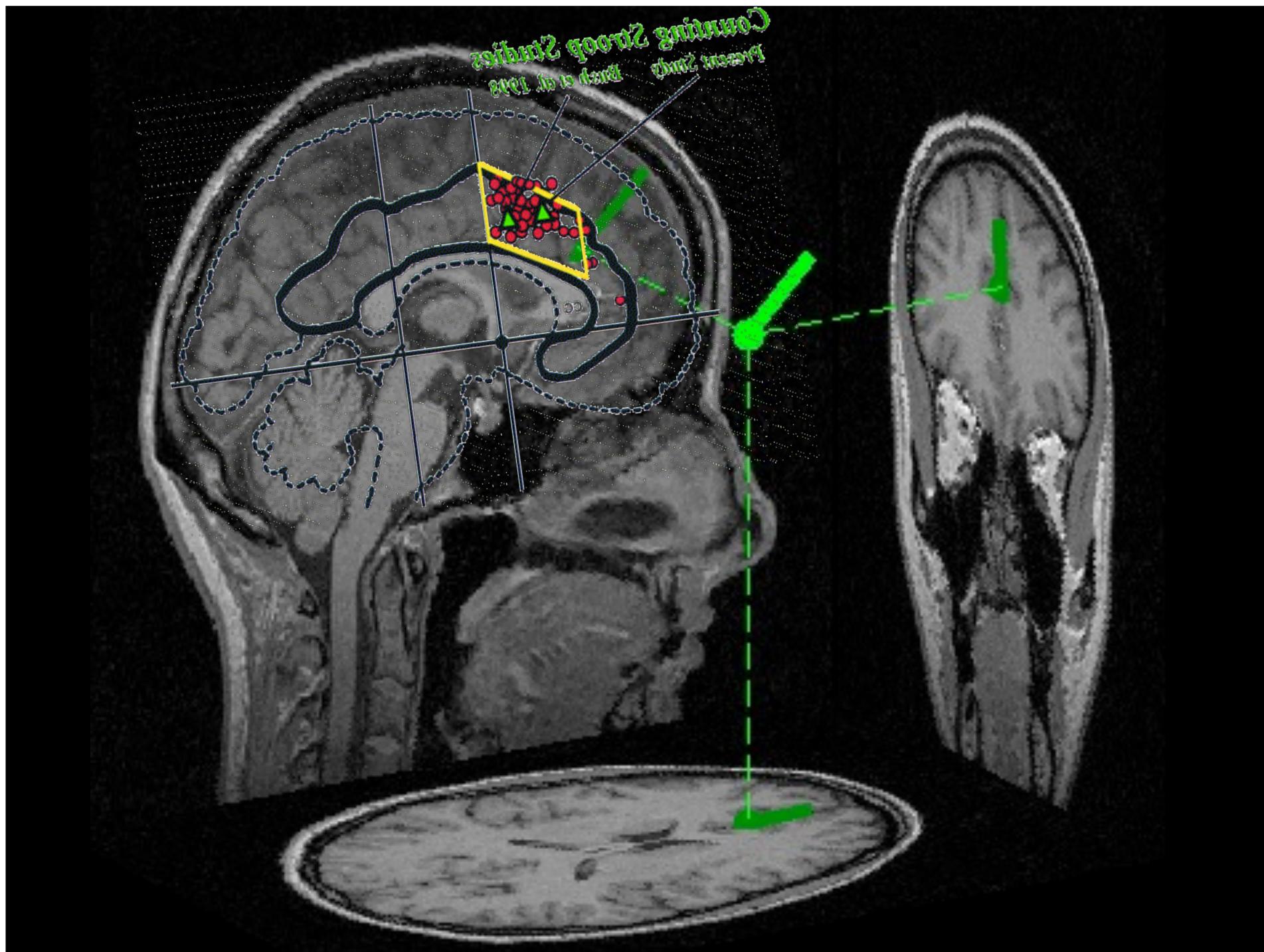
Very likely because the physiological assumptions motivating the use of ICA for EEG data are *substantially* correct...





Frontal Midline Theta Process

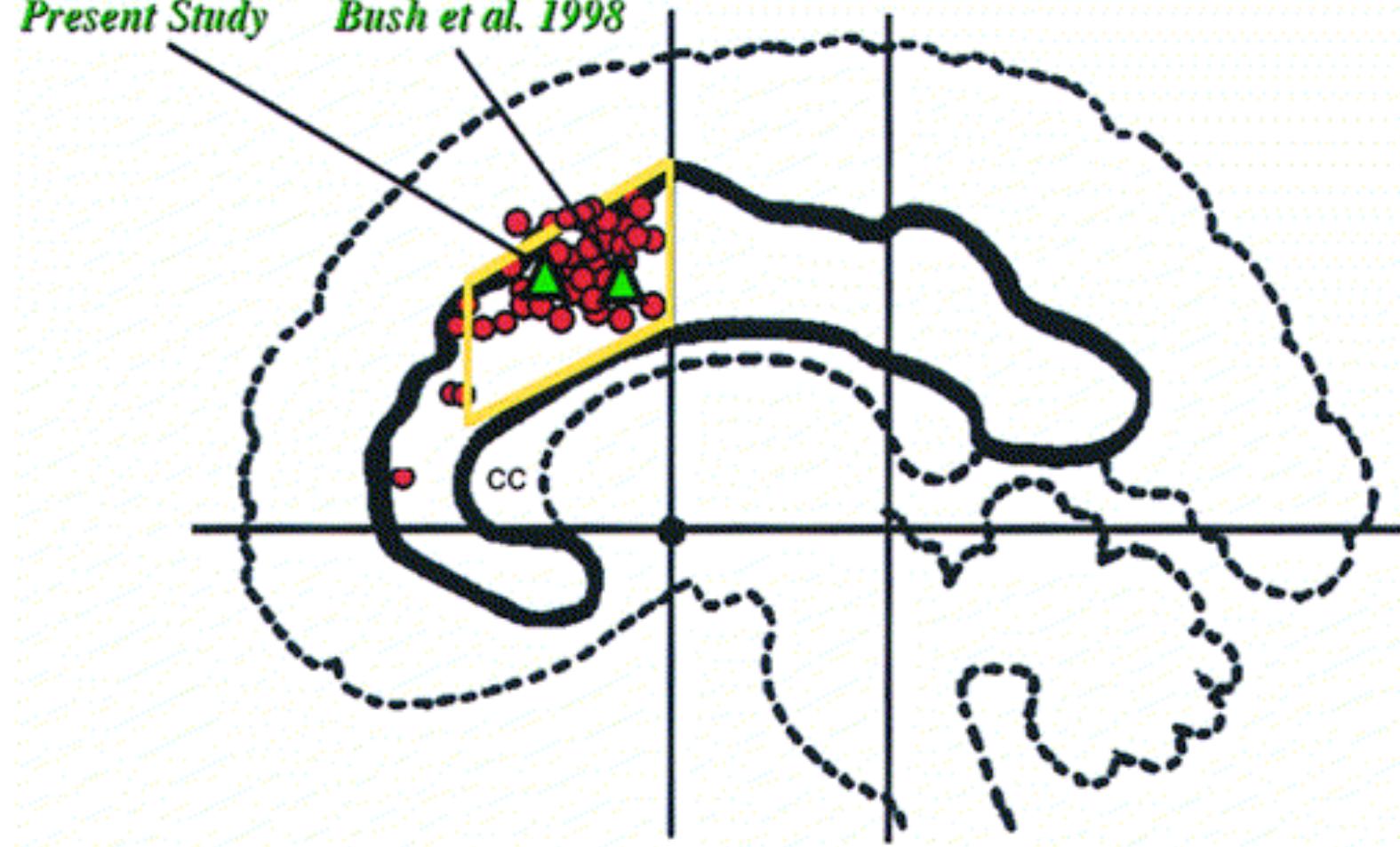




Anterior Cingulate Cognitive Division

Counting Stroop Studies

Present Study Bush et al. 1998

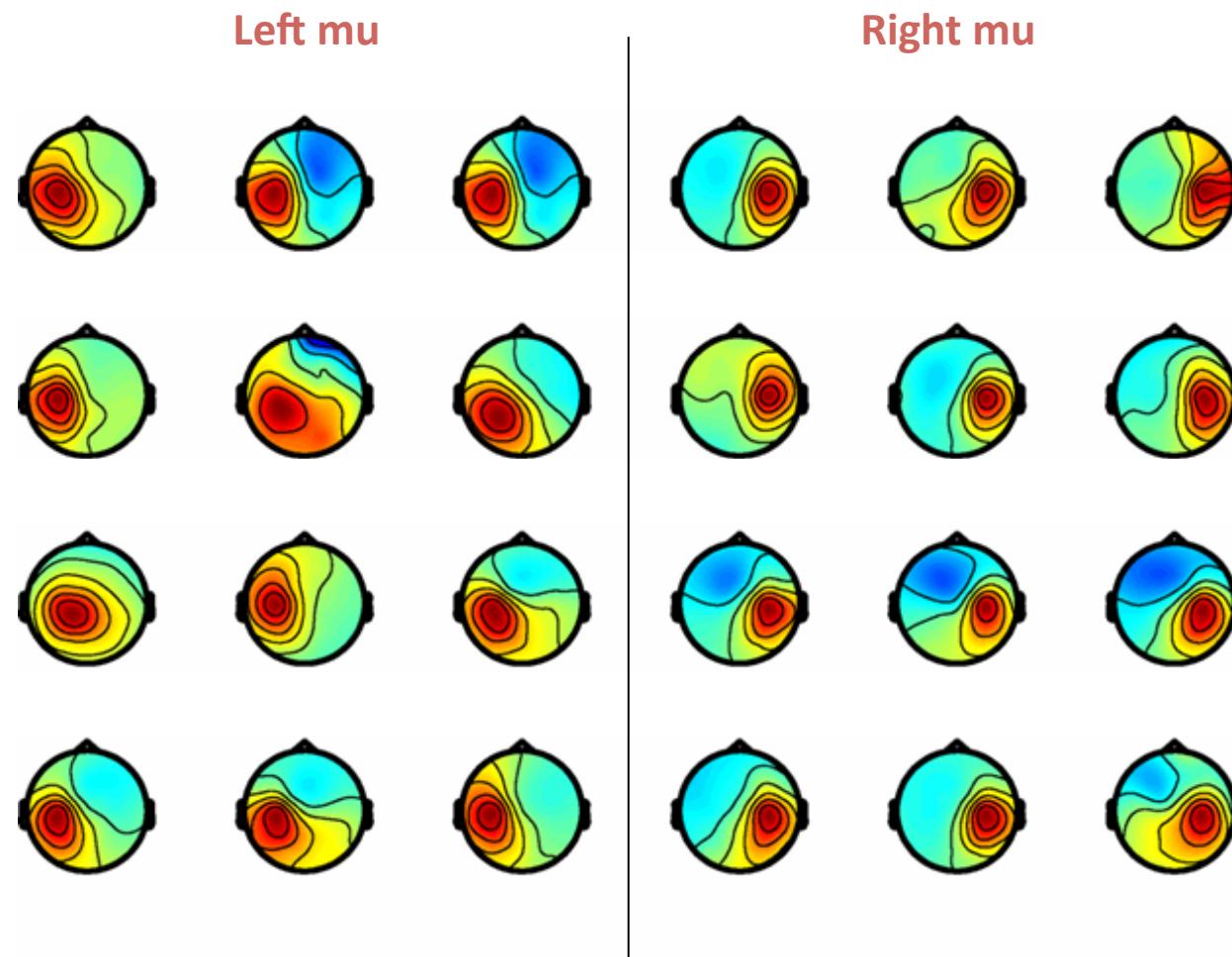


Bush et al., 1999

5

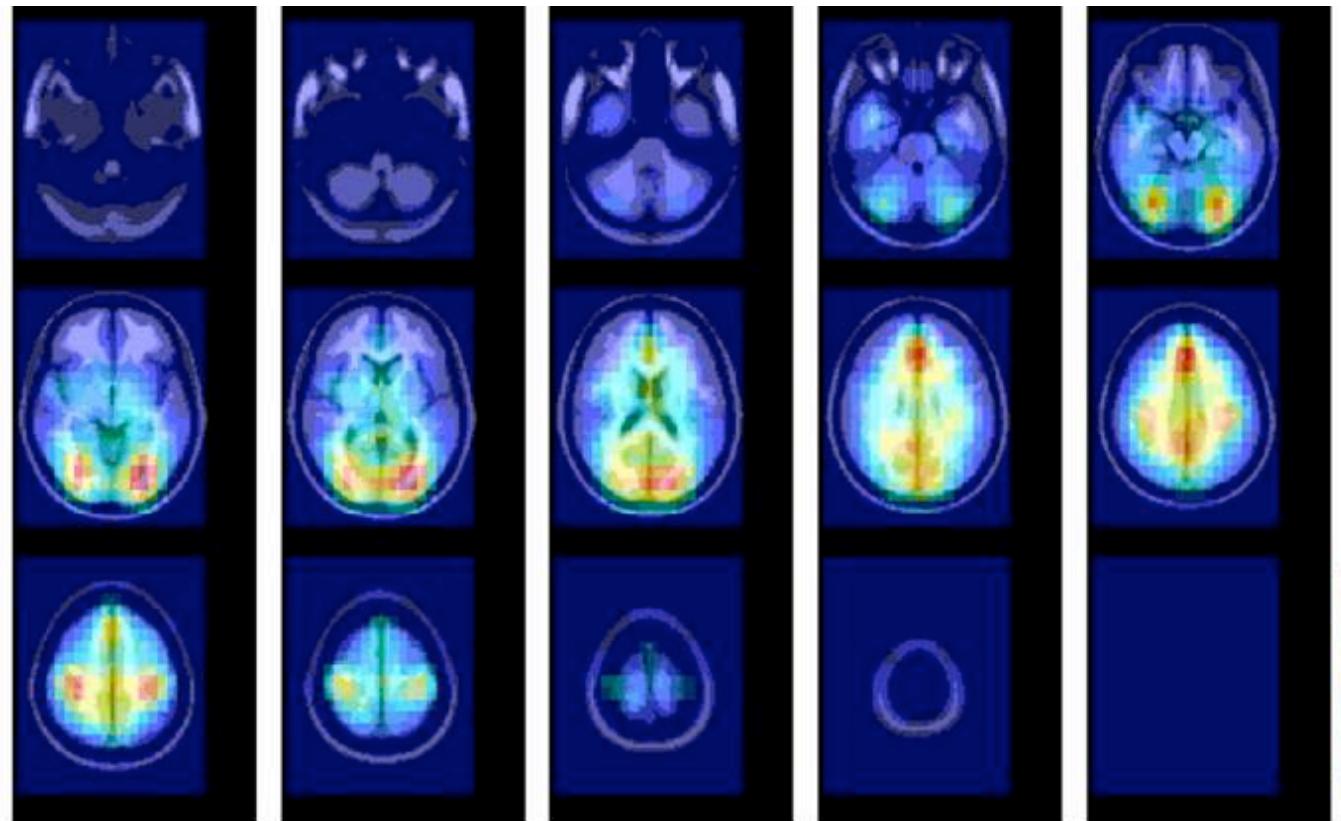
Similar independent components tend to
reappear in different subjects performing the
same task.

Clustering ICA components



Equivalent dipole density

Visual Working Memory



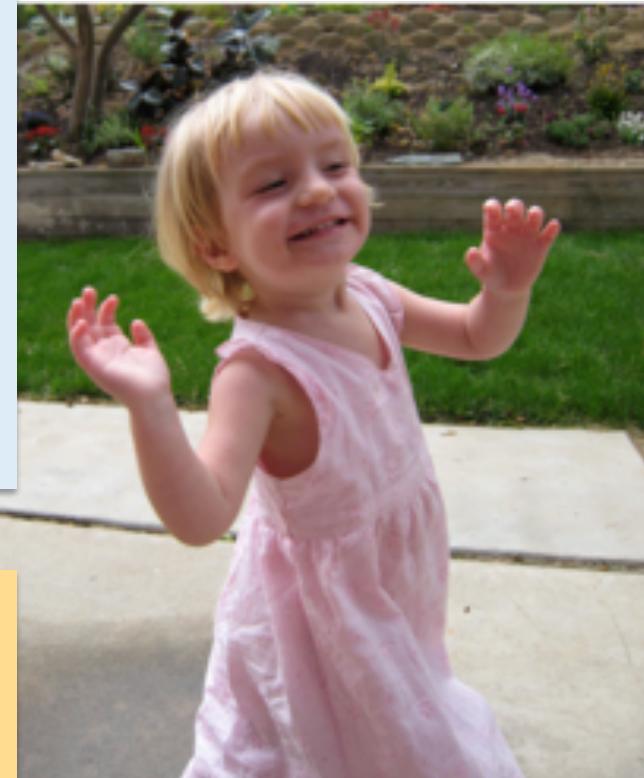
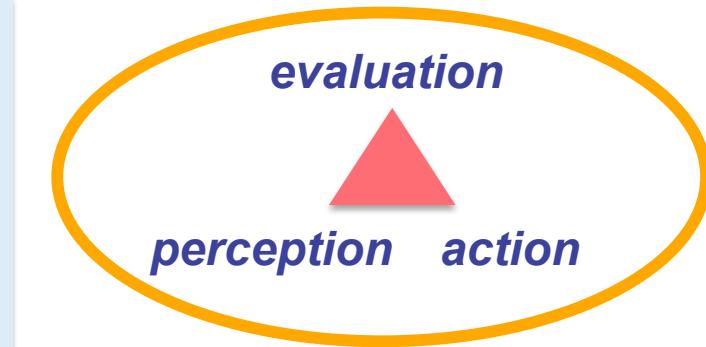
Sternberg
letter
memory
task

6

Independent components of EEG data tend to
be **functionally** independent –
changes in their activity patterns tend to reflect
‘top-down’ changes in cognitive state and/or
cognitive appraisal.

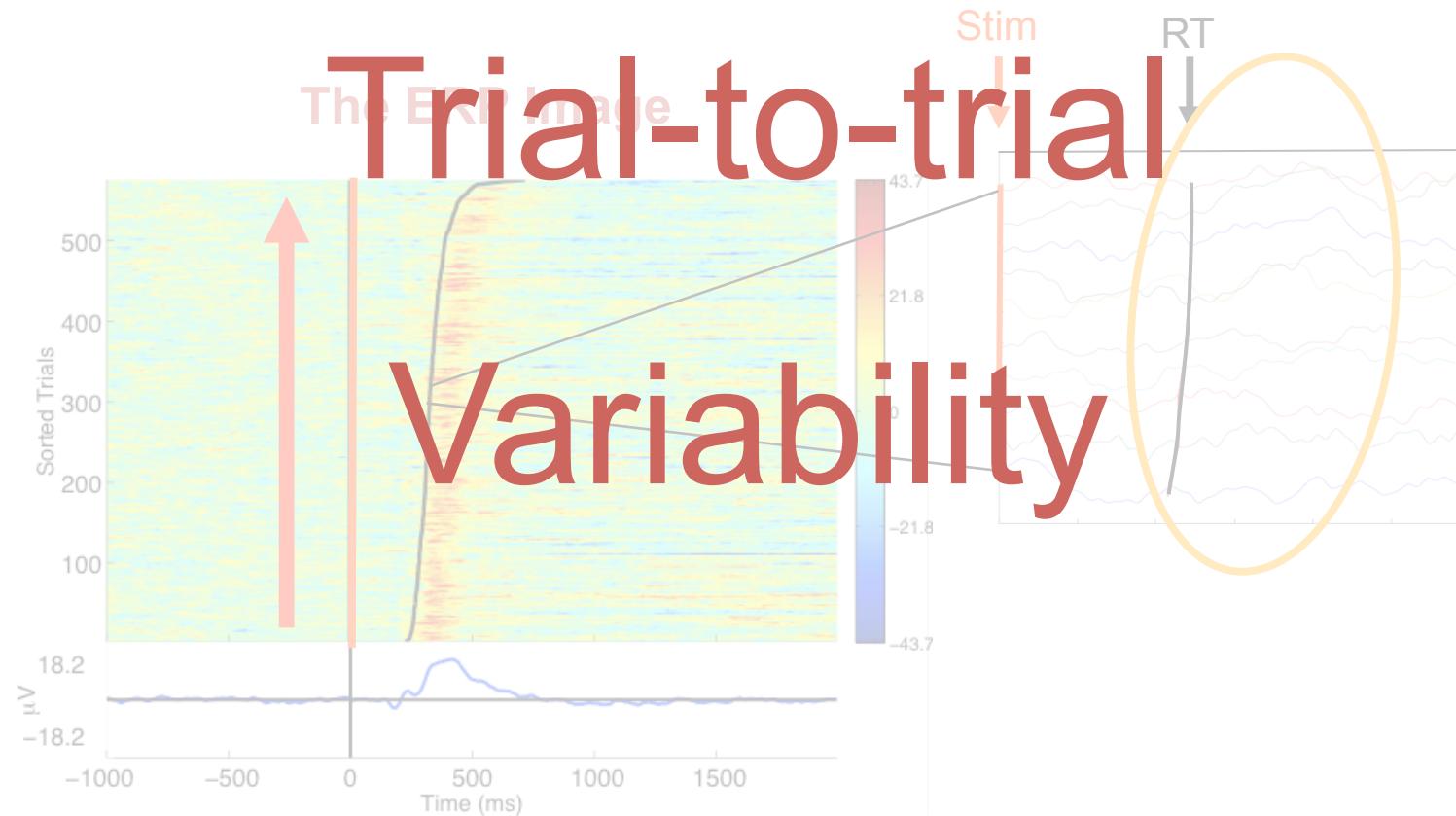
Embodied Cognition & Agency

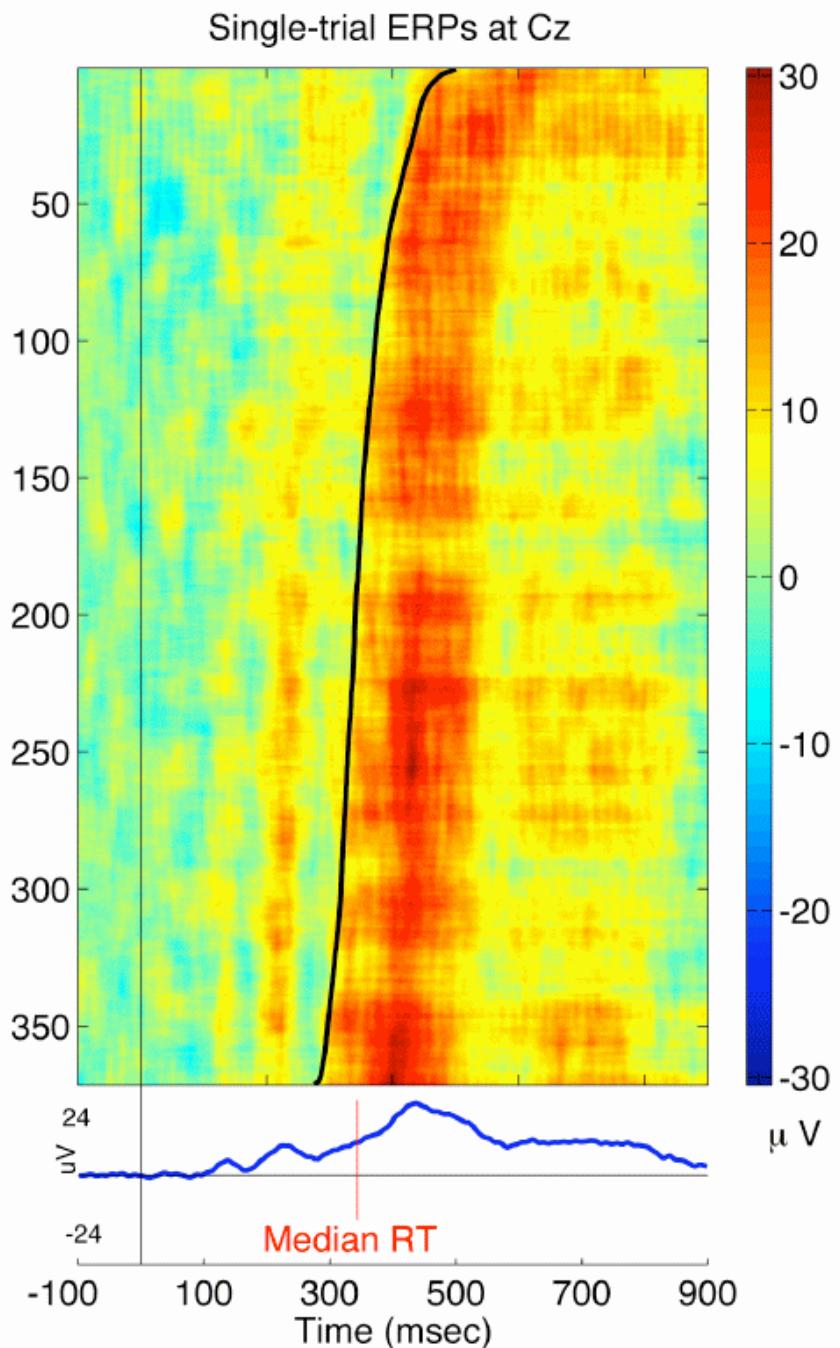
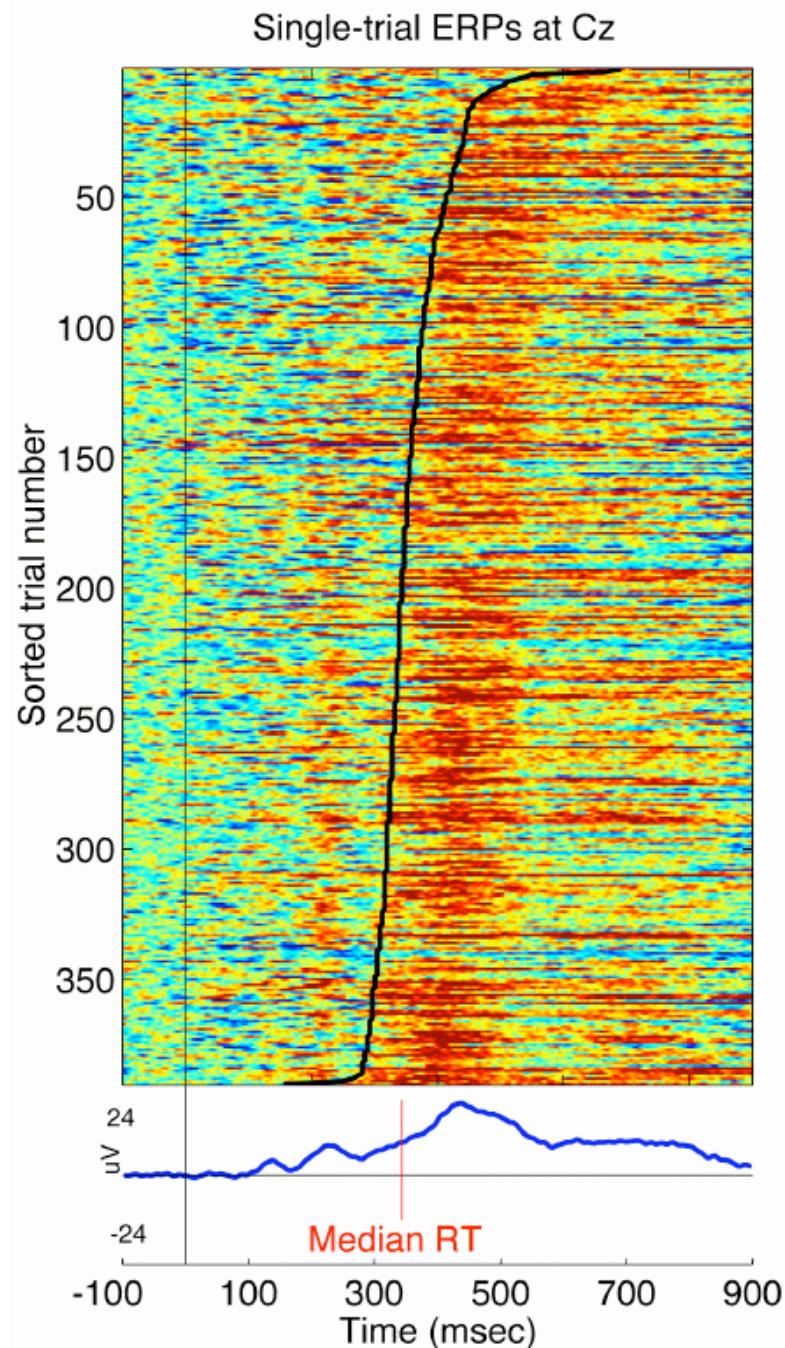
Brain processes
have evolved and function
*to optimize the outcome
of the behavior*
the brain organizes
in response to
*perceived challenges
and opportunities.*



**Brains meet the challenge of
the moment!**

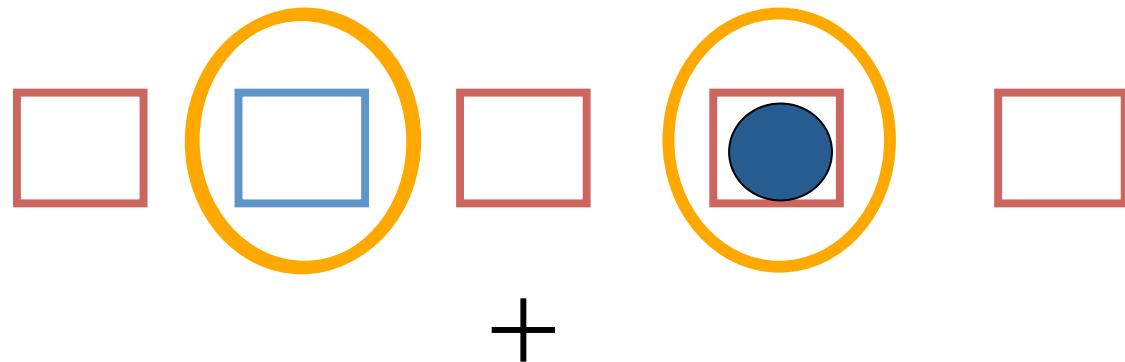
Collections of single trials, even at the source level, are regular, but in multiple ways – so they *appear* noisy!



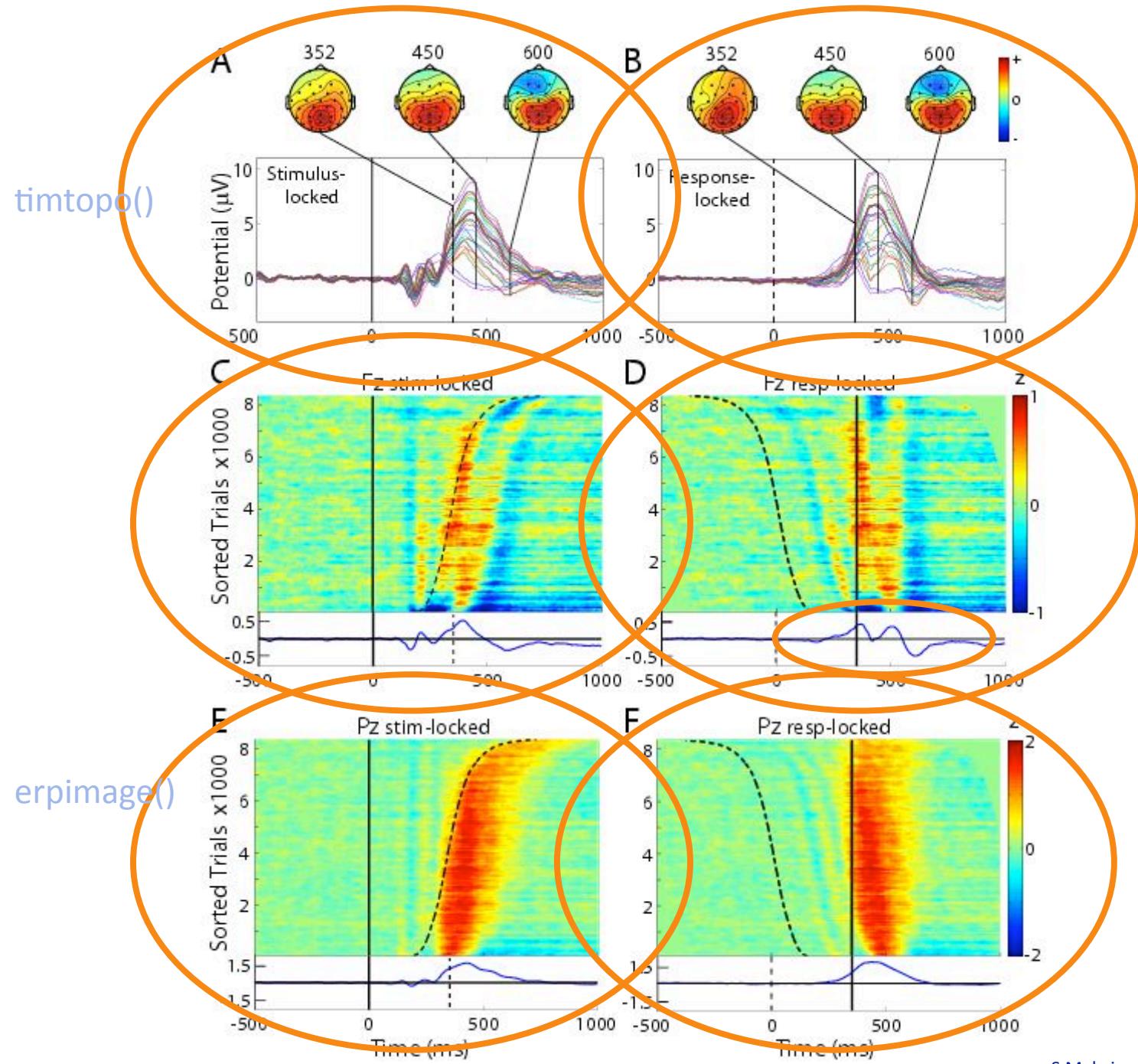


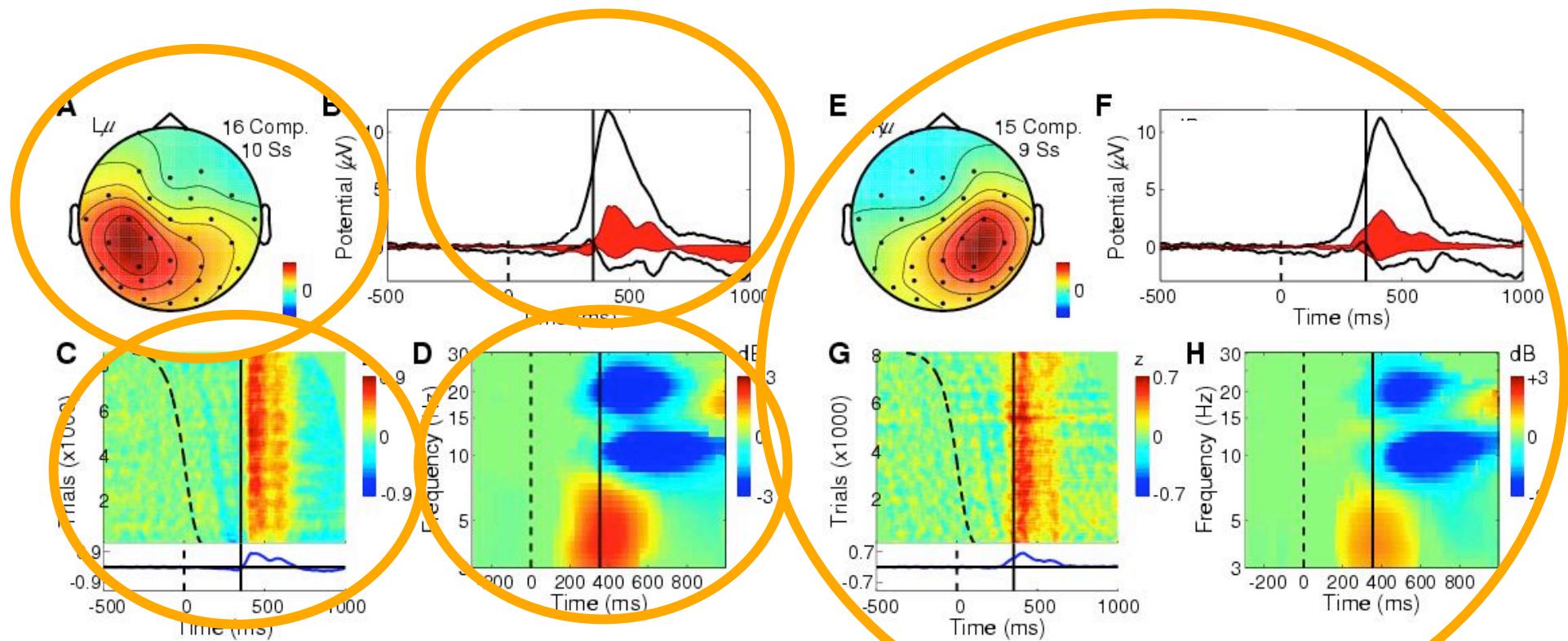
Jung et al., *Human Brain Mapping*, 2001.

Visual Selective Attention Task



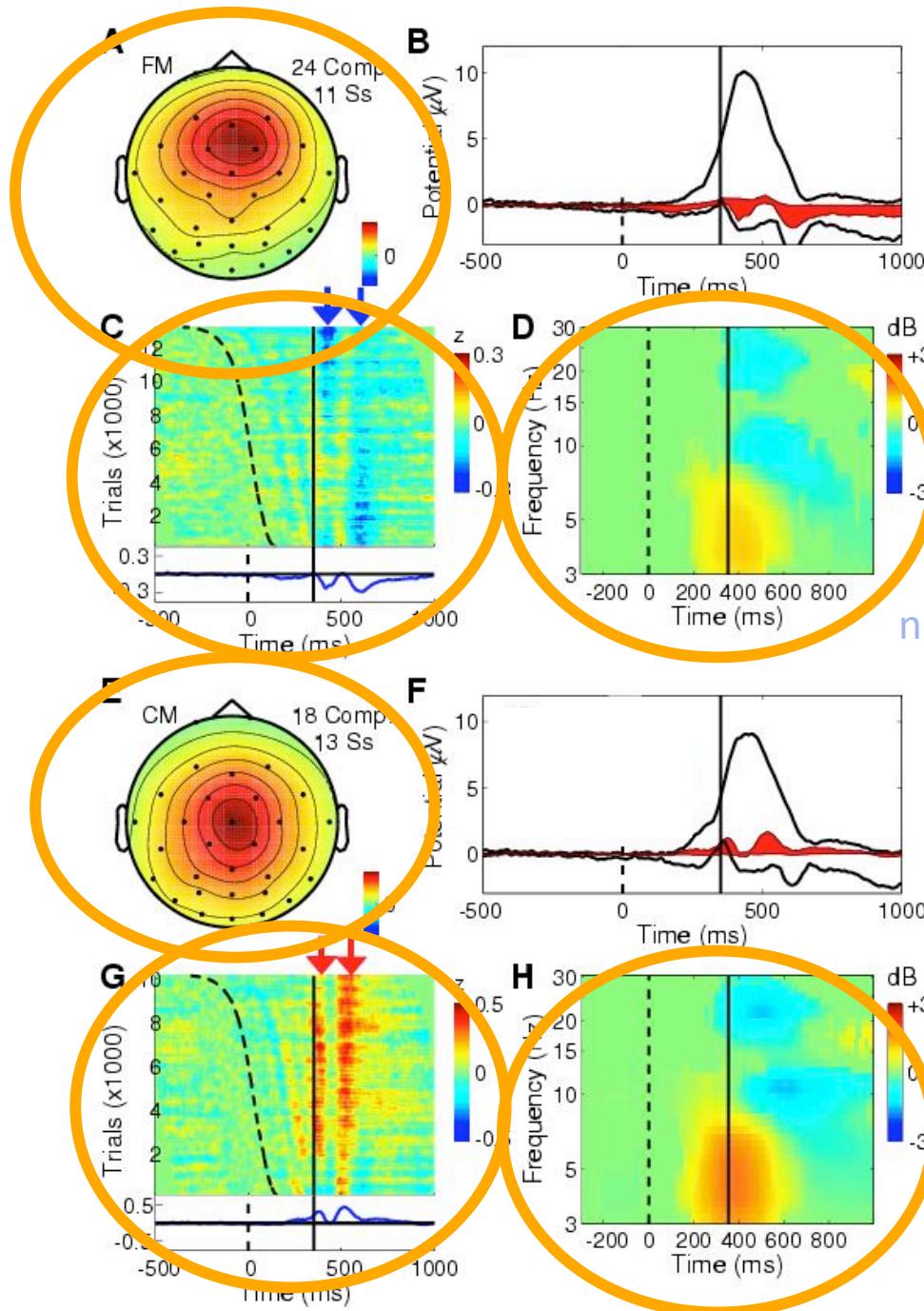
15 subjects





L μ - In or Near
Right Hand
Somatomotor
Cortex

R μ - In or Near
Left Hand
Somatomotor
Cortex



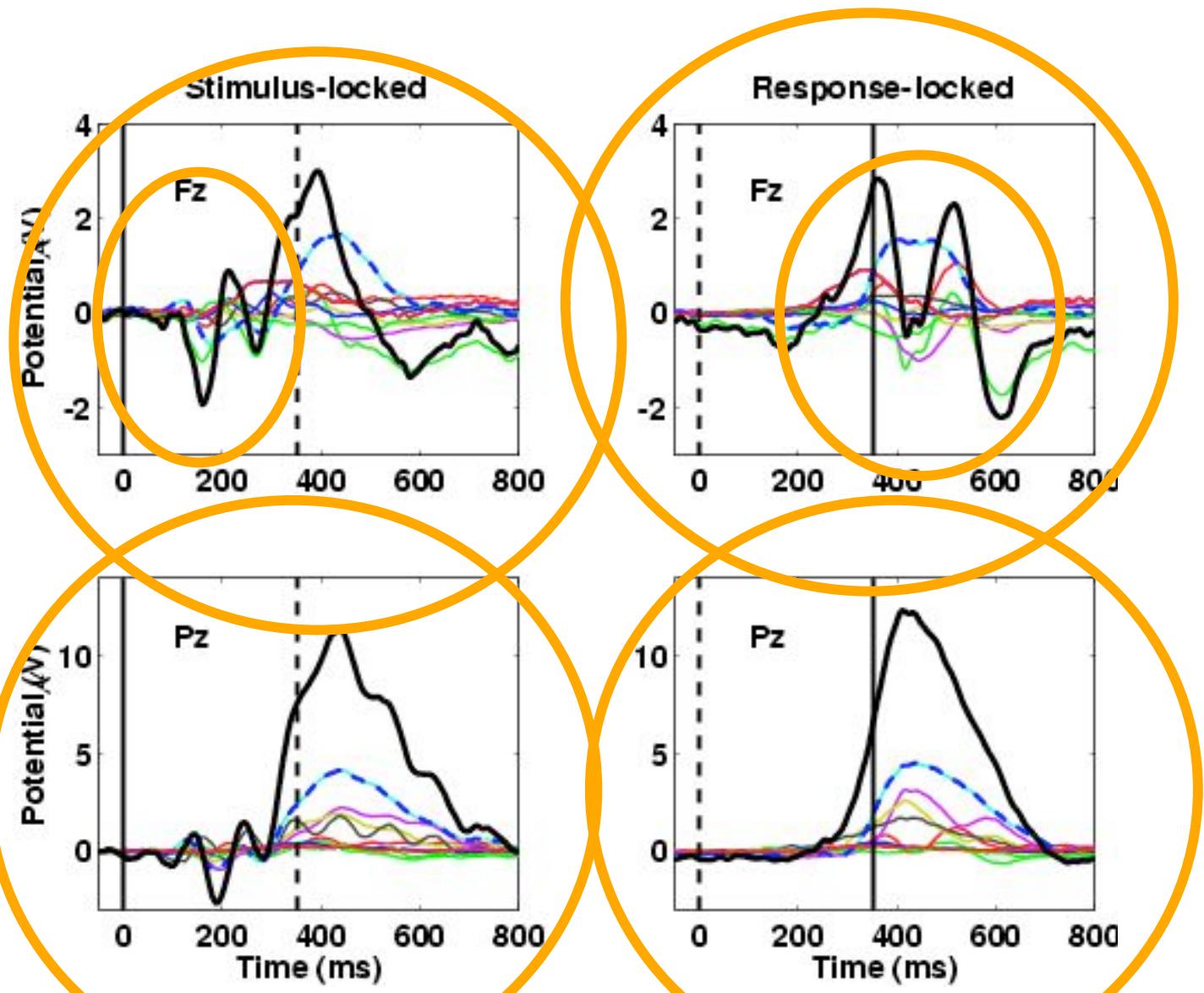
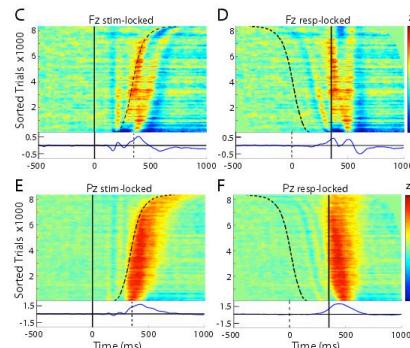
`envtopo()`
`std_envtopo()`

FM - In or Near
Rostral
Cingulate
Zone
(dACC)

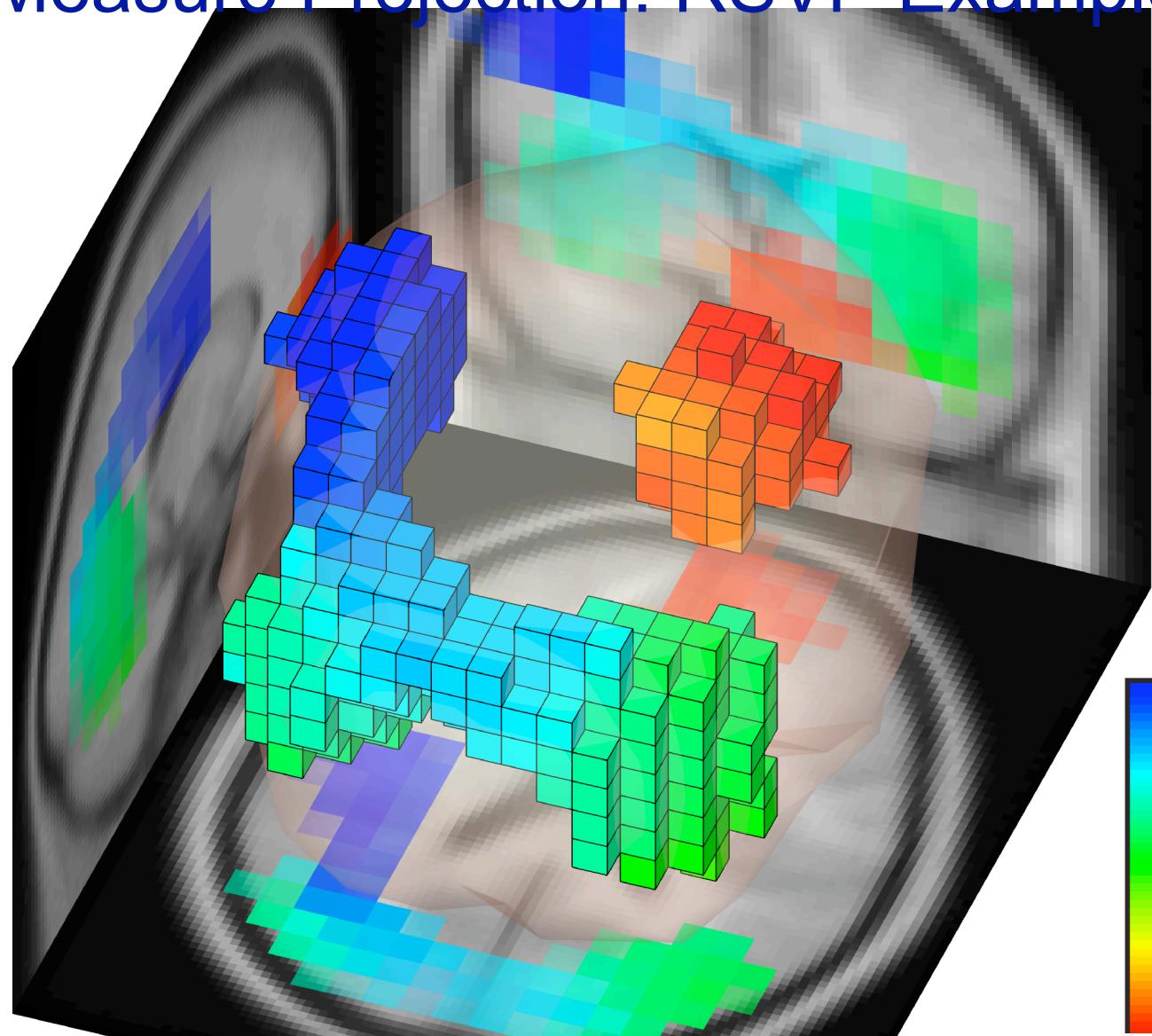
`newtimef()`

CM - In or Near
Motor Cingulate
/ Supplementary
Motor Cortex

Complex event-related dynamics sum to ‘the’ P300



Measure Projection: RSVP Example

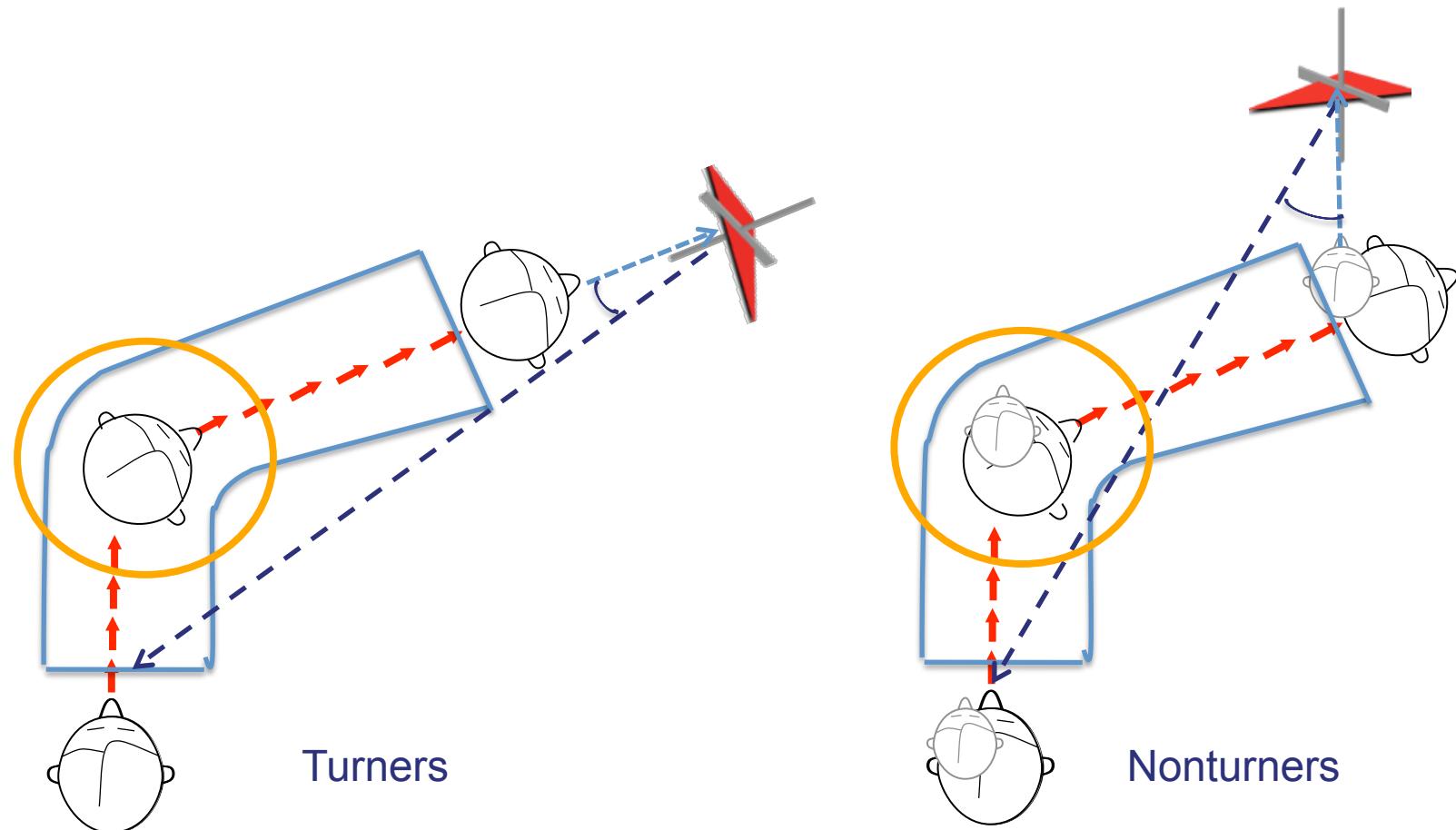


A Passive Spatial Navigation Paradigm

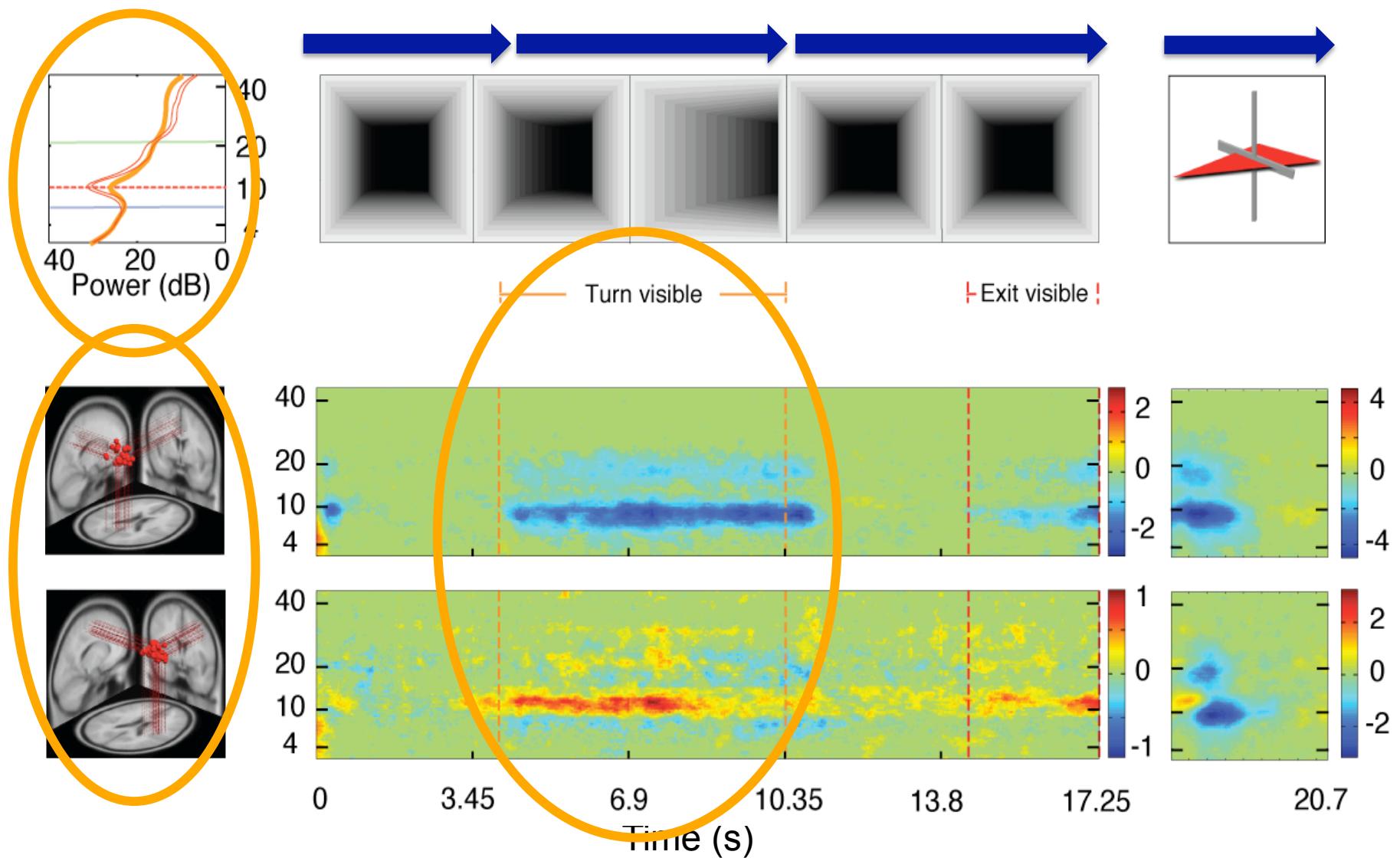
A Passive Spatial Navigation Paradigm



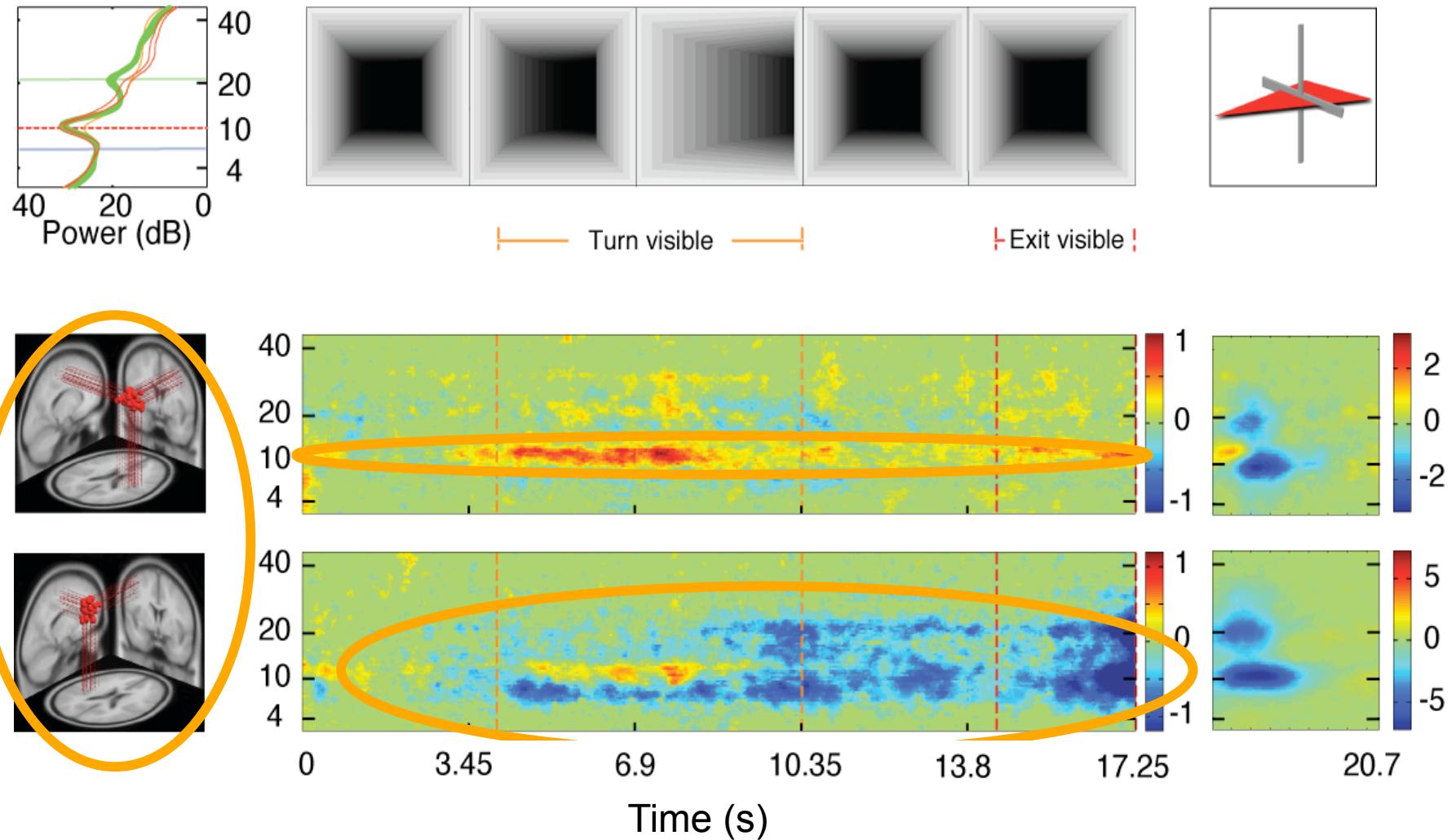
'Turner' and 'Nonturner' subjects use different spatial orienting styles



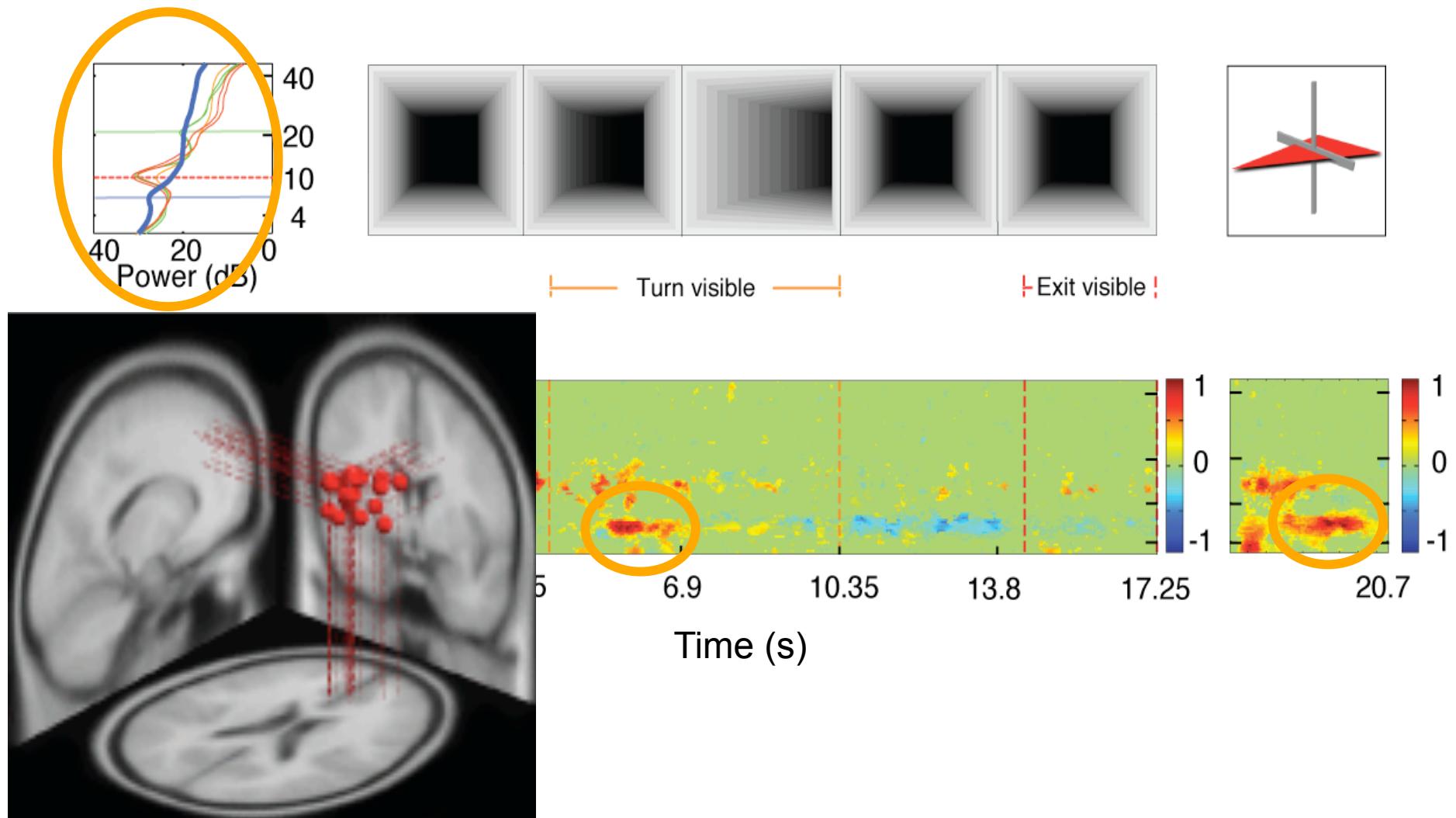
Parietal component clusters



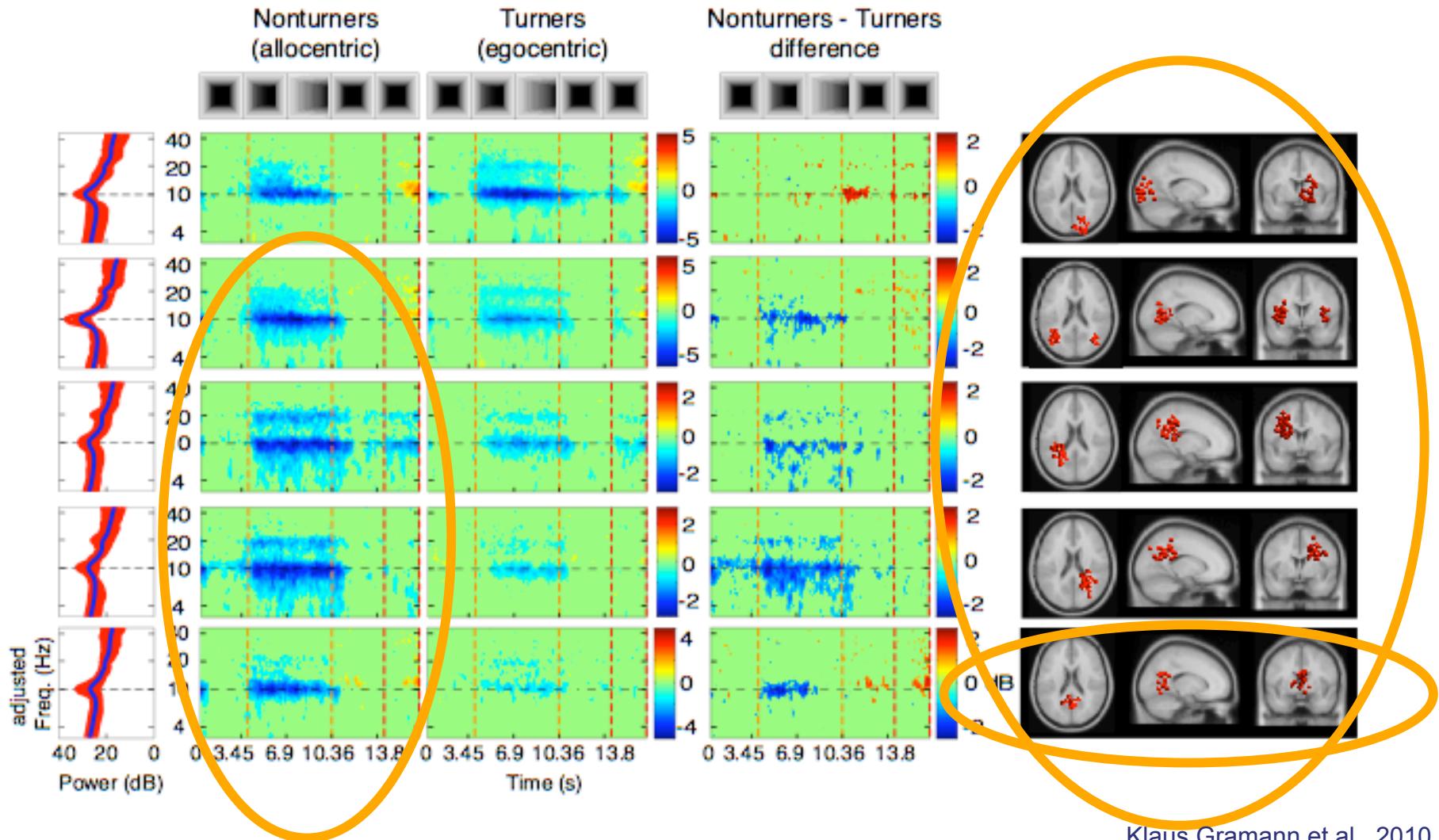
Pre-motor component clusters



Medial prefrontal component clusters



Clusters distinguishing Turners & Nonturners

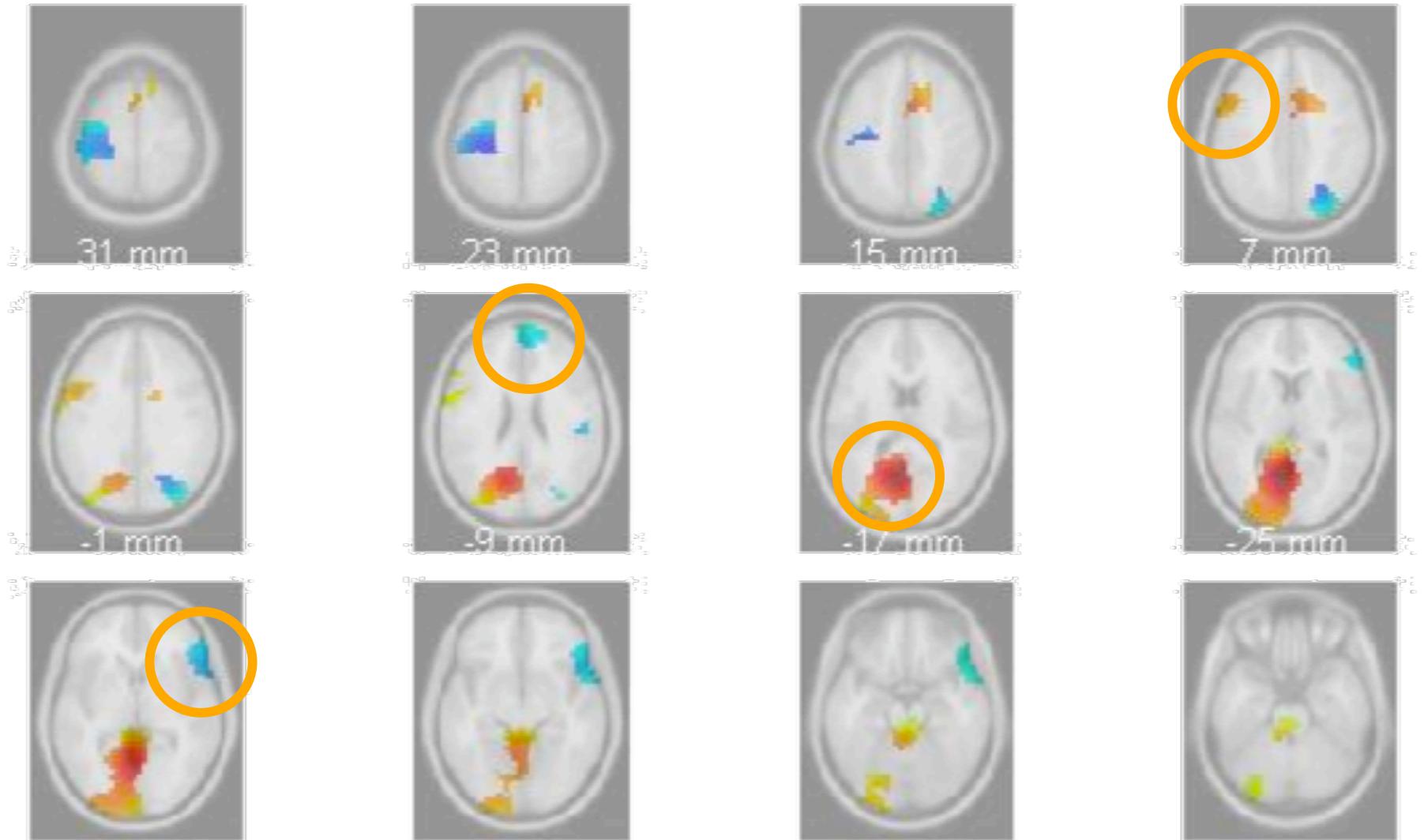


Klaus Gramann et al., 2010

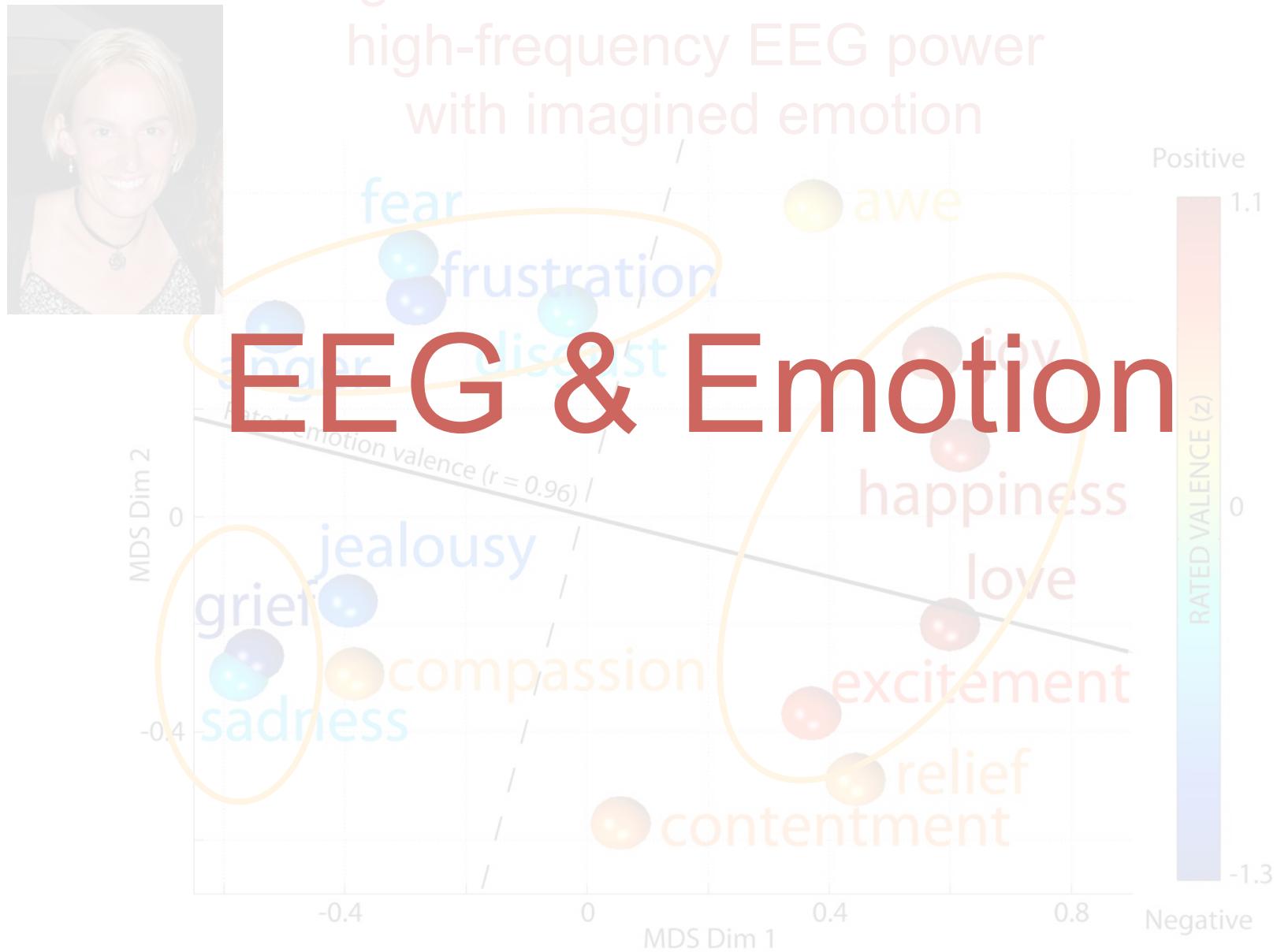
Visual spatial working memory in young and older adults



Young adults – Older adults



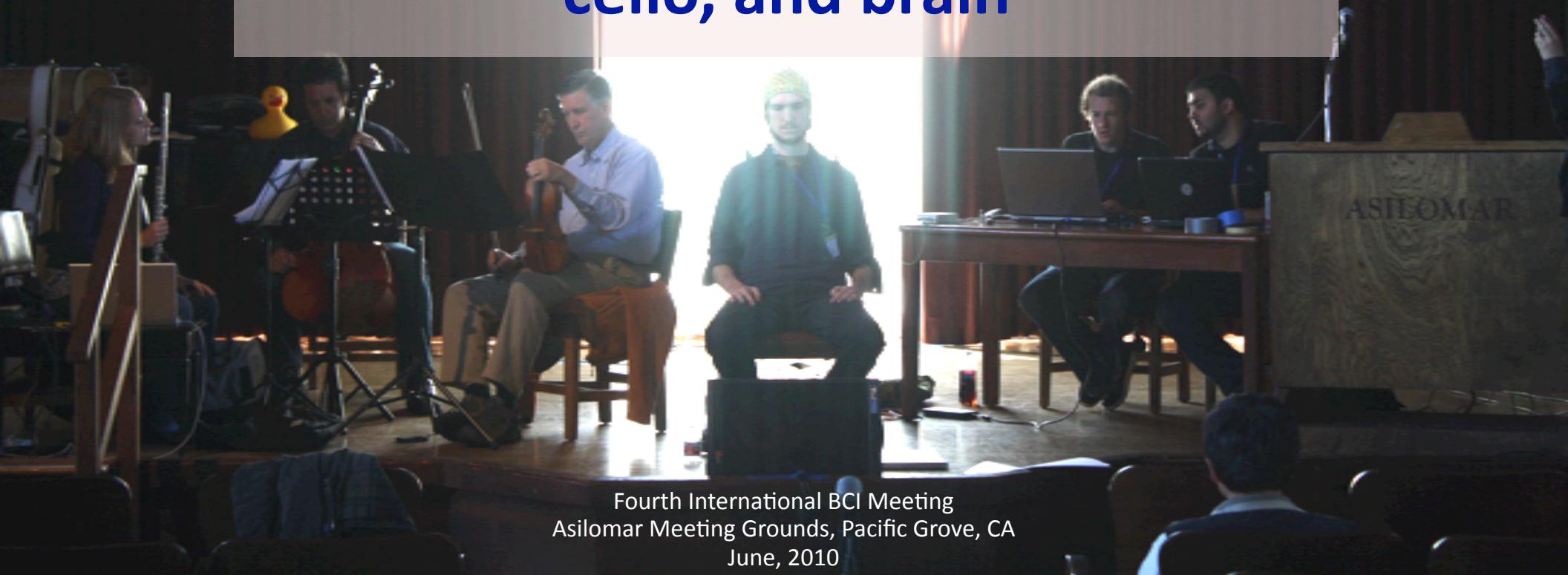
Changes in distribution of broadband high-frequency EEG power with imagined emotion



Julie Onton & Scott Makeig, *Frontiers in Human Neuroscience*, 2009



JUST: A quartet suite for flute, violin, cello, and brain



Fourth International BCI Meeting
Asilomar Meeting Grounds, Pacific Grove, CA
June, 2010

Brain imaging during movement – How?

- Current advances in miniaturization, computer power, and information-based signal processing make possible a new imaging modality:

Mobile

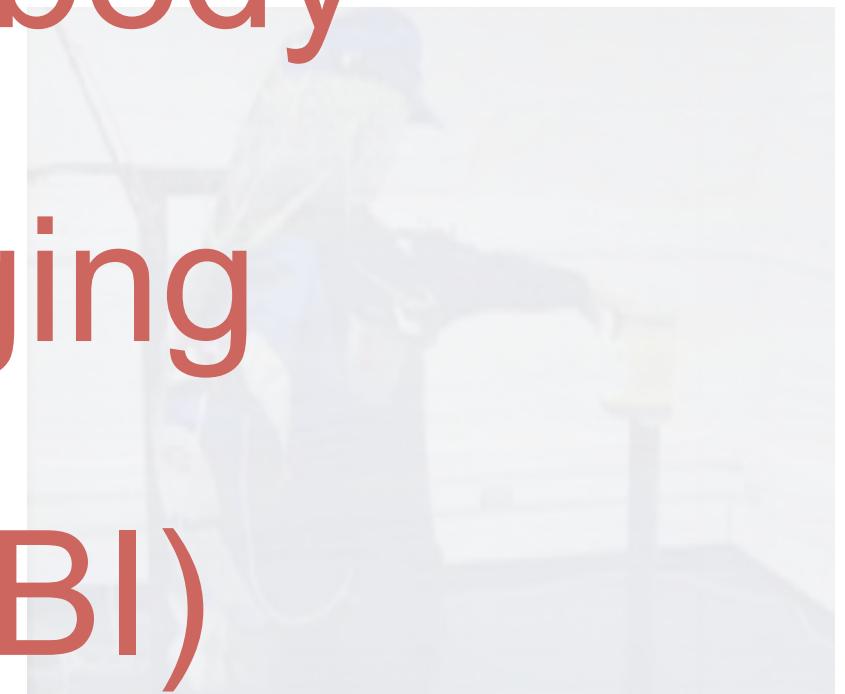
→ Mobile Brain/Body Imaging (MoBI)

Brain/body

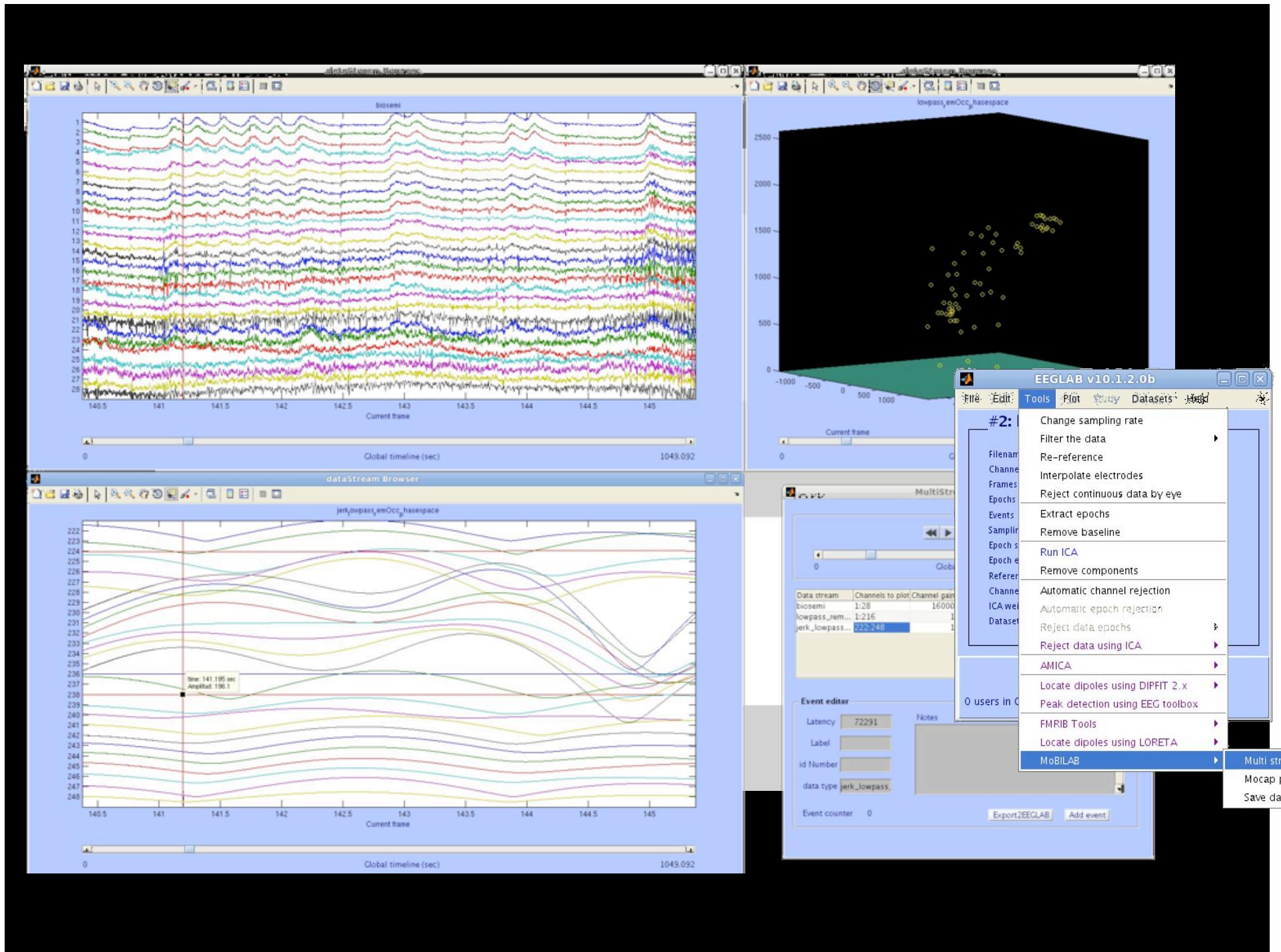
Concept:

Combine whole-head EEG, eye gaze tracking, and whole-body motion capture recording in a real-world 3-D environment.

Imaging (MoBI)

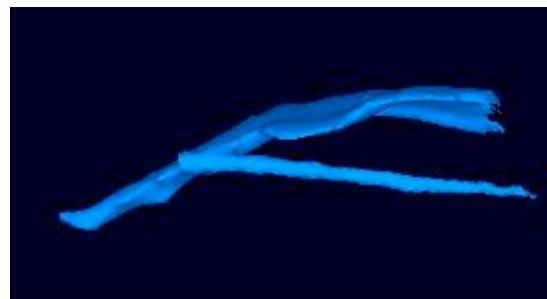
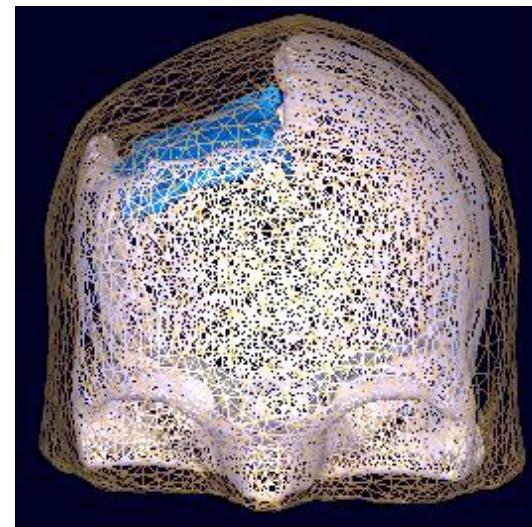
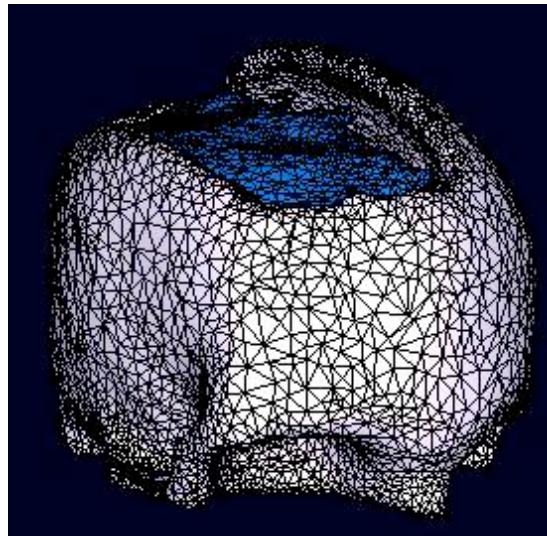






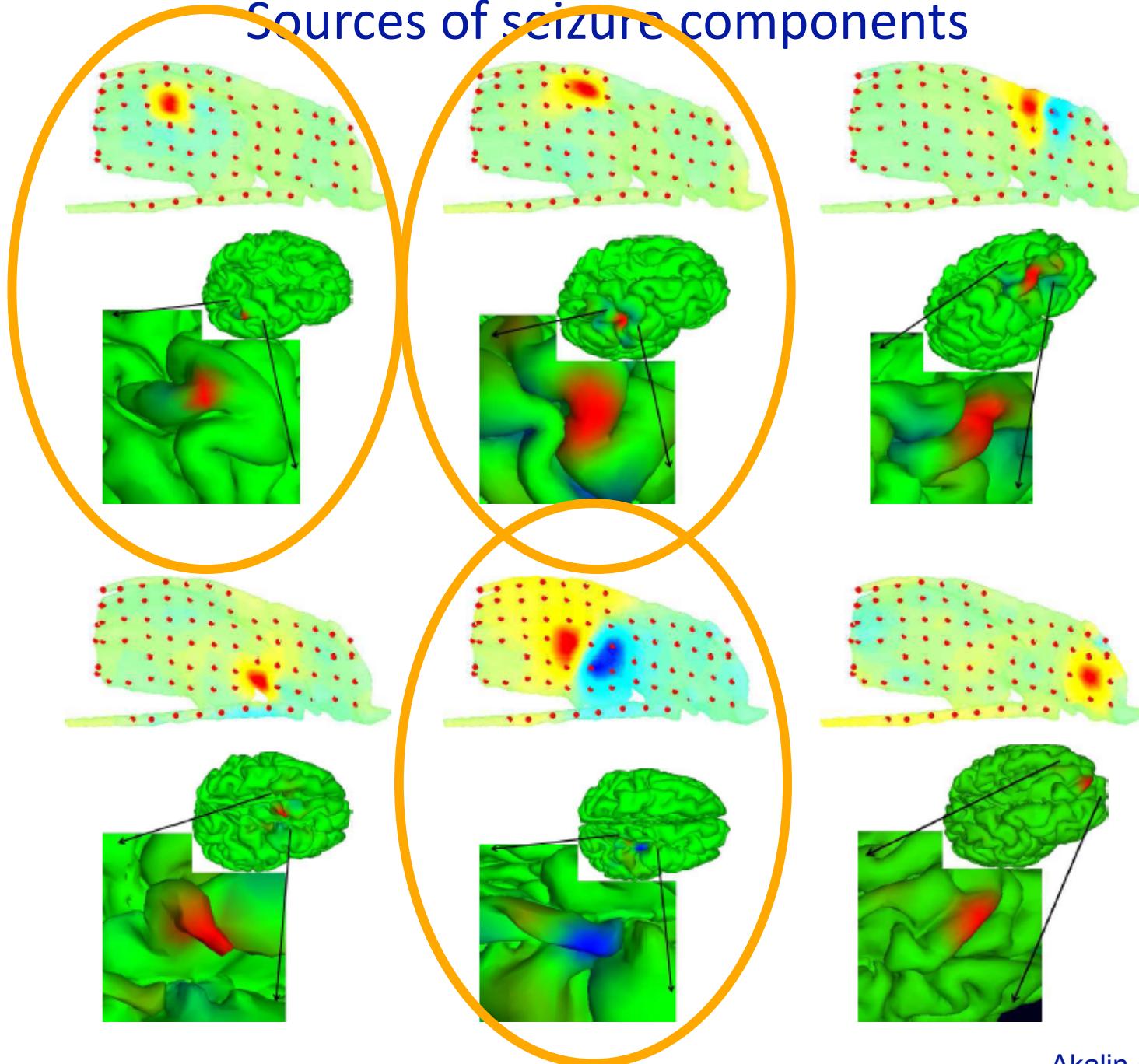
Finding EcoG Sources

(invasive monitoring before surgery for epilepsy)

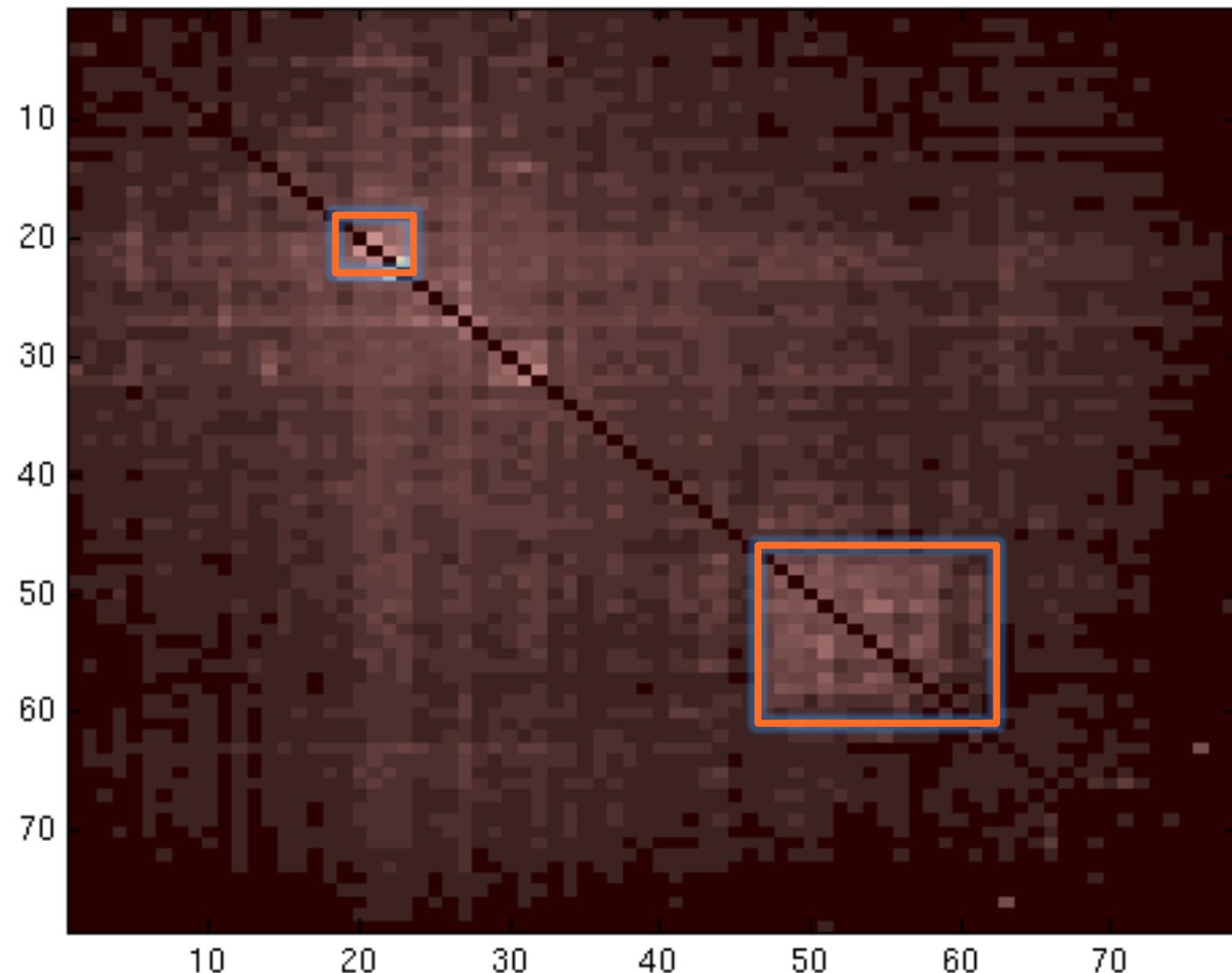


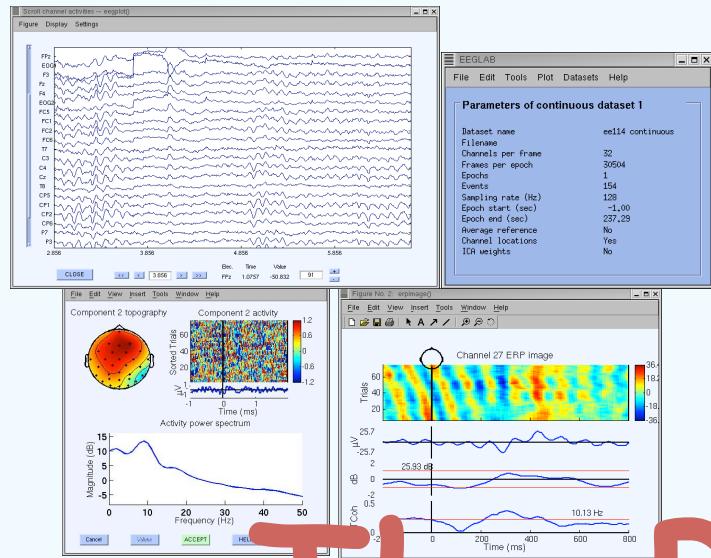
Number of elements:
Scalp: 10,000
Skull: 30,000
Plastic sheet : 7,000

Sources of seizure components



5-model AMICA decomposition (dependent subspaces)





The Beginning

fEEG, BMI, ...