Independent Component Analysis of Electrophysiological Data

Scott Makeig
Institute for Neural Computation
University of California San Diego

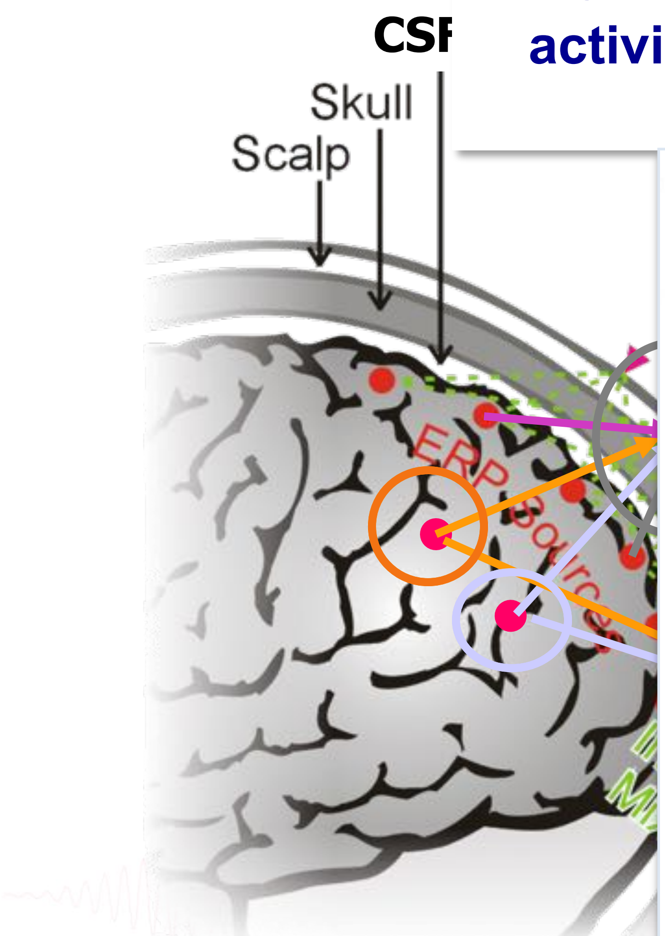
27th EEGLAB Workshop
Pittsburgh, Pennsyvania

September, 2018

Blind EEG Source Separation by Independent Component Analysis

Tony Bell, developer of Infomax ICA

ICA can find distinct EEG source activities -- and their 'simple' scalp maps!



Independent Component Analysis of Electroencephalographic Data

Scott Makeig
Naval Health Research Center
P.O. Box 85122
San Diego CA 92186-5122
scott@cpl.mmag.nhrc.navy.mil

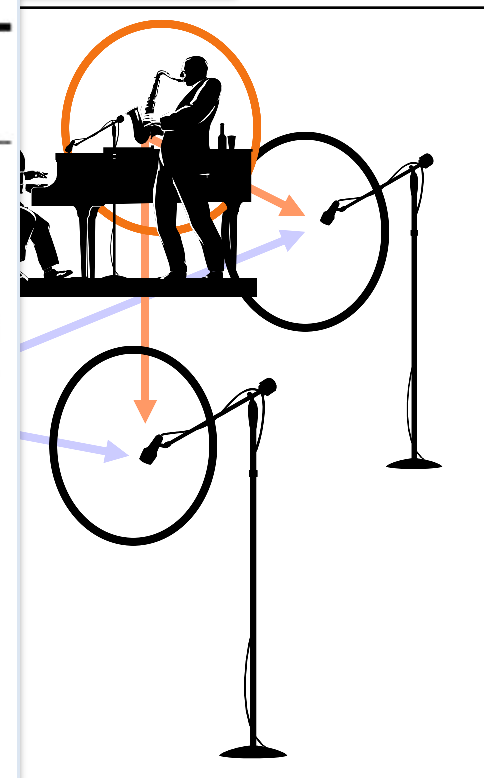
Anthony J. Bell
Computational Neurobiology Lab
The Salk Institute, P.O. Box 85800
San Diego, CA 92186-5800
tony@salk.edu

Tzyy-Ping Jung
Naval Health Research Center and
Computational Neurobiology Lab
The Salk Institute, P.O. Box 85800
San Diego, CA 92186-5800
jung@salk.edu

Terrence J. Sejnowski
Howard Hughes Medical Institute and
Computational Neurobiology Lab
The Salk Institute, P.O. Box 85800
San Diego, CA 92186-5800
terry@salk.edu

Abstract

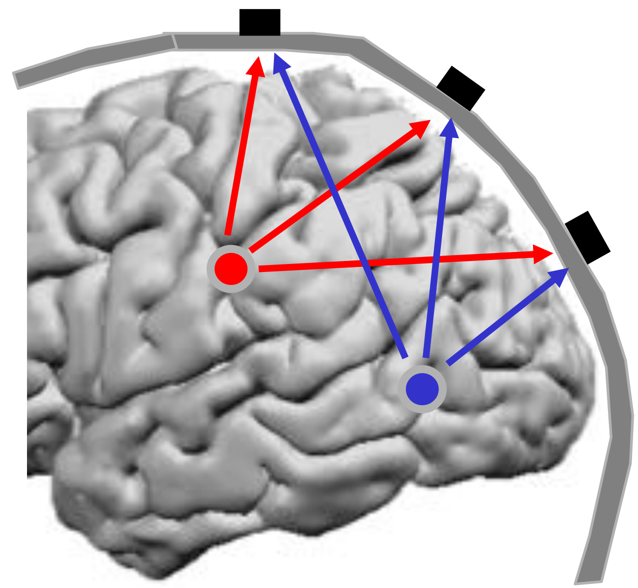
Because of the distance between the skull and brain and their different resistivities, *electroencephalographic* (EEG) data collected from any point on the human scalp includes activity generated within a large brain area. This spatial smearing of EEG data by volume conduction does not involve significant time delays, 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 EEG components (line and muscle noise, eye movements) from other sources. (3) ICA is capable of isolating overlapping EEG phenomena, including alpha and theta bursts and spatially-separable 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.

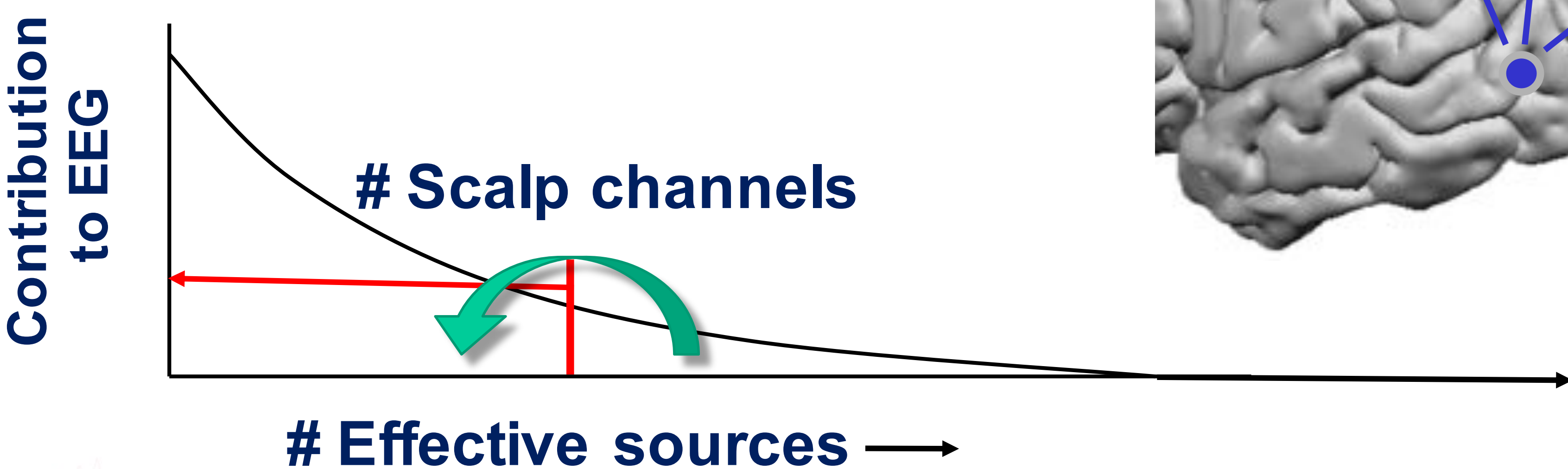


S. Makeig, S. Enghoff (2000)

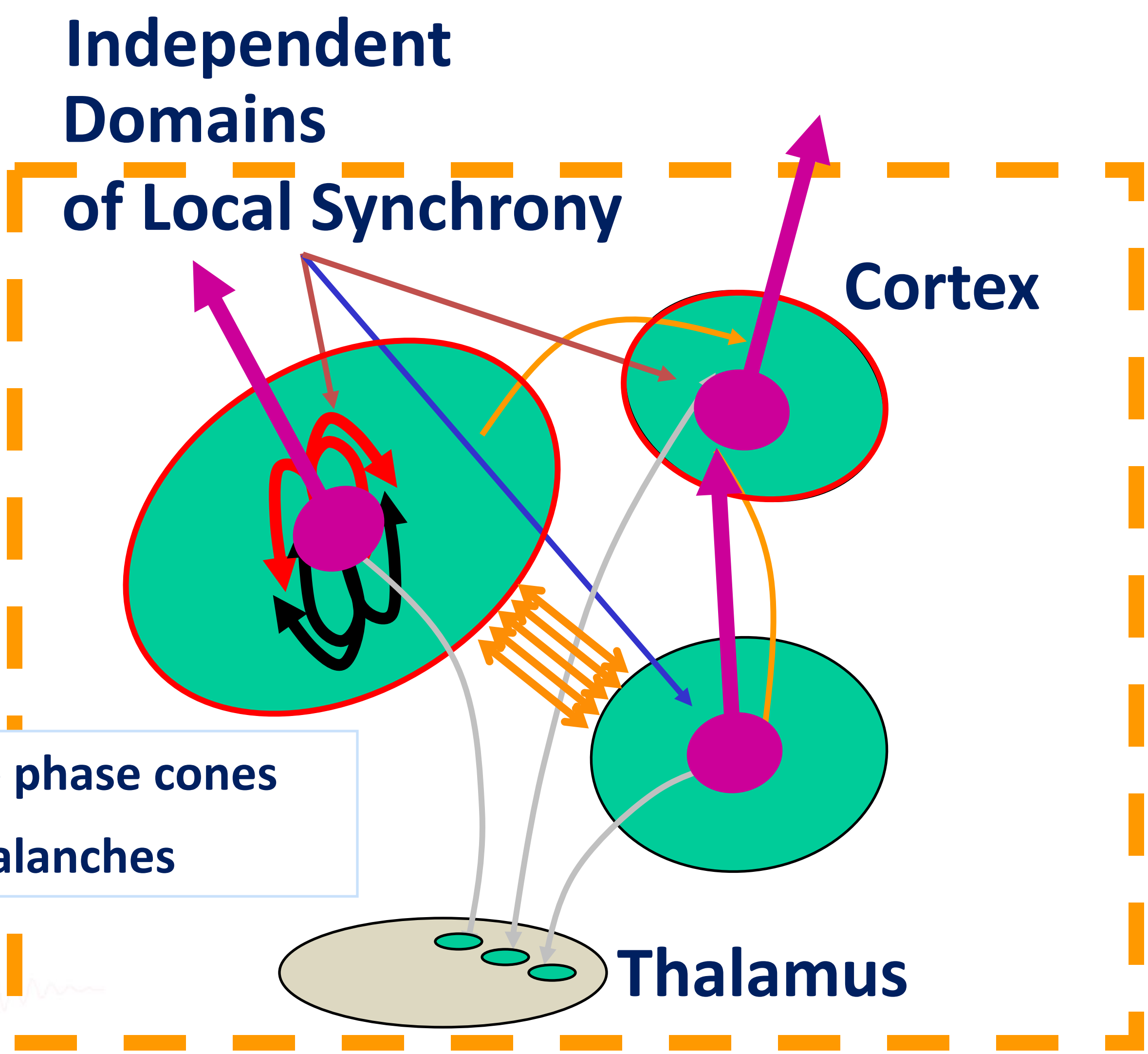
ICA Assumptions

- Mixing is linear at electrodes ✔
- Propagation delays are negligible ✔
- Component locations are fixed ?
- Component time courses are independent ?
- # components <= # scalp channels ?





Are EEG effective source signals independent?



Freeman - phase cones

Plenz - avalanches

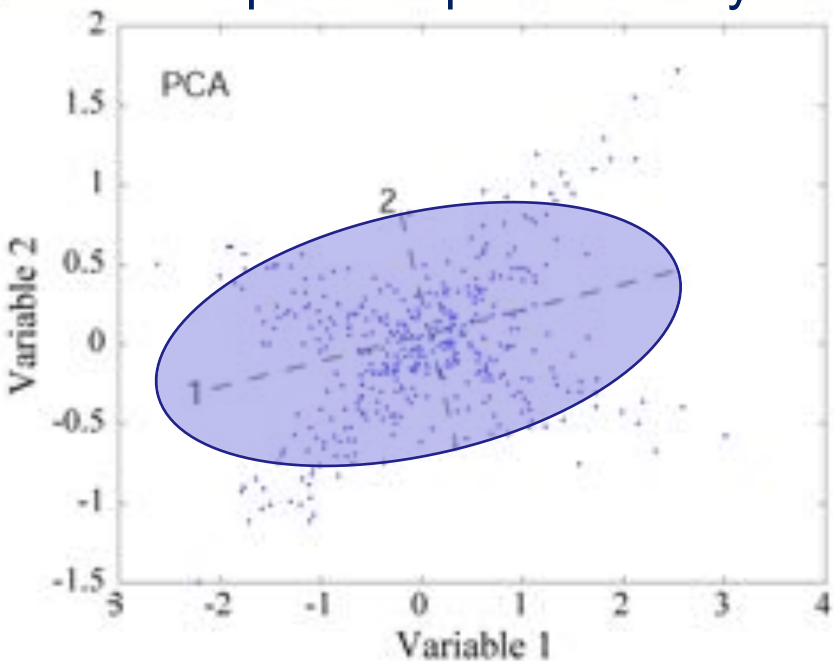
S. Makeig (2007)

Properties of EEG Independent Components

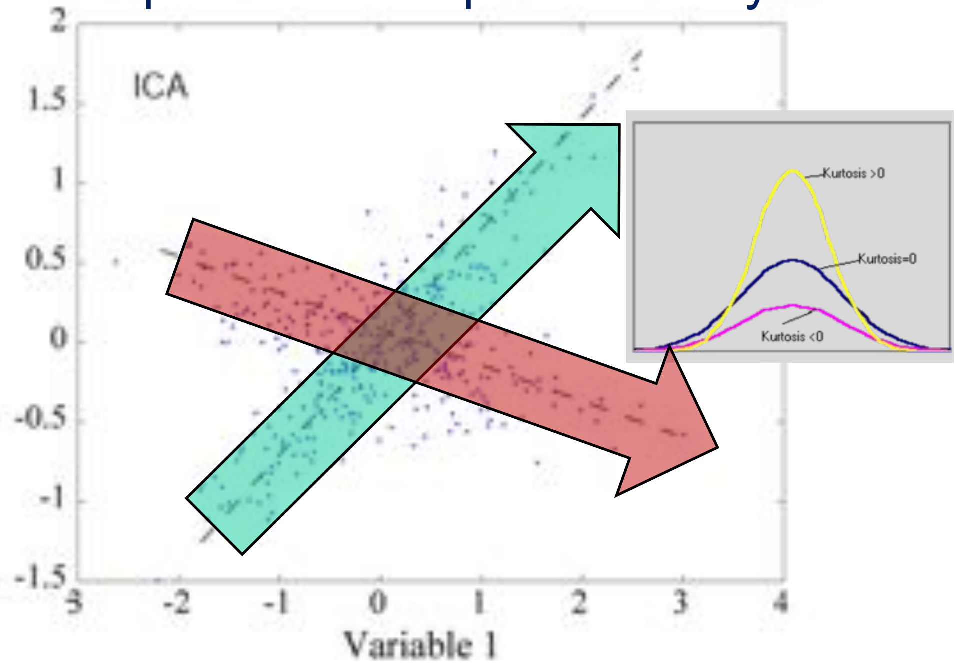
- Maximally Temporally Independent
- Concurrently Active and Spatially Overlapping
- *Dipolar* Scalp Maps (Delorme et al., 2012)
- *Functionally* Distinct
- Between-Subject Similarity / Complexity

ICA vs. PCA

Principal Component Analysis



Independent Component Analysis



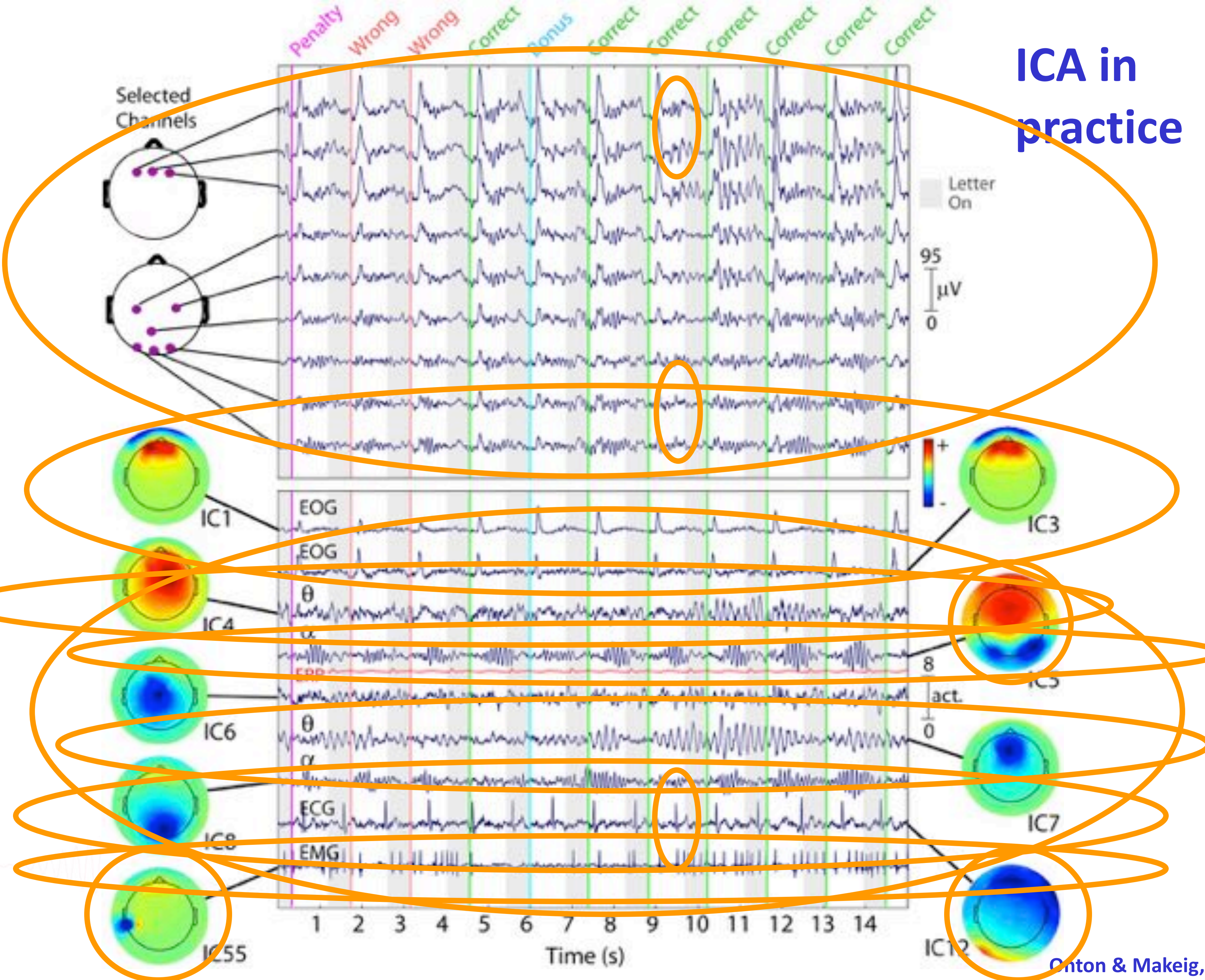
PCA simply decorrelates the outputs using an **orthogonal mixing matrix**.

PCA makes each successive component account for as much **variance** in the data as possible.

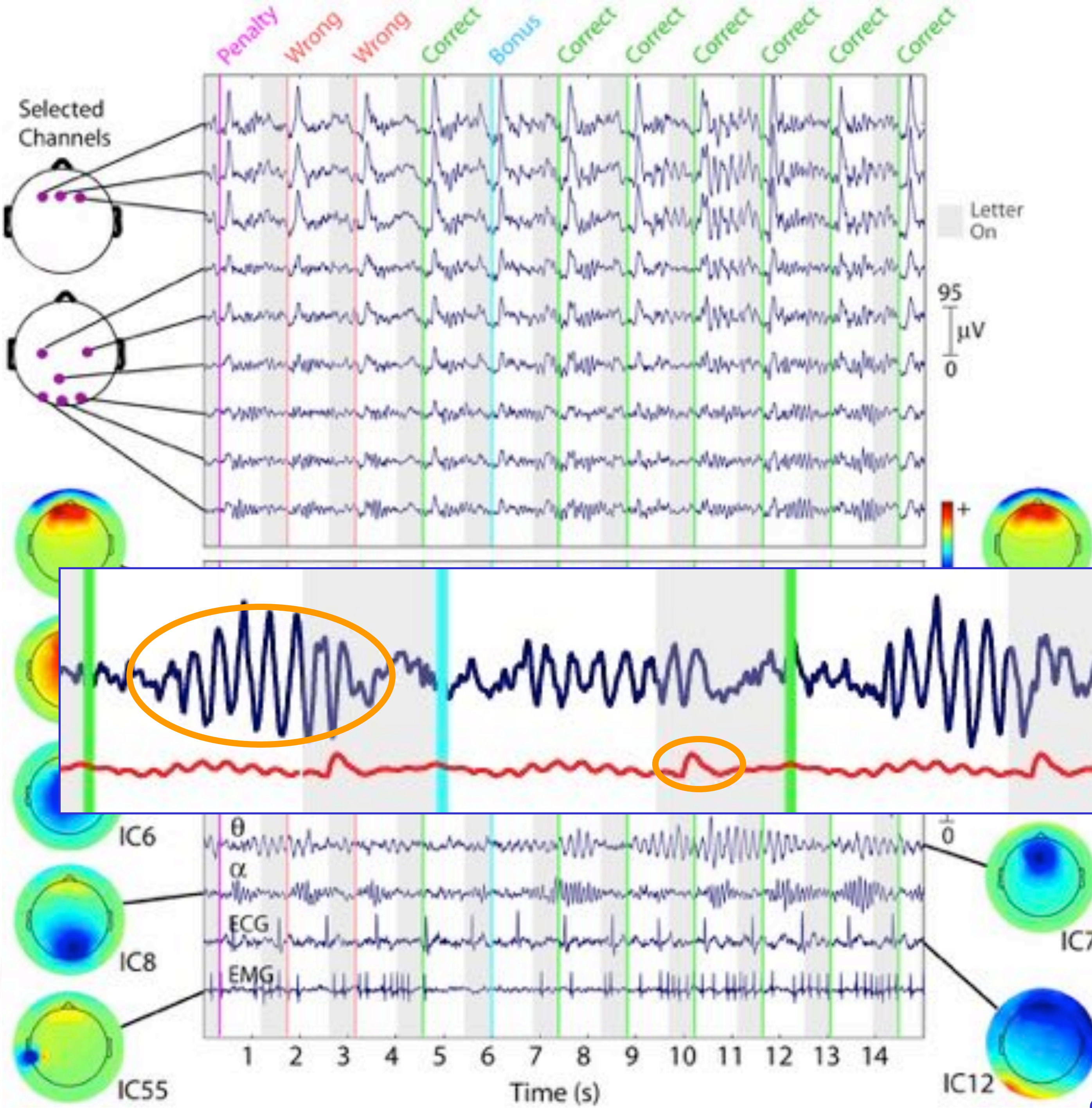
ICA makes each component account for as much **temporally independent information** in the data as possible, with no constraints on the mixing matrix.

PCA lumps – ICA splits!

ICA in practice



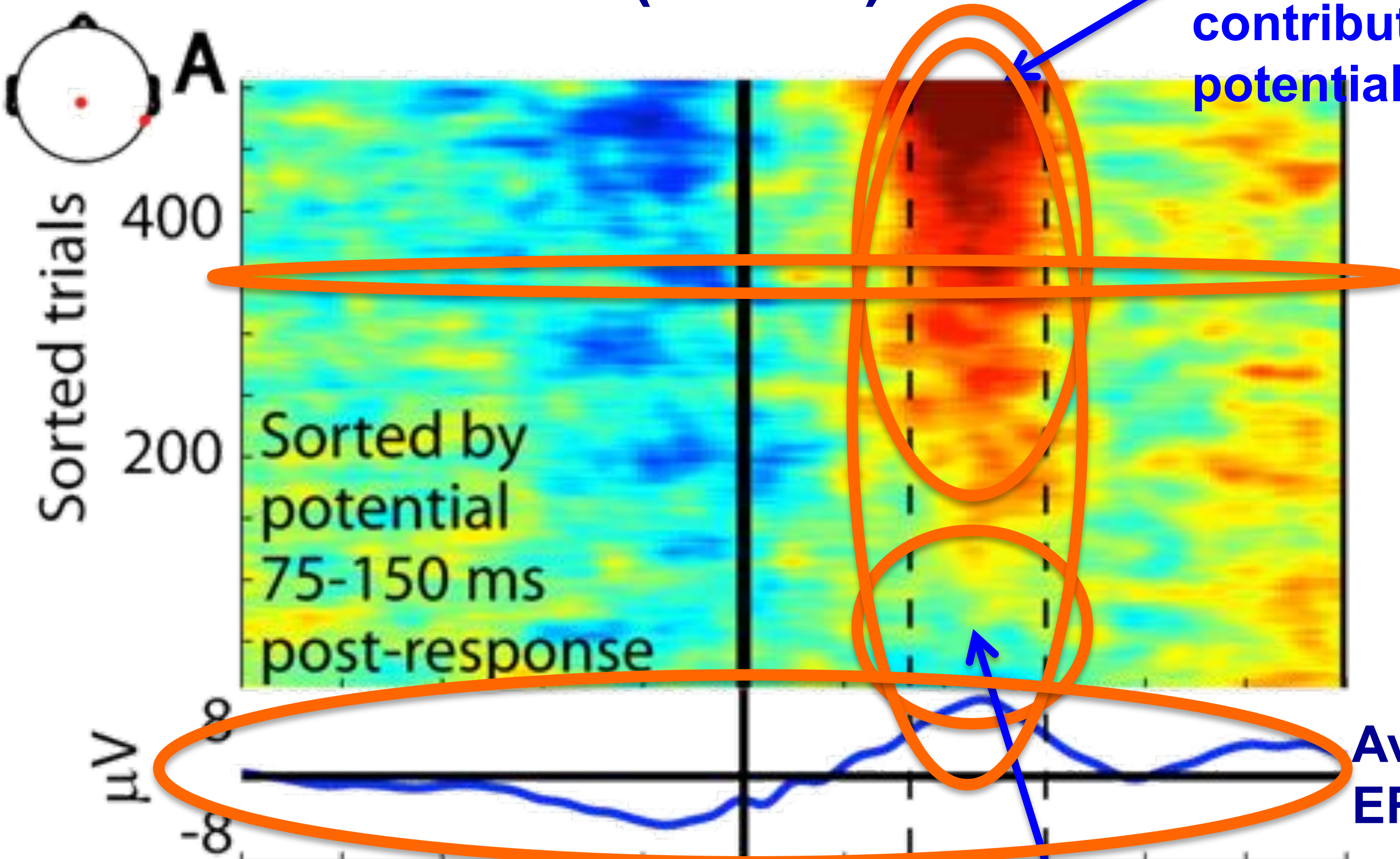
Onton & Makeig, 2006



Onton, Makeig (2006)

A P300' visual target response at electrode Cz (vertex)

What sources contribute to this potential?

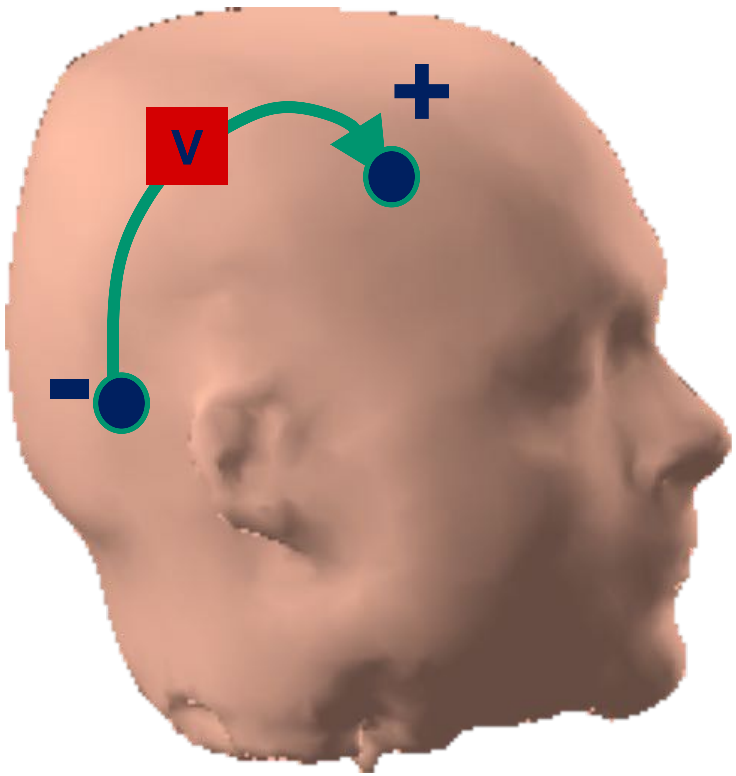


Average ERP

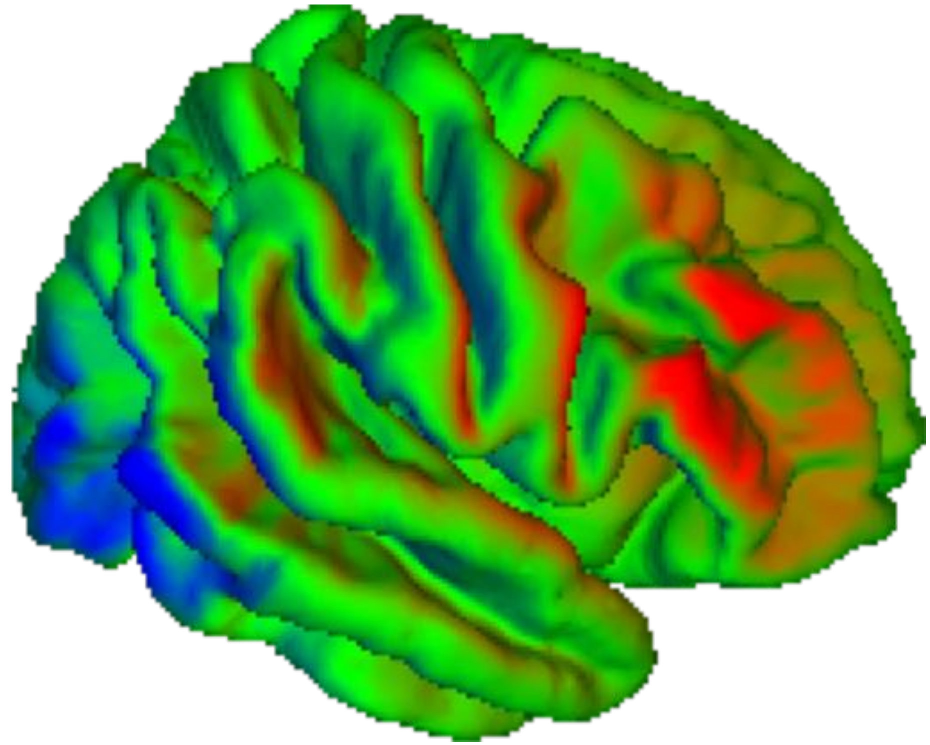
No scalp response in these trials … Why not?

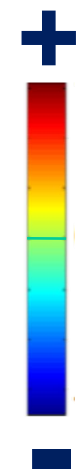
J. Onton & S. Makeig (2009)

The ‘receptive field’ of a bipolar EEG channel!



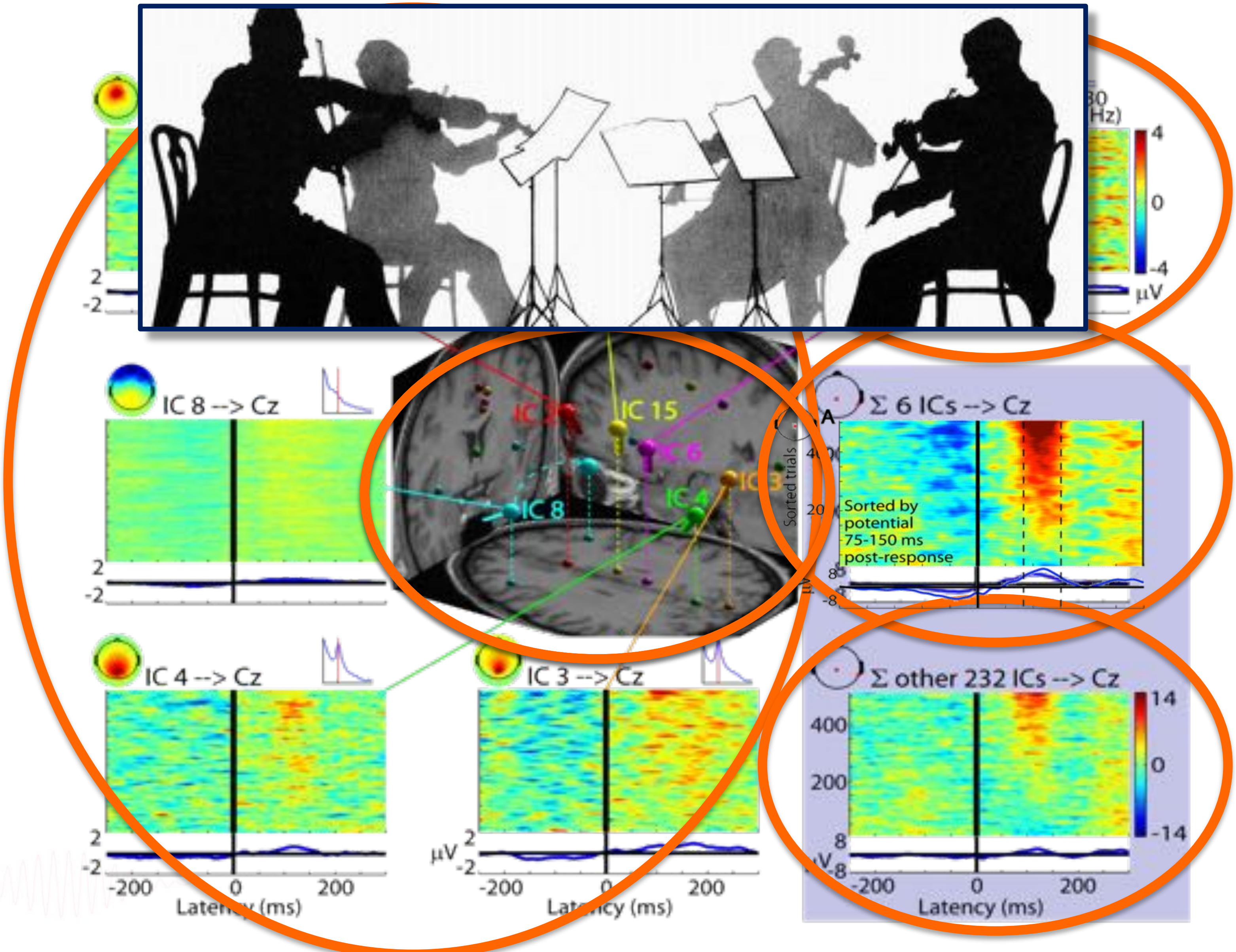
Scalp EEG channel





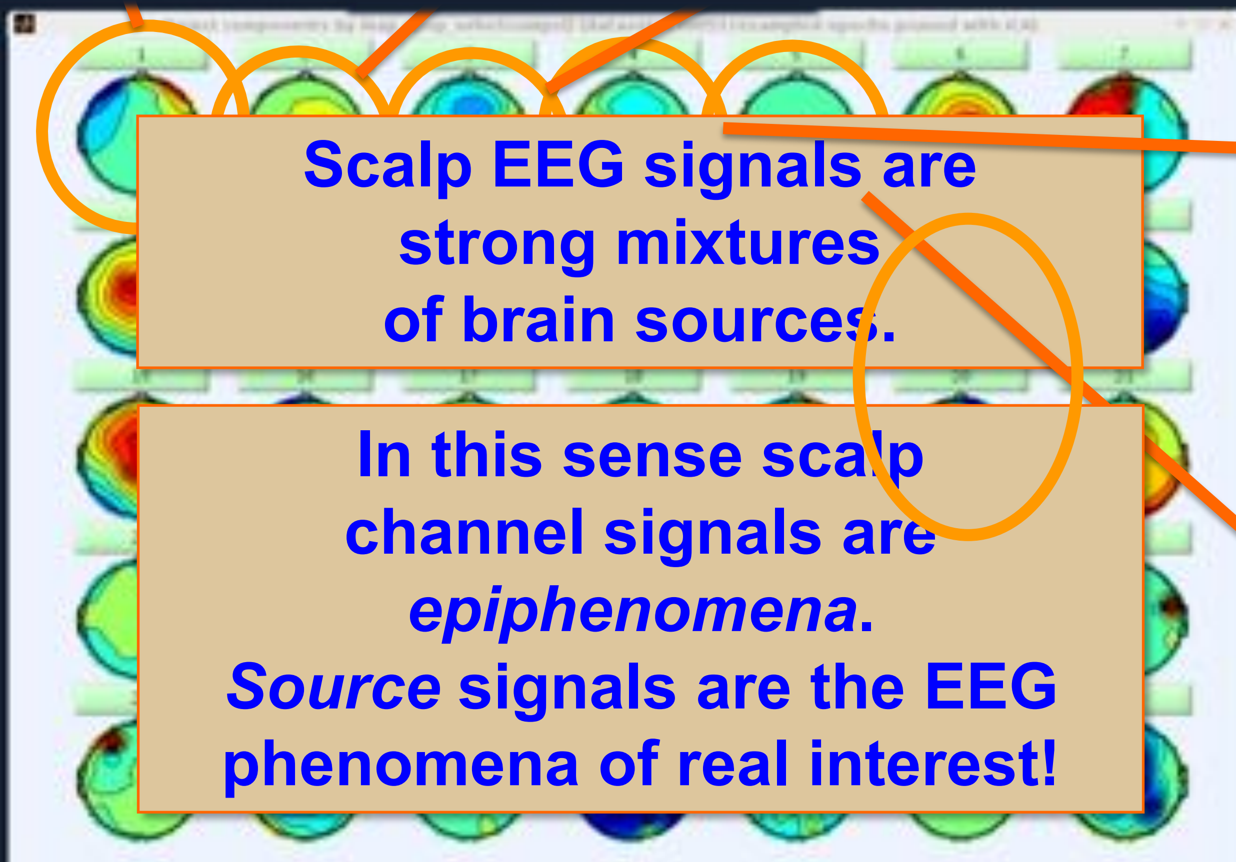
Its cortical ‘receptive field’

The response (at Cz) sums 238 independent sources



J. Onton & S. Makeig (2009)

No more than ~30% of any scalp channel variance is produced by any one brain source!

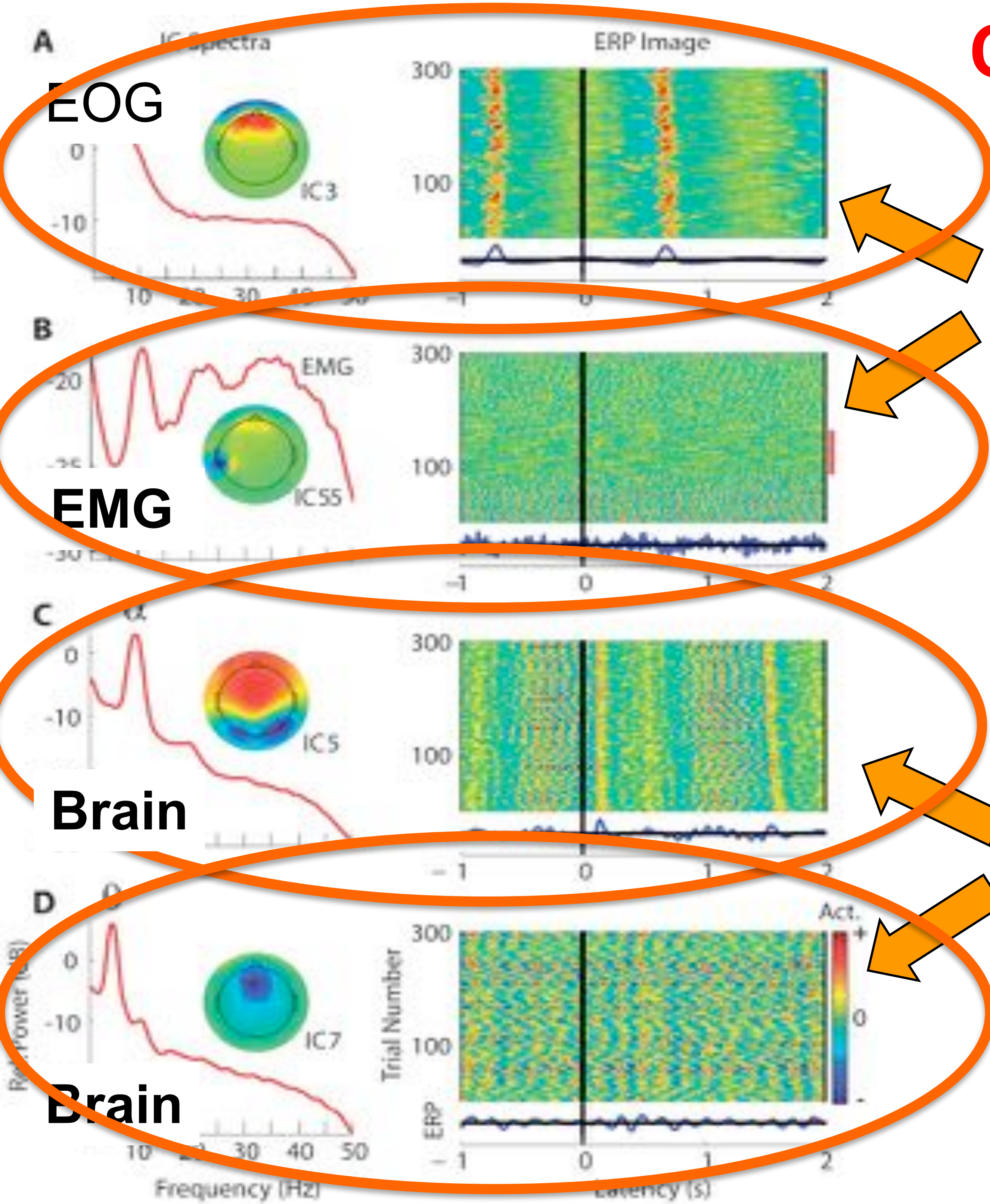


Scalp EEG signals are strong mixtures of brain sources.

In this sense scalp channel signals are *epiphenomena*.
***Source* signals are the EEG phenomena of real interest!**

S. Makeig & M. Miyakoshi, 2015

Classifying ICs

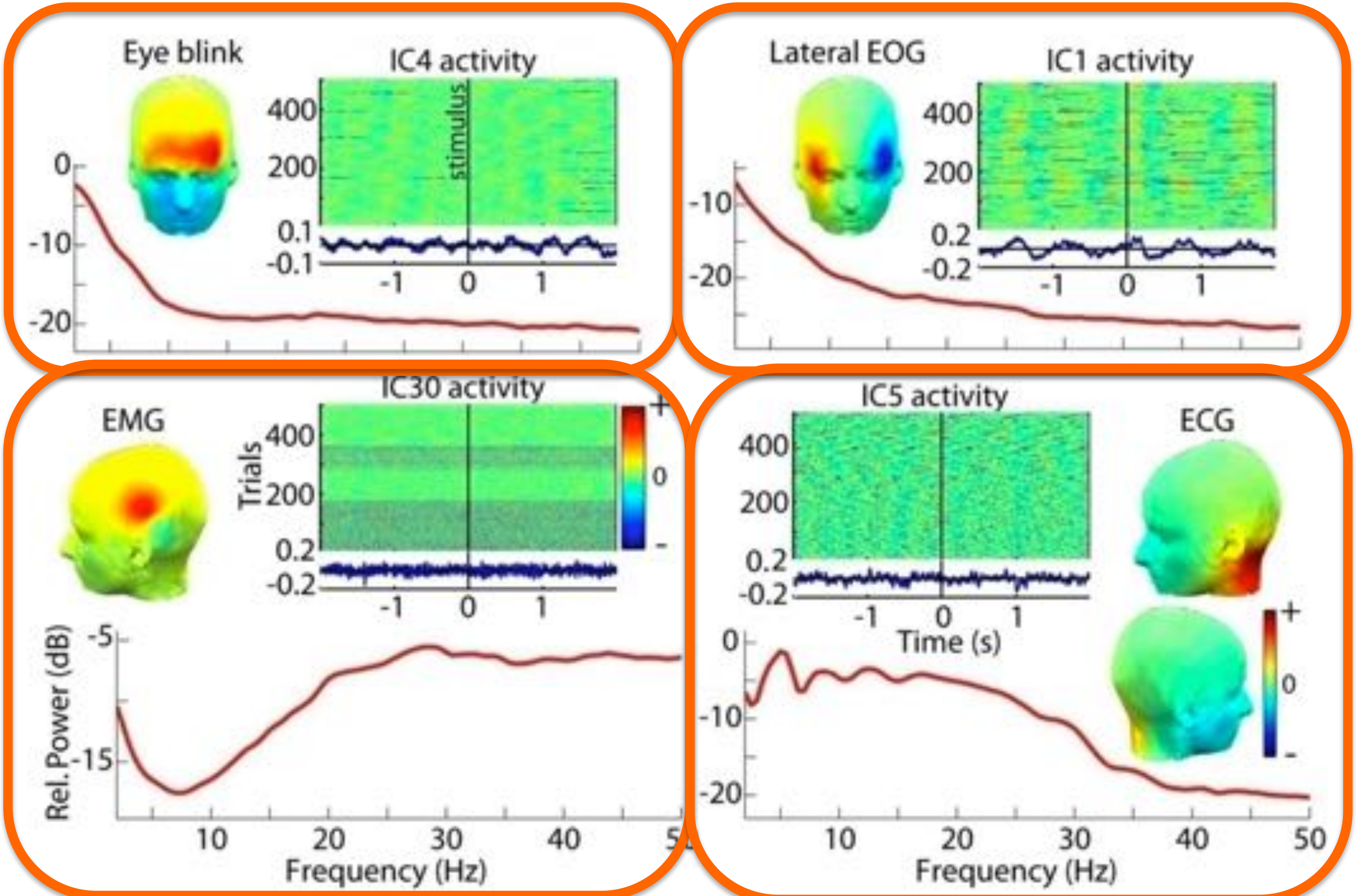


Non-brain sources

Effective brain sources

J. Onton & S. Makeig, 2005

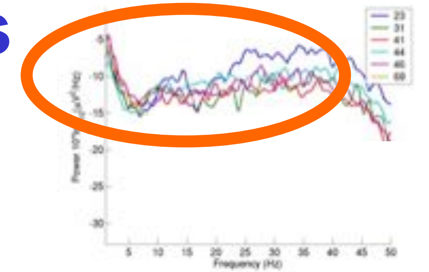
ICA finds Non-Brain Independent Component (IC) Processes …

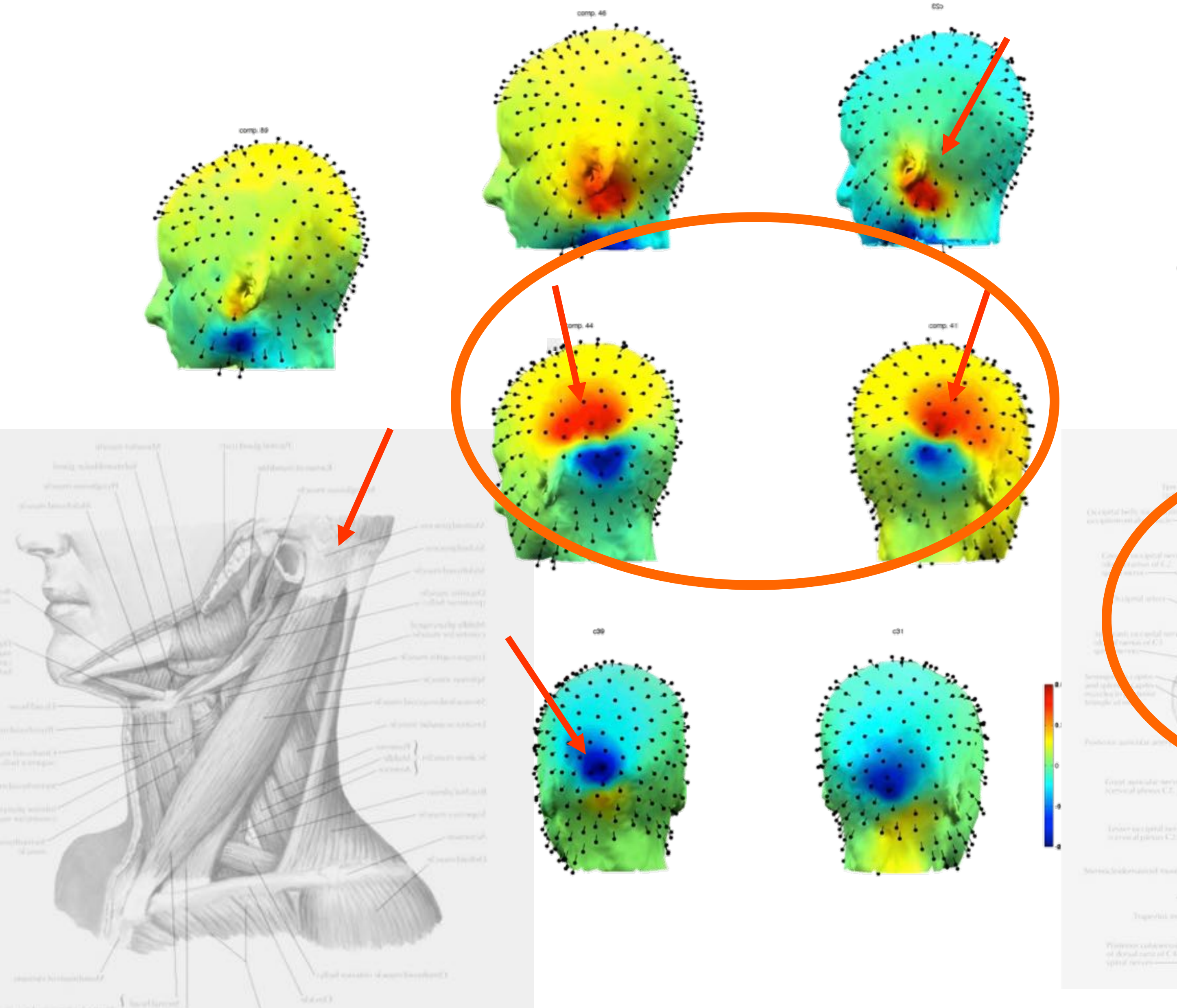


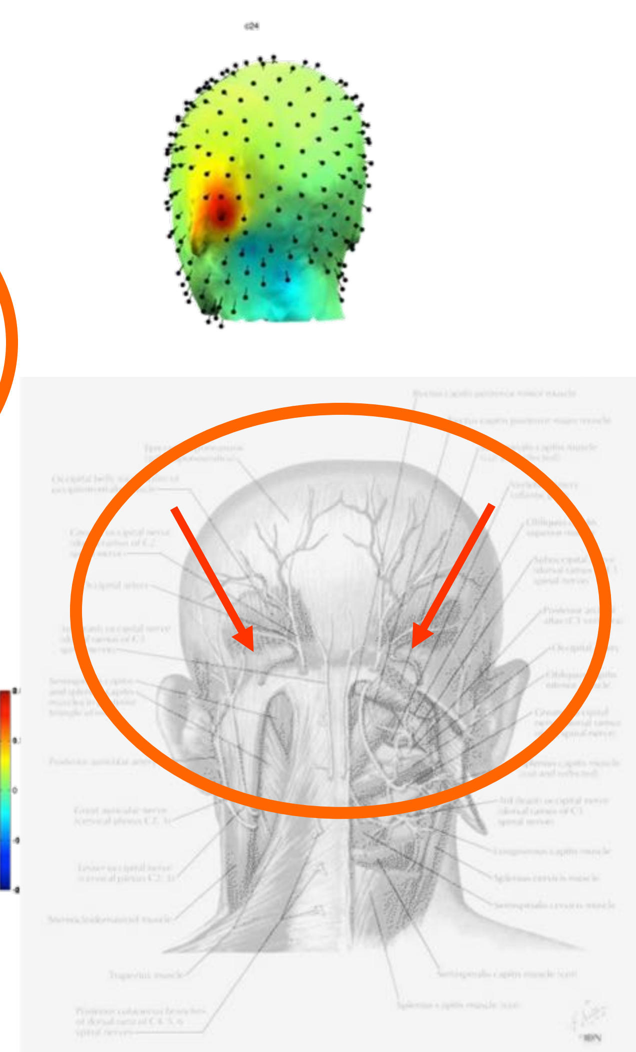
… separates them from the remainder of the data …

J. Onton & S. Makeig

Independent muscle signals

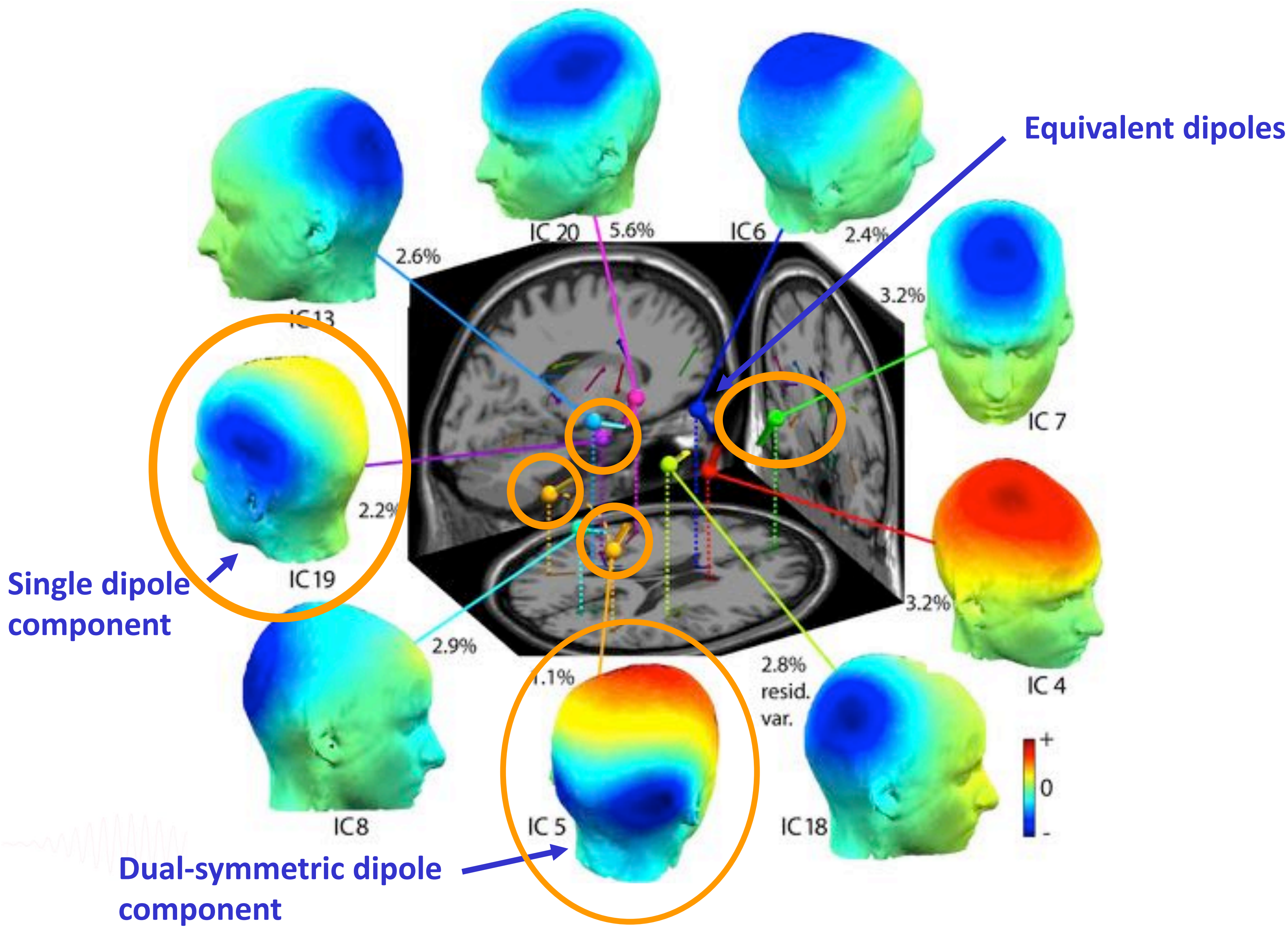






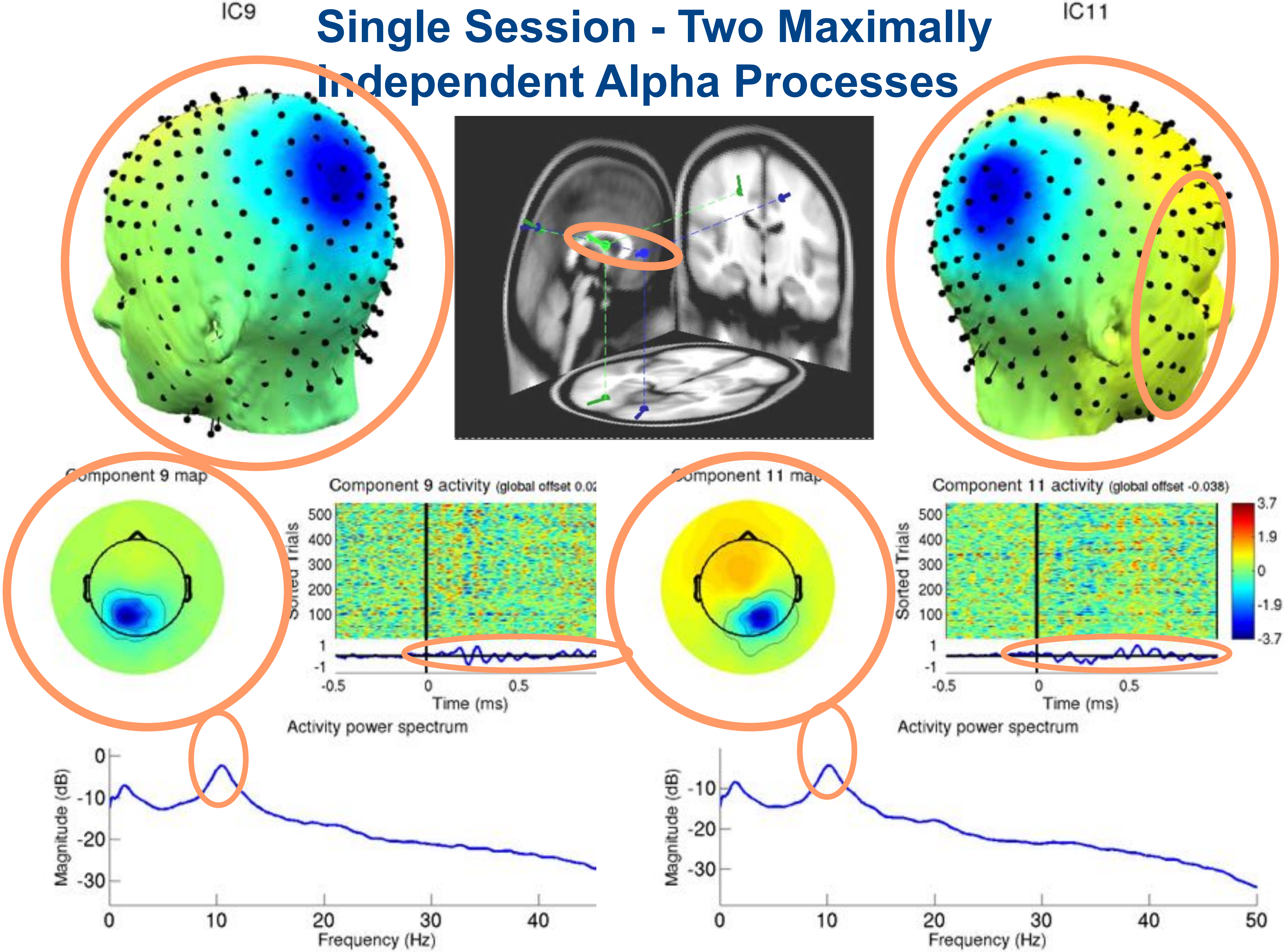
S. Makeig, J. Onton 2005

… and also separates cortical brain IC processes



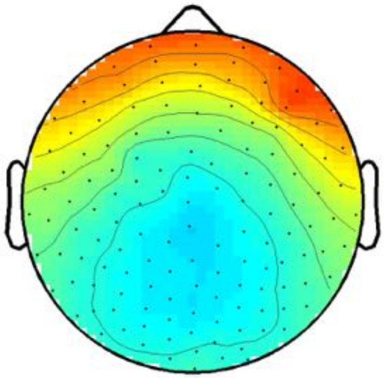
Julie Onton & S. Makeig (2006)

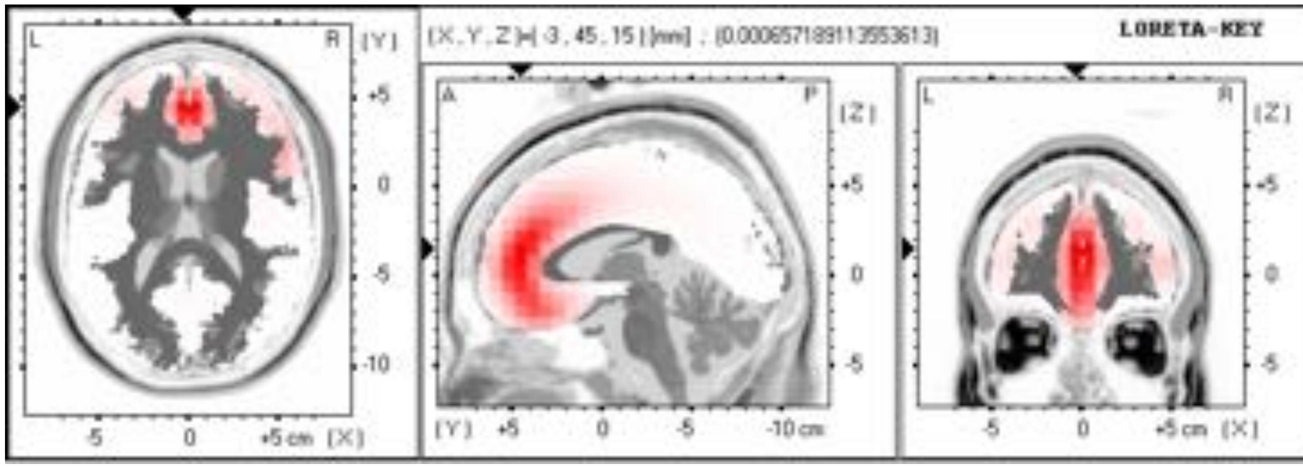
Single Session - Two Maximally Independent Alpha Processes

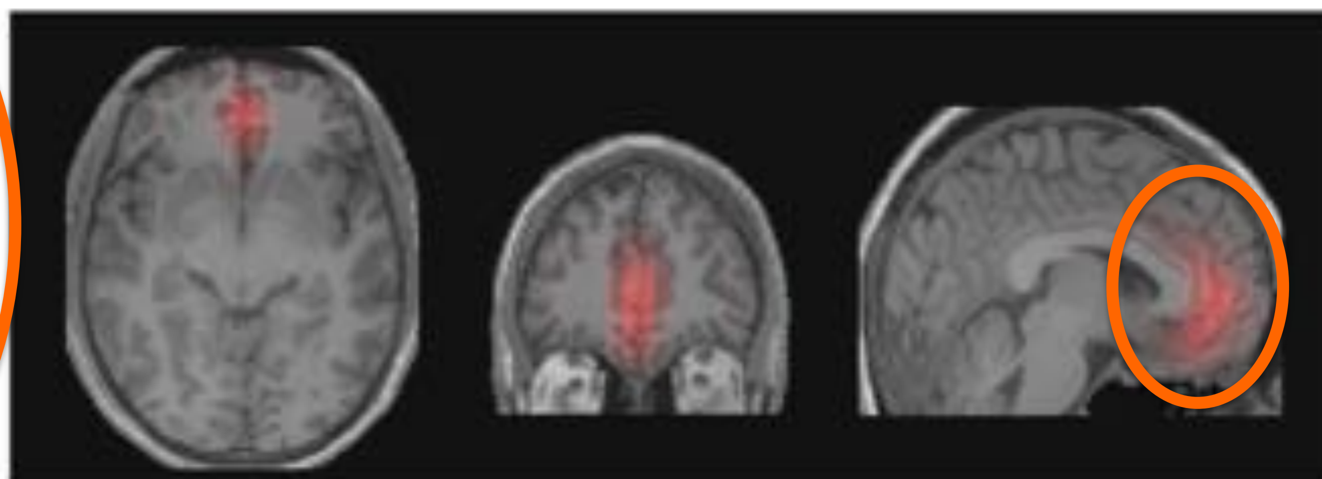


EEG Source Localization

LORETA = Low-Resolution Electrical Tomography

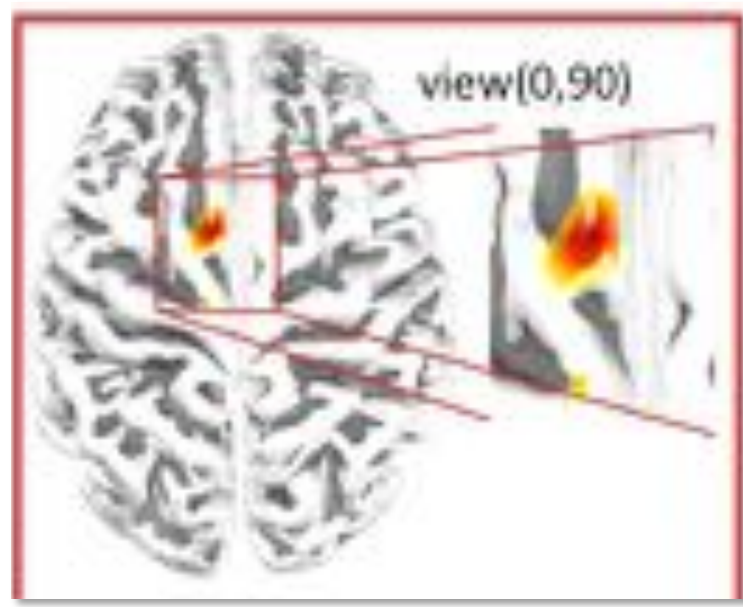




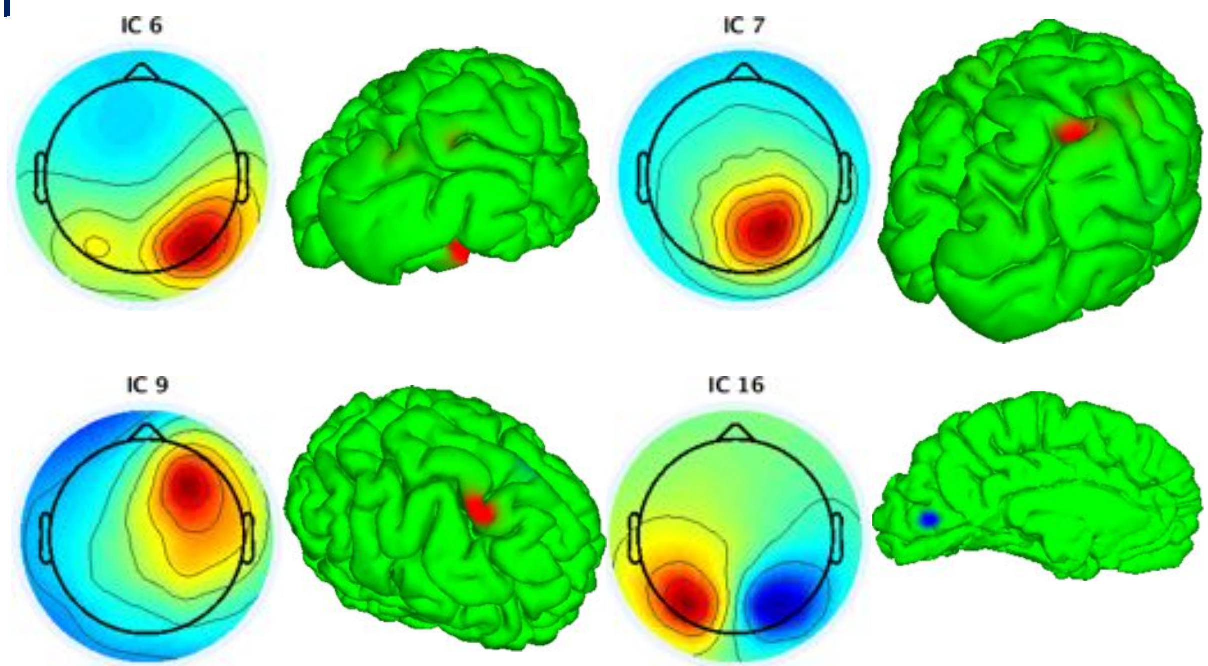


A. Delorme

Sparse
Compact
Smooth
(SCS)

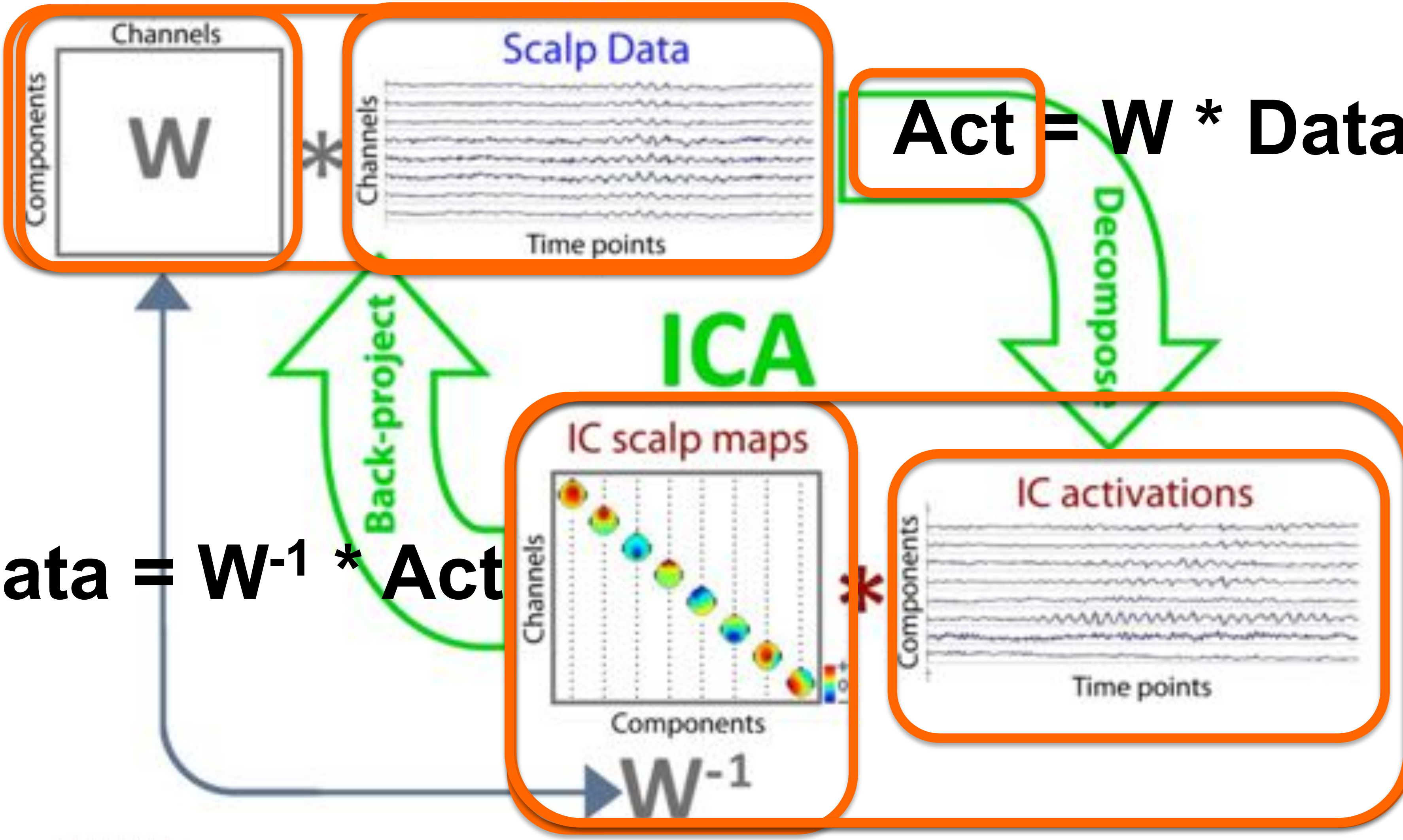


Distributed IC source location estimation using SCALE-optimal head model.



Z. Akalin Acar et al., 2016

ICA is a linear data decomposition method



$$\text{Act} = W * \text{Data}$$

$$\text{Data} = W^{-1} * \text{Act}$$

$$\text{Data} = W^{-1} * (W * \text{Data})$$

Makeig & Onton, 2011

Infomax ICA learning approach

How to make the outputs statistical independent?

Minimize their redundancy or mutual information.

Consider the joint entropy of two components,

$$\boxed{H(y_1, y_2) = H(y_1) + H(y_2) - I(y_1, y_2).}$$

$\boxed{\text{Maximizing } H(y_1, y_2)} \Longrightarrow \boxed{\text{minimizing } I(y_1, y_2).}$

Infomax

Is 0 if the two variables are independent

The learning rule:

$$\boxed{\Delta \mathbf{w}} \propto \boxed{\frac{\partial H(\mathbf{y})}{\partial \mathbf{w}}} \underbrace{\mathbf{w}^T \mathbf{w}}_{\substack{\text{Natural gradient} \\ \text{normalization} \\ \text{(Amari)}}}$$

Historical Remarks

- Herault & Jutten ("Space or time adaptive signal processing by neural network models“, *Neural Nets for Computing Meeting*, Snowbird, Utah, *1986*): Seminal paper
- Bell & Sejnowski (1995): Information maximization (Infomax)
- Makeig, Bell, Jung, Sejnowski (1996); ICA decomposition of EEG
- Amari et al. (1996): Natural gradient learning
- Cardoso (1996): Joint approximate diagonalization (JADE)
- Hyvarinen (1999): (fastICA)
- Lee/Girolami (1999): Mixture model ICA (Extended Infomax)
- Palmer (2006-9): Adaptive mixture ICA (AMICA)

Applications of ICA to biomedical signals

- EEG/ERP analysis (Makeig, Bell, Jung & Sejnowski, *NIPS* 1996)
- fMRI analysis (McKeown et al., 1998)
- Fetal/mother ECG separation (Cardoso, 1998)
- Electrocorticography (ECoG) (Whitmer, 2010)

Important Recent Result (2012)

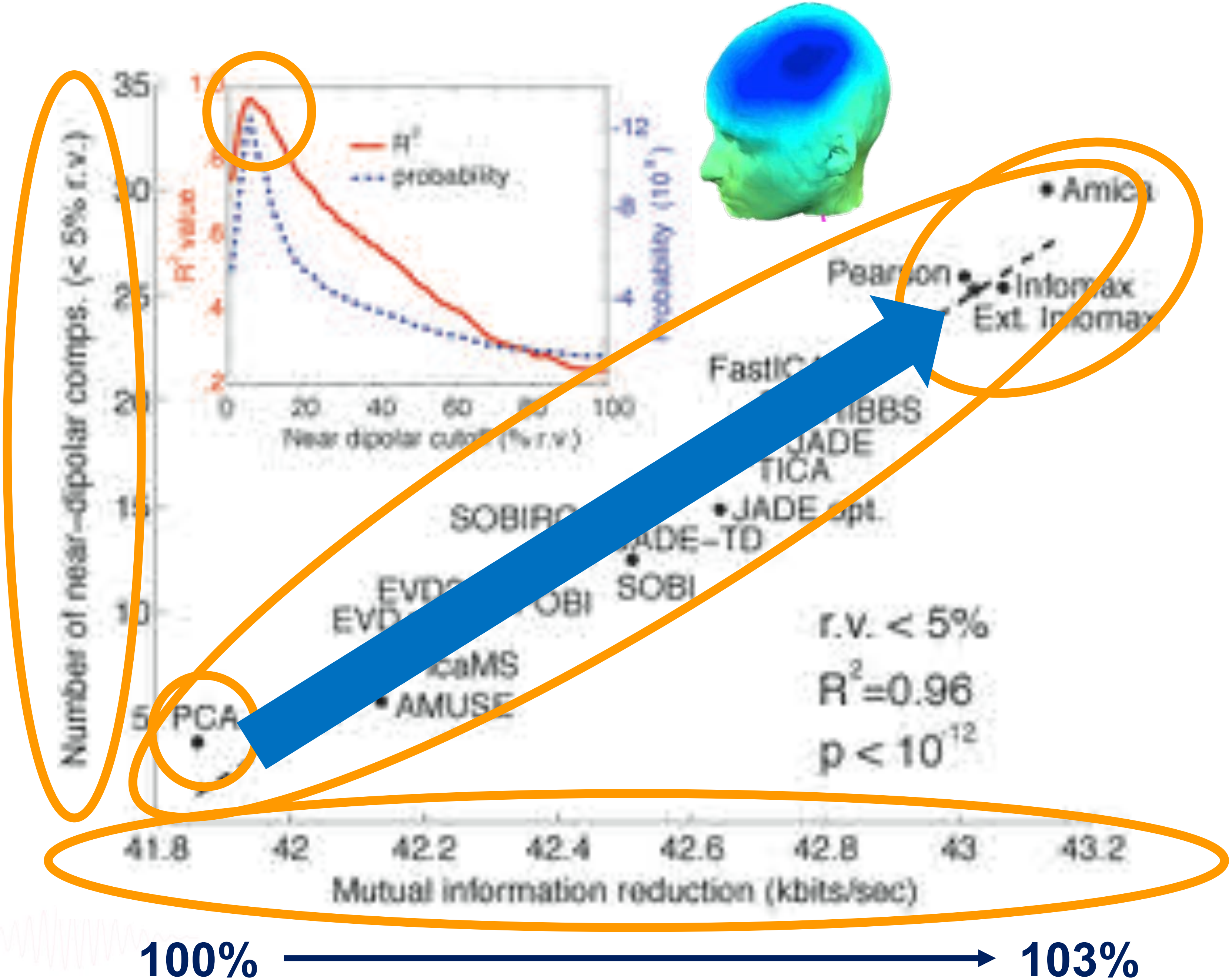
Those linear decompositions of multi-channel EEG data that find ICs whose time courses are **more** temporally **independent …**

Also find more ICs whose scalp maps are highly **'dipolar'** – i.e., ICs compatible with the spatial projection of a single local cortical (or non-brain, artifactual) source process – whose location can be accurately estimated.

More independent time courses ←→ Larger number of dipolar ICs

Hypothesis: Dipolar ICs = Localized cortical source processes

Delorme et al., *PLOS One*, 2012



Delorme et al., *PLOS One*, 2012

S. Makeig, 2011

Important Recent Result

Those linear decompositions of multi-channel EEG data that find ICs whose time courses are **more** temporally **independent …**

Also find more ICs whose scalp maps are highly **'dipolar'** – i.e., ICs compatible with the spatial projection of a single local cortical effective source (or non-brain artifact) – whose cortical location can be accurately estimated given a good forward-problem head model.

More-independent IC time courses

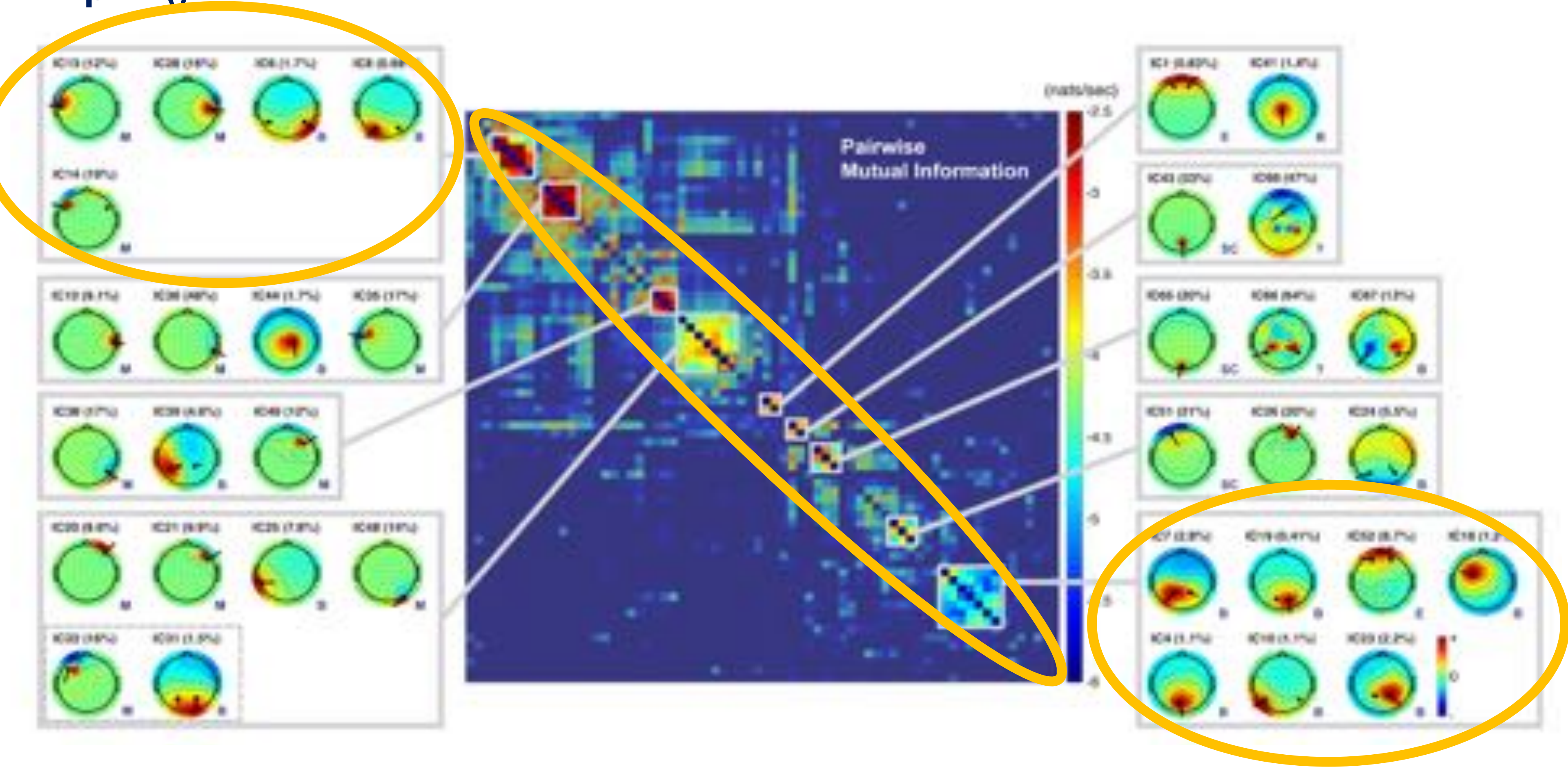
→→→

Larger % of dipolar IC scalp maps

Delorme et al., *PLOS One*, 2012

Pairwise Mutual Information Subspaces

pmi ()

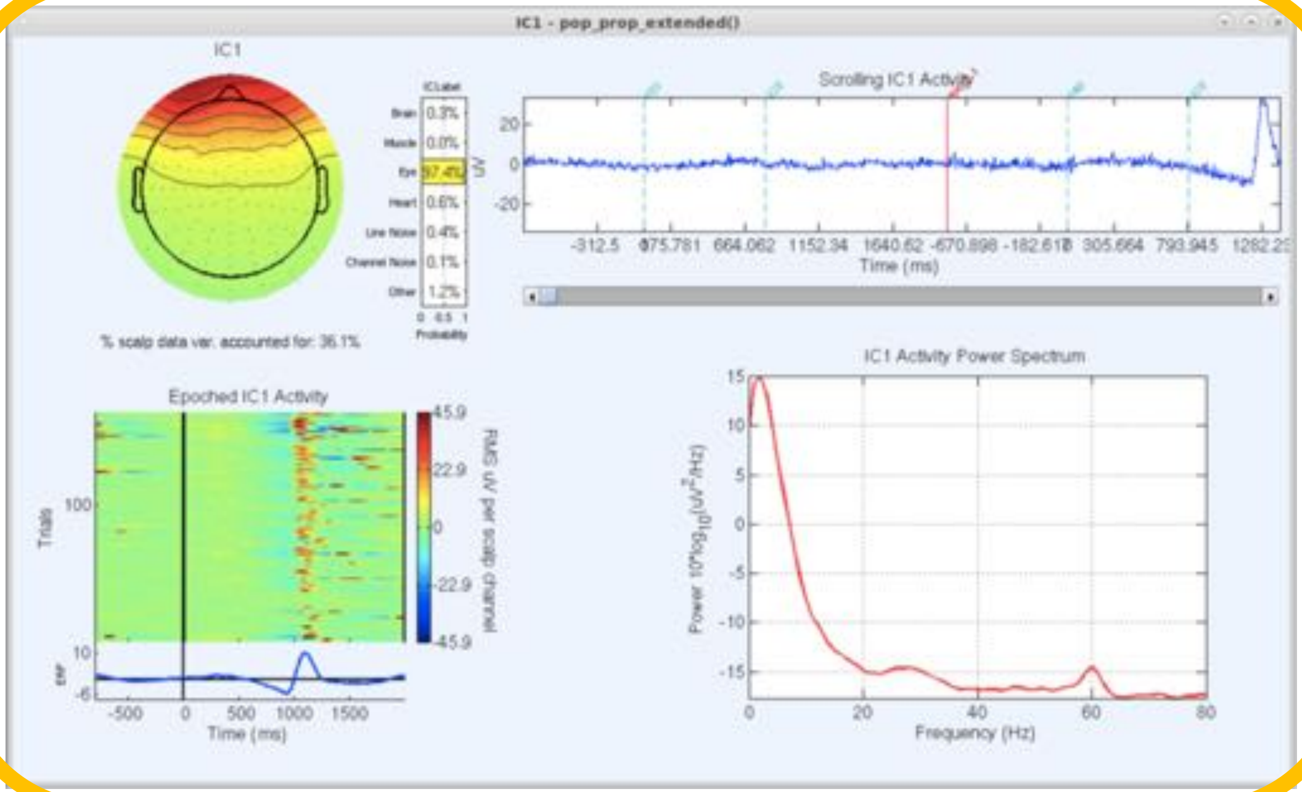


ICA transforms multiple correlated channels into maximally mutually independent component subspaces

Distinguishing IC types: ICLabel

→ https://labeling.ucsd.edu

Info: https://sccn.ucsd.edu/wiki/ICLabel

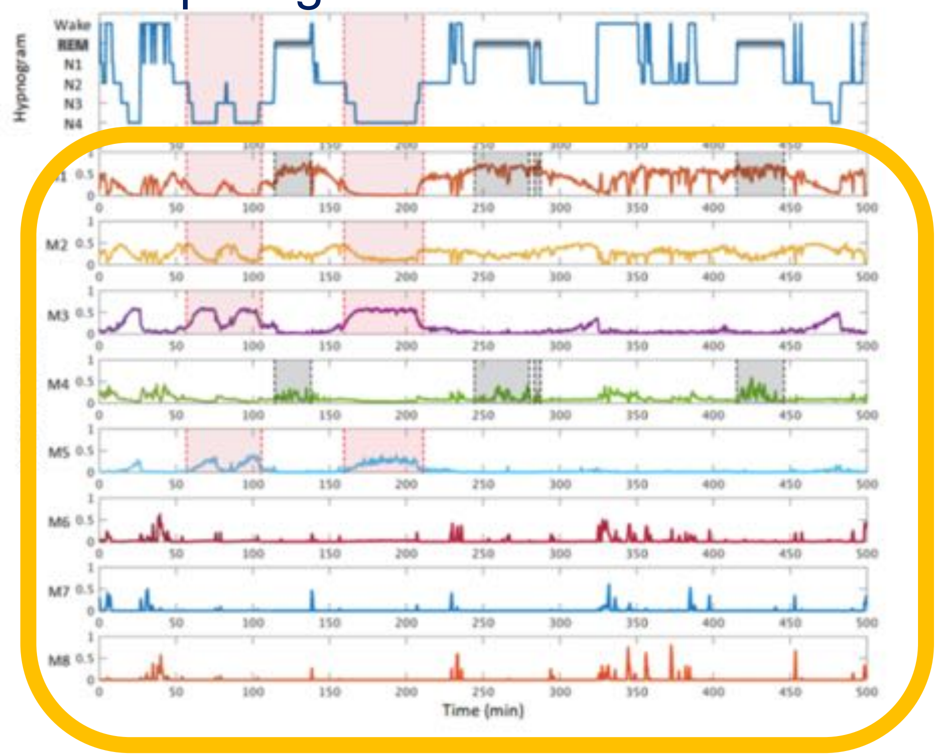


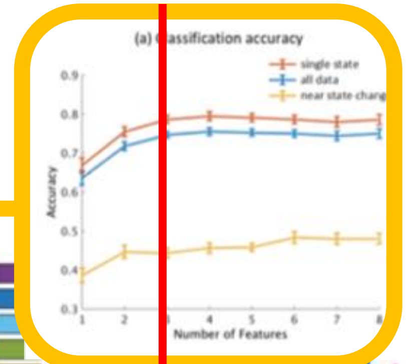
The viewprops plug-in

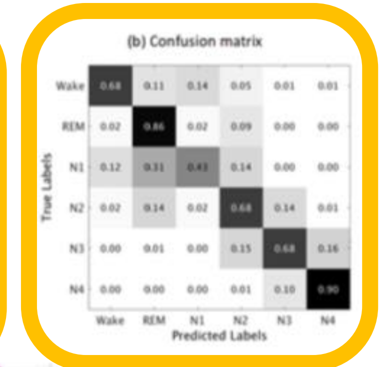
L. Pion-Tonachini, 2018

Multi-model ICA: AMICA

Sleep stages:







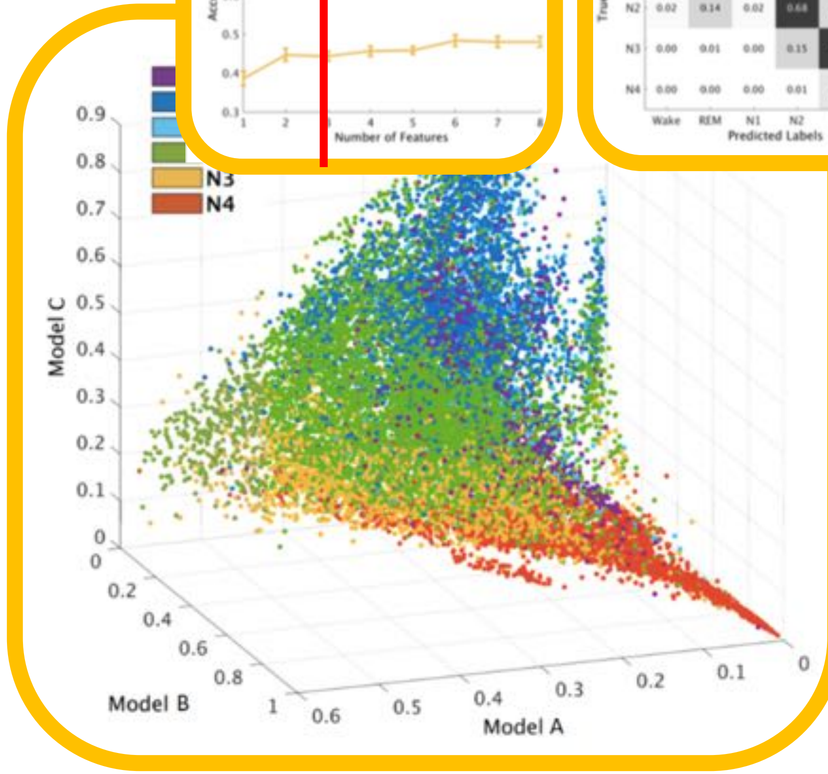


Figure 4: The top panel shows the hypnogram, i.e., sleep stages annotated from the EEG record by a sleep expert, of a sleep session from a single subject. Bottom panels show mean probabilities, within each 30-sec sleep scoring interval, of ICA models learned by an 8-model AMICA decomposition applied to the EEG record. Red-shaded regions highlight changes in model probabilities for relevant models during transitions to and periods of deep sleep (N4). Gray-shaded regions highlight probability value changes for relevant models during REM sleep.

Figure 6: Scatter plot of window-mean model probabilities for AMICA model clusters A, B, and C (cf. Fig. 5), each point representing mean model probability within a 30-sec data segment from sleep recordings of 7 healthy subjects and 10 patients. Colors represent expert designated sleep-stage labels for the same data segments. Note the distinct deep sleep (N4) pattern and the relative closeness of wake and REM sleep characteristics.

S. Hsu et al., Neuroimage, 2018

Multi-model ICA: AMICA

Reaction speed to simulated driving challenge:

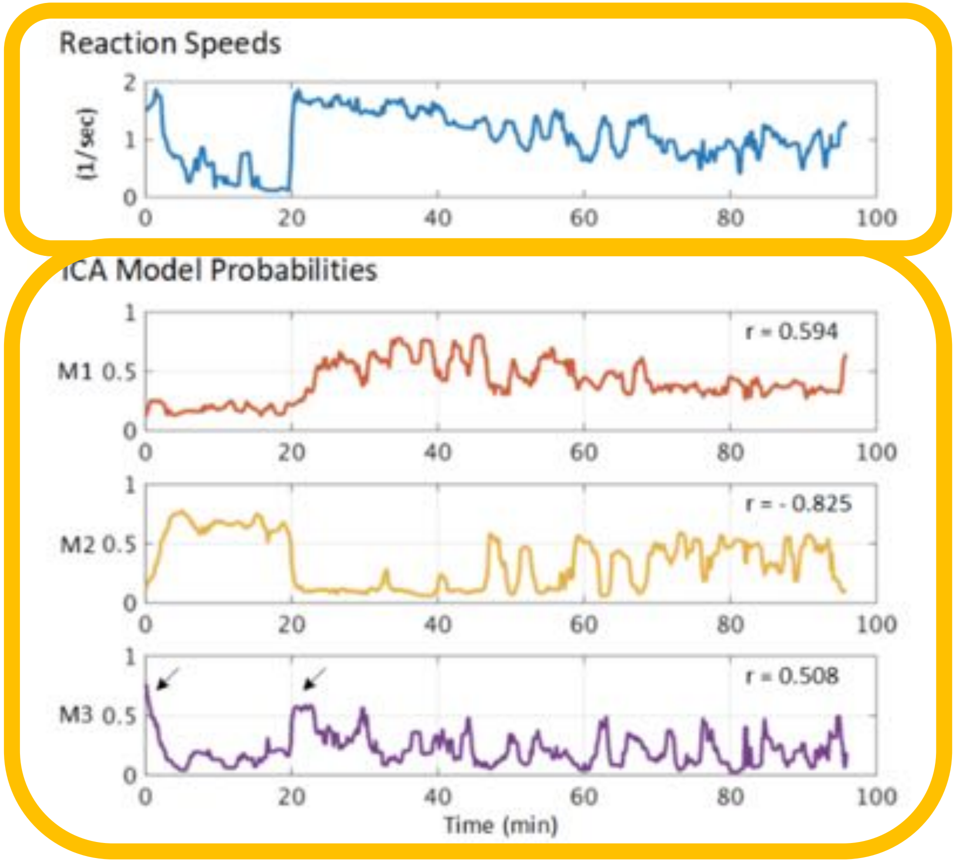
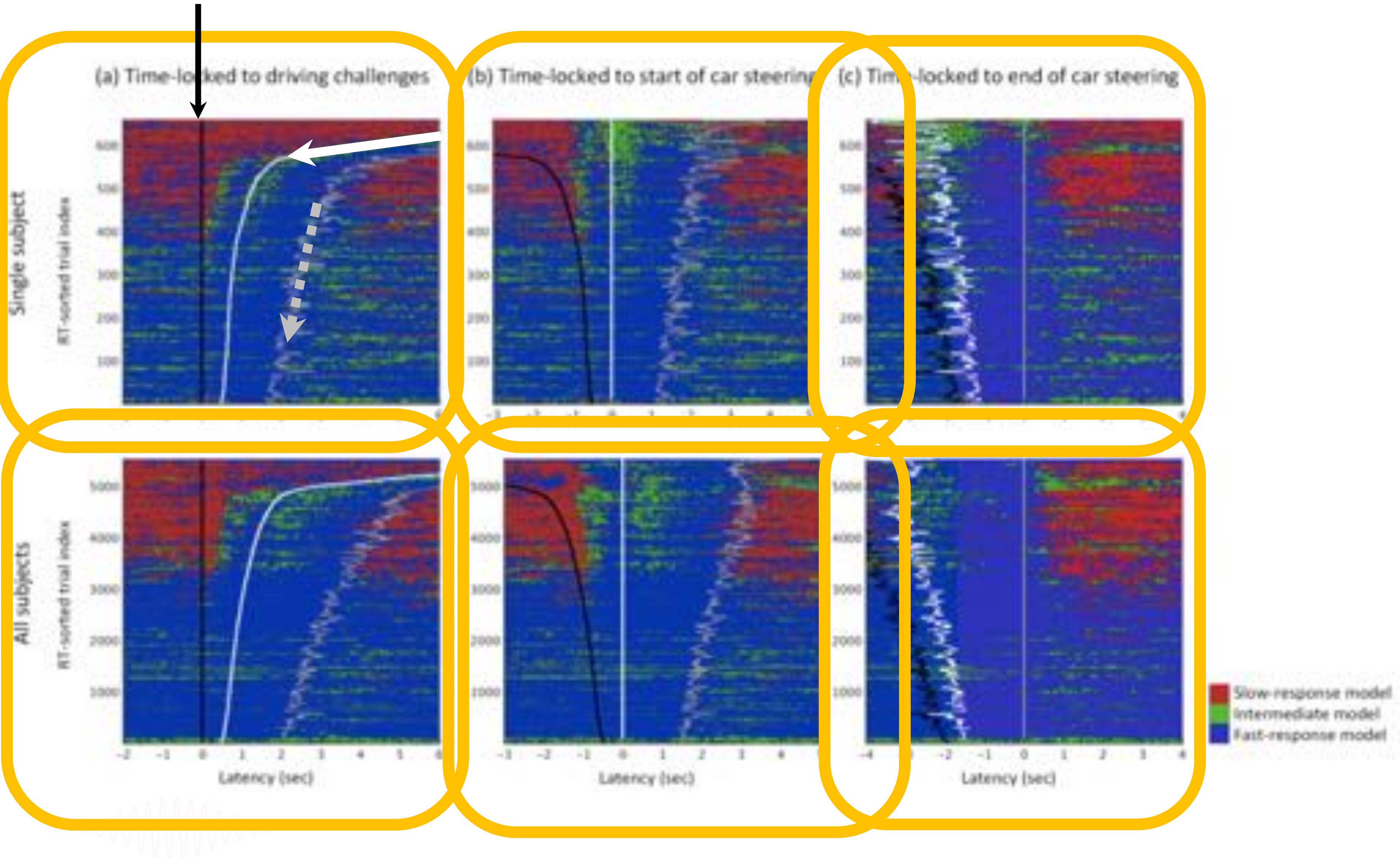


Figure 8: The top panel shows reaction speed changes (inverse of reaction times) in response to lane-departure challenges in one simulated driving session. The three bottom panels show the 5-sec smoothed probabilities of the three ICA models learned by a three-model AMICA decomposition of the whole EEG data session before lane-departure events. Correlation coefficients (*r*) between each model probability time course and reaction speed are indicated. Black arrows in the lower panel mark brief (alert) periods when model M3 was dominate and reaction speed high.

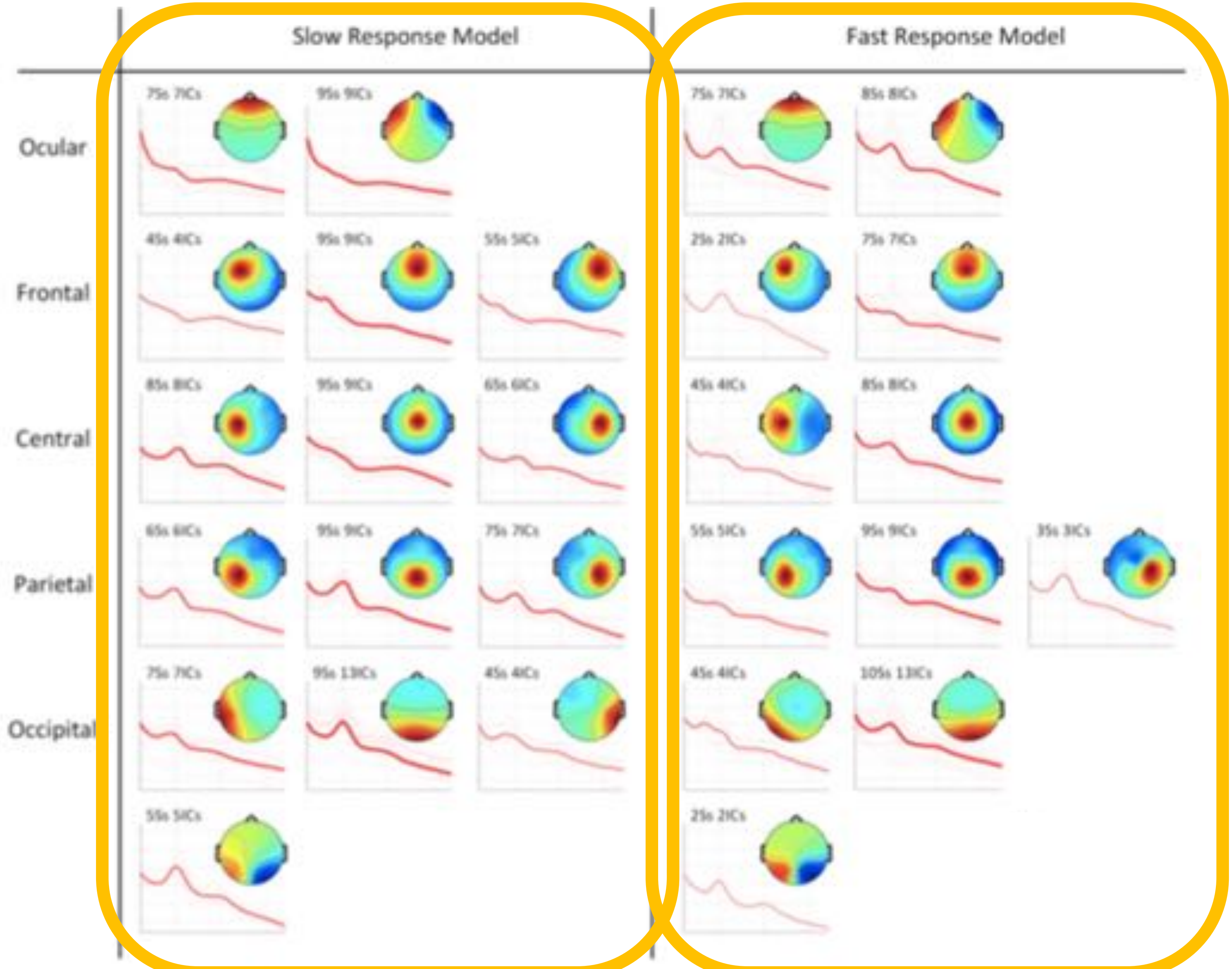
S. Hsu et al., Neuroimage, 2018

Multi-model ICA: AMICA



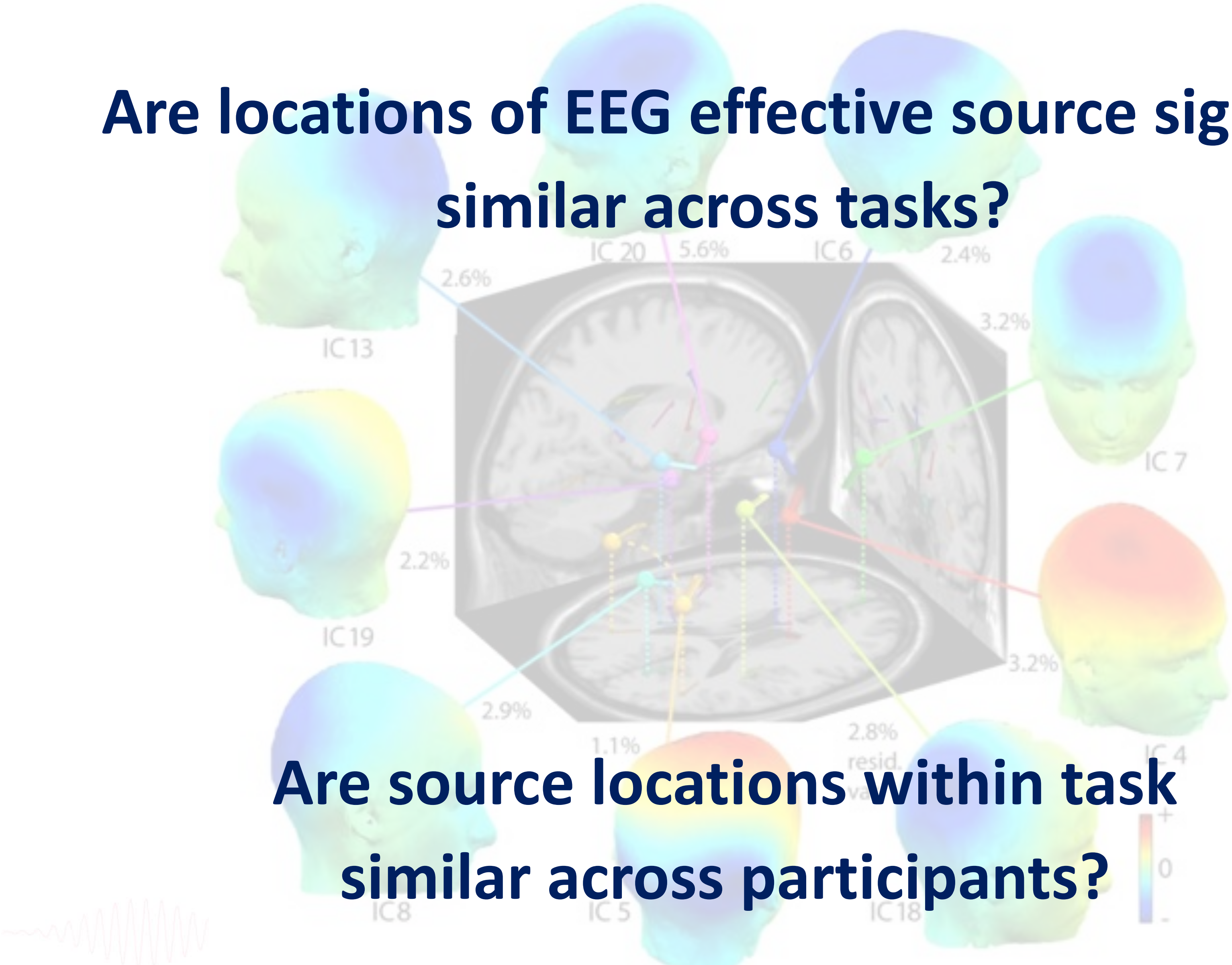
S. Hsu et al., Neuroimage, 2018

Multi-model ICA: AMICA



S. Hsu et al., Neuroimage, 2018

Are locations of EEG effective source signals similar across tasks?

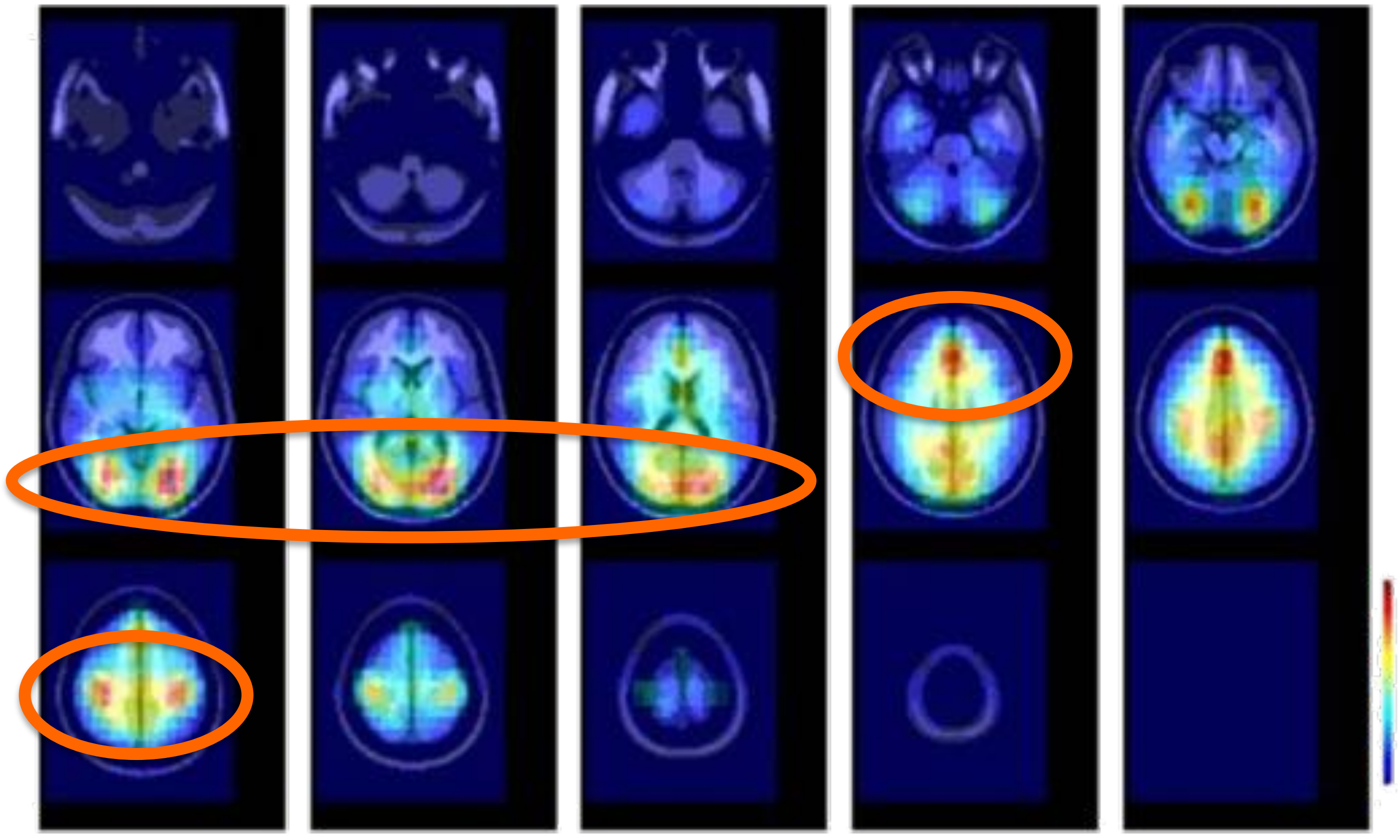


Are source locations within task similar across participants?

S. Makeig (2007)

Effective Source Density

Visual Working Memory



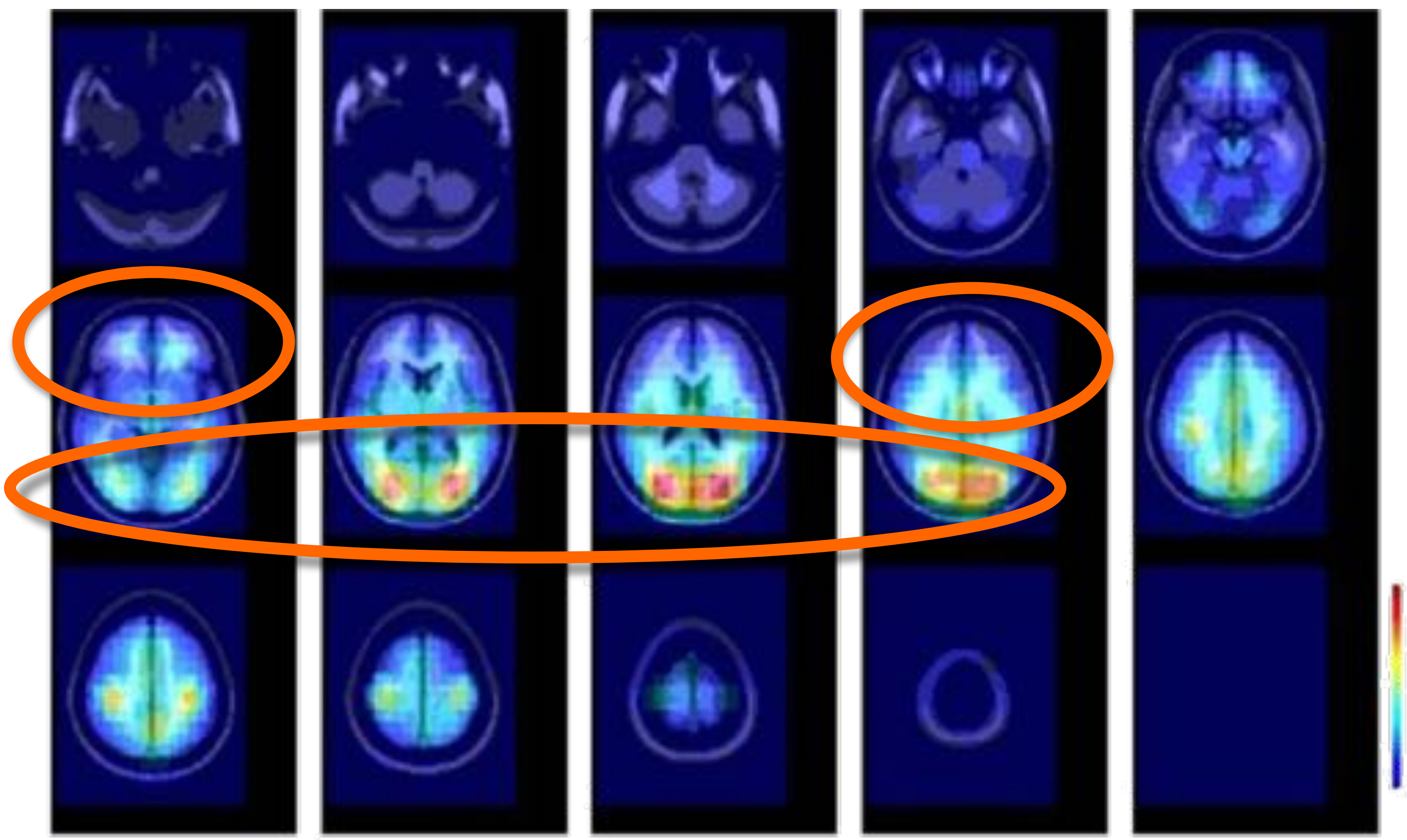
Sternberg letter memory task

dipoledensity()

Onton & Makeig, 2005

Effective Source Density

Eyes-closed emotion imagination

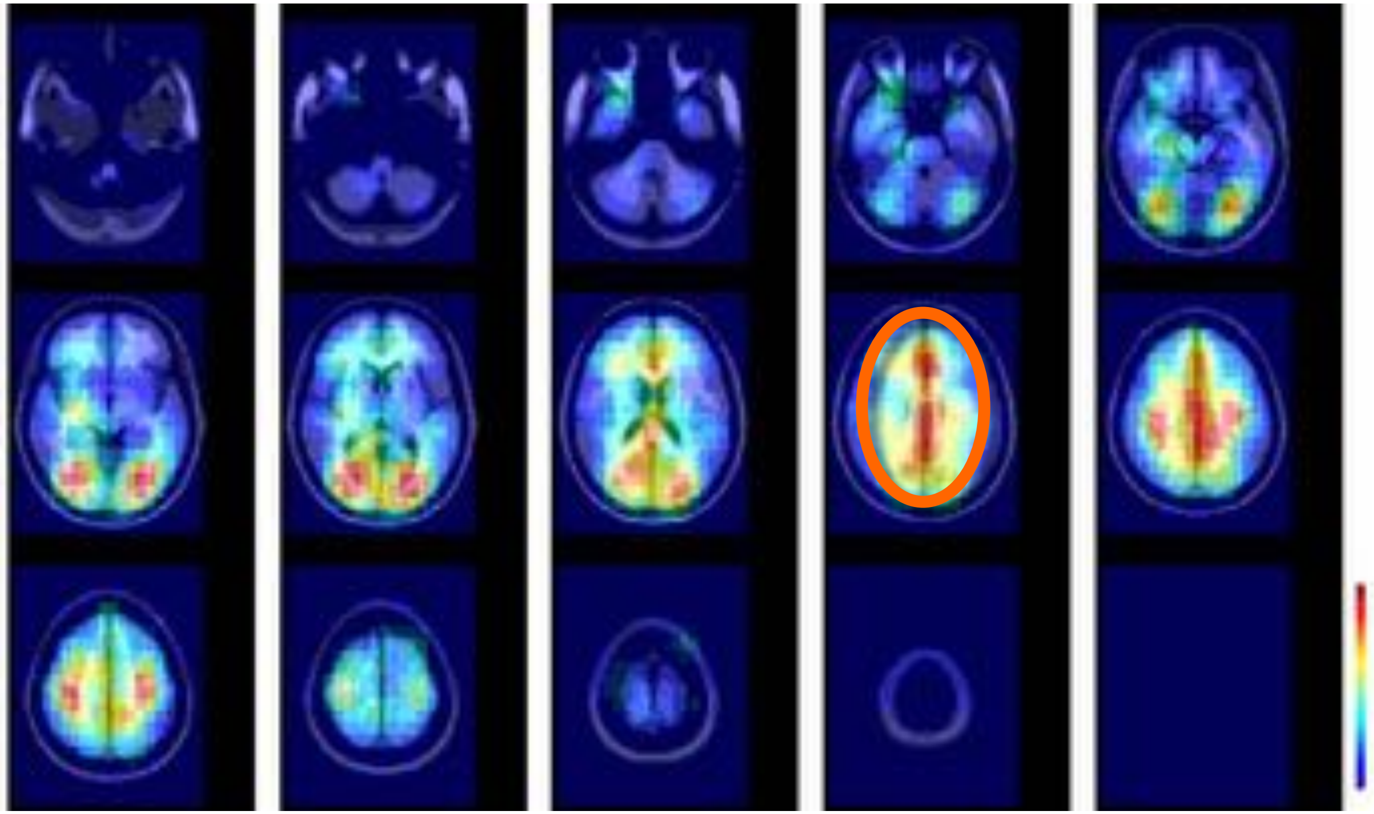


>> dipoledensity()

Onton & Makeig, 2005

Effective Source Density

Letter twoback with feedback

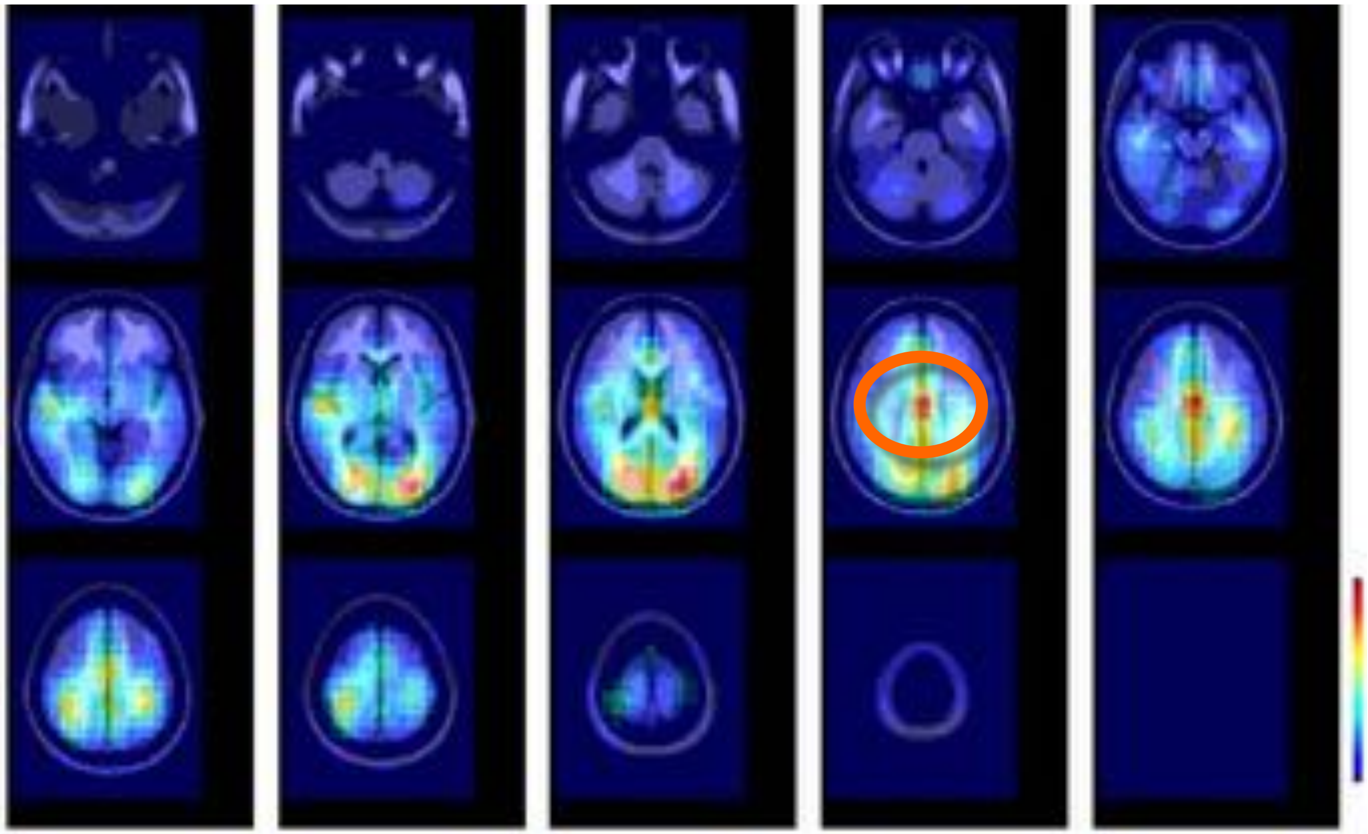


Letter twoback with feedback

Onton & Makeig, 2005

Effective Source Density

Auditory novelty oddball

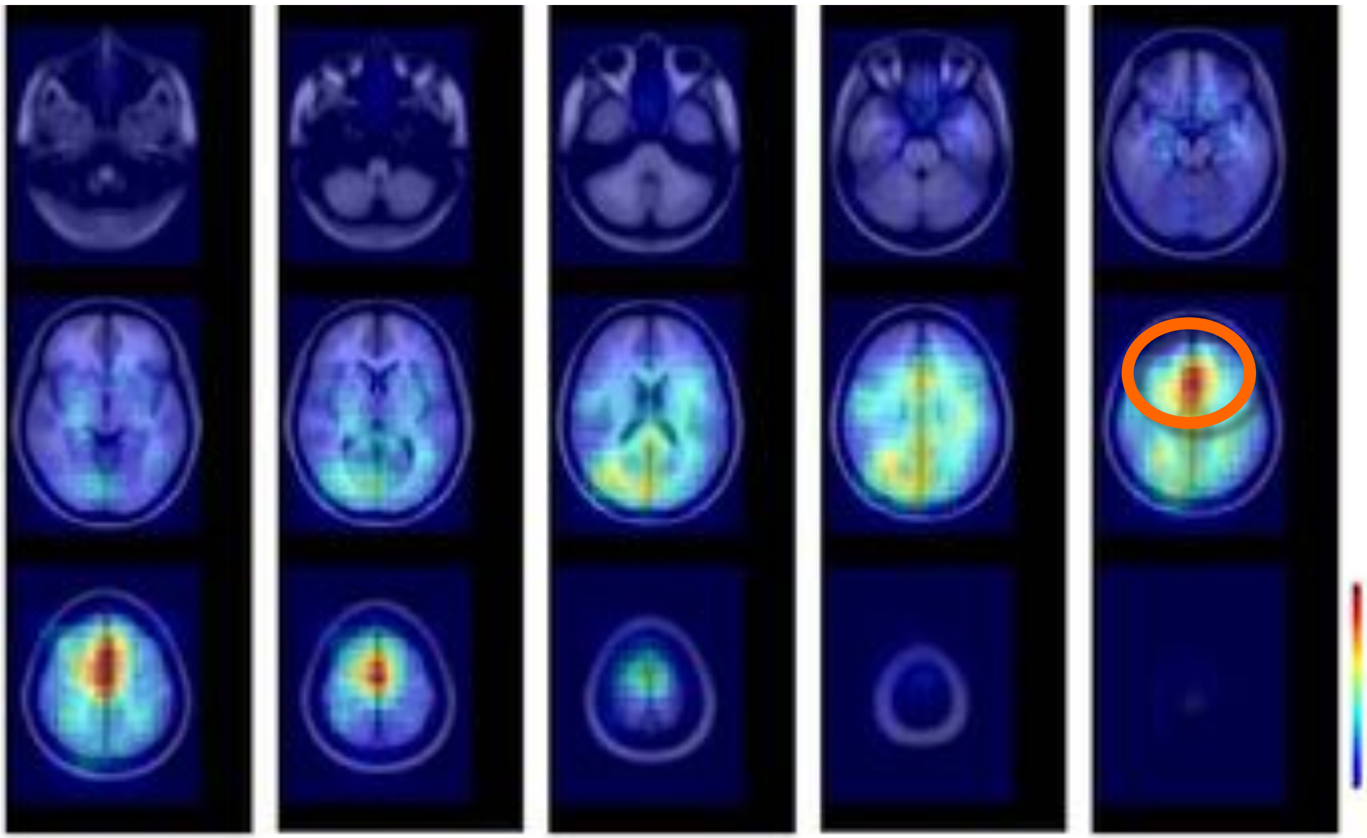


Auditory oddball plus novel sounds

Onton & Makeig, 2005

Effective Source Density

A. Old/new word memory

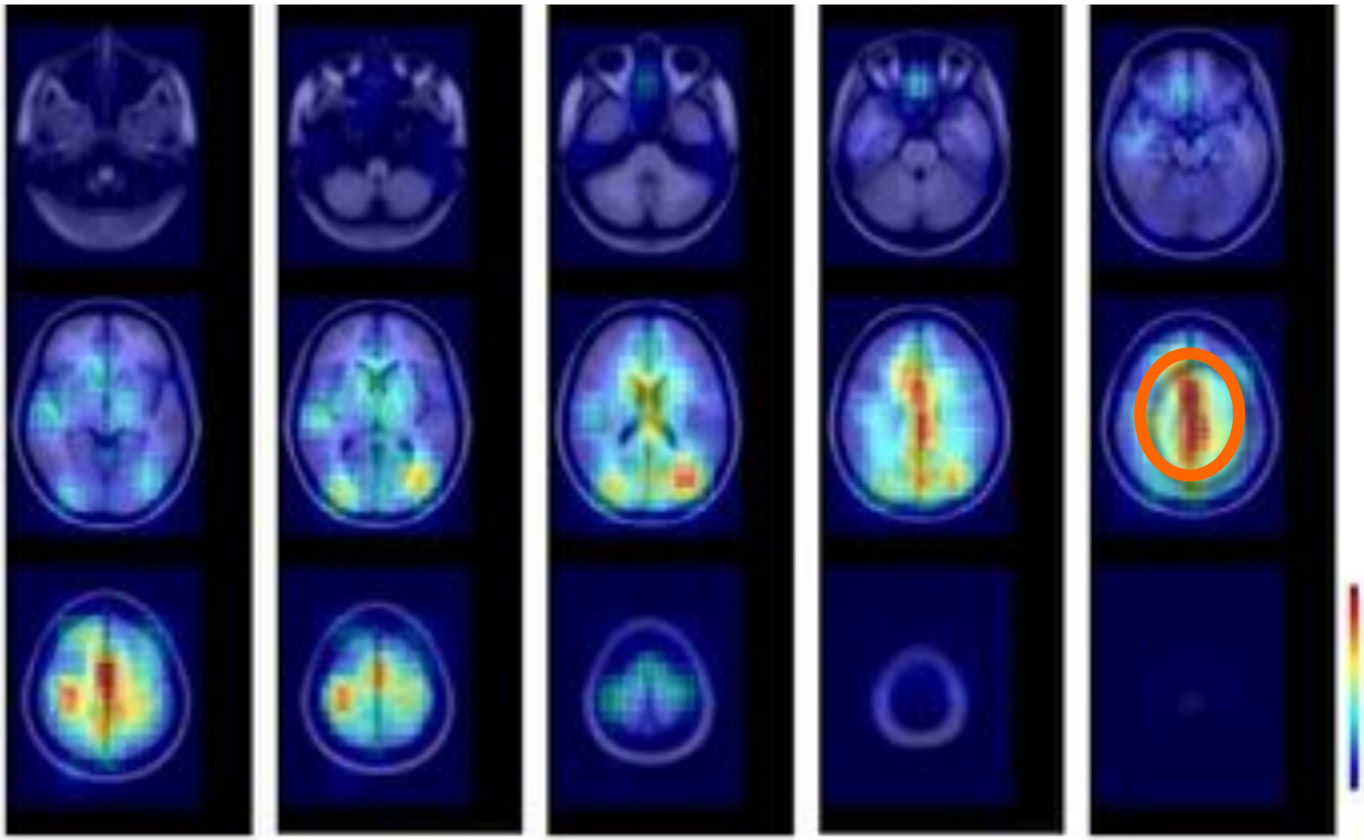


Word memory (old/new) task

Onton & Makeig, 2005

Effective Source Density

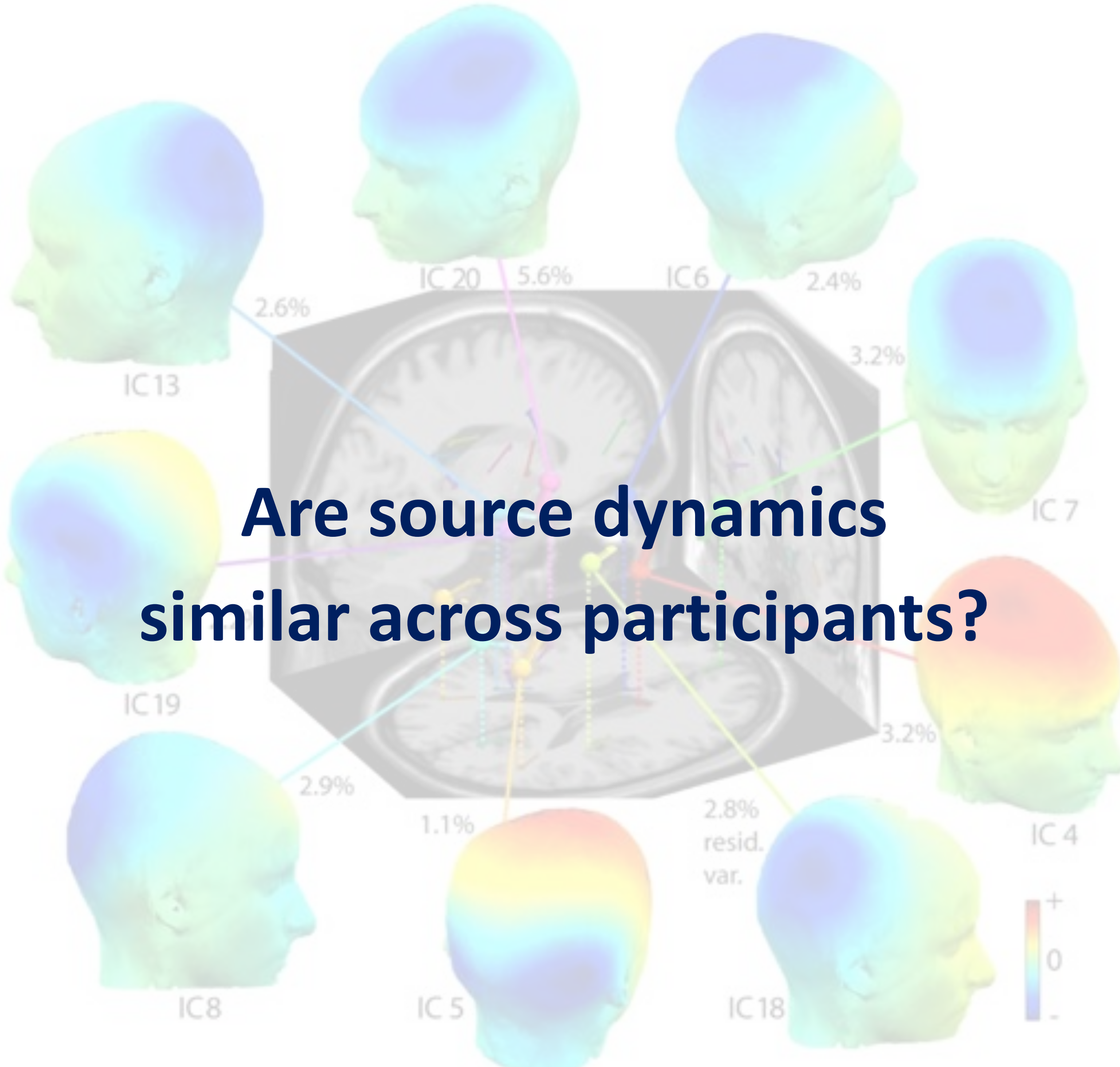
B. Visually cued selective response



Visually cued button press task

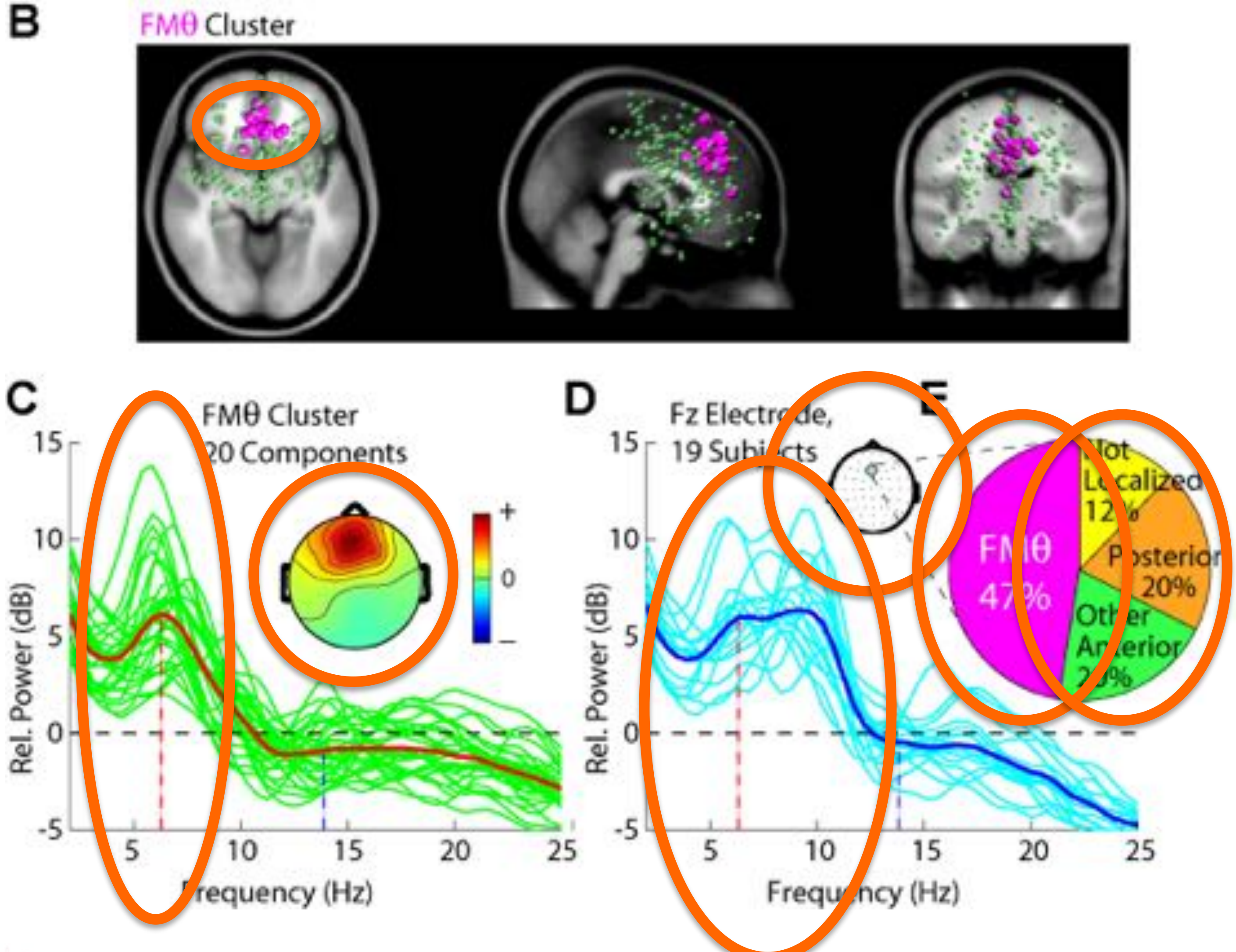
Onton & Makeig, 2005

Are source dynamics similar across participants?



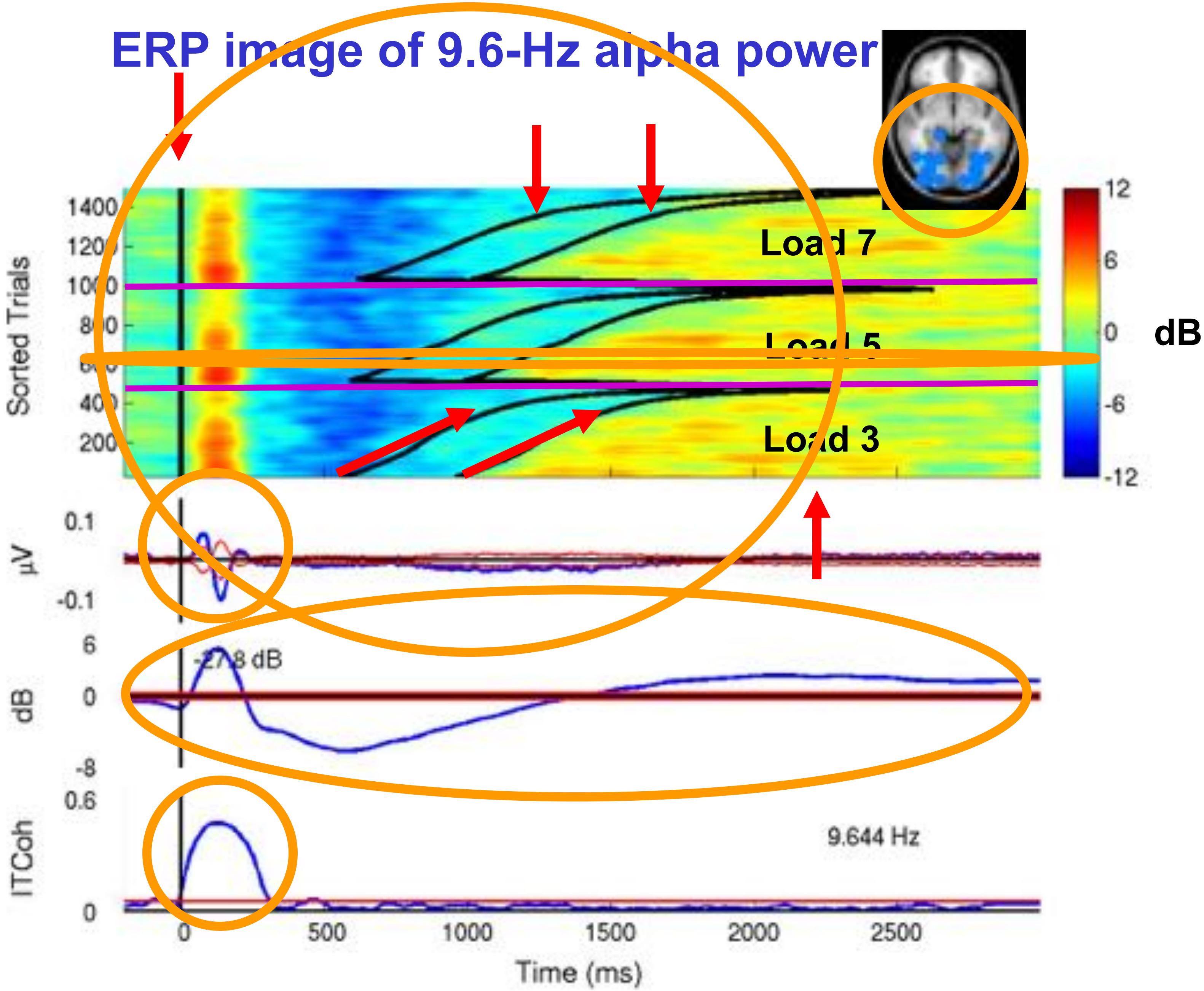
S. Makeig (2007)

Example: frontal midline theta cluster



Onton, Delorme & Makeig, *NeuroImage* (2005)

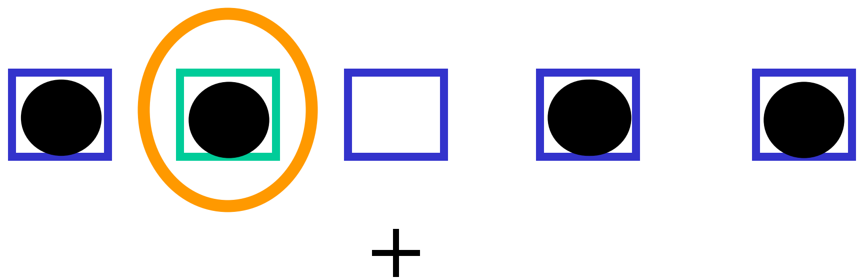
ERP image of 9.6-Hz alpha power



erpimage()

Onton, Delorme & Makeig, 2005.

Visual Selective Attention Task

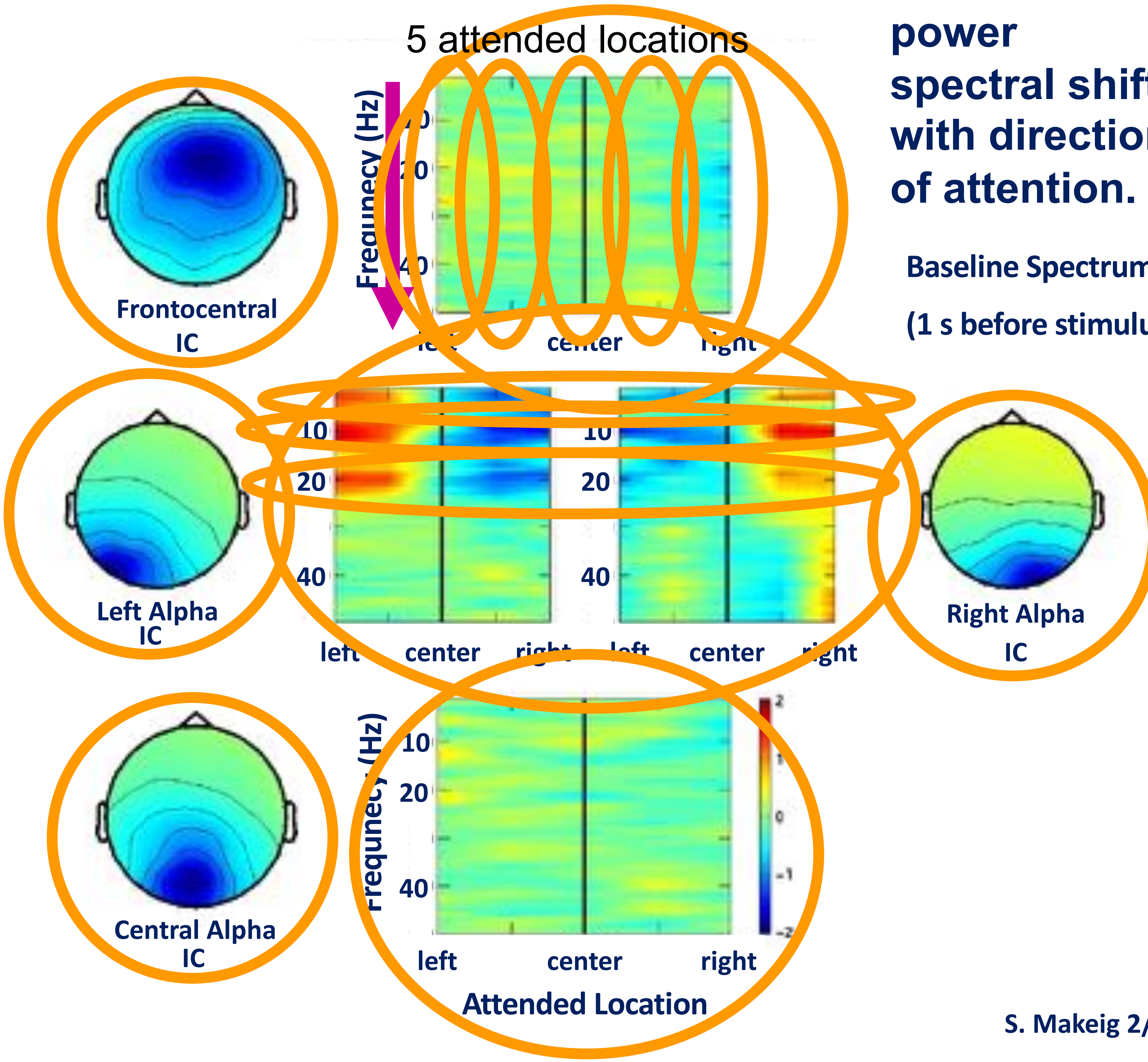


15 subjects

31 channels

Westerfield & Townsend

S. Makeig (2001)



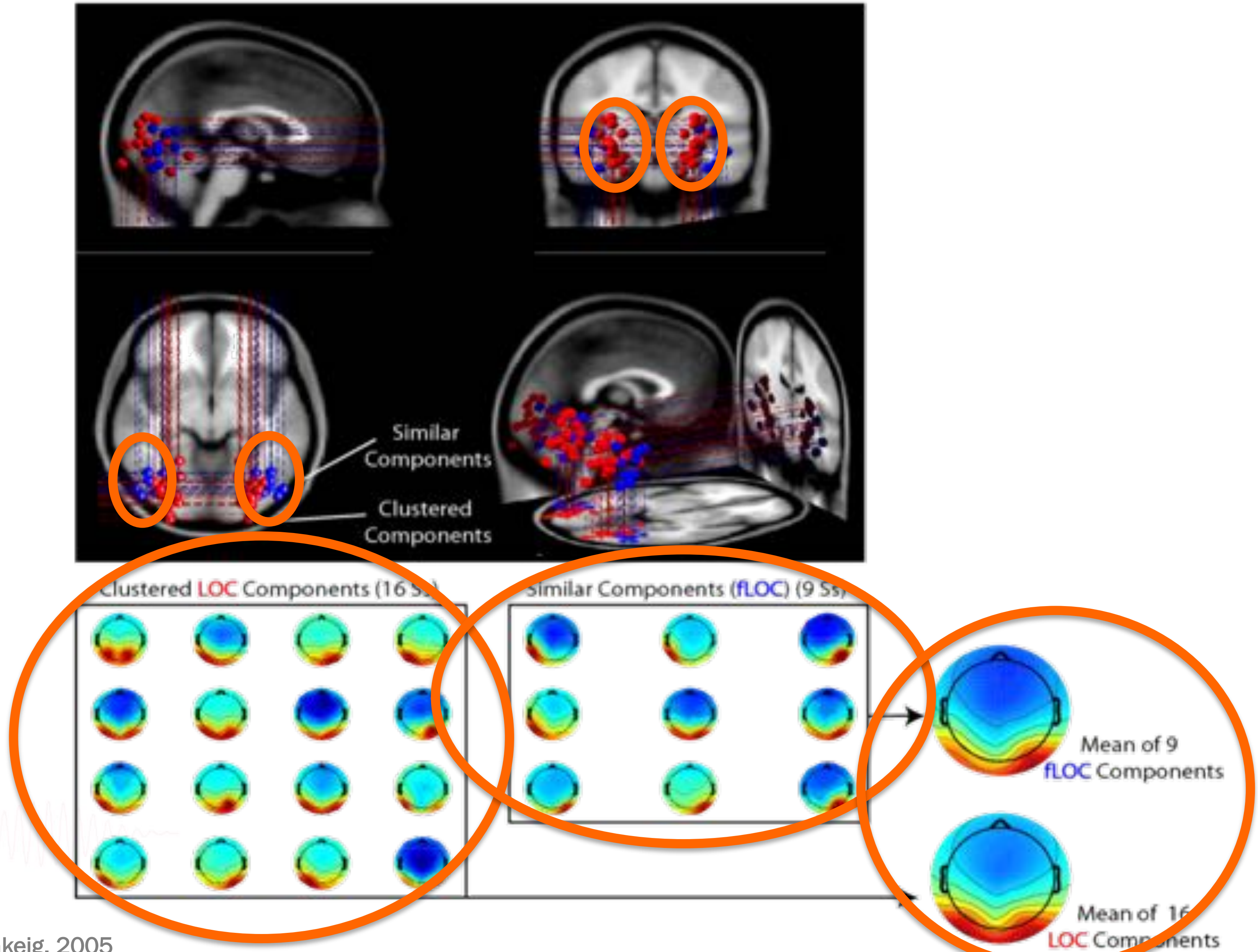
Baseline power spectral shifts with direction of attention.

Baseline Spectrum

(1 s before stimulus)

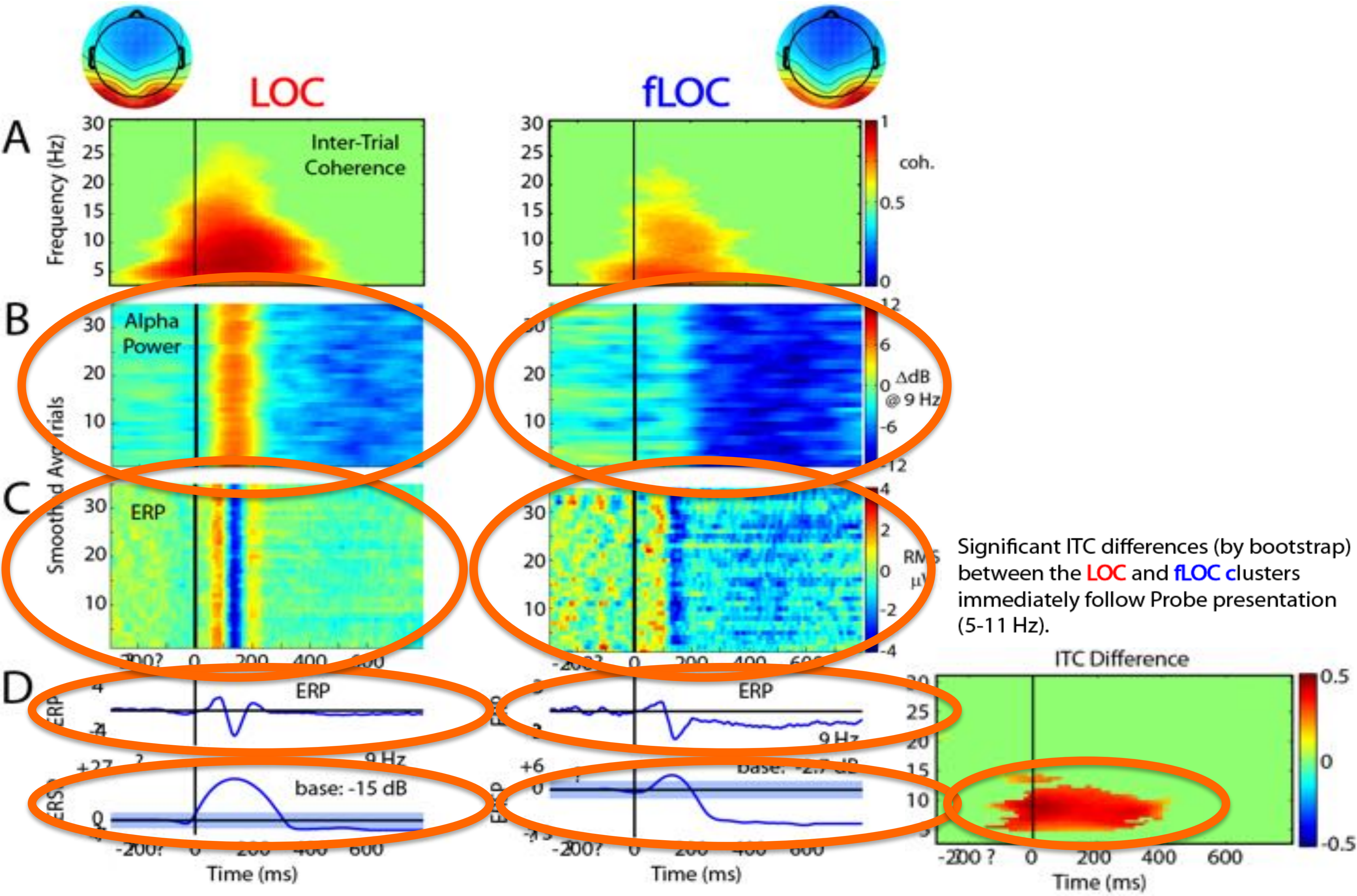
S. Makeig 2/16/01

Why don't all subjects contribute to every IC cluster?



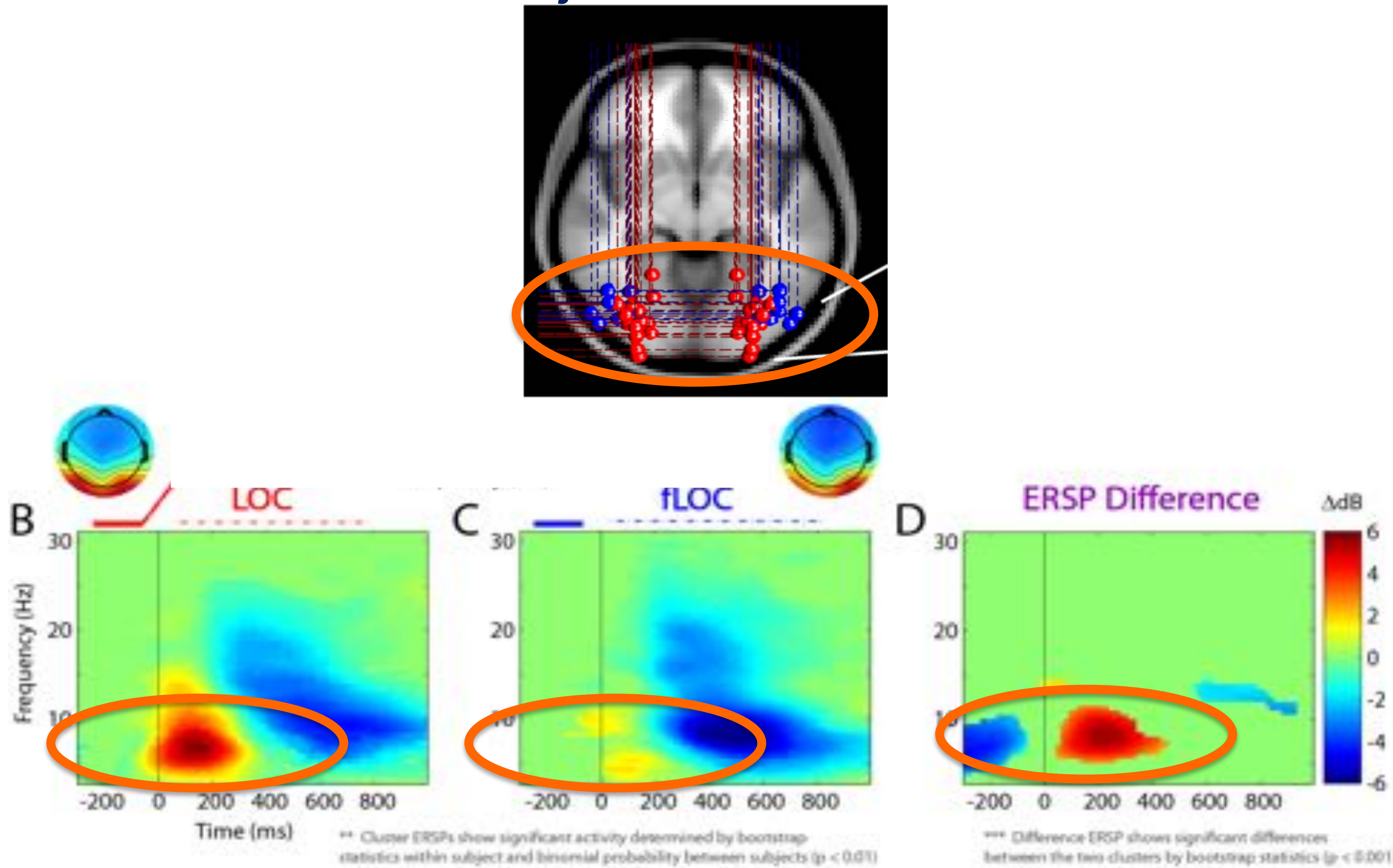
Onton & Makeig, 2005

Subject differences?

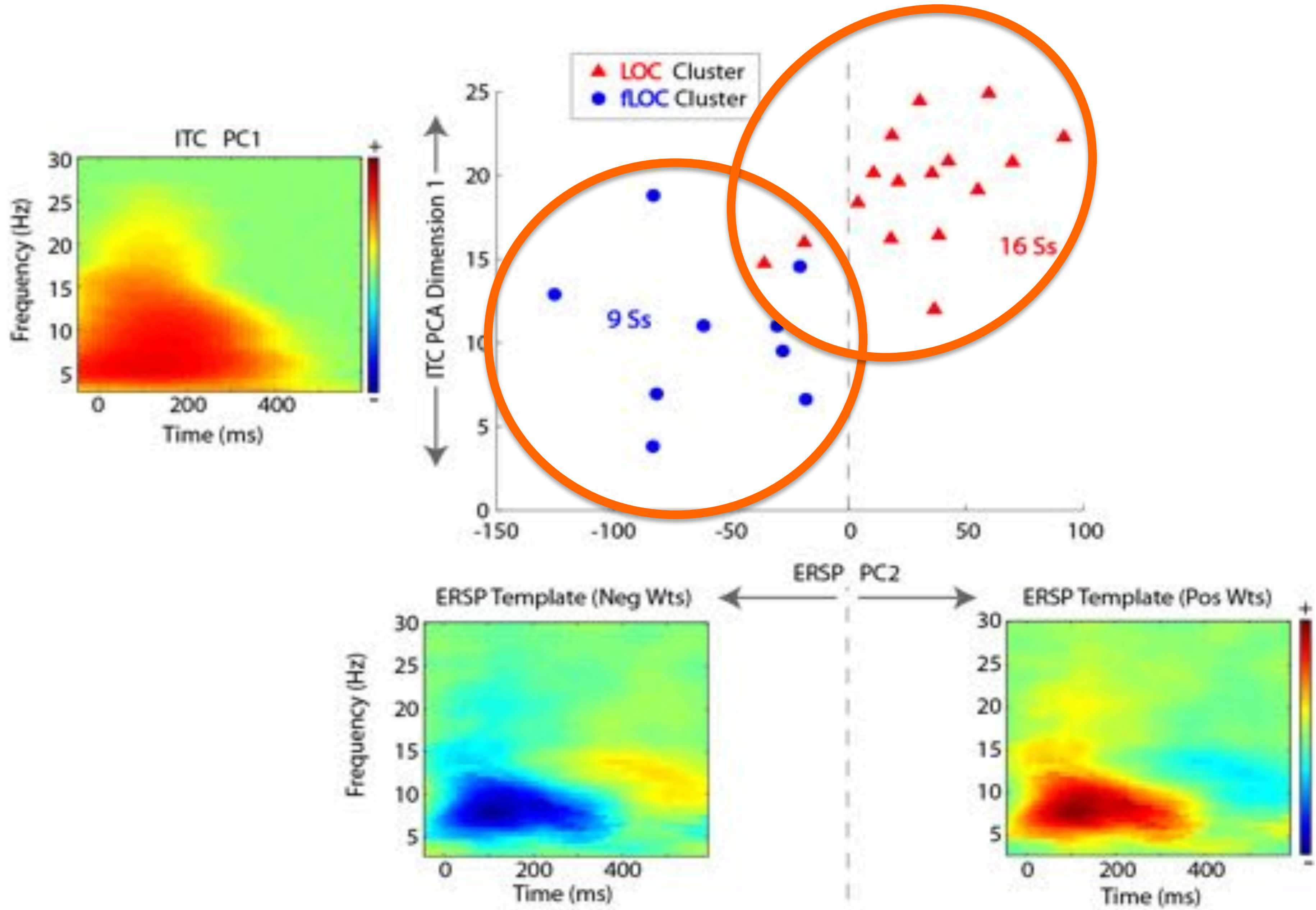


Significant ITC differences (by bootstrap) between the LOC and fLOC clusters immediately follow Probe presentation (5-11 Hz).

Subject differences?

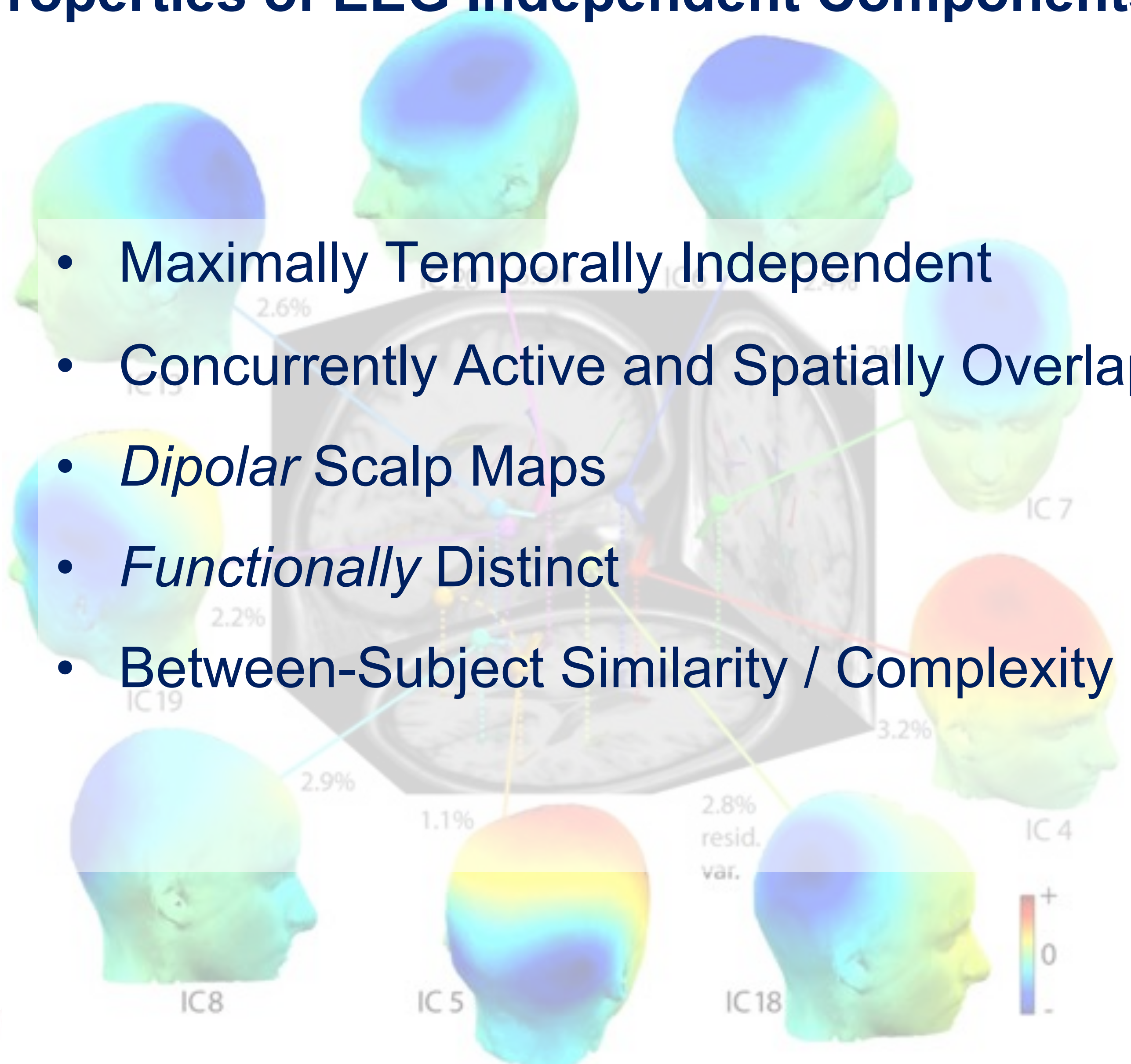


Subject differences?

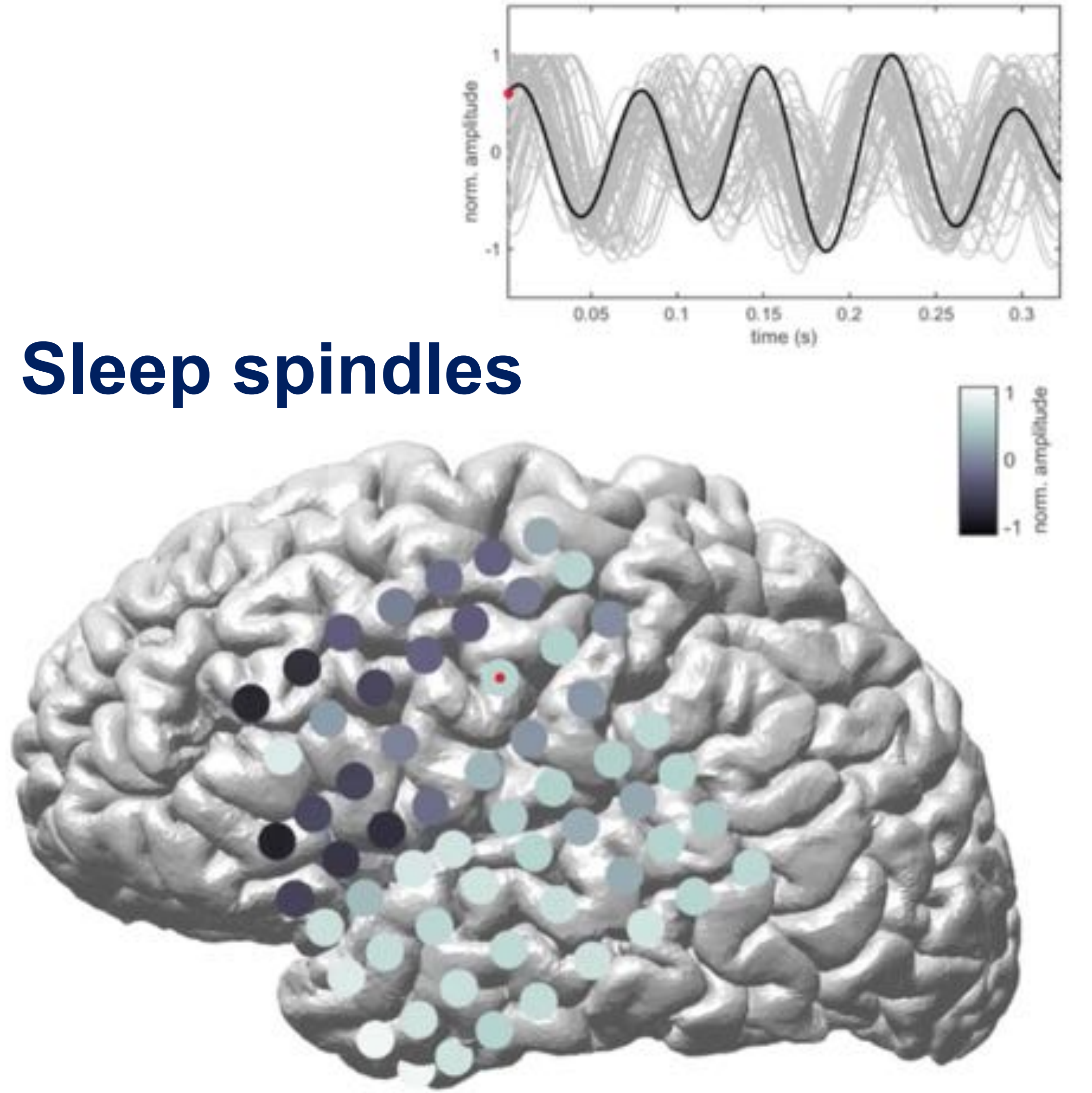


Properties of EEG Independent Components

- Maximally Temporally Independent
- Concurrently Active and Spatially Overlapping
- *Dipolar* Scalp Maps
- *Functionally* Distinct
- Between-Subject Similarity / Complexity



Sleep spindles



Muller et al., 2014

Not the End ...