Towards Robust, Pervasive BCIs

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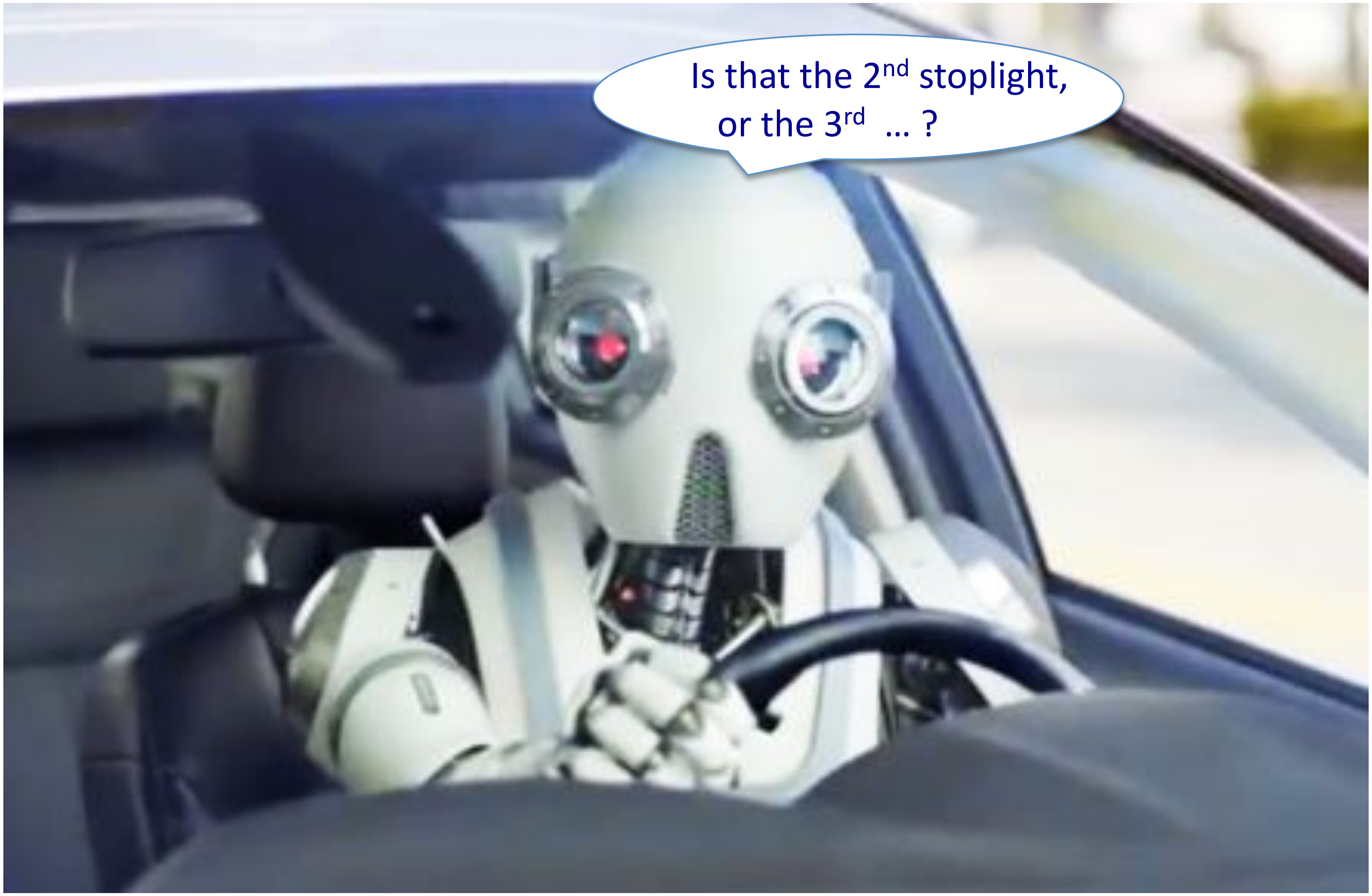
Graz University
BCI Conference
September 17, 2014

Cloud art: Berndnaut

Driverless Cars (1970s)



S. Makeig (2014)

riverless Car 009)

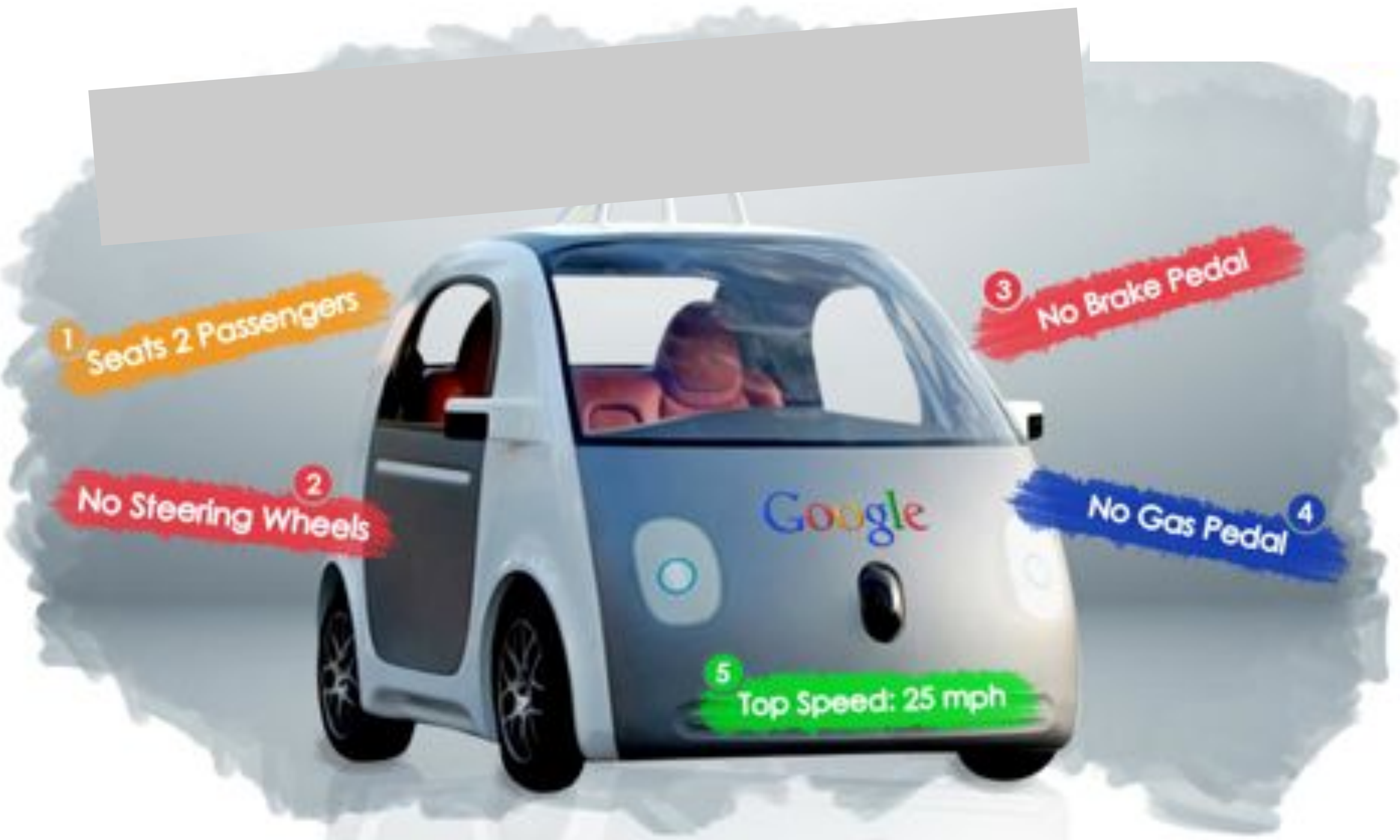
Driverless Cars (2020)

S. Makeig (2014)

Driverless Cars (2014)

S. Makeig (2014)

Driverless Car (2014!)



S. Makeig (2014)

Driverless Car (2014!)

- ❑ **BEGIN** your Bug ride at your current location.
- ❑ **SHOW** your destination on the Bug map.
- ❑ **CALL** a Bug!

Driverless Cars (1970 → 2020)

- ~~1970s computer technology~~
- **New computer technology**
  - Miniaturized hi-res sensors
  - Fast CPU/GPU computing
  - Power-efficient computing
- ~~Rule-driven AI control system~~
- **New math**
  - Machine learning
  - Data-driven / Big data
- ~~Stand-alone 'AI driver' concept~~
- **Vast spatial info 'extrastructure'**
  - GPS satellite grid
  - Road-grid mapping

So -- what conceptual and technological shifts are needed to realize the vision of robust pervasive BCI ?

S. Makeig (2014)

Embodied Agency

Brain processes

have evolved and function

*to optimize the **outcome***

*of the **behavior***

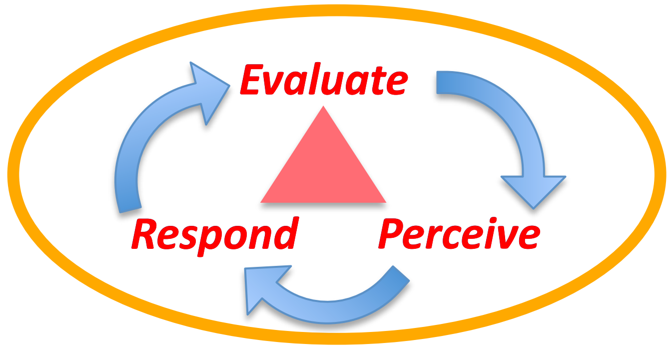
the brain organizes

in response to

perceived challenges

***and opportunities*.**

Brains meet the challenge of each moment!



S Makeig 2010

Four Questions about BCI Research

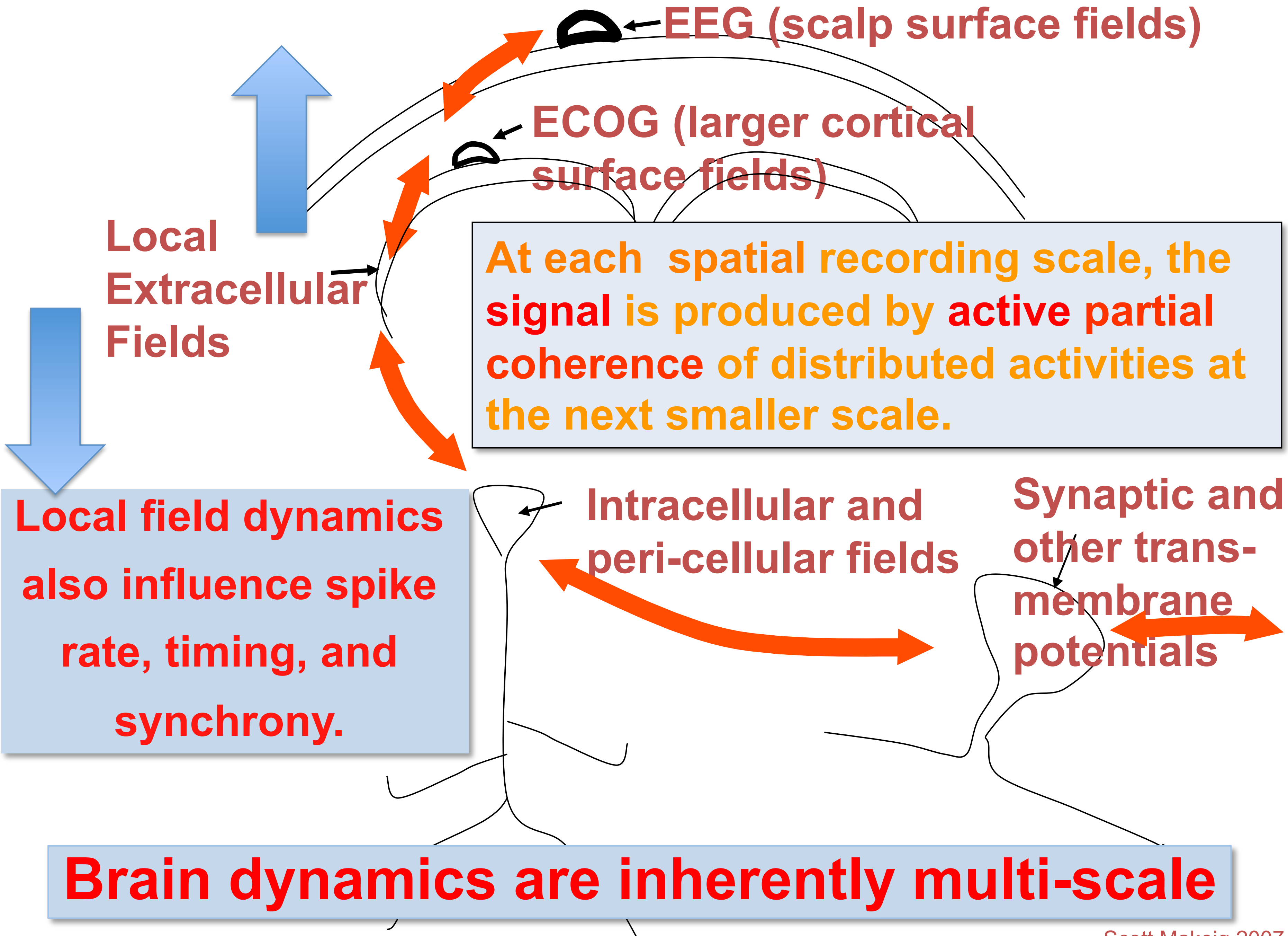
1. **What are the sources of current EEG-based BCI errors?**
2. Are the separate information values from eye, muscle, heart, and brain signals best recovered by any single BCI algorithm?
3. Which of these sources of cognitive information summed in scalp electrical recordings are most stationary over sessions, training, weeks, months, and years? What are their rates of change?
4. What is the upper bound of BCI robustness?

What is EEG?

- Brain electrical activity
- A small portion of *cortical* brain electrical activity
- An even smaller portion of *total* brain electrical activity

- **But *which* portion?**
- **Triggered and modulated *how*?**
- **With *what* functional significance?**

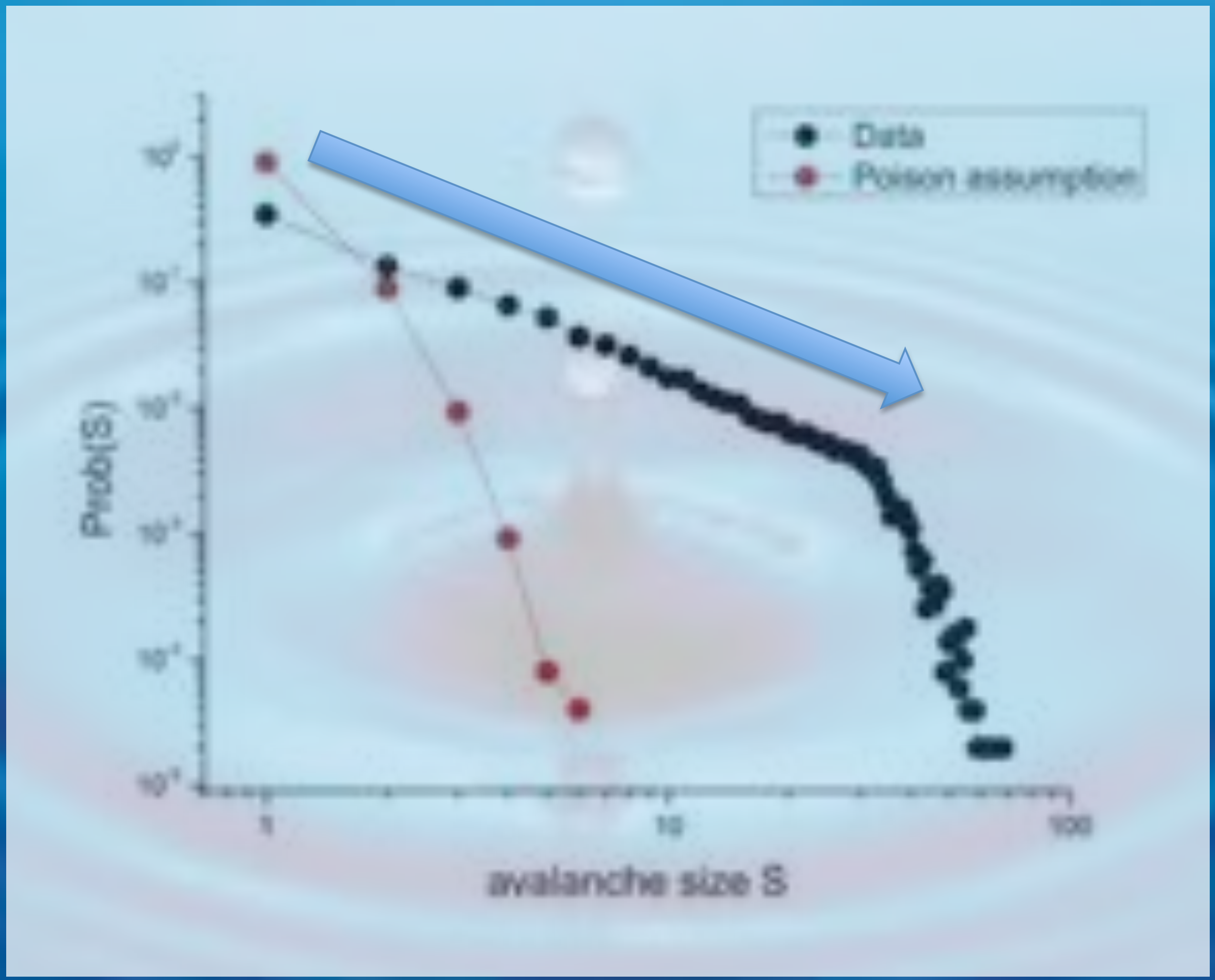
S Makeig, 2014



Scott Makeig 2007

Phase cones (Freeman)
'Event-related *synchronization*'
S. Makeig 2007

= (Circular) Avalanches (Beggs & Plenz)



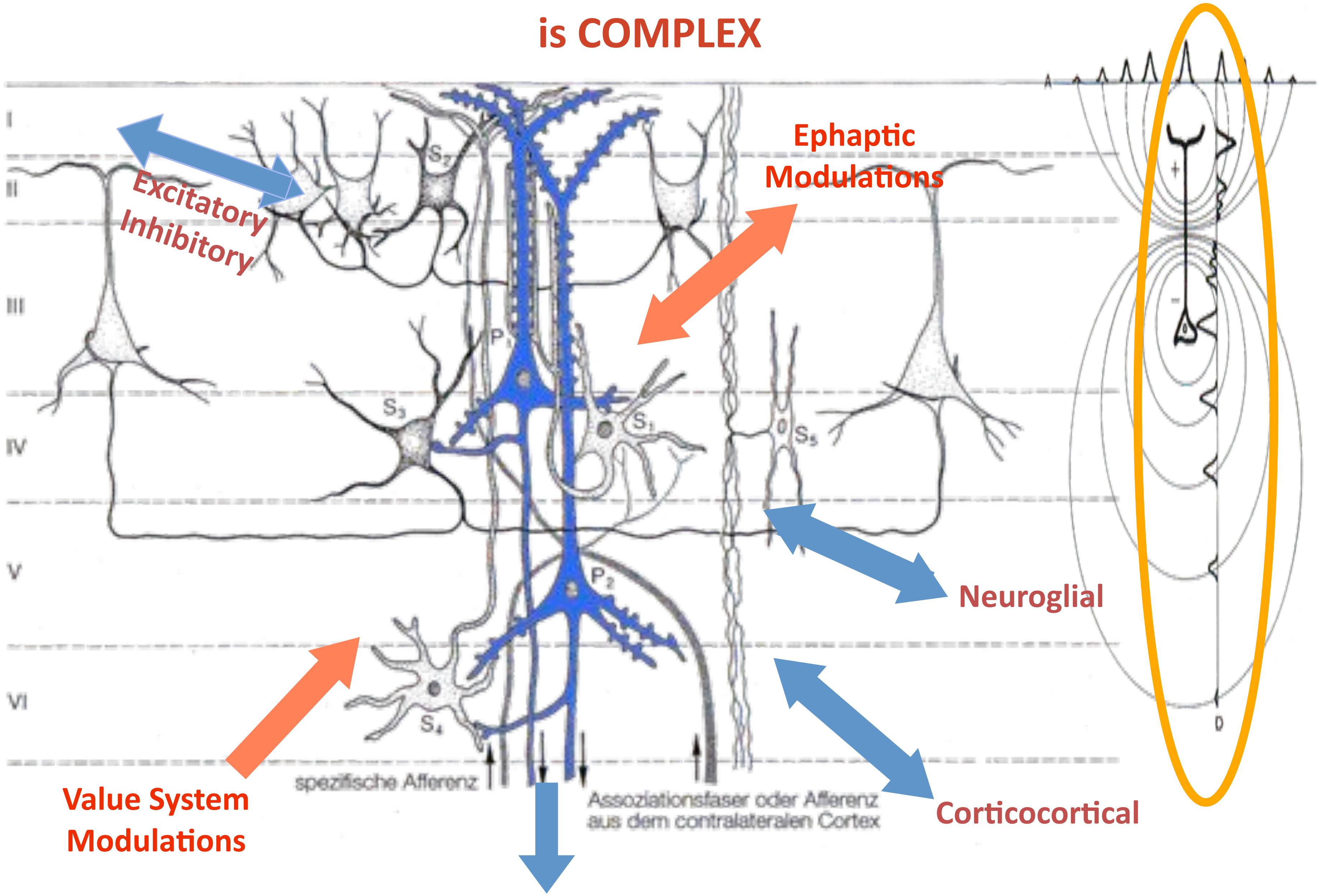
S. Makeig 2007

Macro field dynamics are spontaneous emergent dynamic patterns – in both outer space and cortex.

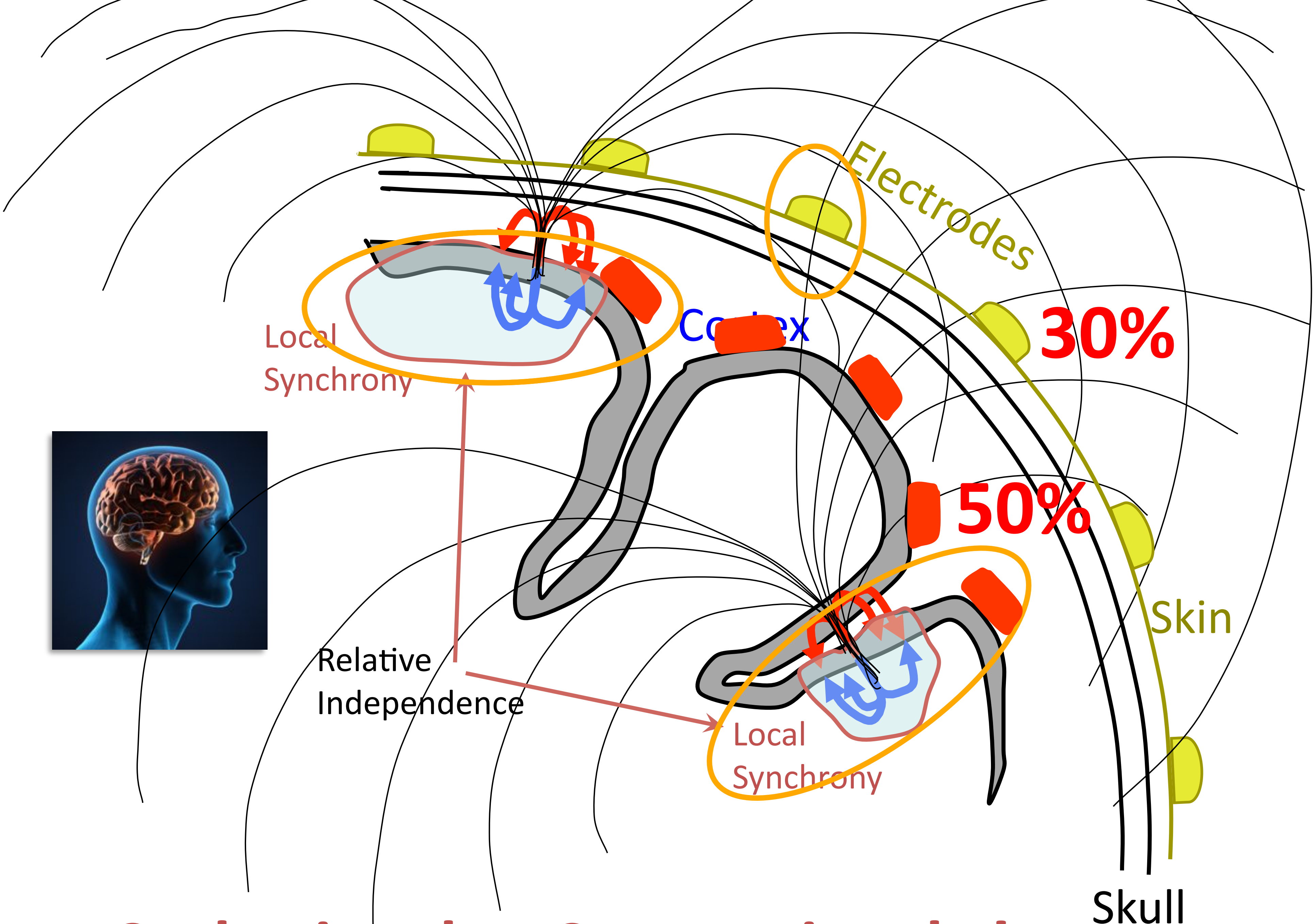
The spatiotemporal *field* dynamics of cortex have not yet been imaged on multiple spatial scales simultaneously !

Alan Friedman

The generation and *modulation* of EEG / LFP is COMPLEX



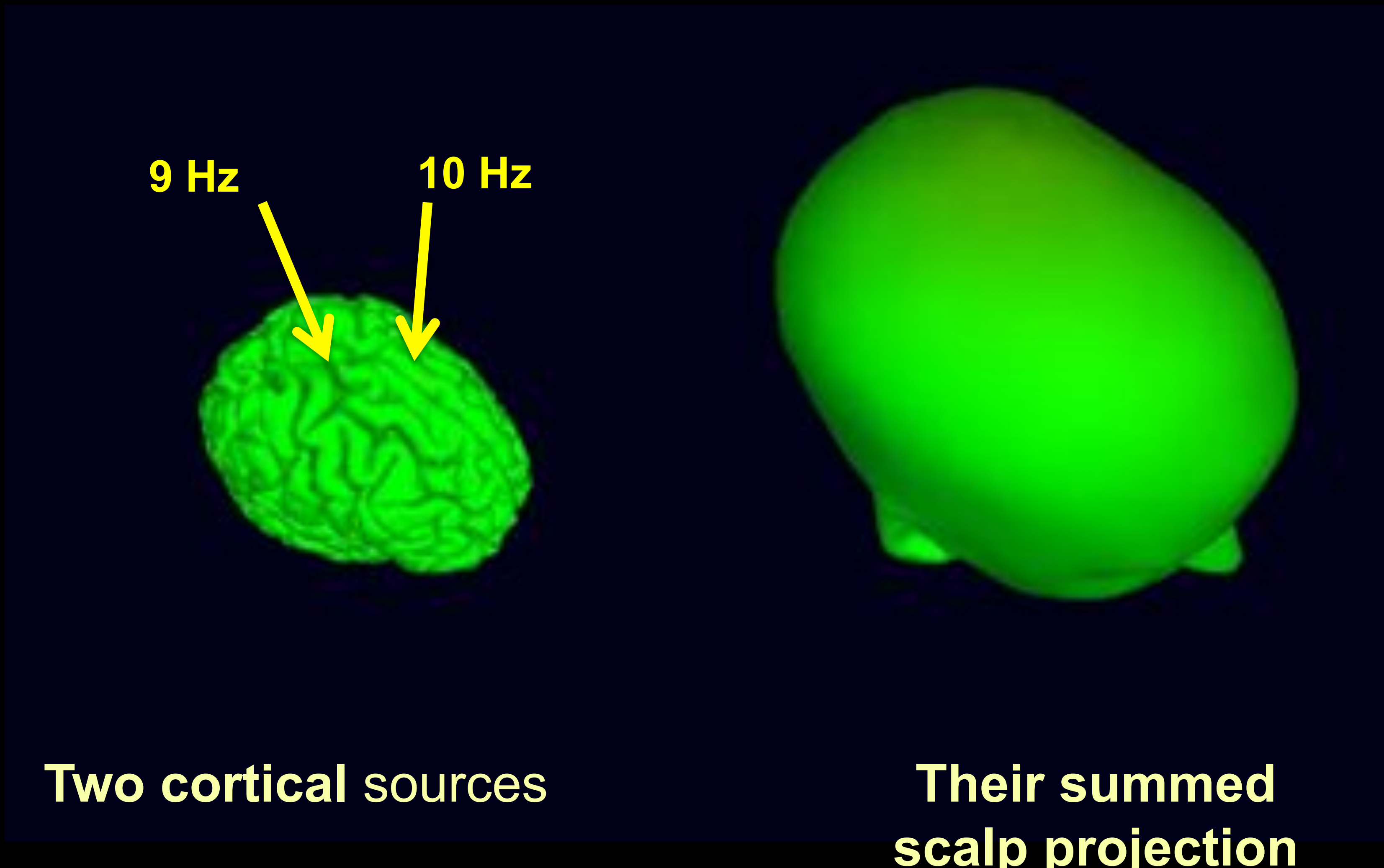
S. Makeig 2007



Scalp signals ≠ Source signals !

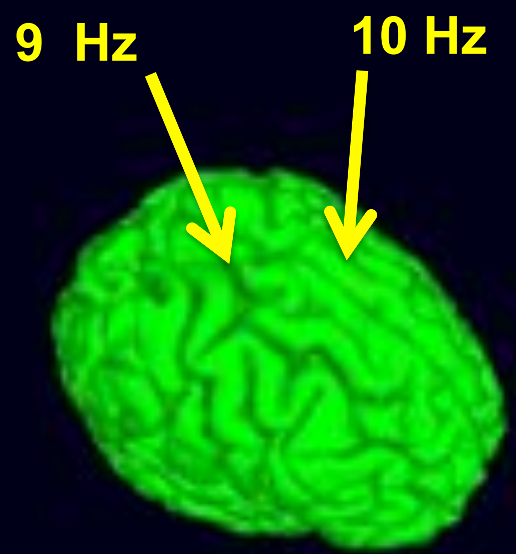
S. Makeig 2007

Effects of volume conduction on scalp EEG

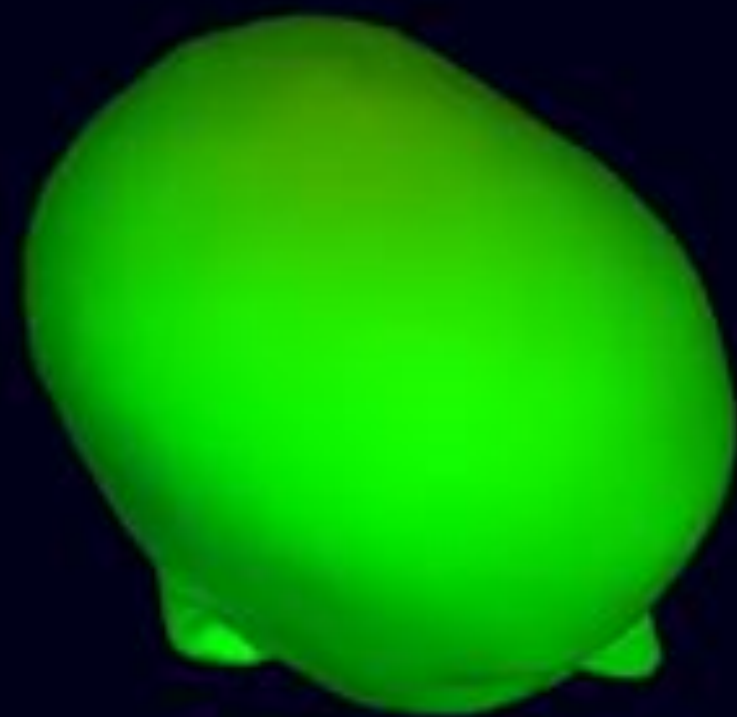


Z. Akalin Acar & S. Makeig (2012)

Effects of volume conduction on scalp EEG



Two cortical sources



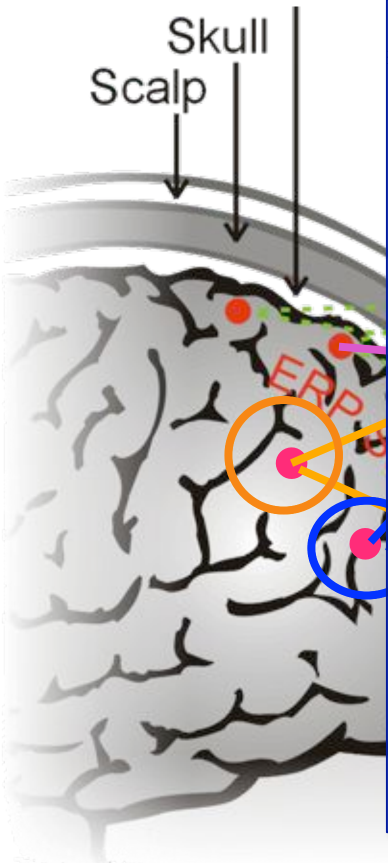
Their summed scalp projection

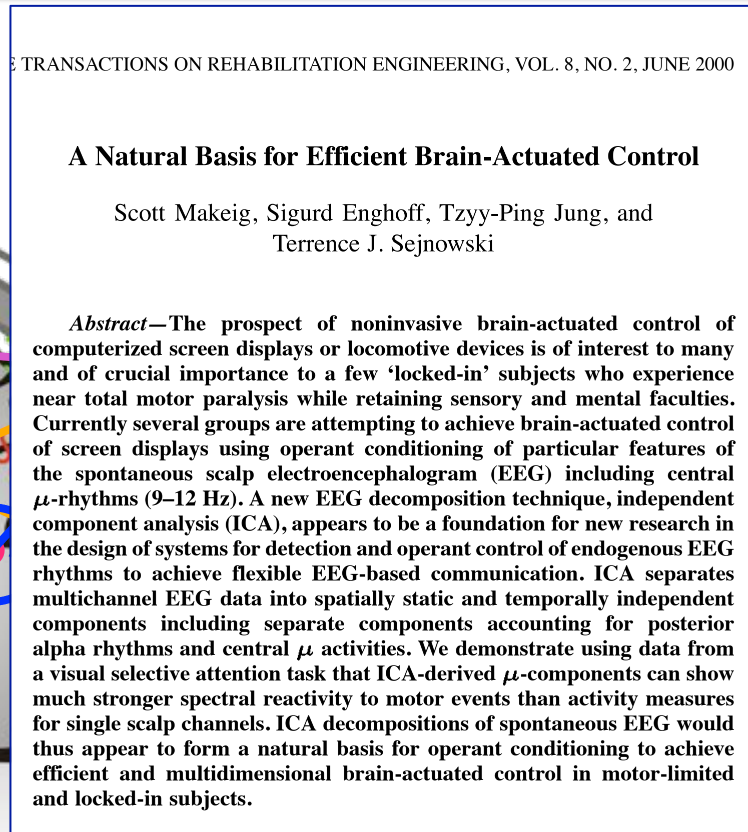
Z. Akalin Acar & S. Makeig (2012)

Blind EEG Source Separation by Independent Component Analysis

ICA can find distinct EEG source activities -- and their 'simple' scalp maps! (1996)

Tony Bell, developer of Infomax ICA



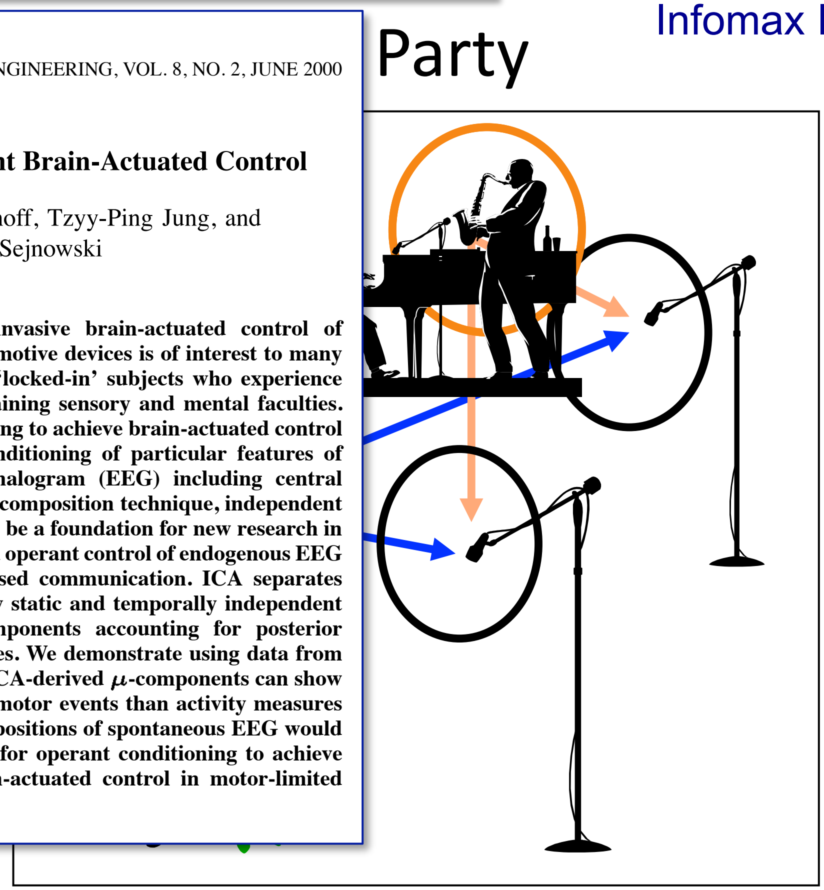


TRANSACTIONS ON REHABILITATION ENGINEERING, VOL. 8, NO. 2, JUNE 2000

A Natural Basis for Efficient Brain-Actuated Control

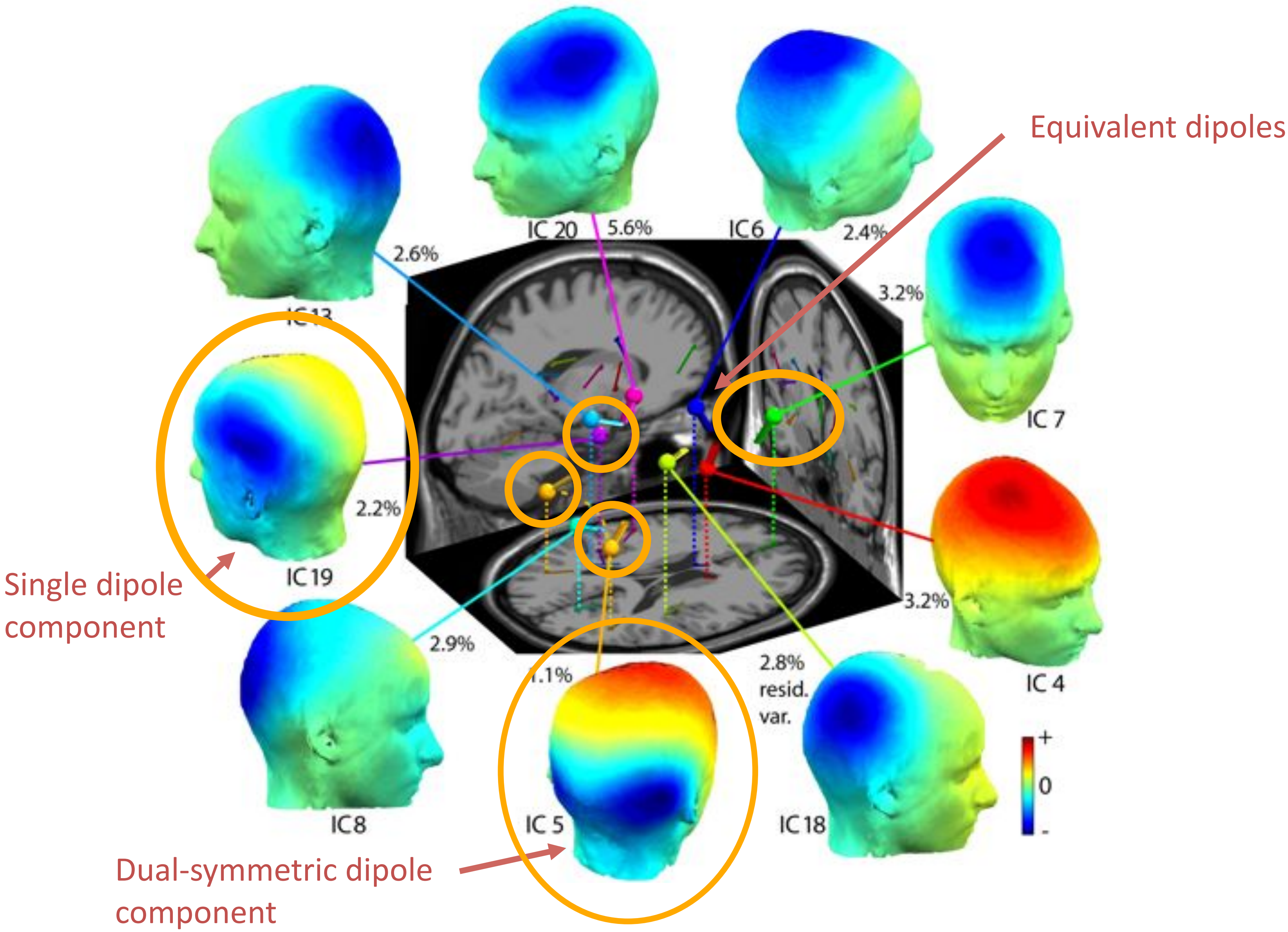
Scott Makeig, Sigurd Enghoff, Tzyy-Ping Jung, and Terrence J. Sejnowski

***Abstract*—The prospect of noninvasive brain-actuated control of computerized screen displays or locomotive devices is of interest to many and of crucial importance to a few 'locked-in' subjects who experience near total motor paralysis while retaining sensory and mental faculties. Currently several groups are attempting to achieve brain-actuated control of screen displays using operant conditioning of particular features of the spontaneous scalp electroencephalogram (EEG) including central μ-rhythms (9–12 Hz). A new EEG decomposition technique, independent component analysis (ICA), appears to be a foundation for new research in the design of systems for detection and operant control of endogenous EEG rhythms to achieve flexible EEG-based communication. ICA separates multichannel EEG data into spatially static and temporally independent components including separate components accounting for posterior alpha rhythms and central μ activities. We demonstrate using data from a visual selective attention task that ICA-derived μ-components can show much stronger spectral reactivity to motor events than activity measures for single scalp channels. ICA decompositions of spontaneous EEG would thus appear to form a natural basis for operant conditioning to achieve efficient and multidimensional brain-actuated control in motor-limited and locked-in subjects.**



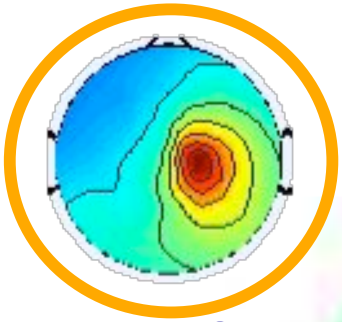
S. Makeig, S. Enghoff (2000)

… and also separates cortical brain IC processes

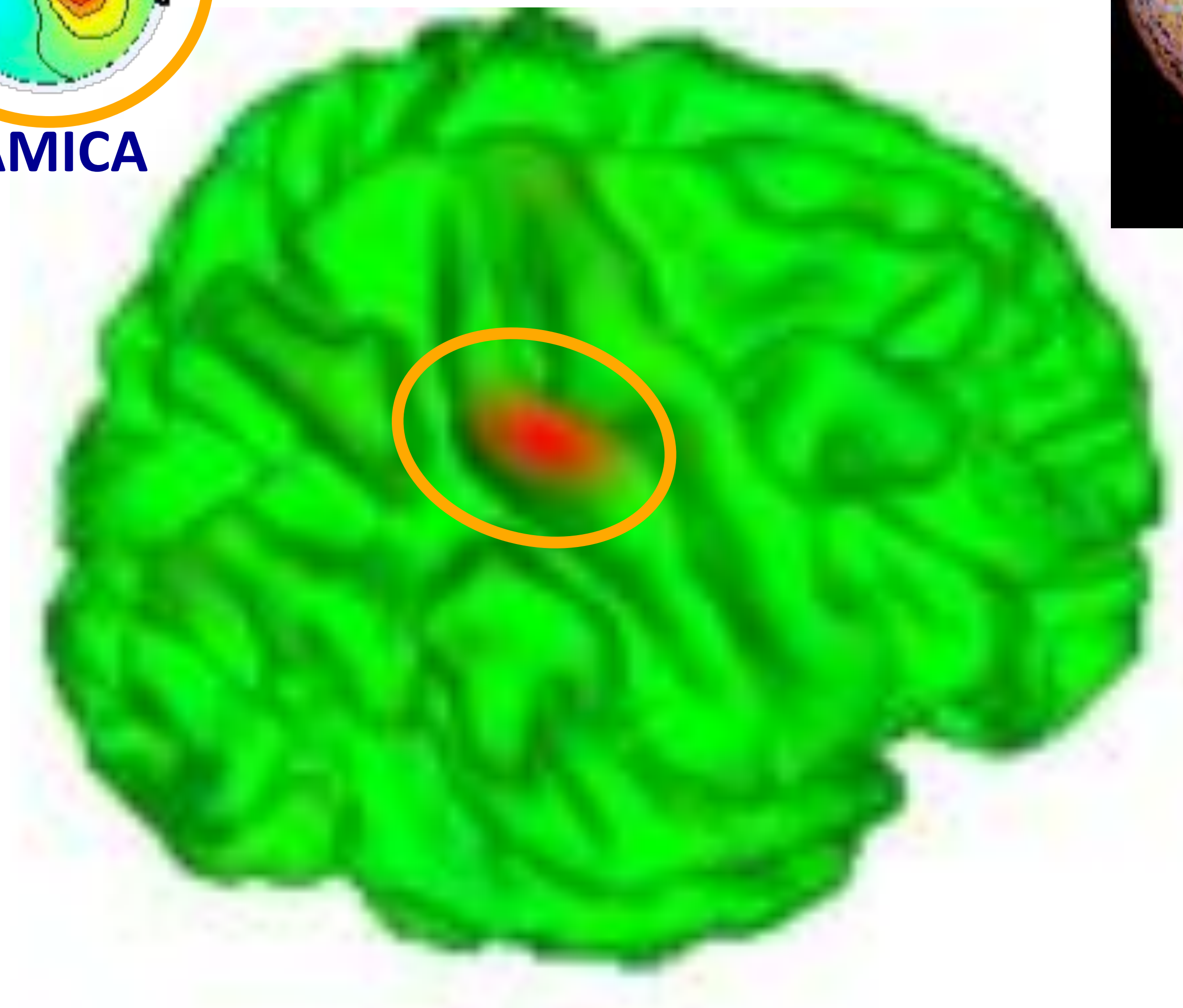


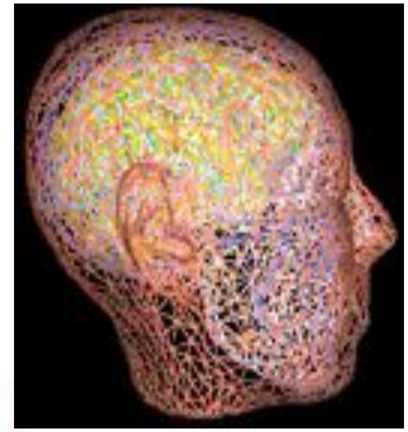
Julie Onton & S. Makeig (2006)

Localizing Independent Component Process Source Domains



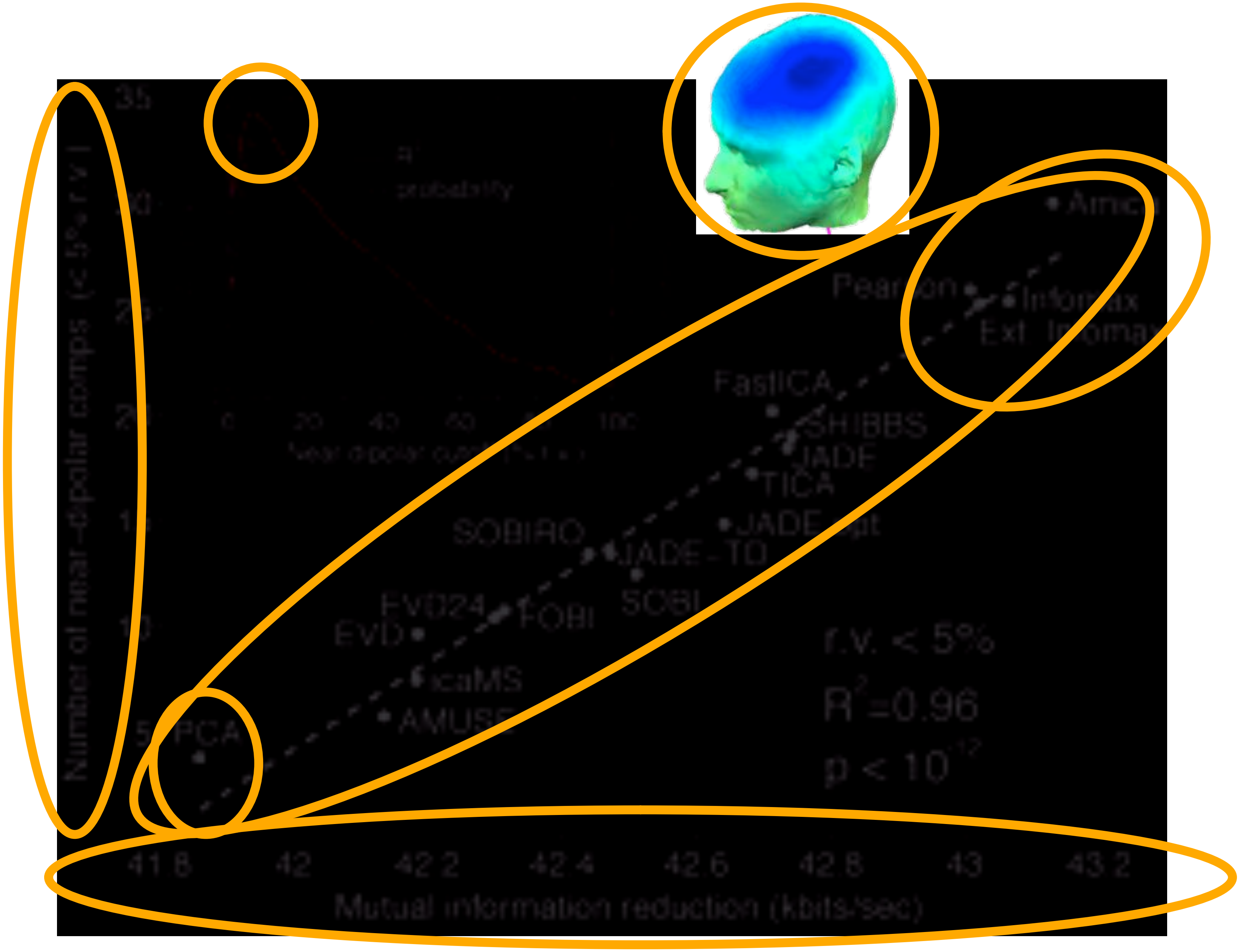
AMICA





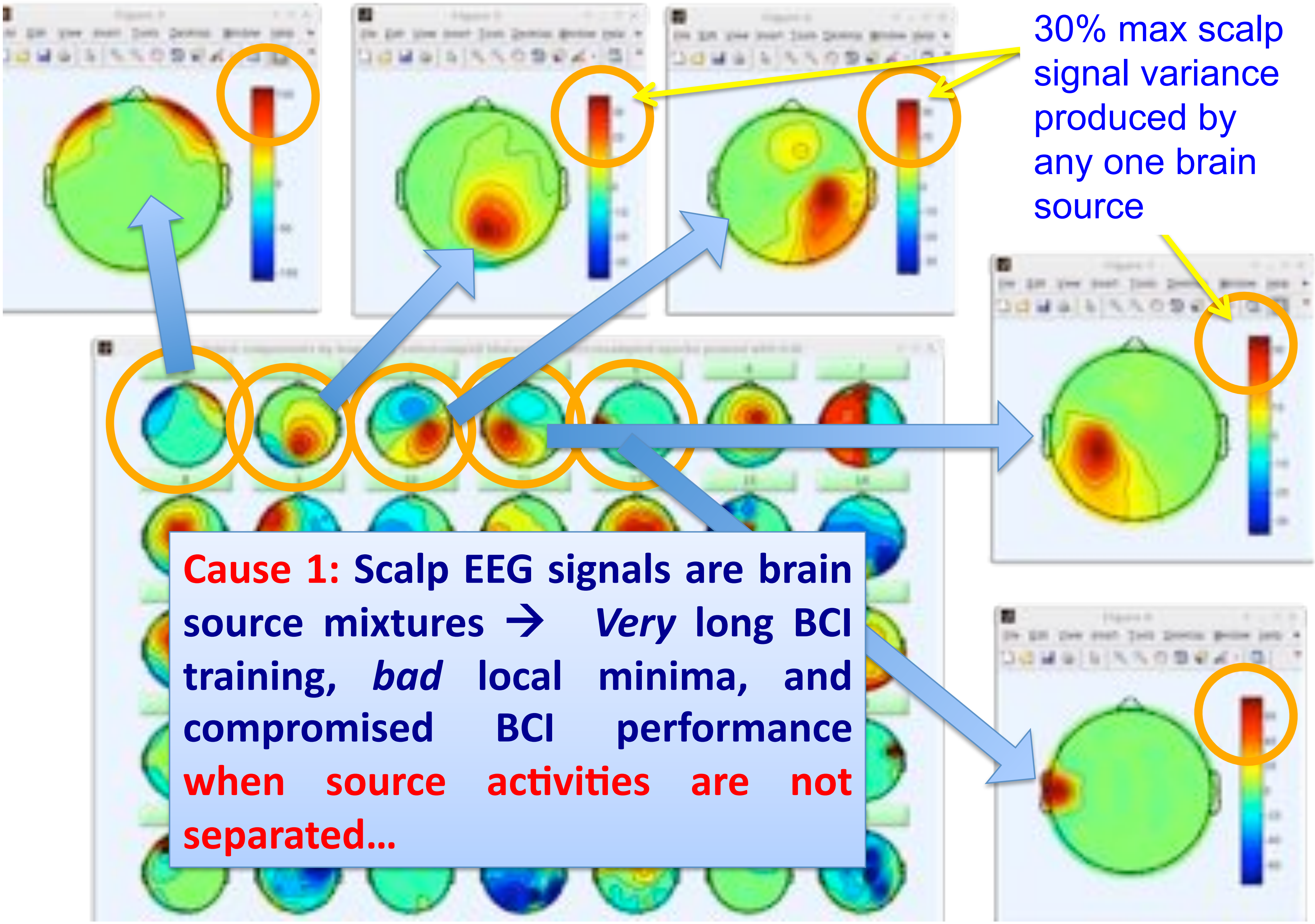
NFT

Z. Akalin Acar & S Makeig, 2013



Delorme et al., *PLOS One*, 2012

A. Delorme & S. Makeig, 2011



M. Miyakoshi & S. Makeig (2014)

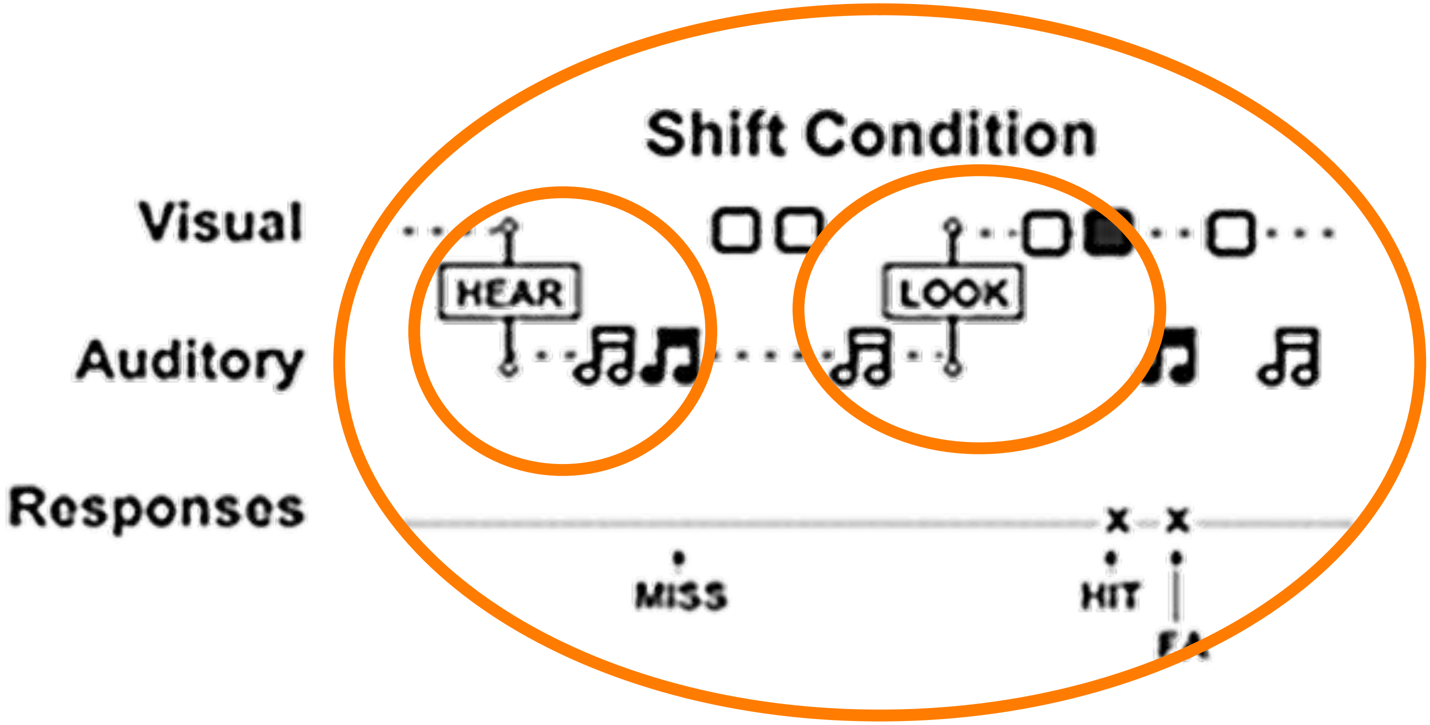
Informative Feature Analysis

of Source-Resolved BCI Modeling

S. Makeig (2014)

Audiovisual Attention Shift Experiment

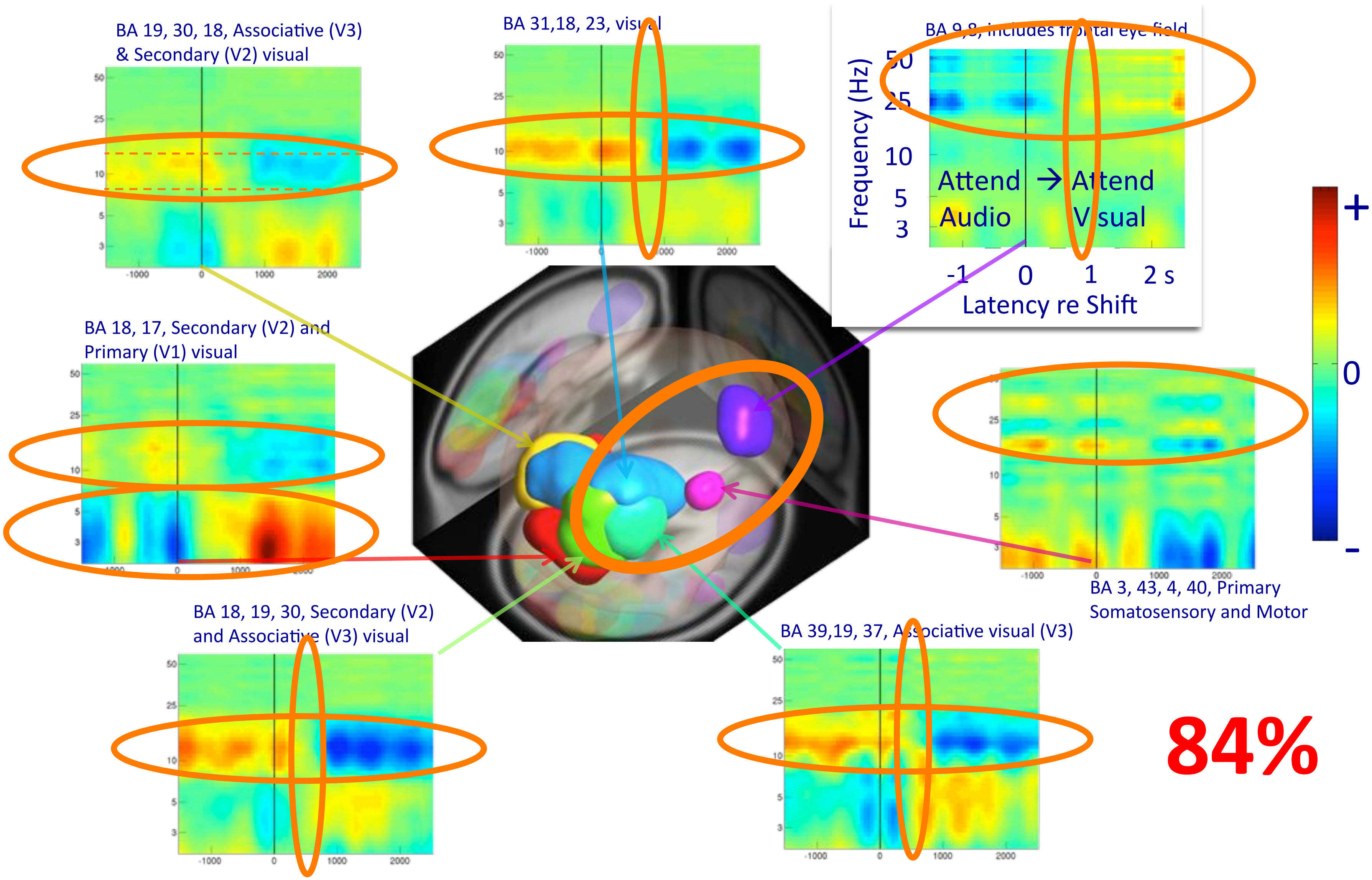
Question: What is the brain activity signature of switching between auditory and visual attention? (DAS)



Paradigm & data: J Townsend et al., 2003

An EEG Attention-Shift Network

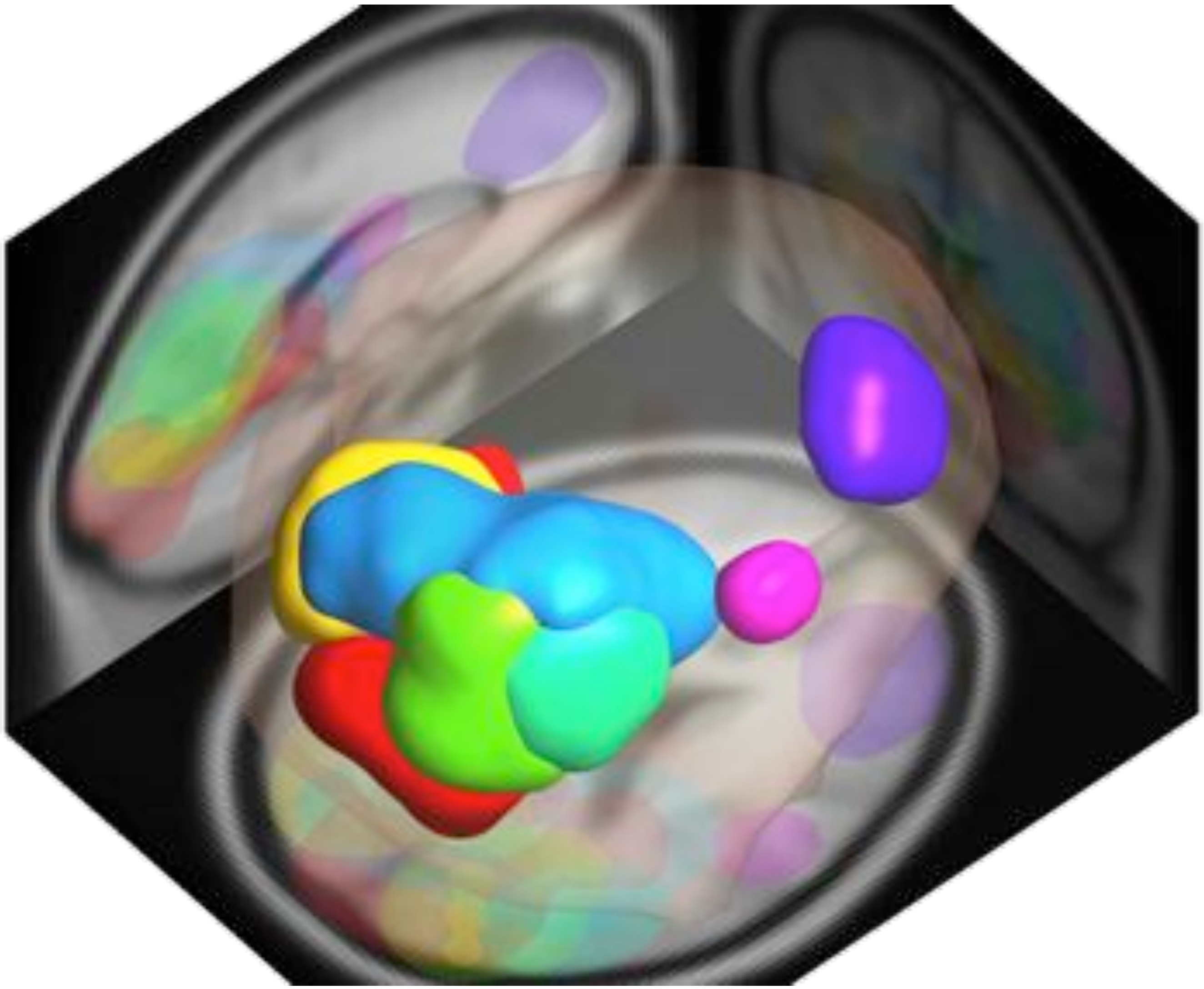
Informative Feature Analysis (IFA)



C Kothe, N Bigdely-Shamlo, S Makeig 2011

Right-sided attention shift network (28 Ss)

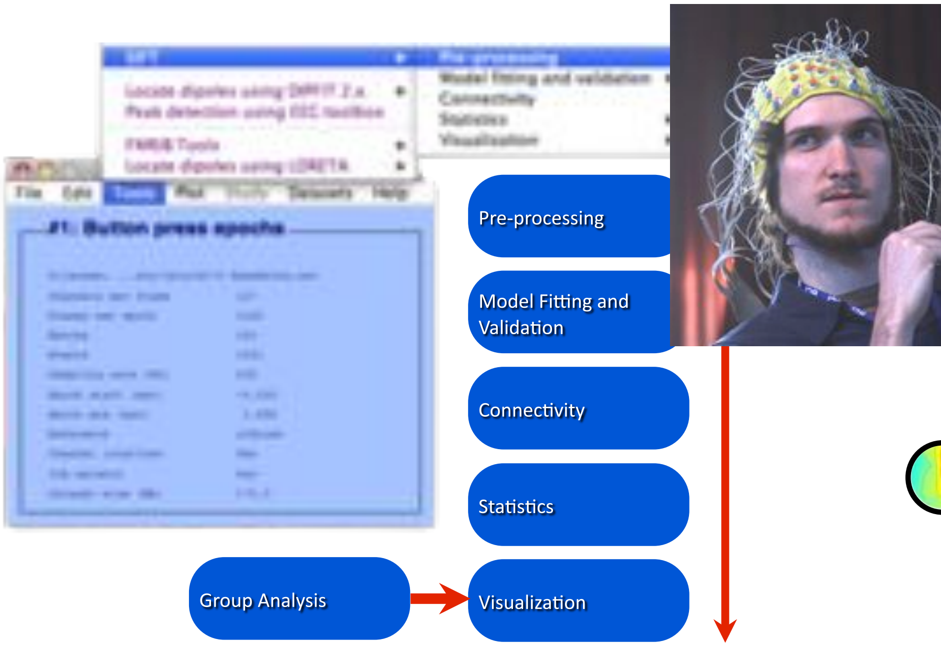
Informative feature analysis

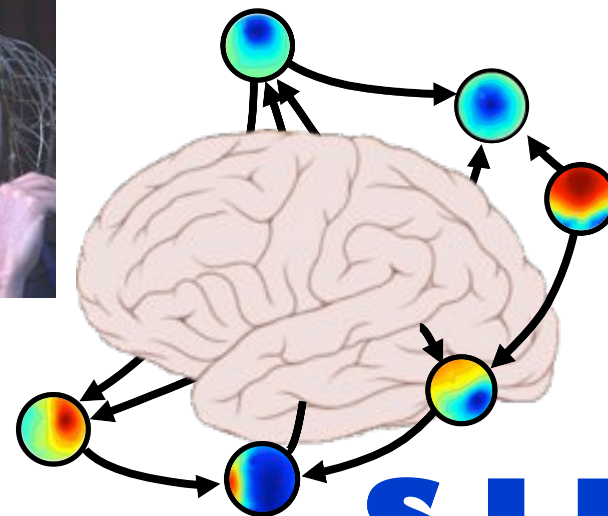


N Bigdely-Shamlo, C Kothe & S Makeig, 2011

Information Flow Features

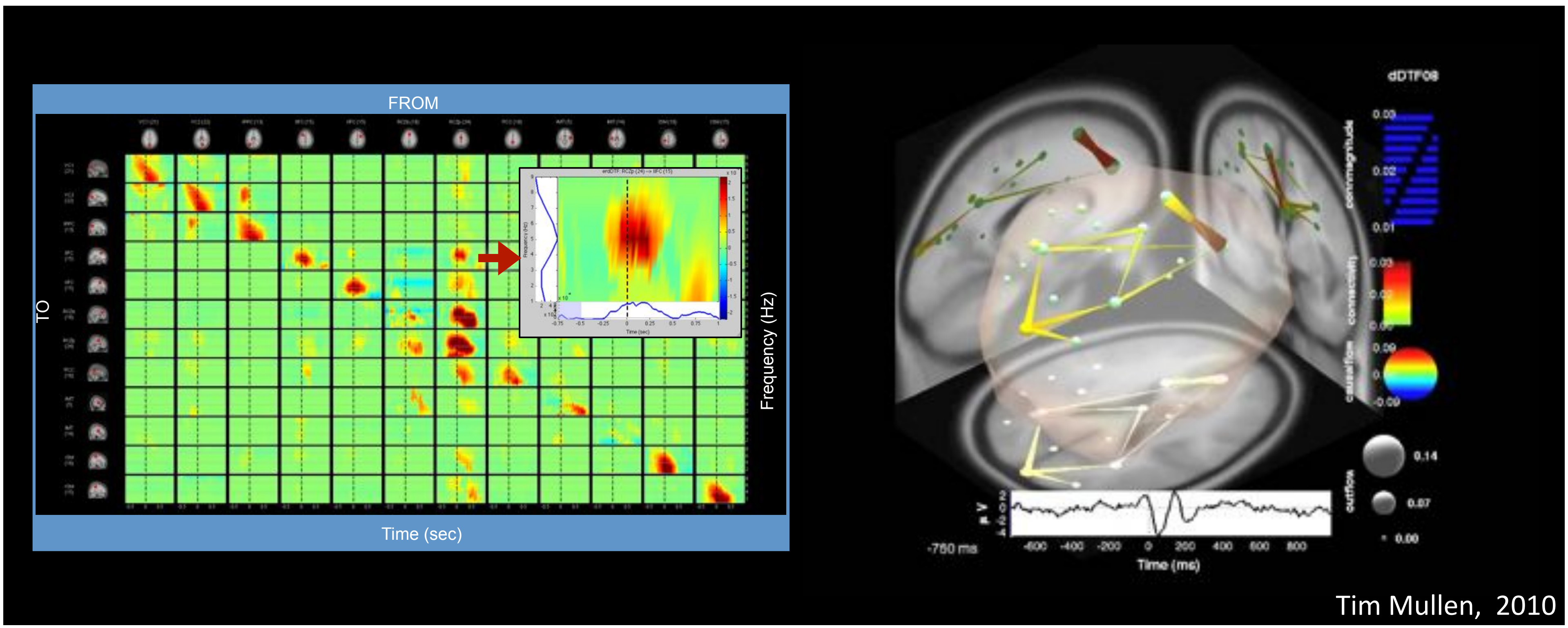
S Makeig, 2014





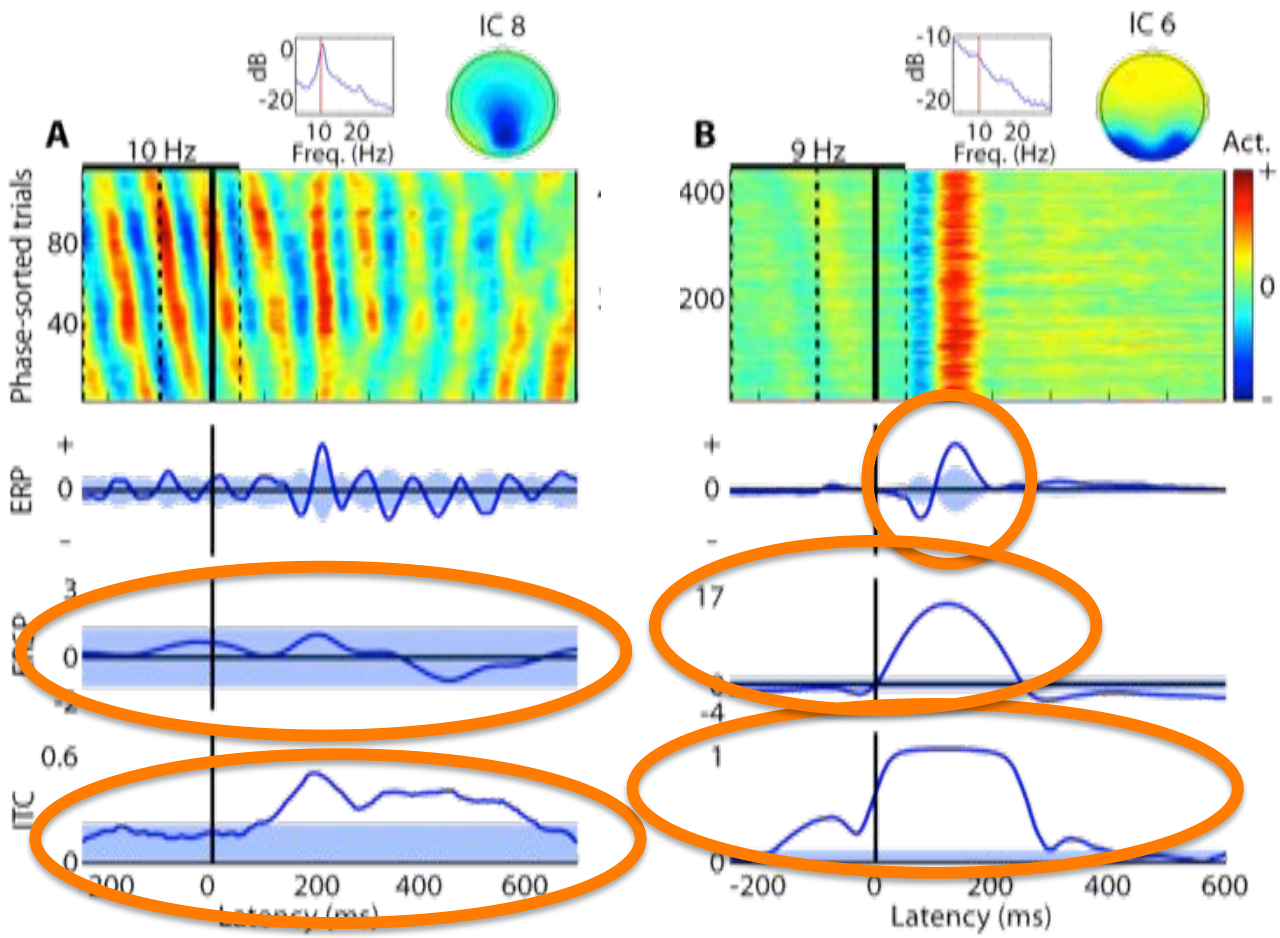
SIFT

Source Information Flow Toolbox



Informative features of different signal source types (brain, eye, muscle) may differ in *kind*.

→ Estimation approaches that attempt to fit the same feature type to each source type will sacrifice accuracy.



S Makeig et al., 2004

Robust BCI

Cause 2: Not combining *informative features appropriate to each source.*

- Measure activities at the (spatially filtered) source level, not from the scalp channel data directly.
- Extract relevant information from each source using most suitable measures for that source.

→'Bio-based BCI'

S. Makeig (2014)

Four Questions about BCI Research

1. What are the sources of EEG-based BCI errors?
2. **Are the separate information values from eye, muscle, heart, and brain signals (etc.) best recovered by any single BCI measure?**
3. Which of these sources of cognitive information summed in scalp electrical recordings are most stationary over sessions, training, weeks, months, and years?
4. What is the upper bound of BCI robustness?

Is it safe to assume that informative features of brain and non-brain signal sources will change at the same rate over repeated recording sessions? That all *brain source processes* contributing informative features (learned from one or more pilot data sessions will be *equally* preserved across changes in subject training, experience, and psychophysiological state?

S. Makeig (2014)

Informative features of different signal source types (brain, eye, muscle) may differ in *kind*.

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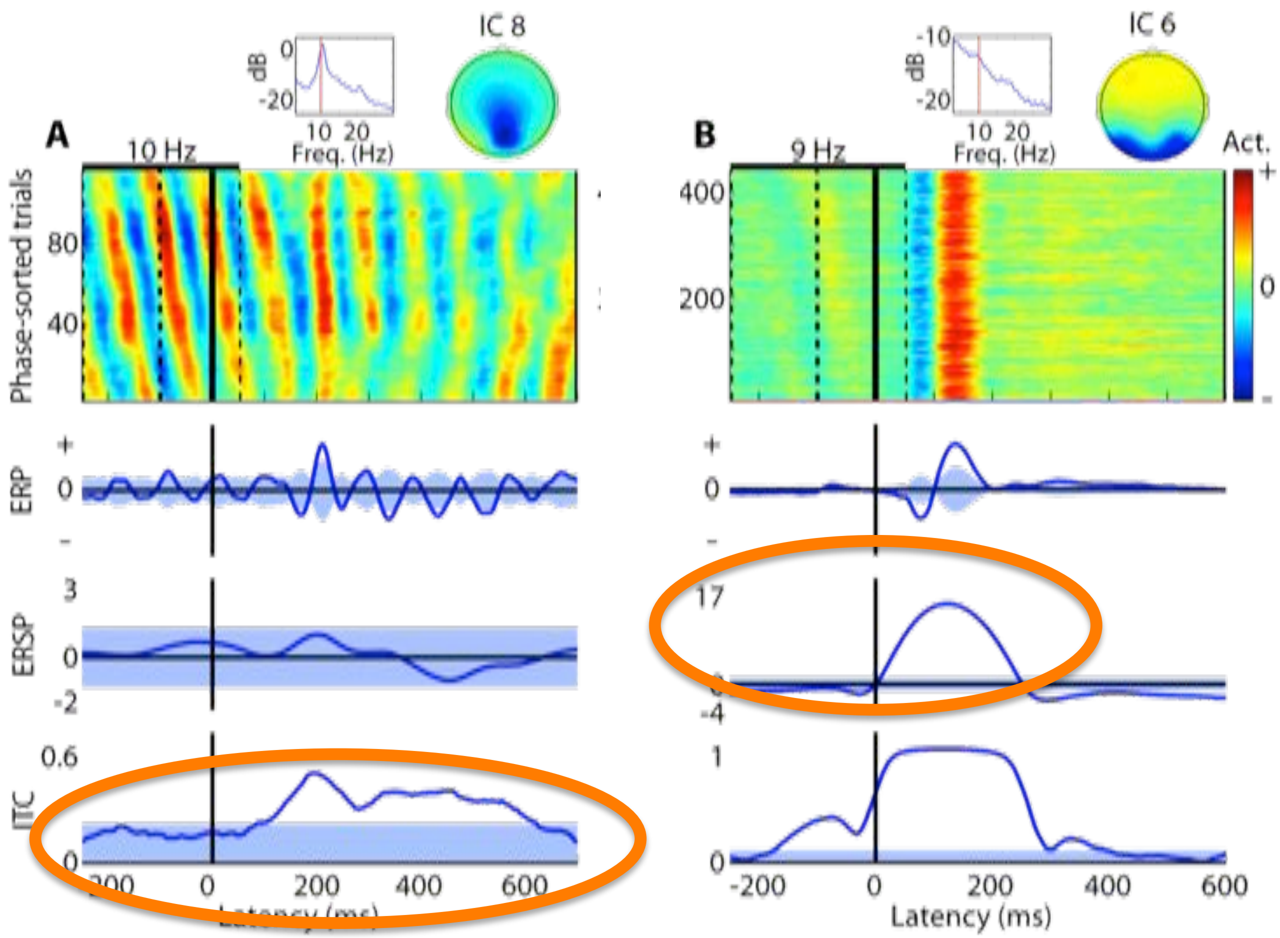
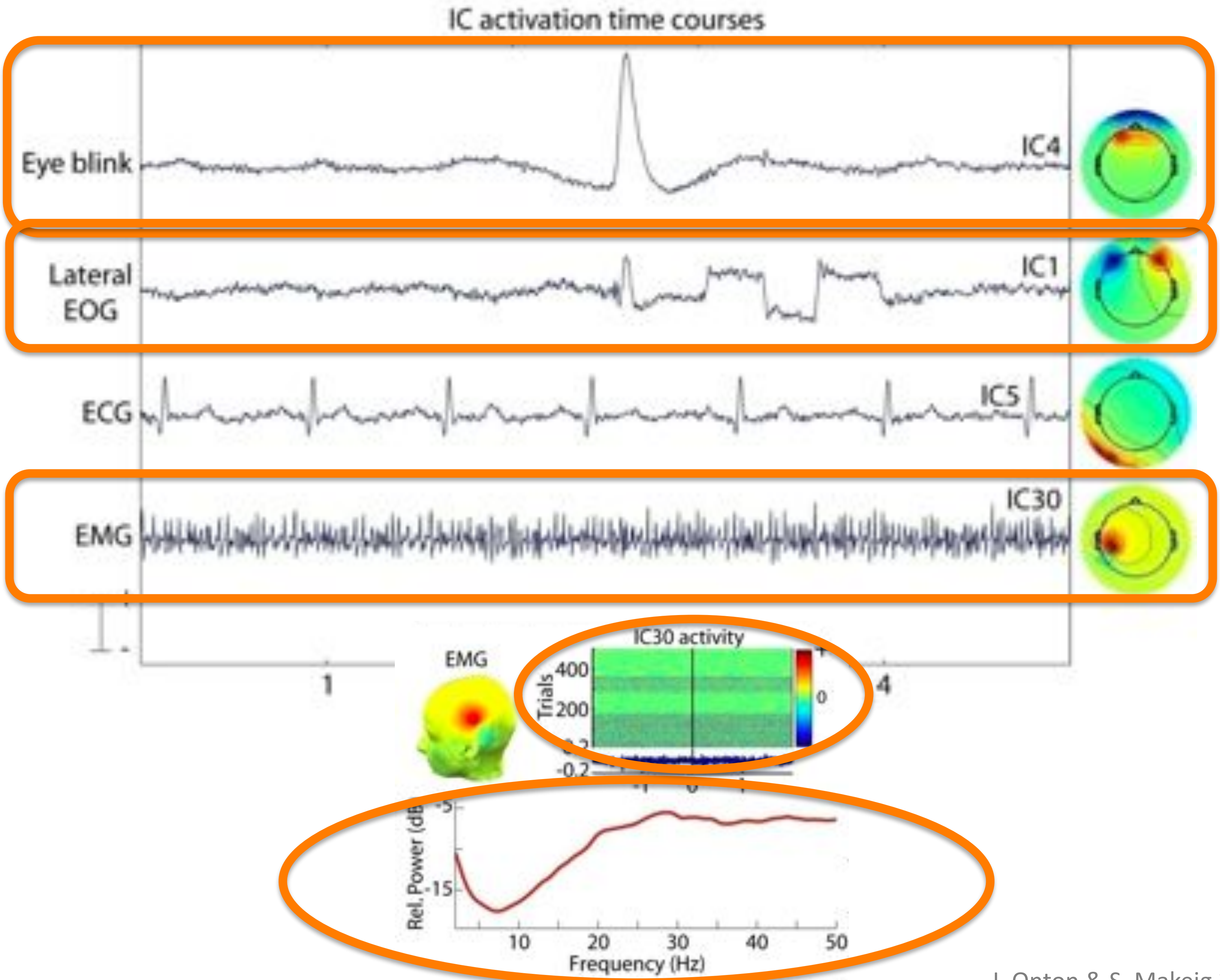
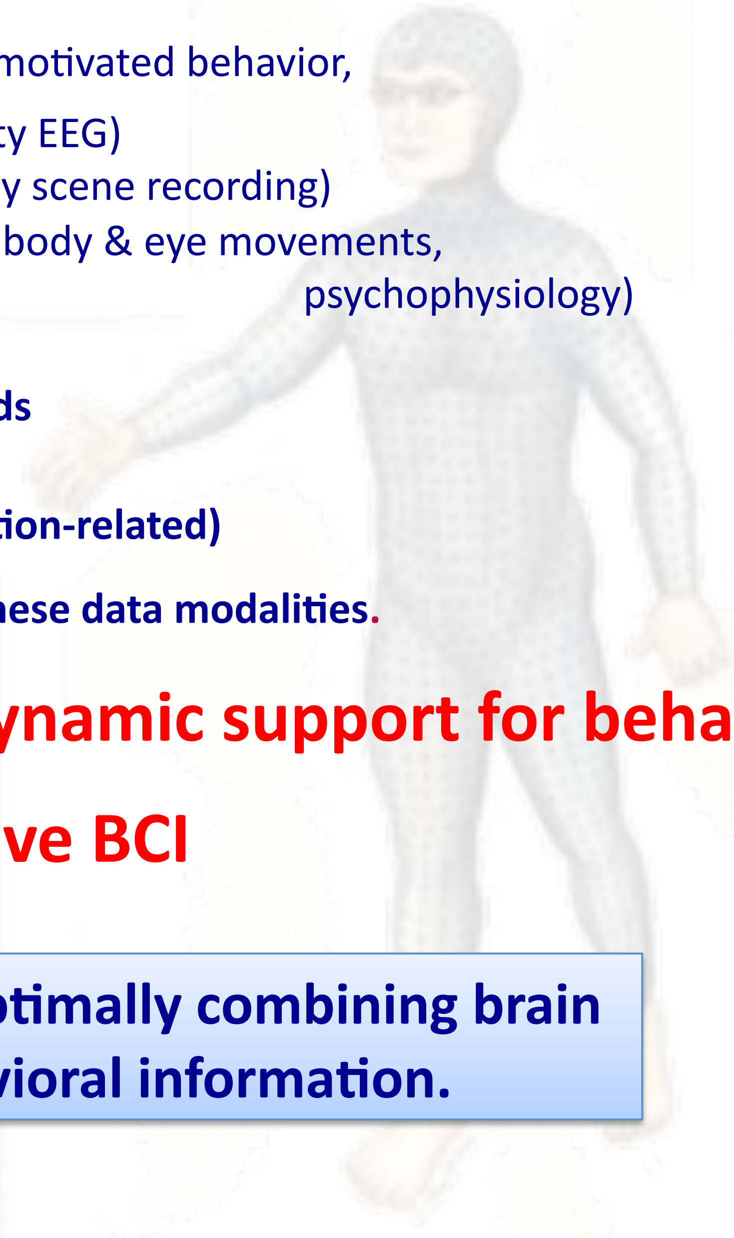


S Makeig et al., 2004



J. Onton & S. Makeig 2006

Mobile Brain/Body Imaging (MoBI)



1. Record simultaneously, during naturally motivated behavior,

What the brain does (high-density EEG)

What the brain experiences (sensory scene recording)

What the brain organizes (body & eye movements, psychophysiology)

2. Then –

Use evolving machine learning methods to find, model, and measure non-stationary (context- and intention-related) functional relationships among these data modalities.

MoBI goals: → Brain dynamic support for behavior

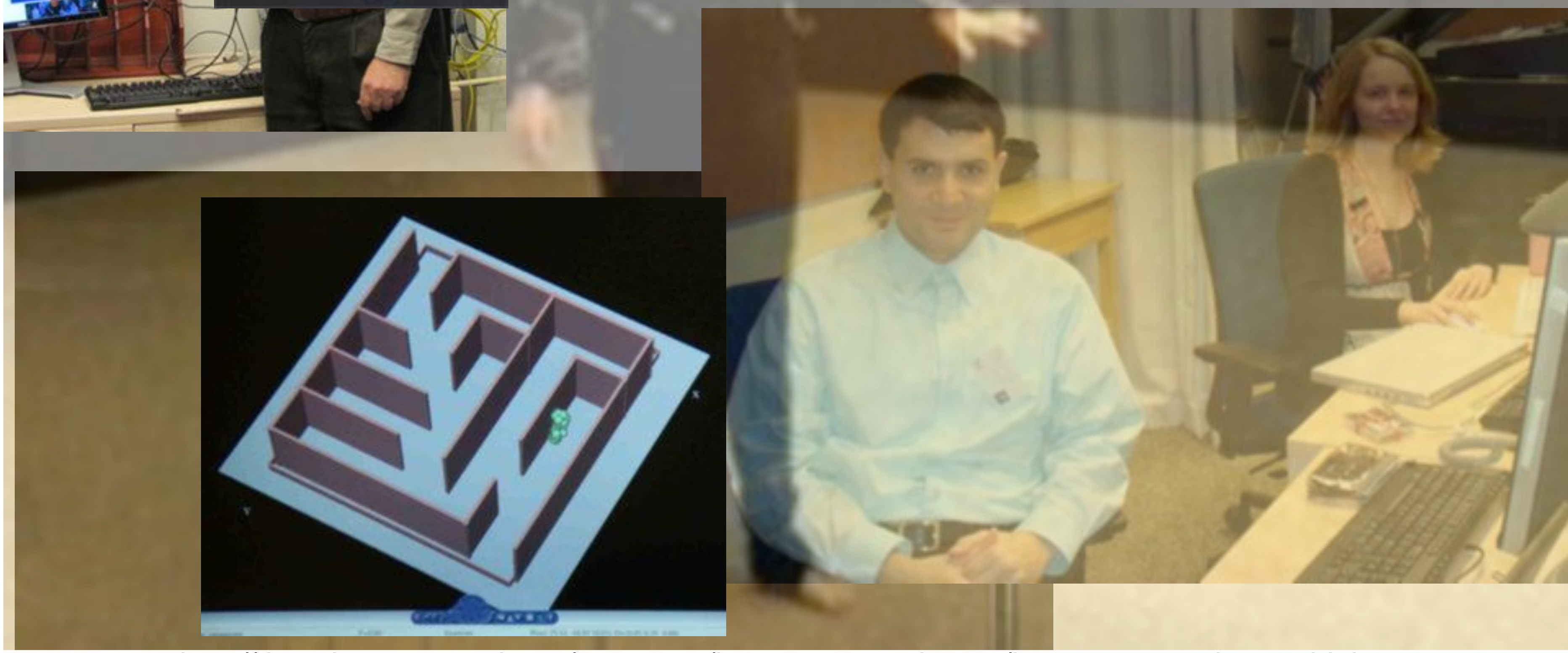
→ Pervasive BCI

Cause 3: Not optimally combining brain and behavioral information.

Scott Makeig, 2011

MoBI Lab at SCCN, UCSD

Lab Streaming Layer software for synchronous multi-stream, multi-platform recording and feedback – freely available on Google Code.



http://thesciencenetwork.org/programs/inc-sccn-open-house/inc-sccn-open-house-hi-lite-reel

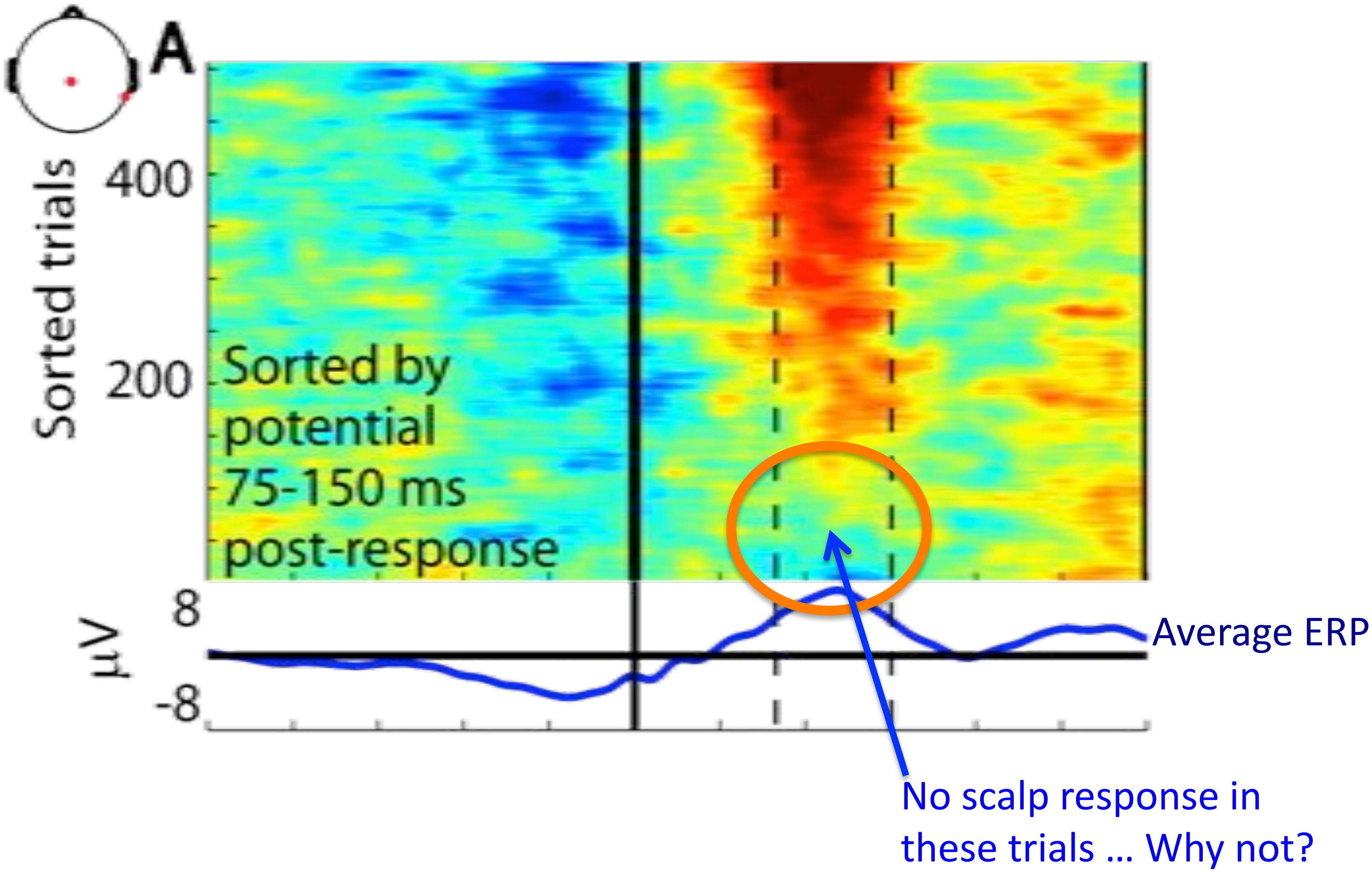
Four Questions about BCI Research

1. What are the sources of BCI errors?
2. Are the separate information values from eye, muscle, heart, and brain signals best recovered by any single BCI algorithm?
3. **Which sources of cognitive state, intent, and response information (summed in scalp electrical recordings) are most stationary over training, and sessions (over weeks, months, and years)?**
4. What is the upper bound of BCI robustness?

Is it safe to assume that informative features of brain and non-brain signal sources will change at the same rate over repeated recording sessions? That all *brain source processes* contributing informative features (learned from one or more pilot data sessions will be *equally* preserved across changes in subject training, experience, and psychophysiological state??

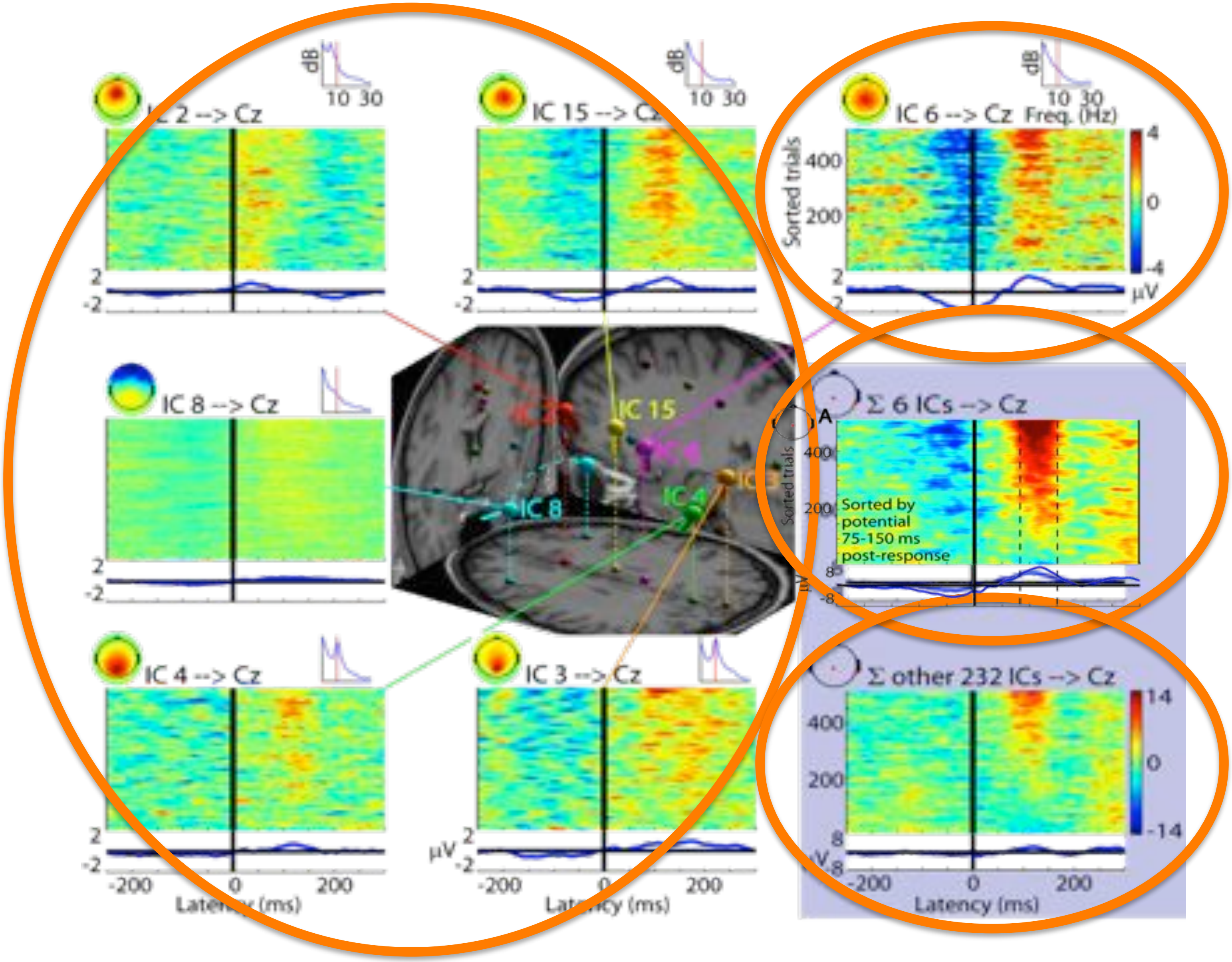
Makeig (2014)

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



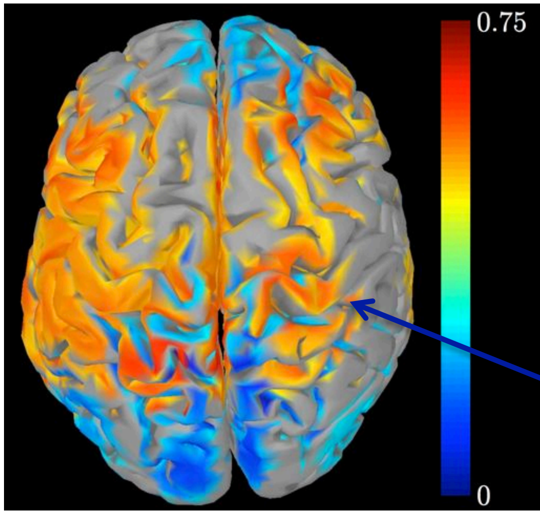
J. Onton & S. Makeig (2009)

The response (at Cz) sums 238 independent sources



J. Onton & S. Makeig (2009)

High gamma power predicts good sensorimotor BCI performance



Moritz Grosse-Wentrup &
Bernard Schoelkopf, 2012

Cause 3: **States of arousal and attention differ session to session and minute to minute. Estimation methods that assume fixed EEG baseline dynamics cannot be maximally robust.**

NB: Low-resolution estimate, too diffuse!?

→ Estimate brain/cognitive state and action intent and/or event response *concurrently*.

→ Train the subject using feedback about brain state.

Cause 4: **Not training the subject to adapt to BCI use as it adapts to subject biology (i.e., to use BCI-augmented subject training to augment BCI performance).**

S. Makeig (2014)

Week-to-Week OSR Model Stability (1^{st} Test)

- **Challenge: Record from the same subject on 5 different days**
  - **Still within-subject, but ACROSS days and small montage differences**
    - **→ Use NO testing-day calibration data !**
  - Learn AMICA decomposition & IF bands from 4^{th} training session
  - Apply the same decomposition to all data (sessions 1-4) & extract IFs
  - Pool all data into single joint sparse logistic regression model
  - Estimate workload during a new (5^{th}) day (a week later)
- **Result: 67.3%** ± 6.9 % correct classification

within-session 94% → 67% across-session

What are the sources of *cross-session* BCI model error?

C Kothe & S Makeig, 2011

Cause 5: **Different scalp electrode locations session to session.**

→ **Estimate/learn the precise scalp locations from the data.**

Cause 6: **Different head tissue & electrode conductances**

→ **Adjust conductances in the head model from the data.**

S. Makeig (2014)

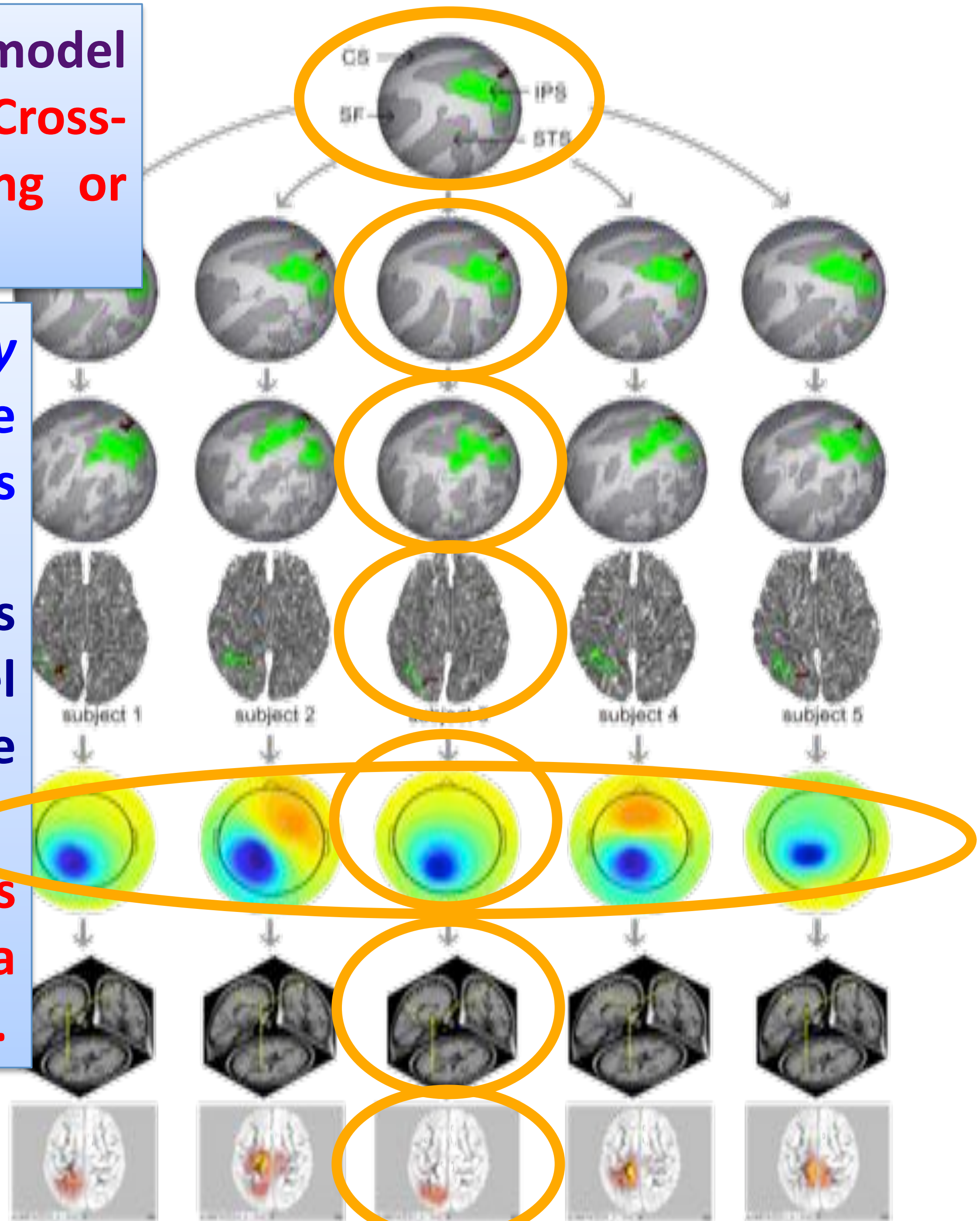
Cause 7: Never enough BCI model training data → Solution: Cross-subject BCI transfer learning or collaborative filtering.

Cause 8: *Functionally equivalent* sources have different scalp projections across subjects

Thus, transfer learning across subjects using channel signals will always be imprecise.

Solution: Co-register sources across subjects using a topological cortical template.

Arthur Tsai – **topological source mapping**



Arthur Tsai et al., *NeuroImage*, 2014

Four Questions about BCI Research

1. What are the sources of EEG-based BCI errors?
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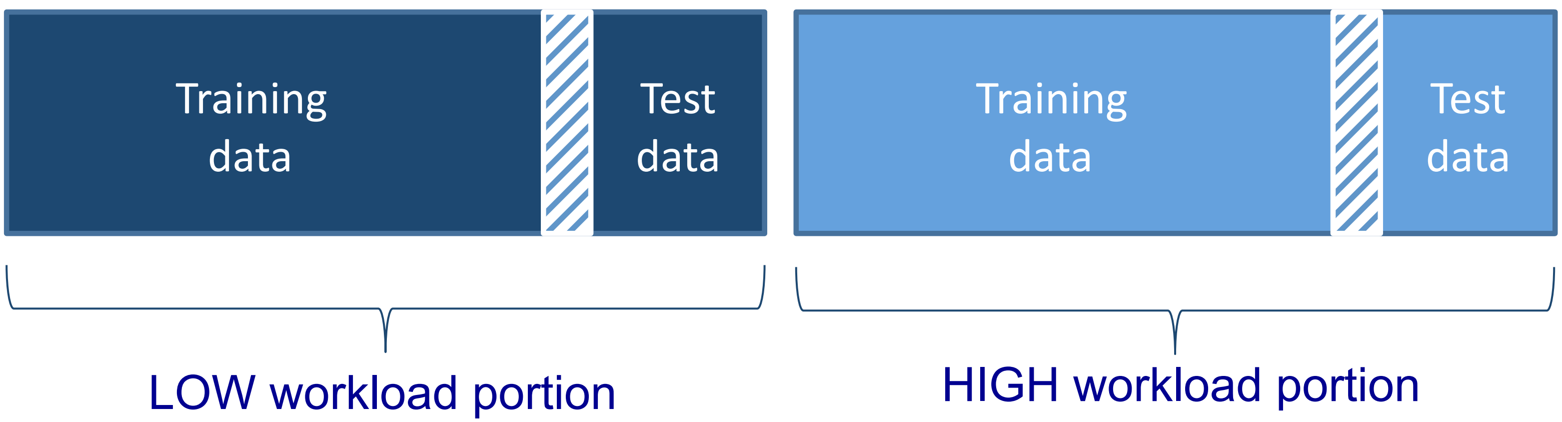
3. Which of these sources of cognitive information summed in scalp electrical recordings are most stationary over sessions, training, weeks, months, and years?
4. **What is the upper bound of EEG-based BCI robustness?**

S. Makeig (2014)

BCI Methods Comparison
Workload Estimation Problem

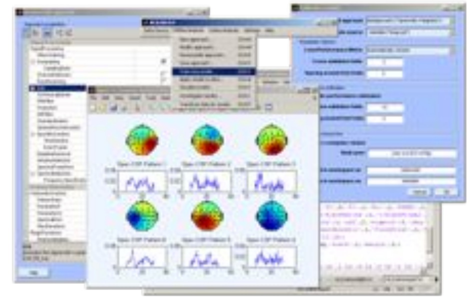
- Five-fold chronological (non-randomized) cross-validation
- 15-second margins left out between training & test sets
- Structure of a single fold (per data set):



- Use nested five-fold cross-validation for parameter search

C Kothe & S Makeig EMBC, 2011

The BCILAB Toolbox



- BCILAB – An open-source MATLAB toolbox

  for single- and multi-subject BCI/CSA analyses
- Runs on Matlab; interoperable with EEGLAB
- Largest collection of machine learning & signal processing tools

  in any BCI package (to our knowledge)
- Support for real-time interactive experiments

  (in combination with BCI2000, LSL, etc.)

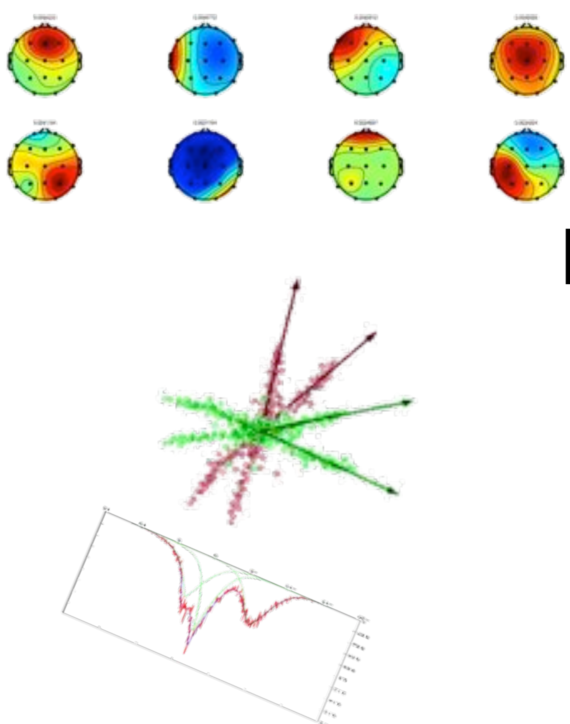
http://sccn.ucsd.edu/**wiki**/**BCILAB**

Christian Kothe, 2011

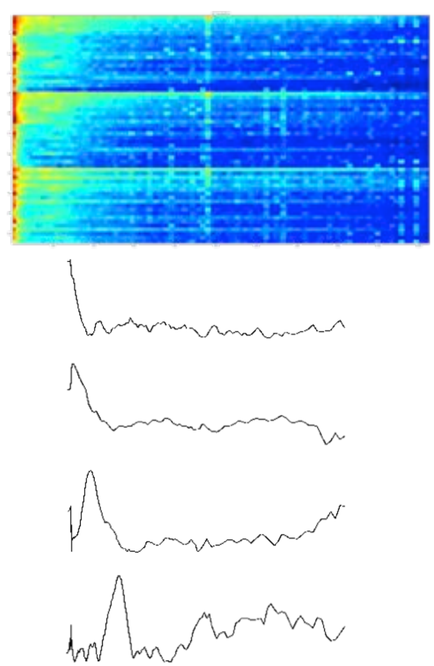
Overcomplete Spectral Regression (OSR)

A new decomposition and feature selection method:

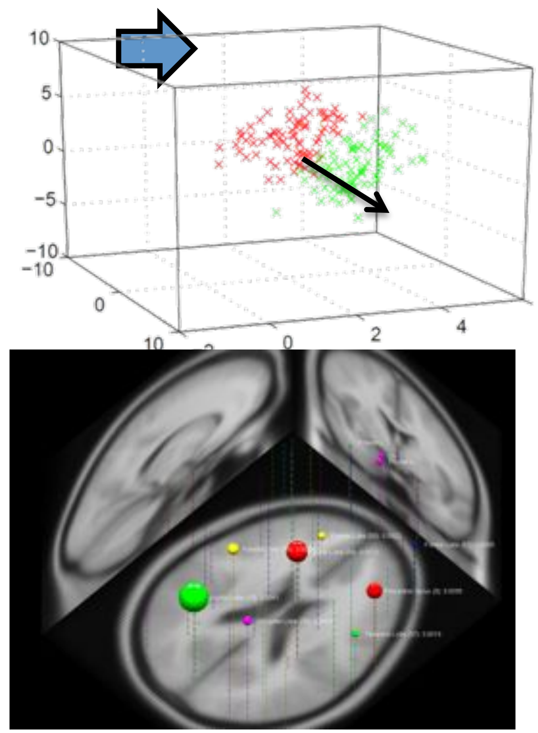
1. Overcomplete linear spatial decomposition via AMICA



2. Log-power decomposition and frequency band learning via multi-taper estimation and shrinkage PCA



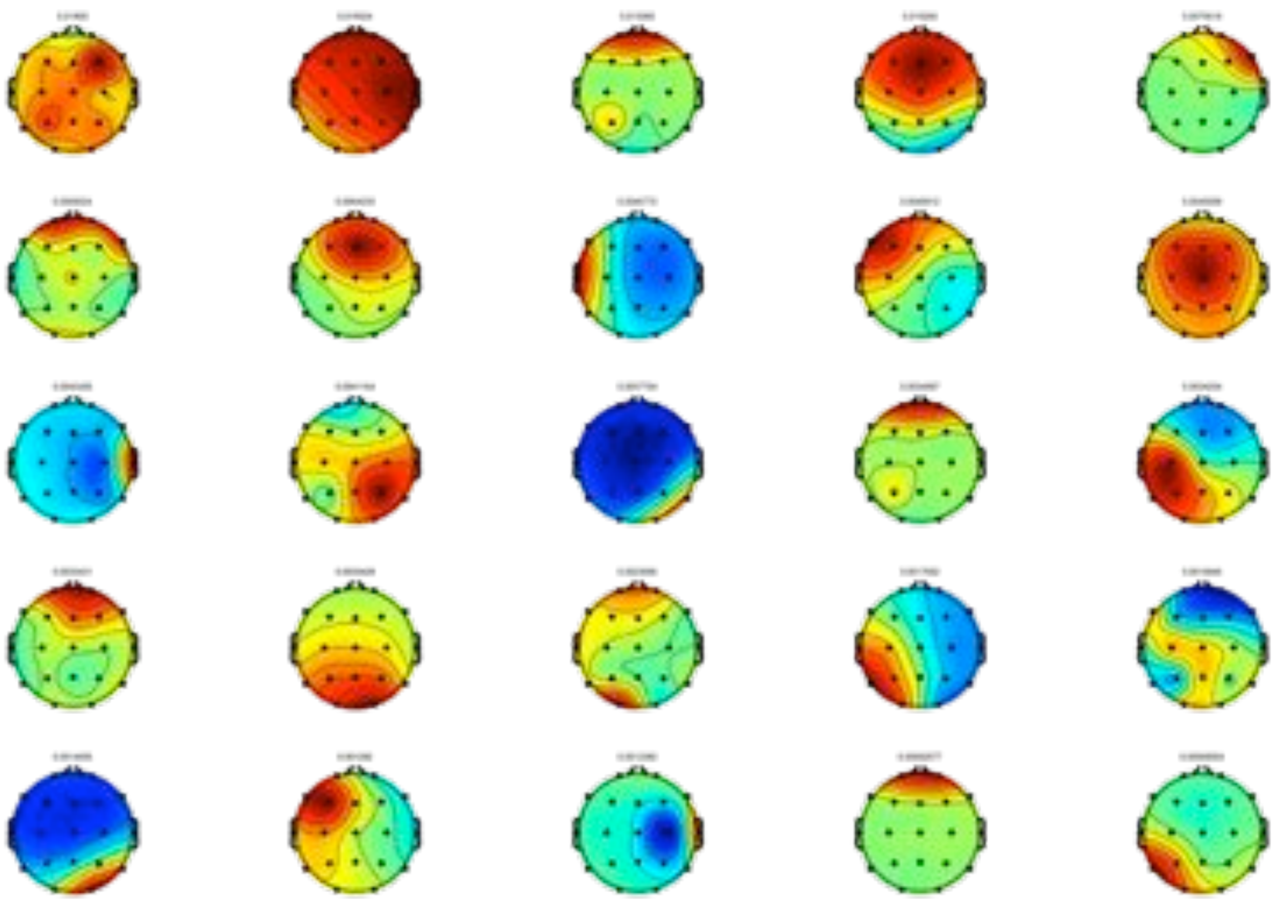
3. Feature selection and statistical learning via sparse logistic regression



C Kothe & S Makeig, 2011

OSR Model Structure

Sample scalp projections of ICA source maps



C Kothe & S Makeig, 2011

Cross-Validation Results

- **Effect of adaptive spectral band learning (*) 77% → 83%**
  - Raw log-power features -- MT-LARS (76.9 ± 11.9)
  - Fixed frequency bands -- MBLP-LARS (80.1 ± 11.8)
  - → **Data-adaptive bands -- MTDC-LARS (82.8** ± 9.6**)**

  Comparisons on channel data features

- **Effect of classifier choice (sparse/nonsparse) (n.s.) 80% → 80%**
  - Linear -- FBCSP-LDA (80.2 ± 14.7)
  - Sparse linear -- FBCSP-VBARD (80.4 ± 11.6)
  - Sparse non-linear -- FBCSP-HKL (80.0 ± 14.5)

  Comparisons on spatially filtered data features

Cross-validation Results

Band Selection and OSR

- **Single band vs. multiple bands (*)   74% → 80%**
  - Single wide band (2-42 Hz) -- BBCSP-LDA (**74.3** ± 11.4)

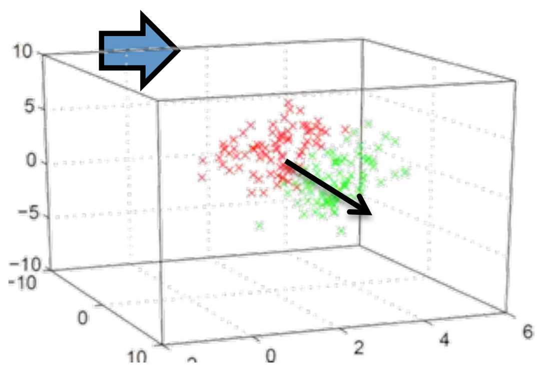
  → **Multiple bands -- FBCSP-LDA (80.2** ± 14.7**)**

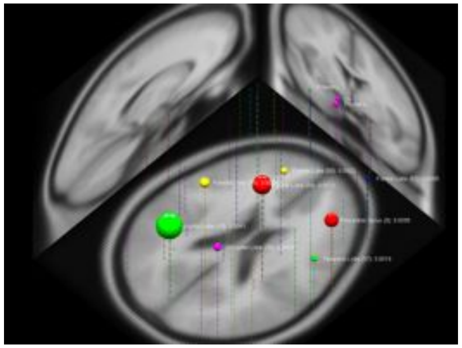
  Comparisons on spatially filtered data

Why the big gain !?

- **Effect of OSR (**)   83% →94%**
  - Best result on channel data -- MTDC-LARS (82.8 ± 9.6)

  → **Result using overcomplete ICA -- OSR-LARS (93.9** ± 5.5**)**

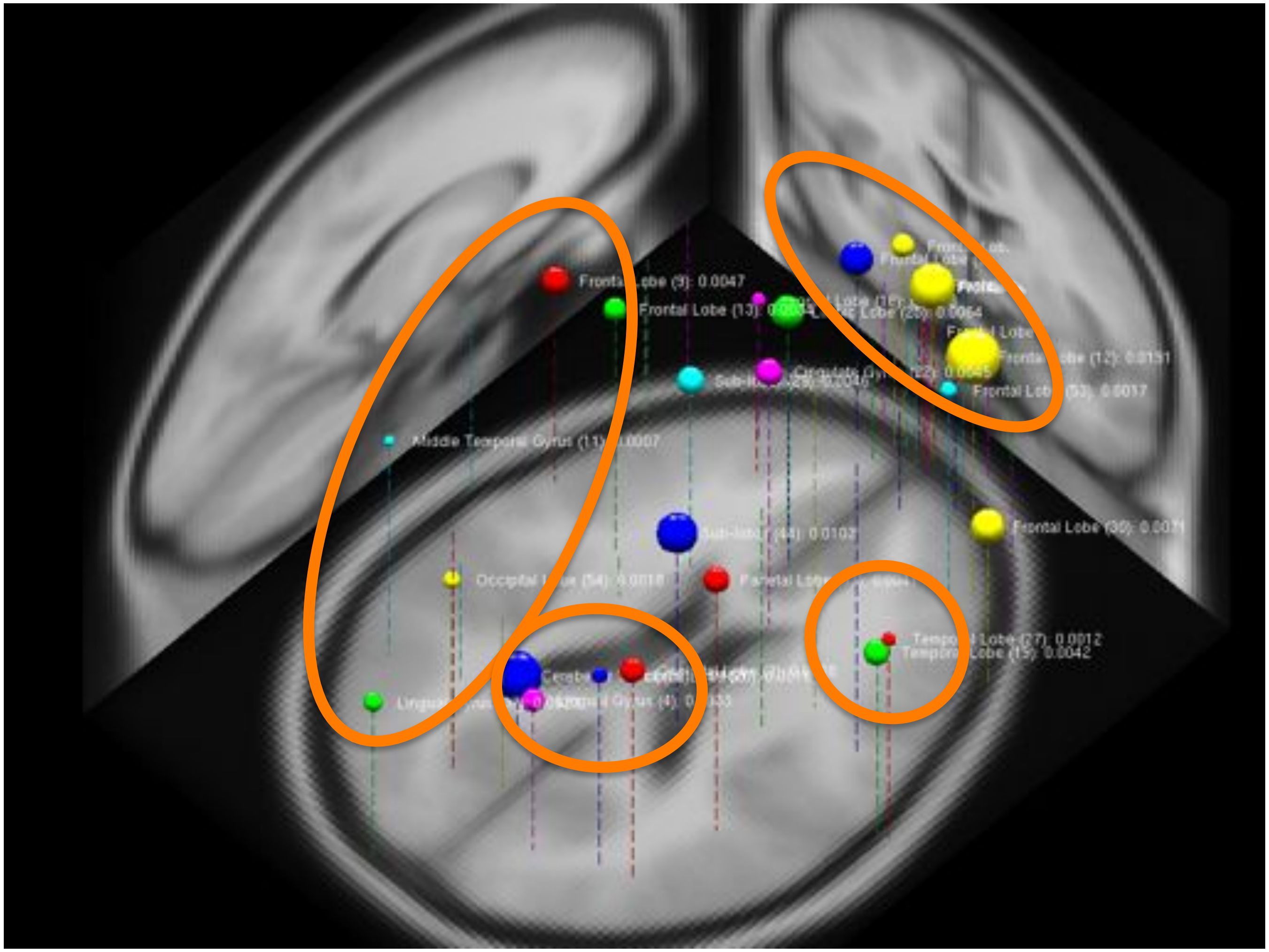




C Kothe & S Makeig, 2011

OSR Model Structure

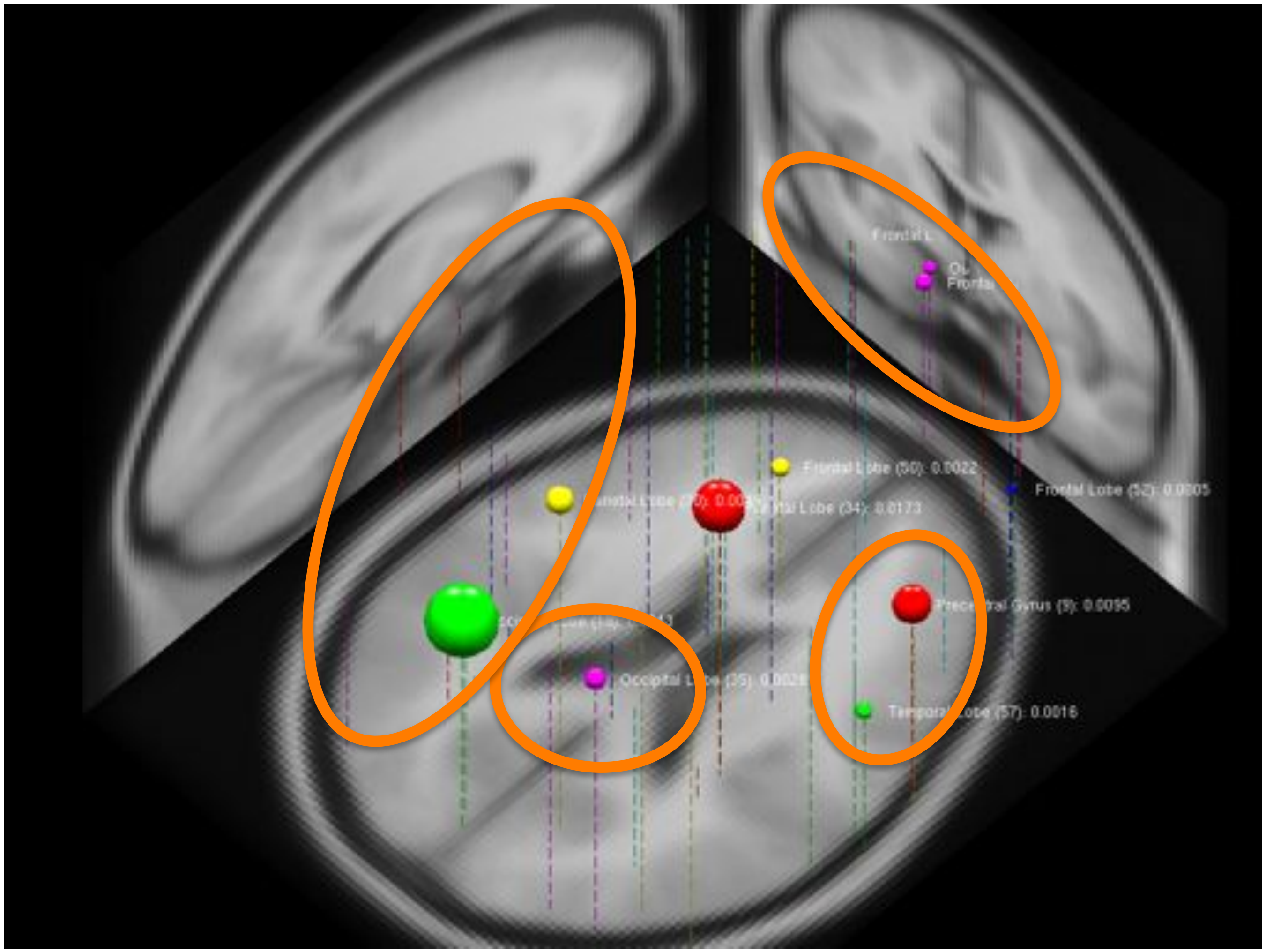
Equivalent dipole IC source locations (Subj 1)



C Kothe & S Makeig, 2011

OSR Model Structure

Equivalent dipole IC source locations (Subj 2)

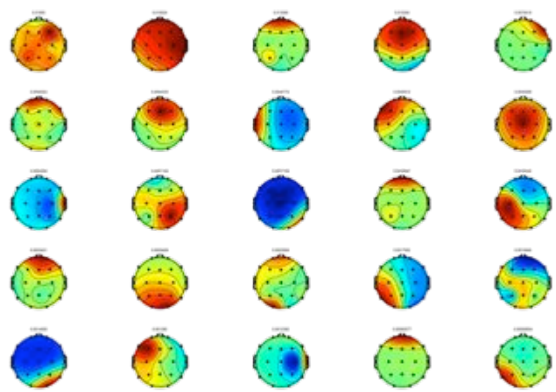


C Kothe & S Makeig, 2011

Biology: Brain dynamic state

→ Nonlinear spectral modulation

→ Linear mixing



OSR : Linear source separation

→ Nonlinear spectral power measurement

→ Brain dynamic state prediction

'Bio-based' BCI

S Makeig, 2011

Building Robust BCI Systems

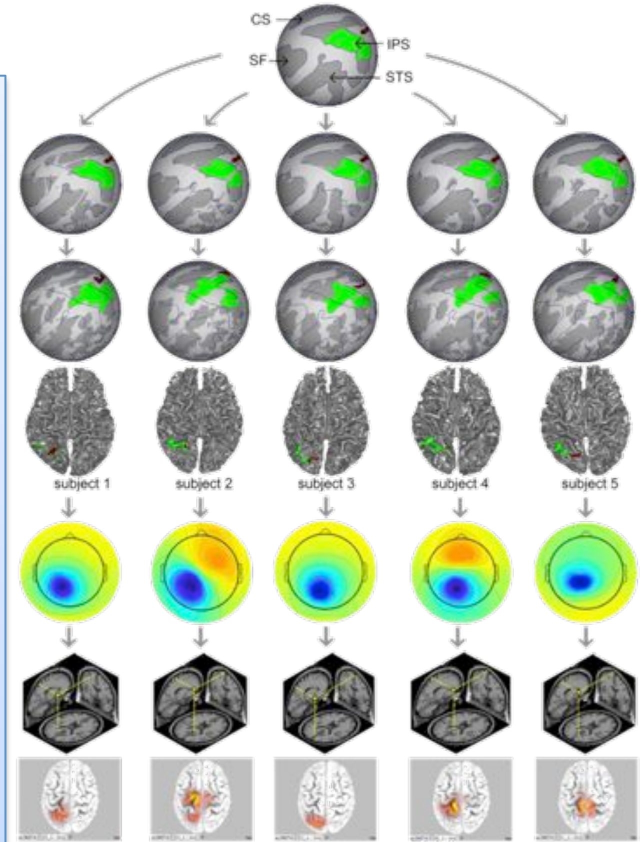
→ Build an electrical forward head model *for every BCI subject.*

→ *Build every BCI subject a MR image-derived geometric head model !*

→ Develop a method for estimating montage co-registration with the head model from the data.

→ Develop methods for adapting the lead field matrix electrode positions and tissue conductances *quickly* based on incoming new-session data.

→ Regularize BCI models using stored, source-resolved data from this and many other subjects.



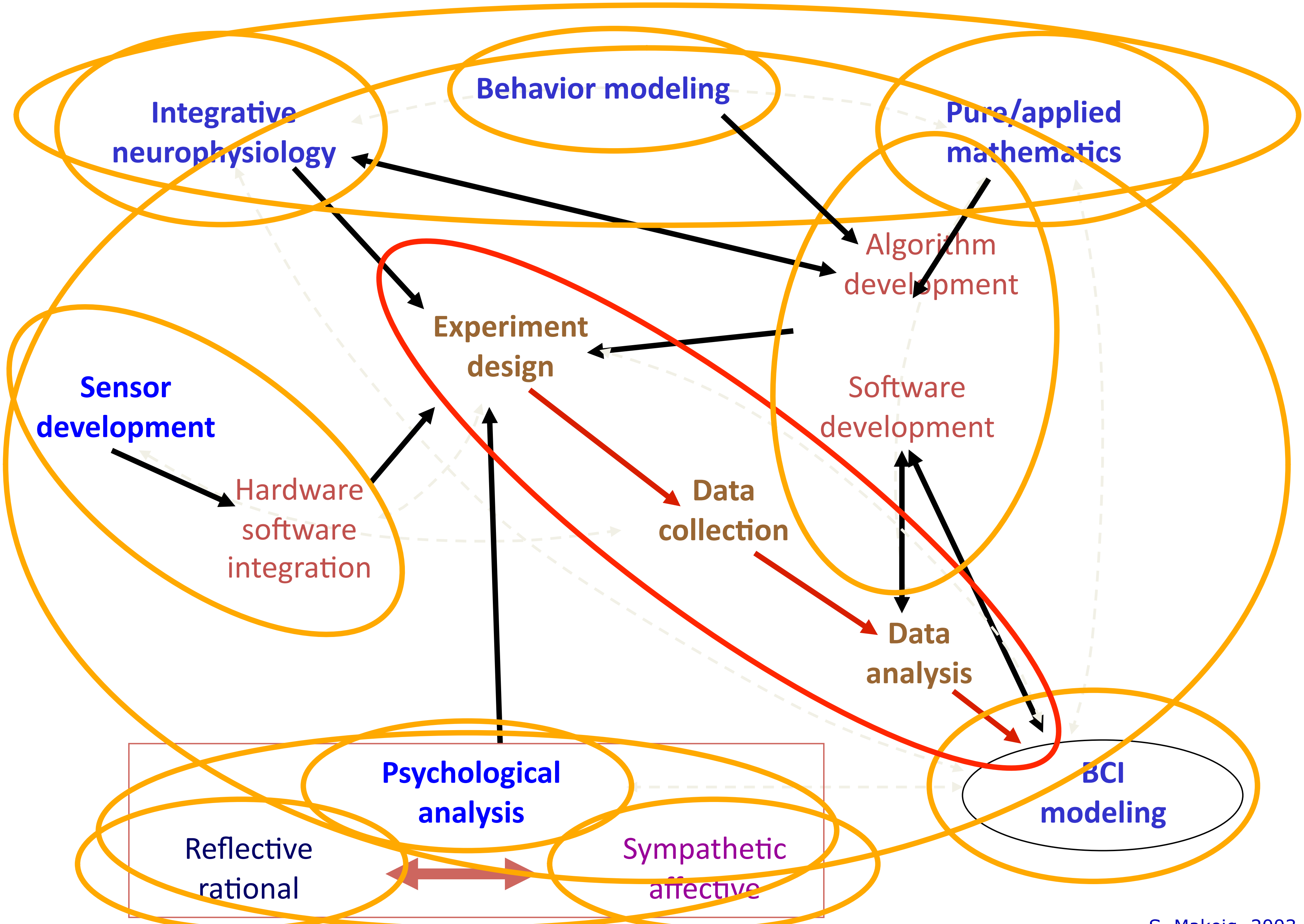
Arthur Tsai et al., *NeuroImage*, 2014

14 Modest Proposals – Toward Robust, Pervasive BCI

1. Use ***high-density recordings*** and ***individual MRI-based head models***.
2. Un-mix ***source signal mixed*** by volume conductance in scalp data.
3. Estimate ***scalp montage placement*** from the source projections + stored data.
4. Measure ***channel conductances*** actively.
5. Estimate ***skull conductance*** passively from data and head model.
6. Model the sources on a topological ***cortical surface template***. (Add DTI?!)
7. Observe and model ***source signal generation and coordination***; extract and combine i***nformative features appropriate for each source*** (***'Bio-based BCI'***).
8. Use BCI-augmented BCI subject training.
9. Collect & analyze existing ***data over many sessions*** from the same subjects; observe and model source dynamics and resultant ***BCI model evolution***.
10. Regularize BCI models based on ***source-resolved and functionally co-registered data*** from ***many*** subjects.
11. Model ***interactions between BCI intent/response estimation*** and ***subject state***.
12. Include stable & informative features of subject ***eye and body activity*** (MoBI).
13. Incorporate concurrent evidence about ***task and environment context***.
14. Rely on and support ***advancing frontiers*** in machine learning, neurophysiology, sensor system design, parallel computing, etc.

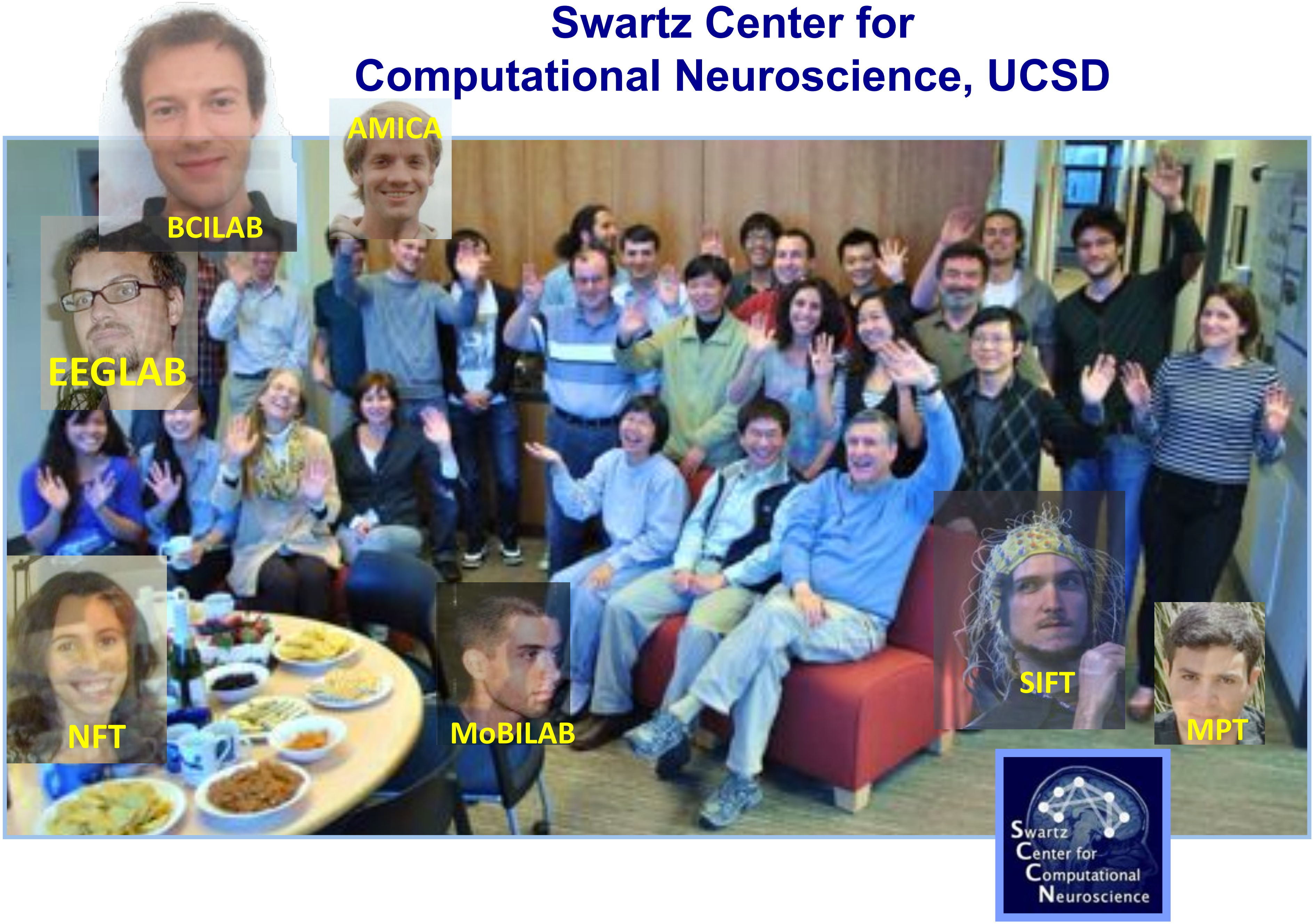
S Makeig, 2014

The BCI Problem Stretches Between Scientific Boundaries → Form Teams!



S. Makeig, 2003

Swartz Center for Computational Neuroscience, UCSD



S Makeig, 2014

10th Anniversary SCCN Impromptu celebration - 2 January 2012