Real-World Neuroimaging and Brain-computer Interfaces

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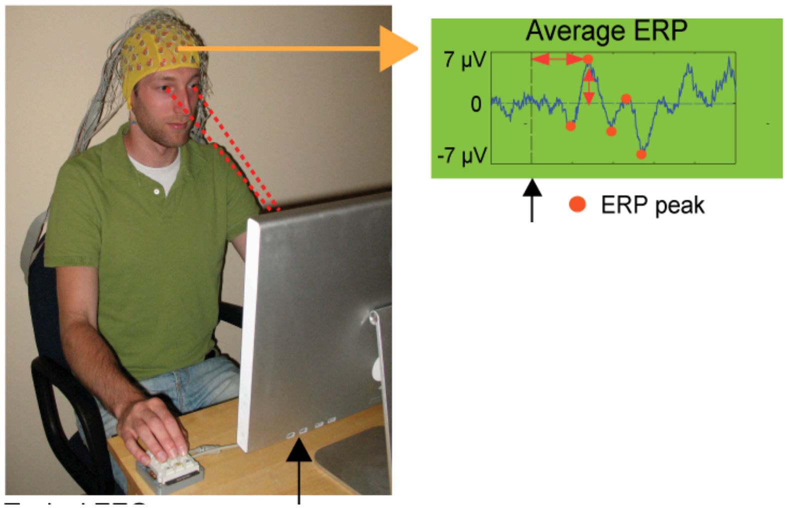
Laboratory EEG -> Real-World MoBI



Constrained Brain/Body Activities in a Well-Controlled Laboratory

From Makeig et al., *Int'l J. of Psychophysiology*, 2009.

Naturalistic Brain Activities in Real-world Environments

What Technologies Do We need for Studying the Brain in the Real World

What technologies do we need to translate laboratory-oriented neuroscience research to study the human brain in real-world environments?

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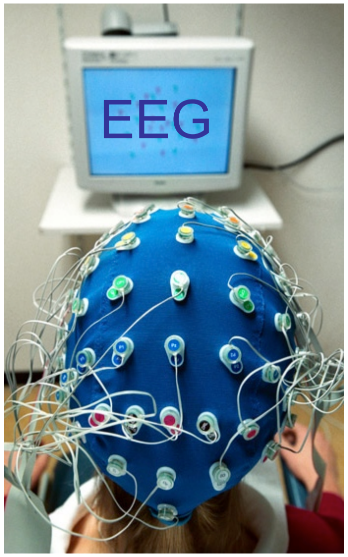
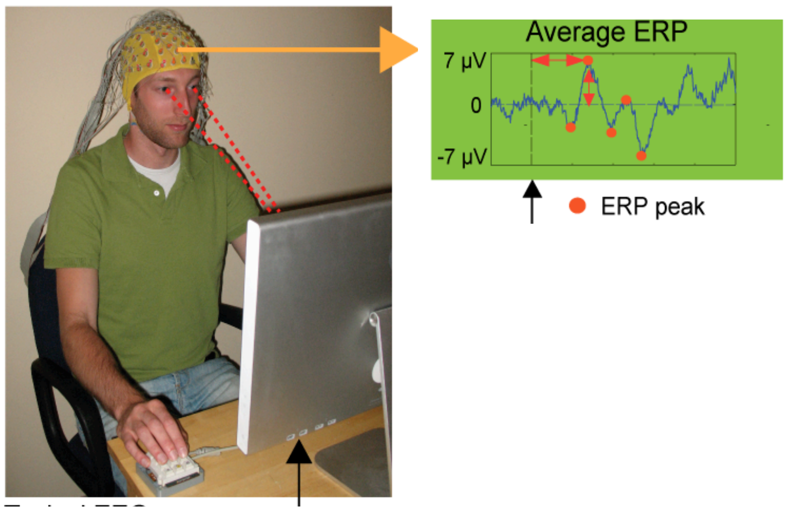
- Signal-processing techniques to find statistical relationships among the variations in environmental, behavioral, and functional brain dynamics.
- An ability to harness continuous and ubiquitous monitoring of the brain and behavior.

Neuroimaging modality for Neuroergonomics



- In all modalities … **heavy**.
- EEG is the only … ire the head/ body to be fixed.
- EEG might enabl… ain functions of unconstrained participants performing normal tasks in the workplace and home. However, …..

Laboratory EEG -> Real-World MoBI



Constrained Brain/Body Activities in a Well-Controlled Laboratory

Naturalistic Brain Activities in Real-world Environments

From Makeig et al., *Int'l J. of Psychophysiology*, 2009.

Requirements in EEG recording in the real world:

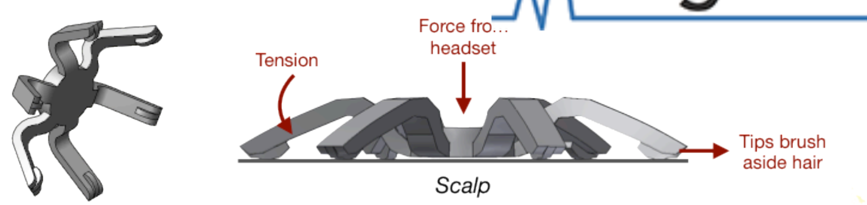
- Non-invasive, non-intrusive
- No skin preparation
- No conductive pastes
- Non-tethered
- No head/body movement constrains

Dry and Wireless EEG Sensors and Systems

Dry and non-prep EEG sensors

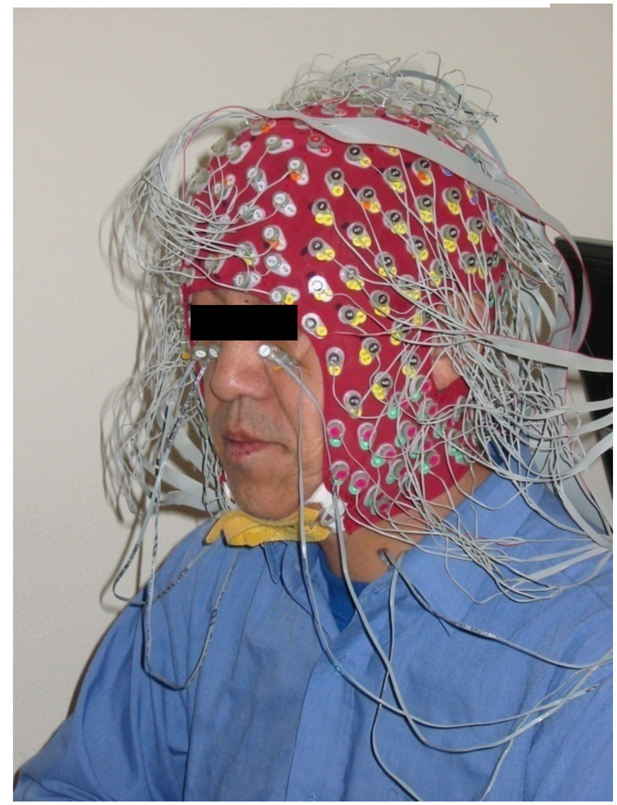
Ultraportable EEG Headgears

Cognionics



High-density (64-chan) EEG Cap

Do We have Sufficient Data to Understand the Brain?



- High-density EEG
- Simultaneous physiological data:
  - ECG
  - Breath
  - Blood Oxygen
  - EMG
- However, the behavioral measurement is usually embarrassingly sparse and low dimensional.

Mobile Brain/Body Imaging (MoBI)

To study the brain and behavior during naturally motivated behavior, we must simultaneously record

- What the brain does (high-density EEG)
- What the brain experiences (sensory scheme recording)
- What the brain organizes (eye & body movements, psychophysiology).

- Makeig et al, 2009

Mobile Brain/Body Imaging (MOBI)

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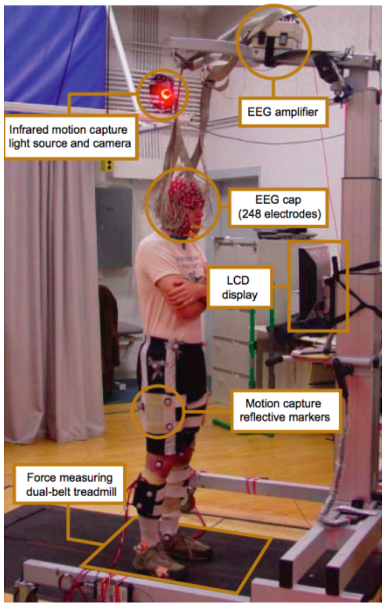
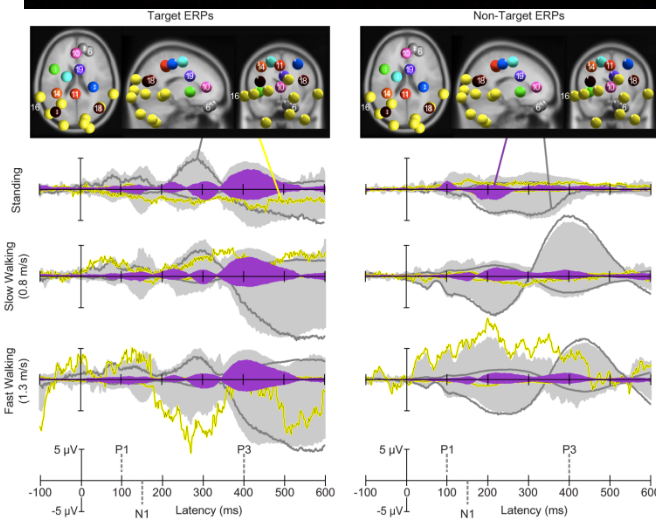
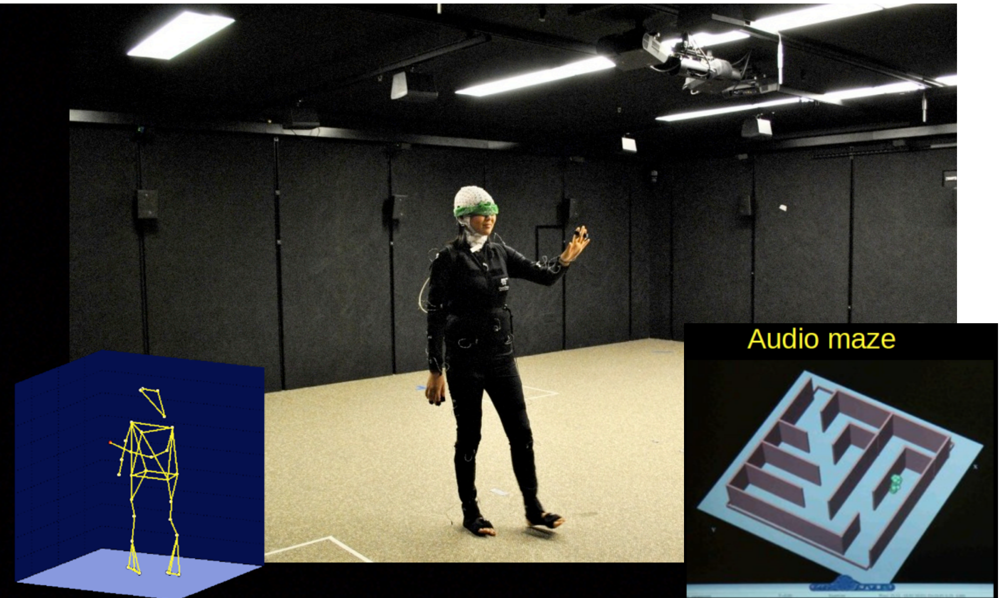
ERP on a Treadmill





Spatial Navigation



The Effect of DBI on EEG and EMG

Development of Shared Attention

Gedeon Deak et al., 2011.

Low-Cost Mobile Brain/Body Imaging (MoBI) Platform

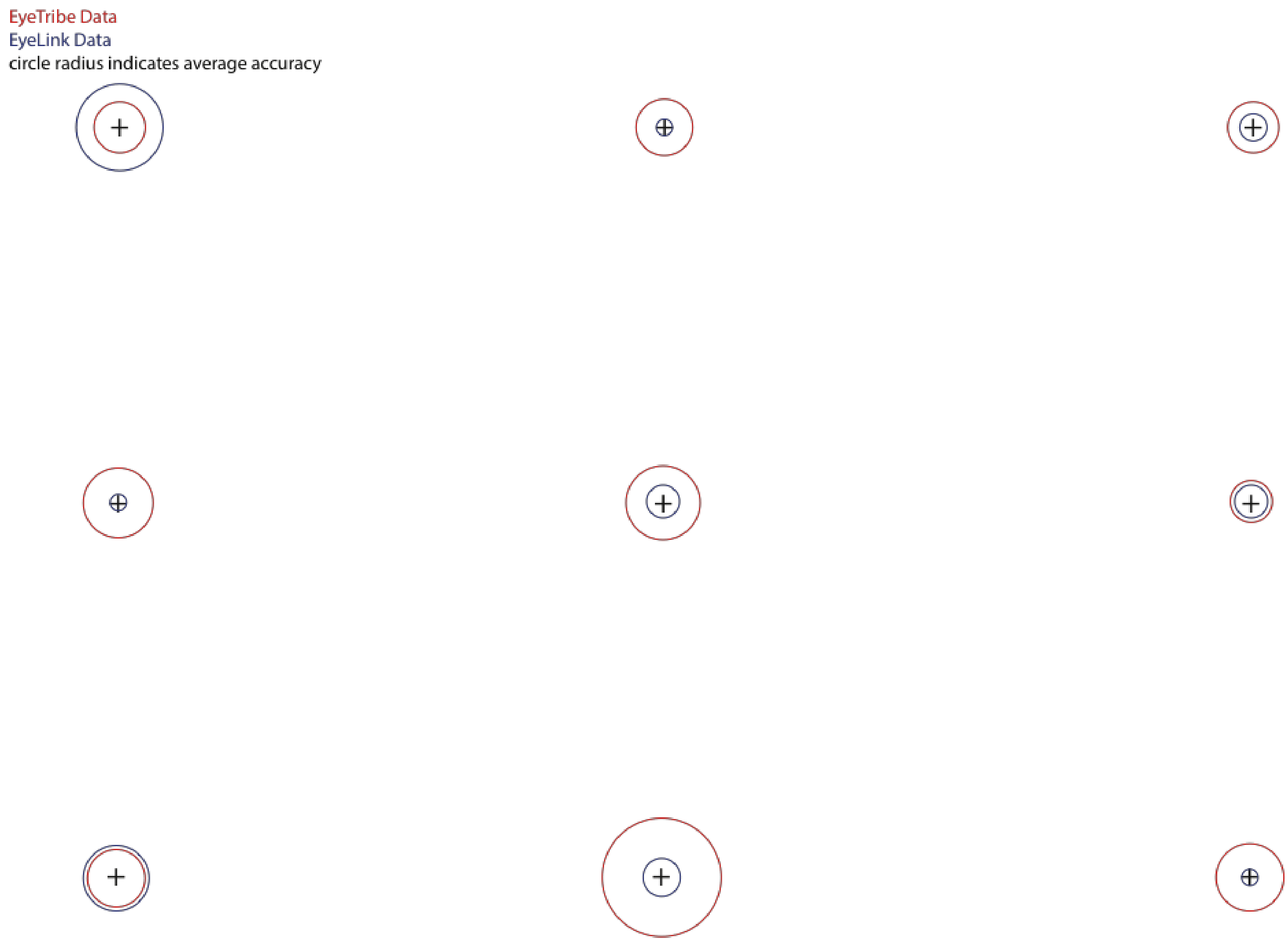


Figure 2: EyeTribe (red) and Eye Link (blue) eye tracker accuracy depicted graphically for nine points representing boundaries of the test monitor. For reference, EyeLink (blue) accuracy (degrees error from fixation cross) for the central point is 0.41 and the EyeTribe (red) accuracy is 0.89. The average accuracy of the EyeTribe tracker is 0.79 (shown in red) and the EyeLink is 0.46 (shown in blue) in our tests.

From Chukoskie *et al.*, in preparation.

The Low-cost MoBI Platform in Research Studies

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e-Learning at home

Learning in a MoBI Classroom

A photo from National Geography. A 30-student MoBI-powered classroom is under development.

An AR/VR-based EEG Goggle – a truly mobile EEG laboratory

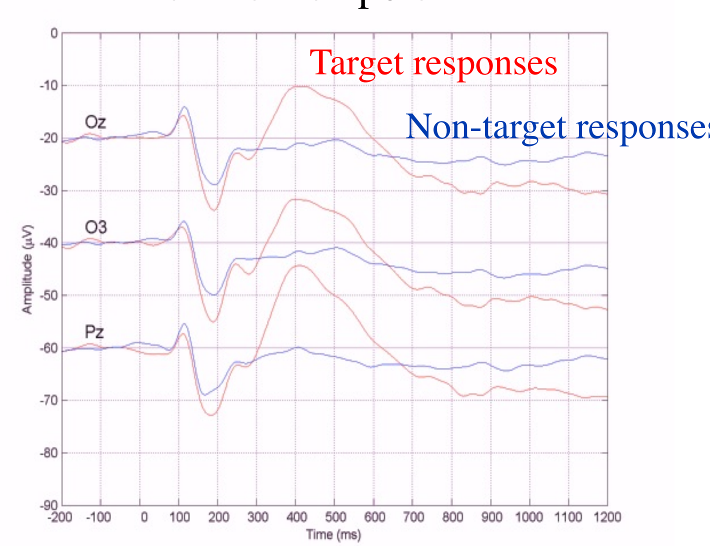
Wireless EEG/EOG Add-on

- Dry & wireless EEG
- EOG-based eye tracking
- Motion capture
- Smartphone-based interactive VR

Zao *et al*., *LNAI*, 2016.

Courtesy of nGoggle, Inc

Event-related potentials



A Truly Wearable Multi-modal Biosensing Platform for Cognitive Experiments

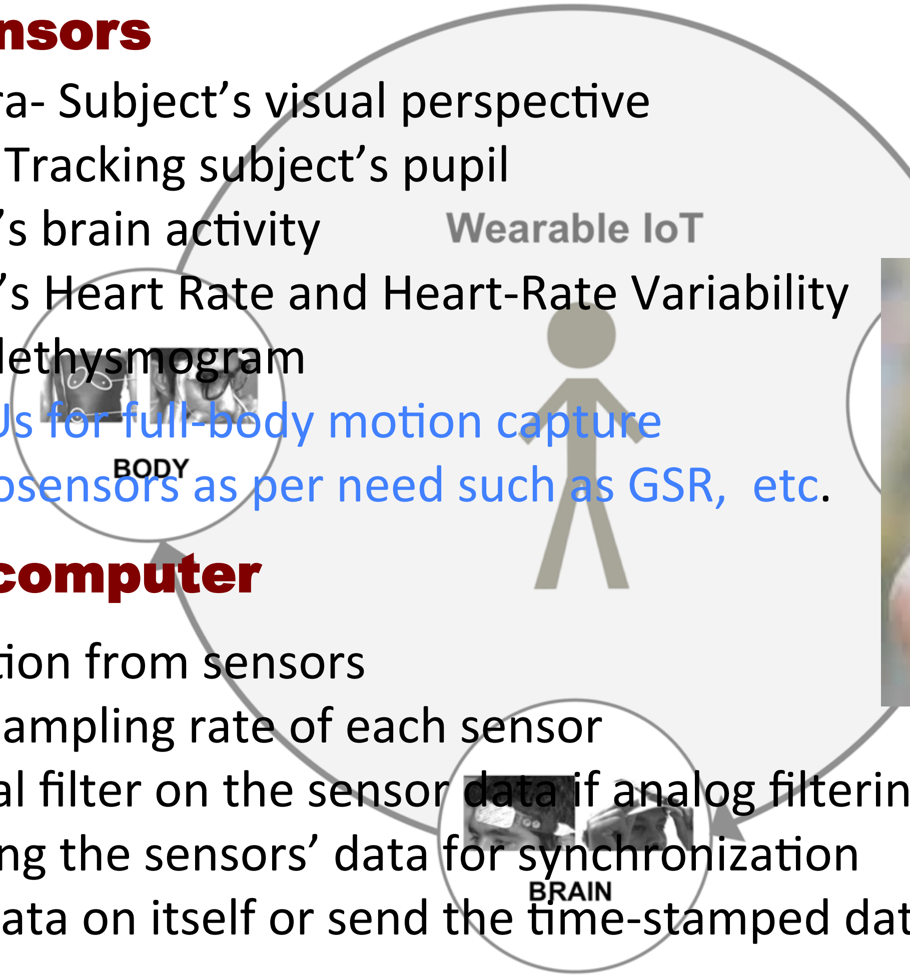
We have developed a low-cost wearable multi-modal bio-sensing system capable of recording (neuro)physiological signals, eye-gaze overlaid on world view, and motion capture in real-world settings.

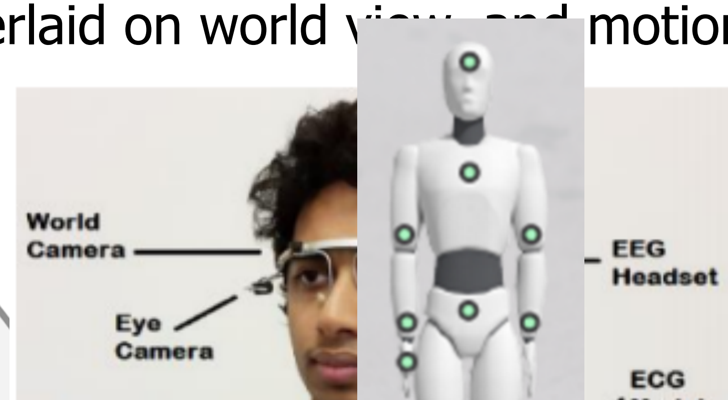
Wearable sensors

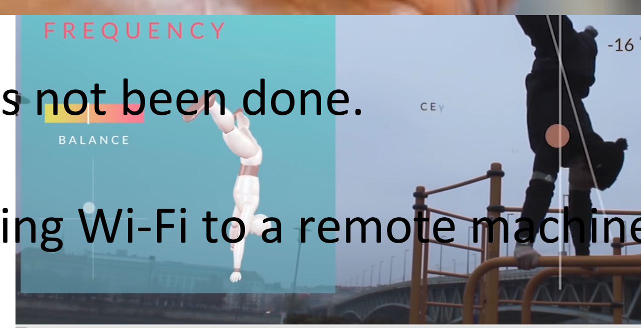
- World camera- Subject's visual perspective
- Eye Camera: Tracking subject's pupil
- EEG: Subject's brain activity
- ECG: Subject's Heart Rate and Heart-Rate Variability
- PPG: Photoplethysmogram
- Up to 18 IMUs for full-body motion capture
- Any other biosensors as per need such as GSR, etc.

A wearable computer

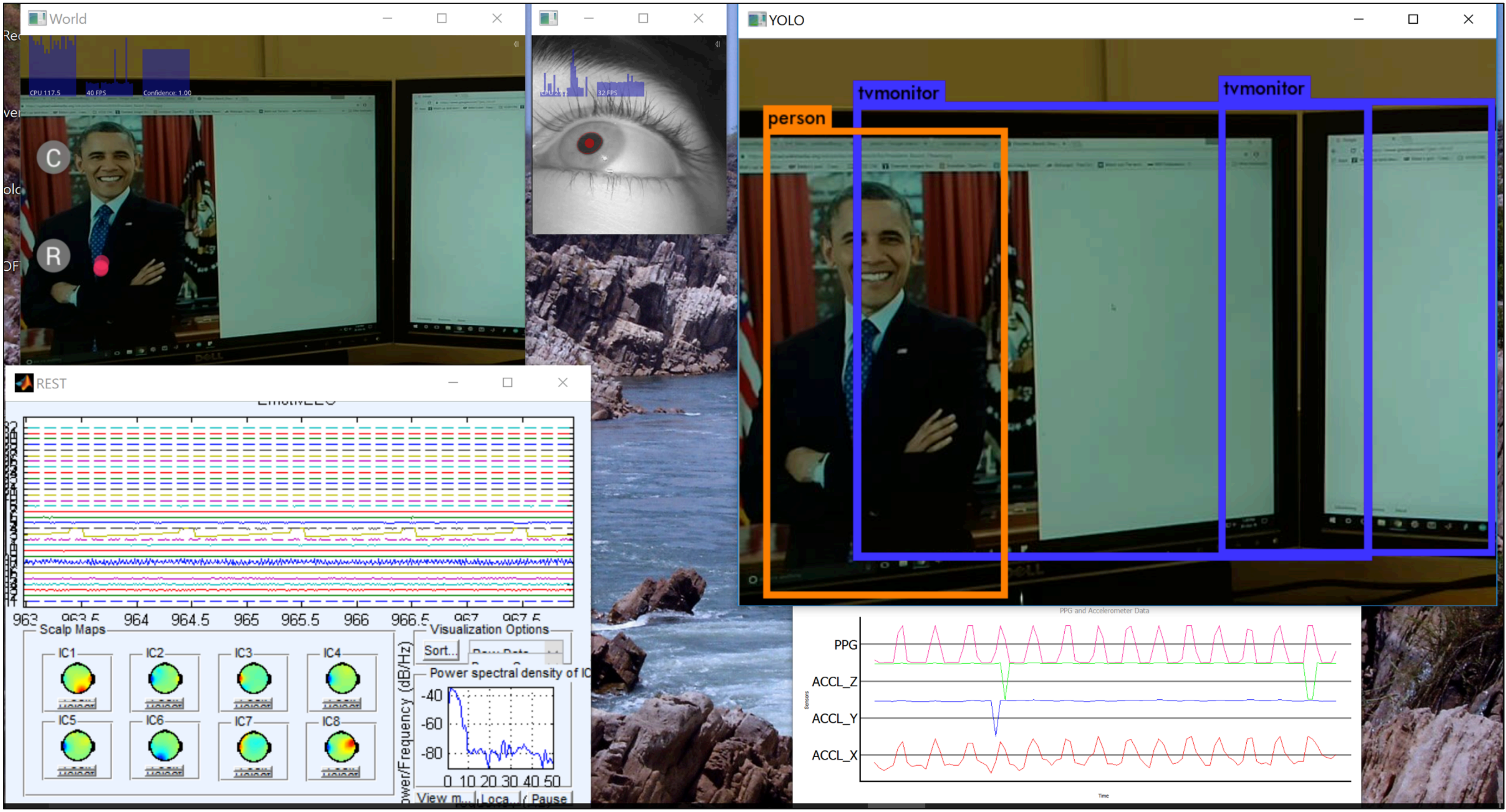
- Data acquisition from sensors
- Control the sampling rate of each sensor
- Using a digital filter on the sensor data if analog filtering has not been done.
- Time-stamping the sensors' data for synchronization
- Record the data on itself or send the time-stamped data using Wi-Fi to a remote machine.







Software on a Host Computer



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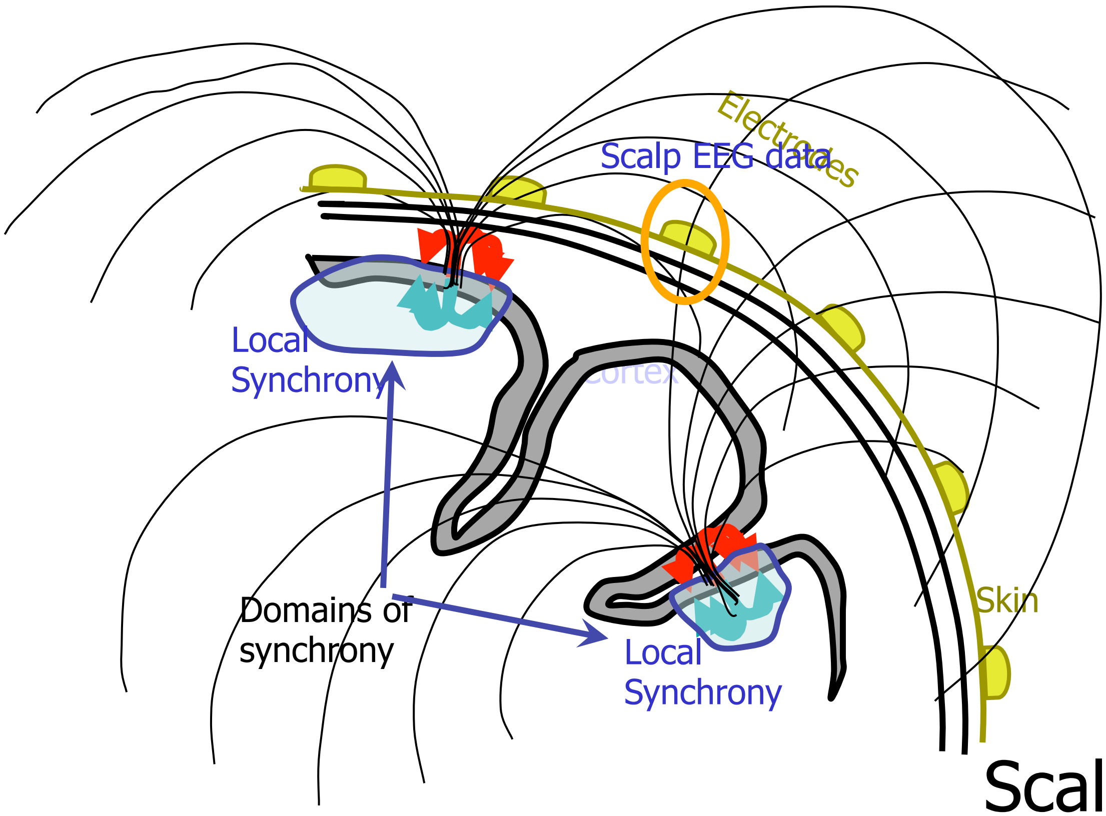
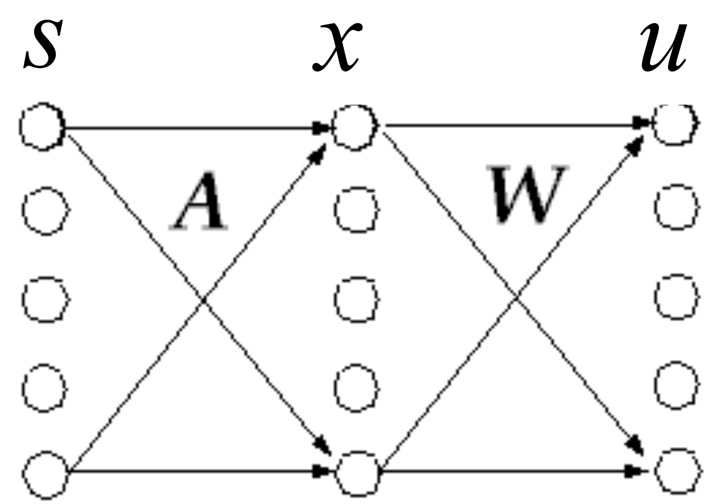
- An ability to harness continuous and ubiquitous monitoring of the brain.

Difficulties in Observing Distributed EEG dynamics



Scalp EEG signals appear to be noisy because they each sum a mixture of signals generated in many brain areas.

Independent Component Analysis



ICA is a method to recover a version, of th original sources by multiplying the data by a unmixing matrix,

$$\mathbf{u} = \mathbf{W}\mathbf{x},$$

where x is our observed signals, a linear mixtures of sources,

$$\mathbf{x} = \mathbf{A}\mathbf{s}.$$

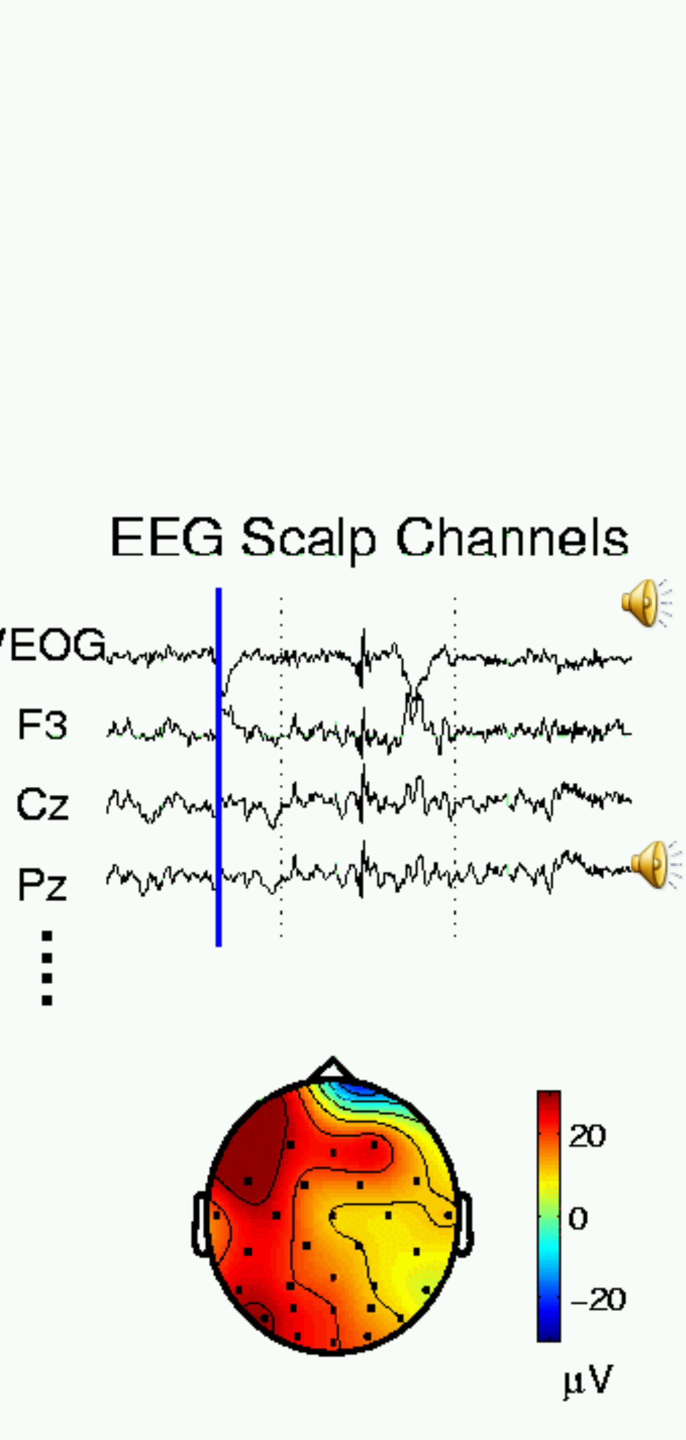
While PCA simply decorrelates the outputs (using an orthogonal matrix **W**), ICA attempts to make the outputs **statistically independent**, while placing no constraints on the matrix **W**.

WA after learning:

$$\begin{bmatrix} \boxed{-4.09} & 0.13 & 0.09 & -0.07 & -0.01 \\ 0.07 & \boxed{-2.92} & 0.00 & 0.02 & -0.06 \\ 0.02 & -0.02 & -0.06 & -0.08 & \boxed{-2.20} \\ 0.02 & 0.03 & 0.00 & \boxed{1.97} & 0.02 \\ -0.07 & 0.14 & \boxed{-3.50} & -0.01 & 0.04 \end{bmatrix}$$

Independent Component Analysis

Courtesy of SoftMax, Inc



EEG Scalp Channels
VEOG
F3
Cz
Pz
20
0
−20
µV

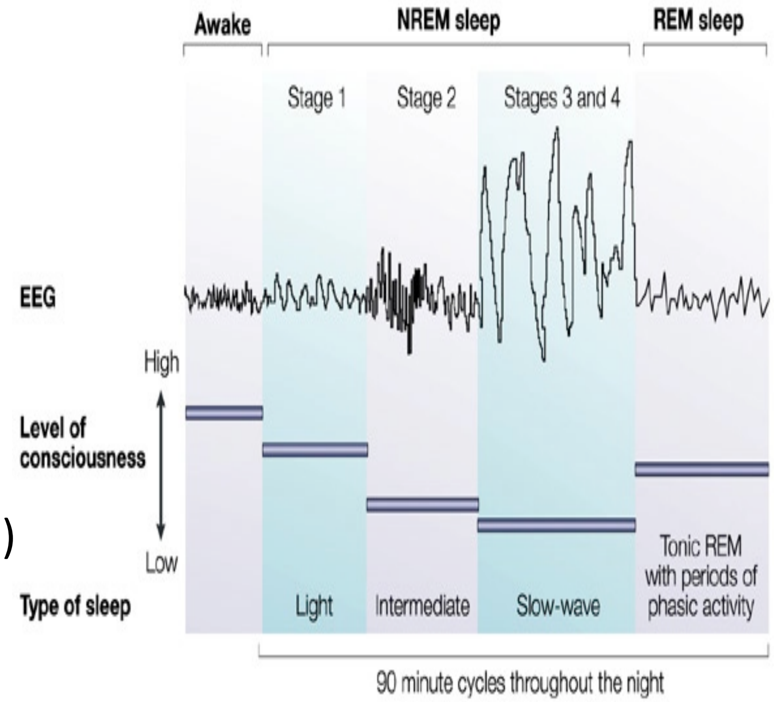
Assumptions of ICA for EEG Analysis

- Mixing is linear at electrodes
- Propagation delays are negligible
- Number of components $\leq$ number of channels.
- Component activations are temporally independent
- Independent components (sources) are spatially fixed over the training data.

Nonstationarity in EEG occurs at multiple time scales

	1 ~ 10 msec	Temporal resolution limit
1 sec	< 1 sec	**Muscle activities**
	3 ~ 14 sec	**Microsleep episodes** (Harison & Horne, 1996)
1 min	secs ~ 5 min	**Seizure episodes** (Trinka et al., 2012)
	> 4 min	**Alertness fluctuation** (Makeig & Inlow, 1993)
1 hour	mins / 90 min	**Sleep stages / cycles** (Carskadon et al., 2000)
	hours / days	**Intra-session / inter-session nonstationarity in BCI** (Arvaneh et al., 2013)

Time



Bryant, *Nat. Rev. Immunology, 2004*

Online Recursive ICA (ORICA) Pipeline

Two-step unmixing process: $y = Wv = WMx$

1. Online recursive least squares whitening

$$M_{n+1} = M_n + \frac{\lambda_n}{1-\lambda_n}\left[I - \frac{v_n v_n^T}{1+\lambda_n(v_n v_n^T - 1)}\right] M_n$$

Zhu et al., *Sci. in China Series F: Info. Sci.*, 2004

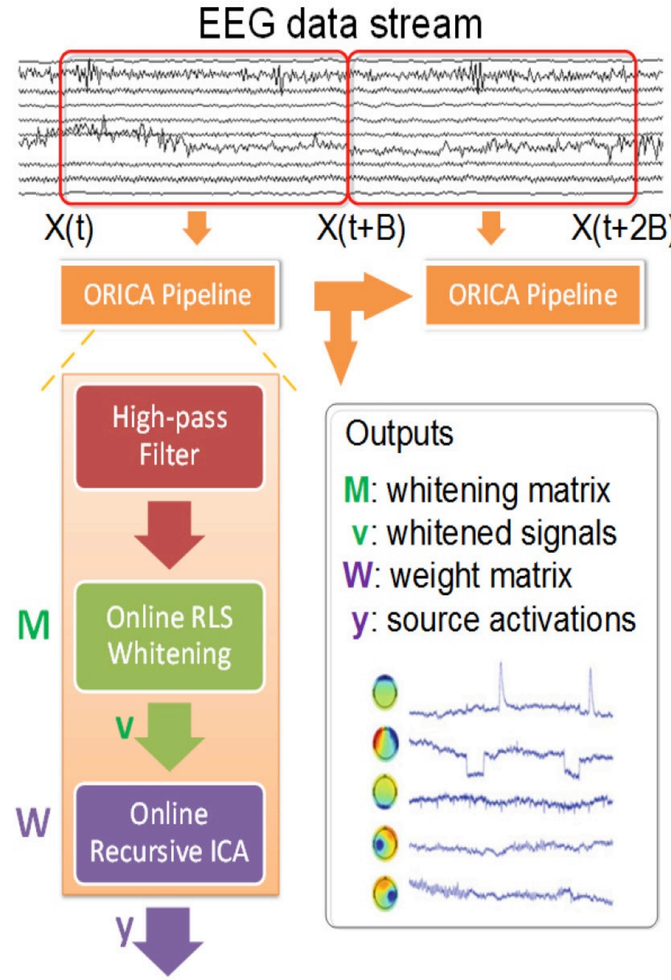
2. Online recursive ICA (ORICA)

$$W_{n+1} = W_n + \frac{\lambda_n}{1-\lambda_n}\left[I - \frac{y_n \cdot f^T(y_n)}{1+\lambda_n(f^T(y_n)\cdot y_n - 1)}\right] W_n$$

$$W \leftarrow (WW^T)^{-1/2} W$$

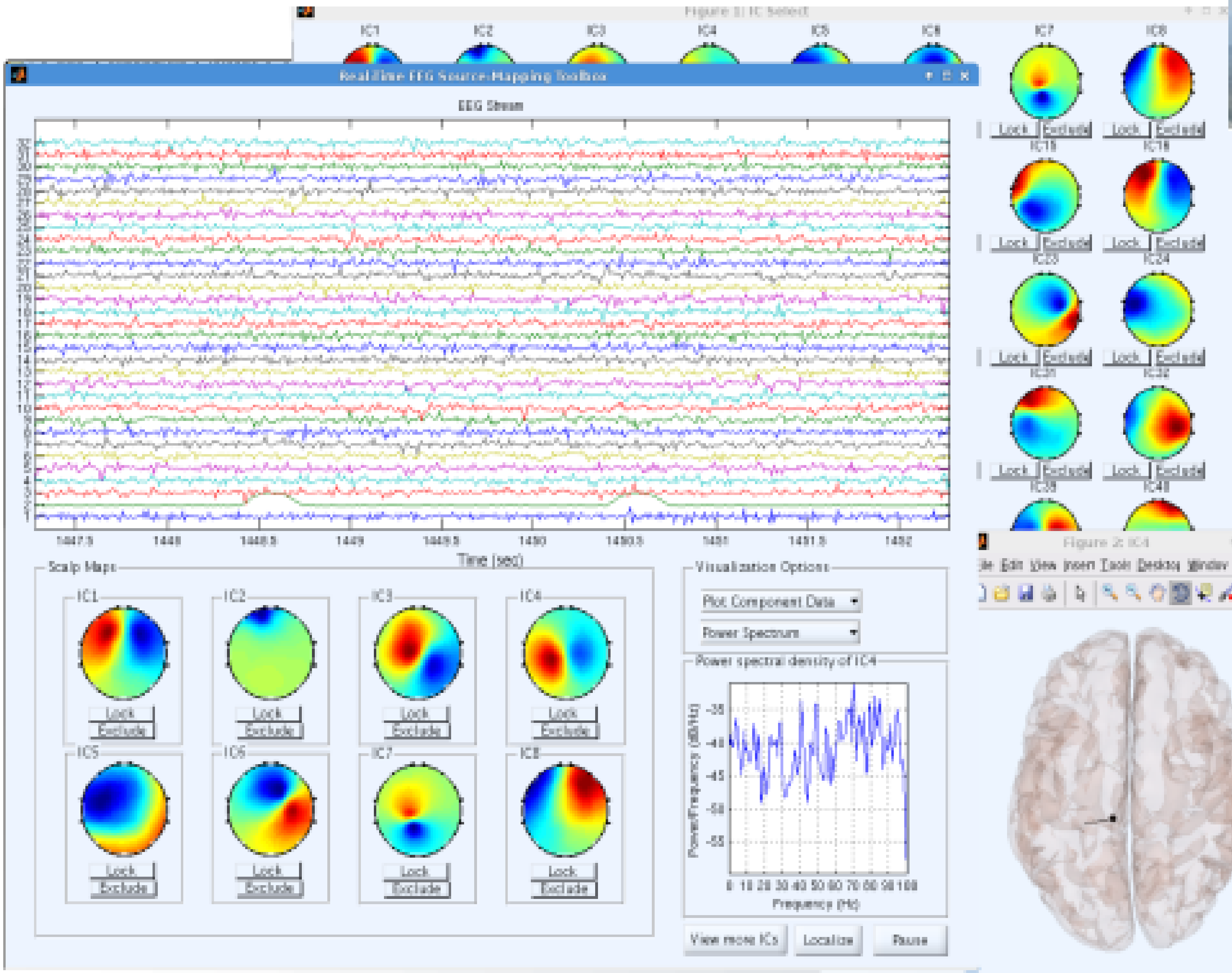
Akhtar et al. *ISCAS*, 2012

$$\lambda_n = \frac{\lambda_0}{n^\gamma} \qquad f = \begin{cases} -2\tanh(y), supergaussian \\ \tanh(y) - y, subgaussian \end{cases}$$

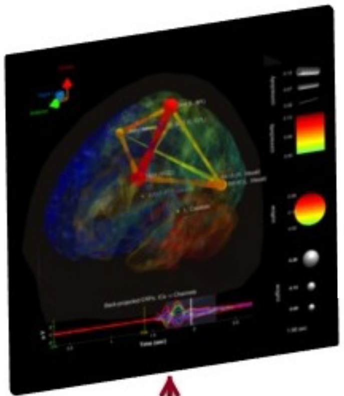


Hsu et al., *IEEE EMBC*, 2014.
Hsu et al., *IEEE EMBC*, 2015.
Hsu et al., *IEEE TBME*, 2016.

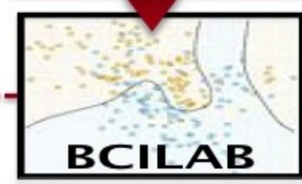
Real-Time EEG Source-Mapping Toolbox (REST)



Real-time Data Processing Pipeline

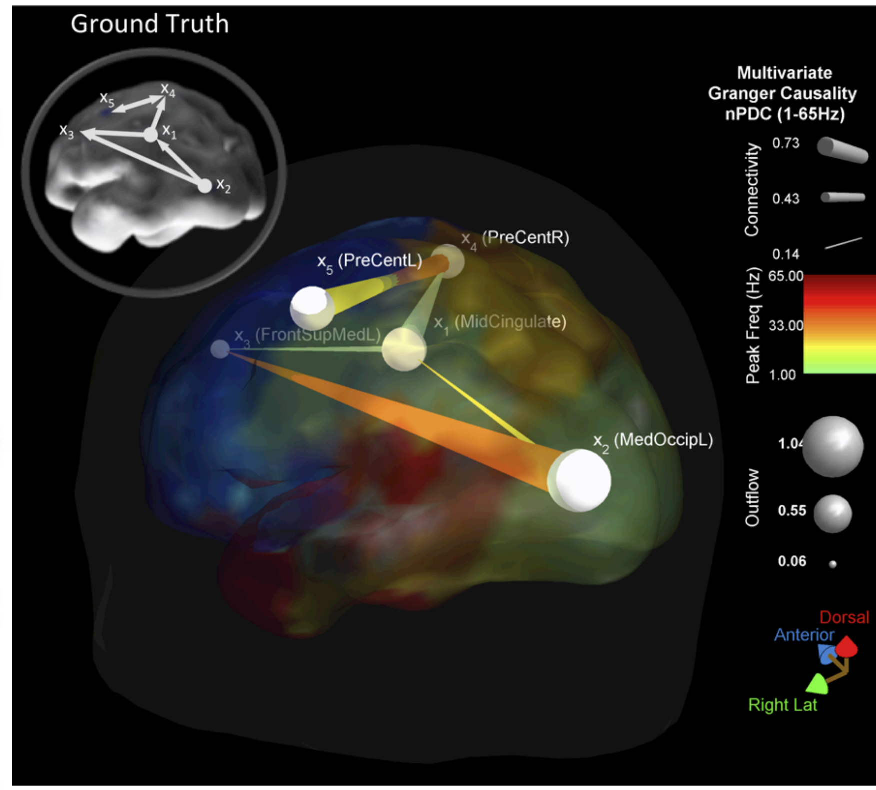


3D Visualization and Feedback

Pre-processing	• Re-referencing, Filtering, Resampling, Artifact rejection and imputation (BCILAB)
Source Identification	• cLORETA (cortically constrained; adaptive Bayesian updates) • CSD integration over ROIs
Model Fitting	• Sparse Adaptive Vector Autoregressive Modeling • Stability and Whiteness tests
Time-Frequency Dynamics	• Spectral and Coherence Estim. • Multivariate Granger Causality • Graph metrics computation
 BCILAB	• Dimensionality Reduction • Classification • Cognitive State Identification

Christian Kothe

Tim Mullen



Mullen et al., Best Technical Poster of *International BCI Meeting*, Asilomar, CA, 2013.

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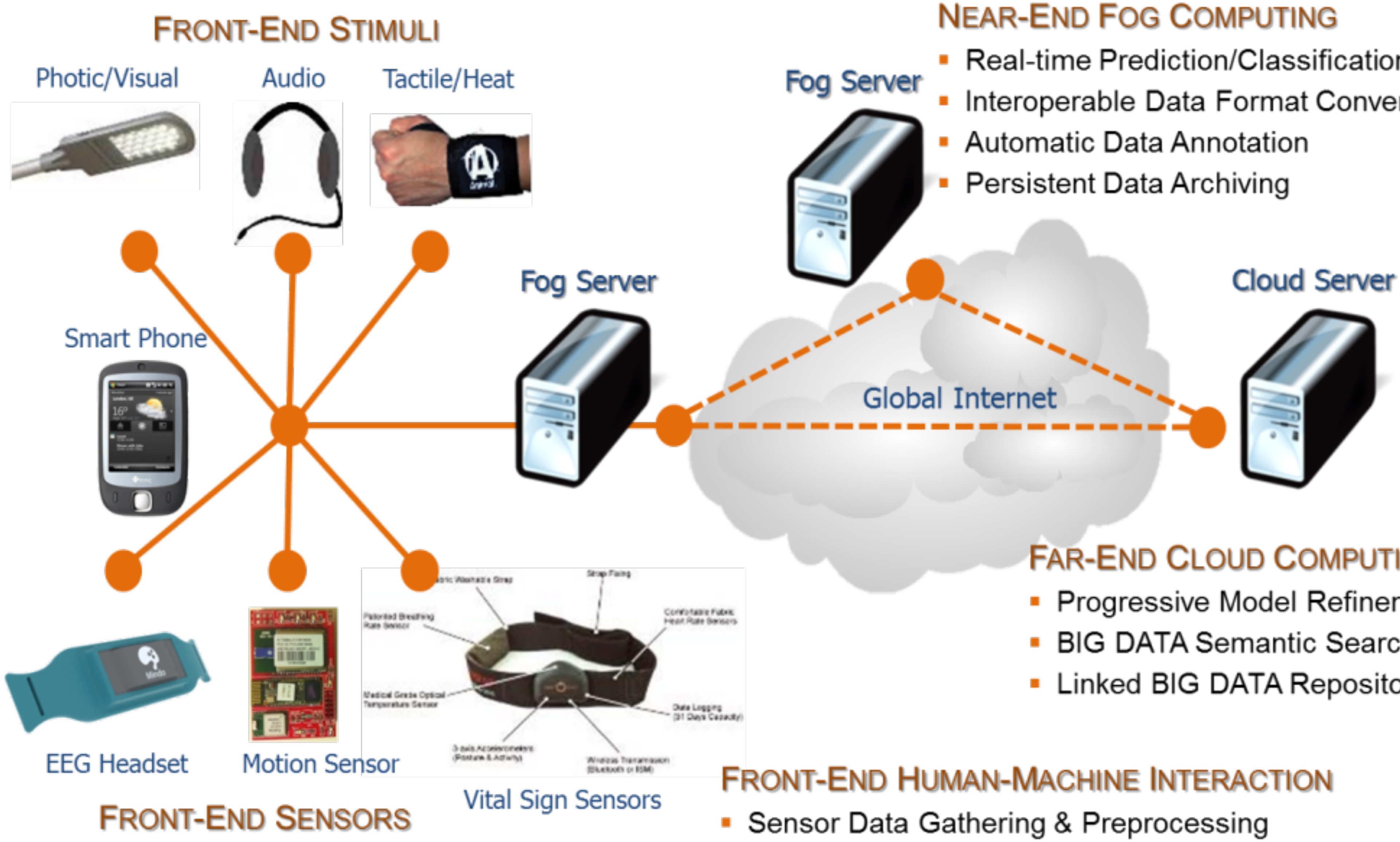
Pervasive MoBI via Cloud Computing



NEAR-END FOG COMPUTING

- Real-time Prediction/Classification
- Interoperable Data Format Conversion
- Automatic Data Annotation
- Persistent Data Archiving

FAR-END CLOUD COMPUTING

- Progressive Model Refinement
- BIG DATA Semantic Search
- Linked BIG DATA Repository

FRONT-END HUMAN-MACHINE INTERACTION

- Sensor Data Gathering & Preprocessing
- Real-time Sensor-Actuator Feedback
- Mobile Human-Machine Interaction

Zao et al., *Frontiers in Human Neuroscience*, 2014.

A sample study conducted in a nearly naturalistic environment

EEG Correlates of Drowsiness

- Lapses of attention or drowsiness can lead to catastrophic incidents for workers in many occupations.
- The US National Highway Traffic Safety Administration (NHTSA) reported that ~25% of police-reported accidents were related to driver inattention.
- National Sleep Foundation (NSF) reported that 60% of adult drivers have driven a vehicle while feeling drowsy and 37% of them have actually fallen asleep.

Objectives of this Study

- To investigate tonic and phasic spectral changes during continuous sustained-attention tasks in a realistic environment.
- To explore effective connectivity among different brain sources.

Brain Dynamics

- To build a brain-machine interface that can continuously monitor brain dynamics and cognitive states of participants actively performing ordinary tasks in natural body positions and situations within real operational environments.

BCI Application

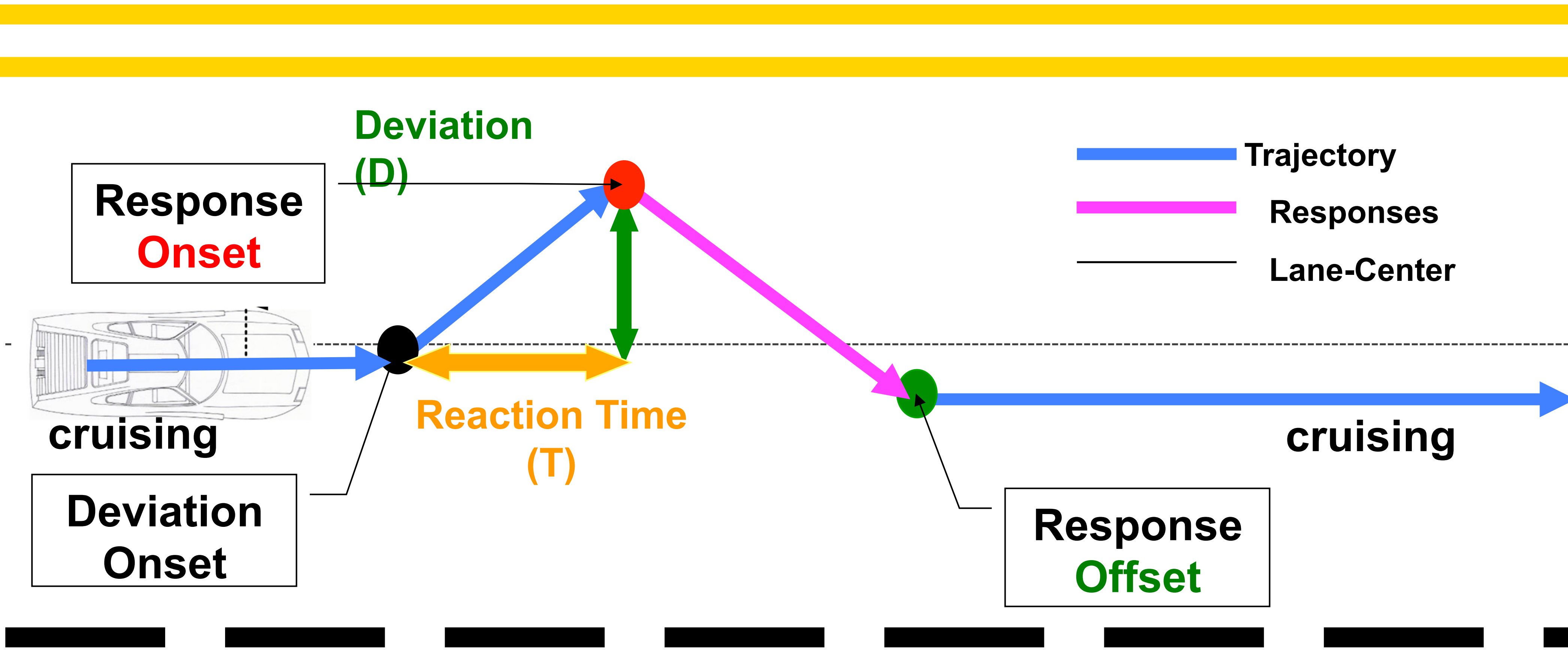
EEG Correlates of Human Performance during Sustained Attention Tasks

Many studies have demonstrated EEG correlates of fluctuations in performance during sustained attention task on the order of one second to several minutes.

Study	Task(s); Measure(s)	Electrode Sites or Brain Regions	δ	θ	α	β
Badia et al. (1994)	Sleep onset	F3, C3, O1		+	+/-	
Baulk et al. (2001)	Simulated driving task in an immobile car, secondary auditory detection task; lane crossing incidents, RT, Karolinska Sleepiness Scale (KSS)	C3-A1		+	+	
Beatty et al. (1974)	Radar monitoring task; target detection time	O1-P3		+		
Belyavin and Wright (1987)	Visual vigilance and letter discrimination tasks; RT, error/missing rate	P3-O1, P4-Oz	+	+	+	-
Campagne et al. (2004)	Simulated driving on mobile platforms; running-off-road incidents, speed variations	F3, C3, P3, O1 (C3, P3 shown)		+	+	
Cantero (1999)	Sleep onset	19 EEG channels		*		
Eoh et al. (2005)	Simulated driving task (static); number of accidents and lap-time per cycle	Fp1, Fp2, T3, T4, P3, P4, O1, O2		+	+	-
Gillberg et al. (1996)	Simulated truck driving; mean speed, S.D. of speed, S.D. of lane position, KSS, RT	C3-A2, O2-P4		*	*	
Harrison and Horne (1996)	Multiple sleep latency test (MSLT)	(C3-A2)		+	*	
Hasan and Broughton (1994)	Sleep onset; MSLT	19 EEG channels		*	*	
Horne and Baulk (2004)	Simulated driving task in an immobile car; KSS, lane drifting	(C3-A1)		+	+	
Huang et al. (2001)	Auditory and visual vigilance tasks; correct rate	C3, C4		+	+	
Huang et al. (2008)	Compensatory tracking task; tracking error, reaction time	70 EEG channels; occipital independent components	+	+	+	
Huang et al. (2009)	Event-related lane departure during simulated driving (static); reaction time	256 EEG channels; occipital and parietal independent components	+	+	+	
Jung et al. (1997)	Auditory oddball task; error rate	Cz, Pz/Oz		+	-	*
Kecklund and Åkerstedt (1993)	Real truck driving; KSS, self-rated performance capacity	Cz-Oz		+	+	
Lal and Craig (2002, 2005)	Simulated driving in a static car frame; facial features (from video) of the driver	19 EEG channels	+	+		
Lowden et al. (2009)	Simulated driving on a moving base; speed, lateral position, steering wheel angle, KSS	Fz-A1, Cz-A2, Oz-Pz			+	+
Makeig and Inlow (1993)	Auditory oddball task; local error rate	13 EEG channels	+	+	-	
Makeig and Jung (1995, 1996)	Auditory oddball task, visual target detection; local error rate	Cz, Pz/Oz	+	+	-	*
Makeig et al. (2000)	Compensatory tracking task; tracking error	F3, C4, P4, O1 (C4 shown)	+	+		
Ogilvie and Wilkinson (1984)	Auditory response task; reaction time	Cz, Pz				
Ogilvie et al. (1991)	Auditory response task; reaction time	14 EEG channels (C3, C4 shown)	+	+	-	-
Ota et al. (1996)	Auditory response task; reaction time	18 EEG channels (F1, F2, O1, O2 shown)		+	+/-	
Otmani et al. (2005)	Simulated driving on a mobile base; S.D. of lateral position, steering wheel angle, KSS	F3, C3, P3, O1		+	+	

A Near-Naturalistic Driving Simulator at BRC of NCTU

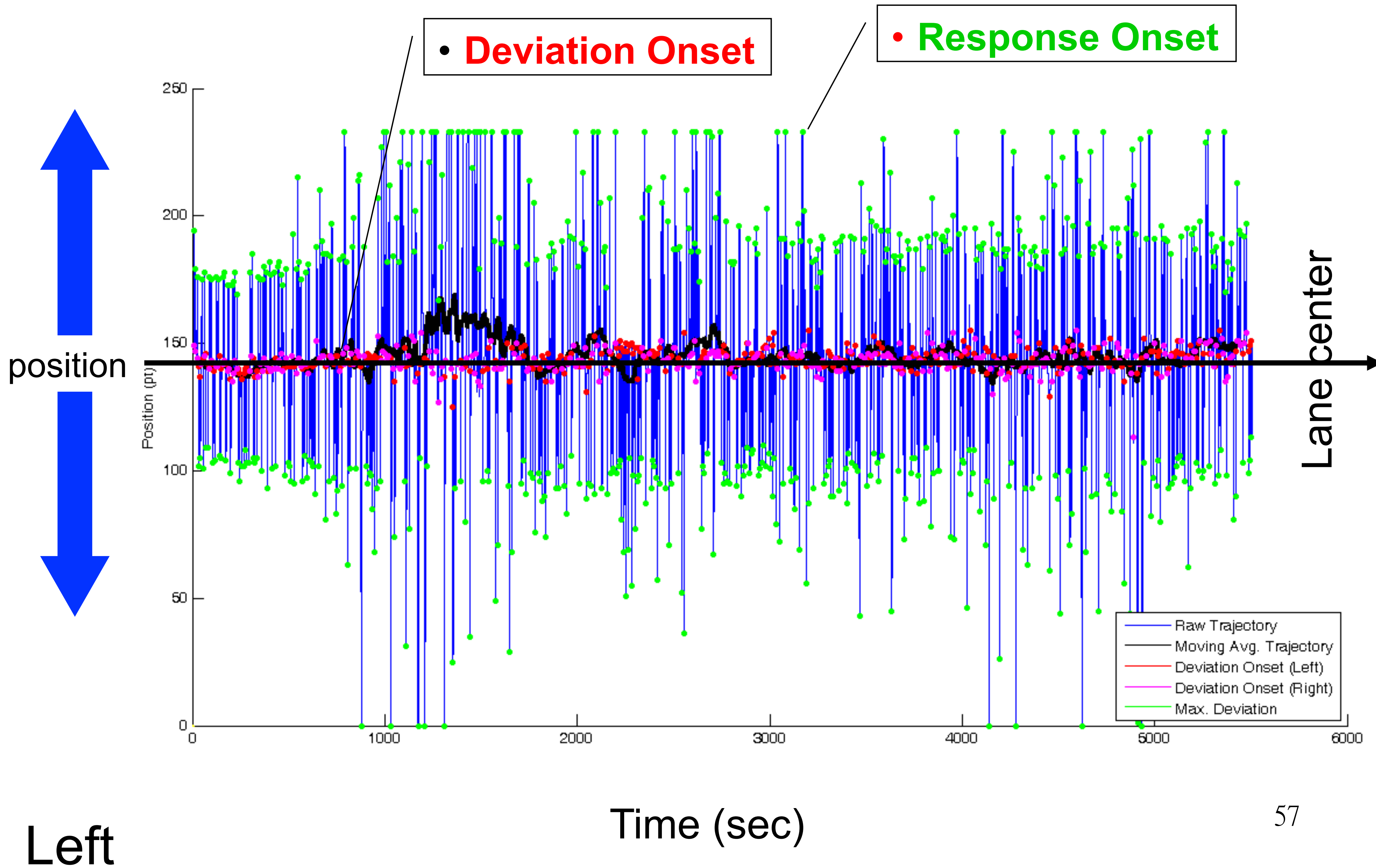
Paradigm: Single Trials Embedded in Continuous Driving

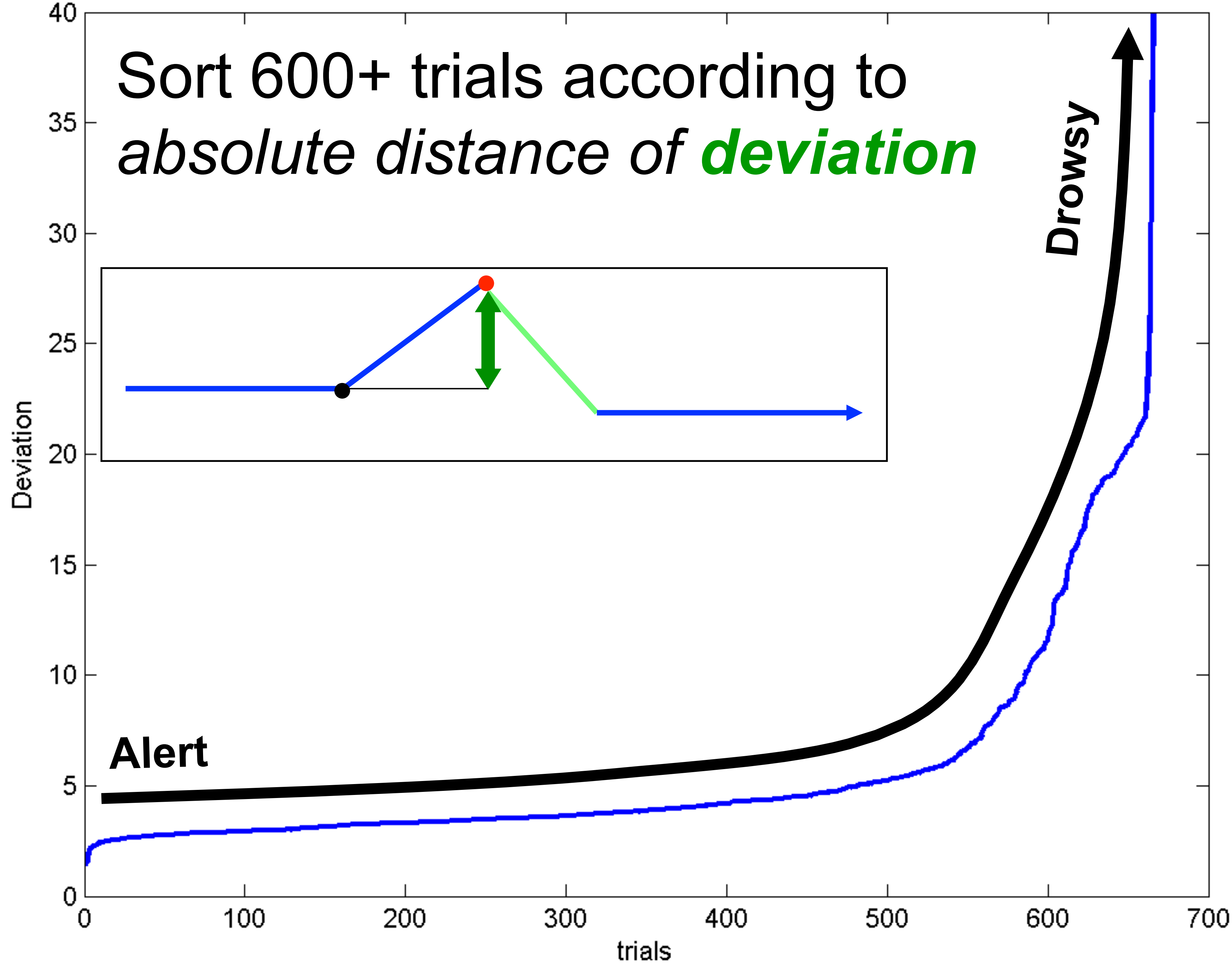


Cruising Speed: 100 km/hr
Linear deviation (D=c T)
Inter-Deviation-Interval: 5 ~ 10 sec
Deviation: 50% leftward, 50% rightward deviation

From Huang et al., 2005, 2007.

Variability in Task Performance



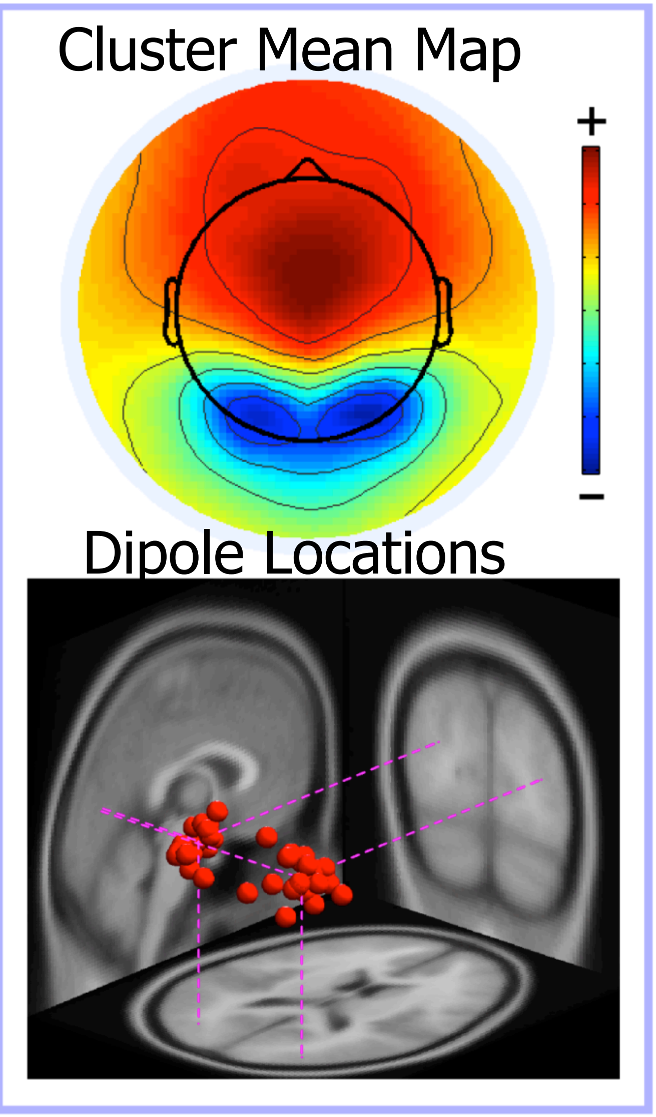


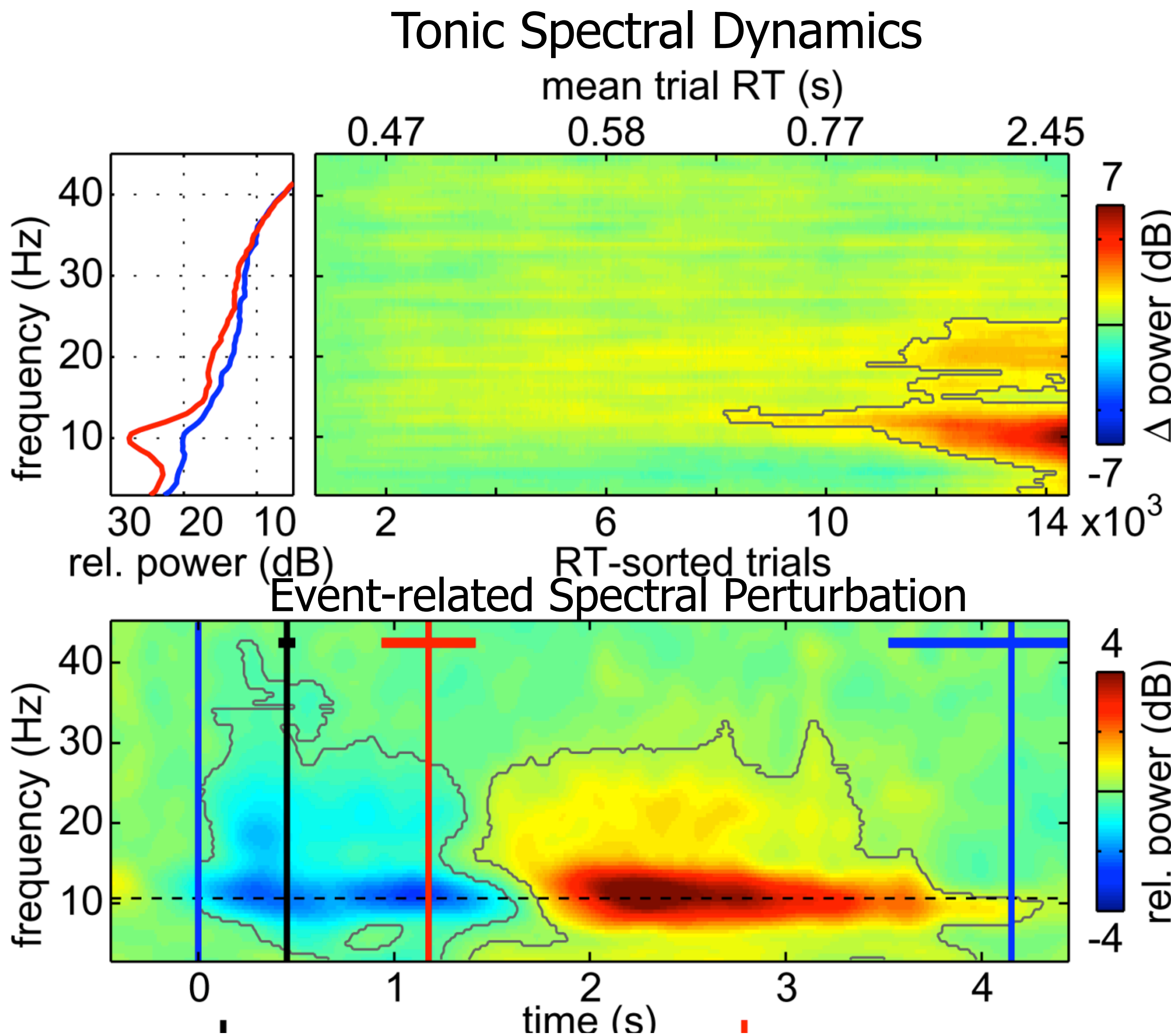
Sort 600+ trials according to
absolute distance of ***deviation***
Drowsy
Alert
Deviation
trials
0
5
10
15
20
25
30
35
40
0
100
200
300
400
500
600
700

Modeling Event-Related Brain Dynamics

1. Remove high-amplitude artifacts using Artifact Subspace Reconstruction
2. Separate cortical and artifact source contributions to the scalp electrodes using ICA or ORICA.
3. Model the event-related dynamics of the IC sources using time/ frequency analysis.
4. Localize the separated IC sources using inverse source mapping methods.
5. Compare similarities in IC dynamics and locations across subjects using IC cluster analysis.]
6. Examine the interactions between brain areas using component effective connectivity.

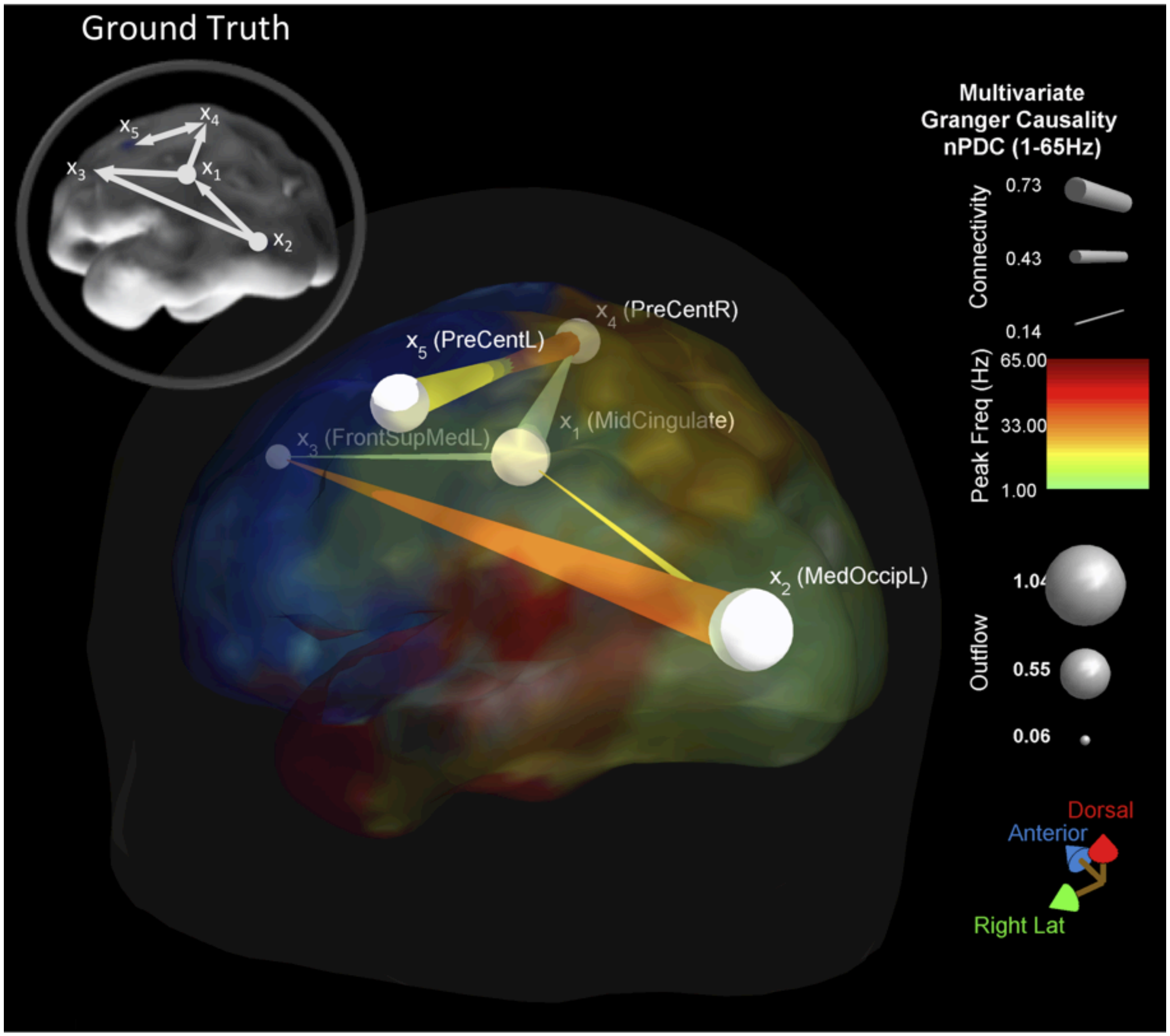
Deviation-induced Brain Dynamics



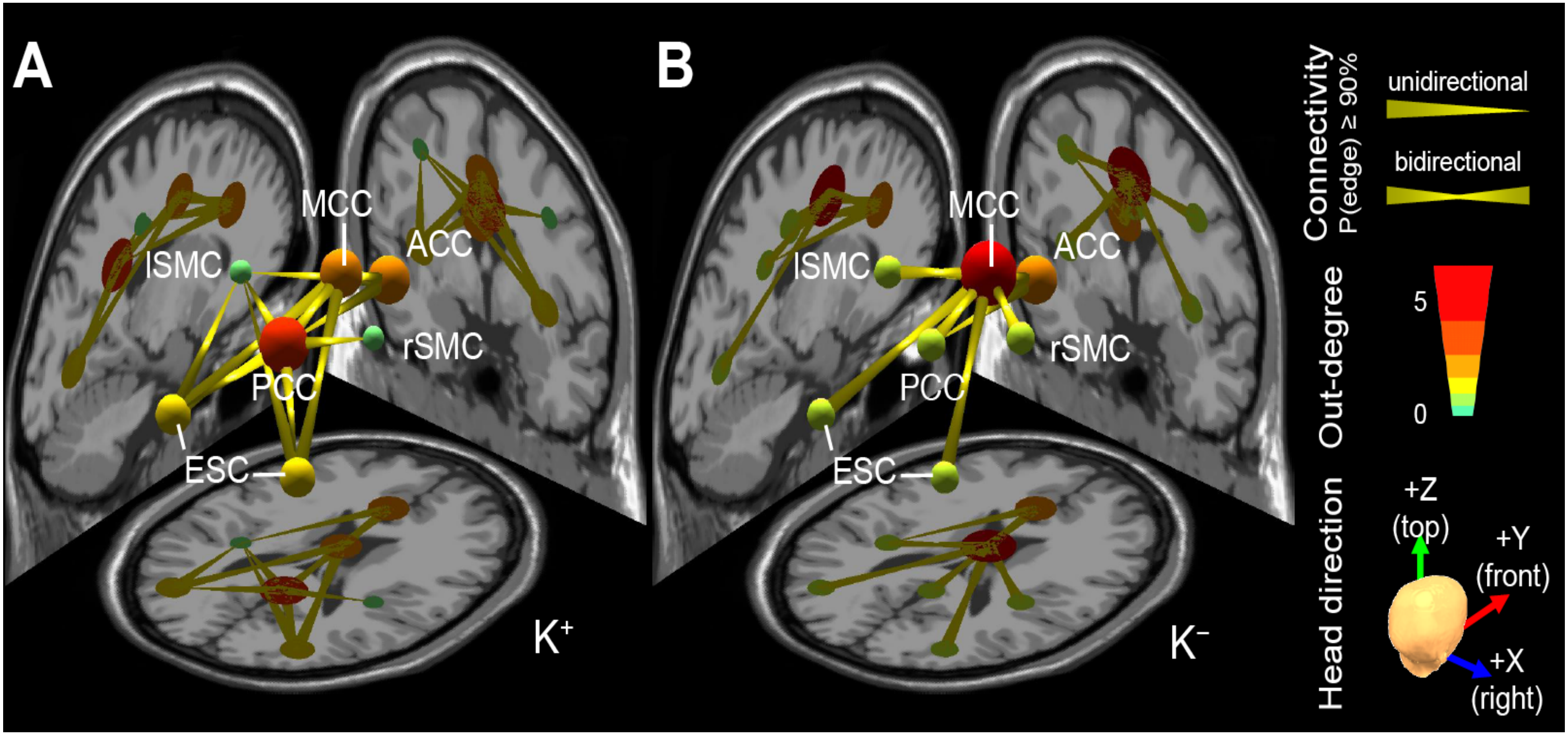


From Chen et al., in preparation.

Interactions among Distinct EEG Sources



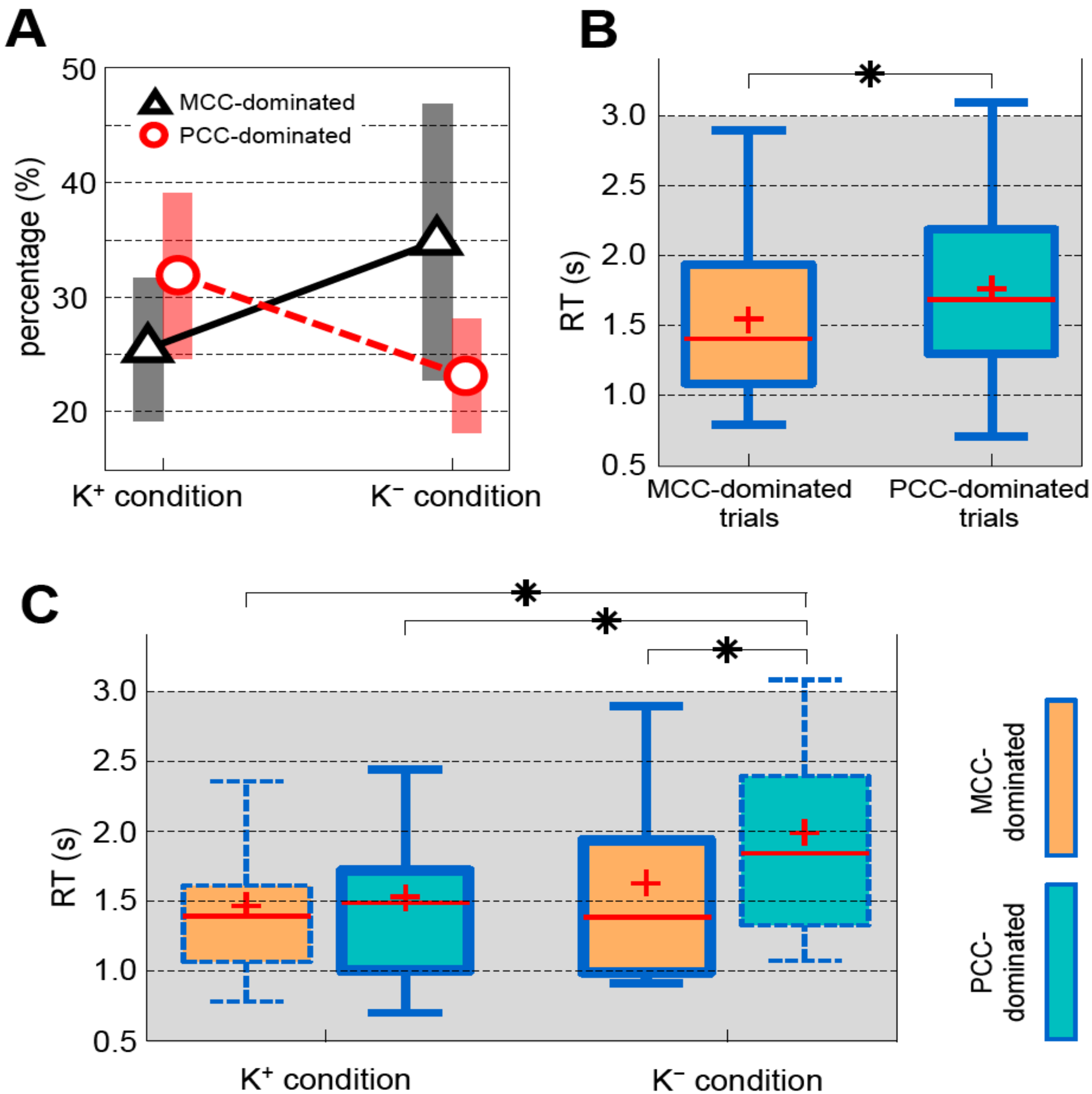
Network Dynamics with and without Motion Cues



Effective connectivity between EEG independent processes estimated under **(A)** K^+ and **(B)** K^- conditions.

From Lin et al., *Scientific Report*, 2016.

Network Dynamics w/ and w/o Motion Cues



From Lin et al., *Scientific Report*, 2016.

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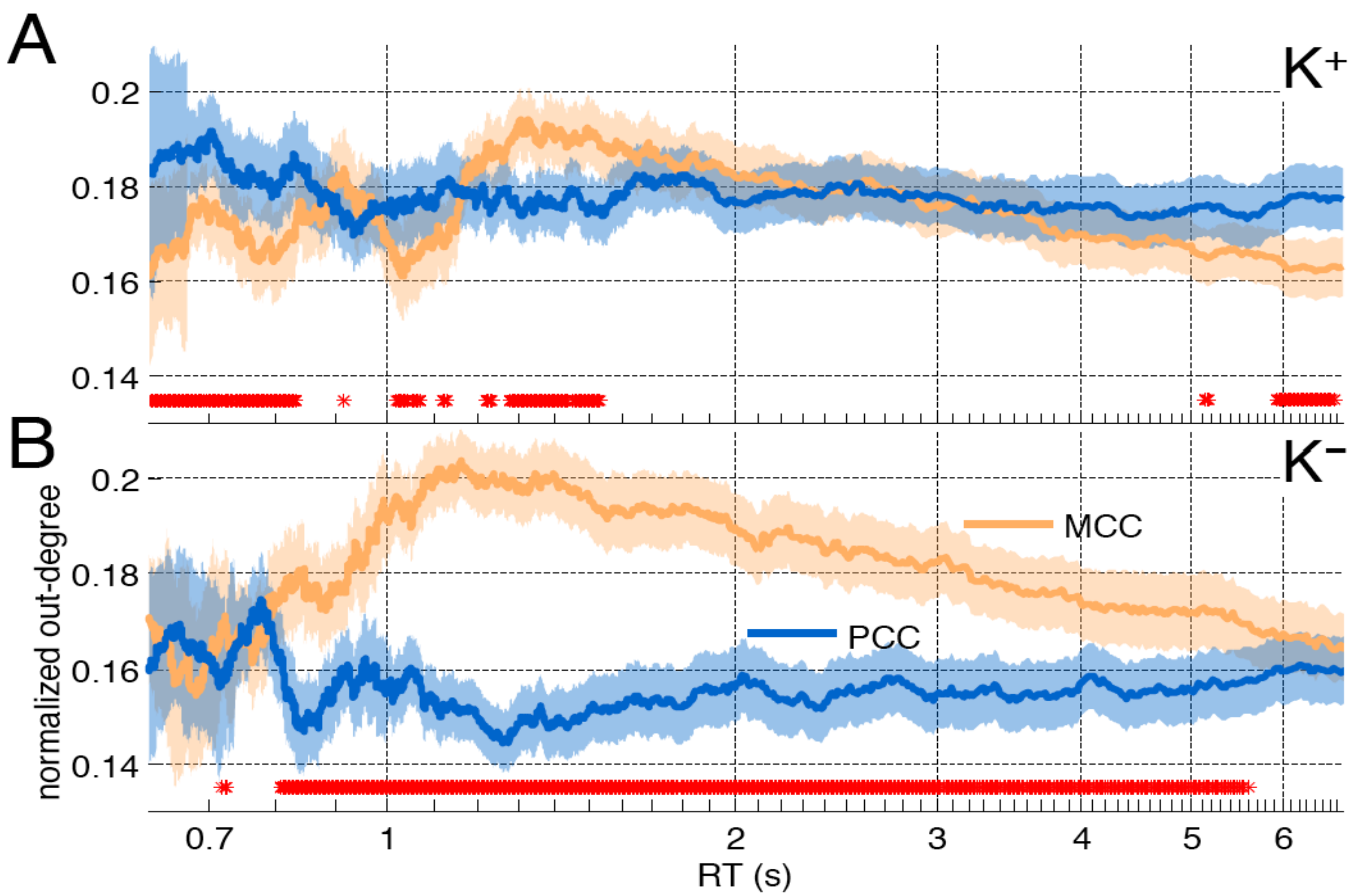

RT-sorted outflow dynamics of MCC (yellow trace) and PCC (blue trace) under **(A)** K^+ and **(B)** K^- conditions.

From Lin et al., *Scientific Report*, 2016.

Real-time Cognitive-State Monitoring

T.P. Jung[1,2], C.T. Lin[1], Scott Makeig[2] and Associates

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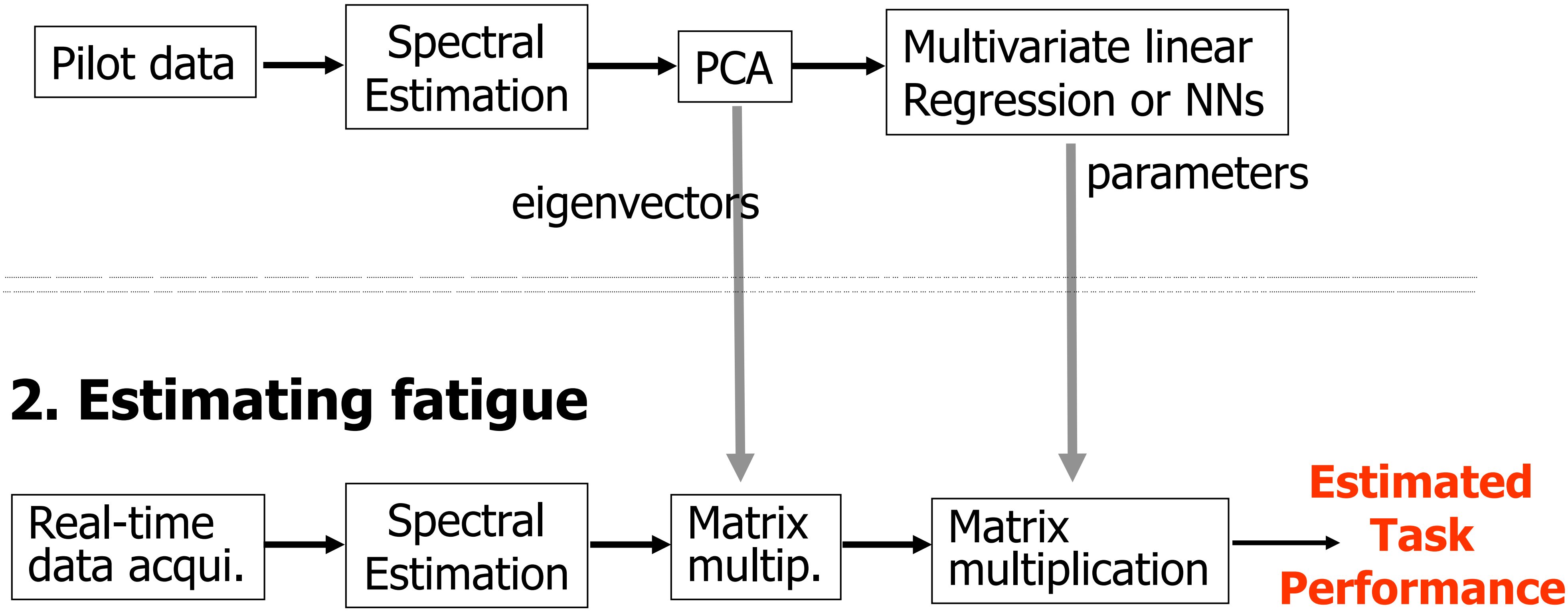
National Chiao Tung University, Hsinchu, Taiwan
[2]Swartz Center for Computational Neuroscience,
University of California San Diego, USA

Real-time Drowsiness Monitoring

1. Training



2. Estimating fatigue

References:
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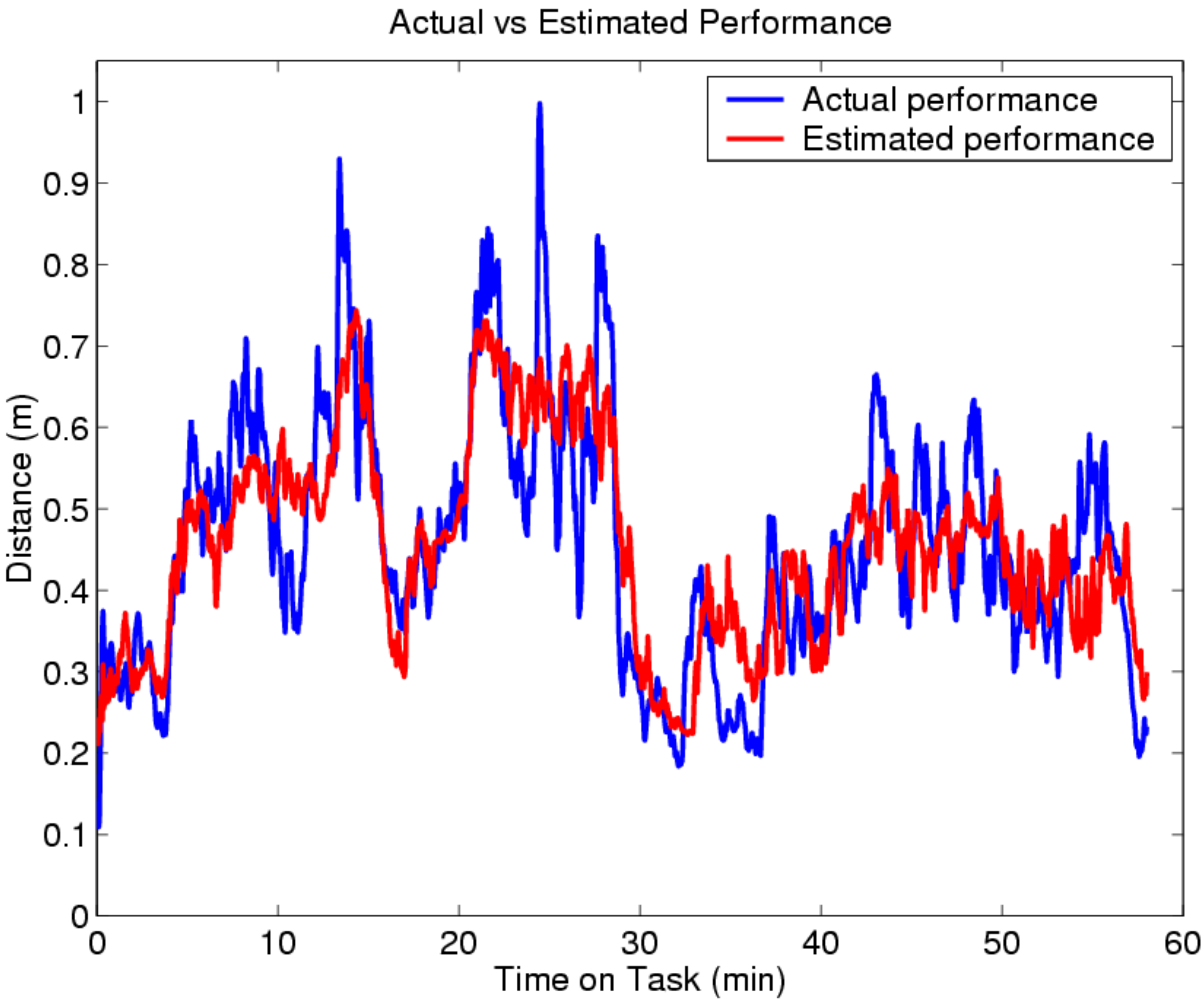
Sample Results



Arousing Feedback Rectifies Lapse in Performance

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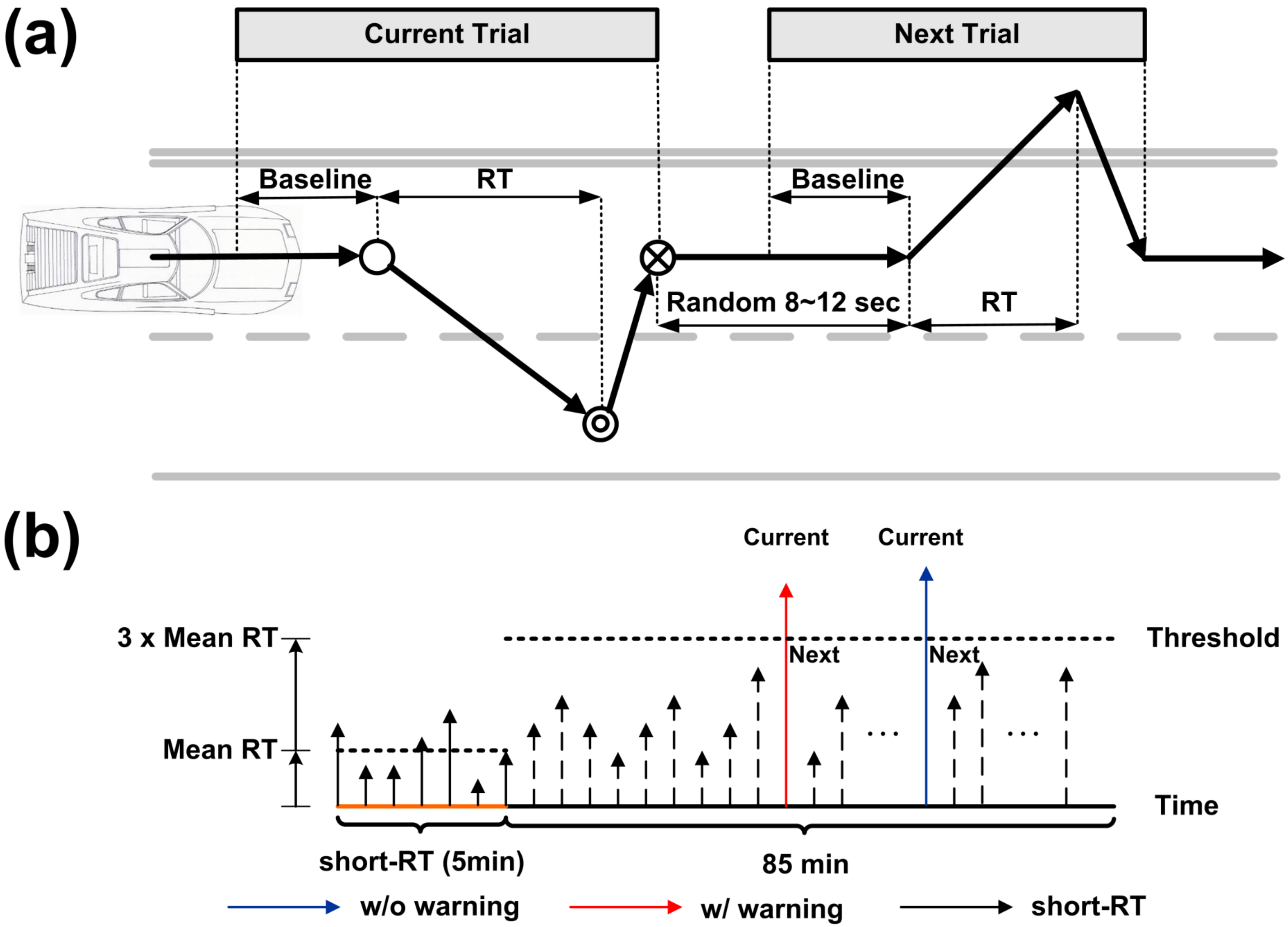
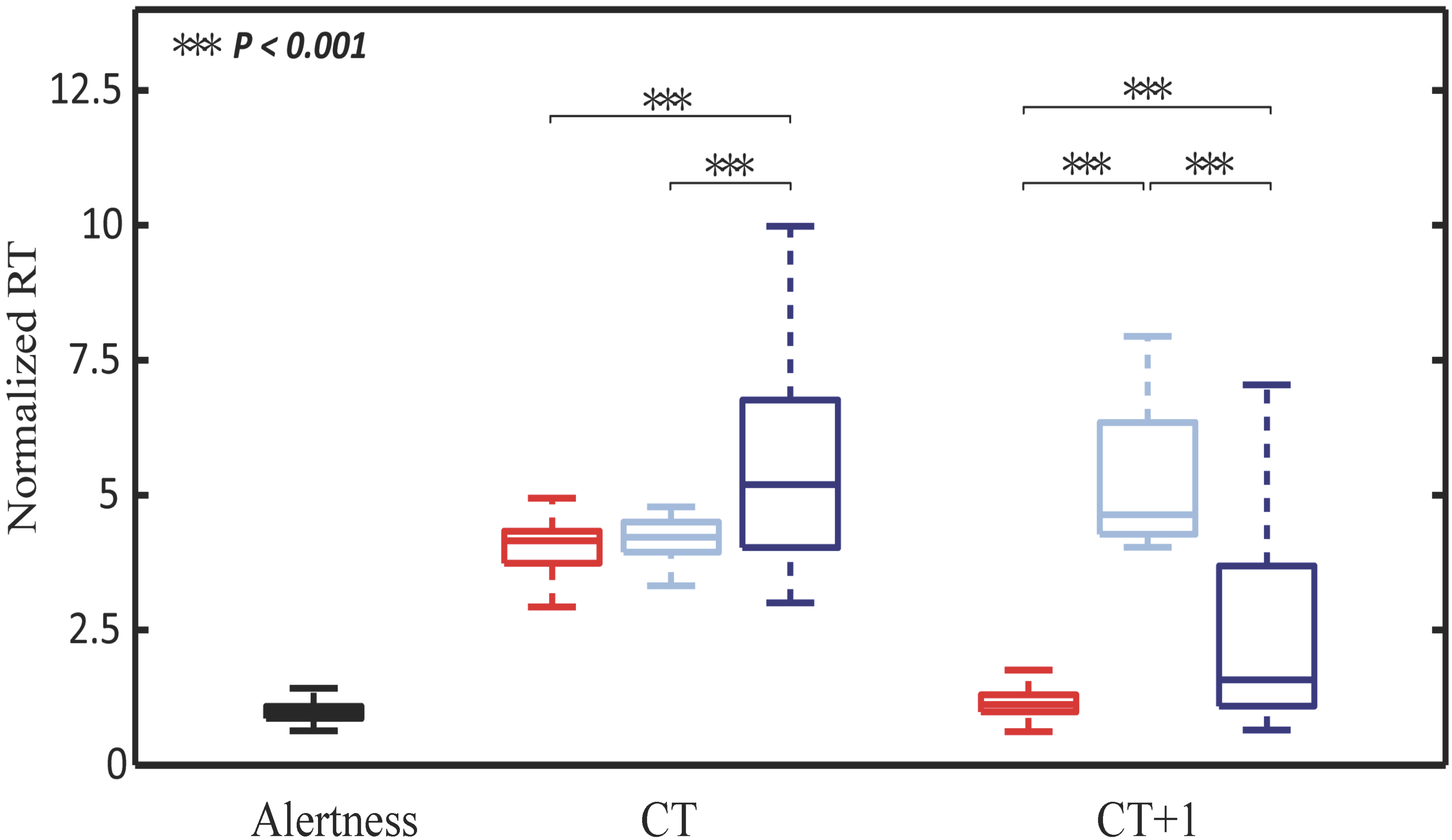
Auditory Feedback to the Drowsy Brain



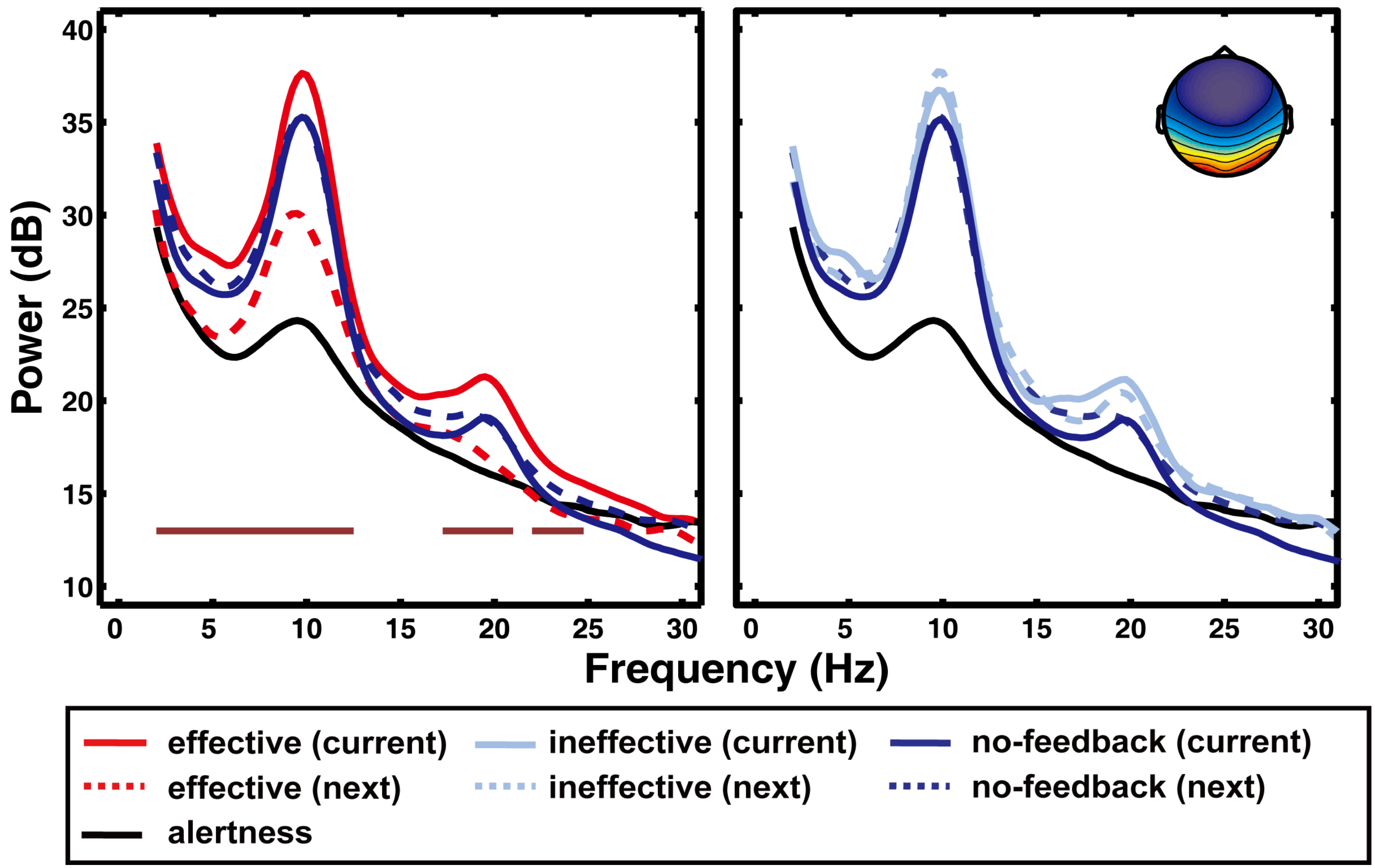
From Lin et al, *NeuroImage*, 2010.

Behavioral Responses to Feedback

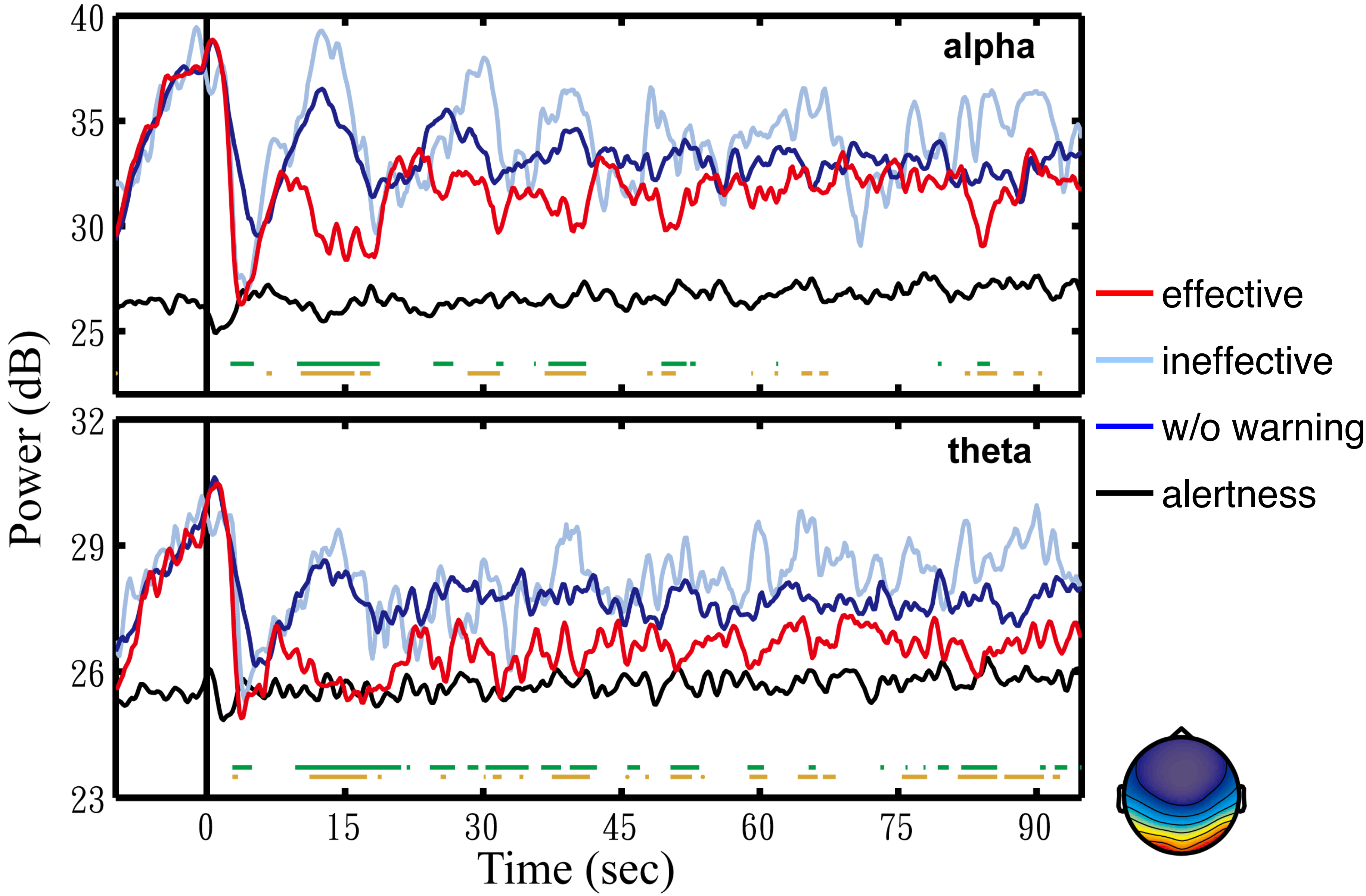


From Wang et al, *Frontiers in Neuroscience*, 2014.

The mean baseline spectra of effective and ineffective trials before and after auditory feedback.

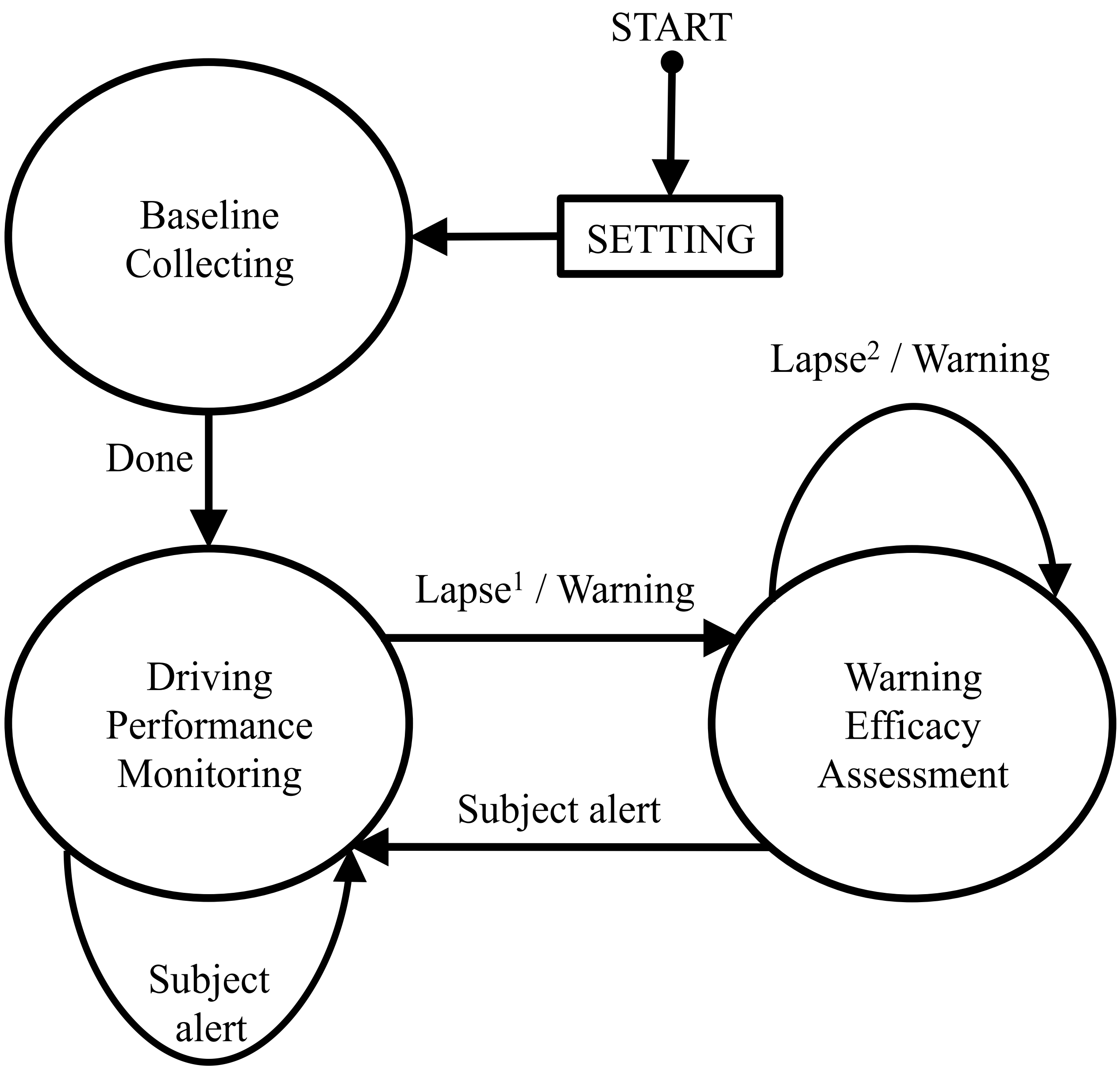


EEG Dynamics following Feedback

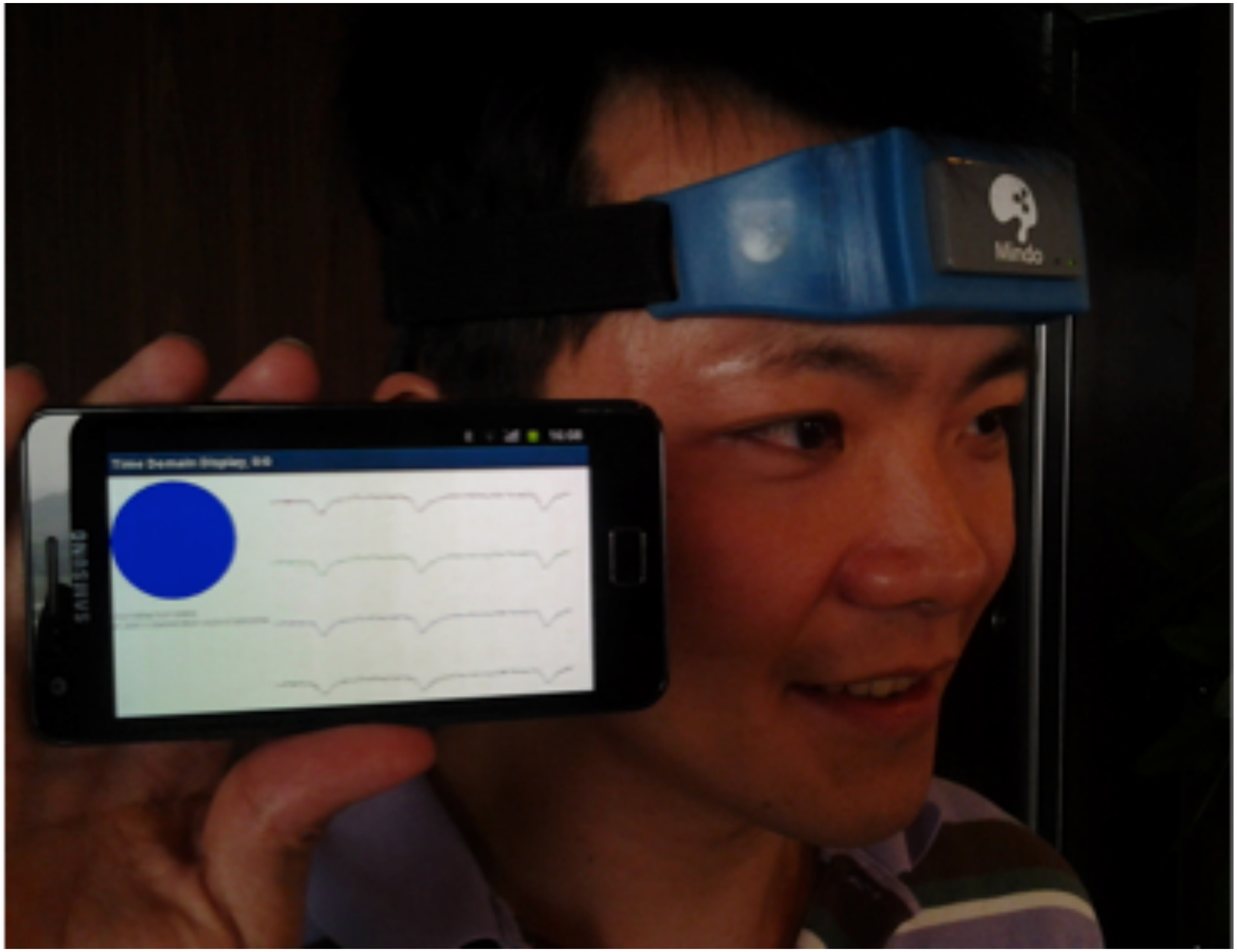


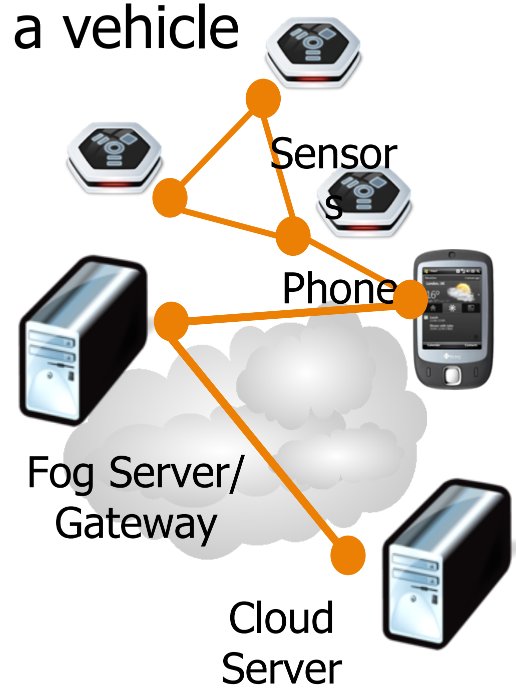
From Wang et al, *Frontiers in Human Neuroscience*, 2014.

Fatigue Monitoring & Mitigation System



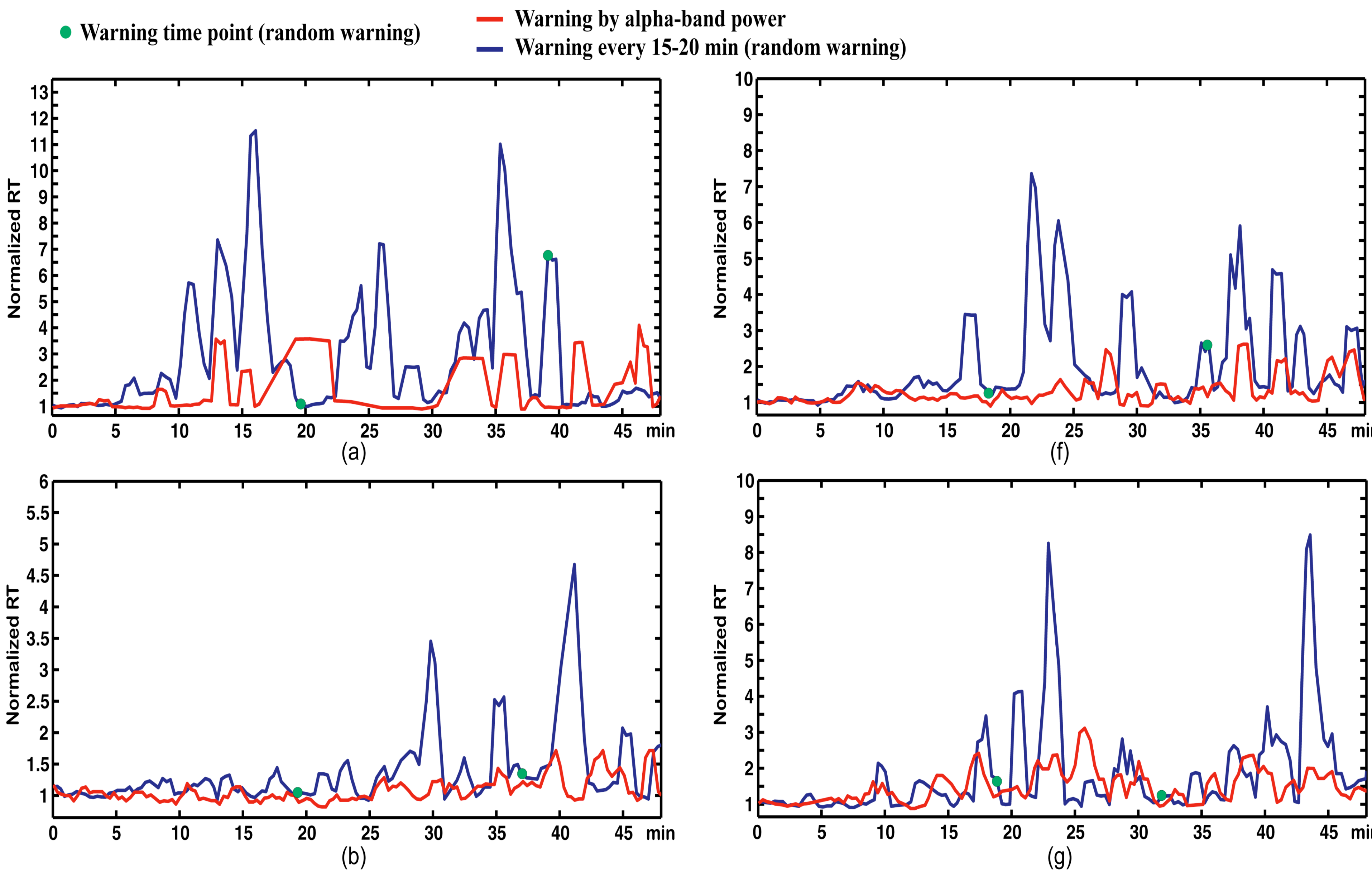
A Wearable and Wireless DMM System





Wang et al., *IEEE BioCAS,* 2012.

Comparing an EEG-based and a non-EEG-based Fatigue Detection and Mitigation Systems



Adapted from Huang et al., *Int'l Journal of Neural Systems*, 2016

Summary

Neural technologies that translate laboratory-oriented neuroscience research to study the human brain in real-world environments?

- Advanced sensors and sensing technologies for measuring neural and behavioral data from unconstrained subjects in ecologically valid environments.
- Signal-processing techniques to find statistical relationships among the variations in environmental, behavioral, and functional brain dynamics.
- An ability to harness continuous and ubiquitous monitoring of the brain.

Summary

- We reported both tonic and phasic spectral dynamics of independent components in response to lane-deviations during a continuous lane-keeping driving task.
- There are fundamental differences in EEG correlates of task performance between K+ and K- conditions.
- Arousing auditory feedback delivered to the cognitively challenged subjects immediately agitated subject's responses to the events.
- The improved behavioral performance was accompanied by concurrent spectral suppression in the theta- and alpha-bands of a lateral occipital component.
- It is feasible to integrate novel dry sensors, advanced signal-processing algorithms and miniature supporting hardware into a mobile & wireless cognitive-state monitoring and management system.

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