Cognitive-State Monitoring and Recent Advances in Neurophysiology and Neurotechnology

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Types of BCIs

- **Active BCI (BMI):** a BCI derives its outputs from brain activity which is directly consciously controlled by the user, independently from external events, for controlling an application.
- **Reactive BCI:** a BCI derives its outputs fron brain activity arising in reaction to external stimulation, which is indirectly modulated by the users for controlling an application.
- ***Passive or Affective BCI (BMI)*** derives its outputs from spontaneous brain activity without the purpose of voluntary control.

Lapses of Attention and 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 had driven a vehicle while feeling drowsy and 37% had actually fallen asleep.

Objectives of this Study

Neurophysiology

- To investigate tonic and phasic spectral changes during continuous sustained-attention task in a realistic environment (car driving).

Neurotechnology

- To build a neuroergonomic system 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.

Neurophysiological Correlates of Cognitive-state Changes

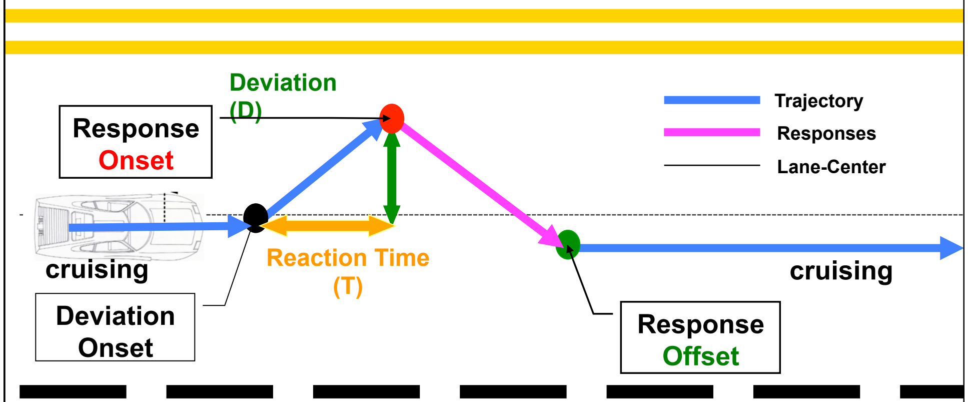
Study	Task(s); Measure(s)	Electrode Sites or Brain Regions	δ	θ	α	β
Badia et al. (1994)	Sleep onset	F3, C3, O1		+	+/-	
Baulk et al. (2001)	Simulated driving task in an immobile car, secondary auditory detection task; lane crossing incidents, RT, Karolinska Sleepiness Scale (KSS)	C3-A1		+	+	
Beatty et 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		[illegible]		
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	F3, C3, P3, O1		+	+	

Many studies have demonstrated EEG correlates of fluctuations in task performance during sustained attention task on the order of one second to several minutes. Chen, Huang, et al. recently conducted a meta analysis on the EEG spectral changes accompany fluctuations in task performance.

A VR-based Dynamic Driving Simulator

UCSD

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

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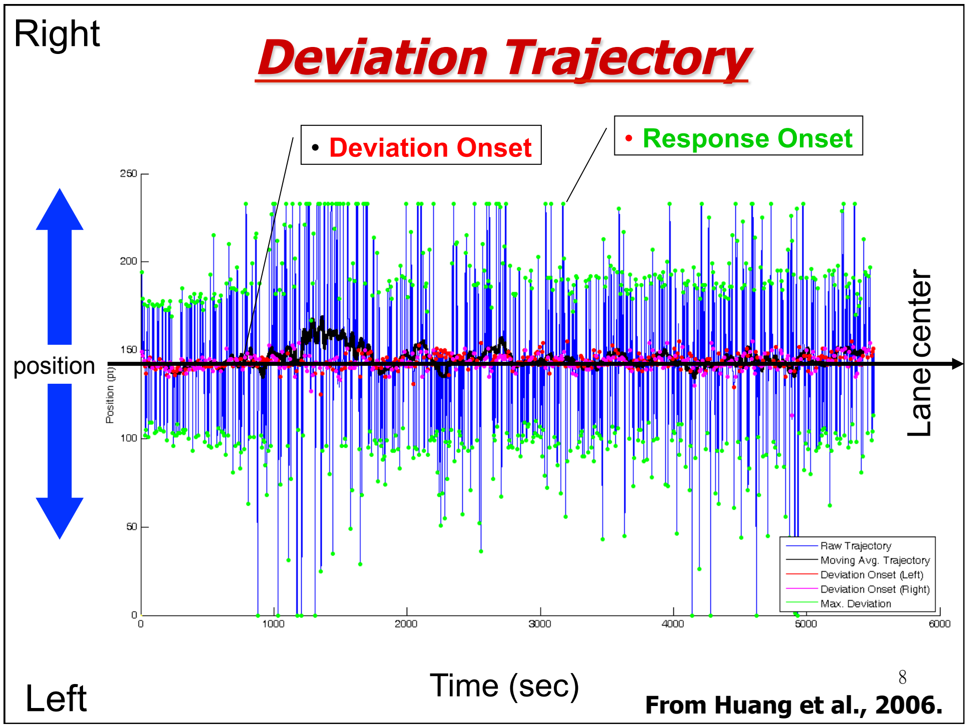
From Huang et al., 2005, 2007.

Deviation Trajectory



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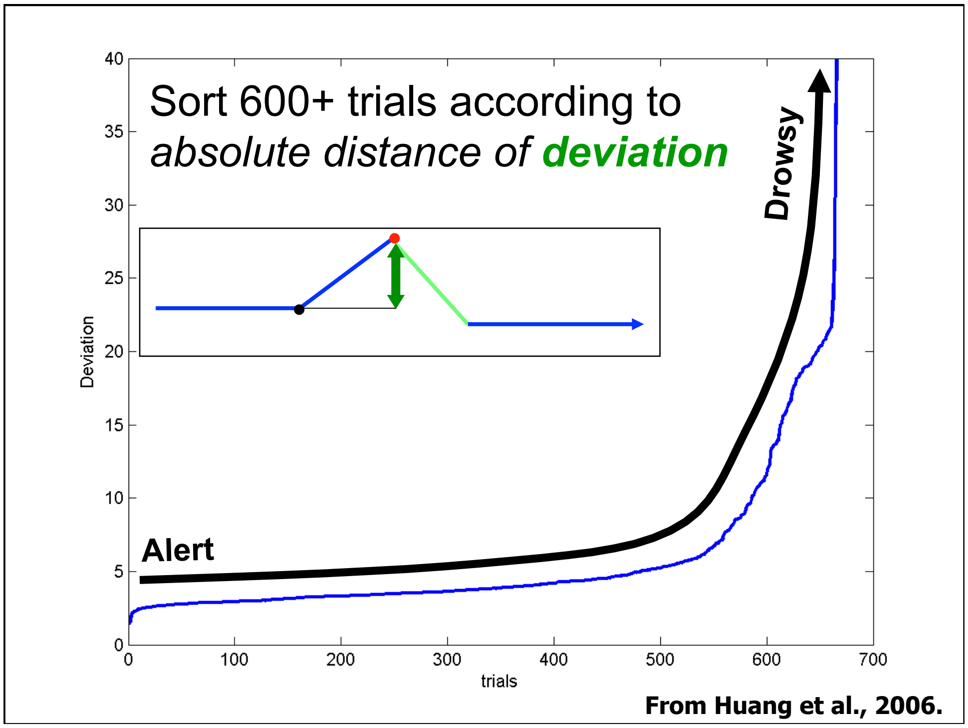
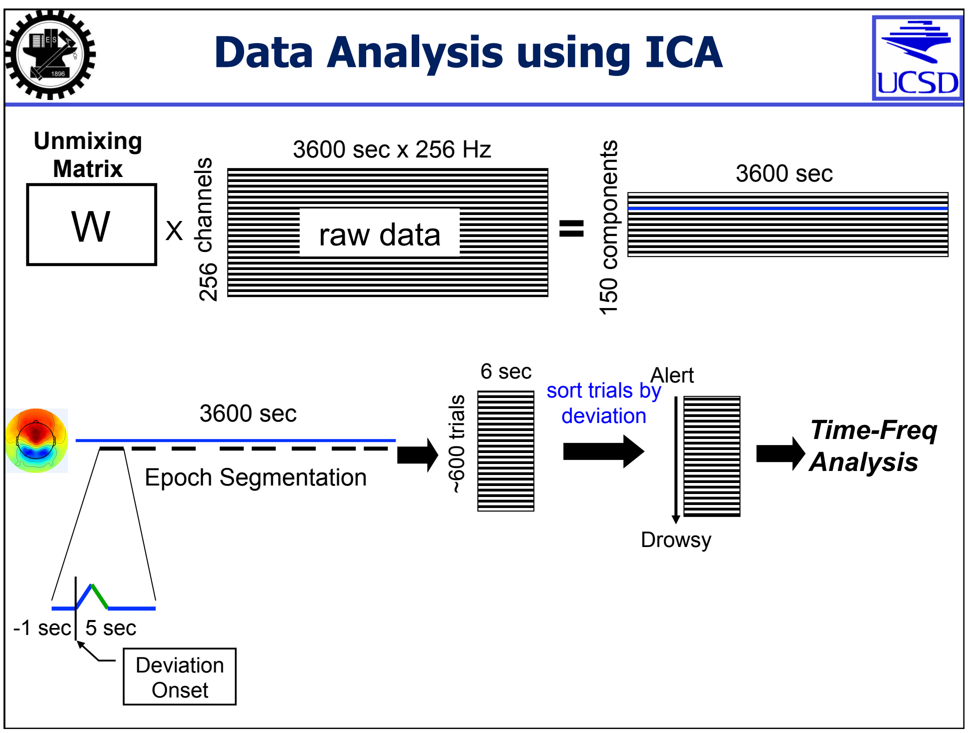
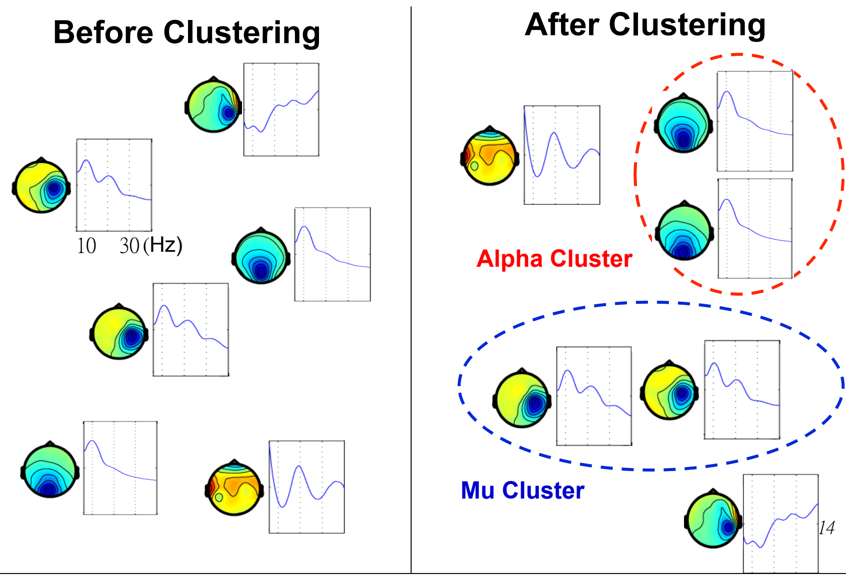
From Huang et al., 2006.

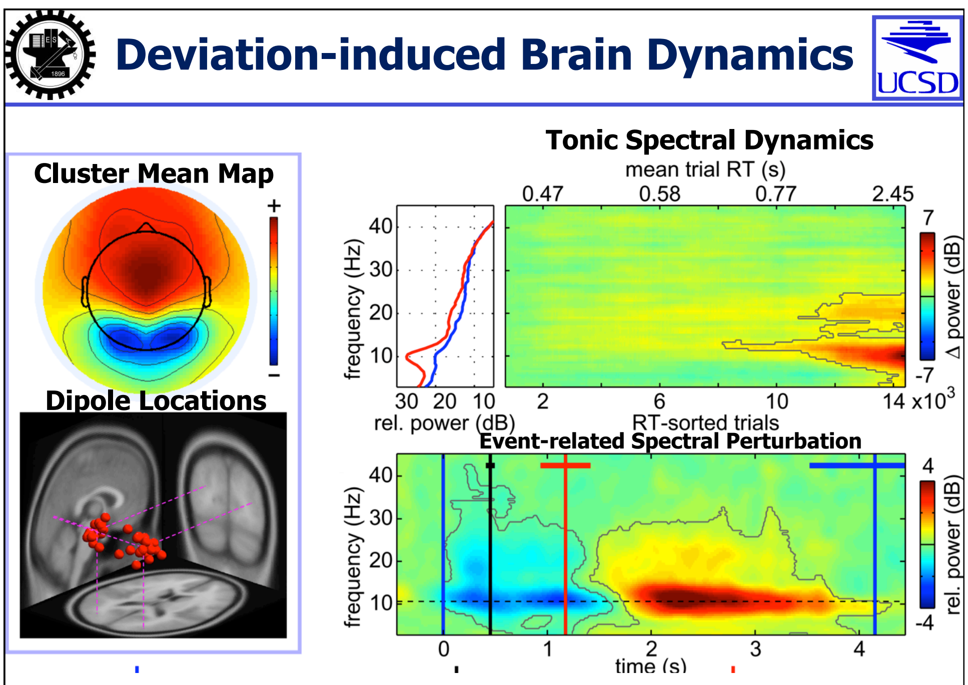

Sort 600+ trials according to
absolute distance of deviation
Drowsy
Alert
Deviation
trials
0
5
10
15
20
25
30
35
40
0
100
200
300
400
500
600
700
From Huang et al., 2006.


Data Analysis using ICA
UCSD
Unmixing Matrix
W
x
256 channels
3600 sec x 256 Hz
raw data
=
150 components
3600 sec
3600 sec
Epoch Segmentation
6 sec
~600 trials
sort trials by deviation
Alert
Drowsy
Time-Freq Analysis
-1 sec
5 sec
Deviation Onset

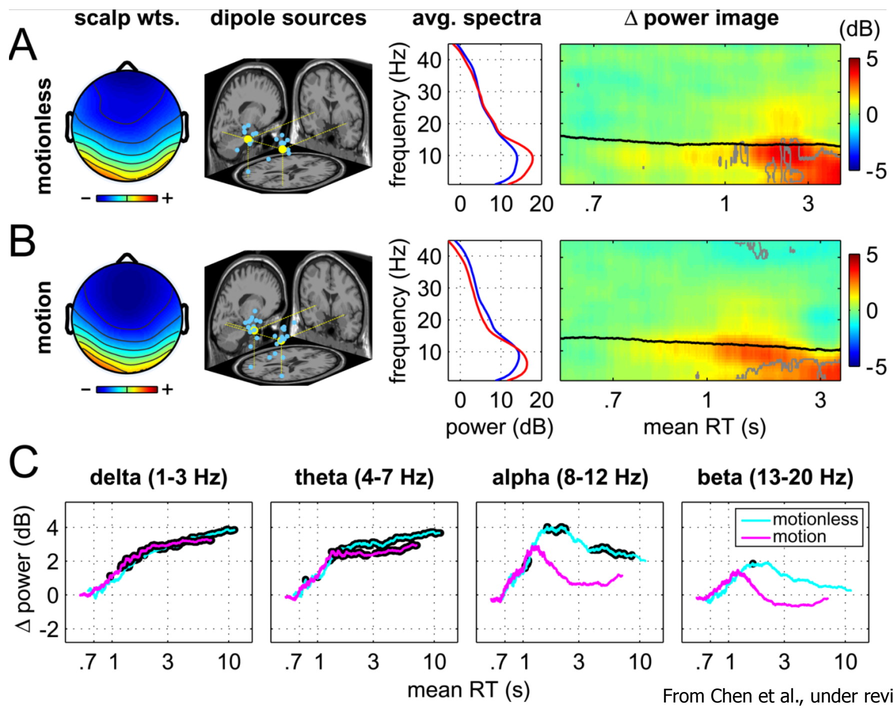
Component Stability: Cross-subject clustering analysis of ICA components



Deviation-induced Brain Dynamics



From Chen et al., under review.



From Chen et al., under review.

Spectral Perturbations as a Function of RT

Cluster / Figure	Trends: Motionless δ	θ	α	β	Motion δ	θ	α	β
Occipital (bilateral) / Fig. 3	↗*	↗*	↗↘	↗↘	↗*	↗*	↗↘	↗↘
Occipital (medial) / Fig. S6	↗	↗	↗↘	↗↘	↗*	↗*	↗↘*	↗↘
Occipital (tangential) / Fig. S8	↗*	↗*	↗↘*	↗↘	↗	↗	↗↘	↗↘
Medial posterior parietal / Fig. 4	↗*	↗*	—	—	↗*	↗	—	—
Left somatomotor / Fig. 5	↗	↗	—	—	↗	↗	—	—
Right somatomotor / Fig. S10	↗	↗*	—	—	↗	↗	↘	↘
Central medial / Fig. 6	↗*	↗*	↗*	↗	↗*	↗*	↗	↗
Frontal medial / Fig. 7	↗	↗	—	—	↗	↗*	—	—

↗monotonic increase, ↘monotonic decrease, ↗↘ biphasic trend, — no difference, * power changes significantly different ($p < 0.01$) from mean reference power of each respective frequency band at 3-s RT.

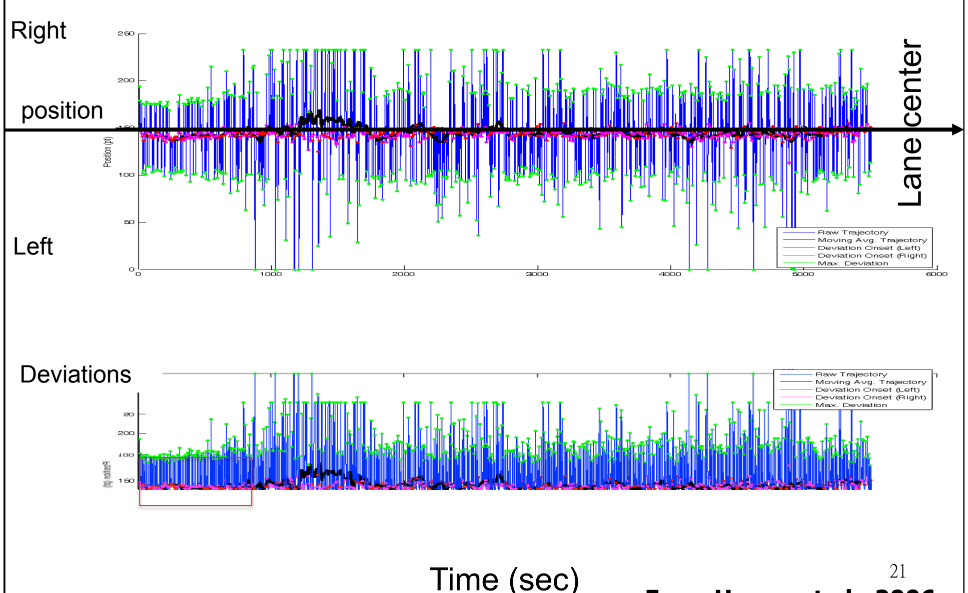
From Chen et al., under review.

Translating Neuroscience Principals and Knowledge into Neuroergonomic Systems

Real-time Cognitive-State Monitoring

Selected References:
1. Makeig & Jung, NeuroReport, 1994.
2. Makeig & Jung, Cognitive Brain Research, 1995.
3. Jung, *et al.*, *IEEE TBME*, 44:60-9, 1997.
4. Lin, *et al.*, *EURASIP J Applied Signal Processing*, 19:3165-74, 2005.
5. Lin, *et al.*, *IEEE TCAS* I, 52(12):2726-38, 2005.
6. Lin, *et al.*, *IEEE TCAS* I, 53(11): 2469-76, 2006.
7. Lin, *et al.*, *Proc. of the IEEE,* 96(7):1167-83, 2008.
8. Chuang, et al., NeuroImage, 2012.

Deviation Trajectory



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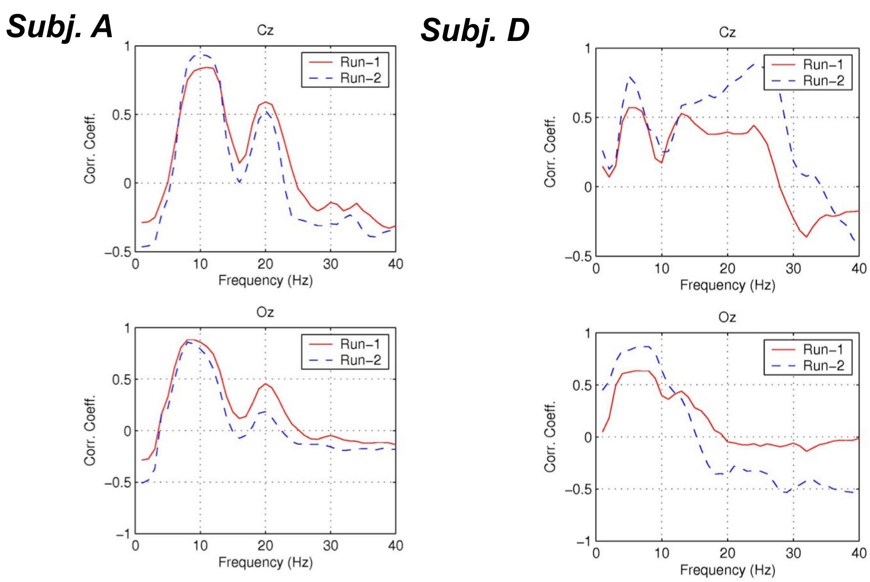
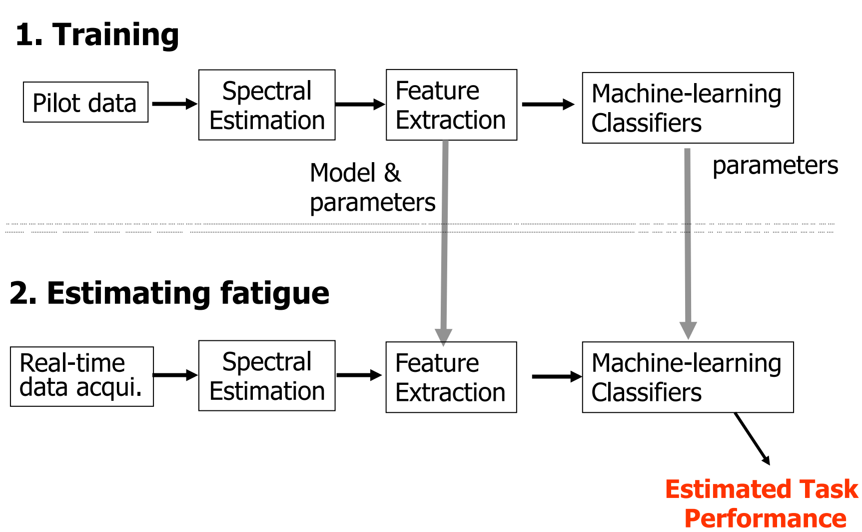
From Huang et al., 2006.

Correlation between Power Spectra and Driving Performance

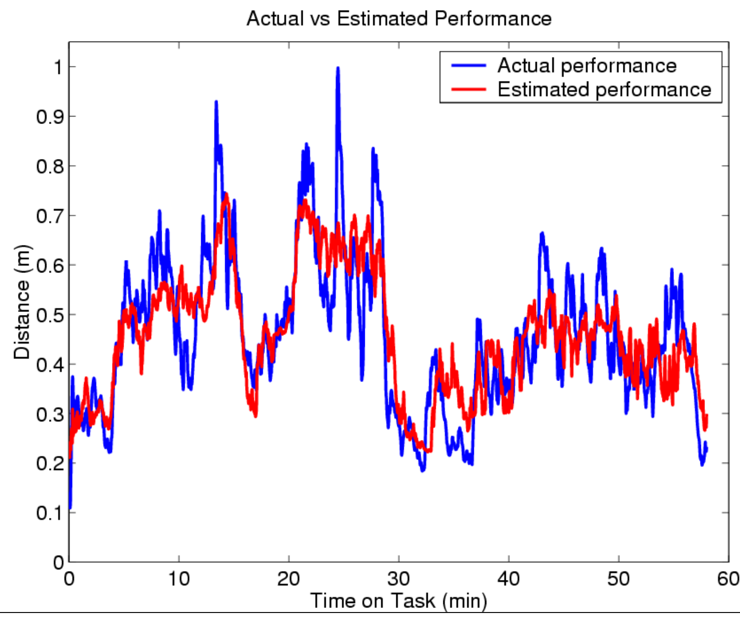


From Lin et al, *EURASIP*, 2005.

Real-time Drowsiness Monitoring



Sample Results

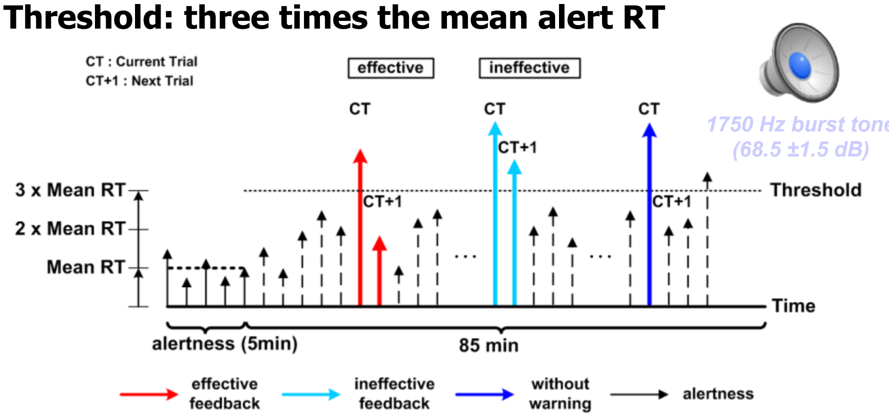


Can Arousing Feedback Prevent Lapse in Performance?

References:
1. Lin, et al., NeuroImage, 2010.
2. Jung, et al., IEEE EMBC, 2010.
3. Huang et al., IEEE EMBC, 2010.
4. Wang et al., IEEE BioCAS, 2012.

Effective & Ineffective Warning Signals

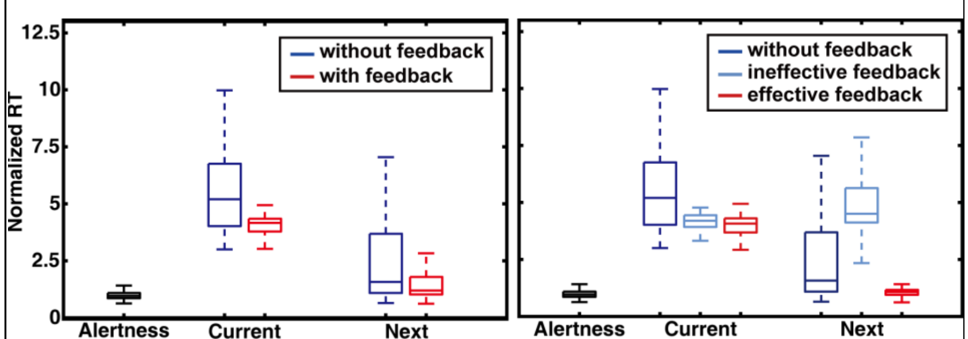
- **Threshold: three times the mean alert RT**



Some of them had RTs Still Longer than three times the mean RT, defined as "ineffective feedback"; others had RTs shorter than two times the mean RT, defined as "effective feedback"

Behavioral Improvements following Arousing Signals

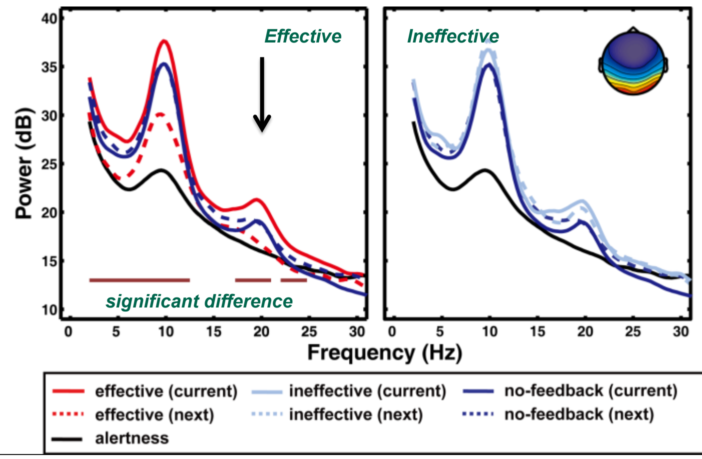
- The RTs of trials following warning were significantly shorter ($p<0.01$) than those without warning (left panel).
- The RTs of effective trials were significantly shorter ($p<0.001$) than those of ineffective trials (right panel).



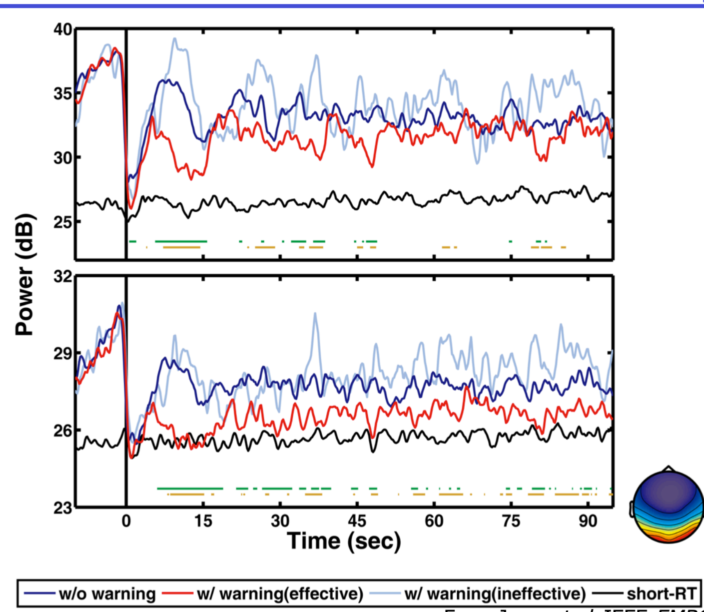
Normalized RT = Recorded RT/mean alert RT

Power Spectra Changes after a Warning Feedback

- Effective trials (left panel): the spectral differences between current (solid line) and next trials (dashed line) were statistically significant ($p<0.005$) and most prominent in the **theta** and **alpha bands** with over 5 dB to 10 dB **decreases** after receiving arousing feedback.

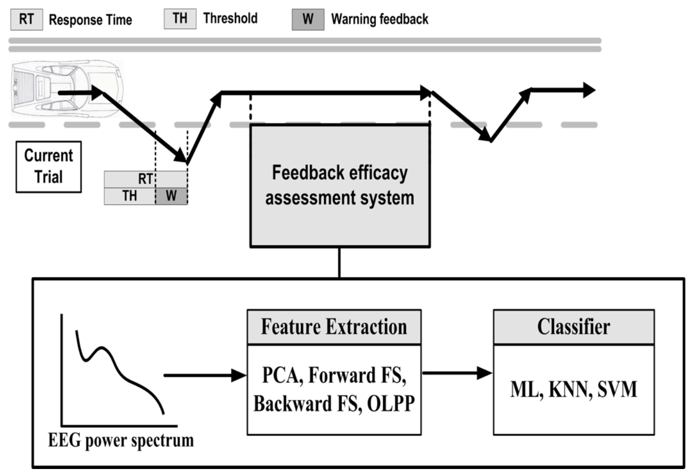


EEG Dynamics following Feedback



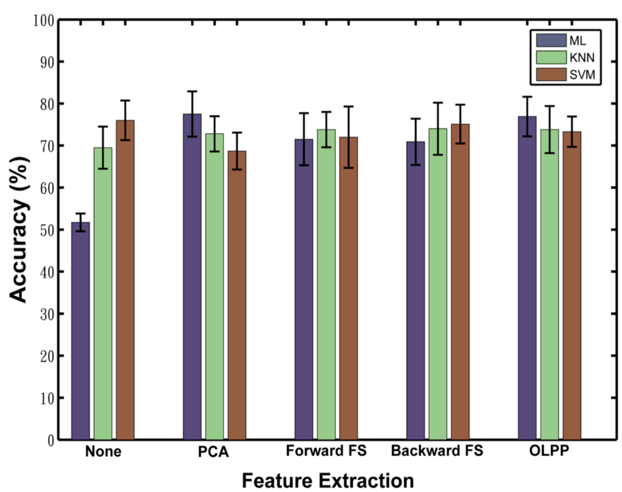
From Jung *et al,* IEEE *EMBC* 2010.

Feedback Efficacy Assessment System



From Huang, Jung *et al,* IEEE *EMBC* 2012.

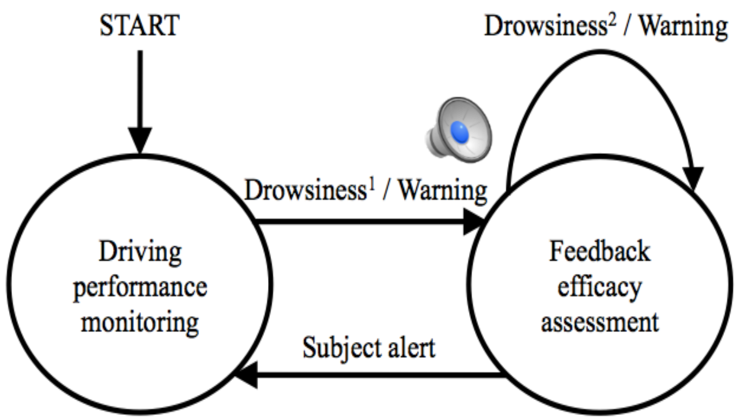
Classification Accuracies obtained by different feature extractions and classifiers



The accuracies of ML, KNN and SVM classifiers were over 70%.

From Huang, Jung *et al,* IEEE *EMBC* 2012.

A Closed-loop Drowsiness Monitoring & Management System



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

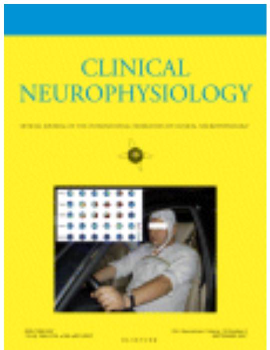
Objectives of this Study

- To investigate tonic and phasic spectral changes during continuous sustained-attention tasks in a realistic environment (car driving).

- **To build a neuroergonomic system 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.**

Missing Link

Clinical Neurophysiology
Volume 118, Issue 9, September 2007

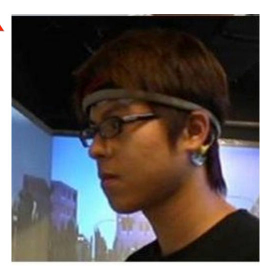


Missing Link: Mobile & Wireless EEG

Laboratory EEG

The current laboratory-oriented EEG systems do not allow assessment of brain activities of participants performing tasks involving natural movements.

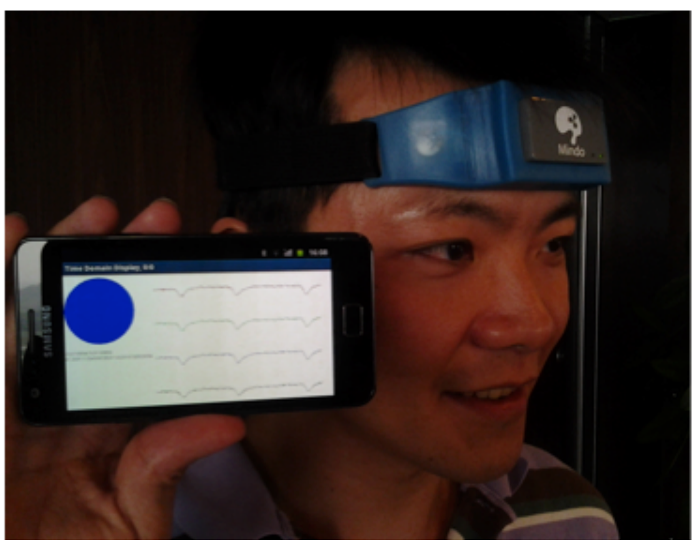
NCTU's MW-EEG



MINDO --- 2ch/4ch Channels

	EEG Headband
Features	Distributed Circuits
Miniaturization Size (mm)	DAQ: 20 x 18  (4 pieces) MCU: 40 x 25 
Weight	< 100 g
Sampling Rate	512Hz
Bandwidth	Filter to 0.5 - 50 Hz
Gain	6000 times
Output current (working)	31.58 mA
Battery Life (3.7V, 1100mA)	33 hours

A Wearable and Wireless DMM System



Summary

- This study has reported both tonic and phasic spectral dynamics of independent components in response to lane-deviations during a continuous lane-keeping driving task.
- Arousing auditory feedback delivered to the drowsy 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 bilateral occipital components.
- We also showed that continuous, accurate, noninvasive and near real-time estimation of subject's cognitive level is feasible in a realistic operational environment.
- 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.

Neuroscience and Neurotechnology

World-wide neuroscience efforts

- 19,821K neuroscience publications (www.scimagojr.com)
- 31 (115) countries produced over 100K (1K) documents (www.scimagojr.com)
- Over 300 neuroscience journal titles
- Neurotech industry has a > $140 billion investment annually (NIO, 2009).

Problem: How to create the ability to leverage the vast world-wide neuroscience efforts to further advance neuroscience research, and improve prevention, diagnosis, and treatment of neurological diseases and injuries?

Major Barriers/Challenges

1. Lack of portable, user-acceptable, robust systems for monitoring brain and body dynamics in real-world environments.
2. Lack of mathematical modeling methods to find statistical relationships among the variations in environmental, behavioral, and functional brain dynamics.
3. Restrictive experimental control and impoverished paradigms and environments.

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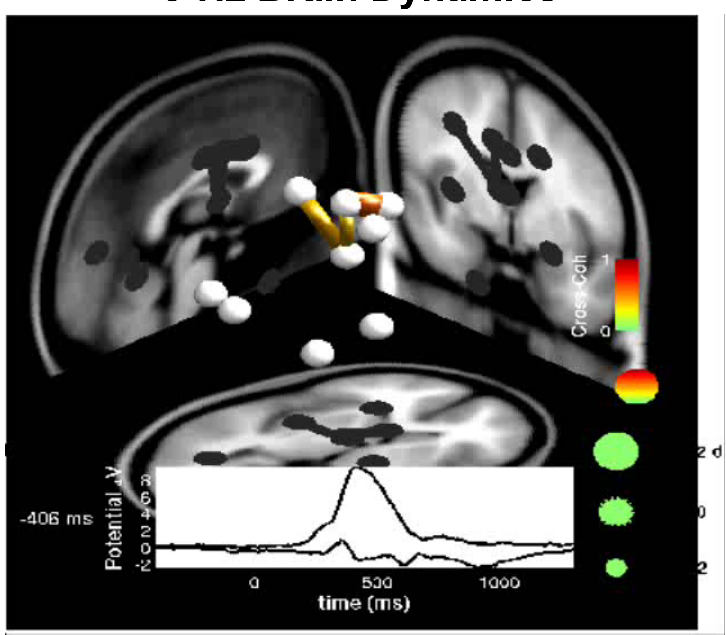
Modeling Event-Related Brain Dynamics

1. Un-mix cortical and artifact source contributions to the scalp electrodes using independent component analysis (ICA).
2. Visualize the activities of independent component (IC) sources across single trials using ERP-image plotting.
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 interaction between brain areas using component cross-coherence or effective connectivity.

5-Hz Brain Dynamics

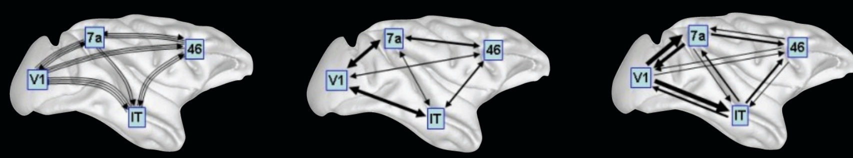


Makeig et al., *PLoS Biology*, 2004.

Categorizations of Large-Scale Brain Connectivity Analysis

(Bullmore and Sporns, *Nature*, 2009)

Structural	**Functional**	**Effective**



state-invariant, anatomical	dynamic, state-dependent, correlative, symmetric	dynamic, state-dependent, asymmetric, causal, information flow

Hours-Years | **milliseconds-seconds**

Temporal Scale

Copied from Mullen, T. *EEGLAB SIFT Toolbox, 2010.*

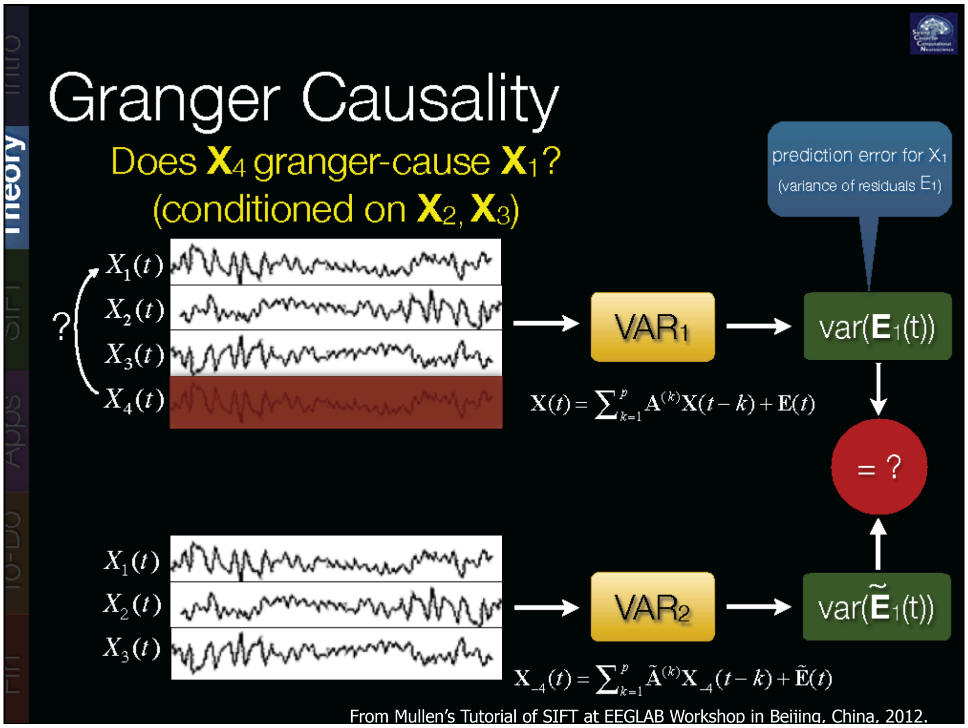
Intro | **Theory** | SIFT | Apps | To-Do | Fin

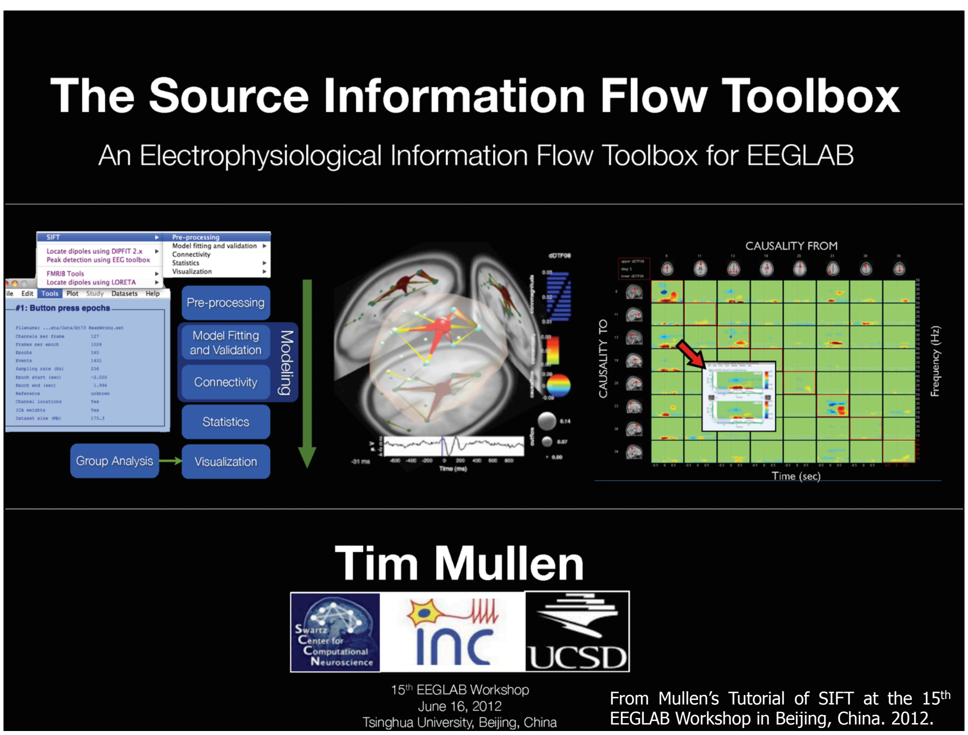
Granger Causality

- First introduced by Wiener (1958). Later reformulated by Granger (1969) in the context of linear stochastic autoregressive models
- Relies on two assumptions:

Granger Causality Axioms
1. Causes should precede their effects in time (Temporal Precedence)
2. Information in a cause's past should improve the prediction of the effect, above and beyond the information contained in past of the effect (and other measured variables)

From Mullen's Tutorial of SIFT at EEGLAB Workshop in Beijing, China, 2012. 15


Granger Causality
Does X4 granger-cause X1?
(conditioned on X2, X3)
prediction error for X1
(variance of residuals E1)
X1(t)
X2(t)
X3(t)
X4(t)
?
VAR1
var(E1(t))
X(t) = ∑_{k=1}^{p} A^{(k)}X(t−k) + E(t)
= ?
X1(t)
X2(t)
X3(t)
VAR2
var(Ẽ1(t))
X_{-4}(t) = ∑_{k=1}^{p} Ã^{(k)}X_{-4}(t−k) + Ẽ(t)
Theory
SIFT
Apps
From Mullen's Tutorial of SIFT at EEGLAB Workshop in Beijing, China, 2012.


The Source Information Flow Toolbox
An Electrophysiological Information Flow Toolbox for EEGLAB
Pre-processing
Model Fitting and Validation
Connectivity
Statistics
Visualization
Group Analysis
Modeling
CAUSALITY FROM
CAUSALITY TO
Frequency (Hz)
Time (sec)
Tim Mullen
Swartz Center for Computational Neuroscience
inc
UCSD
15th EEGLAB Workshop
June 16, 2012
Tsinghua University, Beijing, China
From Mullen's Tutorial of SIFT at the 15th EEGLAB Workshop in Beijing, China. 2012.

Mobile wireless EEG + BCILAB/SIFT

Mindo

MWEEG (NCTU) and BCILAB/SIFT (UCSD)

Major Barriers/Challenges

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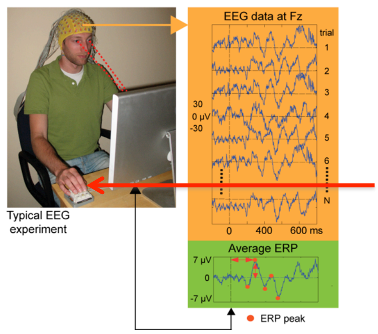
Impoverished EEG Paradigms and Environment

A typical EEG experiment



Measurements:
- 256 active EEG electrodes
- Simultaneous physiological data:
  - ECG, Breath, Blood Oxygen, EMG

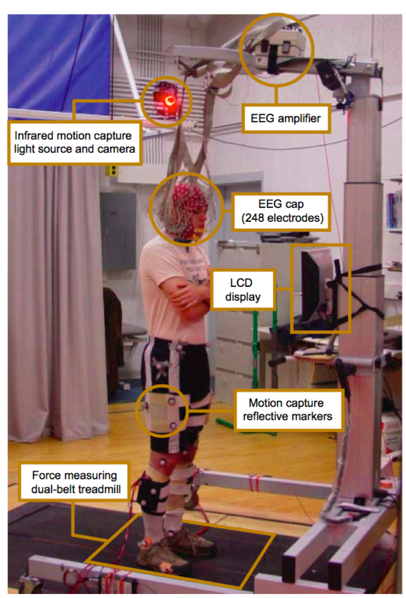
Behavior
- **Button press?**

We must record simultaneously, during naturally motivated behavior,
- 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.

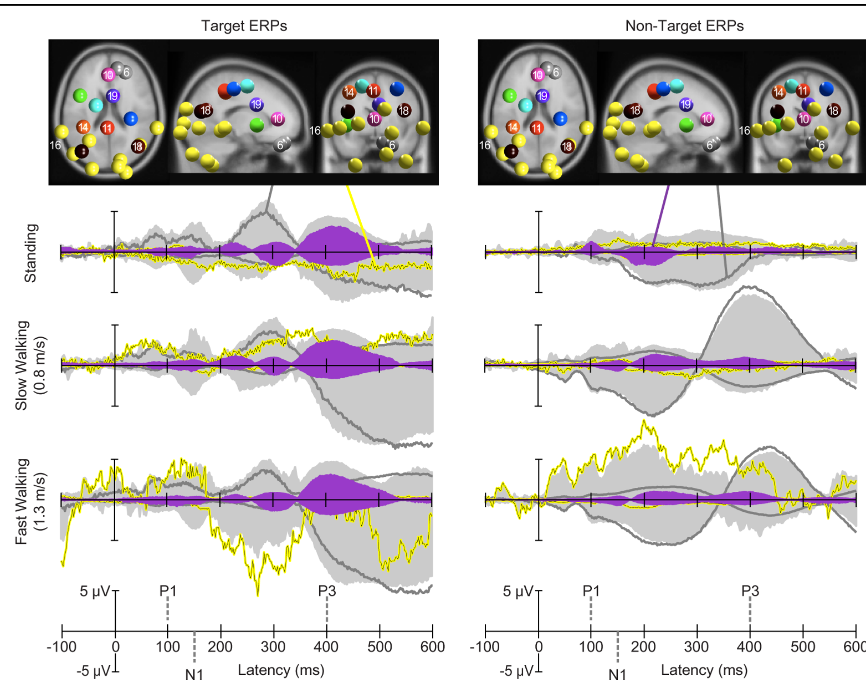
Feasibility Study: VEP on a Treadmill

A



From Gramann et al, *Frontiers in Human Neuroscience*, 2010.

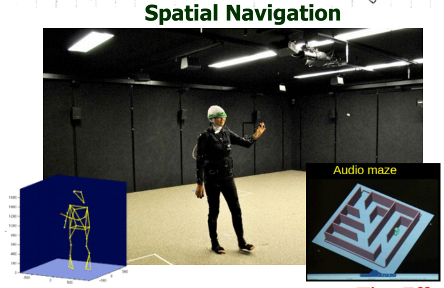
Feasibility Study: VEP on a Treadmill



From Gramann et al, *Frontiers in Human Neuroscience*, 2010.

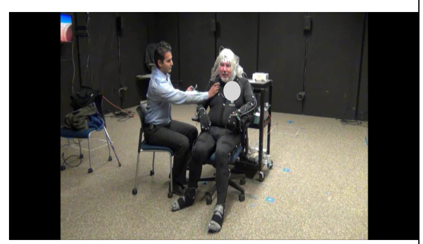
Mobile Brain/Body Imaging (MOBI)

Spatial Navigation



The Effect of DBI on EEG and EMG

Development of Shared Attention



Gedeon Deak et al., 2011.

Progress in BCIs We Expect to See in the Near Future

- **Direct Control**: to comprise the task the user performs (e.g. the movement of a prosthetic).
- **Indirect Control:** to use neural information associated with the human perception of "errors" to augment control systems.
- **Communications:** to enable patients with little to no communication capability to generate speech.
- **Brain-process modification**: to help individuals adjust their own brain function to attain a more desirable state.
- **Neural State Detection:** to detect fatigue, attentional, arousal, and affective levels, allowing systems or environments to adapt to the state of the user, increasing joint user-system performance.