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Decoding Neural Activity at Multiple Spatial and Temporal Scales

… the science and engineering of "mind reading"…

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Can we “read” the brain in real-time?

decoder

1001110…

if YES then

Can we “read” the brain in real-time?

decoder → 1001110…

if YES then

Rehabilitation
Cognitive Neuroscience
Performance Augmentation

requires single-trial analysis

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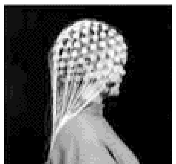
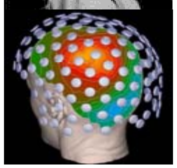
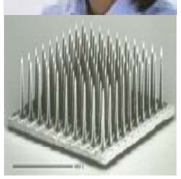
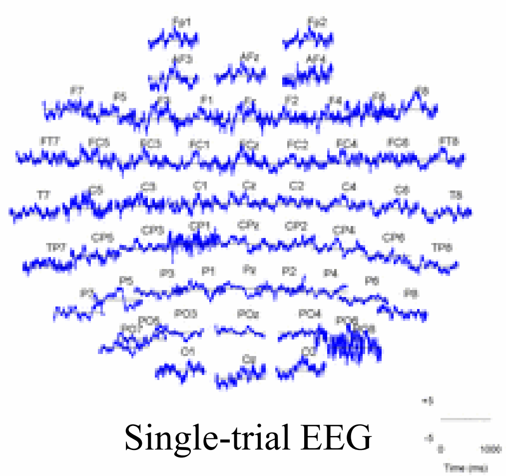
Functional Brain Imaging Modalities

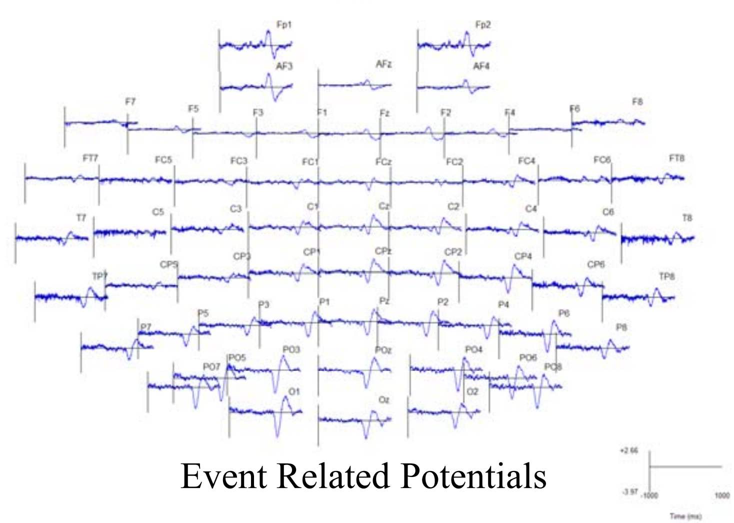
		Cost $K	Temporal resolution	Latency	Spatial resolution	
	EEG	50	ms	ms	cm	Practical tool for clinical applications. Useful research tool for human cognition.
	MEG	1000	ms	ms	mm	Research tool for investigating temporal properties of neuronal and cognitive processes.
	fMRI	4000	s	min	mm	Important for cognition research due to excellent localization of hemodynamic activity.
	PET	2000	min	h	mm	Similar to fMRI. Can target specific metabolites.
	fNIR	200	s	ms	cm	Poor man's fMRI
	MUR	200	ms	ms	µm	Invasive. High SNR. Only local activity.

Single-trial EEG Analysis

- Identifying neural correlates requires assessment of trial-by-trial variability--i.e. single trial analysis.
- High-density EEG systems were designed without a principled approach to handling the volume of information provided by simultaneously sampling from large electrode arrays.
- Typically EEG is averaged over trials to increase the amplitude of the signal correlated with cortical processes relative to artifacts.
- Averaging masks information contained in individual trials and electrodes at specific moments in time.



Single-trial EEG



Event Related Potentials

Outline

- Tutorial on the Linear Analysis of EEG
- Real-time, On-line Applications: Image Triage and Error Correction
- Decoding EEG to Better Characterize the Neural Basis of Perceptual Decision Making in the Human Brain

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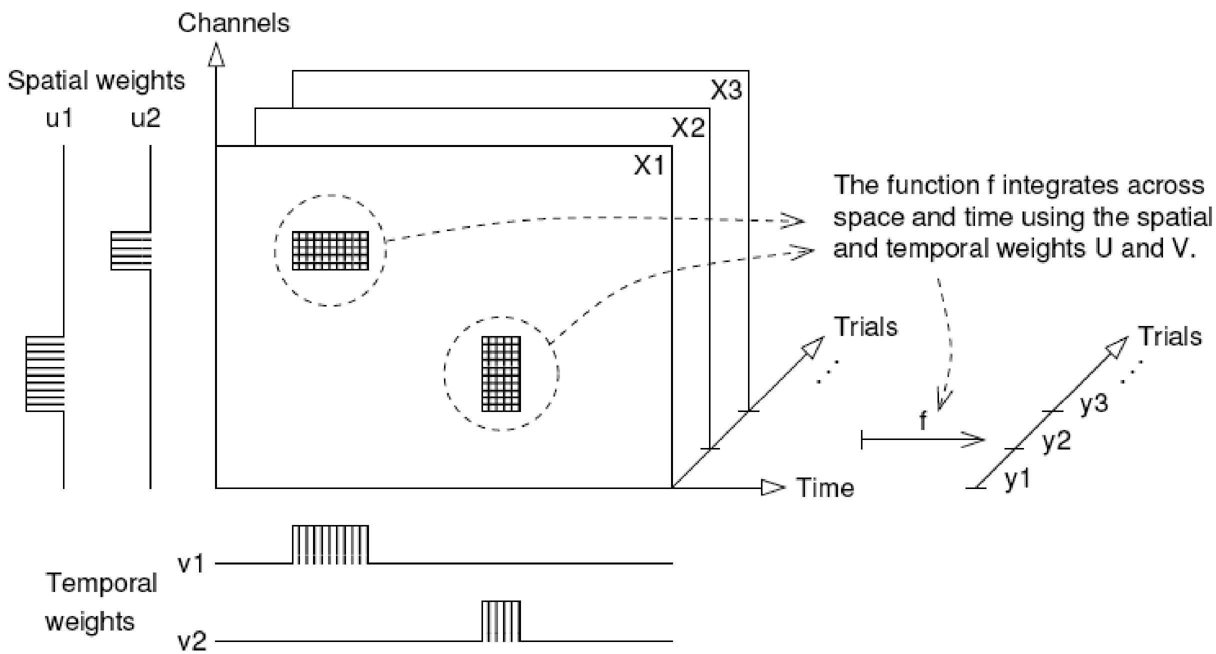
Spatio-temporal Decompositions of EEG



(Parra ….. Sajda, IEEE SPM 2008)

Estimating "Interesting" Components Through Projections

$$y(t) = \mathbf{w}^T \mathbf{x}(t) = \sum_{i=1}^{D} w_i x_i(t)$$

… *what is* **w***?*

Estimating "Interesting" Components Through Projections

Signal summation

noise $n_1(t)$ and $n_2(t)$

$$x_1(t) = s(t) + n_1(t)$$

$$x_2(t) = s(t) + n_2(t)$$

choose $\mathbf{w}^T = [1, 1]$

$$y(t) = 2s(t) + n_1(t) + n_2(t)$$

3dB improvement in SNR

Estimating "Interesting" Components Through Projections

Signal subtraction

$$x_1(t) = s_1(t) + s_2(t)$$

$$x_2(t) = s_2(t)$$

choose $\mathbf{w}^T = [1, -1]$

$$y(t) = x_1(t) - x_2(t) = s_1(t)$$

Estimating "Interesting" Components Through Projections

Linear Model for EEG

forward model

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t)$$

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t)$$

Source Estimation by Linear Projection

backward model

$$\hat{\mathbf{s}}(t) = \mathbf{V}^T\mathbf{x}(t)$$

For Gaussian noise with known correlation structure this is an ML estimator

$$\hat{\mathbf{V}}^T = \mathbf{A}^{\#} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T$$

noise collinear with the source

$$\hat{\mathbf{s}}(t) = \mathbf{s}(t) + \mathbf{V}^T\mathbf{n}(t)$$

Estimating "Interesting" Components Through Projections

Minimizing Interference via Subtraction

$$\hat{\mathbf{s}}(t) \;=\; \mathbf{A}^{\#}\mathbf{x}(t)$$

Estimate interfering source (backward model)

$$\mathbf{x}_{||}(t) \;=\; \mathbf{A}\hat{\mathbf{s}}(t)$$

Estimate contribution to measurements (forward model)

$$\mathbf{x}_{\perp}(t) = \mathbf{x}(t) - \mathbf{x}_{||}(t) = (\mathbf{I} - \mathbf{A}\mathbf{A}^{\#})\mathbf{x}(t)$$

$\mathbf{x}_{\perp}(t)$ has no activity correlated with $\hat{\mathbf{s}}(t)$

however it has reduced rank--
must deal with appropriately

Estimating "Interesting" Components Through Projections

Forward Model Estimate

$$\mathbf{y} = [y(t_1), ..., y(t_N)], \text{ and } \mathbf{X} = [\mathbf{x}(t_1), ..., \mathbf{x}(t_N)]$$

forward model $\hat{\mathbf{a}}_y$ – one column of the matrix $\mathbf{A}$

$\hat{\mathbf{a}}_y$ can be found by linearly predicting $\mathbf{x}(t)$ from $y(t)$

$$\hat{\mathbf{a}}_y = \mathbf{X}\mathbf{y}^T(\mathbf{y}\mathbf{y}^T)^{-1}$$

"scalp projection"

Some Objectives for Finding Interesting Components

… or how do we estimate **w***…*

- Maximum Difference
- Maximum Power
- Statistical Independence

Maximum Difference

$$\Delta\mathbf{x}(\tau) = \frac{1}{N_1}\sum_{t_1}\mathbf{x}(t_1+\tau) - \frac{1}{N_2}\sum_{t_2}\mathbf{x}(t_2+\tau)$$

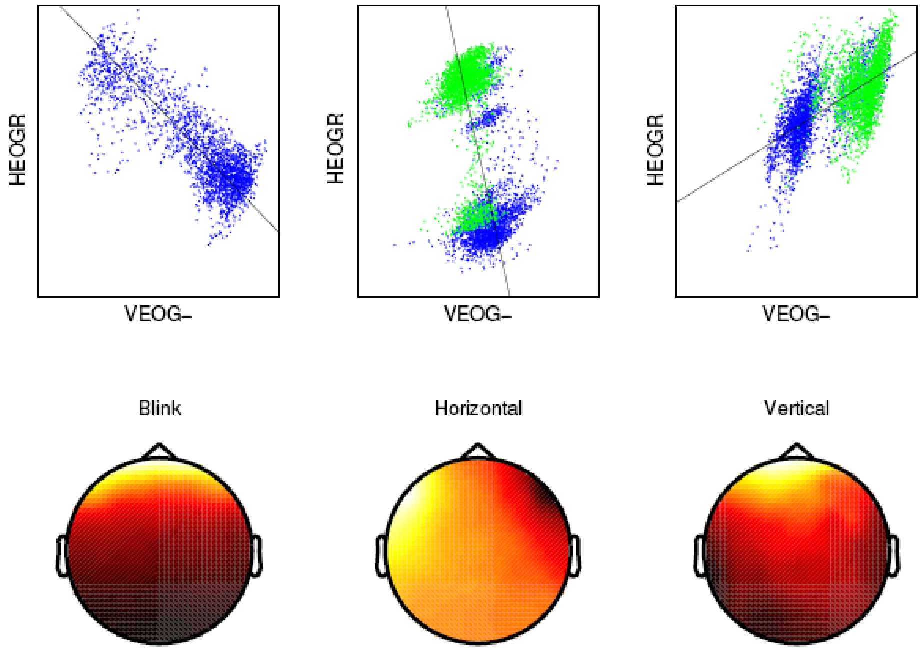
$$\overline{\Delta\mathbf{x}} = \sum_{\tau}\Delta\mathbf{x}(\tau)$$

$$\hat{\mathbf{a}}_y = \frac{\overline{\Delta\mathbf{x}}}{(N_1+N_2)(y_1-y_2)}$$

$$\hat{\mathbf{A}}_{\mathrm{eye}} = [\hat{\mathbf{a}}_{\mathrm{b}}, \hat{\mathbf{a}}_{\mathrm{h}}, \hat{\mathbf{a}}_{\mathrm{v}}]$$

$$\hat{\mathbf{s}}(t) = \hat{\mathbf{A}}^{\#}_{\mathrm{eye}}\mathbf{x}(t)$$

$$\hat{\mathbf{s}}(t) = [\hat{s}_{\mathrm{b}}, \hat{s}_{\mathrm{h}}, \hat{s}_{\mathrm{v}}]^T$$



removal of eye-motion artifacts

$$\mathbf{x}_{EBR}(t) = (\mathbf{I} - \hat{\mathbf{A}}_{\mathrm{eye}}\hat{\mathbf{A}}^{\#}_{\mathrm{eye}})\mathbf{x}(t)$$

Use all electrodes in estimation of interference

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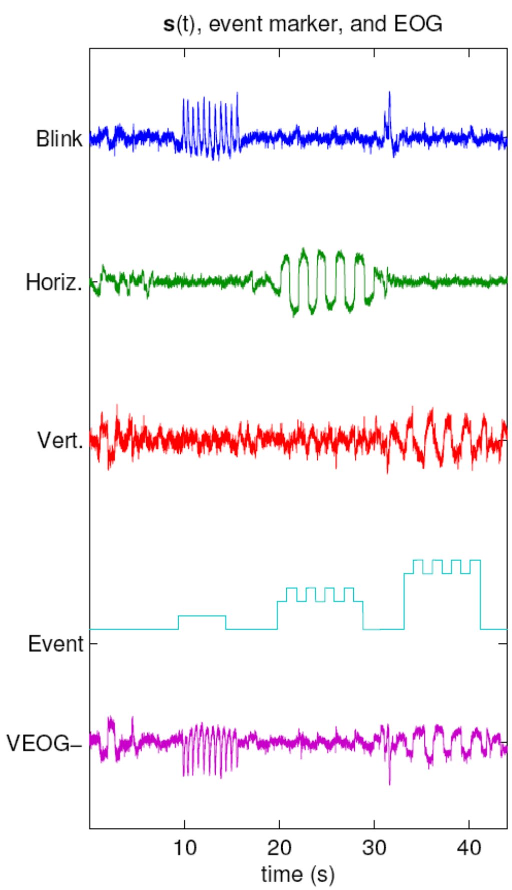
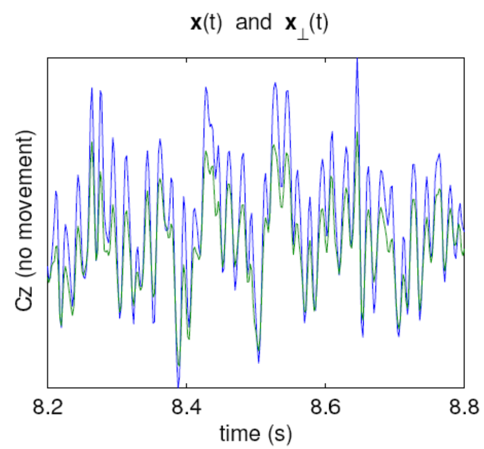
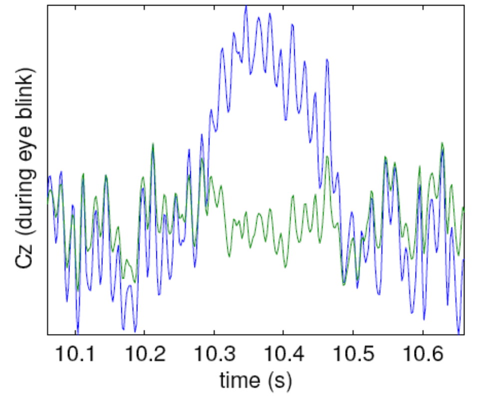
Maximum Difference





No blink



Blink

Maximum Difference

Maximum Magnitude Difference

$$\mathbf{w}_{\text{erd}} = \mathbf{v} = \mathbf{a}^{\#T} = \overline{\Delta x} / \|\overline{\Delta x}\|^2$$

$$\mathbf{w}_{\text{ml}} = \mathbf{R}^{-1}\overline{\Delta x}$$

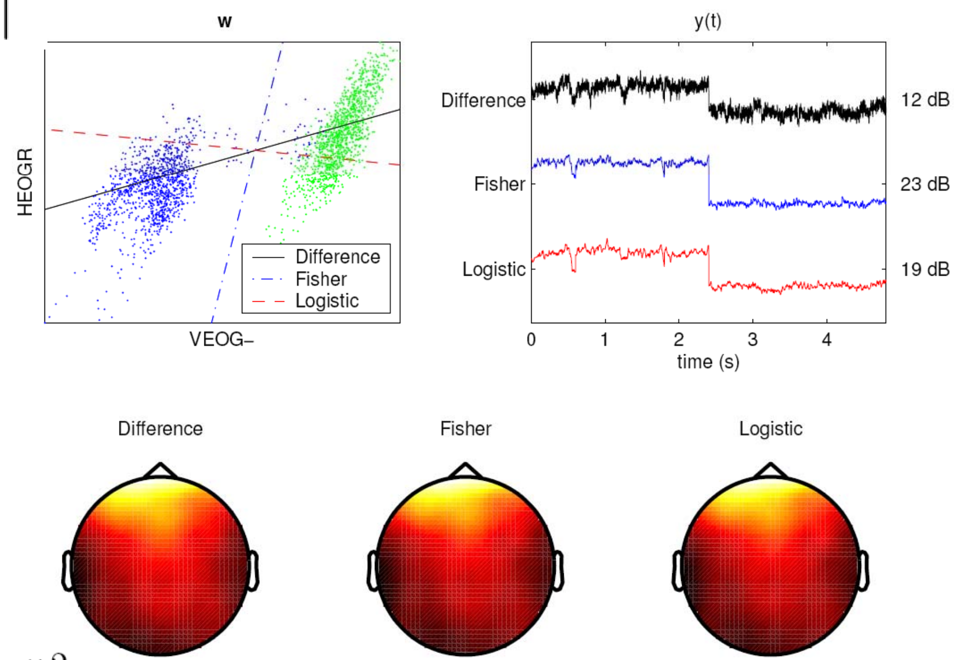
$$\mathbf{w}_{\text{fld}} = (\mathbf{R}_1 + \mathbf{R}_2)^{-1}\overline{\Delta x}$$

$$\mathbf{w}_{\text{lr}} = \arg\min_{\mathbf{w}} L(\mathbf{w}, b)$$

$$L(\mathbf{w}, b) = -\sum_t \log p(c_t|y_t)$$

$$L(\mathbf{w}, b) = -\sum_t \log p(c_t|y_t) + \frac{\lambda}{2}\|\mathbf{w}\|^2$$

$$p(c = +1|\mathbf{x}) = f(y) = \frac{1}{1+e^{-y}} = \frac{1}{1+e^{-(\mathbf{w}^T\mathbf{x}+b)}}$$



Maximum Power

$$\mathbf{w}_{\mathrm{pc}} = \arg\max_{\mathbf{w},\|\mathbf{w}\|=const.} \sum_t y^2(t) = \arg\max_{\mathbf{w}} \frac{\mathbf{w}^T\mathbf{R}\mathbf{w}}{\mathbf{w}^T\mathbf{w}}$$

$$\hat{\mathbf{a}}_{\mathrm{pc}} = \mathbf{R}\mathbf{w}_{\mathrm{pc}}\left(\mathbf{w}_{\mathrm{pc}}^T\mathbf{R}\mathbf{w}_{\mathrm{pc}}\right)^{-1} = \frac{\mathbf{w}_{\mathrm{pc}}}{\|\mathbf{w}_{\mathrm{pc}}\|^2}$$

<u>Maximum Power-Ratio</u>

$$\begin{aligned}\mathbf{w}_{\mathrm{ge}} &= \arg\max_{\mathbf{w},\|\mathbf{w}\|=1} \frac{\sum_{t_2}\sum_{\tau} y^2(t_2+\tau)}{\sum_{t_1}\sum_{\tau} y^2(t_1+\tau)} \\ &= \arg\max_{\mathbf{w}} \frac{\mathbf{w}^T\mathbf{R}_2\mathbf{w}}{\mathbf{w}^T\mathbf{R}_1\mathbf{w}}\,.\end{aligned}$$

Maximum Power

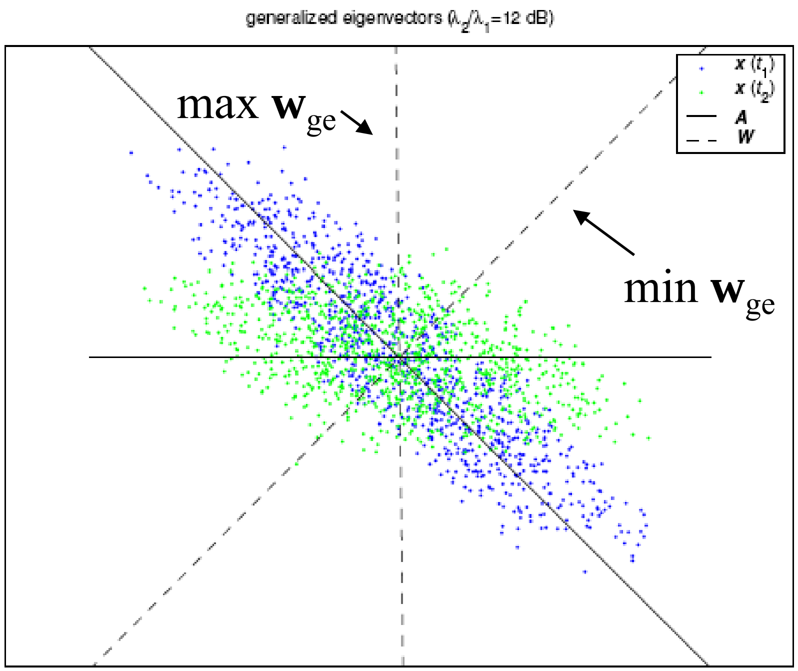


Fig. 5. Generalized eigenvalues and independent components. Dark and light dots indicate (artificial) samples with covariance matrix $\mathbf{R}_1$ and $\mathbf{R}_2$. Dashed lines indicate the projection vectors $\mathbf{w}_{ge}$ that generate the maximum and minimum power-ratio for projected component $y(t)$ on all samples. Solid lines indicate the columns of the corresponding $\hat{\mathbf{A}}_y$.

Maximum Power

ERD/ERS with generalized eigenvalues.

Subject responds to a visual stimulus with a button press.

Prior to the maximum-power ratio analysis, all EEG channels are bandpass filtered between 5-40Hz.

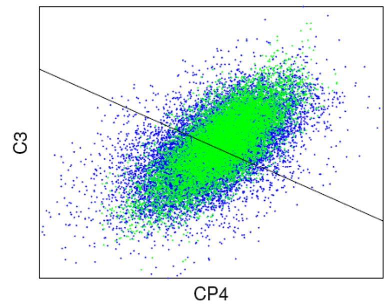
The covariance matrices $\mathbf{R}_1$ and $\mathbf{R}_2$ are computed in a window 200ms before ($\mathbf{R}_1$) and 200ms after ($\mathbf{R}_2$) the button press.

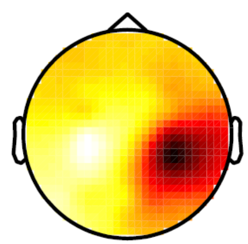
Maximum Power

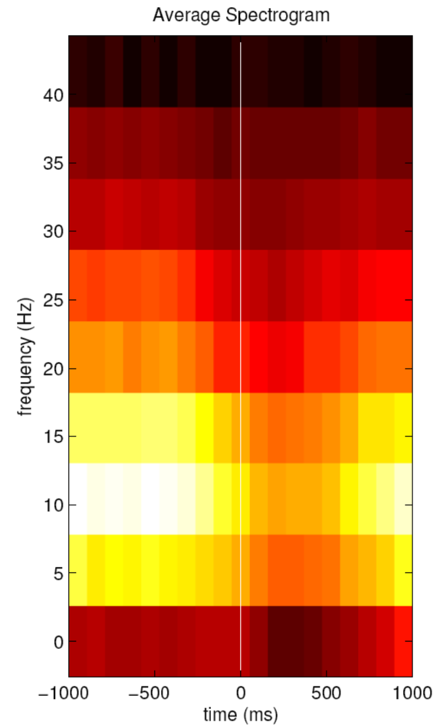
Top left: Scatter plot of the corresponding activity for two of the 64 EEG sensors. Solid line indicates the orientation, $\mathbf{w}_{ge}$, along with the two distributions having a maximum power (variance) ratio, estimated using generalized eigenvalues.

Bottom left: Estimated forward model corresponding to $\mathbf{w}_{ge}$. Clear is that the source activity originates over motor areas (it is maximal over C3 and CP4) and has opposite sign (180 phase delay) between the hemispheres

Right: Spectrogram computed for the component $\mathbf{y}(t)$ (averaged over 300 button press events) Button press indicated with a vertical white line. Alpha band activity (maximal at 12Hz for this subject) decreases (de-synchronizes) for about 500ms after the button push.







Statistical Independence

Statistical independence implies for all $i \neq j, t, \tau, n, m$:

$$E[s_i^n(t)\, s_j^m(t+\tau)] = E[s_i^n(t)]E[s_j^m(t+\tau)]$$

For M sources and N sensors each t, τ, n, m gives $M(M\text{-}1)/2$ conditions for NM unknowns in $\boldsymbol{A}$.

Sufficient conditions if we use multiple:

use	sources assumed	condition	statistic	algorithm
t	non-stationary	$\mathbf{W}\,\mathbf{R_x}(t)\,\mathbf{W}^T = \mathrm{diag}$	covariance	decorrelation
τ	non-white	$\mathbf{W}\,\mathbf{R_x}(\tau)\,\mathbf{W}^T = \mathrm{diag}$	cross-correlation	SOBI
n, m	non-Gaussian	$\mathbf{W}\,\mathbf{C_x}(i,j)\,\mathbf{W}^T = \mathrm{diag}$	4th cumulants	JADE (ICA)

Example: Non-stationary Independent Sources

The independence assumption establishes that the covariance $\mathbf{R_x}(t)$ is diagonalized by $\mathbf{W}$ for all times t:

$$\mathbf{R_y}(t_1) = \mathbf{W}\,\mathbf{R_x}(t_1)\,\mathbf{W}^T = \mathrm{diag}$$
$$\mathbf{R_y}(t_2) = \mathbf{W}\,\mathbf{R_x}(t_2)\,\mathbf{W}^T = \mathrm{diag}$$

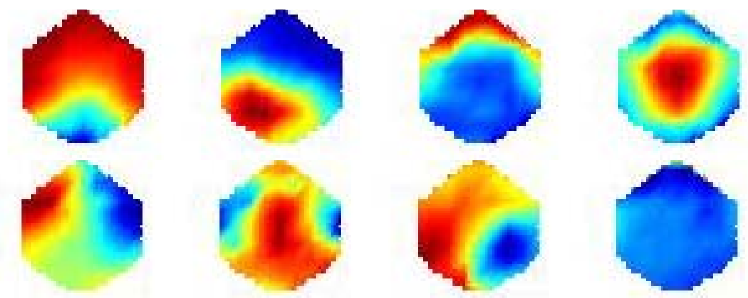
Combining these we obtain the solutions again with the Generalized Eigen-vectors:

$$\mathbf{R_x}(t_2)^{-1}\mathbf{R_x}(t_1)\,\mathbf{W} = \mathbf{W}\,\lambda$$

More robust if we use simultaneous diagonalization of multiple covariances.

Example: First 8 independent components that explain 64 observed EEG sensors $\mathbf{x}$ in visual discrimination task 250 ms before and after stimulus presentation

EEG sensor projections $\mathbf{A}=\mathbf{W}^{-1}$



Using Spatio-temporal Linear Processing

$$Y = WX$$

recovered sources → Y

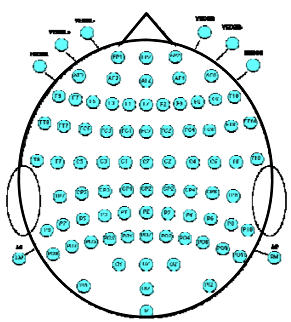
transformation matrix → W

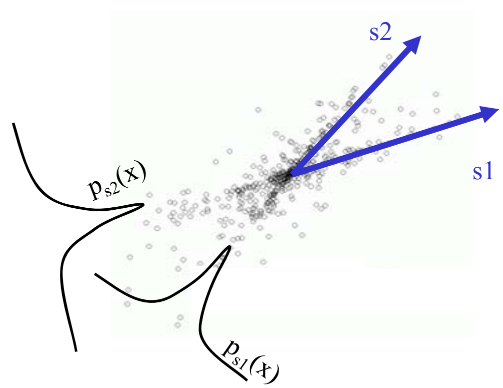
observations → X

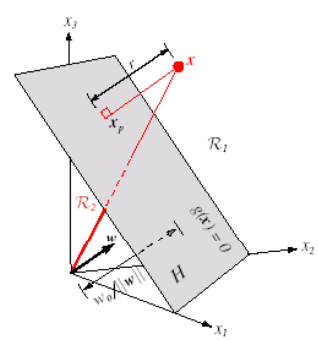
X — $\underbrace{\text{artifact removal and dimensionality reduction} \rightarrow \text{linear discrimination}}_{W}$ — Y

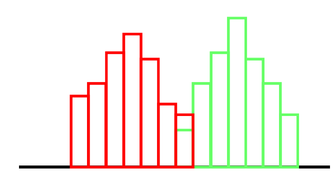
Data → artifact removal and dimensionality reduction → linear discrimination →(1) *P(T)*

64-128 channels









An Example

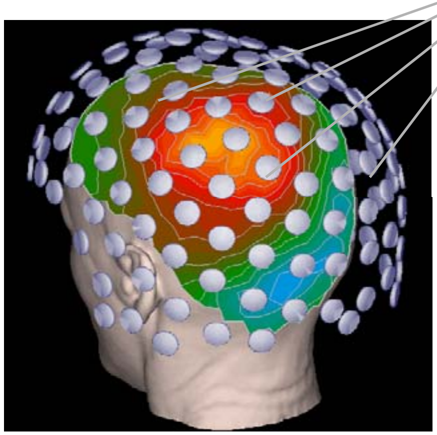
…predicting motor response using linear regression…

Single-trial Detection with Spatial Integration

Conventional Event Related Potentials (ERP) averages over trials.
We substitute trial averaging by spatial integration:

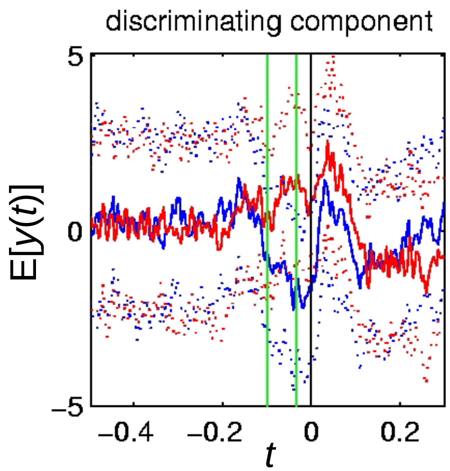
$$s(t) = \mathbf{w}^T \mathbf{x}(t)$$

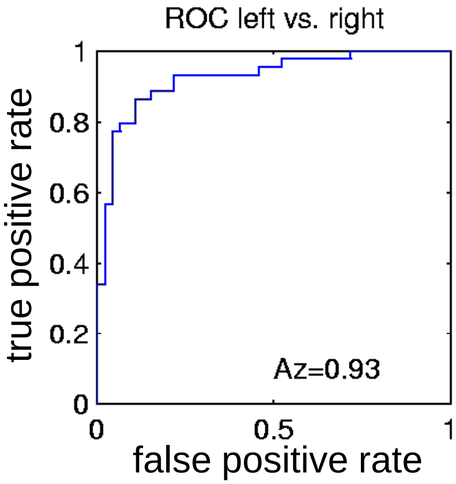
$\mathbf{x}(t)$



Linear discriminants: Compute spatial weighting **w** which maximally discriminates sensor array signals $\mathbf{x}(t)$ for two different conditions.

Ex: Detect motor planning activity Predict button press from 122 MEG sensors with linear discriminator $\mathbf{w}$ such that $s(t)$ differs the most during 100-30 ms window *prior* to button push.

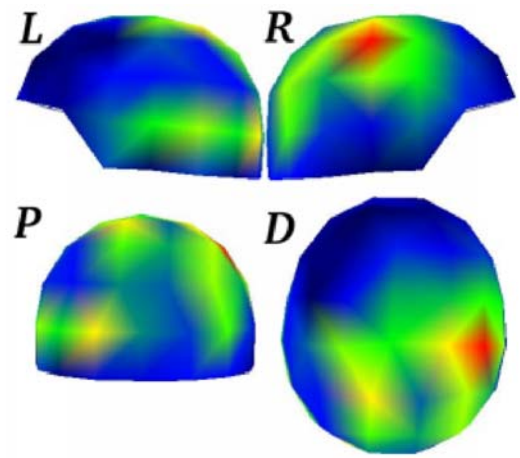




Localization of Discriminating Component

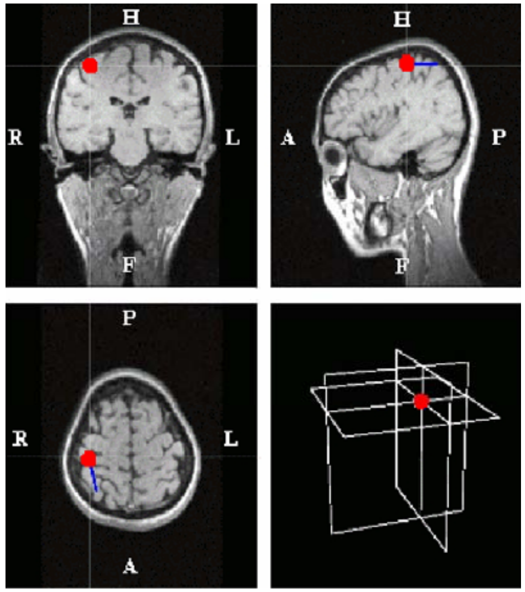
... possible because we have a linear model ...

What is the electrical coupling **a** of the hypothetical source *s* that explains most of the activity **X**?



Least squares solution:

$$\mathbf{a} = \frac{\mathbf{X}\mathbf{y}}{\mathbf{y}^{\mathrm{T}}\mathbf{y}}$$



Strong coupling indicates low attenuation. Intensity on these “sensor projections” **a** indicates closeness of the source to the sensors.

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- Tutorial on the Linear Analysis of EEG
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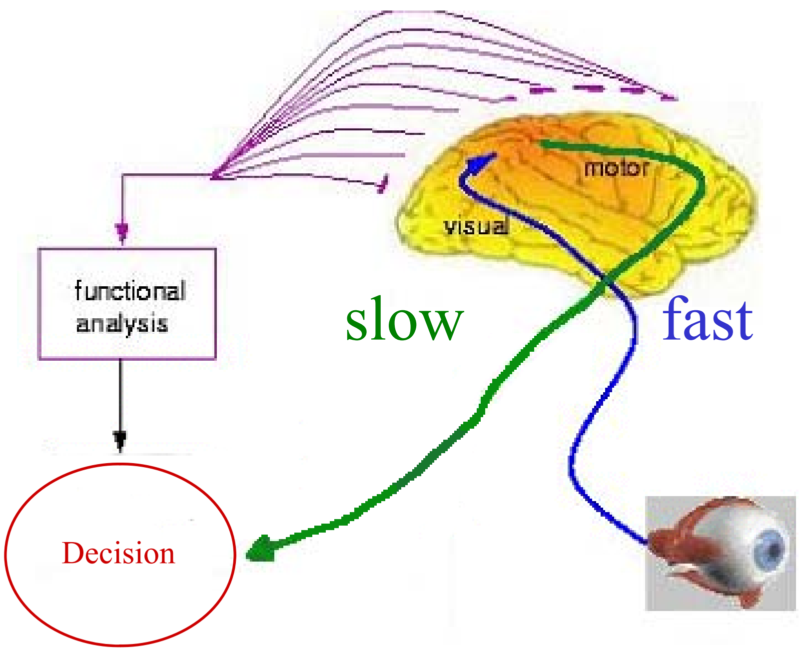
Applications: Cognitive User Interface

Hypotheses:

- EEG can be used to detected cognitive events related to visual target detection, discrimination, and perceived error.
- Such cognitive events can be detected more quickly and reliably than overt (motor) responses.



Objective: Use EEG signatures of cognitive events to improve task performance

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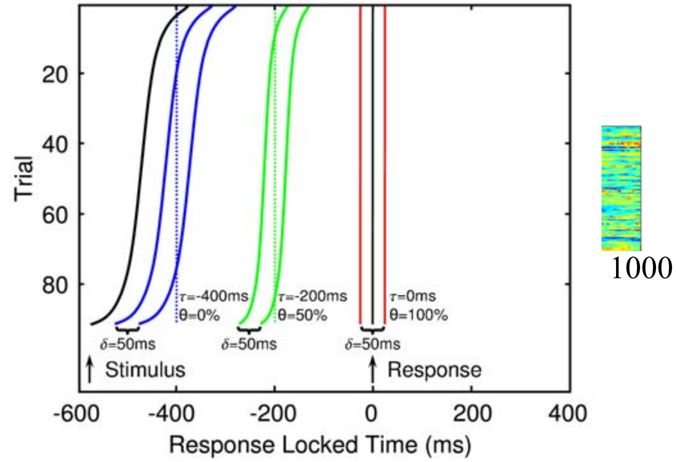
Single-trial Discrimination

Linear discriminants: Compute spatial weighting **w** which maximally discriminates sensor array signals **x**(*t*) for two different conditions.

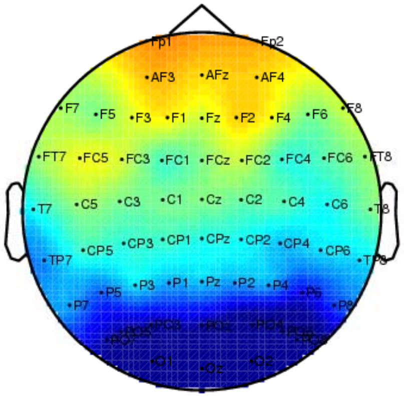
$$\mathbf{y}(t) = \mathbf{w}^T_{\tau,\delta,\theta}\mathbf{x}(t) \qquad \tau = \left\{ t_k - \frac{\delta}{2} \rightarrow t_k + \frac{\delta}{2} \right\}$$



Localization of Discriminating Component
possible because we have a linear model

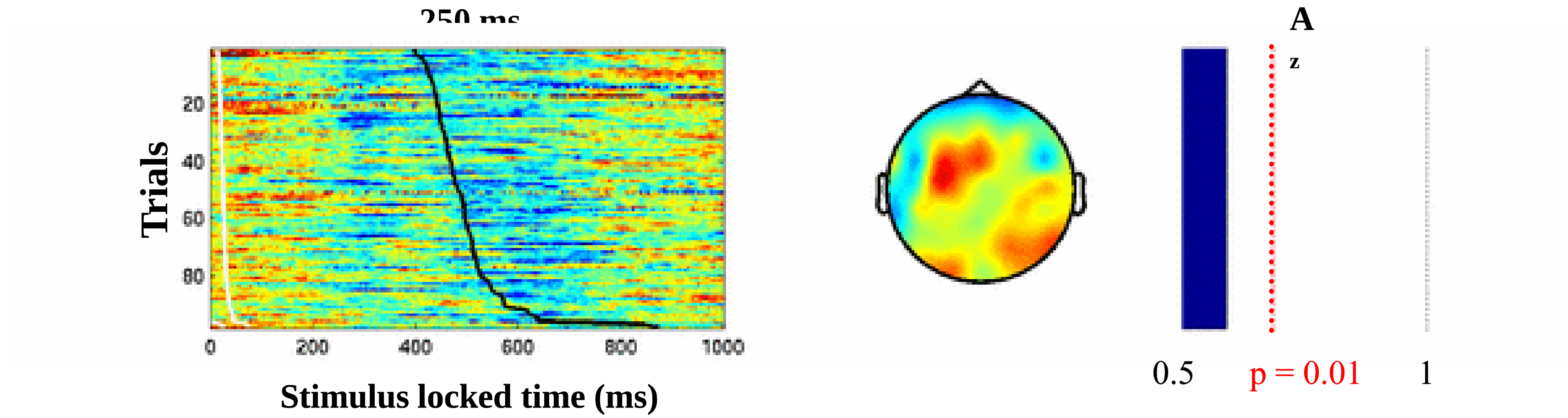
$$\mathbf{a} = \frac{\mathbf{X}\mathbf{y}}{\mathbf{y}^T\mathbf{y}}$$

Strong coupling indicates low attenuation. Intensity on these "sensor projections" $\mathbf{a}$ indicates closeness of the component to the sensors.



Parra, Sajda et al. Neuroimage, 2002
Parra, Spence, Gerson & Sajda, Neuroimage, 2005

Single-trial Analysis using Linear Discrimination



$$\mathbf{y}(t) = \mathbf{w}^{T}_{\tau,\delta,\theta}\mathbf{x}(t)$$

$$\mathbf{a} = \frac{\mathbf{X}\mathbf{y}}{\mathbf{y}^{\mathrm{T}}\mathbf{y}}$$

Discrimination performance

Neural-based Image Triage

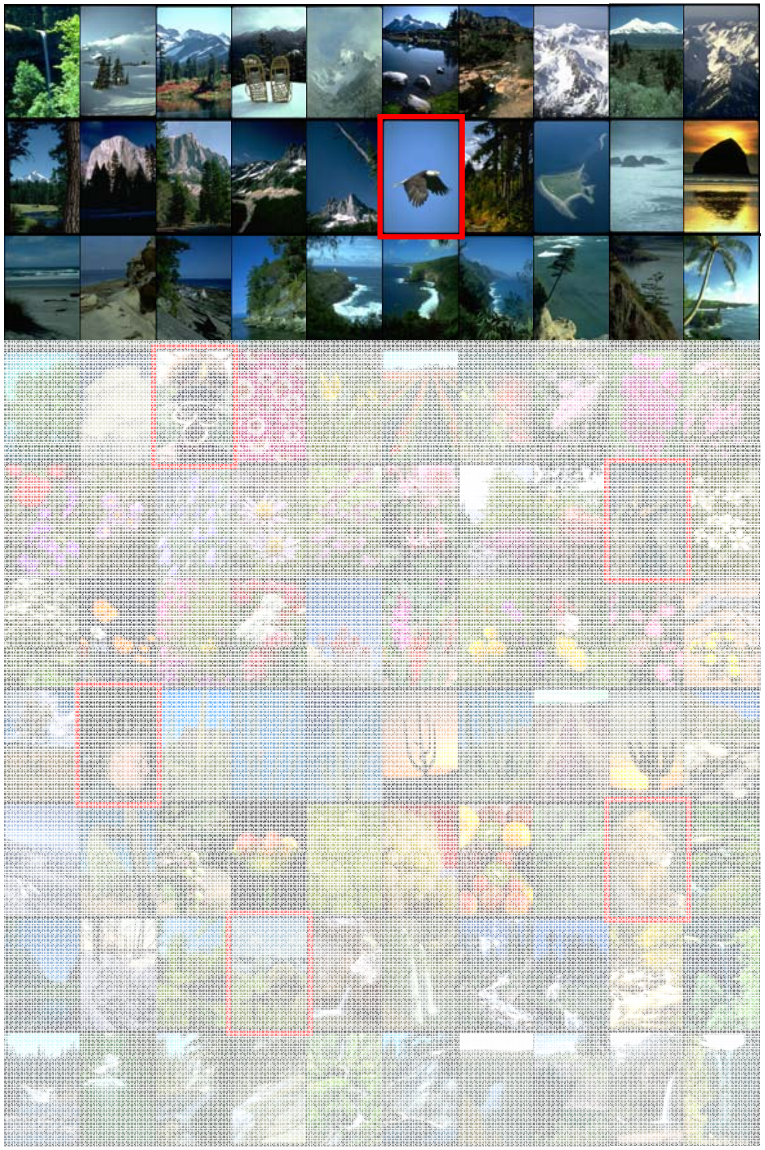


Image Sequence

Neural-based Image Triage

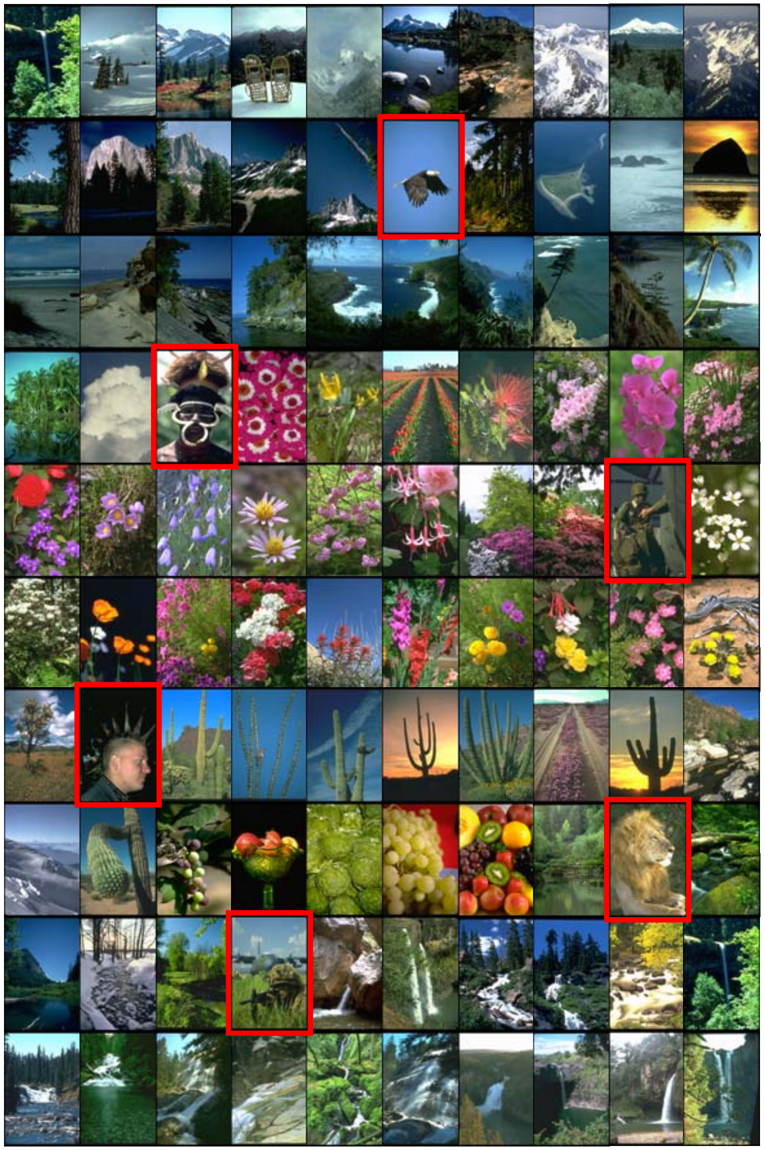
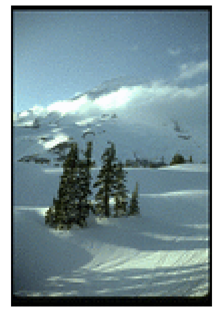
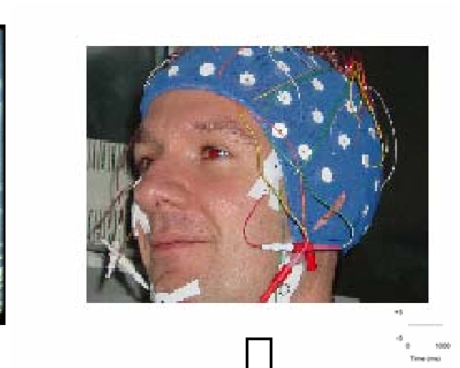


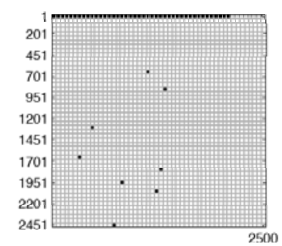
Image Sequence



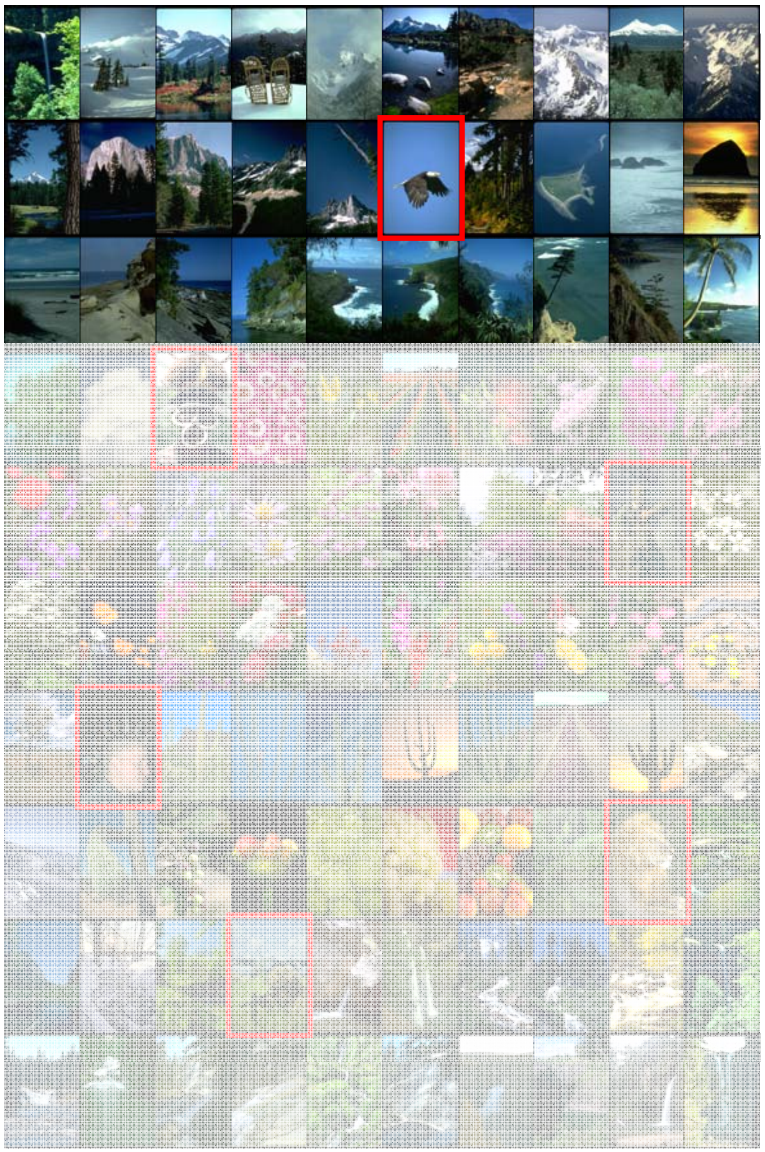


Single-trial decoder

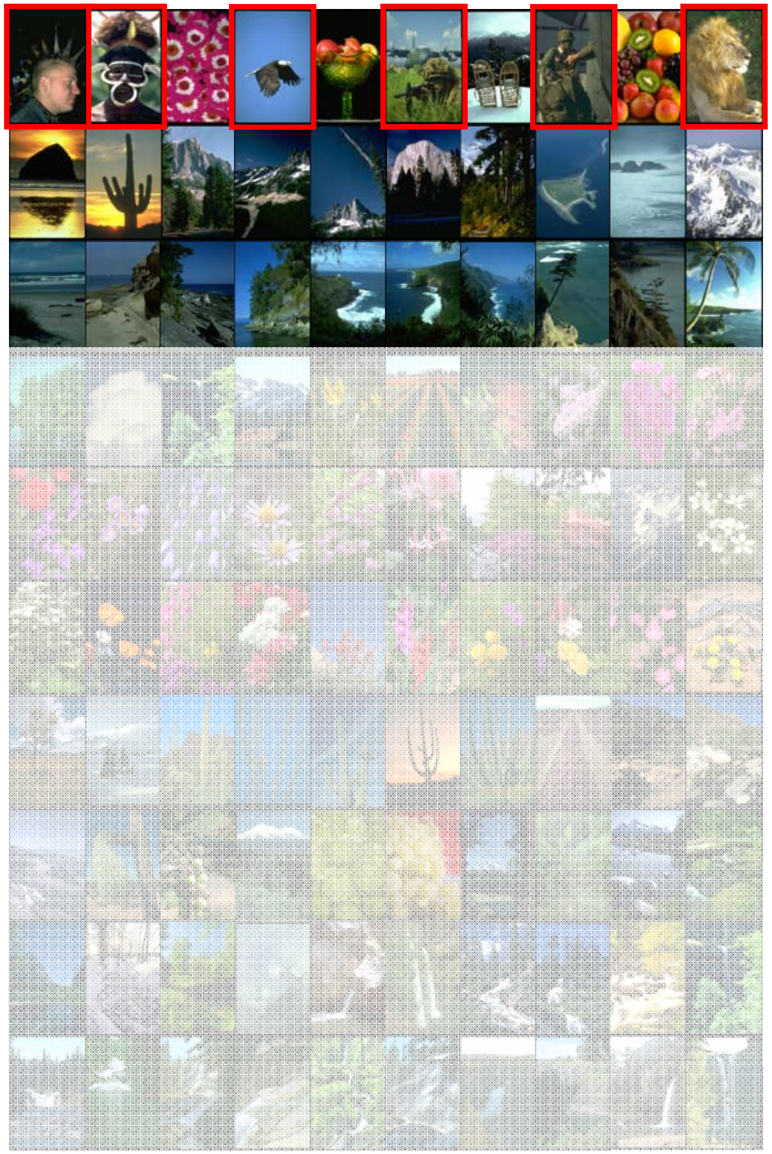
priority list



Neural-based Image Triage

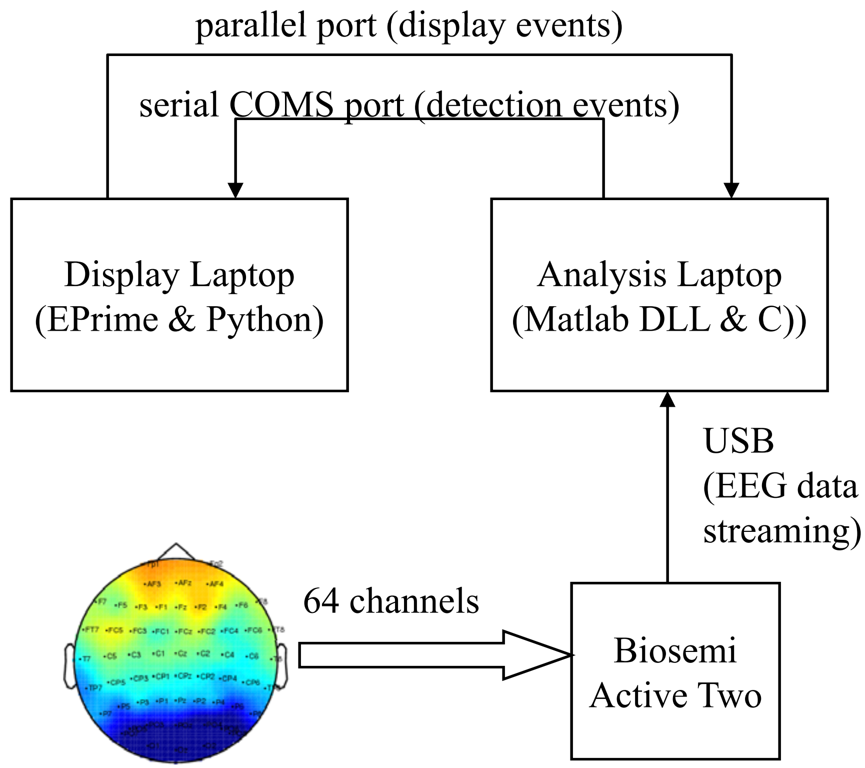


Pre-triage



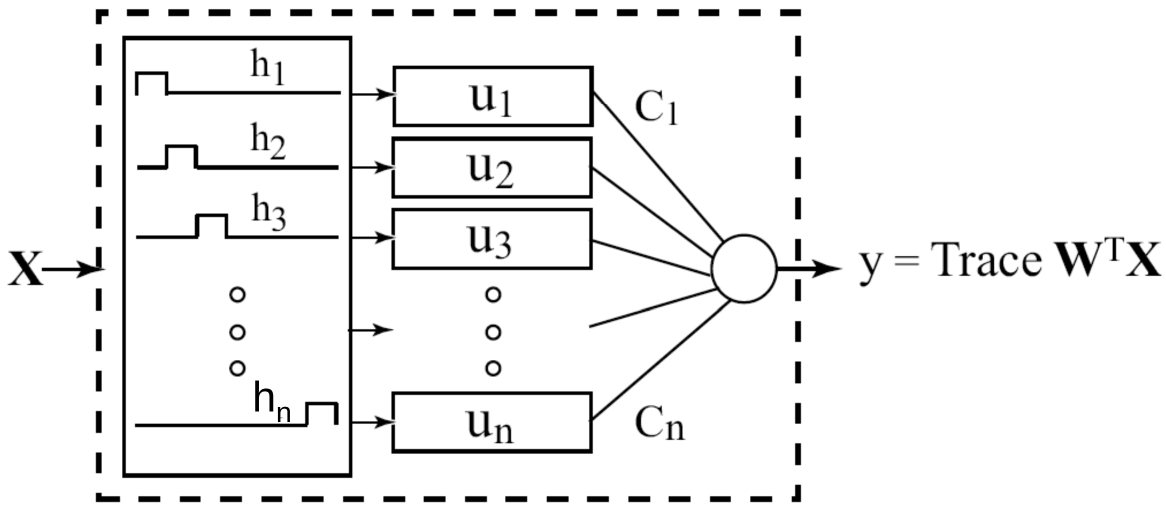
Post-triage

On-line Real-time
Portable Image Triage System



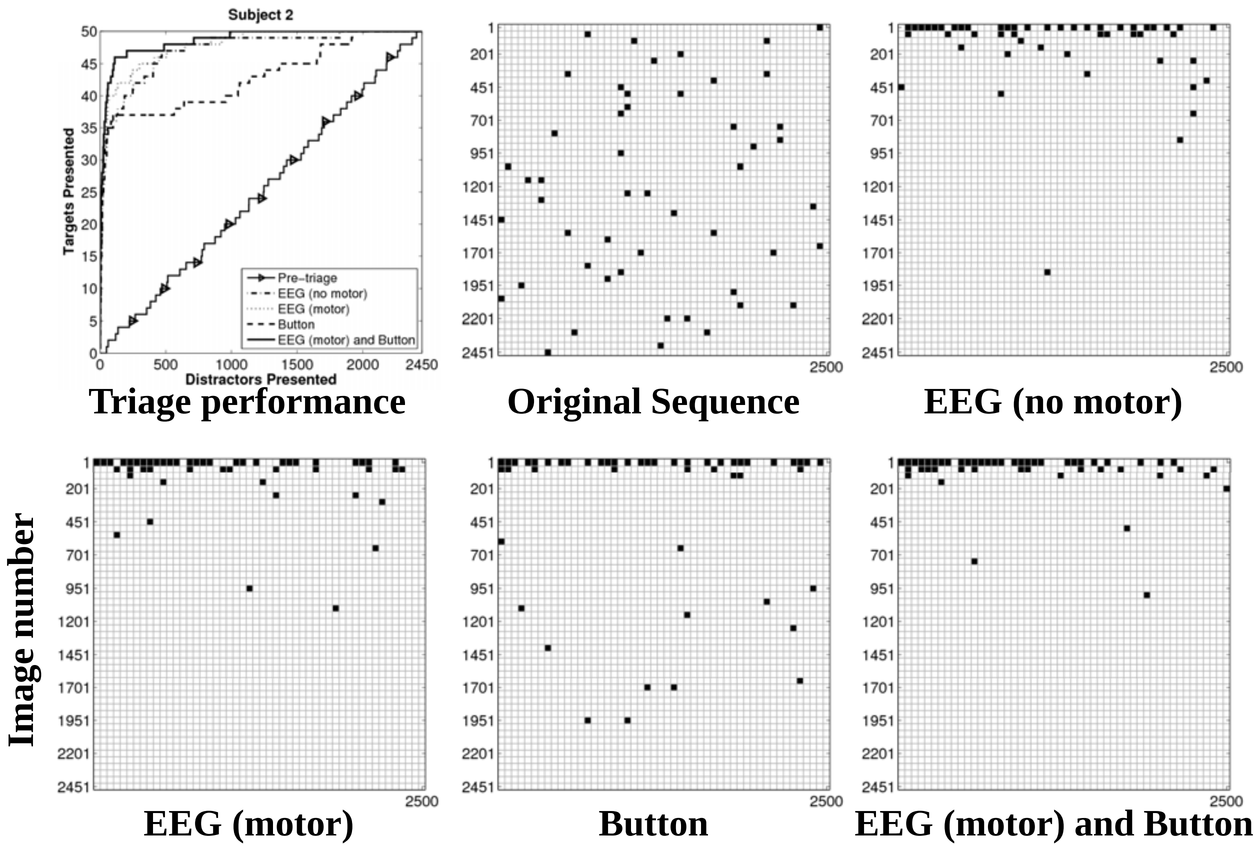
Hierarchical Discriminating Components

…online estimation of all parameters…



$$\mathbf{W} = \sum_{k=1}^{n} u_k (c_k \mathbf{h}_k)^T$$

Triage results



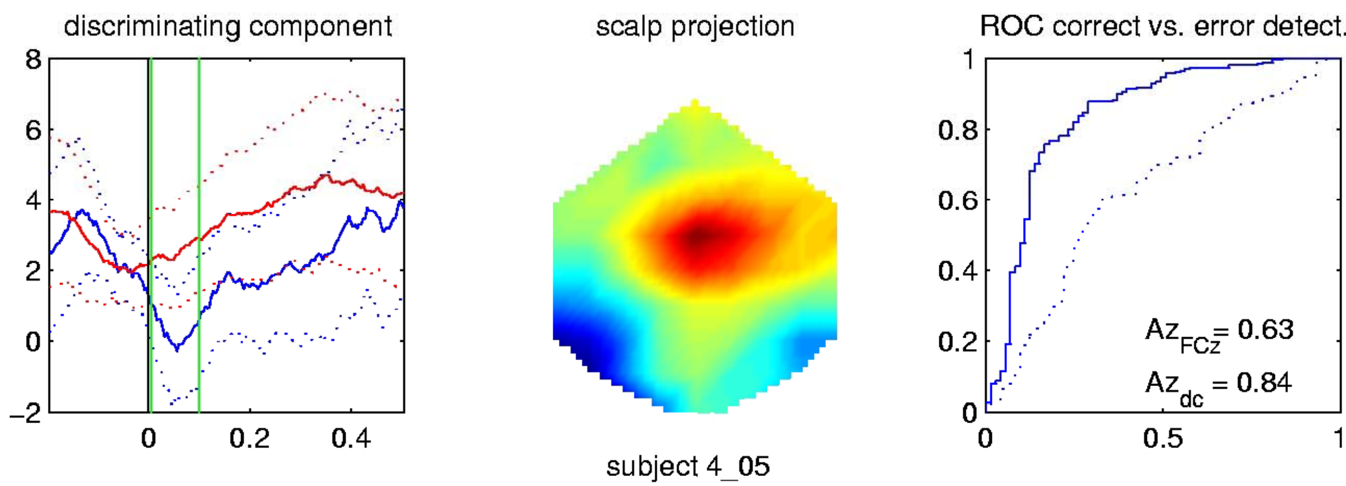
Gerson, Parra & Sajda, IEEE TNSRE, 2006
Sajda et al., Trends in BCI, 2007

Detection of Error Related Negativity During a Visual Discrimination Event

Error Related Negativity (ERN) occurs following perception of errors. It is hypothesized to originate in Anterior Cingulate and to represent response conflict or subjective loss.

Example: Erikson Flanker task

Discrimination of error versus correct response (64 EEG sensors, 100ms)



Real-Time On-Line Error Correction

64 EEG channels

Linear filtering & eye blink removal

Linear classifier for ERN detection

Adaptive threshold for error correction

Machine Corrected Errors

Overall Human-Machine Performance

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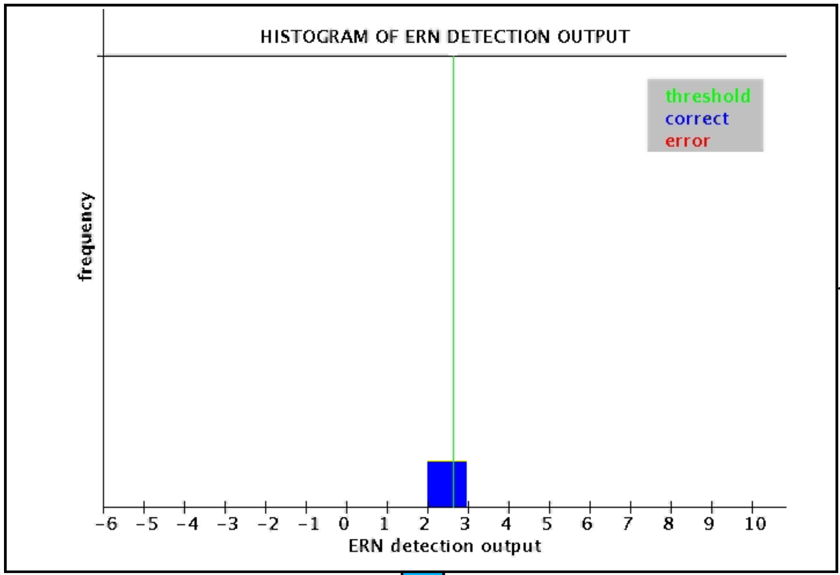
Real-Time On-Line Error Correction

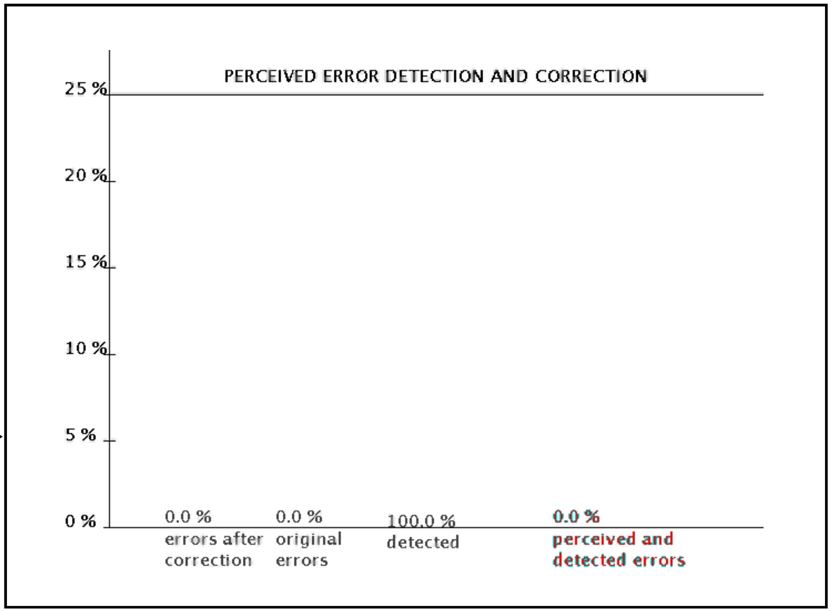
64 EEG channels

Linear filtering & eye blink removal

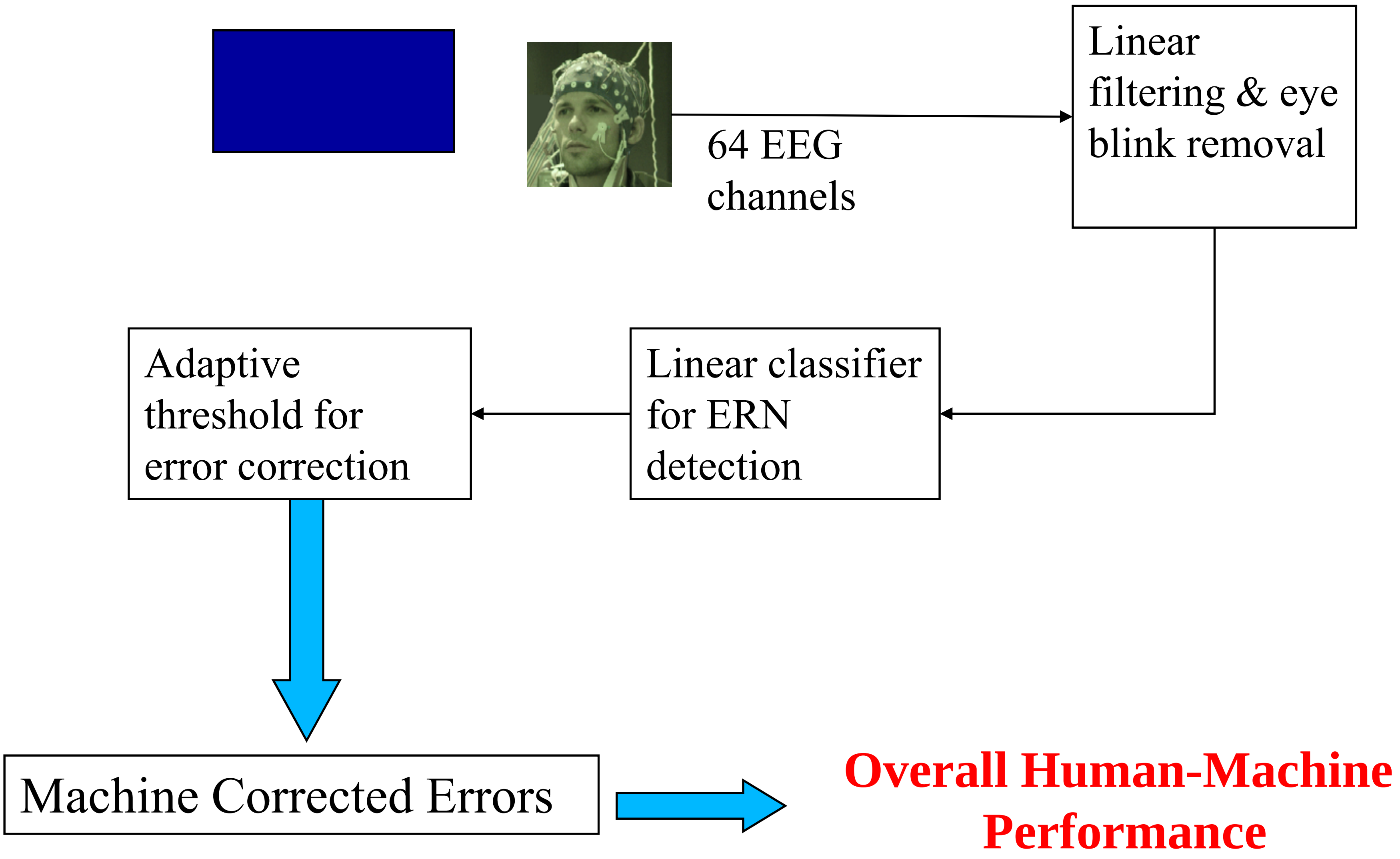


Machine Corrected Errors

200 ms latency



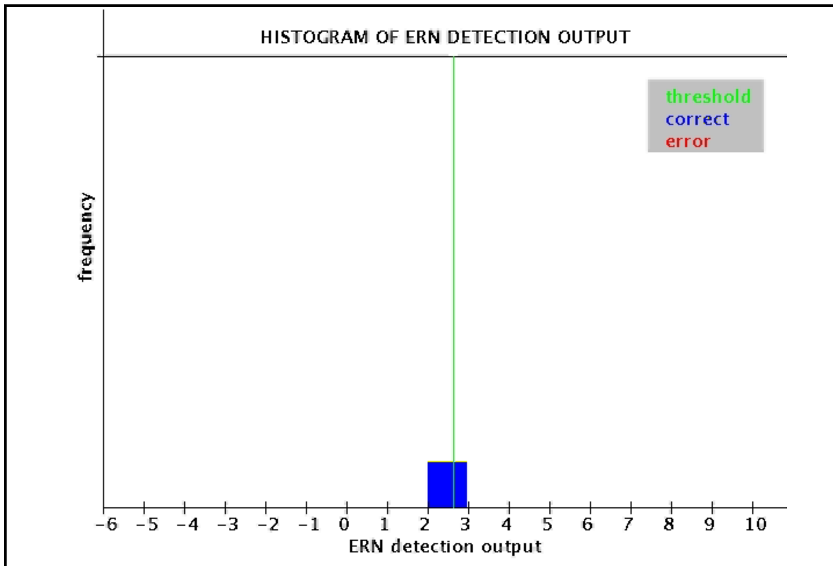
Real-Time On-Line Error Correction



Real-Time On-Line Error Correction

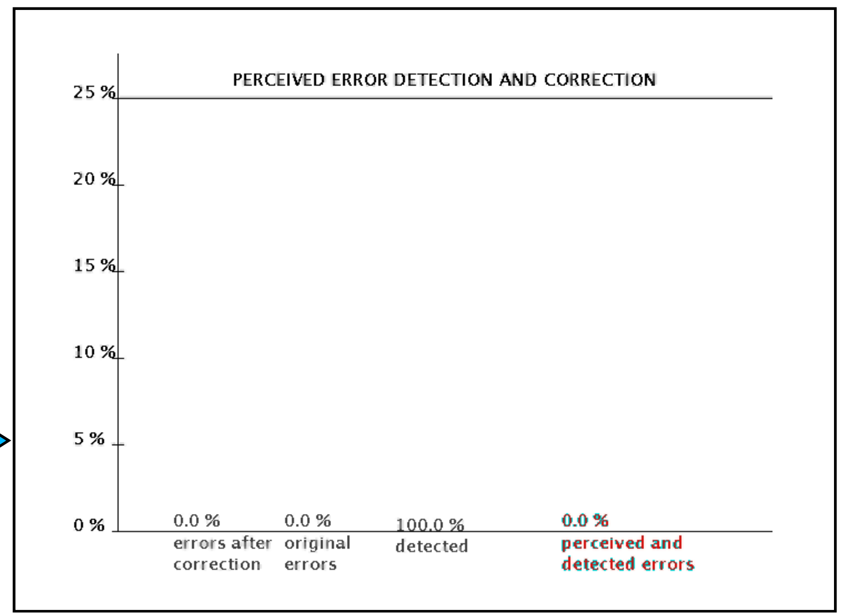
64 EEG channels

Linear filtering & eye blink removal



Machine Corrected Errors

200 ms latency



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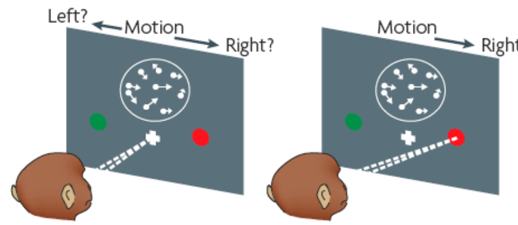
Outline

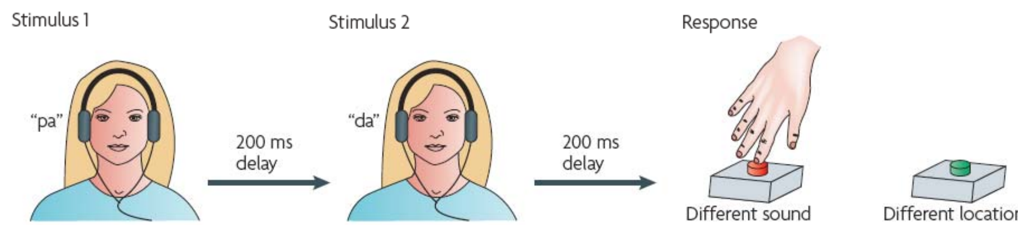
- Tutorial on the Linear Analysis of EEG
- Real-time, On-line Applications: Image Triage and Error Correction
- Decoding EEG to Better Characterize the Neural Basis of Perceptual Decision Making in the Human Brain

Perceptual Decision Making

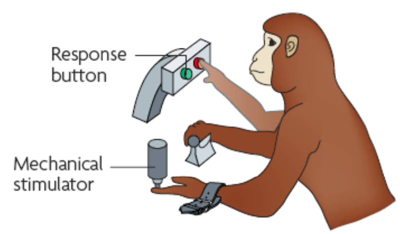
Visual discrimination



Auditory discrimination



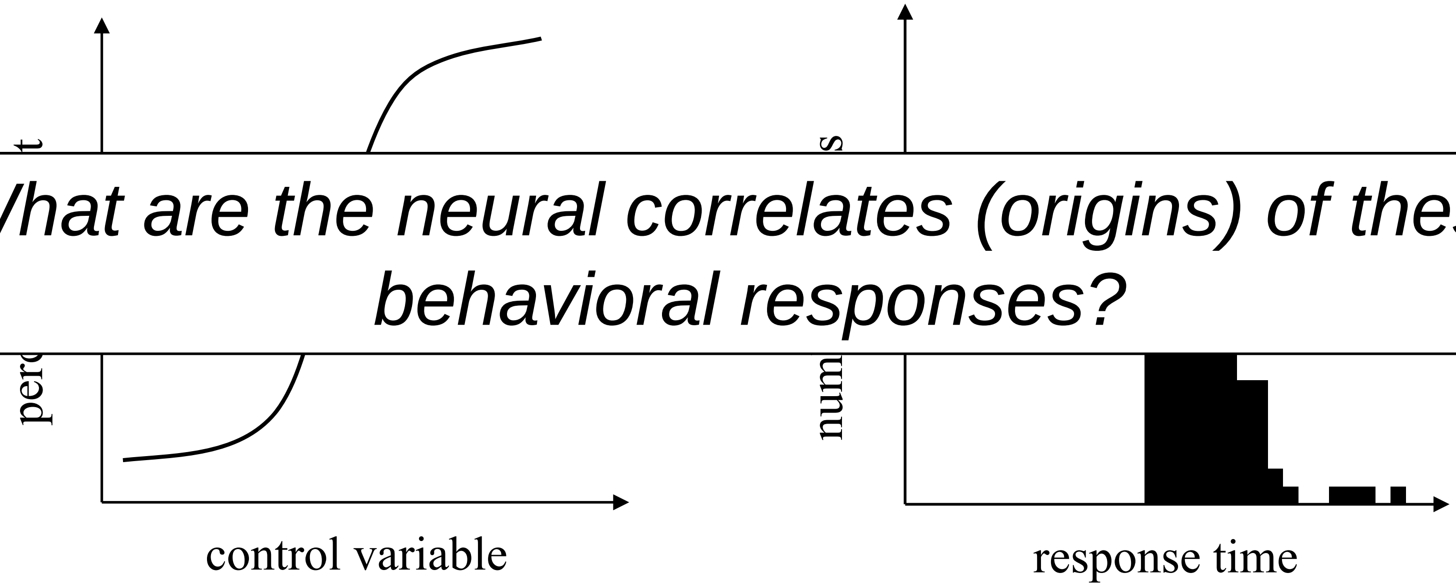
Somatosensory discrimination



from Heekeren et al. *Nature Rev. Neuro*. 2008

Perceptual Decision Making

Behavioral Response



What are the neural correlates (origins) of these behavioral responses?

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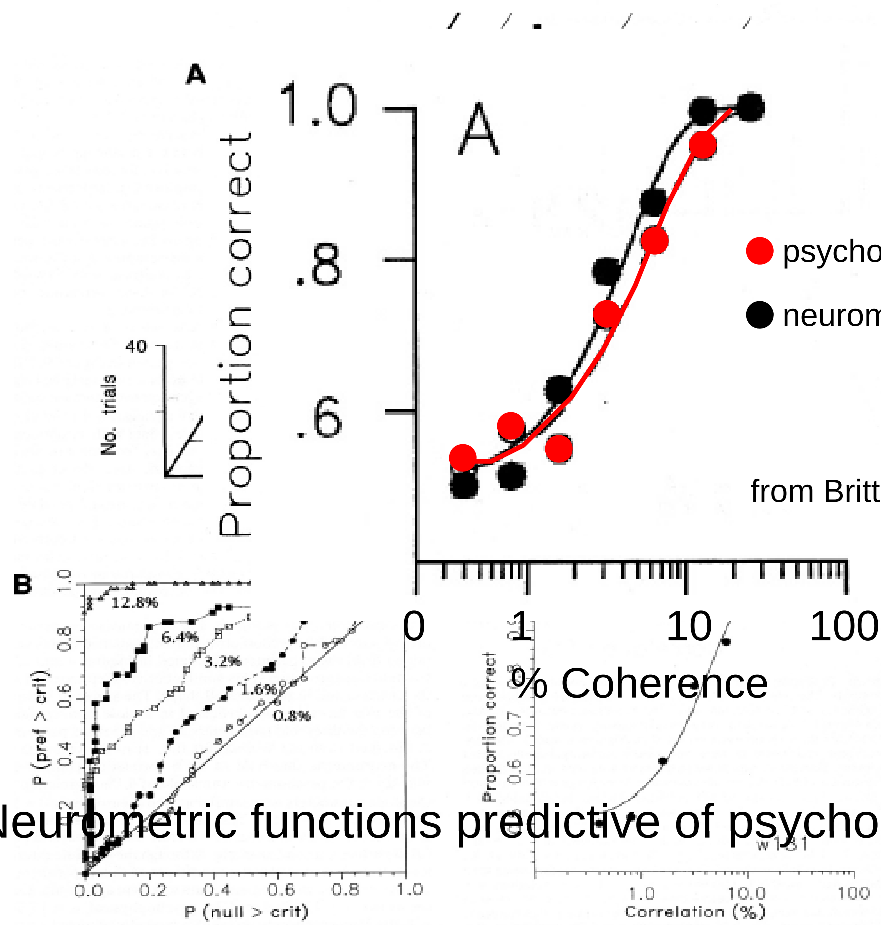
Relating Neural Activity to Behavioral Performance

…previous work: single and multi-unit recordings in primates…

• Signal detection theory used to correlate psychophysical and neuronal responses

Britten et al. '92, '96

QuickTime™ and a
Cinepak decompressor
are needed to see this picture.



psychometric data

neurometric data

responses to "pref" direction

responses to "null" direction

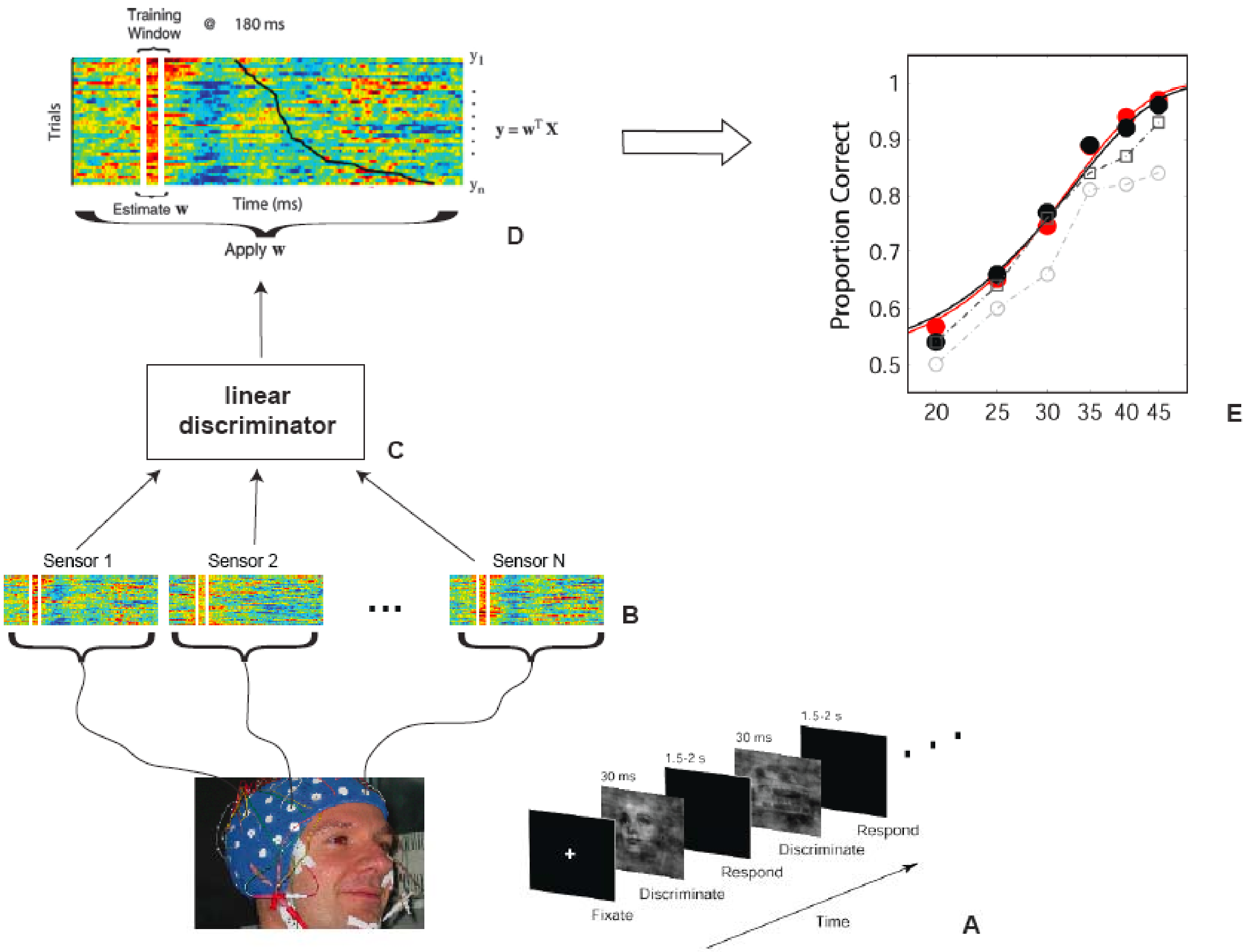
from Britten et al. '92

Neurometric Function

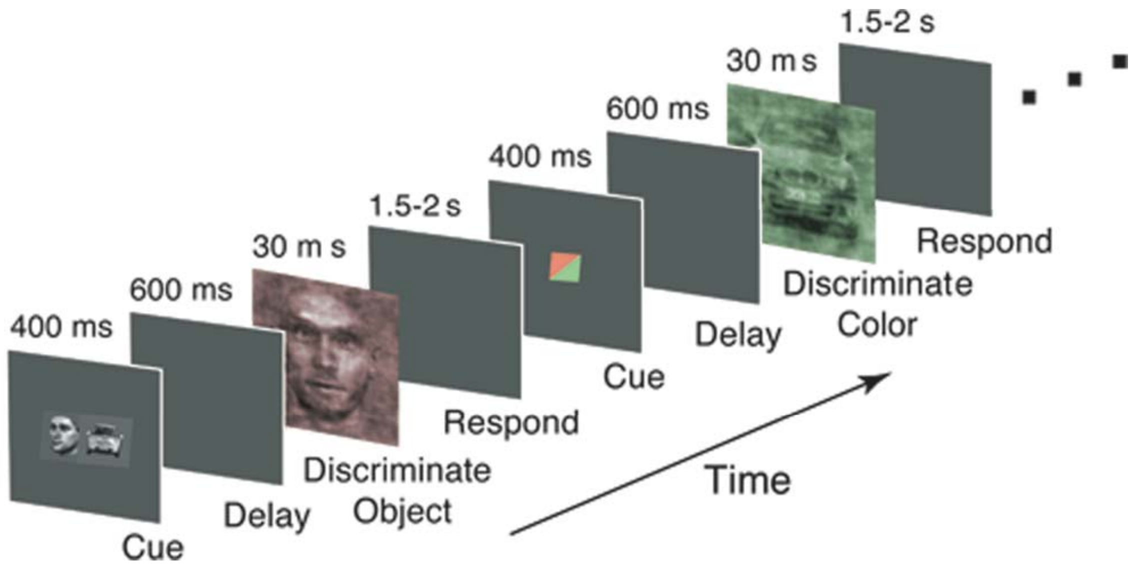
Neurometric functions predictive of psychophysical performance

Identifying Discriminative Components in the EEG

… time-locked spatial filters…



A “Typical” Perceptual Decision Making Task



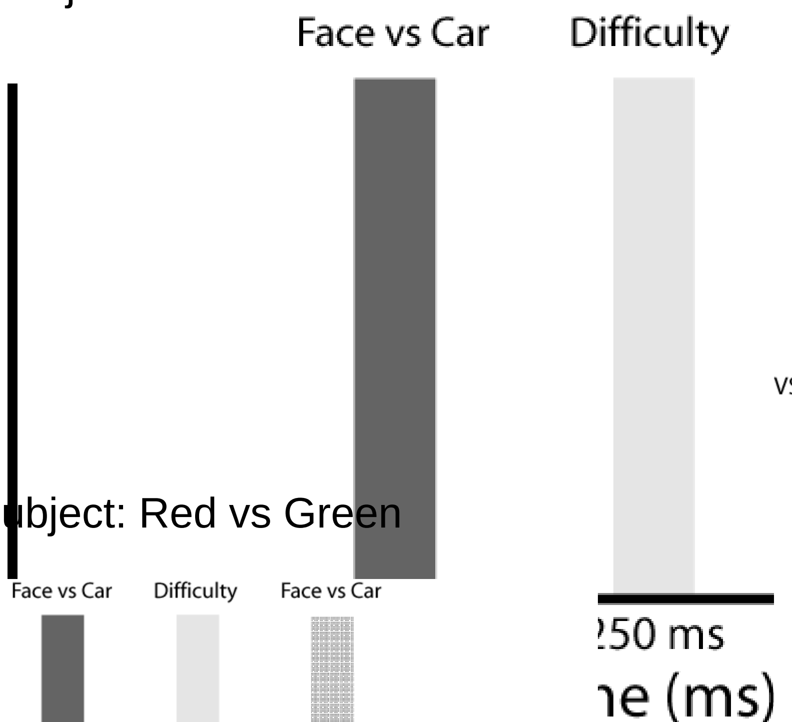
Philiastides, Ratcliff & Sajda, J. Neurosci 2006

Beginnings of a Timing Diagram

High Coherence

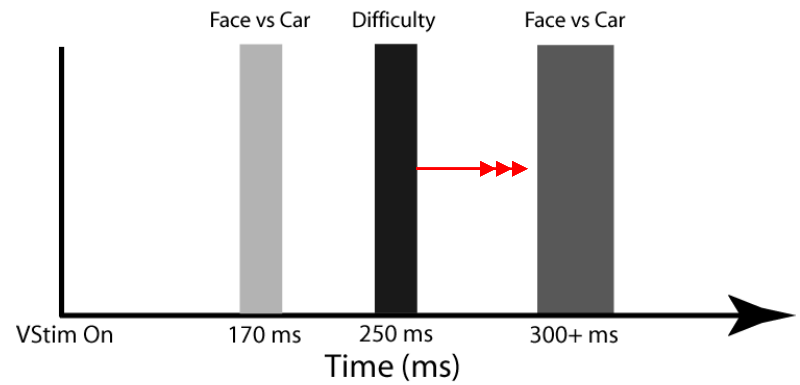
Subject: Face vs Car

High Coherence
Subject: Face vs Car

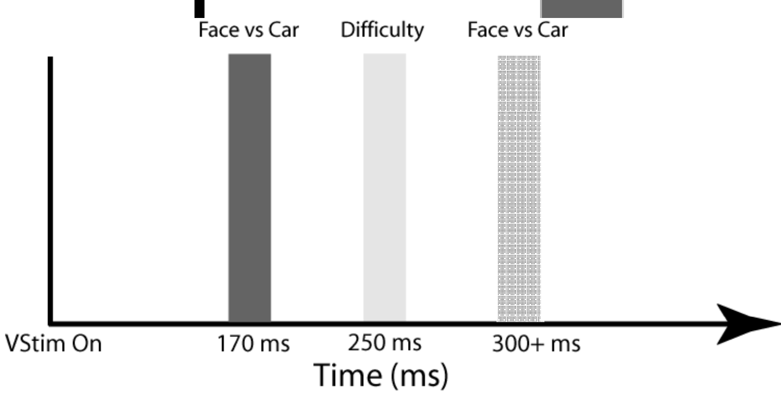


Lower Coherence

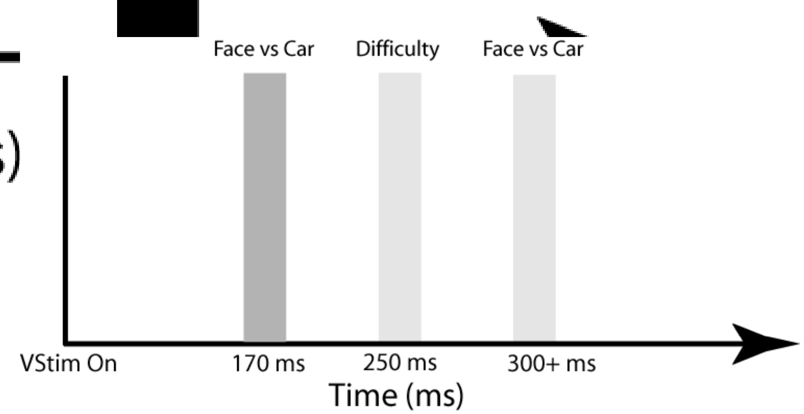
Subject: Face vs Car



Subject: Red vs Green



Subject: Red vs Green



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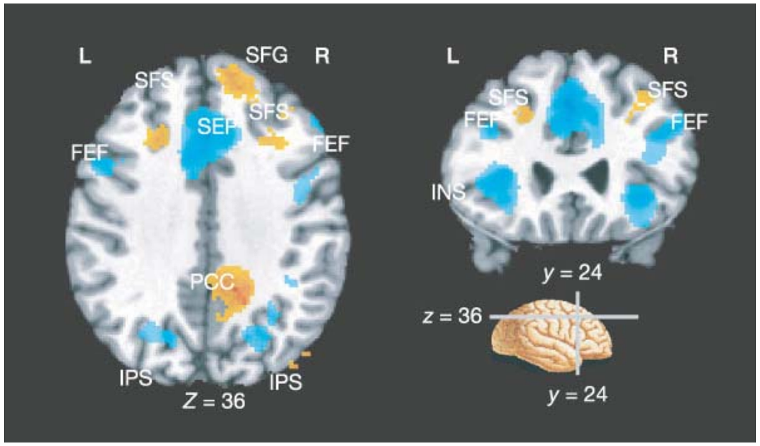
Combining EEG and fMRI

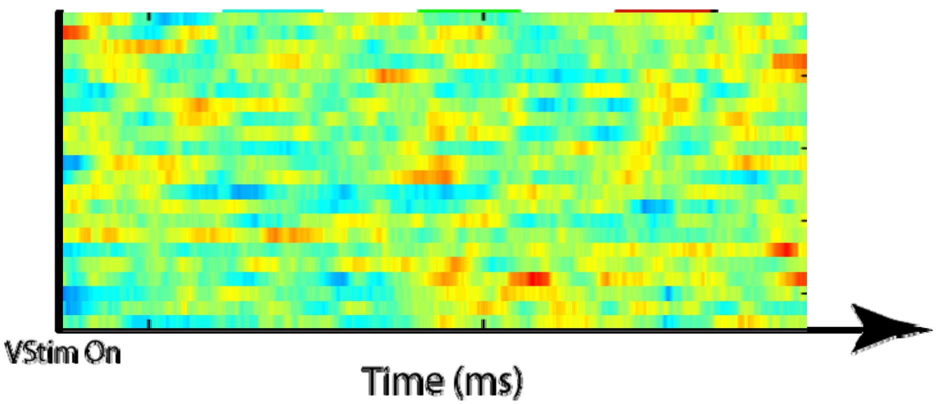
Localization of decision making (fMRI)



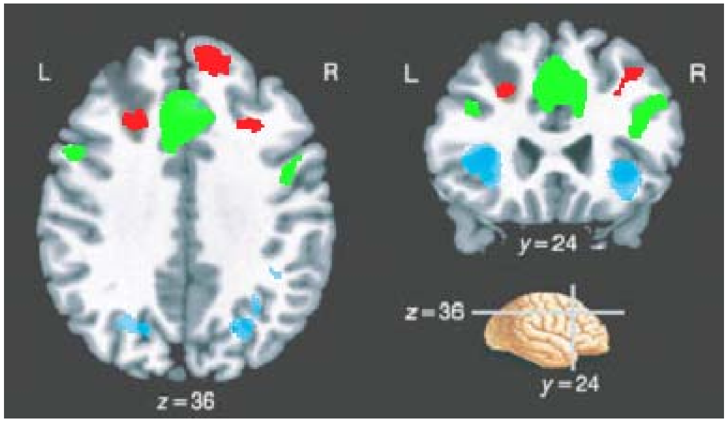
Easy > Hard Decisions
Hard > Easy Decisions

Heekeren et al.
Nature 2004

Timing of decision making (EEG)

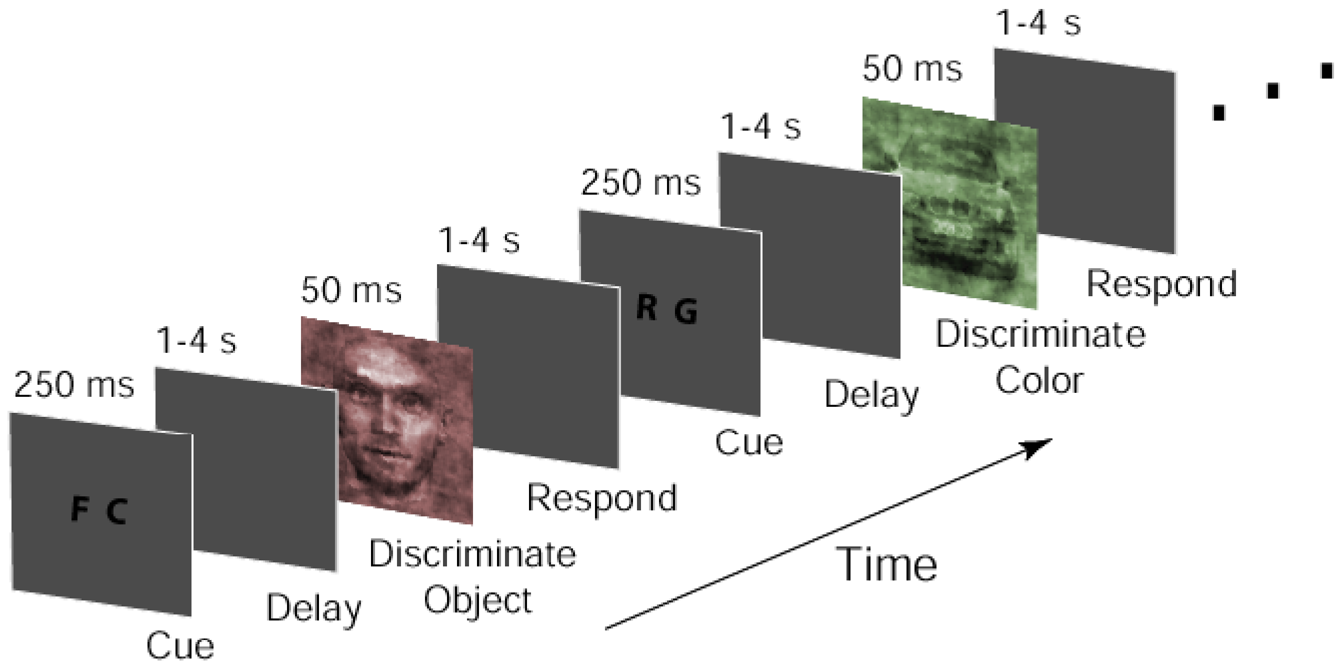


Cortical networks (fMRI/EEG)

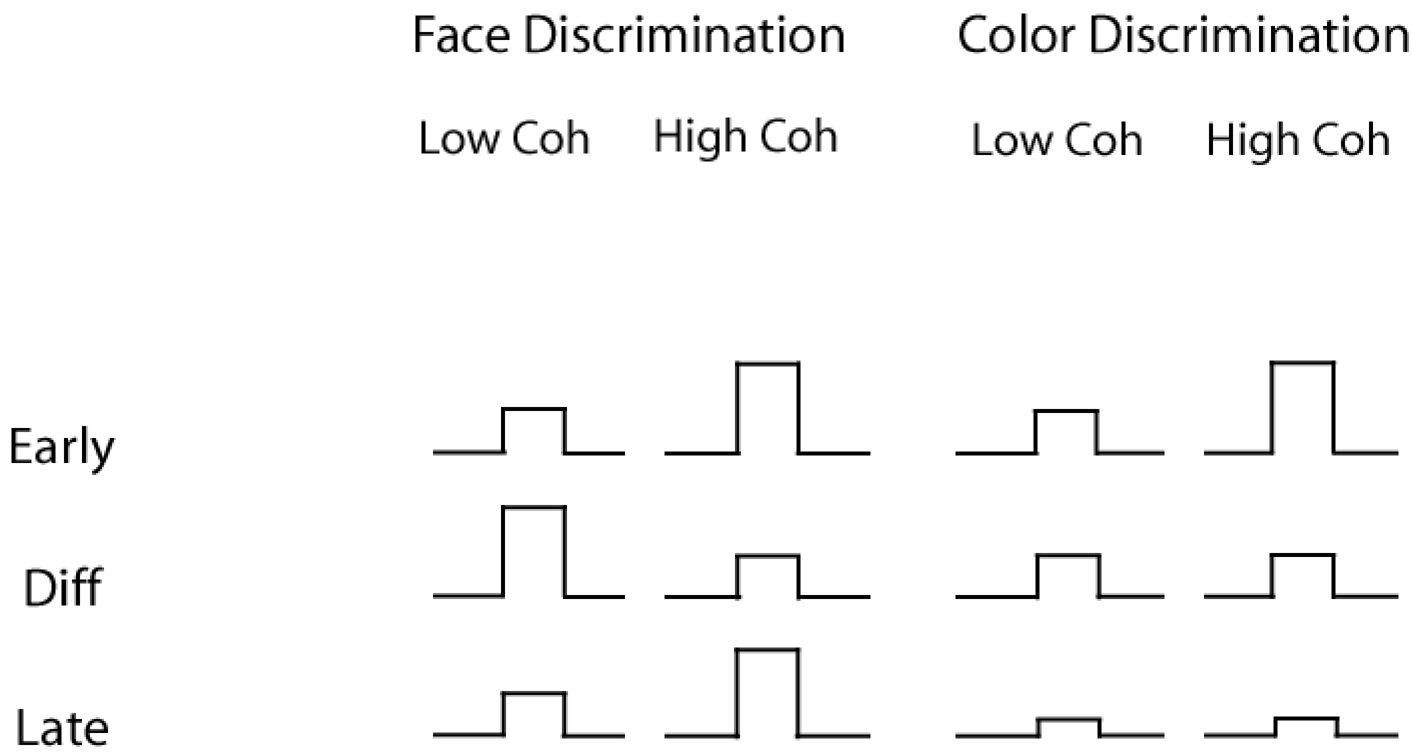


Linking EEG Components to fMRI BOLD

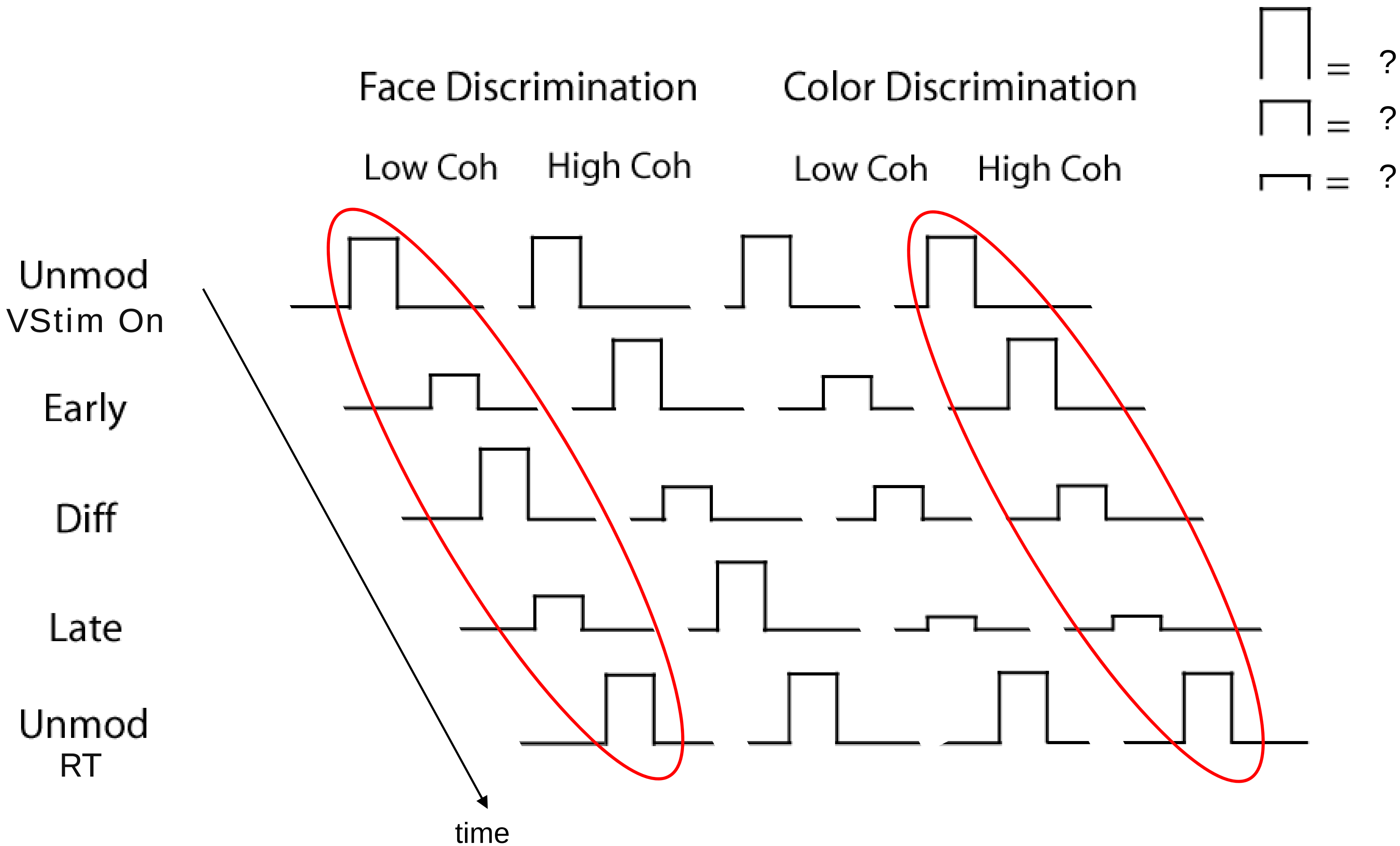
- Simultaneous EEG/fMRI experiment
- EEG-informed fMRI



EEG-informed fMRI Design Analysis



EEG-informed fMRI Design Analysis

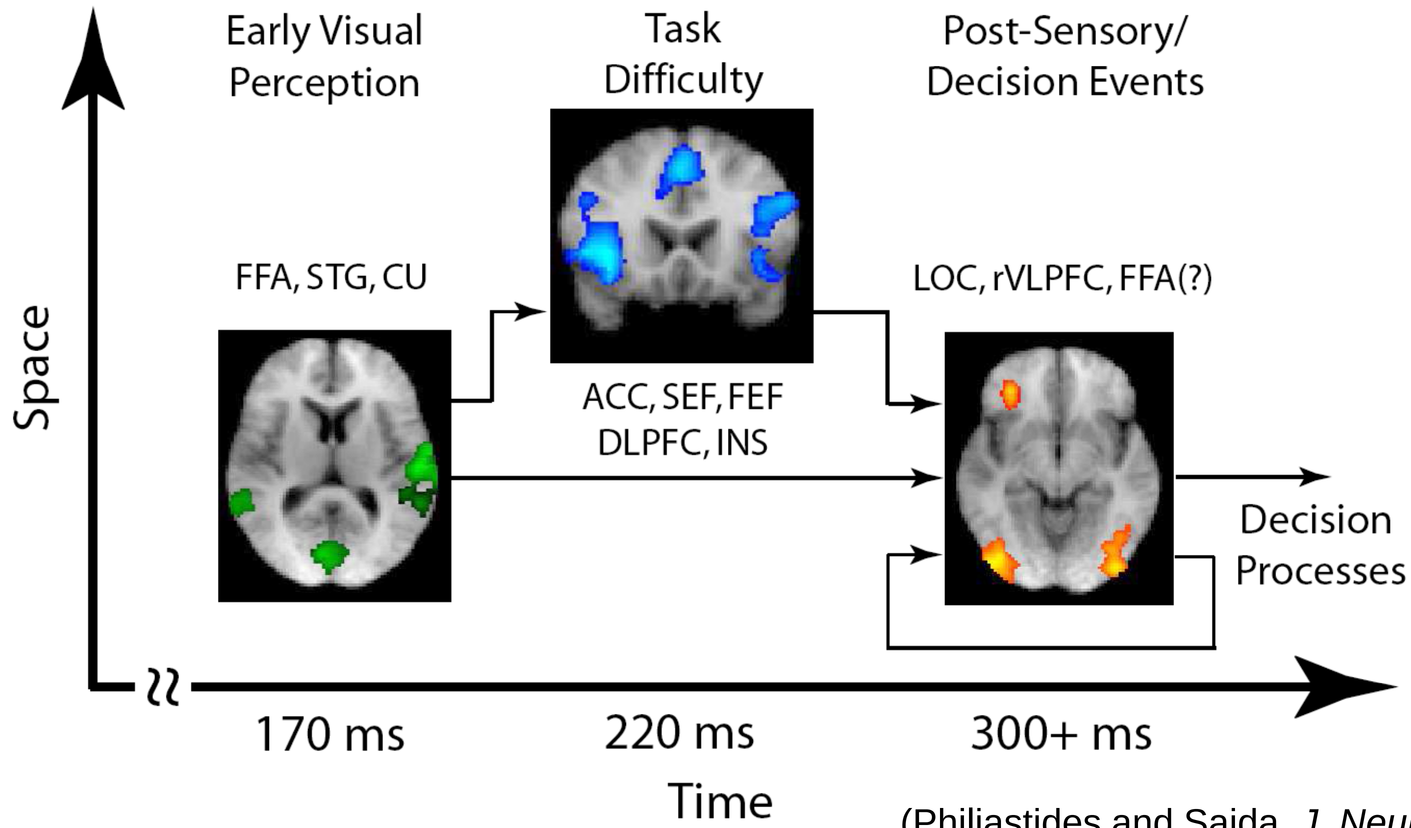


EEG-informed fMRI Design Analysis

	Face Discrimination		Color Discrimination	
	Low Coh	High Coh	Low Coh	High Coh
Early	0.26	0.52	0.26	0.52
Diff	0.34	0.10	0.10	0.10
Late	0.43	0.68	0.12	0.12

Single-trial EEG

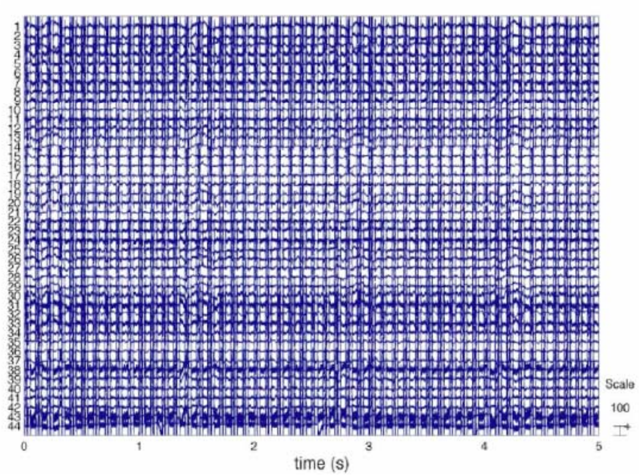
EEG-Informed fMRI: A Spatio-temporal Diagram for Perceptual Decision Making

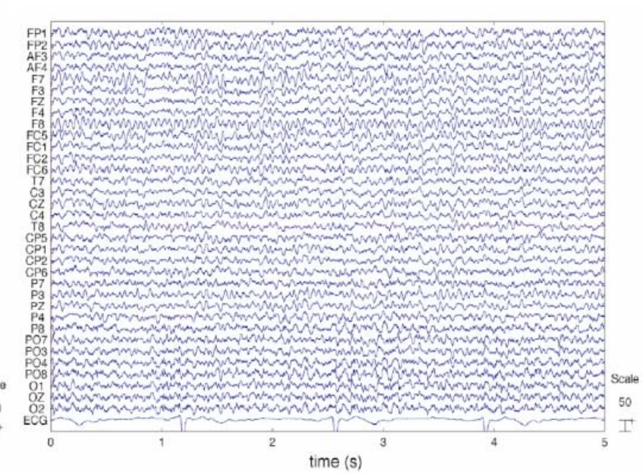


(Philiastides and Sajda, *J. Neurosci* 2007)

What about trial-to-trial variability?
Simultaneous EEG/fMRI

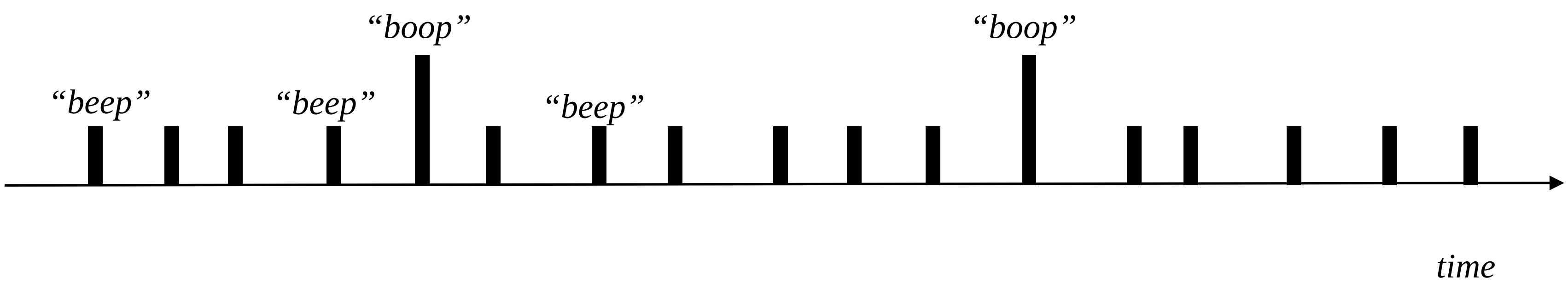
Custom Built Hardware and Software for Simultaneous EEG/fMRI



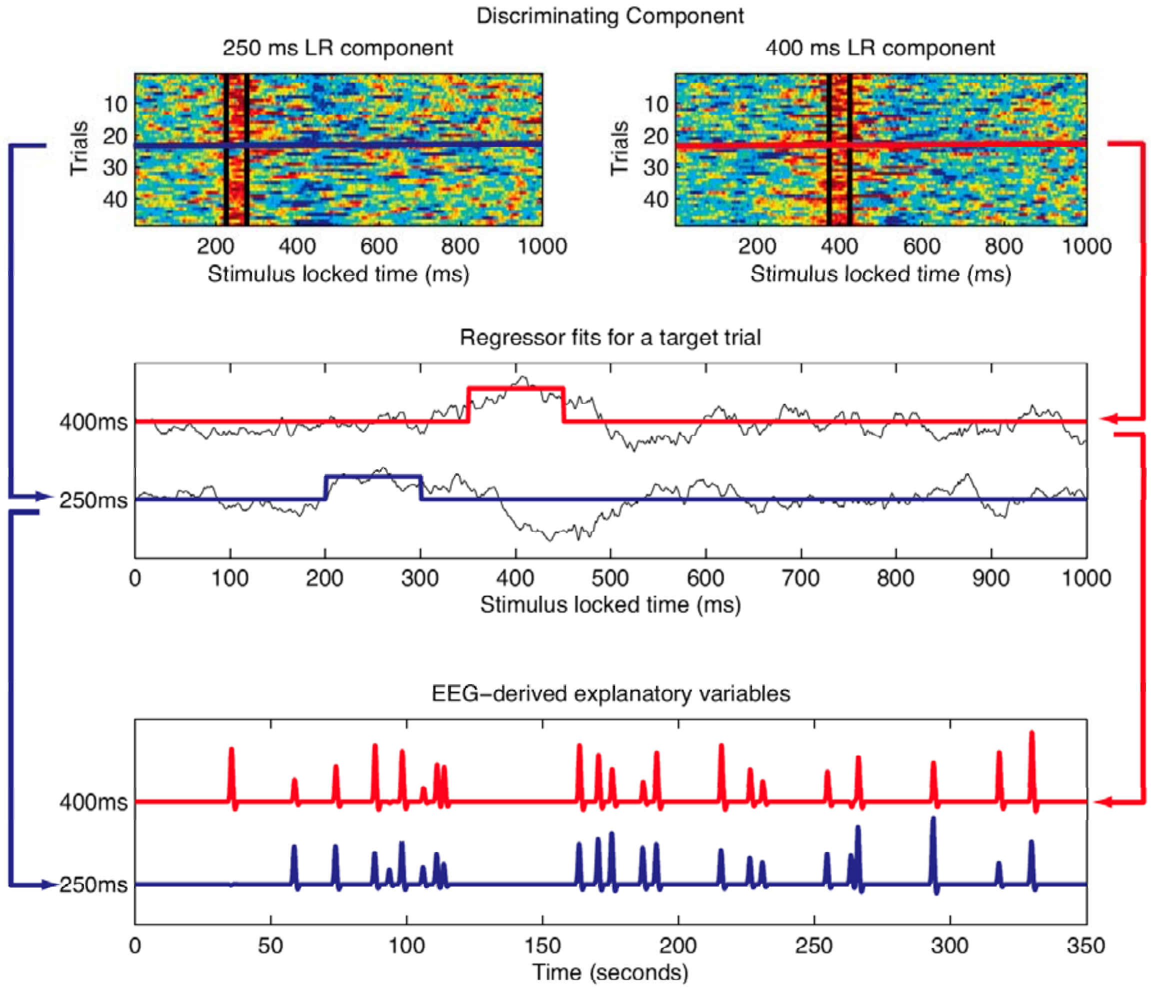


Auditory Oddball

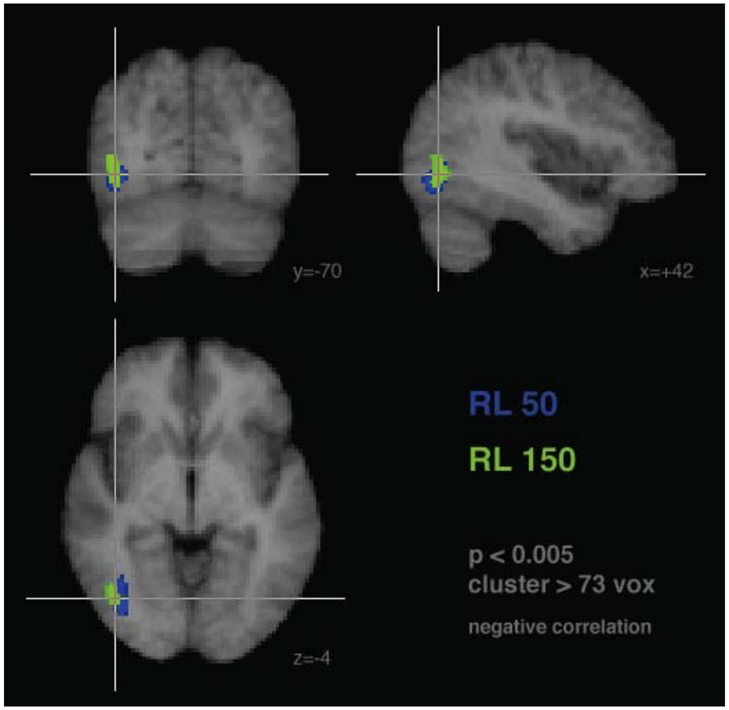
…auditory analog of visual targets amongst distractors…

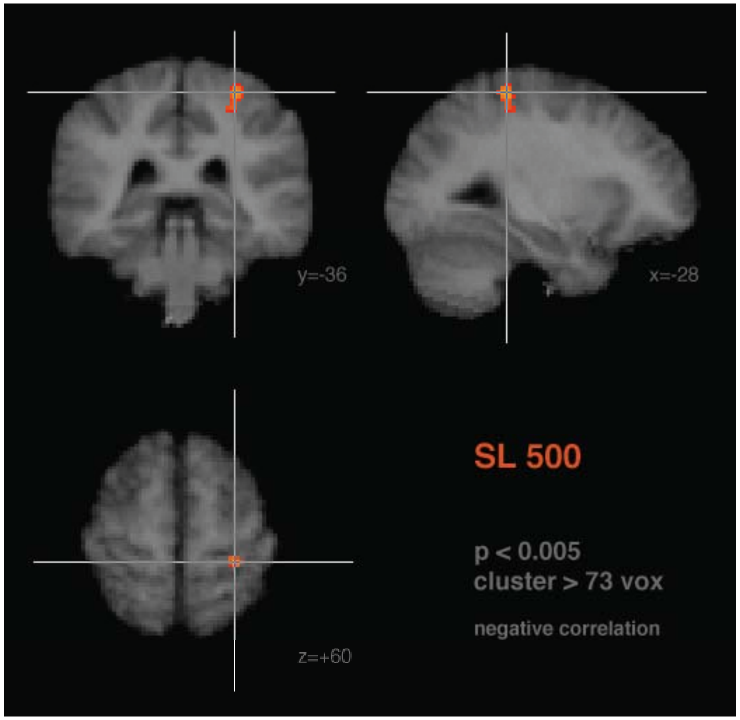


Single-trial Analysis of Simultaneous EEG/fMRI



Correlation of single-trial variability of EEG discriminator with BOLD signal





We see significant activations which are unobservable with standard regressors

Summary

- Spatio-temporal linear filters (i.e. projections), estimated under a variety of objective functions, can be used to identify a variety of "interesting" and neurologically relevant "components".
- From an engineering point of view, such filters are attractive because they can be estimated on-line and in real-time, enabling a variety of brain-computer interfaces.
- We have used such spatio-temporal filters to more precisely characterize perceptual decision making in the human brain.

Further Reading/Info

- Papers and code at http://liinc.bme.columbia.edu

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Collaborators
Truman Brown (Columbia)
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Roger Ratcliff (Ohio State)

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Adam Gerson
An Luo
Marios Philiastides
Mark Wagner

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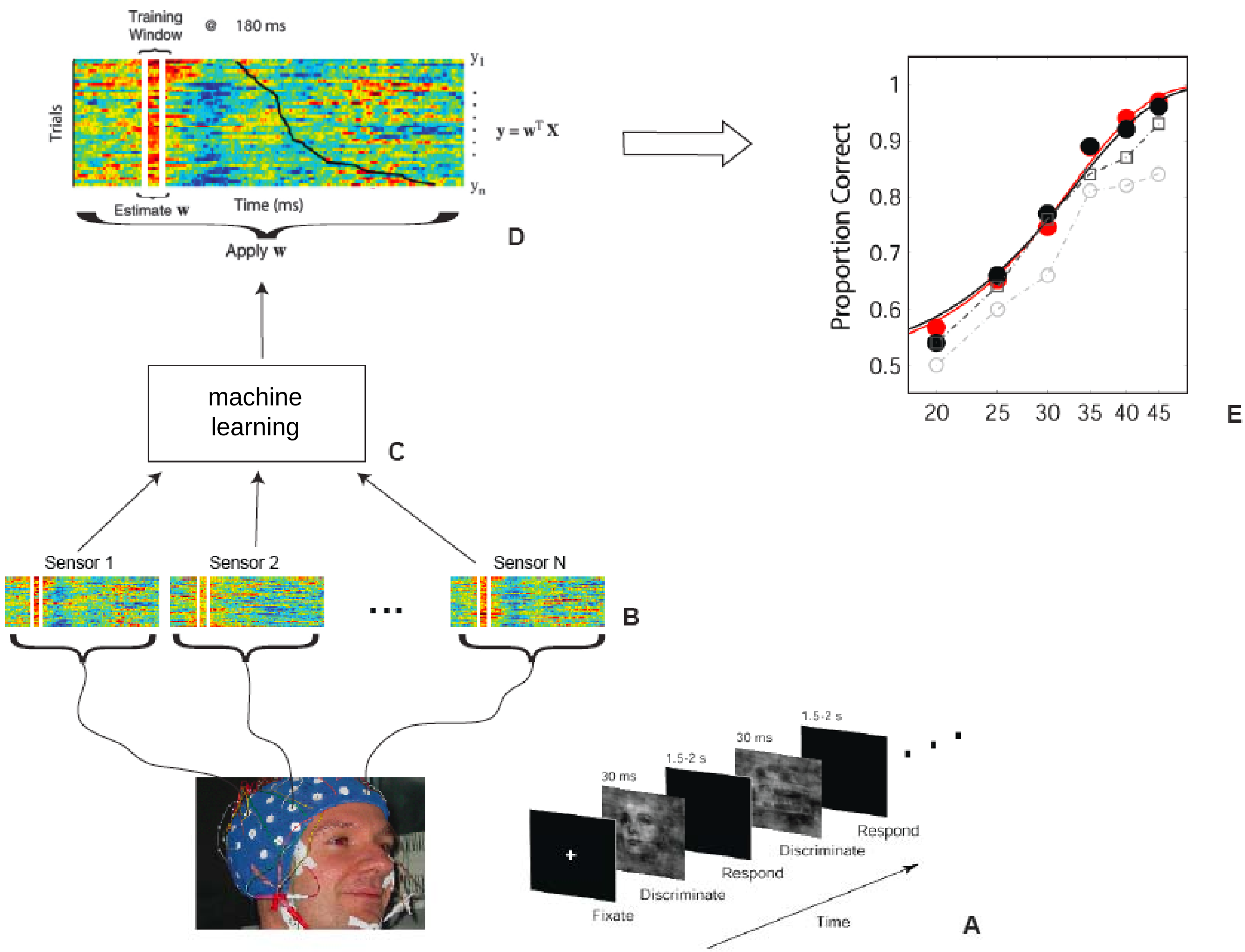
Using Machine Learning to Identify Neural Correlates of Perceptual Decision Making



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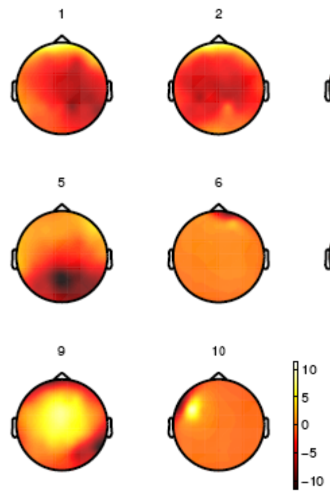
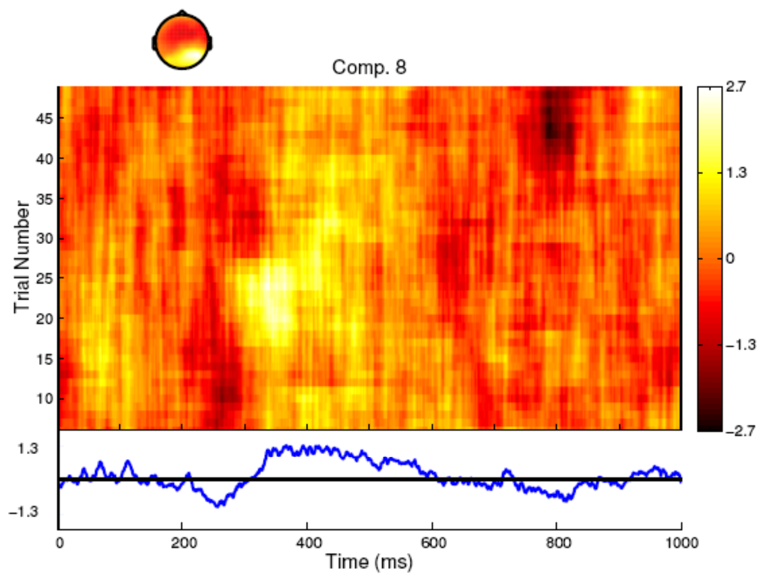
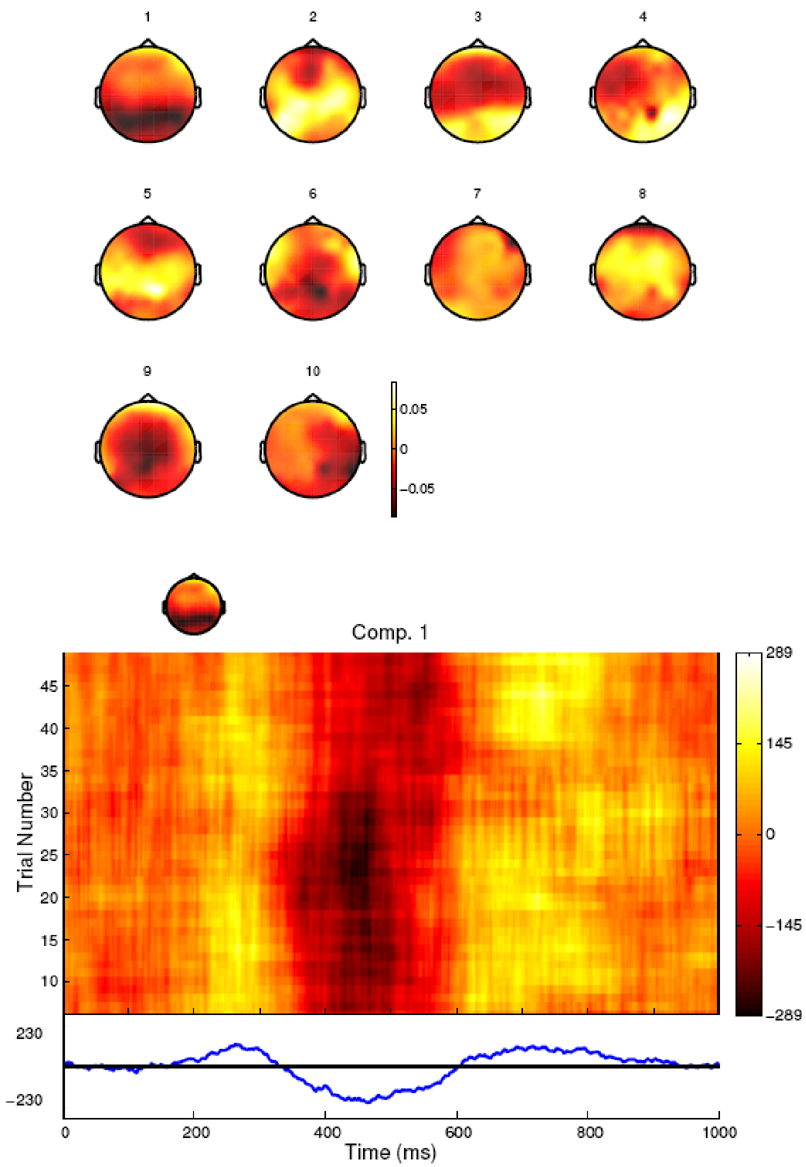
ICA Components

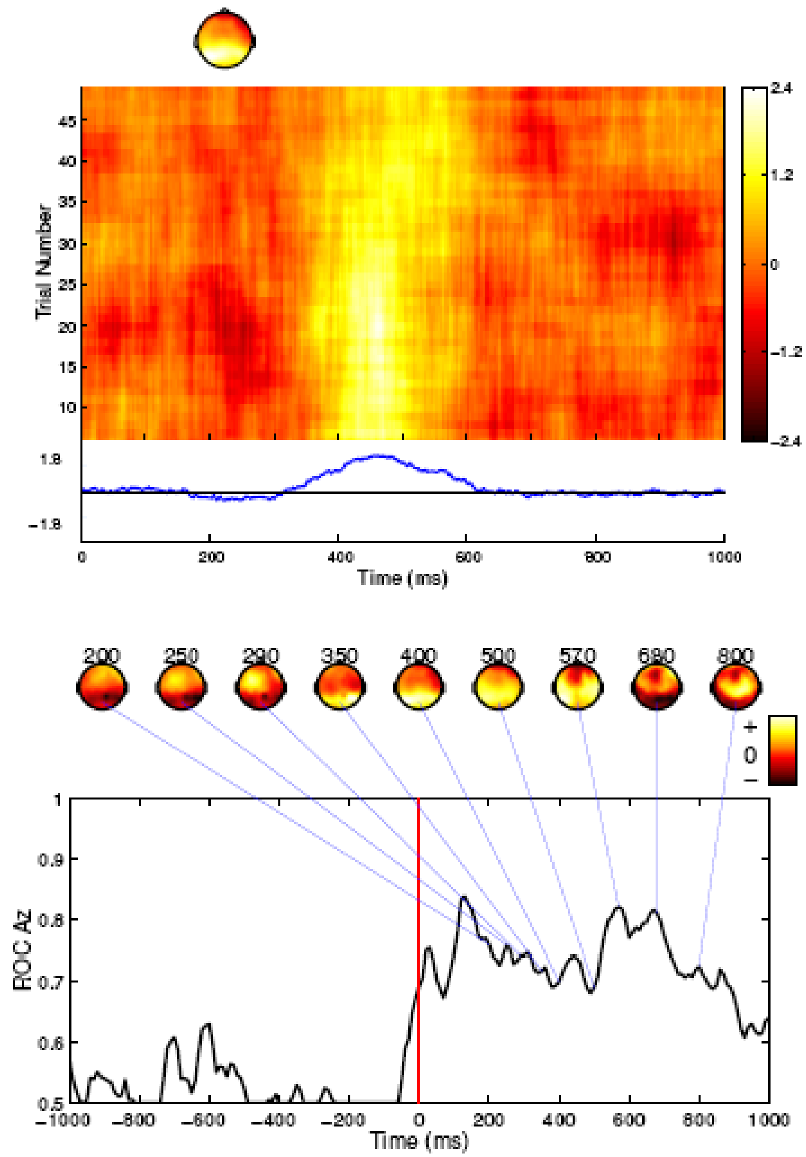




GEVD Components



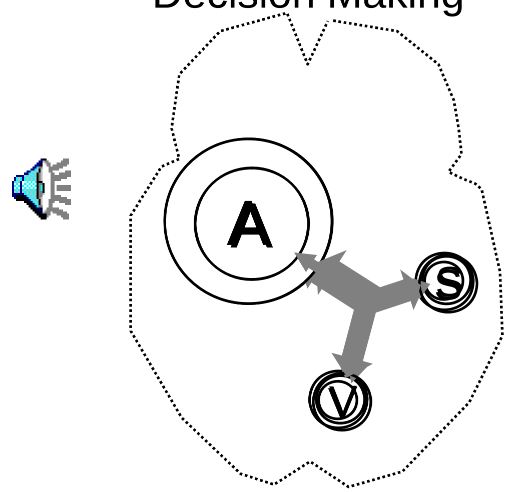
LR Components



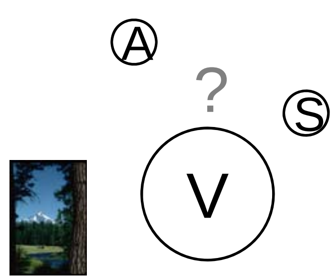
A Push-Pull Circuit for Allocation of Attention to Sensory Stimuli

…single-trial variability reveals cross-modal modulation of visual and somatosensory cortices…

Auditory Stimulus Driven
Decision Making



Visual Stimulus Driven
Decision Making



Somatosensory Stimulus Driven
Decision Making