Decoding Neural Activity at Multiple Spatial and Temporal Scales

… the science and engineering of “mind reading”…

Paul Sajda
Laboratory for Intelligent Imaging and Neural Computing
Department of Biomedical Engineering
Columbia University
psajda@columbia.edu
Can we “read” the brain in real-time?

if YES then

decoder

1001110…
Can we “read” the brain in real-time?

if YES then

Rehabilitation
Cognitive Neuroscience
Performance Augmentation

requires single-trial analysis
## Functional Brain Imaging Modalities

<table>
<thead>
<tr>
<th>Modality</th>
<th>Cost ($K)</th>
<th>Temporal resolution</th>
<th>Latency</th>
<th>Spatial resolution</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EEG</td>
<td>50</td>
<td>ms</td>
<td>ms</td>
<td>cm</td>
<td>Practical tool for clinical applications. Useful research tool for human cognition.</td>
</tr>
<tr>
<td>MEG</td>
<td>1000</td>
<td>ms</td>
<td>ms</td>
<td>mm</td>
<td>Research tool for investigating temporal properties of neuronal and cognitive processes.</td>
</tr>
<tr>
<td>fMRI</td>
<td>4000</td>
<td>s</td>
<td>min</td>
<td>mm</td>
<td>Important for cognition research due to excellent localization of hemodynamic activity.</td>
</tr>
<tr>
<td>PET</td>
<td>2000</td>
<td>min</td>
<td>h</td>
<td>mm</td>
<td>Similar to fMRI. Can target specific metabolites.</td>
</tr>
<tr>
<td>fNIR</td>
<td>200</td>
<td>s</td>
<td>ms</td>
<td>cm</td>
<td>Poor man’s fMRI</td>
</tr>
<tr>
<td>MUR</td>
<td>200</td>
<td>ms</td>
<td>ms</td>
<td>μm</td>
<td>Invasive. High SNR. Only local activity.</td>
</tr>
</tbody>
</table>
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.
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
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
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 \( \mathbf{w} \)?
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 $w^T = [1, 1]$

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

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**

\[ x(t) = As(t) \]

\[ x(t) = As(t) + n(t) \]

**Source Estimation by Linear Projection**

Forward model

\[ \hat{s}(t) = V^T x(t) \]

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

\[ \hat{V}^T = A^\# = (A^T A)^{-1} A^T \]

Noise collinear with the source

\[ \hat{s}(t) = s(t) + (V^T n(t)) \]
Estimating “Interesting” Components Through Projections

Minimizing Interference via Subtraction

\[ \hat{\mathbf{S}}(t) = \mathbf{A}^\# \mathbf{x}(t) \]

Estimate interfering source
(backward model)

\[ \mathbf{x}_\parallel(t) = \mathbf{A} \hat{\mathbf{S}}(t) \]

Estimate contribution to measurements (forward model)

\[ \mathbf{x}_\perp(t) = \mathbf{x}(t) - \mathbf{x}_\parallel(t) = (\mathbf{I} - \mathbf{A} \mathbf{A}^\#) \mathbf{x}(t) \]

\[ \mathbf{x}_\perp(t) \] 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

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

forward model \( \hat{a}_y \) – one column of the matrix \( A \)

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

\[ \hat{a}_y = X y^T (yy^T)^{-1} \]

“scalp projection”
Some Objectives for Finding Interesting Components

... or how do we estimate $w$ ...

- Maximum Difference
- Maximum Power
- Statistical Independence
Maximum Difference

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

\[ \overline{\Delta x} = \sum_{\tau} \Delta x(\tau) \]

\[ \hat{a}_{\text{y}} = \frac{\overline{\Delta x}}{(N_1 + N_2)(y_1 - y_2)} \]

\[ \hat{A}_{\text{eye}} = [\hat{a}_b, \hat{a}_h, \hat{a}_v] \]

\[ \hat{s}(t) = \hat{A}_{\text{eye}}^\# x(t) \]

\[ \hat{s}(t) = [\hat{s}_b, \hat{s}_h, \hat{s}_v]^T \]

\[ x_{E_{\text{BR}}}(t) = (I - \hat{A}_{\text{eye}} \hat{A}_{\text{eye}}^\#) x(t) \]

Use all electrodes in estimation of interference
Maximum Difference

No blink

Blink
Maximum Difference

Maximum Magnitude Difference

\[ w_{\text{erd}} = v = a^{#T} = \frac{\Delta x}{\|\Delta x\|^2} \]

\[ w_{\text{ml}} = R^{-1}\Delta x \]

\[ w_{\text{fld}} = (R_1 + R_2)^{-1}\Delta x \]

\[ w_{\text{lr}} = \arg \min_w L(w, b) \]

\[ L(w, b) = -\sum_t \log p(c_t|y_t) \]

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

\[ p(c = +1|x) = f(y) = \frac{1}{1 + e^{-y}} = \frac{1}{1 + e^{-(w^T x + b)}} \]
Maximum Power

$$w_{pc} = \arg \max_{w, \|w\| = \text{const.}} \sum_{t} y^2(t) = \arg \max_{w} \frac{w^T R w}{w^T w}$$

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

Maximum Power-Ratio

$$w_{ge} = \arg \max_{w, \|w\|=1} \frac{\sum_{t_2} \sum_{\tau} y^2(t_2 + \tau)}{\sum_{t_1} \sum_{\tau} y^2(t_1 + \tau)} \frac{w^T R_2 w}{w^T R_1 w}$$
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 $R_1$ and $R_2$ are computed in a window 200ms before ($R_1$) and 200ms after ($R_2$) 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, \( w_{ge} \), along with the two distributions having a maximum power (variance) ratio, estimated using generalized eigenvalues.

Bottom left: Estimated forward model corresponding to \( w_{ge} \). 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 \( y(t) \) (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 $t, \tau, n, m$ gives $M(M-1)/2$ conditions for $NM$ unknowns in $A$.

Sufficient conditions if we use multiple:

<table>
<thead>
<tr>
<th>use</th>
<th>sources assumed</th>
<th>condition</th>
<th>statistic</th>
<th>algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t$</td>
<td>non-stationary</td>
<td>$W R_x(t) W^T = \text{diag}$ covariance</td>
<td>decorrelation</td>
<td></td>
</tr>
<tr>
<td>$\tau$</td>
<td>non-white</td>
<td>$W R_x(\tau) W^T = \text{diag}$ cross-correlation</td>
<td>SOBI</td>
<td></td>
</tr>
<tr>
<td>$n, m$</td>
<td>non-Gaussian</td>
<td>$W C_x(i,j) W^T = \text{diag}$ 4th cumulants</td>
<td>JADE (ICA)</td>
<td></td>
</tr>
</tbody>
</table>
Example: Non-stationary Independent Sources

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

$$R_y(t_1) = W R_x(t_1) W^T = \text{diag}$$

$$R_y(t_2) = W R_x(t_2) W^T = \text{diag}$$

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

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

More robust if we use simultaneous diagonalization of multiple covariances.

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

EEG sensor projections $A = W^{-1}$
Using Spatio-temporal Linear Processing

\[ Y = WX \]

- **Y**: recovered sources
- **X**: observations
- **W**: transformation matrix

**Data** \(\rightarrow\) artifact removal and dimensionality reduction \(\rightarrow\) linear discrimination \(\rightarrow\) \(P(T)\)

64-128 channels

Telluride 7/08
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:

\[ s(t) = w^T x(t) \]

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

**Ex: Detect motor planning activity** Predict button press from 122 MEG sensors with linear discriminator \( w \) 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:

$$a = \frac{Xy}{y^Ty}$$

Strong coupling indicates low attenuation. Intensity on these “sensor projections” $a$ indicates closeness of the source to the sensors.
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
Applications: Cognitive User Interface

Hypotheses:

• EEG can be used to detect 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
Single-trial Discrimination

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

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

**Localization of Discriminating Component**

Possible because we have a linear model

\[
a = \frac{\mathbf{Xy}}{\mathbf{y}^T \mathbf{y}}
\]

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

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

\[ a = \frac{Xy}{y^{T}y} \]

Discrimination performance

\[ p = 0.01 \]
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

- Display Laptop (EPrime & Python)
- Analysis Laptop (Matlab DLL & C))
- USB (EEG data streaming)
- 64 channels

Connections:
- parallel port (display events)
- serial COMS port (detection events)
Hierarchical Discriminating Components

...online estimation of all parameters...

\[ W = \sum_{k=1}^{n} u_k (c_k h_k)^T \]

\[ y = \text{Trace } W^T X \]
Triage results

Triage performance

Original Sequence

EEG (no motor)

EEG (motor)

Button

EEG (motor) and Button

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

Adaptive threshold for error correction

64 EEG channels

Linear classifier for ERN detection

Linear filtering & eye blink removal

Machine Corrected Errors

Overall Human-Machine Performance
Real-Time On-Line Error Correction

Linear filtering & eye blink removal

64 EEG channels

Machine Corrected Errors

200 ms latency

PERCEIVED ERROR DETECTION AND CORRECTION

Threshold correct error

HISTOGRAM OF ERN DETECTION OUTPUT

Frequency

ERN detection output
Real-Time On-Line Error Correction

- Linear filtering & eye blink removal
- 64 EEG channels
- Adaptive threshold for error correction
- Linear classifier for ERN detection

Machine Corrected Errors

Overall Human-Machine Performance
Real-Time On-Line Error Correction

Linear filtering & eye blink removal

64 EEG channels

Machine Corrected Errors

200 ms latency
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

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

![Graph showing neurometric functions predictive of psychophysical performance](image)

- Neurometric functions predictive of psychophysical performance
  from Britten et al. '92

- Psychometric data
  - Responses to “pref” direction
  - Responses to “null” direction
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

Low Az
High Az
Combining EEG and fMRI

Localization of decision making (fMRI)

Timing of decision making (EEG)

Cortical networks (fMRI/EEG)

Heekeren et al. Nature 2004
Linking EEG Components to fMRI BOLD

- Simultaneous EEG/fMRI experiment
- EEG-informed fMRI
**EEG-informed fMRI Design Analysis**

<table>
<thead>
<tr>
<th>Face Discrimination</th>
<th>Color Discrimination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Coh</td>
<td>High Coh</td>
</tr>
</tbody>
</table>

- **Early**
  - Face Discrimination: Short pulse
  - Color Discrimination: Short pulse

- **Diff**
  - Face Discrimination: Short pulse
  - Color Discrimination: Short pulse

- **Late**
  - Face Discrimination: Short pulse
  - Color Discrimination: Short pulse
EEG-informed fMRI Design Analysis

Face Discrimination
Low Coh  High Coh

Color Discrimination
Low Coh  High Coh

Unmod
VStim On

Early

Diff

Late

Unmod
RT

time

Telluride 7/08


## EEG-informed fMRI Design Analysis

<table>
<thead>
<tr>
<th></th>
<th>Face Discrimination</th>
<th>Color Discrimination</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low Coh</td>
<td>High Coh</td>
</tr>
<tr>
<td><strong>Early</strong></td>
<td>0.26</td>
<td>0.52</td>
</tr>
<tr>
<td><strong>Diff</strong></td>
<td>0.34</td>
<td>0.10</td>
</tr>
<tr>
<td><strong>Late</strong></td>
<td>0.43</td>
<td>0.68</td>
</tr>
</tbody>
</table>

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

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

Discriminating Component

- 250 ms LR component
- 100 ms LR component

Regressor fits for a target trial

EEG-derived explanatory variables

Time (seconds)
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
Acknowledgments

Collaborators
Truman Brown (Columbia)
Robin Goldman (Columbia)
David Friedman (NYPI/Columbia)
Lucas Parra (CCNY)
Roger Ratcliff (Ohio State)

Postdocs and Students
Mads Dyrholm
Adam Gerson
An Luo
Marios Philiastides
Mark Wagner

Funded by NIH, NSF, ONR, DARPA, and NGA
Using Machine Learning to Identify Neural Correlates of Perceptual Decision Making
ICA Components

1  2  3  4
5  6  7  8
9 10

Comp. 8
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