Integration of EEG/MEG/fMRI

Outline

• fMRI/EEG data
• Three Approaches to integration/fusion
  • Prediction
  • Constraints
  • 2nd Level Fusion

EEG/ERP

Event-related Potentials (ERPs)

Blind EEG Source Separation → ICA

Spatial Source Filtering
ICA Applied to EEG Data

Activation of 2 different muscles
Eye movement
Muscle activity
Heart beating, digital watch
Faulty sensor
Breathing, bumps caused by overlearning

EEG Artifact Rejection

Figure 3: Samples of MEG signals, showing artifacts produced by blinking, saccades, hearing and cardiac (x-axis).
**What does EEG tell us?**

Identification of processing stages in millisecond precision:

**BUT**
- poor spatial resolution (inverse problem)

**What does BOLD fMRI tell us?**

Identification of involved areas with millimeter precision:

**BUT**
- poor temporal resolution (>1 sec)
  - Indirect measure of neural activity

Identification of processing stages in millisecond precision:

A B C D
Why EEG-fMRI Integration

**EEG**
- + high temporal resolution (~ ms)
  - poor spatial resolution (~ cm)

**fMRI**
- + high spatial resolution (~ mm)
  - low temporal resolution (~ seconds)

**simultaneous acquisition**

**EEG and fMRI data reflect the same neuronal activity**

**BOLD and LFP (EEG) Signal result from same neuronal process**


**EEG-fMRI Integration: Two Inverse Problems**
EEG: Inverse Problem in Space

**Ill-posed Problem:**
- 2-Dim Measurement: Electrode recordings on the skull
- 3-Dim Solution: Neuronal Activation in the Brain
- Infinite Number of Solutions
- Need for Priors

fMRI: Inverse Problem in Time

**Metabolic & Vascular Response**

EEG/IMRI integration: separate recordings

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EEG/IMRI integration: simultaneous recordings

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• Conclusions

Approaches to EEG-MRI data integration

Data Integration through:

(i) Prediction
• some features of EEG to predict fMRI responses

(ii) Constraints
• Spatial information from fMRI as Priors for Source Reconstruction

(iii) Fusion
• Common forward or generative model to explain EEG and fMRI data

Through Prediction: e.g. Epilepsy

Interictal Epileptiform Discharges predict fMRI response

Benar et al., NeuroImage 2002
EEG/MRI integration: EEG-informed fMRI analysis

How can simultaneously recorded data be integrated such that the direct coupling hypothesis can be tested?

... on a trial-by-trial basis:
  • Debaner et al., (2005, J. Neuroscience)
  • Bichele et al., (2005, PrAS)

Sample
N=12 subjects (age 22-29, 5 m)
EEG
30 channel EEG brainamps
0.1-250 Hz, 5 Hz A/D
fMRI:
Siemens Trio 3-Tesla, TR 2 sec,
22 slices, TE 30 ms
Stimulation:
visual projection

EEG/MRI integration: EEG-informed fMRI analysis

Shallow vs. deep interface

EEG/MRI integration: EEG-informed fMRI analysis

Shallow vs. deep interface

EEG/MRI integration: EEG-informed fMRI analysis

Shallow vs. deep interface
Through Prediction: Alpha Rhythm

- EEG can be recorded simultaneously with fMRI
- A reasonable EEG quality can be obtained
- ICA helps to disentangle otherwise overlapping EEG signals
- EEG-informed fMRI analysis supports direct coupling
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Approaches to EEG-MRI data integration

Data Integration through:

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some features of EEG to predict fMRI responses.

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Spatial Information from fMRI as Priors for Source Reconstruction

(iii) Fusion
Common forward or generative model to explain EEG and fMRI data

(ii) Constraints: fMRI Priors help EEG Analysis

Without fMRI priors

With fMRI priors

Dale & Halgren, Curr Opin Neurobiol. 2001

**Approaches to EEG-MRI data integration**

Data integration/fusion: Previous Work
Data Fusion vs. Data Integration

- Definitions [Savopol ISPRS 2004]
  - Data Integration: The use of another data-type to improve the geometry or other information reconstructed from the first data-type (e.g. MRI constrained EEG).
  - Data Fusion: Images analyzed jointly, hence allowing them to influence one another, to reveal inter-relationships between data-types.

Possible approaches for joint analyses

- Point-based
  - Correlation [Resnick 2002]
  - Straightforward, but difficult to visualize

- Region-based
  - Interregional correlation [Haxby et al., 2002, Mathalon, et al., 2003]
  - Structural equation modeling or dynamic causal modeling [McIntosh and Bookstein, et al., 1996]
  - Useful for model testing, does not take into account all brain regions/time

- Transformation-based
  - A natural set of tools for this problem include those that transform from one modality separately
  - Singular value decomposition [Friston et al., 1993; Friston et al., 1996]
  - Independent Component Analysis [Beckmann, et al., 2002]
  - Canonical Variates Analysis [Strother et al., 1995]
  - Partial Least Squares [McIntosh, Bookstein, et al., 1996], et al., 1996]
  - Interregional correlation [Horovitz, et al., 2002, Mathalon, et al., 2003]

Separate vs. Joint Estimation

Linear mixtures with shared mixing parameter

\[ x^{(1)} = \sum_{i=1}^{n} a_i s_i^{(1)} \quad \text{and} \quad x^{(2)} = \sum_{i=1}^{n} a_i s_i^{(2)} \]

In a non-joint analysis, we maximize the likelihood functions for each modality separately...

Resulting in two unmixing parameters, that then have to somehow be fused together

In contrast: for a joint analysis we maximize the joint likelihood parameters, that then have to somehow be fused together

\[ w^j = \arg \max p(x^{(1)}, x^{(2)}, w) \]

Joint ICA Approach

Mixing Model: \( X^{(i)} = A S^{(i)} \) and \( X^{(j)} = A S^{(j)} \)

For two sources: \( X = \begin{bmatrix} x^{(1)} \\ x^{(2)} \end{bmatrix}, \) where \( m = \{E,F\} \)

Shared mixing matrix: \( A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \)

The mixing equations are:

\[ x^{(1)} = a_{11} s_1^{(1)} + a_{12} s_2^{(1)} \]
\[ x^{(2)} = a_{21} s_1^{(2)} + a_{22} s_2^{(2)} \]

Update equation: \( AW = \begin{bmatrix} 1 - 2y^T y & 2y^T \\ 2y & 1 \end{bmatrix} W \)

where \( y = g(w^m) \) and \( g(x) = 1/(1 + e^{-x}) \)
Auditory Oddball Task

Group Averaged fMRI/ERP Features

Preprocess
Feature Extraction
fMRI
EEG
Normalize
Noise Removal
jICA
Subject 1
Subject 2
Subject N

FMRI Snapshots (movie)

ERP (temporal) Components: \( T = [t_1 \ldots t_x] \)
FMRI (spatial) Components: \( S = [s_1 \ldots s_x] \)
FMRI Image Snapshot: \( M_f(t) = T' \cdot S(t) \)
ERP Snapshot: \( M_e(t) = T \cdot [S(t)] \)
Parallel ICA

- Impose additional inter-modality correlation to improve ability to identify connections between EEG and fMRI

\[ \Delta \mathbf{W} = \eta \{ \mathbf{I} - 2 \mathbf{y}_{\mathbf{EF}}(\mathbf{u}_{\mathbf{EF}}) \mathbf{T} \} \mathbf{W}, \] where \( \mathbf{y}_{\mathbf{EF}} = \mathbf{g}(\mathbf{u}_{\mathbf{EF}}) \) and \( \mathbf{g}(x) = \frac{1}{1+e^{-x}} \) is the nonlinearity in the neural network…
Fusion ICA Toolbox (FIT)