

A Bayesian Hierarchical Framework for Spatial Modeling of fMRI Data

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July 18, 2008

OUTLINE

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I. Introduction

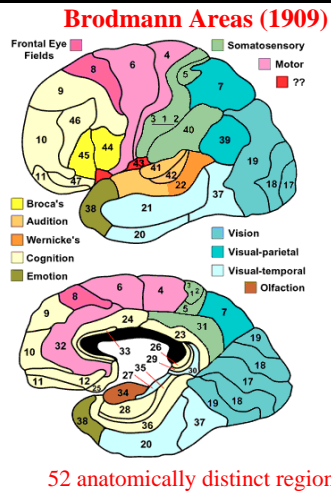
Functional Specialization

(Localization): Specific mental processes link to particular brain regions

[Gall, 1796; Broca, 1861; Brodmann, 1909]

Functional Integration:

Interactions between specialised neuronal populations



Imaging Modalities

Functional Neuroimaging

- Noninvasively measures localized *brain activity* using correlates of blood flow

Modalities

Vascular methods

- **fMRI:** Functional Magnetic Resonance Imaging
- **PET:** Positron Emission Tomography
- **SPECT:** Single photon emission computed tomography

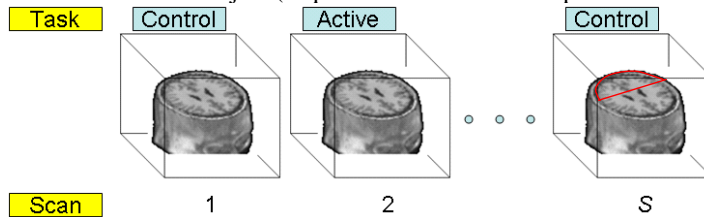
Electrophysiological methods

- **EEG/MEG:** electro-/magneto-encephalogram

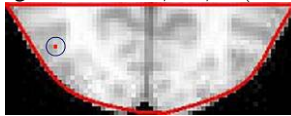


Data Representation

- Serial scans for each subject (acquired under different experimental tasks)



- Voxels $v = (x, y, z)$ range from $v = 1, \dots, V$ (hundreds of thousands)



Data Representation

General Data Characteristics

Response

- Localized measurements of "brain activity" (BOLD response)
 - Temporally and spatially correlated

Design Matrix

- Experimental conditions
- Covariate adjustments
 - Motion parameters
 - Low frequency trends, e.g. due to artifacts from scanner

Pre-processing

- Realignment - motion correction
- Spatial normalization - warping brains to a standard space (Talairach)
 - Provides exact coordinates for anatomical locations
- Spatial smoothing*

II. Conventional Analyses

Functional Specialization: Activation Studies*

- To identify specific regions of the brain that are more active under one experimental condition relative to another
 - Voxel-level
 - Stage 1 (individual) model
 - Stage 2 (group) model
 - Thresholding (Bonferonni, FDR, RFT)
 - Region of Interest (ROI)
 - Average data over voxels within ROI

Functional Integration: Connectivity Studies

- Functional connectivity - correlations between distinct brain regions
 - Local correlations
 - Long-range correlations
 - Effective connectivity - the influence one neural system exerts over another
- [Friston, 1993]

III. Experimental Data

fMRI Study of Inhibitory Control in Cocaine Addicts

- $n = 28$ subjects ($n_p = 12$ cocaine addicts, $n_c = 16$ controls)
- Study Conditions: Inhibitory Control
 - ▷ Correctly inhibiting a prepotent response
 - Response primed with frequent occurrence of "go cues"
 - "Stop signal" is an auditory tone signaled after a "go cue"
- Sessions: Two Sessions (170 scans per subject in each session)
 - ▷ Addicts: Pre- and Post-Treatment
 - ▷ Controls: Baseline and Follow-up
- 176 million measurements per subject! 4.9 billion for all subjects!!
- Objective: Treatment-emergent neural processing changes related to response inhibition in cocaine-addicts

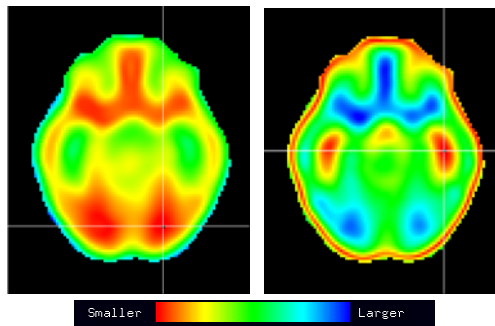
IV. Spatial Modeling

- Key Considerations
 - ▷ Correlation as a function of *Distance*
 - Local correlations
 - Long-range correlations due to neurophysiology
 - ▷ Volume of data (billions of voxel pairs!)
 - ▷ Complexity of neuroanatomy (billions of axons!)
- Approaches:
 - ▷ **Model 3:** Spatial Bayesian Hierarchical Model (BHM) [Bowman et al., 2008]
 - ▷ **Model 2:** Spatial Modeling using Functional Distances [Bowman, 2007]
 - ▷ **Model 1:** Cluster-based Spatial Autoregressive Model [Bowman, 2005]

Exploring Spatial Associations

- Define *functional* distance between activity in voxels i and j

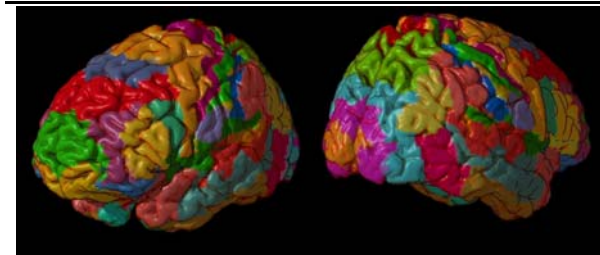
$$d_{ij} = [(\mu_i - \mu_j)'(\mu_i - \mu_j)]^{1/2}, \quad \mu_i \text{ is a summary statistic.}$$



Spatial Modeling Approaches

Spatial Bayesian Hierarchical Model

- Define regions using neuroanatomical templates



$G = 116$ (Anatomical regions); $G = 52$ (Brodmann regions)

[Tzourio-Mazoyer et al., 2002]

[Brodmann, 1909]

NOTE: Also considered alternative partitions of the V voxels into G regions such as data-driven clustering methods based on the functional distances d_{ij} .

[Bowman et al., 2004; Bowman and Patel, 2004; Bowman, 2005]

Model

Stage I

$$Y_{ig}(v) = X_{igv}B_{ig}(v) + H_{iv}\nu_{ig}(v) + \epsilon_{ig}(v)$$

where

- $Y_{ig}(v)$ ($S \times 1$) serial brain activity at location v (e.g. BOLD) (within *cluster g*)
- X_{igv} ($S \times q$) design matrix containing independent variables (common to all v)
- $B_{ig}(v)$ ($q \times 1$) parameter vector containing individualized effects
- $\epsilon_{ig}(v)$ ($S \times 1$) random error about k^{th} subject's individualized mean
- H_{iv} ($S \times m$) contains other covariates, e.g. high-pass filtering

Model Assumptions

- $\epsilon_{ig}(v) \sim N(0, \tau_{gv}^2 \mathbf{I}_S)$
- Brain activity measurements from different scans are independent

Spatial Modeling Approaches

Stage II: Spatial Bayesian Hierarchical Model

1. $B_{igg}(v) | \mu_{gj}(v), \alpha_{igg}, \sigma_{gg}^2 \sim N(\mu_{gj}(v) + \alpha_{igg}, \sigma_{gg}^2)$ *Data*
2. $\mu_{gj}(v) | \lambda_{gj}^2 \sim N(\mu_{0gj}, \lambda_{gj}^2),$ *voxel means*
 $\sigma_{gg}^{-2} \sim G(a_0, b_0)$ *common voxel variances*
 $\alpha_{ij} | \Gamma_j \sim N(\mathbf{0}, \Gamma_j), \quad \alpha_{ij} = (\alpha_{i1j}, \dots, \alpha_{iGj})'$ *subj-spec. random effects*
3. $\lambda_{gj}^{-2} \sim G(c_0, d_0)$ *variances of voxel means*
 $\Gamma_j^{-1} \sim W((h_0 \mathbf{H}_{0j})^{-1}, h_0)$ *spatial covariance matrix*

- Priors:** $(a_0, b_0) = (0.1, 0.005)$
 $(c_0, d_0) = (0.1, 0.01)$
 $h_0 = G$ ($h_0 \geq G$ to ensure proper posterior, non-informative as $h_0 \rightarrow 0$)
 $\mathbf{H}_{0j} = \hat{\Gamma}_j$ (sample covariance matrix)

[Bowman et al., 2008]

Estimation

- MCMC (Gibbs Sampler)
- Draw samples from the joint posterior distribution of all model parameters
 - ▷ Can estimate functions of the model parameters from the joint posterior samples, e.g.
 - ▷ Intra-regional *task-related functional connectivity* is given by

$$\rho_{gj} = \frac{\gamma_{gg}^{(j)}}{\gamma_{gg}^{(j)} + \sigma_{gj}^2}$$

Reflects similarity in brain function between voxels *within* anatomical regions

- Conjugate model specifications lead to *relatively fast* estimation

Results

Treatment-emergent changes in activity related to inhibitory control for patients relative to controls

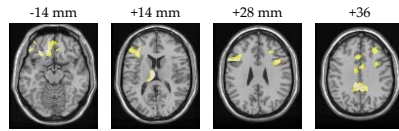
$$A = [(\text{Post-tx} - \text{Pre-tx in Patients}) - (\text{Follow up} - \text{BL in Controls})]$$

Target

- Voxel-Specific Activation Maps
- Regional Activation Maps
- Within-Region Task-Related FC
- Inter-Regional Task-Related FC

Results: Inhibitory Control in Cocaine Addicts

fMRI Voxel-Specific Activation Maps



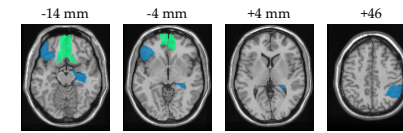
$$\Pr(A(v) > 0) \geq 0.70$$

Treatment-related changes are probable in

- ▷ -14 mm: Medial orbital frontal cortex (OFC) (BA 11)
- ▷ +14 mm: Left thalamus and left middle frontal gyrus (BA 46)
- ▷ +28 mm: Left and right middle frontal gyrus (BA 9)
- ▷ +36 mm: Cingulate gyrus, with most spatially extensive in the posterior cingulate gyrus (BA 31, 32)

Results

fMRI Regional Activation/Deactivation Maps



$$\Pr(|A(g)| > 0) \geq 0.80$$

Treatment-related changes are probable in

Increases:

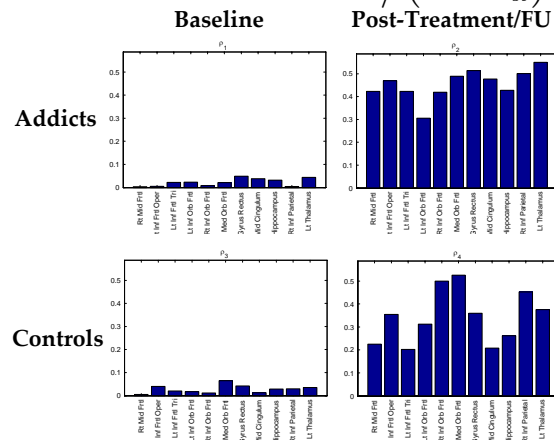
- ▷ -14 mm: Gyrus rectus and medial OFC
- ▷ -4 mm: Medial OFC

Decreases:

- ▷ -14 mm: Left inferior OFC
- ▷ -4 mm: Right hippocampus (from -14 to +4) and left inferior OFC
- ▷ +46 mm: Right inferior parietal region

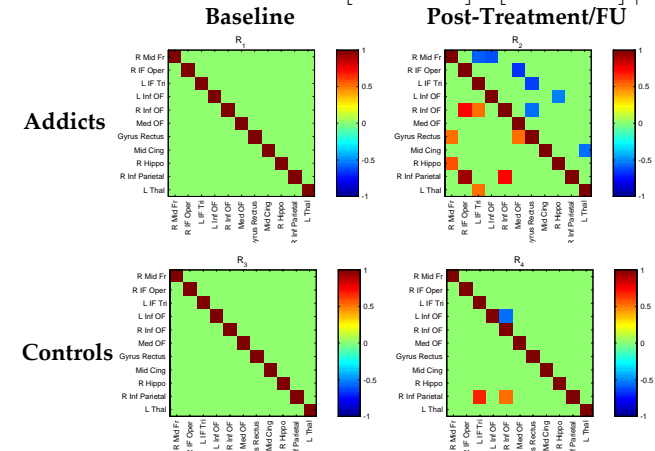
Results

Within-Region Task-Related FC: $\rho_{gj} = \gamma_{gg}^{(j)} / (\gamma_{gg}^{(j)} + \sigma_{gj}^2)$



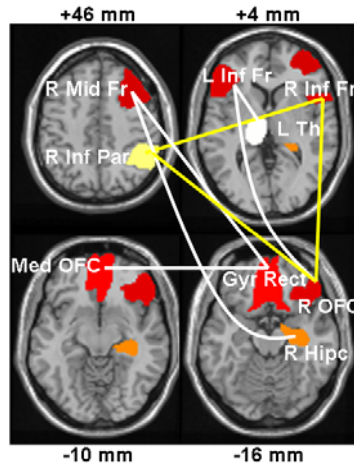
Results

Inter-Regional Task-Related FC: $R_j = [\text{diag}(\Gamma_j)^{-1/2}] \Gamma_j [\text{diag}(\Gamma_j)^{-1/2}]$, $|\hat{R}_j(r, c)| \geq 0.5$:



Results

Inter-Regional Task-Related FC: Patients Post-Treatment



Yellow: $\hat{R}_j(r, c) \geq 0.75$
 White: $0.5 \leq \hat{R}_j(r, c) < 0.75$

Other Considerations

- Sensitivity of results to choice of priors, e.g.

$$H_{0j}^* = (1 - \omega)H_{0j} + \omega[\text{diag}(H_{0j})], \quad 0 \leq \omega \leq 1$$

- Convergence diagnostics
- Unified estimation of spatio-temporal model parameters
 - Computational costs may be *too high*

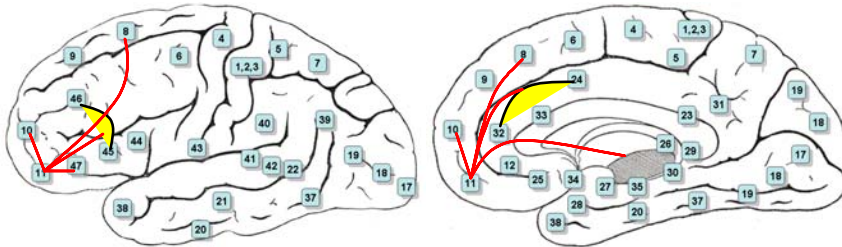
Other Considerations

- Assess changes in task-related FC: treatment-related changes in FC:

$$D_{\text{pre}}(r, c) = R_{\text{pats, pre}}(r, c) - R_{\text{ctls, pre}}(r, c)$$

$$D_{\text{post}}(r, c) = R_{\text{pats, post}}(r, c) - R_{\text{ctls, post}}(r, c)$$

$$\Pr\{[D_{\text{pre}}(r, c) - D_{\text{post}}(r, c)] > \delta_0\} \geq \alpha$$



V. Summary

Spatial modeling approaches

- Feasible* for functional neuroimaging data
- Quantifies task-related functional connectivity
 - Within clusters or neuroanatomical regions
 - Between neuroanatomical regions (Spatial BHM)
- Allows voxel-specific and regional inferences
 - Activation inferences account for task-related FC's detected in the data

Project Collaborators

Emory University

- **Clint Kilts**, Ph. D., Department of Psychiatry and Behavioral Sciences
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- **Brian Caffo**, Ph. D., Department of Biostatistics
- **Susan Spear Bassett**, M. D., Department of Psychiatry and Behavioral Sciences

References:

- Bowman et al. (2008). Bayesian Hierarchical Framework for Spatial Modeling of fMRI Data. *NeuroImage* 39: 146-156.
- See <http://www.sph.emory.edu/bios/CBIS/index.html>

