

CBIS EMORY

Center for Biomedical Imaging Statistics

Statistical Approaches for Exploring Brain Connectivity with Multi-Modal Neuroimaging Data

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INTRODUCTION

- Two main classes of brain imaging:
- Functional: commonly measured by fMRI

ROLLINS

SCHOOL OF

PUBLIC HEALTH

Structural: measured by diffusion tensor imaging (**DTI**)

Functional Connectivity (FC) measures the temporal coherence between the BOLD signal (a proxy for brain activity) of spatially remote brain locations.

- **FC network**: a set of functionally connected brain regions
- FC networks can be identified from fMRI data.
- **Independent Component Analysis (ICA)** is a popular data-driven method for extracting FC networks, and has several advantages over other techniques.

Structural Connectivity (SC) measures the anatomical connections between brain areas

Probabilistic tractography estimates the SC distribution in the brain based on DTI data.

FC analysis excludes information about the underlying structural connectivity in the brain, yet it is thought that structural fiber tracts facilitate inter-regional interactions in brain activity.

Why combine information across modalities (i.e. fMRI and DTI)?

- 1. To better understand the relationship between brain structure and function. FC is usually, but not always accompanied by strong SC³
- 2. To characterize pathophysiology of disease. Many disorders exhibit disruptions in FC and/or SC (e.g. Multiple Sclerosis, Stroke, Alzheimer's Disease)

•Our Goal: develop statistical methods that combine FC and SC, and provide a convenient framework to conduct statistical inference

Functional pipeline



sSC measure







We test 4 conditions, 300 simulation runs each.

<u>Steps</u>: generate fMRI data, run group ICA to estimate FC network maps, and generate N^* to estimate SC. Estimate Σ by fitting an empirical semivariogram, and calculate $Var(\theta_{i})$ for use in hypothesis testing. Compare to results using a bootstrap variance estimator.

2. Does sSC differ between two FC

$$H_0: \theta_\ell = \theta_{\ell'}$$
 vs. $H_1:$

Use permutation test (permute network id within subject) to evaluate

b) Theoretical variance term tends to slightly underestimate the variance of sSC. The bootstrap estimator performs well. c) Coverage prob. is close to 95% using the theoretical and bootstrap terms. <u>Conclusion</u>: we recommend using the bootstrap estimator of variance when V is large, in order to avoid estimating Σ

CBIS website: http://web1.sph.emory.edu/bios/CBIS/ Structural pipeline

- \bar{p}_i : average probability of SC between voxel *i* and rest of brain
- The **sSC measure** represents the above-baseline strength of SC underlying an FC network. We divide by the maximum possible value to standardize and make comparable between FC networks of different sizes

Inference Framework

 Ω_{ℓ} : set of voxels in IC ℓ

METHODS

where:

Research Questions:

 $heta_\ell = rac{\sum\limits_{j,k\in\Omega_\ell} [{m
ho}_{jk} - (ar {m
ho}_j + ar {m
ho}_k)/2]}{\sum\limits_{k \in \Omega_\ell} \ [1 - (ar {m
ho}_j + ar {m
ho}_k)/2]}$

If we consider the $\binom{V}{2}$ x1 vector, **N**^{*}, as the set of N_{ik} for all voxel pairs (j,k), we can express $\hat{\theta}_{\ell}$ as a function of **N**^{*}

Estimated by: $\hat{ heta}_\ell =$

if
$$\mathbf{N}^* = \begin{pmatrix} N_{12} \\ N_{13} \\ \vdots \\ N_{V-1,V} \end{pmatrix}$$
 then $\hat{\theta}_{\ell} = \left(\frac{(\mathbf{C}_{\ell} - \mathbf{A})\mathbf{N}^*}{b - \mathbf{A}\mathbf{N}^*} \right)$ where: $\mathbf{A} = \frac{(V_{\ell} - 1)}{2(V - 1)} \sum_{j \in \Omega_{\ell}} \mathbf{C}_j$, $b = \frac{V_{\ell}(V_{\ell} - 1)}{2}$, C_{ℓ} and C_j are binary indicator vectors $V = \#$ voxels in brain, $V_{\ell} = \#$ voxels in IC ℓ

We assume $\mathbf{N}^* \sim \text{MVN}(\mathbf{\mu}, \mathbf{\Sigma})$ where $\mathbf{\Sigma}$ is a $\binom{v}{2} \mathbf{x} \binom{v}{2}$ variance-covariance matrix with elements $cov(N_{ik}, N_{i'k'})$

- Estimation of Σ is difficult because it is high-dimensional and has spatial dependencies.
- We can model $cov(N_{ik}, N_{i'k'})$ as a function of distance using a parametric semivariogram model.
- Once Σ is estimated, we can estimate $Var(\hat{\theta})$ by the Delta method:

$$Var(\hat{ heta}_{\ell}) \simeq \left[rac{(m{C}_{\ell}-m{A})\mu}{b-m{A}\mu}
ight]^2 \left[rac{(m{C}_{\ell}-m{A})\boldsymbol{\Sigma}(m{C}_{\ell}-m{A})'}{[(m{C}_{\ell}-m{A})\mu]^2} + rac{m{A}\boldsymbol{\Sigma}m{A'}}{[b-m{A}\mu]^2} - 2rac{[-rac{(-\mu)}{b-m{A}\mu}]^2}{[(m{C}_{\ell}-m{A})\mu]^2} + rac{m{A}\boldsymbol{\Sigma}m{A'}}{[b-m{A}\mu]^2} - 2rac{[-rac{(-\mu)}{b-m{A}\mu}]^2}{[(m{C}_{\ell}-m{A})\mu]^2} + rac{m{A}\boldsymbol{\Sigma}m{A'}}{[b-m{A}\mu]^2} - 2rac{[-\mu]}{b-m{A}\mu}$$

H

$$H_{0}: \theta_{\ell} = 0 \text{ vs. } H_{1}: \theta_{\ell} > 0$$
$$T^{*} = \frac{\overline{\hat{\theta}_{\ell}}}{\sqrt{\hat{Var}(\hat{\theta}_{\ell})/n}} \sim N(0, 1)$$

$$H_{\alpha}: A_{\alpha} - A_{\alpha}$$
 vs H_{α}

1. What is the strength of SC underlying FC networks estimated by data-driven methods like ICA? Due to the stochastic nature of ICA, results vary. Can SC be used to inform the reliability of FC networks estimated by ICA?

We propose a novel measure of the strength of SC (**sSC**) underlying an FC network:

$$\sum_{l \in \Omega_\ell} [N_{jk} - (ar{N}_j + ar{N}_k)/2] \ \sum_{l \in \Omega_\ell} [N - (ar{N}_j + ar{N}_k)/2]$$

 N_{ik} : # of streams connecting voxels j and k in IC ℓ p_{jk} : probability of SC between voxels j and k within IC ℓ (max: 1) \overline{N}_j : avg # of streams that pass through voxel j and the rest of the brain N: total # of streams initiated in the probabilistic tractography procedure

 $rac{-(oldsymbol{\mathcal{C}}_\ell-oldsymbol{A})oldsymbol{\Sigma}oldsymbol{A'}}{-oldsymbol{A})\mu][b-oldsymbol{A}\mu]}$

3. Does sSC of an FC network differ between subject groups? Hypotheses and test statistic:

$$\theta_\ell \neq \theta_{\ell'}$$

$$^{*} = \frac{\frac{\bar{\hat{\theta}}_{\ell,1} - \bar{\hat{\theta}}_{\ell2}}{\sqrt{\frac{\hat{Var}(\hat{\theta}_{\ell,1})}{n_1} + \frac{\hat{Var}(\hat{\theta}_{\ell,2})}{n_2}}} \sim N(0, 1)$$

Non-parametric alternative: use permutation test (permute group id)

Simulation Results:

		Table 1:	Results based on 30	00 simulation runs		
Noise level	θ	$s\hat{S}C$ mean (SD)	Theoretical SE (SD)	Bootstrap SE (SD)	Cov. Prob. I* (Theoretical)	Cov. Prob. II* (Bootstrap)
Low	0.3077	0.3081 (0.0091)	0.0083(0.00035)	0.0093 (0.0016)	92.6	94.3
High	0.3077	0.3074 (0.0104)	0.0093(0.00043)	0.0105(0.0018)	91.6	94
Low	0.3077	0.3084(0.0061)	0.0053 (0.00019)	0.0060(0.00063)	90.7	93.7
High	0.3077	0.3078 (0.0069)	0.0059 (0.00023)	0.0068 (0.00071)	91	94.7
Low	0.64	0.6405 (0.0120)	0.0112(0.00041)	0.0115 (0.0018)	93.3	93
High	0.64	0.6389 (0.0134)	0.0126 (0.00040)	0.0127(0.0020)	94.6	93.6
Low	0.64	0.6409 (0.0080)	0.0071 (0.00019)	0.0074(0.00073)	90.7	93
High	0.64	0.6394 (0.0088)	0.0080 (0.00017)	0.0082(0.00081)	93.7	93
ilities I:	Based on V	Wald-type CI using th	neoret cal SE. Cov	erage piobabilities II: Bo	otstrap percentile confidence interval.	

a) Estimator of sSC shows low bias in all conditions.

DATA APPLICATION

<u>Data</u>

- resting-state fMRI and DTI scans for 20 subjects with Major Depressive Disorder (MDD) & 20 healthy controls
- Studies of MDD do not agree about the mechanism of connectivity disruption, and the pathology is unclear⁴ <u>Analysis</u>
- Group ICA on controls' rs-fMRI data yields 9 resting state networks:



(IC 12) • For each IC, estimate the SC distribution by running a probabilistic tractography procedure, initiating N=5000 streams from each voxel in the IC mask.



CONCLUSIONS

• The proposed sSC measure combines info from the fMRI and DTI modalities

• sSC can be used to inform the reliability of networks estimated by ICA

REFERENCES

- 1. Smith et al., 2009
- 2. Calhoun et al., 2009
- 3. Damoiseaux & Greicius, 2009
- 4. Northoff et al., 2011

 $H_0: \theta_{\ell,1} = \theta_{\ell,2}$ vs. $H_1: \theta_{\ell,1} \neq \theta_{\ell,2}$