**Abstract**

We address the problem of identifying structural brain networks from brain signals measured by resting-state functional magnetic resonance imaging (fMRI). Functional brain activity is modeled as graph signals generated through a linear diffusion process on the unknown structural network. A network deconvolution approach is advocated to: (i) use the fMRI signals to estimate the eigenvectors of the structural network from those of the empirical covariance; and (ii) solve a convex, sparsity-regularized inverse problem to recover the eigenvalues that were discarded by diffusion. The inferred structural networks capture key patterns matching known pathology and may serve as biomarkers for further diagnosis.

**Motivation and context**

- Understanding brain function is a fundamental scientific challenge
- Network science with graph-centric tools valuable for brain analysis
- Neuroimaging studies are time-consuming and expensive
  - Functional (FC) and structural connectivity (SC)
  - FC and SC differ in resolution, running-time, acquisition
  - Costly to measure FC and SC separately
- Relation between FC & SC worth exploring

**Graph signal processing - 101**

- Network as graph $G = (\mathcal{V}; \mathcal{A})$: encode pairwise relationships
- Interest here not in $\mathcal{V}$ itself, but in data associated with nodes in $\mathcal{V}$
  - The object of study is a graph signal
- Ex: Opinion profile, buffer congestion levels, neural activity, epidemic
- Graph SP: need to broaden classical SP results to graph signals
  - Our view: GSP well suited for brain network and signal analysis

**Structural brain networks and functional signals**

- Structural brain networks represent anatomical brain connections
  - Modeled via a weighted, undirected graph $G = (\mathcal{V}; \mathcal{A})$
  - SC: Sparse and symmetric adjacency matrix $A = \mathcal{W}^T \mathcal{W}$
- Brain signals: quantity level of neuronal activity in brain regions
  - fMRI readings on N brain regions over T timepoints

**Numerical tests: simulated signals on known graph structure**

- Generate synthetic signals via diffusion model with Gaussian inputs
- Network deconvolution to recover structural network $\hat{G}$

**Numerical tests: simulated signals on known graph structure**

- Ground-truth preprocessed structural brain network $G_0$ (left)
- Generate synthetic signals via diffusion model with Gaussian inputs
- Network deconvolution to recover structural network $\hat{G}$ (right)

**Numerical tests: simulated signals on known graph structure**

- Edge normalized and thresholded to maintain connected graphs
- Recovery error of 11.1% over 10 Monte Carlo realizations

**ADHD data-group-level analysis: Network recovery**

- Data: Preprocessed BOLD signals from ADHD-200 dataset
  - 182 healthy subjects and 107 ADHD type-1 patients
  - Signals registered on AAL-116 brain atlas
  - Concatenate brain signals of subjects in each group into $X \in \mathbb{R}^{107 \times 116 \times T}$ for the control group
  - $X \in \mathbb{R}^{182 \times 116 \times T}$ for the patient group
- Network deconvolution: recover SC for control (left), patient (right)

**ADHD data-group-level analysis: Network recovery**

- Effective and spatially thresholded SCI
- More general diffusion model and sparsity promotion
- Competitive with results of ADHD-200 global competition

**Discussion and road ahead**

- Network deconvolution framework to identify SC from fMRI signals
- Built upon linear diffusion model between FC and SC
- Group-level and subject-level analysis matches existing results
- Identified brain regions with discriminative power for patient diagnosis
- Envisioned research topics
  - Further validate recovery of SC from observed signals
  - Exploring graph frequency domain for discriminative features
  - Subject-level network inference and disease diagnosis

**References**


**Identifying structural brain networks from functional connectivity: a network deconvolution approach**

Yang Li and Gonzalo Mateos

E-mail: yli131@ur.rochester.edu

Dept. of Electrical and Computer Engineering, University of Rochester

http://www.ece.rochester.edu/~yli131/