Large-scale nested hierarchical structural brain network

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NONSTANDARD BRAIN IMAGE ANALYSIS

Satellite Meeting of 2018
OHBM Singapore

June 22-23, 2018
Peter Bandettini (National Institute of Mental Health): plenary talk
Jean-Baptiste Poline (University of California – Berkeley, USA): plenary talk

**Session on Deep Learning**
Dinggang Shen (University of North Carolina – Chapel Hill, USA)
Daniel Alexander (University College London, UK)
Jong Chul Ye (Korea Advanced Institute of Science & Technology, Korea)
Jong-Hwan Lee (Korea University, Korea)

**Session on Imaging Genetics**
Anqi Qiu (National University of Singapore, Singapore)
Li Shen (Indiana University, USA)
Hongtu Zhu (MD Anderson Cancer Center, USA)
Tomas Nichols (University of Oxford, UK)

**Session on Nonstandard EEG Analysis**
Hernando Ombao (King Abdullah University of Science and Technology, Saudi Arabia)
Hakmook Kang (Vanderbilt University, USA)
Mak Fiecas (University of Warwick, UK)
Tim Johnson (University of Michigan, USA)

**Session on Nonstandard fMRI Analysis**
Martin Lindquist (Johns Hopkins University, USA)
Alex D. Leow (University of Illinois – Chicago, USA; BiAffect)
Bharat Biswal (New Jersey Institute of Technology, USA)
Christian F. Beckmann (Radboud University Nijmegen, Netherlands)

**Session on Nonstandard Brain Connectomics**
Moo K. Chung (University of Wisconsin – Madison, USA)
Andrew Zalesky (University of Melbourne, Australia)
James C. Gee (University of Pennsylvania, USA)
Carl-Fredrik Westin (Harvard University, USA)

**Poster Session**
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Ross Luo, Nagesh Adluru,
Andrew Alexander,
Richard Davidson, Hill Goldsmith

University of Wisconsin-Madison

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HERITABILITY OF HIERARCHICAL STRUCTURAL BRAIN NETWORK


University of Wisconsin-Madison, USA

ABSTRACT

We present a new structural brain network parcellation scheme that can subdivide existing parcellations into smaller subregions in a hierarchically nested fashion. The hierarchical parcellation was used to build multilayer convolutional structural brain networks that preserve topology across different network scales. As an application, we applied the method to diffusion weighted imaging study of 111 twin pairs. The genetic contribution of the whole brain structural connectivity was determined. We showed that the overall heritability is consistent across different network scales.
Preliminary
multiscale image analysis
Weighted-SPHARM

Chung et al., 2007 IEEE Transactions on Medical Imaging 26:566-581


heat kernel bandwidth, diffusion time
Question: How to build a multiscale network?

+25000 nodes
+0.6 billion connections
Voxel-level functional network

Chung et al. 2017 IPMI
Winsconsin Twin Project

58 Monozygotic (MZ) twin pairs
53 same-sex dizygotic (DZ) twin pairs

111 pairs = 222 subjects

6 non-DWI: b=0
63 DWI: b=500 (9 dir.), 800 (18 dir.), 2000 (36 dir.)
Isotropic 2mm resolution
Hierarchical Parcellation
Standard brain parcellation with 116 regions

Precentral gyrus
20-layer hierarchical parcellation
20-layer hierarchical parcellation
Courant nodal domain theorem

\[ \Delta \psi_j(p) = \lambda_j \psi_j(p) \]

\[ 0 = \lambda_1 < \lambda_2 \leq \cdots \]

\[ \psi_0(p) = \frac{1}{\sqrt{\mu(M)}} \]

\[ \int_M \psi_1(p) \, d\mu(p) = 0 \]
Number of voxels in each layer
Hierarchical Connectivity
Hierarchical connectivity $S_{j k}^i$

\[
S_{j k}^i = \sum_{R_{l}^{i+1} \subset R_{j}^i} \sum_{R_{m}^{i+1} \subset R_{k}^i} S_{lm}^{i+1}
\]
Hierarchical connectivity matrix
Heritability of structural network
Heritability Index

\[ HI = 2(\rho_{MZ} - \rho_{DZ}) \]

Spearman’s rank correlation was used on tract counts.

\[(1 \quad 2 \quad 3) \quad (2 \quad 3 \quad 10)\]

Pearson’s : 0.92

Spearman’s : 1
Twin correlations & heritability index
Twin correlations & heritability index

MZ

DZ

HI
Exact Topological Inference
Betti-0 plot (number of connected components)

- MZ
- DZ

$D_q$

Layers: 1 to 6

$B(\lambda)$ vs $\lambda$
Exact topological inference

Maximum gap between plots

\[ D_q = \sup_{1 \leq j \leq q} \left| B(G_{\lambda_j}^1) - B(G_{\lambda_j}^2) \right| \]

\[ P\left( \frac{D_q}{\sqrt{2q}} \geq d \right) \approx 2 \sum_{i=1}^{\infty} (-1)^{i-1} e^{-2i^2d^2} \]

Chung et al. 2017 IPMI