Graph Theoretical Analysis: Current Research, Methodological Issues and Its Applications

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Outline

• Principles & Computational Algorithms
• Methodological Issues & Computational Platform
• Applications to Brain Disorders

Graph Theoretical Analysis

• Principles & Computational Algorithms
  - Small Worlds
  - Social network
  - Brain network

Graph Theoretical Analysis

Graph definition

A graph is composed of a finite non-empty set of vertices and a set of edges between vertices, usually expressed as:

\[ G = (V, E) \]

G represents a graph, V is the set of vertices in graph G, and E is the set of edges between vertices in graph G.

\[ |V(G)| = 5, |E(G)| = 8 \]
Graph Theoretical Analysis

Type of Graph

(a) undirected
(b) directed
(c) weighted

Technology network

WWW
Internet
Power network

Social network

Friendship network
Citation network

Transportation network

Airline network
Public transportation network
Road network

Biological network

Ecological network
Neural network
Brain network

Brain Network: Principles

- Tract tracing
- Functional MRI
  - Achard et al., 2006. J Neurosci
- Diffusion MRI
  - Hagmann et al., 2007. PLoS ONE
- MEG
  - Biswal et al., 2006. PNAS
- EEG
  - Stein et al., 2007. Cereb Cortex
- Structural MRI
  - Hu et al., 2007. Cereb Cortex

Computational Methodology

Graph theoretical analysis

- Regular: high $C_p$ high $L_p$
- Small-world: high $C_p$ low $L_p$
- Random: low $C_p$ low $L_p$

Small-world networks contain many local links and a few long-distance links (so-called “shortcuts”).

Cp: average clustering of a network
Lp: average shortest path length of a network

Description of the network structure

- Geometric quantities and their distribution
  - Degree: number of friends
  - Clustering coefficient: Friends of friends are friends
  - Shortest path: The path with the least number of edges between two vertices
  - Betweenness: The number of shortest paths that go through me

Brain Network: Principles

- Brain hubs
  - Yan et al., 2011. PLoS ONE

Computational Methodology

Brain hubs

- A: driving Hub
  - Participant A
  - Participant B
  - Participant C
  - Participant D
- B: driving Hub
  - Participant E
  - Participant F
  - Participant G
  - Participant H
Community Structures

The connections within the community are tight, and the connections between the communities are relatively sparse

Computational Methodology

Community Structures

Assortativity

- If the vertices with high degree value in the network tend to be interconnected with the vertices of other height values, the network is said to have the same direction matching property; (social network)
- If the vertices with high degree value in the network tend to be interconnected with vertices with low degree value, the network is said to have reverse matching properties; (biological network)

Computational Methodology

Assortativity

• Correlation

Zhang and Raichle, 2010. Nat Rev Neurol

• Correlation

Li, et al., 2021. Hum Brain Mapp

Computational Methodology

• Independent Component Analysis

Birn 2015

Computational Methodology

• Functional network connectivity

Jafari et al., 2008. Neuroimage
Methodological Issues

Thresholding

Yan et al., 2013. Front Hum Neurosci.

Outline

- Resting-State fMRI: Principles
- Data Analysis: Computational Algorithms
- Data Analysis: Methodological Issues
- Data Analysis: Computational Platform
- Applications to Brain Disorders
Traditional fMRI Preprocessing Toolbox

- Numerous steps and configurations
- High learning curve
- Big data era of neuroimaging calls for new pipelines

Computational sharing platform for fMRI

- Incorporating DPARSF
- Prior work, cited 2704 times
- Adapting methodological updates
- Head motion (cited 1159 times)
- Standardization (cited 340 times)
- Multiple comparison correction (cited 176 times)
- Standardized preprocessing pipeline
- Statistical toolbox
- Platform for data sharing

Yan et al., 2016. Neuroinformatics
Corresponding author

Peer Evaluation

Cited by 1532 times, ESI Top 1% top cited paper and hot paper

Seiji Ogawa
Inventor of MRI BOLD

DPARSF

Data Organization

ProcessingDemoData.zip

- FunRaw
  - Sub_001
  - Sub_002
  - Sub_003
- T1Raw
  - Sub_001
  - Sub_002
  - Sub_003

Functional DICOM data

Structural DICOM data

DPABI

Yan et al., 2016. Neuroinformatics
ESI Top 0.1% Highly Cited Paper
Future Directions

• R-fMRI methodology
• Mechanism of R-fMRI: electrophysiology/fMRI recording
• Modulation and intervention: medication and brain stimulation
• Application to brain disorders

Further Help

The R-fMRI Course V3.0

http://rfmri.org/Course

http://rfmri.org/wiki

The R-fMRI Journal Club

Official Account: RFMRILab

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