Consensus clustering approach to group brain connectivity matrices

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GOAL

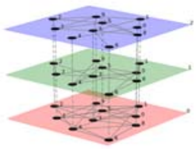
To disentangle the heterogeneity inherent to psycho-physiological conditions by clustering subjects according to their brain connectivity pattern

METHOD

For each brain node, a distance matrix in subject space $d_{ij} = \sqrt{2 \cdot (1 - r_{ij})}$

r_{ij} the pearson correlation coefficient between i subject's whole-brain connectivity pattern of that node and j subject's connectivity pattern

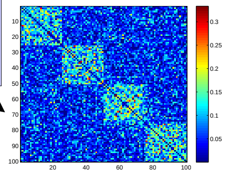
***k*-medoids to each layer.**



➢At fixed k, the consensus matrix of the partitions corresponding to different brain nodes is evaluated

➢A final consensus matrix is reached after averaging over the different k's

Community detection by modularity optimization



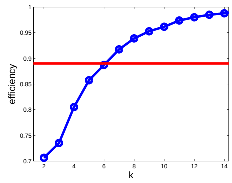
Partition into communities of subjects

TOY MODEL

We simulated a set of 100 subjects, made of four groups of 25 each. The subjects are supposed to be described by 30 nodes. We compare our proposed approach (blue line on right side plot) with a standard procedure such as averaging the distance matrices and then applying the clustering algorithm to the average distance matrix (red line).

Ten nodes are such that the corresponding distance matrix exhibits closer pairs of subject in the same group with respect to pairs belonging to different groups. The remaining twenty nodes are supposed to provide homogeneous distance matrices; in other words, these nodes do not provide any information about groups.

Maximum efficiency clustering information by modularity maximization

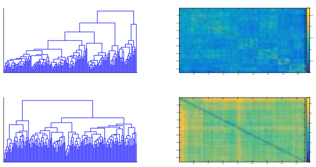


FUNCTIONAL AND STRUCTURAL DATA

http://umcd.humanconnectomeproject.org

N=171 healthy subjects where 200 x 200 fMRI and DTI matrices were obtained (Age: [5-85]; Sex [M/F]: 97/74). Our method applied to both sort of data exhibits a rich hierarchical structure and better organised than using the average distance matrix instead

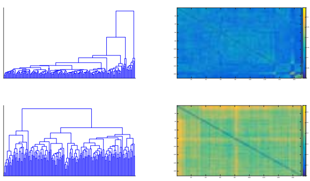
STRUCTURAL DATA



Up: Dendogram from hierarchical clustering on nodes using the proposed method

Down: Dendogram from hierarchical clutering using the averaged distance matrix

FUNCTIONAL DATA



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Our proposed method finds communities significantly differentiated by Age (10^{-10} for the structural and 10^{-5} for the functional data).

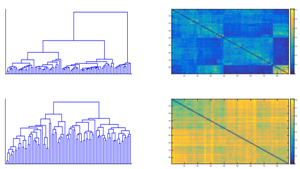
Using instead k-medoids over the average distance, two groups with different age, t-test with probability 10^{-3} using the functional distance, while no significant difference in age using the structural. Combining the structural and functional consensus matrices does not improve the separation w.r.t. age.

FUNCTIONAL LONGITUDINAL DATA

http://myconnectome.org/wp/

N=89 Scan sessions on one subject recorded over a period of 18 months. 268 x 268 functional connectivity matrices were obtained in each session.

The consensus matrix is more hierarchically structured using our method than using the average distance matrix



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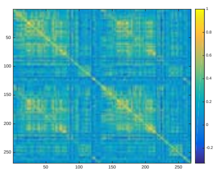
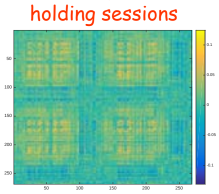


Averaged brain connectome over all sessions

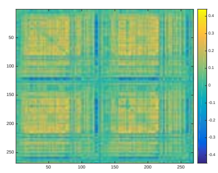
Our method separates the sessions in 3 Clusters with significant:

Number of breath-holding sessions



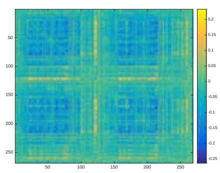
Departure of the average brain connectome over sessions of cluster1 from the global average

High levels of tiredness



Departure of the average brain connectome over sessions of cluster2 from the global average

High levels of relaxation



Departure of the average brain connectome over sessions of cluster1 from the global average

REFS:

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- Mikail Rubinov, Olaf Sporns, *Complex network measures of brain connectivity: Uses and interpretations, NeuroImage*, 52, 3, Sep 2010, pages: 1059-1069
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