Title

Modular structure of high-order interactions in the human brain

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Introduction

A network is highly modular when different communities of nodes have high intra-connectivity within them and low inter-connectivity between them. Different methods and strategies have been used to maximize modularity in brain networks, see for instance [1] and references therein, resulting in a list indicating which node belongs to which community. Despite some strengths and weaknesses between the different methods, most of them start from a connectivity matrix that defines pairwise interactions between network nodes. Following previous work [2]–[4], we built here connectivity matrices defining node high-order interactions, from triplets to n-plets, and compared different communities obtained across different modularity methods.

Methods

K = 86 healthy subjects from the Human Connectome Project (HCP), all of them were healthy unrelated subjects, 43 females, with a mean age of 28,28 years (σ=3,6 years). Resting-state fMRI data was pre-processed with the ICA-FIX pipeline provided by HCP. We extracted M = 32 region-level time-series of the different 8 resting-state networks (RSNs) incorporated into the CONN platform [5], namely, Default Model Network (DMN), Sensory-Motor Network (SMN), Visual Network (VN), Salience Network (SN), Dorsal Attention Network (DAN), Fronto-Parietal Network (FPN), Language Network (LN) and Cerebellear Network (CERN). We first calculated the O-information that accounts for high-order interactions in n-plets of regions [2], and particularized for subsequent analyses to n=3, i.e. the high-order interactions in triplets, also known as interaction information [6], [7]. If the value of the O-information is greater than 0, the interaction in the triplet is said to be redundant, and, if it is lower than 0, it is said to be synergetic. Next, we built connectivity matrices C_m for each value of m by defining:

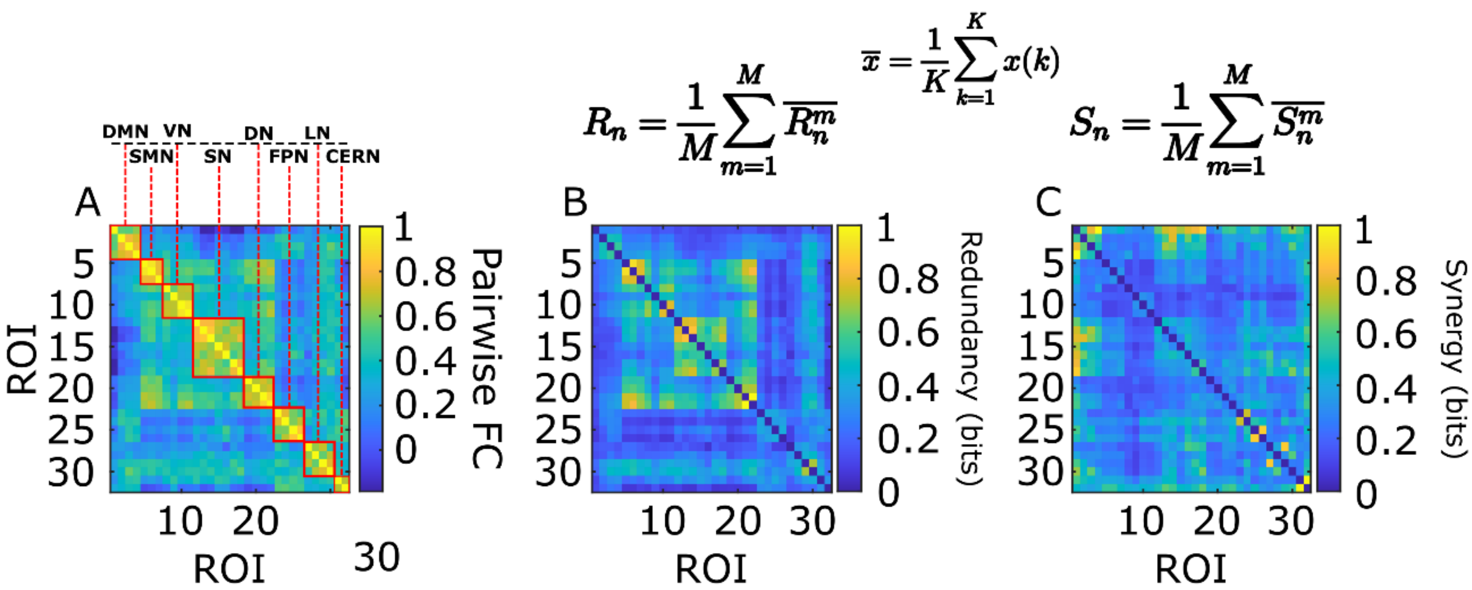
$$C_m \equiv \lambda * R_m + (1-\lambda) * S_m \quad \text{(Eq. 1)}$$

where λ is a free parameter and R_m and S_m are respectively the redundancy and the synergy in the triplet interaction between any two regions when interacting with region m. Notice that we have a different connectivity matrix C_m for each value of m. Eq. (1) allows to parametrize different nature of high-order interactions by tuning the parameter λ, eg., $C_m = S_m$ for λ=0, $C_m = R_m$ for λ=1, while competing redundant and synergetic interactions exist for λ values between 0 and 1. Finally, when considering each region m=1,..., M as one possible node in the network, and using different maximization algorithms, the modularity of different interacting networks C_m is maximized, e.g., using the Louvain algorithm, and the different resulting communities are discussed.

We also made use of different network partitions such as the Brain Hierarchical Atlas[8], Desikan[9] and Schaefer[10] .

Results

The submitted figure illustrates different scenarios. For M=32 regions defined in the partition of the CONN RSNs, Fig 1A illustrates the pairwise functional connectivity matrix obtained for comparison purposes. Figs 1B-C show average across subjects and regions of the different matrices R_m and S_m. We have obtained different network communities in the different scenarios, comparing different methods and using different atlases. We also analysed a continued parameterization depending on λ, and assess the participation that different brain regions play across different communities.



Discussion

High-order interactions in the human brain reveal undetectable relations by pairwise-interaction strategies. The study assesses the modular structure of the space governing those high-order interactions.

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