The edge-centric representation of functional brain networks

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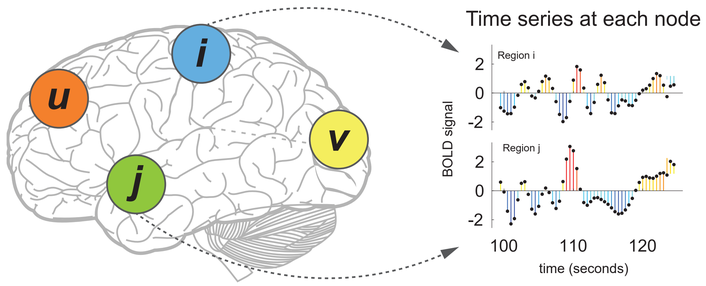
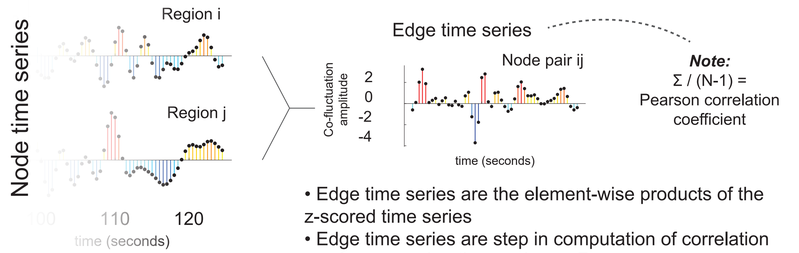
Introduction

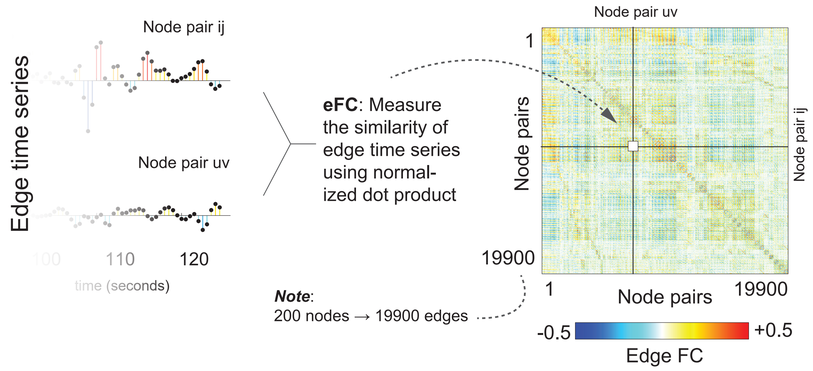
To date, functional brain networks have been constructed by measuring the statistical relationship (e.g. correlation, coherence) of residual BOLD time series between distinct cortical areas[1]. This representation is conceptually node-centric, treating the nodes (i.e. parcels, regions of interest) as the irreducible units on which our network algorithms operate. Here, we introduce a novel edge-centric representation of functional brain networks, which we refer to as ***edge functional connectivity*** (eFC)[2].

Edge time series and eFC construction





- Edge time series are the element-wise products of the z-scored time series
- Edge time series are step in computation of correlation
  - Average edge time series → Pearson's *r*



- Edge time series[3] are an intermediate step when calculating Pearson's *r*
  - These time series are same temporal resolution as input time series
- The eFC matrix indexes the similarity of co-fluctuation between each edge
- Intuitively, high co-fluctuation could be interpreted as similar "conversation" between node pairs, across time

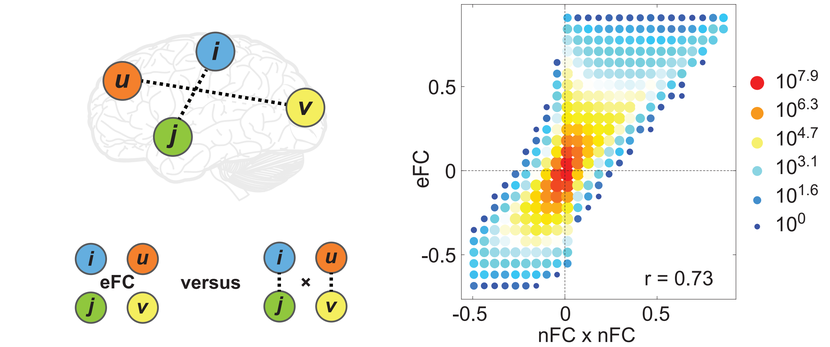
***Preprint*: https://www.biorxiv.org/content/10.1101/799924v1**

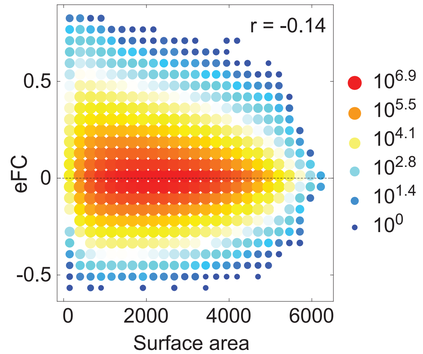
Results

Application to fMRI data

- Three datasets in our study: Human Connectome Project (HCP) unrelated 100, Midnight Scan Club (MSC) 10 subjects, Healthy Brain network serial scanning initiative (HBN) 10 subjects; resting state fMRI
- Preprocessed with HCP pipelines or fMRIPrep; Satterthwaite 36p[4] strategy

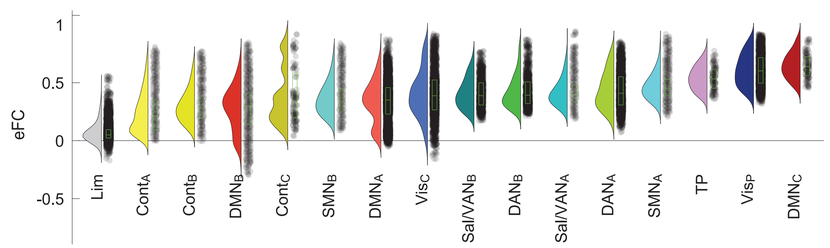
eFC properties





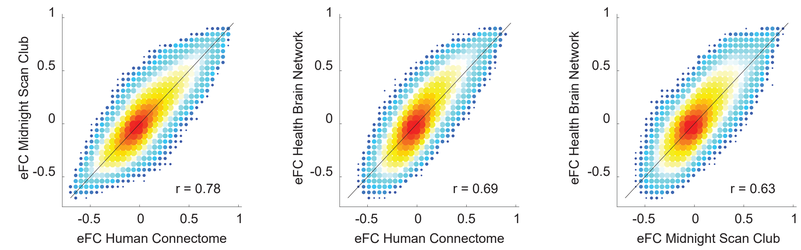
- Additional test: minimum distance between four nodes versus eFC: r = -0.03

- eFC related to, but not fully captured by, node functional connectivity (nFC)
- nFC and eFC are derived from same data, but index different properties of data and have different dimensionality; nonlinear relationship
  - nFC → co-activation, eFC → co-fluctuation
- Weak evidence of spatial influence on eFC as measured by surface area



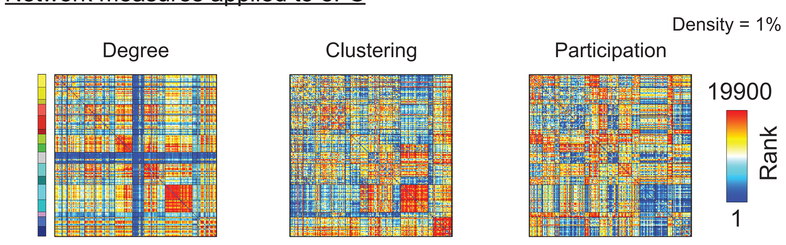
- eFC values corresponding to two edges that fall within the same system[5] are consistently positive, indicating relationship with nodal systems
- eFC values are more positive within- than between-system

eFC across datasets

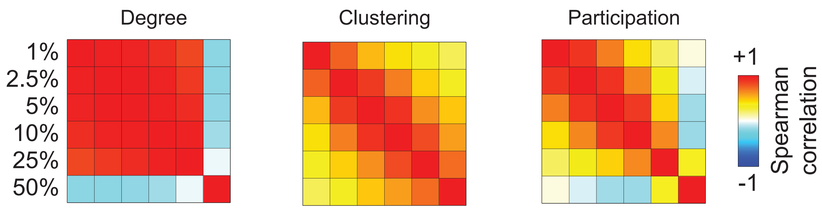


- Relationship of group-averaged eFC values across HCP, MSC, and HBN
- Evidence of consistency across datasets, which vary based on scanner site, scan strengths (3T and 1.5T), and acquisition quality

Network measures applied to eFC



- Algorithms producing row-wise network statistics on the eFC matrix map to the upper triangle of node by node matrix
- Network measures on eFC matrix: degree, indicates number of highly co-fluctuating partners; clustering: indicates propensity of edges to form triangles of high co-fluctuationl; participation: indicates dispersion of edge's connections within and across edge communities



- Since the eFC is dense, to compute some network measures a threshold needs to be applied; similarity of patterns across eFC density thresholds

Conclusion

The edge-centric perspective adds complementary edge-level information to functional brain network understanding[236]. Using the eFC matrix, we can ask questions like: Which edges' activity are most similar to all other edges? How might edge relationships cluster to form strong triangles (i.e. clustering coefficient)? Finally, we note that the eFC framework is general and could be applied to alternative task states or neural data modalities.

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