Local Brain Connectivity Dynamics Using a Graph-Theoretical Approach

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Introduction: Graphs form a good abstraction and representation for brain connectivity where the nodes represent neural elements (neurons, brain regions etc.) and the edges represent some measure of structural or functional connectivity between nodes. While a number of graph based metrics such as the clustering coefficient capture connectivity at a global level (integrated view), often it is necessary to examine changes at the local level (segregated view). One example of alteration in brain connectivity is the development of re-routings that restore functionality typically after a local injury [1]. Scholz et al. report changes in white matter fiber connectivity following behavioral training of a complex skill [3]. While these changes take place over a length of time, brain connectivity could be quite dynamic even in a short time scale. While graph theoretical methods have been extensively used in neuroimaging, the dynamics aspect of brain connectivity is relatively less explored. In this work we investigate the short term dynamics of connectivity within a graph based representation. We propose to quantify the dynamics at the local level by quantifying changes in the neighborhood connectivity across time.

Methods: For each of 10 participants, 10 runs of resting state fMRI (7 minute long, TR/TE=2000/30 ms, FA = 75°, 2 mm in-plane resolution with 4 mm slice thickness) were obtained using a GE Discovery 750 3T MR scanner. The 10 runs for the same participant were obtained over two sessions (5 runs each session). A T1-weighted image was also acquired for normalization to atlas. The data were slice time corrected, motion corrected, coregistered, spatially transformed to MNI space, spatially smoothed and nuisance removed (by regressing motion parameters, global signal, top 90% of WM and CSF signal using PCA, COMPCOR, [4]) using SPM8 software.

Our experimental set up was as follows. We considered sliding windows (sizes 30 – 100) seconds covering the time course. Within each sliding window a graph was constructed as follows. The nodes represented 264 seeds spread across various regions of the brain as in [2]. For each pair of seeds the correlation between the corresponding time courses was computed and converted to z-scores, these formed the edge weights. The weighted graph was converted into a binary graph by applying a threshold on the z-score (1.25, 1.5, 1.75 were tried in our experiments), this ensured that only very strong correlations were retained. For each seed the change in the neighborhood connectivity across the time windows was computed as follows. Consider a seed s, let N1 and N2 be the sets of neighbors of s in the graphs corresponding to time windows w and w+1 respectively. Compute the Dice coefficient between N1 and N2 (=2* |N1∩N2|/(|N1| + |N2|), repeat for windows w+1 and w+2 and so on. The Dice coefficients so computed were averaged over the number of windows to obtain a consolidated score over the entire time course. Finally, a rank ordering of the average Dice coefficient was used to identify top dynamic and stable candidates across multiple subjects and sessions.

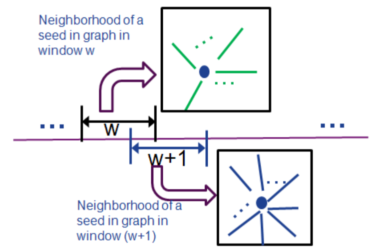

Figure1. Illustration of neighborhood measurement using overlapping windows

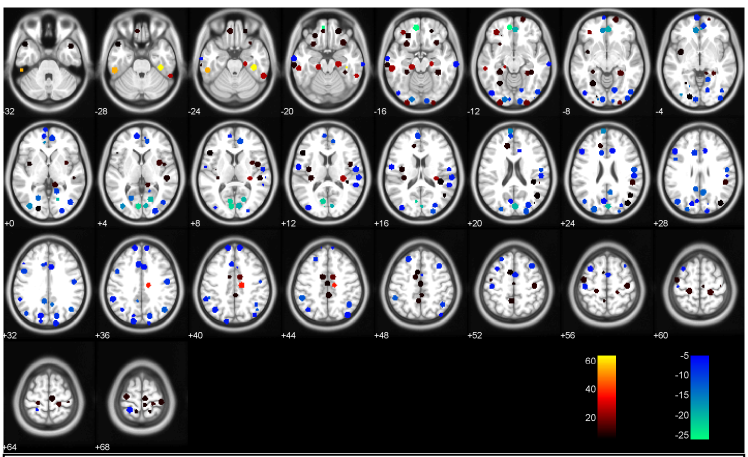

Figure 2. Stability of seeds overlaid on anatomical cross sections of the brain. (Window size 70 seconds, overlap 0, z-score threshold = 1.5). Red-yellow colors used for dynamic seeds and green-blue for stable seeds

Results: Regions (seeds) which exhibited few changes in neighborhood connectivity between consecutive windows across the time course were regarded as stable and those which exhibited significant changes were regarded as dynamic. We investigated multiple thresholds (1.25, 1.5, 1.75 z-score), multiple window sizes (30, 70 and 100 seconds) and multiple degrees of overlap (0 to 50%). The results for one experiment (window size = 70 s, 0 overlap, z-score threshold =1.5) are shown in Figure 2.

Discussion and Conclusions: In this work we explored an approach for capturing the dynamics of brain connectivity based on changes in the neighborhood connectivity of brain regions across time varying connectivity graphs. In our data, nodes belonging to primary motor network regions and inferior temporal lobes were found to be very dynamic across a range of parameter values. Nodes belonging to primary visual and default mode network were found to be very stable. While measurements of stability of the nodes are reliable, dynamics of nodes may be sensitive to noise. Qualitative validation indicates that this is a viable approach for capturing local changes of network allegiance. While in our study we were concerned with short term dynamics, this approach can also be used to study dynamics over a longer term and varying time scales.

References:

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