Identification of state transitions and durations in resting-state functional connectivity

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Target audience Researchers who are exploring the dynamics of resting- state functional connectivity.

Purpose Dynamic analysis of resting-state functional MRI (rsfMRI) scans can be used to explore the dynamics of functional connectivity networks in the brain. Sliding window approaches are typically used to determine the variation in connectivity over the course of a scan[1-3]. The resulting maps of connectivity over time can also be clustered to identify common brain states [4]. However, the choice of window length and other parameters remains mostly arbitrary, and without a 'ground truth' it is difficult to optimize the sensitivity of the analysis method to meaningful changes in brain connectivity. This study applies sliding window correlation (SWC) and k-means clustering to a model network with known transitions to examine the effect of window length and offset on sensitivity to network dynamics.

Methods rsfMRI scans with TR=0.645s [5] were used to create model networks with 7 nodes that have low and high mean correlations ,shown by blue solid lines in Figure 2. In order to ensure the state transition at specific time points, discontinuities were created in the networks as shown by the blue solid lines in Figure 2 to create a 'ground truth' for dynamic analysis. Four networks with different state durations (variable length, 50TR, 100TR, 200TR) were formed. SWC was calculated between each pair of nodes using windows of 25TR, 50TR, 100TR and 200TR Offsets of 1 scan and one fourth of the window length were applied. K-means clustering was applied to each set of sliding window time courses to separate the correlation into 5 states.

Results It was observed that SWC was sensitive to changes in actual correlation between node pairs regardless of the magnitude of change, if the window size was equal to the state duration (100TR) and the window offset was 1TR (Figure 1, cyan). Reducing the window size to half (50TR) resulted in SWC transitions exactly at half way between the change points (Figure 1 (top), red). K-means clustering was successful in identifying the state change points by changing the color at discontinuities in Figure 2 (top) and durations (identified by same color between two discontinuities in Figure 2 (top)). Changing the window offset to 1/4th of the window length (25TR) resulted in loss of SWC ability to identify the state transition points (Figure 1 (bottom), cyan), and k-means capability to identify the correct state transitions and durations (Figure 2 (bottom)). Data are shown for state durations of 100 TRs and high mean correlation but results were similar for other values and for low mean correlations.

Discussion/Conclusion SWC is sensitive to even small changes in correlation if the state durations are equal to the window size and window offset is 1TR. Under the same conditions, k-means works well for identifying the network transitions and durations. Both of these capabilities are lost if the window size or offset are changed for the same network. In actual functional connectivity networks, the correlation changes are gradual with variable durations between transition points, suggesting that an adaptive window approach will be most appropriate for dynamic analysis.

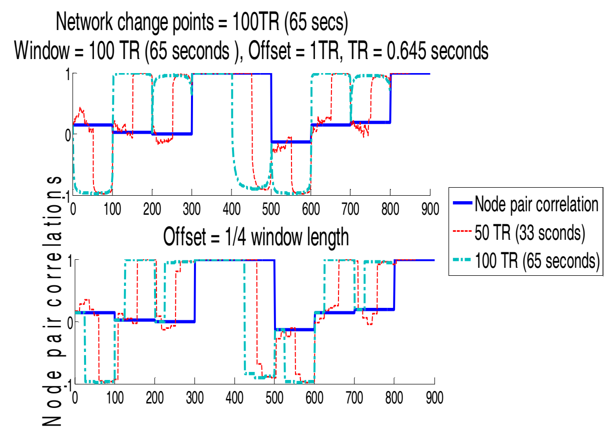

Figure 1 Node pair correlations. **Top:** Sliding window correlation was sensitive to correlation change points (blue) for window size equal to state durations, and offset of 1TR (cyan). **Bottom:** This sensitivity was lost when the offset was increased to ¼ the window length.

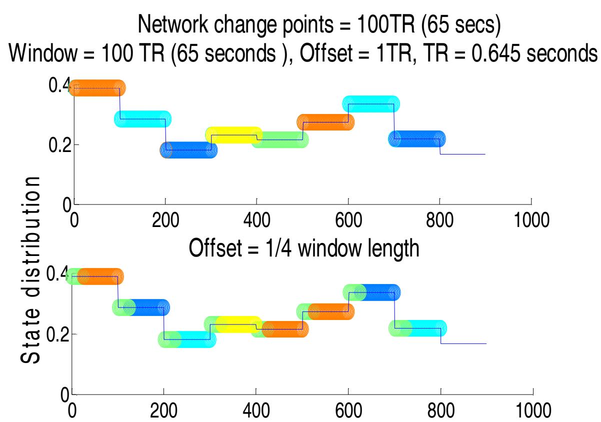

Figure 2 State transitions. Top: State durations and transitions were correctly identified for the window for window size equal to state durations, and offset of 1TR **Bottom:** States transitions were not identified and durations were identified correctly for 75% of the times if the offset is increased to ¼ of the window length.

References

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