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Investigating hippocampal-cortical resting state functional connectivity using static and dynamic measures

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How to view this poster: this poster is arranged vertically and each panel contains a complete section or result. Scroll down to move from objectives, to methods, to results. In the results section, large bold font conveys the take home message. Fine print gives methodological details.

Objectives

- Investigate static functional connectivity of the hippocampus
- Investigate dynamic functional connectivity of the hippocampus
- Investigate how cortical parcellation choice impacts data-driven hippocampal parcellation

Methods

Data: We obtained extensively processed resting state frmi (2mm3) data from 280 unrelated subjects of the Human Connectome Project [1,2] . Cortical regions were defined using one of three parcellations (Glasser [3], Gordon [4], Yeo [5]) in order to track effects of region definition. HC voxels were defined using the Harvard-Oxford probability atlas [6].

Functional Connectivity: For static FC, we computed Fisher-z transformed HC-cortical correlation matrices for each subject and averaged across the group. For dynamic FC, we used a tapered sliding window (window size=100 TRs, step=3 TRs, sigma=20TRs, 1 TR=720ms) to compute windowed correlation matrices for each subject. We computed the standard deviation connectivity of each hc voxel - cortical region, and averaged each subjects standard deviation matrix to create a group average.

Parcellation: Each of 6 computed correlation matrices (3 atlases x 2 FC methods) was clustered using orthogonal projective non-negative matrix factorization (OPNMF) [7,8,9]. OPNMF decomposes an input matrix (m x n) into a component matrix W (m x k) and weight matrix H (k x n), k=#of components, m = HC voxels, n = cortical regions (static) or HC voxels (dynamic). The component matrix W describes component scores for each HC voxel. Clusters are assigned with a winner take all approach across component scores. We analyze k=2-4 component solutions currently and compare clusterings using adjusted rand index (ARI).

Results

Choice of parcellation scheme leads to quantifiable variation in hippocampal clusters derived from RSFC patterns. Different connectivity methods (static vs dynamic) show low agreement.

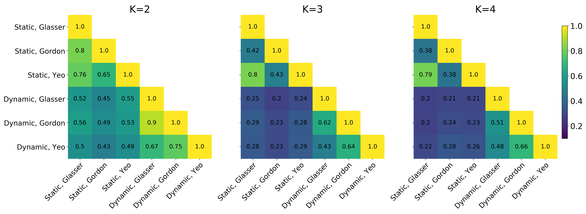

Figure 1: Adjusted rand index for clusterings of the right hippocampus for each pairwise combination of connectivity method (static, dynamic) and parcellation scheme. Within a connectivity method, choice of atlas parcellation leads to spatial variability of output clusters, evidence by low (<0.6) adjusted rand index. This variability increased with the number of output clusters. Across metrics (static vs dynamic), ARI is low - suggesting static and dynamic approaches capture complementary variation. We analyzed 2 to 4 component clusters to observe how ARI varies with increasing granularity.

Hippocampal clusters show static RSFC variation along predominantly along the anterior-posterior axis, but also along the medial-lateral axis in the hippocampal head. Patterns across parcellations are qualitatively similar.

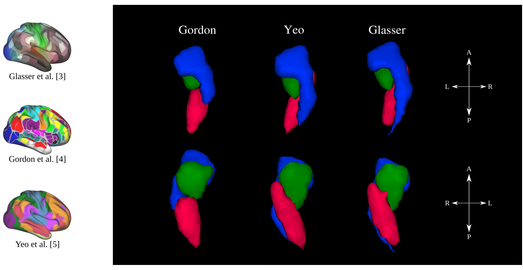

Figure 2: Superior (top row) and inferior (bottom row) views of 3 cluster opNMF solution for each of the Gordon (left column), Yeo (middle), and Glasser (right) atlases. Most prominent is differentiation along the anterior-posterior axis, denoted by the red (posterior) vs blue (anterior) clusters. In the head of the hippocampus, superior-inferior and lateral-medial separation occurs, with the green cluster consistently lying infero-medial to the blue cluster. Across parcellation schemes, qualitative conclusions on presence/absence of anterior-posterior differentiation, and separation of the hippocampal head, are consistent. The most prominent visual difference exists in the extension of the blue cluster across most of the lateral extent of the hippocampus in results derived using Yeo and Glasser atlases in comparison to the Gordon atlas.

Hippocampal clusters derived from standard deviation of RSFC windows show minimal differntiation along the anterior-posterior axis. Superior-inferior and lateral-medial seperation is localized to the anterior hippocampus, suggesting more variability in RSFC patterns here.

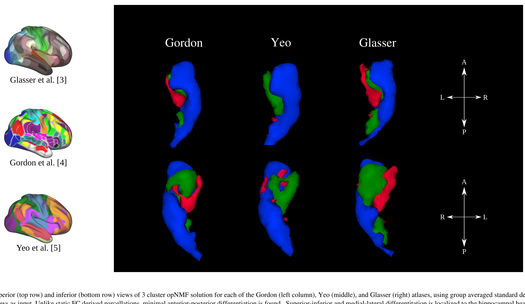

Figure 3: Superior (top row) and inferior (bottom row) views of 3 cluster opNMF solution for each of the Gordon (left column), Yeo (middle), and Glasser (right) atlases, using group averaged standard deviations across windows as input. Unlike static FC derived parcellations, minimal anterior-posterior differentiation is found. Superior-inferior and medial-lateral differentiation is localized to the hippocampal head, suggesting the majority of variation in changes in connectivity over time is localized to this region.

Conclusions

- Measures of static FC vary along all axes of the hippocampus. While anterior-posterior differences are prominent, superior-inferior and lateral-medial speration can be identified in the hippocampal head.
- Dynamic FC, measured as the standard deviation of measured RSFC correlations, is variable in the hippocampal head. Anterior-posterior differences are not as prominent as when using static FC.
- Choice of cortical parcellation has a quantifiable impact on spatial clusters. While similar qualitative conclusions can be drawn, localized, voxel-wise comparisons can be significantly influenced. This effect was most visible in the hippocampal body.

References

[1] Van Essen, D. C. (2013). The WU-Minn Human Connectome Project: an overview. NeuroImage, 80, 62–79.
[2] Glasser, M. F. (2013). The minimal preprocessing pipelines for the Human Connectome Project. NeuroImage, 80, 105–124.
[3] Glasser, M. F. (2016). A multi-modal parcellation of human cerebral cortex. Nature, 536(7615), 171–178.
[4] Gordon, E. M. (2016). Generation and Evaluation of a Cortical Area Parcellation from Resting-State Correlations. Cerebral Cortex , 26(1), 288–303.
[5] Yeo, B. T. T. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. Journal of Neurophysiology, 106(3), 1125–1165.
[6] Desikan, R. S. (2006). An automated labeling system for subdividing the human cerebral cortex on MRI scans into gyral based regions of interest. NeuroImage, 31(3), 968–980.
[7] Sotiras, A. (2015). Finding imaging patterns of structural covariance via Non-Negative Matrix Factorization. NeuroImage, 108, 1–16.
[8] Yang, Z. (2010). Linear and nonlinear projective nonnegative matrix factorization. IEEE Transactions on Neural Networks / a Publication of the IEEE Neural Networks Council, 21(5), 734–749.
[9] Patel, R. et al. Investigating microstructural variation in the human hippocampus using non-negative matrix factorization. Neuroimage 207 (2020): 116348.

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