A Deep Biclustering Framework for Brain Network Analysis

Supplementary Material

1. Brain network Construction: sFNC

Group ICA decomposes the brain imaging volumes into intrinsic connectivity networks (ICNs), Functional network connectivity (FNC) provides a way to study functional interaction and integration. FNC is defined as the temporal dependency among ICNs and is commonly estimated using Pearson's correlation coefficient between ICN time courses [7]. At first, we run the Infomax ICA algorithm to identify the independent sources (ICNs) in the image collection. Infomax has been widely used and compares favorability with other algorithms [4]. For each model order (N = 25, 50, 75, and 100), the Infomax ICA algorithm was run 100 times and clustered together within the ICASSO framework [5]. The run with the closest independent components to the centroids of stable clusters (ICASSO cluster quality index $>$ 0.8) was selected as the best run. This is an important point and facilitates replicable results. Next, the subject-specific independent components time courses were calculated using the spatial multiple regression technique [3]. At each time point, the contribution of each independent component to the BOLD signal was calculated using linear regression [3]. Then, we select a subset of independent components as ICNs if they are stable (ICASSO stability index > 0.8) and depict common ICN properties including (a) dominant low-frequency fluctuations of their time courses evaluated using dynamic range and the ratio of low-frequency to high-frequency power; (b) peak activations in the gray matter; (c) low spatial overlap with vascular, ventricular; and (d) low spatial similarity with motion and other known artifacts. Finally, ICNs were grouped into functional domains based on prior knowledge of their anatomical and functional properties [1].

We calculated static functional network connectivity between every single pair of ICNs across all model orders to effectively capture functional integration and interaction across different spatial scales [6]. For a subset of data (15 percent) with a sampling rate different from 2 s, ICN time courses were interpolated to 2 s. Minimum data length across all subjects was selected for further analysis. Static FNC (sFNC) was estimated by calculating the Pearson correlation between each pair of ICN time courses. This resulting matrix is the adjacency for the brain network. The ICNs are given in figure 1.

2. Biclusters demographics

Table 1 shows the extracted biclusters and their included brain network edges and subjects from both patient and healthy control groups. These results are computed on the combined dataset (fBIRN, COBRE, and MPRC).

Table 1. Biclusters Demographics

Bic	sFNC connections	SZ subjects	HC subjects
1	63	47	72
2	74	61	87
3	48	65	57
4	38	41	67
5	46	43	37

3. Hyper Parameters Sensitivity

We also review the sensitivity of the model for diverse configurations and tuning parameters. While examining the outcome of the tweak in a parameter, we kept others unchanged. Figure 6(a) demonstrates the APCC in extracted bicluster for $k = 5$ for a range of values of α and β. These thresholds are used in the metaheuristic for selecting subjects and features based on activation and weight matrix. We observe the best results for $\alpha = 0.5$, and $\beta = 0.3$. However, the bicluster identification is not strictly dependent on these thresholds as we observe there is a wide range of values for α and β that can achieve competitive results. Figure 6(b) presents the model's performance analysis based on the tweaks in tuning parameters γ, δ. Likewise, we can see slight variations in APCC for the distinct value of γ and δ that manifest the weak dependency on the tuning parameters. These analyses also evidence the robustness of the model to initialization.

4. Cognitive Measurements

The cognitive scores are obtained using two different batteries for three datasets and harmonized across post hoc implementations. Computerized Multiphasic Interactive Neuro-cognitive System (CMINDS)[8]. Neurocognitive domain z-scores are calculated from computerized neuropsychological tests, from computerized neuropsychological tests, which are similar to those in the MATRICS Consensus Cognitive Battery (MCCB) system [2]. The CMINDS includes computerized neuropsychological tasks that are structurally and functionally similar to standard paper-and-pencil neuropsychological tasks and allows for immediate electronic raw data capture and automated scoring of test results.

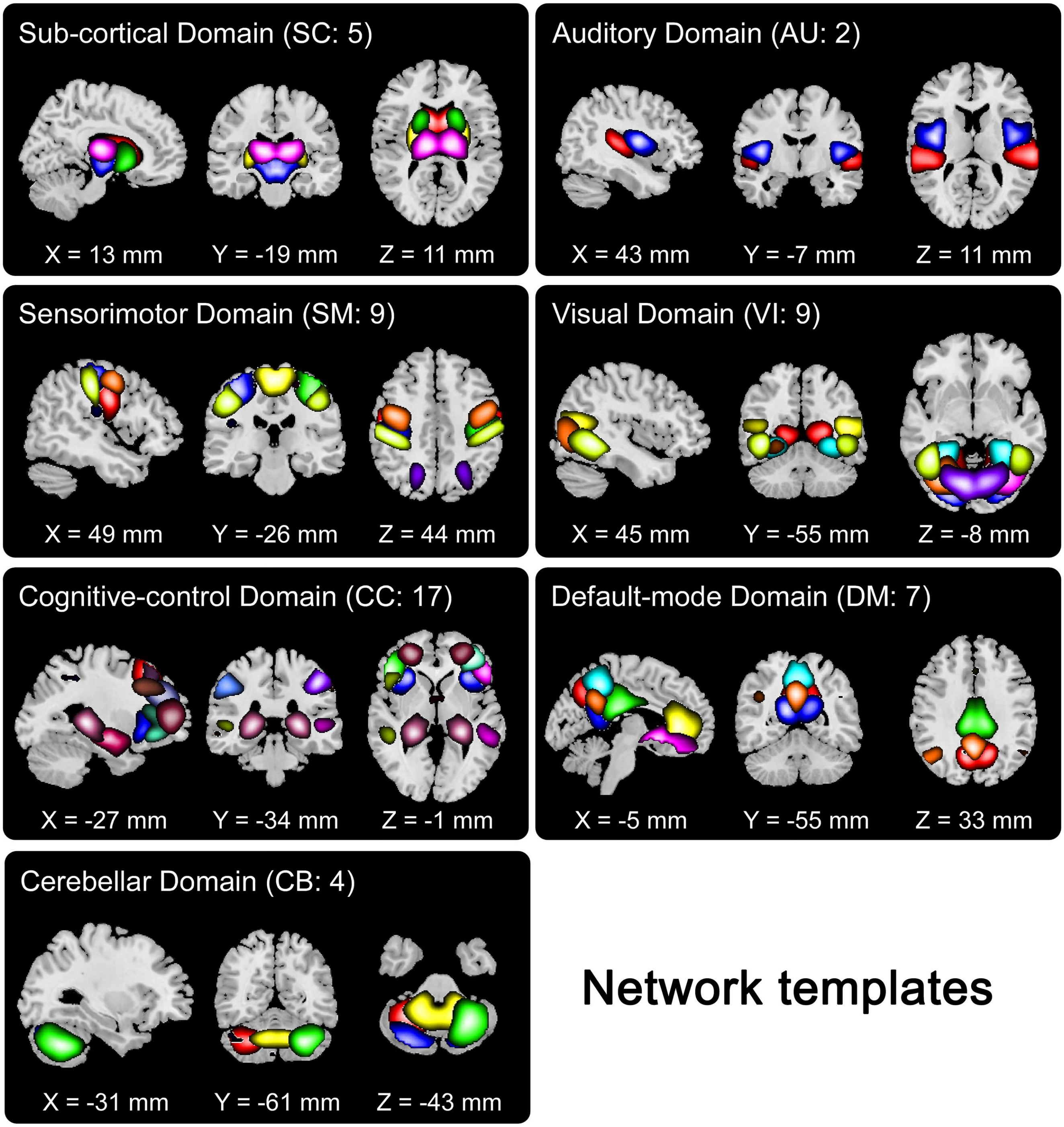

Figure 1. Brain parcellation using group ICA. Spatial maps of the 53 ICNs are arranged into 7 functional domains according to anatomic and functional prior knowledge.

The CMINDS-based cognitive domains, based on comparable tests to those assessed by the MCCB, were as follows: (1) Speed of Processing. This domain score was based on the mean of (a) the log-transformed, negated (worse performance is lower) elapsed transformed, negated (worse performance is lower) elapsed time (in seconds) during Trails A, (b) the number of correct in set responses in 60 seconds on trial 1 of Category Fluency Test - Animals, and (c) the number of correct responses during the Symbol Digit Association Test z-scores; (2) Attention/Vigilance. This do-

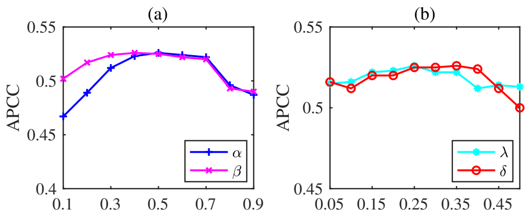

Figure 2. Model's sensitivity towards the tuning parameters and bi-cluster formation thresholds. 6(a) for various values of α and β. 6(b) various values if tuning parameters (γ, δ).

main score was based on the d-prime across blocks A–C of the Continuous Performance Test z -scores; (3) Working Memory. This domain score was based on the mean of (a) the sum of the number of correct on the Visual-Spatial Sequencing Test –Forward and backward condition, and (b) the total correct on the Letter Number Span z -scores; (4) Verbal Learning. This domain score was based on the total number of correctly recalled target words for all three trials on the Semantic Verbal Learning Test z-scores; (5) Visual Learning. This domain score was based on the square-transformed total of the Visual Figure Learning Test z-scores, and (6) Reasoning/Problem Solving. This domain score was based on the square transformed Maze Solving Test total score z-scores. Finally, the CMINDS composite score was defined as the mean of all six normalized domain scores.

For the COBRE dataset, composite cognitive scores are measured by the MATRICS Consensus Cognitive Battery (MCCB) system, introduced by NIMH. It includes one more domain (social cognition) than CMINDS. Both batteries CMINDS and MCCB are analogous in measuring cognitive deficits in schizophrenia. However, there are some differences between these systems reported in this study [8].

References

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