FLEXIBILITY SIGNATURES IN EEG TEMPORAL NETWORKS OF WORKING MEMORY

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Summary

Starting with EEG data collected from adolescents at high risk for disordered thinking and a low risk control group, we produce temporal correlation networks of theta wave activity as they engage in tasks involving attention and working memory. We run multilayer modularity community detection with GenLouvain to calculate the node-level flexibility in these temporal networks. We find that these flexibility measures distinguish between the two groups high accuracy, and use the discriminating hyperplane between the groups to examine how the brains in the two groups are processing the tasks differently. We show that more basic network measures are ineffective at discriminating between the classes.

Method

Data: Subjects of high and low clinical risk for disordered thinking had EEG neuronal activity data recorded at 64 locations on the skull under different memory tasks in two batches separated by a social anxiety stressor. Each batch of tasks consisted of 3 fractal N-back tests of $N = 0, 1, 2$, with fractal images appearing for one second, followed by two seconds in between images. For each subject and task type, the three-second windows where they successfully identified the images were isolated. The EEG signals were decomposed into frequency bands, binned into 301 0.01sec windows, and then averaged over all successful three-second windows (with the image appearance at $t =$ 1s). At each time point, Pearson correlations of the theta frequency band (4–8 Hz) signal were calculated between the 64 electrode node locations. We then took the absolute value of these correlations, yielding a $64\times64\times301$ temporal correlation network for each subject and task type. There is also similar data from the same tests for the alpha frequency band (8–13 Hz).

Basic network measures: In order to justify turning to community based measures, we first calculated several more basic measures on the network with weights W_{ij} given by the absolute values of correlations. We then took these, flattened them into feature vectors, and performed Support Vector Machine (SVM) classification to see how well these measures could distinguish between the low and high risk groups. For each layer of the multilayer networks, we calculated node strength, characteristic path length (based on edge lengths of $1/W_{ij}$), local efficiency, and a weighted version of the clustering coefficient [4],

$$C_i^{wei,O} = \frac{1}{k_i(k_i-1)} \sum_{j,l\neq i} (W_{ij}W_{il}W_{jl})^{1/3}\,.$$

Community assignments to Flexibility: Multilayer modularity community detection was performed separately on the temporal correlations for each subject and task type, using repeated calls of the iterated GenLouvain algorithm [3], selecting the result with highest multilayer modularity. The results presented here are obtained using the same resolution parameter $\gamma = 0.8$ across all temporal layers and the same interlayer coupling parameter $\omega = 1$ between nearest-neighbor-in-time layers (see [3] for details). GenLouvain finds a hard partition of node-layers into communities. Let c_i^t be the community label of node i in time layer t. Motivated by previous use of community flexibility in task-based fMRI data [1], we calculate node flexibility in terms of the numbers of times that the node switches communities in a time window. For sliding windows of length s, f_i^t is the normalized number of times that node i switches communities between temporal window t and $t+s$, that is,

$$f_i^t = \frac{1}{s}\sum_{l=t}^{t+s}\left[1-\delta(c_i^l, c_i^{l+1})\right]\,,$$

where δ is the Kronecker delta function. Whereas previous work has primarily used flexibility averaged over nodes, we leave the node dependence intact here.

Separating Hyperplanes in Flexibility Space: For each s, the $6\times64\times(301-s)$ flexibility values for a single subject over all 6 tests were flattened into a single feature vector, $\vec{x}_p$, with class label $y_p \in \{+1,-1\}$ (corresponding here to low v. high clinical risk). We then used SVM classification to identify a separating hyperplane between the classes, defined by normal $\vec{n}$ and bias β, which maximizes the projected distance between the points in each class closest to the hyperplane (the *support vectors*) [2].

Results

Accuracy of Discrimination: Using the flattened feature vectors combined from the six task types, SVM was trained on 60 of the 75 subjects. The remaining points were assigned a label depending on which side of the hyperplane they fall on, and compared to the known risk label of the subject. This was run and averaged over 100 times each for various window sizes and features: the basic network measures mentioned earlier, flexibility of the theta correlation matrices, and flexibility of the alpha correlation matrices. The resulting accuracies of prediction using these different features are displayed in Figure 1. We see that the theta-flexibility measure performs far above all others at all but the lowest window sizes.

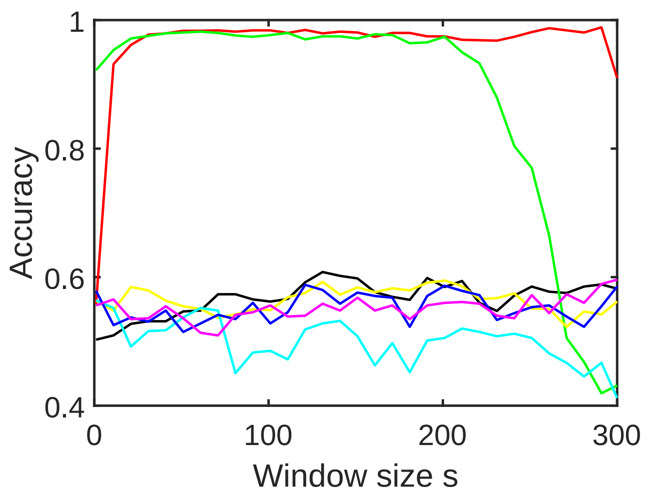

Figure 1: Window size vs accuracy of various methods, with a train/test split of 60/15, averaged over 100 runs; red is theta-flexibility, black is alpha-flexibility, green is node-averaged theta-flexibility, yellow is node strength, cyan is local efficiency, blue is CPL, magenta is clustering coefficient

Analysis of Results: From Figure 1, we can see that flexibility is a significantly better predictor of risk than more basic network measures. This provides further support for the use of flexibility as a measure on temporal brain networks and the importance of community structure in the way these systems operate.

We see that for mid-range window sizes, node-averaged flexibilty performs with similar accuracy as node-dependent flexibility. Since node-dependent flexibility carries more information about the underlying systems, this seems to justify the choice to not average over nodes.

These results seem to justify one of the initial hypotheses of the project, that theta band activity is more of a driver in carrying out these memory tasks than alpha band activity.

Analysis of the unit normals of the separating hyperplanes should be able to help us understand how the low and high risk subjects' EEG signals differ, pointing the way to understand how their brains process these tasks differently. Much work remains in this analysis, but some initial results are shown in Figure 2. For $s = 300$, corresponding to flexibility averaged over the entire time window, we took the averaged normal of the hyperplanes found over 100 runs, and unfolded it back into the 64 regions of the 6 tests. This seems to indicate the regions which differ strongly between the two risk groups on the basis of flexibility.

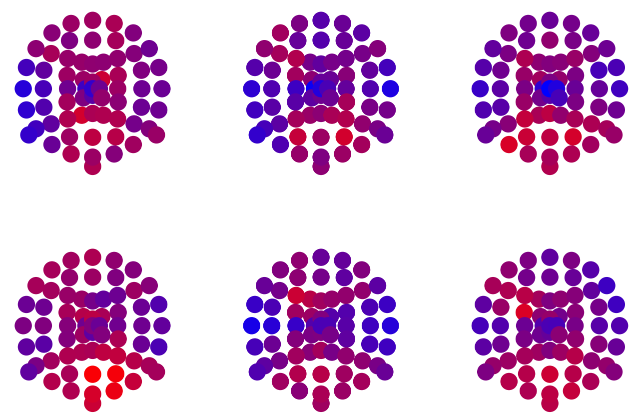

Figure 2: Unraveled normal of separating hyperplane for $s = 300$ discrimination, projected onto a from-above representation of the EEG electrode locations. Values range from -0.09 (blue) to 0.55 (red). Top row is before-stressor, bottom is after, and the first/second/third column corresponds to 0/1/2-back test

References

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