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GSP-DERIVED BRAIN FEATURES FOR CLASSIFICATION IN ANXIETY AND DEPRESSION

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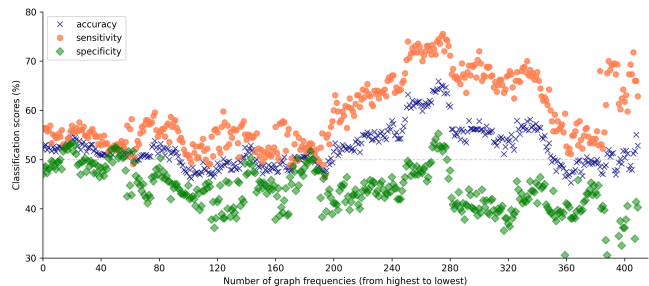
Anxiety and depression in adolescents are mental health conditions that negatively affect the quality of life. Our project aims to enhance our understanding of the biological mechanisms underlying those disorders by leveraging Graph Signal Processing (GSP) to integrate diffusion MRI and fMRI modalities. Here, we propose a classification pipeline based on the extraction of GSP-based measures to identify anxiety and depression features, using the Boston Adolescent Neuroimaging of Depression and Anxiety (BANDA) dataset [1].

1. DATA AND PREPROCESSING

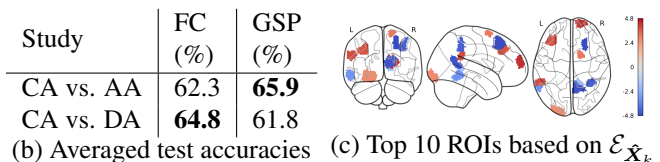
The BANDA study is one of the disease studies that uses Human Connectome Project protocols. Parents provided informed consent and adolescents assent for the project. We preprocessed images of 60 Control (CA), 72 Anxious (AA) and 61 Depressed Adolescents (DA), using QSIPrep [2] and fMRIPrep [3]. The brain parcellation Schaefer atlas with 400 cortical [4] and 16 subcortical regions [5] was adopted. Whole brain probabilistic tractography was performed using a spherical deconvolution approach, followed by the Spherical-deconvolution Informed Filtering of Tractograms 2 [6].

2. METHODS

We modeled structural connectivity as a graph, represented by an adjacency matrix containing the number of fibers that links two ROIs. We defined $\mathbf{X} \in \mathbb{R}^{N \times T}$ as the BOLD signal for N ROIs over the course of T timepoints. We computed the graph's normalized Laplacian matrix and its eigenvectors \mathbf{U} form an orthogonal basis. Therefore, we defined the $(N \times N)$ matrix called $\mathbf{U}_k^{(\text{high})}$ containing the eigenvectors associated with the k highest eigenvalues and the filtered fMRI signals $\hat{\mathbf{X}}_k$ were obtained as follows: $\hat{\mathbf{X}}_k = \mathbf{U}_k^{(\text{high})} \mathbf{U}^\top \mathbf{X}$. The energy of the graph filtered component averaged across time, was computed as $\mathcal{E}_{\hat{\mathbf{X}}_k} = \frac{1}{T} \sum_{t=1}^T \hat{\mathbf{X}}_k(\cdot, t)^2$. Then, we performed a classification analysis based on these features to quantify the frequencies that give the best accuracies. They were compared with the best performance obtained among different graph metrics on functional connectivity (FC), in our case: clustering coefficient, strength and eigenvector centrality. We thus trained a linear support vector machine model in a cross-validation scheme with a train-test split of 80/20%, using a stratified shuffle over 30 splits. The best features were ordered via ANOVA and the classification was performed until all features were considered.



(a) Classification scores of CA vs. AA using the energy of graph filtered time series, with decreasing graph frequencies



(b) Averaged test accuracies (c) Top 10 ROIs based on $\mathcal{E}_{\hat{\mathbf{X}}_k}$

Fig. 1. Classification performance to discriminate our groups.

3. RESULTS AND DISCUSSION

Figure 1(b) shows that GSP provides better accuracy to discriminate CA from AA in comparison to using only FC with a gain of more than 3%, but is less discriminative for CA and DA. In Figure 1(a), we can observe that by considering the GSP approach, the best performance for the CA vs. AA classification is obtained for the 272 highest graph frequencies. Figure 1(c) displays the most discriminative regions belonging to the default mode, frontoparietal and salience ventral attention networks, which are all involved in anxiety in adolescence [7].

Our results demonstrated that multimodal methods outperformed classical unimodal graph-based approaches for more homogeneous diseases such as anxiety.

The authors declare that there are no conflicts of interests.

4. REFERENCES

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