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Graph Frequency Analysis of Brain Signals

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Project Summary

The methods behind graph signal processing (GSP) have a wide range of applications, and offer benefits in multiple research areas. In our paper, we aim to connect graph signal processing with nueorscience and biological communities. In neuroscience, different studies on brain activity patterns and functional brain networks have led to the identification of neurological diseases and behavioral traits [1]. Considering that the individual study of signals and networks have similar focus problems, we advocate an intermediate path in which we interpret brain activity as a signal supported on the graph of brain connectivity. GSP tools can therefore be used to glean information from brain signals using the network as an aid to identify patterns of interest.

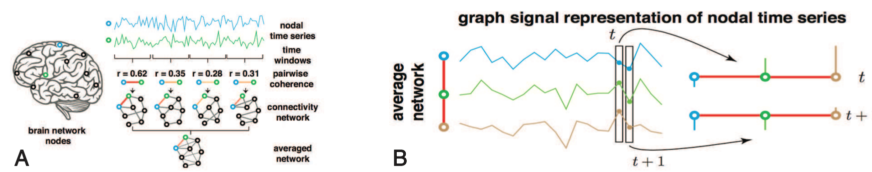

Figure 1: (A) Brain network representation using average functional coherence values. (B) Brain graph signal using regional fMRI data for each time point t.

Motivation

Although all faculty members wish to see undergraduate students incorporated into high level research, the minimal conceptual background that these students start with is a large hindrance in achieving this goal. Projects which involve too many unfamiliar concepts make it difficult to (i) spark interest in undergraduate students and (ii) allow students the ability to explore, connect concepts, and extract results independently, with little supervision. For students interested in data sciences, they have to grapple with the concept of transforming data into information, typically through finding an alternative representation for the data. This is a formidable task, as it is not always easy to find suitable representations [2]. Students who have taken introductory classes in signal processing can begin to understand fundamental transforms, such as the DFT, multidimensional DFT and PCA, and thus can pursue research in these areas. It is our hope, though, to extend this understanding and likewise extend these students' scope of research. The graph Fourier transform (GFT) is an umbrella for signal processing concepts, and also encompasses all other relationships between elements of signals [3,4]. Therefore, in an attempt to incorporate undergraduates into research, we present to them the connection between GSP and signal processing, and consequently provide a platform where students have suitable background for autonomous research in a much broader area.

The project presented here introduces GSP techniques to a neuroscience application. In designing an application based project, especially in neurscience, we are incorporating GSP theory with tangible, observation-based results. Therefore, our project is appealing to multiple communities, in addition to undergraduates with little background in research, since the student can learn through observations. Our focus for this research is analyzing human learning through subject performance in a simple visual-motor task. We present notions of the GFT and graph filters to decompose a given subject's brain signal into sections that represent different modes of variability. This type of analysis enforces the student's understanding of graph frequency by challenging them to apply the concept to a different domain, being the variability across brain regions, a type of spatial analysis. Exploration of this concept offers the student autonomy in exploring different frequency levels, temporal variability and the underlying network.

Methods

We collected fMRI data from two separate experiments during which subjects were tasked with responding to visual cues by pressing down on a corresponding response box. The experiments tracked how fast the subjects responded to these cues over a set training period. Figure 1 A shows that given nodes at different brain regions, we can take the collected fMRI signal and create an average connectivity network representing regional coherence. Figure 1 B illustrates how we can view our graph signal as the vector of fMRI values at each node for an individual time point t. From the collected fMRI brain signal and the calculated brain network, we used graph low pass, band pass, and high pass filters, respectively, to decompose the signal into low ($\mathbf{x}_\mathrm{L}$), middle ($\mathbf{x}_\mathrm{M}$) and high ($\mathbf{x}_\mathrm{H}$) frequency components, such that our original signal $\mathbf{x} = \mathbf{x}_\mathrm{L} + \mathbf{x}_\mathrm{M} + \mathbf{x}_\mathrm{H}$. This gives the notion that $\mathbf{x}_\mathrm{L}$ represents parts of the signal which vary slowly over the brain regions, whereas $\mathbf{x}_\mathrm{H}$ represent parts of the signal which change rapidly.

Notable Highlights

The methods described above and results we present here have recently been accepted for publication [5].

Decomposed Graph Signals

A visualization of the energy of the decomposed signals, $\|\mathbf{x}_\mathrm{L}\|_2$, $\|\mathbf{x}_\mathrm{M}\|_2$, and $\|\mathbf{x}_\mathrm{H}\|_2$, in Figure 2 shows that even though we normalize the brain signals, therefore expecting to see similar distributions across brain regions, the signals $\mathbf{x}_\mathrm{L}$ and $\mathbf{x}_\mathrm{H}$ clearly possess the majority of the energy, whereas $\mathbf{x}_\mathrm{M}$ possesses very few regions that pass the applied thresholding. The brain combines some degree of disorganized behavior with regularity, and when these coexist, the complexity of the system is high [6]. This gives the notion that when forming systems in the brain, signals varying smoothly across the brain (regular behavior) and rapidly across the brain (disorganized behavior) are favored.

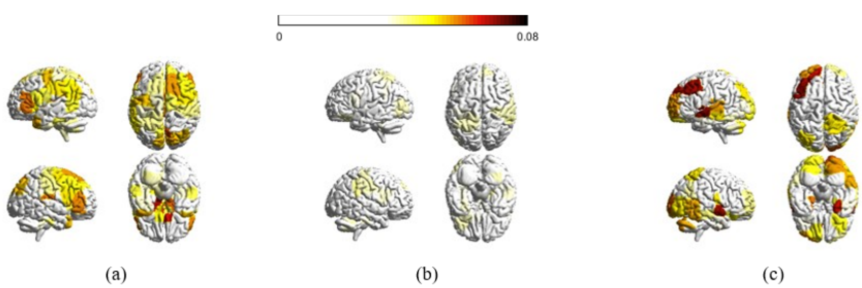

Figure 2: Example distribution of decomposed signals across all brain regions for first experiment. Average energy with respect to (a) $\mathbf{x}_L$ (b) $\mathbf{x}_M$ and (c) $\mathbf{x}_H$. A thresholding is applied.

Association with Learning

The most interesting point is to find how these decomposed signals relate to subjects' performances when learning a task. For each training point, we evaluated learning rates for all participants based on their change in time to complete a given visual sequence. We then calculated the Pearson correlation between a subject's decomposed signal and learning rate, respectively (i.e. $\|\mathbf{x}_\mathrm{L}\|$ vs learning rate), for each training session. Figure 3 plots these correlation coefficients for all training points. We found that for $\mathbf{x}_\mathrm{L}$ corresponding to smooth spatial variation, its correlation with learning is positive at the start of training, and gradually decreases to become negative at the end of the experiment when individuals are highly familiar with the sequence. The exact opposite is observed for $\mathbf{x}_\mathrm{H}$ corresponding to rapid spatial variation. Its correlation with learning is negative at the start of training, and gradually increases until it is positive at the end of the experiment. For $\mathbf{x}_\mathrm{M}$, no significant trend between correlation and training intensity is observed. This result implies that the most association with learning comes from the brain signals that either vary smoothly ($\mathbf{x}_\mathrm{L}$, regularity) or rapidly ($\mathbf{x}_\mathrm{H}$, randomness) with respect to the brain network. Therefore, graph frequency decomposition could be used to capture more informative brain signals by filtering out non-informative counterparts, most likely associated with middle graph frequencies. From a neuroscience perspective, we observe that when faced with an unfamiliar task, smooth, spread, and cooperative signals are favored. As we become more familiar with a task, these become less important, and in fact, when we have high task familiarity, we favor varied, spiking, and competitive signals.

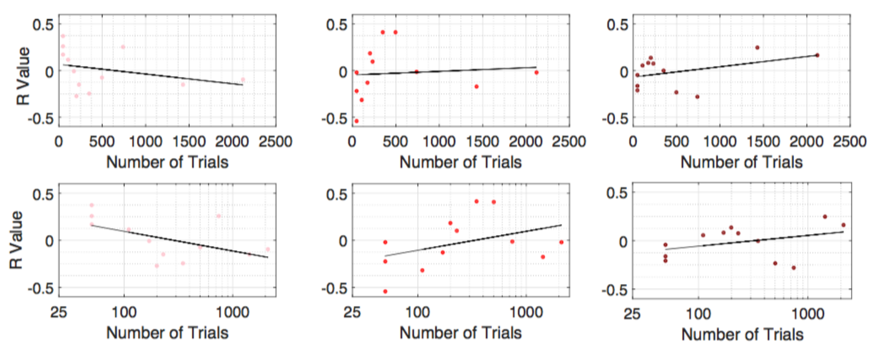

Figure 3: Scatter plots from first experiment depicting the level of task familiarity and R values, defined here as correlations between learning rate parameters and the norm of the decomposed signal (i.e. Pink points on Left: $\mathbf{x}_L$, Red points in Middle: $\mathbf{x}_M$, and Maroon points on Right: $\mathbf{x}_H$). Top row: number of trials described in linear scale. Bottom row: number of trials evaluated in logarithm scale.

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