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A Graph Signal Processing Framework based on Graph Learning and Graph Neural Networks for Mental Workload Classification from EEG signals

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Electroencephalography (EEG) is a non-invasive technique for recording the brain’s electrical activity, known for its high temporal resolution. It identifies different frequency bands (δ [0.5-4 Hz], θ [4-8 Hz], α [8-13 Hz], β [13-30 Hz], lower γ [30-80 Hz], and upper γ [80-150 Hz]), each corresponding to specific brain activities and mental states, for instance, the δ band signals are dominant during deep sleep stage.

Machine learning has leveraged EEG for tasks such as sleep stage classification, seizure prediction, brain-computer interface (BCI) applications, emotion recognition, and mental workload classification. This approach typically begins with extracting features, especially from the frequency domain, like power spectral density (PSD) metrics for each frequency band. Research has also delved into time-frequency and time-scale analysis using wavelet transforms, and spatial domain features that reveal interactions between different brain regions, offering insights into brain region activities. Techniques like common spatial pattern filtering are used to highlight these patterns before the data is analyzed using classifiers such as linear discriminant analysis (LDA), minimum distance to mean (MDM), and random forest (RF).

The brain’s network structure can effectively be modeled by graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathbf{W}\}$, with vertices \mathcal{V} representing electrodes and edges \mathcal{E} denoting electrode interactions, encapsulated in the weight matrix \mathbf{W} . This matrix quantifies the interaction strength between electrode pairs. Recently, functional brain networks, representing EEG-based brain activity, have attracted considerable interest for their potential to reveal brain function dynamics through graph representations. These networks are characterized using various similarity metrics like Pearson correlation, phase locking value (PLV), and phase lag index (PLI), which quantify the statistical relationships between EEG signals. Such analyses often incorporate thresholding to address volume conduction problem.

In this work, we consider multivariate EEG signals of t seconds recorded by N electrodes, positioned on the scalp of a subject, at a sampling frequency F_s , and stacked in a matrix $\mathbf{X} \in R^{N \times (tF_s)}$, the aim is to predict a class from a set of possible classes of mental workload corresponding to different difficulty levels of tasks (easy, medium and difficult). Our approach consists of two main steps: (1) functional network construction, (2) classification based on graph neural network (GNN).

Functional network construction. Graph structure, specifically edge weights, is determined through the learning of the graph Laplacian from EEG data, adhering to structural constraints such as sparsity levels and connectivity. This process aligns with a maximum a posteriori (MAP) parameter estimation for a Gaussian-Markov Random Field (GMRF) model, whose precision matrix is the graph Laplacian [1]. By noting \mathbf{C} the covariance matrix of the EEG signals, it can be formulated as

$$\begin{aligned} \tilde{\mathbf{L}} = \arg \min_{\mathbf{L}} & \text{Tr}(\mathbf{L}\mathbf{S}) - \log \det(\mathbf{L}) \\ & \text{subject to } \mathbf{L} \in \mathcal{L}(\mathbf{A}) \end{aligned}$$

where,

$$\mathcal{L}(\mathbf{A}) = \left\{ \mathbf{L} \mid \mathbf{L} \succeq 0, \begin{cases} (\mathbf{L})_{ef} \leq 0 & \text{if } (\mathbf{A})_{ef} = 1 \\ (\mathbf{L})_{ef} = 0 & \text{if } (\mathbf{A})_{ef} = 0 \end{cases} \text{ for } e \neq f \right\},$$

and $\mathbf{S} = \mathbf{C} + \mathbf{H}$ with \mathbf{H} a regularization matrix defined as:

$$\mathbf{H} = \sqrt{\alpha \|\mathbf{C}\|_F} \cdot [\mathbf{I} - \mathbf{1}\mathbf{1}^T]$$

α is the regularization parameter, $\mathbf{1}$ denotes a column vector of ones, and \mathbf{I} the identity matrix. $\tilde{\mathbf{L}}$ is the learned positive semi-definite ($\mathbf{L} \succeq 0$) graph Laplacian (i.e. estimated precision matrix), \mathbf{A} corresponds to the connectivity matrix. A non-zero diagonal element $(\tilde{\mathbf{L}})_{ef}$ denotes a positive partial correlation between the electrodes e and f . The weight matrix \mathbf{W} (i.e. the edge attributes) is then derived from the learned Laplacian by zeroing the diagonal entries, and computing the opposite of the off-diagonal elements. To finalize the graph creation, we compute the relative power spectral density (PSD) features across different frequency bands for each node. Consequently, the feature vectors of the nodes will comprise the 3-dimensional positions of the electrodes concatenated with the relative PSD values of the six frequency bands.

Classification. Spatial Graph Neural Networks (GNNs) are a class of neural networks that derive node embeddings through a message-passing mechanism, which involves aggregating messages from a node and its neighbors. These networks can also incorporate edge attributes, allowing for layers that learn not only from the features of individual nodes but also from the connections between nodes as depicted by the edges. The chosen architecture for our application is a GNN, emphasizing its capability to leverage both node characteristics and the network structure. It consists of three consecutive graph convolutional layers to progressively refine the node embeddings, with each layer’s output activated by a ReLU function for non-linearity. Following the convolutional layers, a global max pooling operation aggregates the node embeddings to produce a graph-level representation, which is then passed through a dropout layer for regularization and a linear layer to produce the final class predictions. The optimizer chosen for the task is Adam, paired with a categorical cross-entropy loss function.

Dataset and performance. The framework is assessed on a mental workload classification task using a public EEG dataset [2], with 15 participants performing tasks of varying complexity across two sessions. Signals were captured using 61 electrodes. The data were segmented into overlapping 2-second windows, with a 1-second overlap. On average, this framework outperforms traditional machine learning approach applied on this dataset by computing covariance matrices of the filtered signals and using them with a Riemannian Minimum Distance to Mean (MDM) classifier. Furthermore, its performance is comparable to that of the Common Spatial Pattern technique when combined with a one-versus-rest strategy for managing non-binary classification problems.

- [1] H. Egilmez et al, “Graph learning from data under structural and laplacian constraints,” IEEE Journal of Selected Topics in Signal Processing, vol. PP, 11 2016.
- [2] M. Hinss et al “An eeg dataset for cross-session mental workload estimation: passive bci competition of the neuroergonomics conference 2021,” 2021.