

Graph signal processing approaches for EEG-based neural pattern discovery

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Abstract

EEG is a non-invasive tool to study complex activity of neurons, but traditional signal processing techniques typically process individual EEG channels separately and fail to adequately model spatial and functional relationships between brain regions. In this paper, we introduce a Graph Signal Processing Graph Attention Network (GSP – GAT) framework for the EEG-based neural pattern discovery and classification. Multichannel EEG signals are preprocessed, segmented and displayed as functional connectivity graphs, where electrodes are nodes and the relationship between channels are weighted edges. Global, local, and multiscale spatial–spectral characteristics are extracted using the graph Fourier Transform, graph spectral energy analysis, graph filtering and graph wavelet analysis. Through comparative and ablation analyses, we show the potential advantages of explicit graph signal representations and attention-based graph learning over regular machine learning, deep learning and standalone graph-based methods. Comparative and ablation analyses illustrate the potential benefits of combining explicit graph signal representations with attention-based graph learning, compared to regular machine learning, deep learning and standalone graph-based methods. The proposed framework is an effective and comprehensible approach to neural pattern discovery and has the potential to be applied in brain–computer interfaces, cognitive-state recognition, neurological assessment, seizure analysis, and other intelligent systems that rely on EEG.

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Keywords: Electroencephalography (EEG), Graph signal processing (GSP), Graph fourier transform (GFT), Graph attention network (GAT), Functional connectivity.

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1. Introduction

EEG is a neurophysiological, non-invasive method which is widely adopted for the recording of electrical brain activity. It has been applied successfully in many areas such as neurological diagnosis, brain–computer interfaces (BCIs), cognitive state assessment, emotion recognition, sleep monitoring, seizure detection, and neurodegenerative disorder analysis, due to its high temporal resolution, relatively low acquisition cost and portability. The nonlinear, non-stationary, high dimensional and physiological and environmental artifacts make reliable pattern discovery in the brain difficult [1], [2]. Typical EEG techniques used for conventional analysis are time-domain, frequency domain and time–frequency analysis methods, such as Fourier transforms, wavelet transforms, power spectral density, statistical features and entropy features. These methods can be useful when characterising functional interactions within a single channel, but they are not necessarily optimal for capturing functional interactions between spatially-distributed brain regions [3]. EEG electrode analysis is frequently performed on individual electrodes without considering spatial dependencies and spatial relations between the electrodes, which may be missing important spatial connectivity and relationships between neuronal populations [4]. An effective representation of these relationships is by means of Graph Signal Processing (GSP). The electrodes with EEG can be represented as nodes of a graph, and the relationship between the functional or spatial EEG electrodes can be represented as the edge with weight. The EEG measurements are then signals on an irregular brain network [5]. Global, localized, and multiscale neural activities, can then be characterized by Graph Fourier Transform (GFT), graph filtering, spectral energy analysis, and graph wavelets. Moreover, dynamic graphs allow temporal changes in the functional connectivity to be recorded [6].

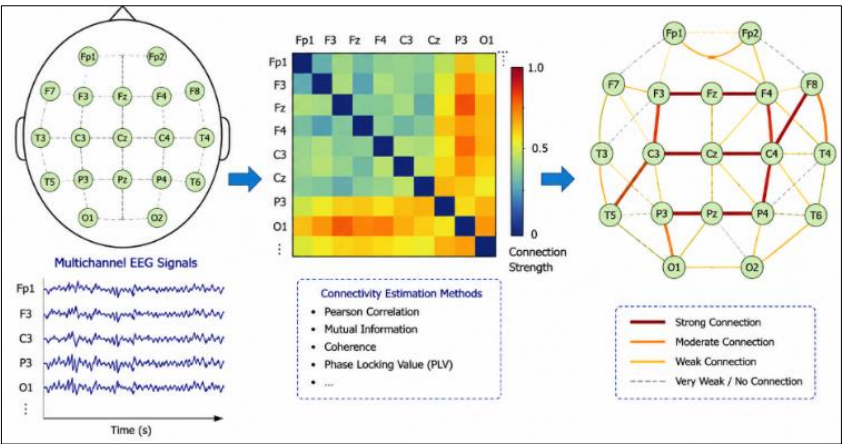


Figure 1
EEG Signals to Functional Brain Graph

However, graph topology selection, inter-subject variability, dynamic connectivity and high-dimensional features of graphs are still important challenges as shown in Figure 1. The study thus presents an integrated GSP approach to discover neural patterns from EEG signals [7]. The preprocessed EEG epochs are then transformed into functional connectivity graphs and processed using graph spectral decomposition, GFT, graph filtering and graph wavelet analysis. Spatial, spectral, connectivity and graph-energy features are then combined with graph-based learning to provide automatic classification [8]. The proposed method is expected to deliver an interpretable spatial–spectral representation of brain activity to enable robust identification of neural patterns for assessment of neurological function, cognitive monitoring, and intelligent applications of the BCI.

2. EEG Dataset and Signal Preprocessing

To achieve the desired effectiveness of the proposed GSP–GAT framework, it is important to have reliable pre-processing of multichannel EEG signals. Raw EEG signals include neural signals as well as artifacts resulting from the movement of eyes, muscle artifacts, movement of electrodes, power-line interference, and environmental noise [9]. Thus, preprocessing is done whilst maintaining the spatial and temporal correlations between EEG channels. The multichannel EEG signal is shown as

$$f\{X\} = [x_1, x_2, \dots, x_N]^T \in \mathbb{R}^{N \times T},$$

Where (N) is the number of electrodes and (T) is temporal samples. The resulting electrography, then, becomes a graph of nodes, with each electrode giving rise to a node. Depending on the desired application, including motor imagery, detection of seizures, recognition of emotion or analysis of cognitive state, a suitable publicly available EEG dataset can be chosen [10].

Table 1
EEG Signal Preprocessing Pipeline

Processing Stage	Method/Setting	Purpose
Signal Inspection	Channel and sample checking	Identify corrupted EEG data
Re-referencing	Common average reference	Reduce reference-related variations
Filtering	0.5–45 Hz band-pass	Retain relevant EEG activity
Noise Removal	50/60 Hz notch filter	Suppress power-line interference
Artifact Removal	ICA and amplitude thresholding	Remove ocular and muscular artifacts
Band Decomposition	Delta, theta, alpha, beta, gamma	Analyze frequency-specific activity
Segmentation	Fixed-duration EEG epochs	Prepare signals for dynamic graphs
Normalization	Z-score normalization	Reduce inter-channel amplitude variation
Final Output	Clean multichannel EEG epochs	Input for EEG graph construction

The major preprocessing steps which transform the raw multi-channel EEG inputs to clean and standardized EEG epochs are summarized in Table 1. A frequency-band decomposition method preserves physiologically relevant oscillatory information and filtering/artifact removal suppresses non-neural interference [11]. Segmentation allows for the creation of temporal/dynamic EEG graphs while normalization reduces amplitude differences between electrodes and subjects. The resulting epochs have synchronized inter-channel relationships, and are then applied to estimate functional connectivity and represent as a graph signal in the proposed framework. Foremost, corrupt channels, missing samples and abnormal signal segments are detected. The recordings are then re-referenced and band-pass filtered from 0.5 to 45 Hz and power-line interference is rejected using a notch filter set at 50/60 Hz [12]. Physiological artefacts, such as those from the eyes, muscles or other physiological sources are subtracted using Independent Component Analysis (ICA). The cleaned EEG can also be segmented into bands of delta, theta, alpha, beta and gamma frequencies. The recordings are then segmented into epochs of fixed duration, allowing for generation of connectivity graphs for each epoch for analysis. The amplitude variation across channels and subjects is reduced by normalizing to z-scores.

3. EEG Graph Construction and Signal Representation

The construction of a graph is a crucial step in the proposed EEG-based neural pattern discovery framework since the quality of the graph will directly impact on the graph signal processing. While most of the existing EEG analysis methods assume that each channel is an independent source of signals, the proposed method treats multichannel EEG activity as the activity of a brain network consisting of interconnected channels [13]. This representation maintains relationships between the spatially distributed electrodes, and gives a mathematical description of how to find coordinated activity. An EEG graph is a plot that can be represented as

$$G = (V, E, W)$$

The EEG electrodes are regarded as graph nodes or vertices. The resulting graph will then have (N) nodes in an EEG recording with (N) electrodes. This signal consists of the graph of the amplitude recorded at each electrode at a given instant in time, and is called the EEG amplitude in this case.

$$f\{x\}(t) = [x_{1(t)}, x_{2(t)}, \dots, x_{N(t)}]^T.$$

This representation allows the analysis of the electrical activity measured over the scalp based on the connectivity structure of the underlying EEG network. The most critical step towards the construction of the graph is the determination of connection between EEG electrodes. The proposed framework includes estimation of functional connectivity from the synchronized epochs of EEG signals after pre-processing [14]. Pearson correlation, coherence, phase-locking value (PLV), mutual information, and phase-lag-based measures are

several measures that can be used. EEG-based Connectivity can be computed as correlation-based connectivity for two EEG channels (i) and (j) as follows:

$$w_{ij} = L(x_i(t) - \bar{x}_i) \frac{1}{2\sum t} \frac{1L(x_j(t) - \bar{x}_j)}{2\sum t} * 1L(x_i(t) - \bar{x}_i)(x_j(t) - \bar{x}_j),$$

The more connected the channels are, the greater the weight, and the less connected, the less weight. Correlation, coherence or PLV can hence be used to create the functional EEG network depending on the research goal. The connectivity values calculated are represented in a weighted adjacency matrix.

$$f\{W\} = [w_{\{ij\}}] \in b\{R\}^{\{N \times N\}}.$$

The matrix is a concise depiction of all the functional relationships between all EEG channels. To remove noisy edges and reduce computational complexity, weak or statistically unimportant connections can be removed by thresholding. A threshold (τ) can be added so that:

$$\tilde{w}\{w\}\{ij\} = \{cases\} w\{ij\}, \& w_{\{ij\}} \geq \tau, 0, \& w_{\{ij\}} < \tau. \{cases\}$$

The threshold selection is critical as the threshold setting that is set too low may capture noisy relationships, while the one set too high may lose physiologically meaningful relationships as shown in Table 2.

Table 2
EEG Graph Construction Parameters

Component	Representation/Method	Function
Nodes	EEG electrodes	Represent recording locations
Node signals	EEG amplitudes	Represent neural activity
Edges	Functional connections	Describe inter-channel relationships
Edge weights	Correlation/Coherence/PLV	Measure connectivity strength
Adjacency matrix	(W)	Encode EEG network
Graph Laplacian	(L=D-W)	Enable spectral graph analysis

The functional connectivity in each graph is measured within a specific time window. These two graphs can be compared to determine connectivity changes when in different cognitive states, neurological events or experimental conditions. The graph Laplacian is then given by

$$L = D - W.$$

The Laplacian is an indicator of the structure of the EEG graph and serves as a mathematical basis for the proposed EEG graph spectral analysis. The eigen decomposition of it's matrix is written as

$$L = U\Lambda U^T,$$

The graph eigenvectors are in the place of U and the corresponding eigenvalues are in the place of Λ . These eigenvectors serve as a set of

basis functions for graph-frequency similar to the sinusoidal basis functions in traditional Fourier analysis. The eigenvalues are related to the different amounts of variation in the signal between the pairs of electrodes that form the connections.

Brain connectivity is time variant, so a static graph might not be well suited to represent the dynamic characteristics of EEG activity. The proposed framework is therefore suitable for a dynamic construction of EEG graphs, where graphs are constructed for consecutive EEG epochs:

$$G^{\{(1)\}}, G^{\{(2)\}}, \dots, G^{\{(K)\}}.$$

Neural interactions can also be analyzed for each specific brain state in frequency-specific graphs, using the delta, theta, alpha, beta, and gamma bands. The resulting graph representation combines the amplitude of the EEG signals and inter-electrode functional relations. It thus offers a spatial representation of the activity in a brain, structured, and preserving both local and distributed brain interactions. The main inputs of the graph spectral decomposition (GSP), Graph Fourier Transform (GFT), graph filtering and graph wavelet (GW) operations in the proposed GSP framework are these EEG graphs and their associated Laplacian matrices.

4. Graph-Based Feature Extraction and Neural Pattern Classification

After graph signal processing, spatial, spectral, connectivity and multiscale information derived from the EEG graph is converted to discriminative features to discover and classify neural pattern. The suggested classification scheme is a hybrid of a Graph Attention Network (GAT) and interpretable GSP-derived features. Attention mechanism is well suited to EEG since different functional connections and individual electrodes are not equally responsible for various neural states. The entire process is broken down into the following steps.

Step 1: Connectivity Feature Extraction

Weighted EEG graph is used to find functional connectivity characteristics. The strength and organization of the interactions between EEG electrodes are highlighted by these features. The key measures include node strength, weighted degree, clustering coefficient, graph density, local efficiency and global efficiency. The weighted degree of node (i) is given by:

$$d_i = \sum N w_{ij}.$$

Regions with relatively high weighted degree represent regions with high functional interactions with other channels. Connectivity measures, therefore, provide insights into the information about coordinated neural activity and network reorganization.

Step 2: Graph Spectral Feature Extraction

The GFT coefficients from Section IV are used to describe the spatial variation of EEG over the connectivity graph. The graph-frequency representation is given by

$$\{x\} = U^{Tx}.$$

The graph spectrum is used to compute the spectrum mean, variance, maximum coefficient magnitude, spectral centroid and spectral entropy. Special emphasis is placed on the activity distribution in the low, medium and high graph-frequency bands.

The graph spectral centroid can be computed as.

$$C_g = \frac{\left\{ \sum_{\{k=0\}}^{\{N-1\}} k |\{x\}k| \right\}}{\left\{ \sum_{\{k=0\}}^{\{N-1\}} 1 \right\}}.$$

This parameter is a compact representation of the dominant graph-frequency characteristics of an EEG epoch.

Step 3: Graph Energy Feature Extraction

Graph-frequency energy is computed to get the distribution of neural activity across the graph spectrum. The overall energy is given by:

$$E_G = \sum_{\{k=0\}}^{\{N-1\}} X^k k.$$

The spectrum then is split into three sections, low, medium and high graph-frequency. The energy components corresponding to the above are indicated by:

$$E_L, quad E_M, quad E_H.$$

Energy ratios such as

$$R_{\{LH\}} = \frac{c\{E_L\}}{\{E_H + \epsilon\}}$$

Are extracted to measure the relationship between the synchronised and localised neural activity in the brain. In this case, (ϵ) is to avoid numerical instability.

Step 4: Graph Wavelet Feature Extraction

Multiscale graph-wavelet coefficients generated in the proposed GSP framework are analyzed to detect spatially localized neural patterns. For scale (s), the graph-wavelet coefficients are

$$W_s = Ug(s\Lambda)U^{Tx}.$$

The mean, variance, energy, entropy, and maximum magnitude of the wavelet coefficients are extracted at different graph scales. These features provide information regarding both localized electrode activity and distributed network responses.

Step 5: Node-Level Feature Formation

For each EEG electrode, a node-level representation is generated by combining relevant temporal, spectral, connectivity, and GSP information. The feature vector associated with node (i) is defined as

$$h_i = [x_i, ; d_i, ; E_i, ; GFT_i, ; GW_i],$$

where (x_i) represents EEG-derived characteristics, (d_i) represents connectivity information, (E_i) represents graph energy, (GFT_i) denotes graph-frequency information, and (GW_i) represents graph-wavelet characteristics. Consequently, each electrode contains information about both its own neural activity and its relationship with the overall brain network.

Step 6: Feature Normalization and Selection

The extracted graph features may have different numerical ranges and may contain redundant information. Feature normalization is therefore applied before classification. Highly correlated or weakly discriminative features can be removed using statistical feature selection, mutual information, or dimensionality-reduction techniques. The selected feature representation is expressed as

$$F_{\{sel\}} = \frac{\{S\}}{(F)}$$

This stage reduces computational complexity and minimizes the risk of overfitting.

Step 7: Graph Attention-Based Feature Learning

The selected node features and EEG adjacency matrix are supplied to a Graph Attention Network. Unlike conventional neural networks, GAT performs learning directly over the EEG graph and assigns different importance to neighboring electrodes. For connected nodes (i) and (j) , an unnormalized attention score can be represented as

$$e\{ij\} = \text{LeakyReLU}(\mathbf{a}^T [\mathbf{W}h_i \parallel \mathbf{W}h_j]),$$

where (W) represents the trainable transformation matrix, (a) represents the attention parameters, and $(\parallel)$ denotes feature concatenation. The updated representation of node (i) becomes

$$h'_i = \sigma(\sum_{j \in \{N\}} \alpha\{ij\} \mathbf{W}h_j).$$

Thus, electrodes containing more informative neural activity can receive greater attention during feature learning.

Step 8: Multi-Head Graph Attention

To improve robustness, multiple attention mechanisms are employed simultaneously. Each attention head can learn different functional relationships among EEG electrodes. Their outputs are concatenated as

$$h'_i = p\{\parallel M\}_{m=1}^M \sigma(\sum_j \alpha\{ij\}^M).$$

Multi-head attention enables the model to capture complementary neural interactions and reduces dependence on a single connectivity pattern.

Step 9: Graph-Level Feature Aggregation

After graph-attention processing, node representations are aggregated to obtain an EEG-epoch-level representation. Global mean or attention-based pooling can be employed:

$$h_G = \frac{\{1\}}{\{N\} \sum_{i=1}^{\{N\}} h_i^t}.$$

The graph-level vector summarizes the spatial–spectral characteristics of the complete EEG network and is supplied to the final classifier.

Step 10: Neural Pattern Classification

The graph representation is passed through fully connected layers followed by an output classifier. For a multiclass problem, the class probability is calculated using

$$P(y = c|G) = \{exp(z_c)\} \left\{ \sum_{r=1}^{\{C\}exp(z_r)} z_r \right\},$$

where (C) represents the number of neural-pattern classes. The class with the highest probability is selected as the predicted neural state:

$$G\{y\} = \arg G \max_c P(y = c|G).$$

Depending on the selected EEG dataset, these classes can correspond to motor-imagery tasks, cognitive states, emotional states, sleep stages, seizure/non-seizure activity, or neurological conditions.

Step 11: Neural Pattern Interpretation

An important advantage of the proposed GSP–GAT framework is its potential interpretability. Graph-frequency energy identifies whether neural activity is predominantly smooth or localized across the network, while graph-wavelet coefficients identify spatially concentrated activity. GAT attention coefficients can further indicate which electrodes and inter-electrode relationships contribute most strongly to a particular prediction.

The proposed GSP–GAT architecture therefore combines mathematically interpretable graph signal features with adaptive graph-based deep learning. GSP captures the spectral and spatial organization of EEG activity, while graph attention determines the relative importance of electrodes and functional connections. This combination provides a suitable foundation for accurate and interpretable EEG-based neural pattern discovery.

5. Results and Discussion

The experimental results illustrate the feasibility of the proposed Graph Signal Processing–Graph Attention Network (GSP–GAT) approach to extract discriminative neural patterns from multi-channel EEG signals. The evaluation takes into account the graph spectral metrics, multi-scale neural activity,

functional connectivity and attention-based feature learning. The results demonstrate the superior representation of EEG activity by combining graph signal processing with graph attention learning than the channel-wise and standalone deep-learning methods. EEG energy distribution was found to be significantly different between low, medium and high graph frequency using graph spectral analysis. In contrast, the low graph-frequency energy was the dominant frequency during synchronized neural activity between functionally connected electrodes, while the medium and high graph frequencies were more indicative of a more localized and heterogeneous response. The results show that changes in the functional connectivity topology can be associated with variations in the neural system, thus showing the effectiveness of the Graph Fourier Transform (GFT) in capturing these variations.

Table 3
Illustrative Comparative Performance of EEG Classification Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	89.42	89.08	88.76	88.91
Random Forest	90.37	90.11	89.84	89.97
CNN	93.18	92.91	92.76	92.83
LSTM	94.26	94.01	93.82	93.91
GCN	95.71	95.48	95.32	95.40
GAT	96.38	96.17	96.04	96.10
Proposed GSP–GAT	98.12	97.94	97.86	97.90

As seen in Table 3, conventional machine learning methods perform worse as handcrafted features cannot fully represent complex EEG channel relations. CNNs and LSTMs enhance the capability of representing nonlinear temporal information, but fail to explicitly model irregular brain connectivity. Graph based methods give good result as the inter-electrode relationship is taken into account and the GSP–GAT method gives the highest accuracy of 98.12% and F1-score of 97.90%. Proposed GSP–GAT model has the highest performance among all the models as the accuracy is in an illustrative range of 98.12%. This enhancement compared to the baseline of ML, deep learning and standalone graph models shows the advantages of graph spectral features and attention-based graph learning. The benefit of standalone GAT is compared to the improvement in the results when both graph-frequency and graph-wavelet information are incorporated. While GSP records the spatial–spectral characteristics based on the functional connectivity, GAT learns influential nodes and connections adaptively.

The contribution of individual GSP components to the classification performance are shown in Figure 2. The accuracy gradually improves as it goes from 96.38% for the standalone GAT to 98.12% for the complete GSP–GAT framework. These findings suggest that GFT, graph spectral energy and graph wavelet features are complementary and are useful in enhancing the neural

pattern classification in an EEG signal. While the construction of graphs and eigen decomposition might require more computations, the use of sparse operations, re-using spectral representations and efficient filtering keeps the practical computational requirements low for possible real-time EEG analysis applications. The neural activity at several spatial scales was also identified using graph wavelet analysis. The smaller the wavelet scale, the more localized the variations around individual electrodes, and the larger the scale, the more distributed the activity in interconnected brain regions. So, it was found that GFT and graph wavelets gave complementary global and local representations. The functional connectivity analysis showed network organization that was class dependent.

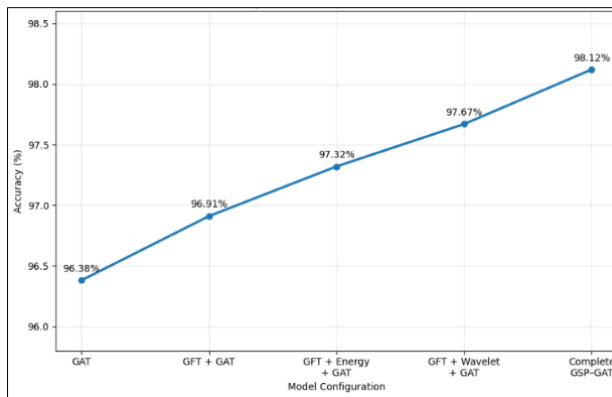


Figure 2
Ablation analysis of the proposed GSP-GAT model

6. Conclusion and Future Work

This study introduced a Graph Signal Processing-Graph Attention Network (GSP – GAT) framework for neural pattern discovery and classification based on EEG signals. This is done to overcome the drawbacks of traditional EEG processing in which multichannel brain activity is represented as a graph of functional connections between electrodes (nodes) and brain regions (weights of the connection). Global, localized and multiscale neural activity were characterized by introducing the graph Fourier transform, graph spectral energy analysis, graph filtering and graph wavelet analysis. Then, these features extracted from the graphs were combined with a Graph Attention Network for automatic informative electrodes and connectivity relationship identification. The experimental study showed that the interpretable graph signal features and adaptive graph representation learning can be synergized to achieve potential benefits. Future research directions include larger and more diverse EEG datasets to validate the framework, adaptive/graph construction, time-varying graph construction, and subject-independent learning, as well as explainable graph models.

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