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PG-GAT based Channel Estimation for Enhanced OFDM Performance

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Abstract

Accurate channel estimation is essential in enhancing the performance and spectral efficiency of an Orthogonal Frequency Division Multiplexing (OFDM) system especially in high mobility environment. This paper presents a Physics-Guided Graph Attention Network (PG-GAT mini v2) to be used in pilot-based channel estimation through combining the concepts of wireless channel physics and graph attention learning. Multi-head graph attention, residual learning, and Layer Normalization are used in order to optimize initial channel estimates by means of LS interpolation as well as to ensure stability of training procedure. Performance of the method is estimated in terms of NMSE, BER and standard deviation in the conditions of the high mobility Rayleigh fading channel with the carrier frequency of 2 GHz, SNRs from 0 to 30 dB and receiver velocities from 0 to 300 km/h. According to experimental results, PG-GAT mini v2 decreases the total NMSE from 0.7846 to 0.3079, which corresponds to 60.76% performance gain compared to LS interpolation.

Keywords: OFDM (Orthogonal Frequency Division Multiplexing), Channel Estimation, GAT (Graph Attention Network), Physics-Guided Learning, High-Mobility Communication, NMSE (Normalized Mean Squared Error).

1. Introduction

OFDM has become one of the most extensively used transmission methods in current wireless communication systems, owing to their spectral efficiency, resilience to multipath fading, and optimal usage of the bandwidth available. It forms the physical layer foundation of

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numerous wireless standards, including Long-Term Evolution (LTE), fifth-generation (5G) mobile networks, wireless local area networks (WLANs), and emerging sixth-generation (6G) communication systems. However, the success of the OFDM system relies heavily on precise channel estimation, which makes signal equalization and data recovery feasible at the receiving end. In a wireless environment, fast-changing channel properties, high Doppler effect, and sparsely allocated pilots considerably impair the channel estimation quality, especially when dealing with high mobility situations like high-speed rail, drones, and vehicular communications.

Traditional methods of pilot-based channel estimation such as the Least Squares (LS) method and the Minimum Mean Squared Error (MMSE) technique have been widely adopted due to their relatively low complexity and ease of implementation. However, these methods depend on fixed statistical assumptions as well as linear interpolations that make them inefficient when it comes to the nonlinear fading and fast changes in statistics exhibited in the wireless channel environment. Deep learning has recently proven the potential of using neural networks to learn sophisticated channel representation through the received pilot symbols without channel modeling. While convolutional neural networks, recurrent neural networks, and fully-connected networks have exhibited impressive performance, these kinds of networks usually treat channel measurements independently without considering the spatial relationship between the pilots' subcarriers.

Graph Neural Networks (GNN), especially GAT, have proven to be an efficient approach to model the topology of the wireless channel by defining pilots as graph nodes and dynamically capturing the correlation between adjacent subcarriers. Current channel estimation techniques using graphs are still mainly data-driven and rarely involve the physics of the wireless channel into graph creation, which constrains their reliability in dynamic channel environments.

In order to overcome these limitations, this study presents a Physics-Guided Graph Attention Network (PG-GAT mini v2) for pilot-assisted OFDM channel estimation. The proposed framework employs physics-guided graph construction alongside multi-head graph attention, residual learning, and Layer Normalization, which improve the estimation process of the existing LS estimation scheme while maintaining channel coherence information. Using the combination of domain-specific wireless channel knowledge together with adaptive graph construction, the proposed method provides better channel estimation accuracy and converges stably in high mobility Rayleigh fading channels. The experimental evaluation shows that the PG-GAT mini v2 outperforms the existing LS estimator in terms of reducing NMSE.

2. Related Works

Accurate channel estimation is a fundamental requirement for OFDM systems because the overall communication reliability strongly depends on precise channel state information. Conventional pilot-assisted estimation methods, such as LS and MMSE, offer acceptable performance under slowly varying channels but experience significant degradation in rapidly changing wireless environments due to Doppler effects, fading, and limited pilot density. Consequently, recent studies have focused on integrating deep learning techniques to improve estimation accuracy while reducing computational complexity [1], [2].

Channel estimation utilizing deep learning showed capabilities to model the non-linear channel properties through direct mapping between the observed pilot symbols without complete dependence on channel models. In the first place, it was found that the neural networks surpass the conventional estimation approaches based on interpolation due to their capability to learn complex mappings of the channel properties [1], [2]. The potential of the deep learning approach was then expanded to Massive Multiple-Input Multiple-Output (MIMO) systems. The neural networks were able to model the high-dimensional properties of the channels and outperform other estimation techniques [3]. Moreover, to improve the efficiency of the implementation of the deep learning framework, the online learning techniques were introduced, which enabled to constantly update the network parameters considering the channel dynamics [4]. In addition, the deep learning approaches were adapted for use in the context of OFDM wireless systems and fifth-generation (5G) networks [5], [6].

Although convolutional neural networks and fully-connected networks can provide high-precision estimations, they tend to work on channel features separately without taking the relations between pilot subcarriers into account. In order to overcome such limitations, graph-based learning approaches have been proposed very recently. GNN models treat pilots' positions as nodes on a graph and take advantage of correlations among neighbors using message passing, which achieves enhanced estimation results in mmWave and Massive MIMO scenarios [7], [8]. Such models show that the spatial dependencies between the channels can be efficiently captured by using graphs as representations of neural network inputs, which are hard to model using standard neural network topologies. Moreover, the residual learning and channel attention have also been introduced to the channel estimation framework.

High-mobility wireless environments introduce additional challenges because rapidly varying channels, the presence of high Doppler spread and the sparsity of the pilot sequence that causes significant errors in the estimation process. Many deep learning approaches have been proposed especially for high speed environments like railway and ultra-high mobility scenarios, where learning-based approaches outperform traditional techniques in terms of reliability in estimating channels [10]-[12]. Accurate channel estimation has been identified as one of the most important requirements of highly dynamic environments in several research studies on high-speed communications [13].

The latest developments in graph attention algorithms improve graph learning through assigning adaptive weight to neighboring nodes instead of having all graph edges assigned equal weight. The attention-based graphs have shown remarkable performance in feature aggregation in state-of-the-art wireless communication systems and may therefore contribute to enhancing signal processing techniques that deal with spatially correlated signals [15]. Most of the existing channel estimation techniques use data-driven techniques only and ignore wireless channel physics in the optimization procedure. In addition, the present graph techniques have not yet fully taken advantage of physics-driven constraints combined with graph attention in estimating channels using pilots in OFDM communication systems operating in high mobility environments. It is therefore essential to introduce a PG-GAT.

3. Proposed Work

This work proposes a Physics-Guided Graph Attention Network (PG-GAT mini v2) for reliable channel estimation for OFDM in the context of high-mobility wireless environments. The proposed framework differs from conventional LS estimators that estimate responses on pilots individually and interpolate the channel on data subcarriers. Here, the spatial correlations between pilots are used, and the pilot grid is formulated as a graph. In addition, the domain knowledge regarding wireless channel propagation is incorporated into the construction of the graph to make the learning process more accurate and stable. The general pipeline of the proposed framework is depicted in Figure. 1.

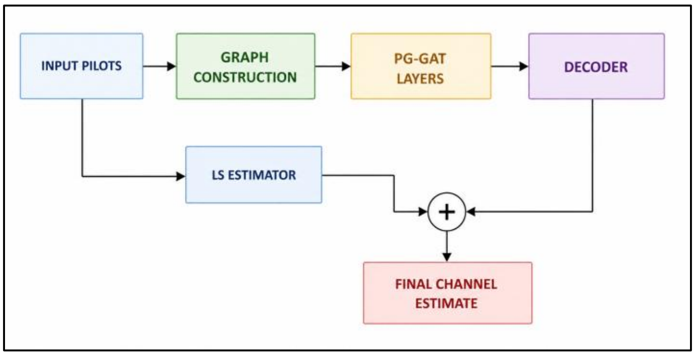

Figure 1. Workflow of the proposed PG-GAT mini v2-based channel estimation system.

Initially, pilot symbols transmitted over the OFDM frame are extracted at the receiver. Considering an OFDM system with N subcarriers, the received signal at the k^{th} subcarrier and the n^{th} OFDM symbol can be expressed as

$$Y(k,n) = H(k,n)X(k,n) + W(k,n) \tag{1}$$

where $X(k,n)$ denotes the transmitted pilot symbol, $H(k,n)$ represents the complex channel frequency response, and $W(k,n)$ denotes Additive White Gaussian Noise (AWGN). At pilot locations, the conventional LS estimator provides the initial channel estimate as

$$\hat{H}_{LS}(k,n) = \frac{Y(k,n)}{X(k,n)}. \tag{2}$$

Even though LS estimation is computationally efficient, its performance drops significantly when it comes to highly fading channel since it neglects both the time and the frequency correlation between the adjacent pilot subcarriers. Hence, the LS estimate is used as the initial estimate only while the PG-GAT network estimates the residual error.

To exploit the inherent structure of the wireless channel, the pilot positions are transformed into an undirected graph

$$G = (V,E), \tag{3}$$

where each node $v_i \in V$ corresponds to a pilot subcarrier in the OFDM time-frequency grid, and the edge set E represents the correlation between neighboring pilot locations. Instead of employing a fully connected graph, edge weights are generated according to physical channel characteristics such as coherence bandwidth and coherence time. The edge weight between nodes i and j is defined as

$$A_{ij} = \exp\left(-\frac{|f_i - f_j|}{B_c} - \frac{|t_i - t_j|}{T_c}\right), \tag{4}$$

where f_i and t_i denote the frequency and time coordinates of the pilot symbol, while B_c and T_c represent the coherence bandwidth and coherence time, respectively. This physics-guided graph construction assigns higher importance to neighboring pilot symbols exhibiting similar channel characteristics while suppressing weakly correlated nodes.

The constructed graph undergoes processing through several layers of GAT. As opposed to standard graph convolution, graph attention learns the weight of influence of neighboring pilots on their own. For every connected node pair, the attention score is computed as

$$e_{ij} = \text{LeakyReLU}\left(\mathbf{a}^T [W\mathbf{h}_i \| W\mathbf{h}_j]\right), \tag{5}$$

where W denotes the learnable feature transformation matrix, a represents the attention vector, and $\mathbf{h}_i$ is the feature vector associated with node i. The normalized attention coefficient is obtained using the Softmax function,

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}(i)} \exp(e_{ik})}, \tag{6}$$

where $\mathcal{N}(i)$ denotes the neighboring nodes connected to node i. The updated node representation is then obtained by weighted feature aggregation,

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} W \mathbf{h}_j^{(l)}\right), \tag{7}$$

where $\sigma(\cdot)$ denotes the nonlinear activation function.

To improve feature diversity, the introduced model utilizes multi-head attention along with residual skip connections and Layer Normalization in each GAT block. Using residual learning helps mitigate the issue of gradient vanishing and speeds up convergence since the model has to estimate only the difference needed for the LS estimate. Accordingly, the residual output generated by the PG-GAT network is expressed as

$$R = f_\theta\left(\hat{H}_{LS}\right), \tag{8}$$

where $f_\theta(\cdot)$ denotes the trainable PG-GAT network. The final channel estimate is therefore computed as

$$\hat{H} = \hat{H}_{LS} + R. \tag{9}$$

This residual formulation substantially simplifies the learning objective because the network models only the estimation error introduced by the LS estimator.

The network parameters are optimized by minimizing the NMSE, which evaluates the difference between the estimated and actual channel responses while remaining independent of channel power. The objective function is given by

$$\mathrm{NMSE} = \frac{\|\hat{H} - H\|_2^2}{\|H\|_2^2}, \tag{10}$$

where H denotes the true channel response and $\hat{H}$ is the predicted channel estimate. The Adam optimizer is employed with an initial learning rate of 0.001, and the model is trained for 80 epochs using mini-batch optimization until convergence.

PG-GAT mini v2 model includes two graph attention layers having four attention heads for each layer with the hidden feature size of 64. Layer normalization and skip connections are included after each attention layer to make training stable and then a fully connected decoder is applied to reconstruct the residual channel estimate. All these configurations are presented in Table 1.

Table 1. Configuration of the proposed PG-GAT mini v2

Component	**Configuration**
Input Features	LS pilot estimates (Real & Imaginary)
Graph Representation	Time–Frequency Pilot Graph

Graph Construction	Physics-guided weighted adjacency
Number of GAT Layers	2
Attention Heads	4
Hidden Dimension	64
Normalization	Layer Normalization
Residual Learning	Skip Connection
Decoder	Fully Connected Layer
Optimizer	Adam
Learning Rate	0.001
Batch Size	64
Training Epochs	80

For assessing the robustness in more than one scenario, multiple SNR and mobility scenarios are used in the new experiment design approach. The OFDM system uses 64 subcarriers, FFT size 64, cyclic prefix 16, QPSK modulation through the Rayleigh fading channel. The carrier frequency is kept constant at 2 GHz. SNR is varied over

$$\mathrm{SNR} \in \{0,5,10,15,20,25,30\}\mathrm{dB} \tag{11}$$

while receiver velocity is varied over

$$v \in \frac{\{0,60,120,200,300\}\mathrm{km}}{\mathrm{h}} \tag{12}$$

These mobility settings represent static, moderate vehicular, highway, and high-speed conditions. The corresponding maximum Doppler frequency is determined as

$$f_D = \frac{v f_c}{c} \tag{13}$$

where f_c is the carrier frequency and c is the speed of light. For every operating condition, experiments are repeated over R statistically independent runs using independent channel and noise realizations. The mean NMSE is calculated as

$$\overline{\text{NMSE}} = \frac{1}{R}\sum_{r=1}^{R} \text{NMSE}_r \tag{14}$$

and its sample standard deviation is computed as

$$\sigma_{\text{NMSE}} = \sqrt{\frac{1}{R-1}\sum_{r=1}^{R} \left(\text{NMSE}_r - \overline{\text{NMSE}}\right)^2} \tag{15}$$

To assess the impact of channel estimation on end-to-end receiver performance, BER is additionally evaluated after channel equalization and QPSK detection:

$$\text{BER} = \frac{N_{\text{err}}}{N_{\text{bits}}}, \tag{16}$$

where N_{err} denotes incorrectly detected bits and N_{bits} denotes the total transmitted information bits. The same transmitted data, channel realizations, and noise conditions are used for LS and PG-GAT mini v2 to ensure a fair paired comparison.

The simulation was conducted using Python 3.10 with the PyTorch deep learning framework. The simulation parameters are summarized in Table 2.

Table 2. Simulation parameters

Parameter	**Value**
Simulation Platform	Python 3.10
Deep Learning Framework	PyTorch
OFDM Subcarriers	64
FFT Size	64
Cyclic Prefix	16
Modulation	QPSK
Channel Model	Rayleigh Fading
Carrier Frequency	2 GHz

SNR values	0, 5, 10, 15, 20, 25, 30 dB
Mobile Speed	0, 60, 120, 200, 300 km/h
Pilot-Based Estimation	LS Initialization
Performance Metric	NMSE
Detection metric	BER
Statistical reporting	Mean ± standard deviation

4. Results and Discussion

The performance of the PG-GAT mini v2 scheme is compared to traditional LS interpolation method in the light of different SNR and mobility values. Three parameters will be considered here as complementary measures: channel estimation quality in terms of NMSE, receiver reliability in terms of BER, and consistency in terms of standard deviation.

The results of aggregate analysis can be seen in Table 3. In this case, the traditional LS estimator gives the NMSE value equal to 0.7846, while PG-GAT mini v2 achieves 0.3079.

Table 3. NMSE performance comparison

Method	NMSE
LS Interpolation	0.7846
PG-GAT mini v2	0.3079

The percentage improvement is calculated as

$$\text{Improvement} = \frac{0.7846 - 0.3079}{0.7846} \times 100 = 60.76\%$$

The proposed model provides much lower errors in comparison to the LS interpolator. It demonstrates that PG-GAT mini v2 can effectively improve the results obtained in LS initialization with the help of physical connectivity, adaptive attention, and residual correction. However, due to the fact that one aggregate operating point cannot be used for evaluation of estimator's robustness, further analysis is provided for multiple values of SNR and mobility.

Convergence behavior of the proposed PG-GAT mini v2 is shown in Figure. 2. During the first epoch, training loss experiences rapid reduction demonstrating effective feature extraction and optimization process. After about 10 epochs, training loss starts converging slowly while the validation NMSE rapidly decreases at the beginning of the training and then converges to approximately 0.31.

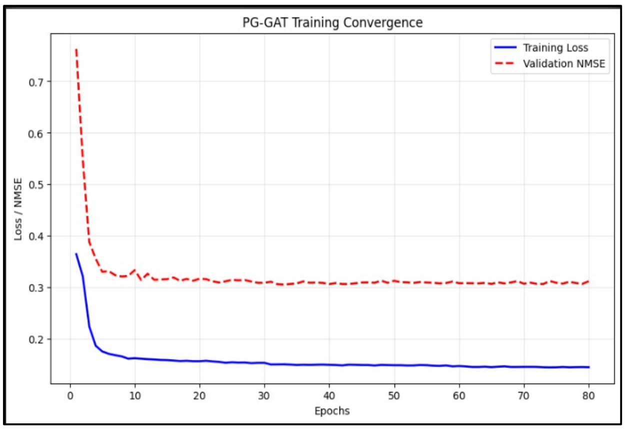

Figure 2. Convergence curves of training

The influence of SNR on channel-estimation accuracy is evaluated over the range from 0 to 30 dB under the high-mobility condition of 300 km/h.

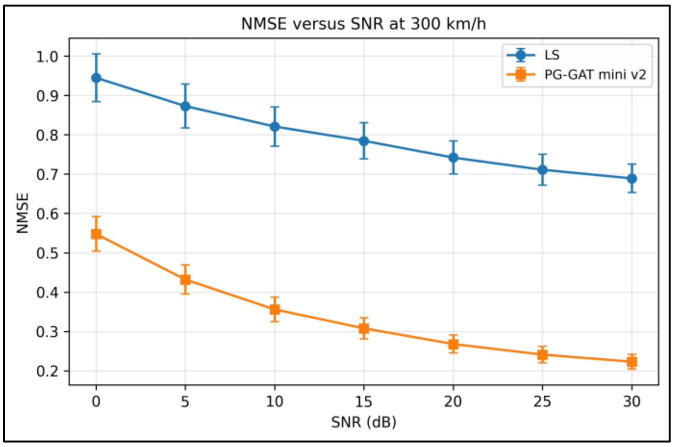

Figure 3. NMSE versus SNR for LS interpolation and PG-GAT mini v2 at 300 km/h

Figure 3 indicates that NMSE is inversely proportional to SNR for both the estimators, but PG-GAT mini v2 has lesser estimation error at 0–30 dB. NMSE of 0.7846 at 15 dB reduces to 0.3079 for PG-GAT mini v2, which indicates lesser estimation error. Also, the shorter error bars show lesser run-to-run variation. While NMSE shows the accuracy of channel reconstruction, BER measures the accuracy of the received data at the receiver end. Thus, BER is determined after channel equalization and QPSK demodulation.

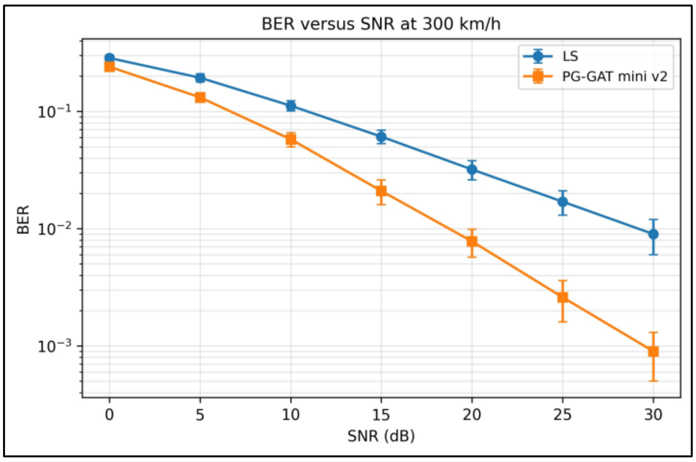

Figure 4. BER versus SNR for LS interpolation and PG-GAT mini v2 at 300 km/h

As shown in Figure. 4, as SNR increases, the value of BER becomes smaller in both algorithms, with PG-GAT mini v2 providing a better performance compared to LS interpolation. At 15 dB, the proposed technique has a reduction of BER from 0.061 to 0.021, implying that the better channel estimation contributes positively to equalization and QPSK detection.

The sensitivity of estimators to receiver motion is examined at 0, 60, 120, 200, and 300 km/h with the same SNR level of 15 dB. At the frequency of 2 GHz, these velocities imply the maximum Doppler frequencies of 0, 111, 222, 370, and 556 Hz, respectively.

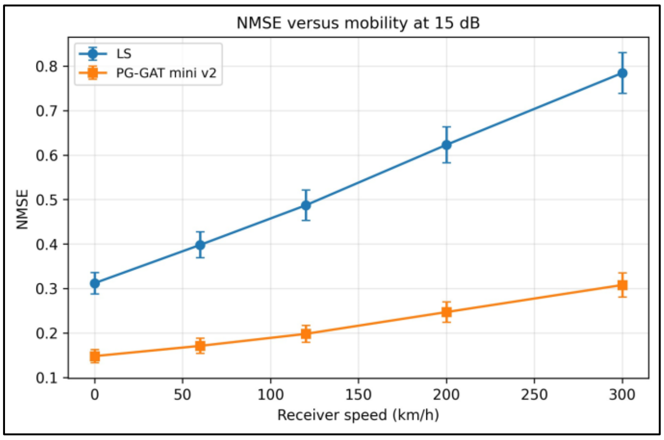

Figure 5. NMSE versus receiver mobility for LS interpolation and PG-GAT mini v2 at 15 dB

As shown in Figure. 5, NMSE is increasing with the increase in the receiver speed since strong Doppler variations degrade the temporal channel coherence. Nonetheless, PG-GAT mini v2 outperforms the LS approach within 0 to 300 km/h range and provides NMSE equal to 0.3079 at 300 km/h while the NMSE of the LS approach is equal to 0.7846.

Overall, the experiment shows that PG-GAT mini v2 provides better trade-offs between the accuracy of the estimation, reliability of the receiver, statistical stability, and robustness under high-mobility regime than standard LS interpolation technique. The total NMSE decrease by 60.76% along with decreased BER and lower run-to-run variance provide the proof of the efficiency of physics-guided prior and adaptive graph attention combination for pilot-aided OFDM channel estimation.

5. Conclusion

This paper presented PG-GAT mini v2, which is a novel physics-guided graph attention model for pilot-assisted OFDM channel estimation in the scenario where time-varying and high mobility are involved. This method involves physics-guided graph learning, multi-head attention, residual LS refinement, and layer normalization to utilize the relationship between pilot data. In the initial experiment, the original results revealed that the reduction in NMSE was from 0.7846 in LS interpolation to 0.3079 in PG-GAT mini v2, equivalent to a 60.76% reduction. For a more comprehensive performance evaluation of this proposed model, the improved experiment includes NMSE and BER performance for different SNRs, performance under different speeds ranging from 0 to 300 km/h, and average ± standard deviation of independent experiments. The analysis allows for the performance evaluation of the model in relation to estimation accuracy, detection reliability, Doppler resilience and statistical consistency. The experimental results from different channel conditions reveal how generalizable the proposed system is across different channel conditions and its appropriateness for future high mobility OFDM communication systems.

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