Prediction of Wireless MmWave Massive MIMO Channel Characteristics Based on Graph Attention Networks

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SUMMARY This paper proposes a procedure of predicting millimeter wave (mmWave) massive multiple-input multiple-output (MIMO) indoor channel characteristics based on graph attention networks (GAT). We use the K-nearest neighbor (KNN) algorithm to construct the real channel measurement data into a graph dataset. Different from existing machine learning (ML) based channel characteristics prediction algorithms using all data points at the same time, we only use some data with high correlation to train our model in order to reduce complexity and the number of iterations. Scenario parameters including transmitter (Tx) and receiver (Rx) coordinates, Tx–Rx distance, and carrier frequency are used to characterize the correlation between data points, while the output parameters are channel statistical properties, including the received power, root mean square (RMS) delay spread (DS), and RMS angle spreads (ASs). The predicted channel characteristics can fit those of real channels well, which indicates the effectiveness of the proposed method.
key words: *Machine learning, graph attention networks, massive MIMO*

1. Introduction

To satisfy the requirements of high transmission rate and spectral efficiency of the sixth generation (6G) communication systems [1], mmWave and massive MIMO have been considered as key technologies and also brought new challenges on channel modeling [2]. A wireless channel model with high accuracy is always the basis for design and theoretical analysis of wireless communication systems. However, with the bandwidth, the number of antennas, and the diversity of scenarios explosively increase, the future wireless network will have unprecedented complexity, which will generate big data and make traditional wireless channel measurements and modeling methods more difficult or even no longer applicable [3], [4]. Due to its excellent ability to automatically mine the internal information and mapping rules of big data, ML is regarded as an indispensable tool to make up for the inadequacy of traditional methods and is increasingly applied to the field of wireless communications [5], [6].

ML applications in wireless communication channels can be roughly divided into four categories: scenario classification, multipath components (MPCs) clustering, channel modeling, and prediction of channel characteristics. How to distinguish between line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios is of great significance for channel modeling. In [7] and [8], the authors proposed a LOS/NLOS identification method based on random forest and convolutional neural network (CNN), respectively. However, they cannot predict the channel statistical characteristics. MPCs clustering algorithms play an important role in traditional geometry-based stochastic models (GBSMs), such as the general three-dimensional (3D) massive MIMO GBSM [9] and COST 2100 channel model [10]. MPC distance was first proposed in [11]] and K-power-means algorithm was used for clustering in [12]. A power-angle-spectrum based clustering and tracking algorithm that could track the dynamic changes of clusters in real time was proposed in [13]. All clustering algorithms mentioned above can be considered as auxiliaries to GBSMs. On the contrary, the author in [14] proposed a method applying principal component analysis (PCA) to reconstruct the amplitude and phase of massive MIMO channel impulse response directly. This method utilized hidden features and structures extracted from channel measurement data and combined scenario and antenna configurations information to predict the channel capacity. In [15], the authors proposed a generative adversarial network (GAN)-based channel modeling framework to avoid complex theoretical analysis and sophisticated data processing, which succeeded in approximating the distribution of additive white Gaussian noise channel. However, the two channel modeling methods in [14] and [15] considered only one channel statistical characteristic. Prediction of channel characteristics is taking advantage of ML to mine the internal mapping relationship between channel scenario information and channel statistical characteristics. In [16], feed-forward neural network (FNN) and radial basis function neural network (RBF-NN) were used to characterize the relationship between channel characteristics and scenario parameters, which showed that RBF-NN had better performance. Authors in [17] and [18] used multi-layer CNN to predict channel excess attenuation for satellite communication systems at Q-band with weather data and propagation measurements as input and to predict channel parameters, such as delay, power, and angles, with Tx and Rx coordinates as input parameters.

All above-mentioned ML based channel characteristics prediction algorithms use all data points at the same time to train the model, without considering the correlation between data points, which results in more complex structures and more training time. In this paper, we proposed a GAT-based [19] model to predict indoor channel characteristics which only

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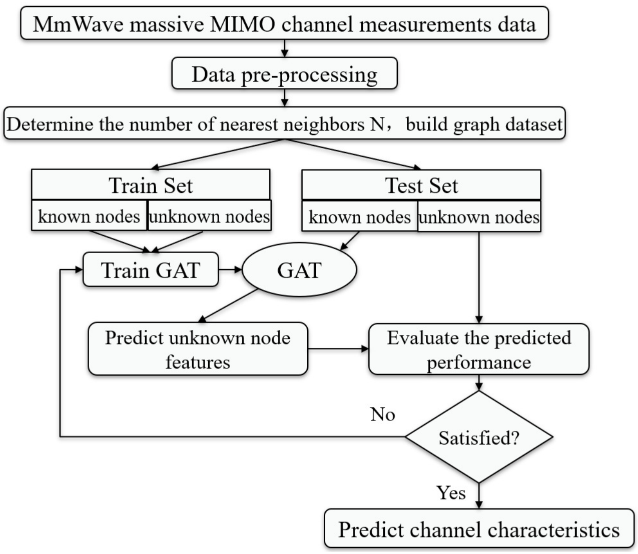

Fig. 1 Flowchart of the channel characteristics predicting procedure.

uses some data points with high correlation to train, rather than all data points at the same time, thus simplifying the model structure and reducing the number of iterations.

The rest of this paper is organized as follows. The procedure based on GAT to predict channel statistical characteristics is described in Section 2. In Section 3, we introduce the real indoor channel measurement dataset and the principle of the graph dataset. The architecture of the proposed GAT is presented in Section 4. In Section 5, we discuss and analyze the predictive performance of proposed procedure. At last, conclusions are drawn in Section 6.

2. System Model

The flowchart of the procedure based on GAT to predict channel statistical characteristics is presented in Fig. 1. Firstly, we get the real mmWave massive MIMO indoor channel data through channel measurements [16]. After data processing, we can get the channel statistics characteristics. Then, we treat each group of data as a node, and build edges between a node and its neighbor nodes to form a graph dataset. The dataset formed is divided into train set and test set with a ratio of 3:1. Both two sets have known nodes channel statistics characteristics as input vector and unknown nodes as output vector. The train set is used to train GAT, while the mean square errors (MSEs) between the predicted unknown nodes characteristics by trained GAT and unknown nodes characteristics of the test set determine whether to continue training the model.

3. Graph Dataset Generation

Channel measurements were carried out in an indoor office environment with room size of 7.2×7.2×3 m^3 [20]. With Rx fixed and Tx placed at four positions, the authors measured four mmWave frequency bands including 11, 16, 28, and 38 GHz, and extracted MPC parameters from different sub-arrays measurement data through space-alternating generalized expectation-maximization (SAGE) algorithm. More details on channel measurement and data processing could be found in [20]. Finally, 400 nodes (i.e., 400 groups of data) consisting of scenario parameters and channel characteristics were obtained, which were divided into 300 for training and 100 for testing. The scenario parameters were Tx and Rx coordinates, Tx–Rx distance, and carrier frequency, while the channel characteristics were received power P, RMS DS σ_{DS}, and RMS azimuth angle of departure spread (ADS) σ_{ADS}, azimuth angle of arrival spread (AAS) σ_{AAS}, elevation angle of departure spread (EDS) σ_{EDS}, and elevation angle of arrival spread (EAS) σ_{EAS}.

Table 1 Parameters of dataset time for model training with different number of neighbor nodes.

Dataset	Number of nodes	Number of edges	Time for training
GAT_N10	400	4000	70.6898s
GAT_N20	400	8000	136.5315s
GAT_N30	400	12000	229.6373s
GAT_N40	400	16000	316.9865s
GAT_N50	400	20000	378.6503s

It is easy to understand that the channel characteristics are similar in the context of similar scenario parameters, thus scenario parameters are used to represent the correlation between nodes. Since scenario parameters have practical physical significance and have different variation ranges, we need to normalize them to the range of 0-1. According to the normalized scenario parameters, KNN algorithm is used to find N nodes with the highest correlation, called neighbor nodes for each node and edges are established between each node and every one of its neighbor nodes. When a node is a neighbor node for another, the reverse is not necessarily true, so all edges are directed. According to the different values of N, we create 5 graph datasets, including Data_N10, Data_N20, Data_N30, Data_N40, and Data_N50, corresponding to N values of 10, 20, 30, 40, and 50, respectively. Parameters of datasets are presented in Table 1. Meanwhile, the times for model training of different datasets are also listed in the table. It can be seen that even when N is 50, the time of 300 iterations using the central processing unit (CPU) is less than 400 seconds.

4. Architecture of the Proposed GAT for Channel Characteristics Prediction

The architecture of GAT with multi-head attention at node 1 is shown in Fig. 2 [19], which can be found at each node. Vector $\vec{h}_i$ or $\vec{h}_j$ (i, j=1,2, . . . , 6) is normalized channel characteristics at node i or j. Vector $\vec{\alpha}_{ij}$ (i, j=1,2, . . . , 6) is attention coefficient, indicating the importance of node j to node i, which is obtained through a FNN based on channel characteristics of node i and j. Thus, the prediction of node

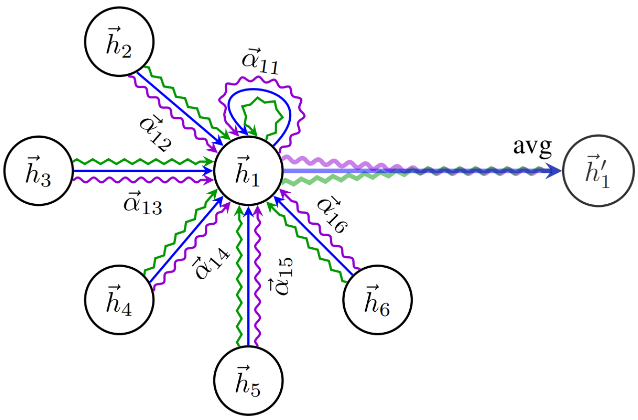

Fig. 2 Architecture of GAT with 3 heads attention at node 1 (node 2-6 are neighbor nodes of node 1).

channel characteristics is obtained by weighted average of the characteristics of its neighbor nodes. To make the prediction more stable, multiple independent attention mechanisms are used, called multi-head attention, denoted by different arrow styles and colors. Single layer GAT prediction can be expressed as

$$\vec{h}'_i = \frac{1}{K}\sum_{k=1}^{K}\sum_{j\in N_i}\vec{\alpha}_{ij}W_k\vec{h}_j \tag{1}$$

where K is the number of independent attention mechanisms, N_i denotes the set of neighbor nodes of node i, k denotes the k-th attention mechanism, and $\mathbf{W}_k$ is a weight matrix to transform characteristics into higher dimensions.

Our model consists of two layers GAT with 32 heads, GATconv1 and GATconv2. GATconv1 takes 1×6 vector as input and 1×32 vector as output, while GATconv2 takes output of GATconv1 as input and 1×6 vector as output. The activation function between two layers is *ELU* (exponential linear unit), given as

$$ELU(x) = \begin{cases} x, & x > 0, \\ e^x - 1, & x \le 0. \end{cases} \tag{2}$$

In the training, Adam optimization algorithm are selected, MSE is used as loss function and the number of iterations is 300, as mentioned in Section 3.

5. Results and Analysis

GAT_K10 to GAT_K50 are five models, corresponding to the models trained from five datasets of Data_N10 to Data_N50. The root mean square errors (RMSEs) of channel characteristics of the five models and the RBF-NN model in [16] are listed in Table 2. As we can see, model GAT_K30 has better predictive performance on almost all characteristics, which shows that model GAT_K30 is significantly better than RBF-NN model. The same conclusion can be drawn from Fig. 3, which compares GAT_K30 with the other four GAT models in RMS AAS predicted performance. As is shown in Fig. 3, when N increases from 10 to 30, the prediction performance of the model keeps improving, but it will decline slightly when N continues to increase to 40 or 50. If we increase N further to 100, the predicted characteristics curves will tend to be horizontal, fluctuating around the average. In our analysis, this is because when the number of neighbor nodes is less than 30, the effective information for prediction maybe not sufficient, while when N more than 30, some nodes with low correlation are also connected edges, thus interfering the performance. Among other characteristics prediction, predicted channel statistical characteristics of GAT_K30 also shows a good fitting with the channel measurement data. Thus, it turns out that 30 is an appropriate number of neighbor nodes.

Table 2 RMSE loss of channel characteristics of different models.

RMSE	P	DS	AAS	ADS	EAS	EDS
GAT_K10	3.23	1.49	24.47	20.62	7.73	9.10
GAT_K20	3.90	1.47	22.70	19.92	7.14	**8.78**
GAT_K30	**2.33**	**1.30**	**14.21**	**12.41**	**6.79**	8.90
GAT_K40	3.53	1.57	19.42	22.62	7.34	9.37
GAT_K50	3.06	1.64	18.90	20.78	8.18	9.93
RBF-NN [16]	3.05	1.71	32.48	30.13	10.76	12.63

6. Conclusions

In this paper, we have proposed a procedure of predicting mmWave massive MIMO indoor channel characteristics based on GAT without using all data. The data used to train the GAT have been obtained by measurement campaigns in an indoor office environment. By building different datasets to train the model, we have found that the appropriate number of neighbor nodes used to predict the channel characteristics of a node is about 30, using which there are good fittings between the predicted channel statistical characteristics and the real ones. To better predict channel characteristics, how to better represent the correlations between nodes and dynamically determine the number of neighbor nodes will be meaningful work to be solved in the future.

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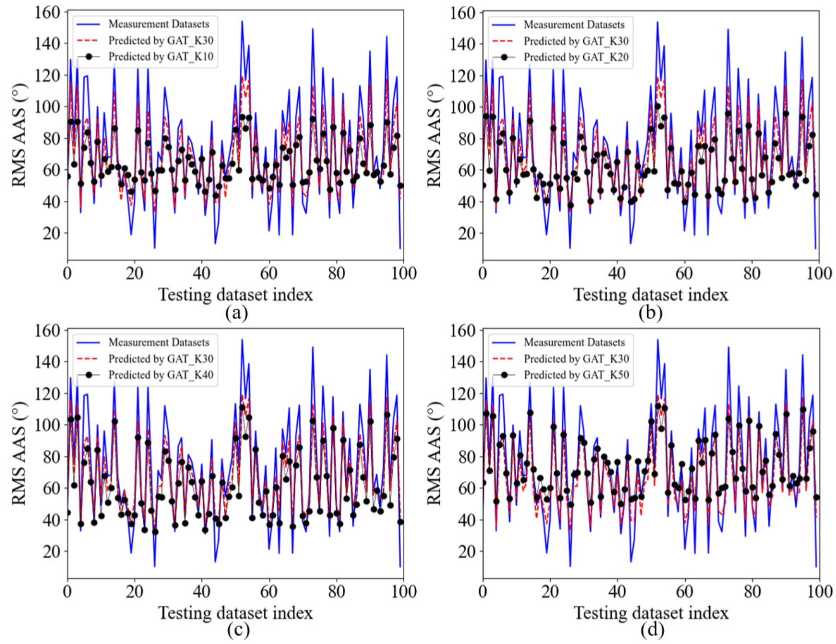

Fig. 3 Comparison of RMS AAS predictive performance between GAT_K30 and (a) GAT_K10, (b) GAT_K20, (c) GAT_K40, and (d) GAT_K50.

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