

Channel Estimation for mmWave Massive MIMO Systems based on Deep Learning

Zhang Miyuan*, Cai Xibiao, Li Yangyang, Zhang Yan

Information and Communication Engineering, Liaoning University of Technology, Liaoning Jinzhou, China

E-mail: *zhangmiruan@163.com

Abstract

Channel estimation is a key part of communication systems. However, the channel of millimeter-Wave (mmWave) Massive Multiple-Input Multiple-Output (Massive-MIMO) system has sparse characteristics, and the conventional channel estimation method is prone to noise factors and tends to achieve low estimation accuracy. Therefore, in this paper a channel estimation method is proposed for mmWave Massive MIMO systems based on deep learning. Firstly, a dataset to simulate a real-world environment, is generated by setting specific parameters. Furthermore, the generated channel matrix is adopted as the input of the neural network. Secondly, the attention mechanism is integrated into the deep learning method with ResUNet to enhance the ability of feature extraction. Finally, the channel estimation matrix is obtained via the aforementioned network model. The experimental results indicate that the Massive-MIMO method is superior to the conventional channel estimation methods in channel estimation accuracy and convergence rate, and has a good application prospects.

Keywords: mmWave massive MIMO; channel estimation; deep learning; attention mechanism; denoising

1. Introduction

With the advent of the fifth-generation mobile communication technology (5th Generation/ 5G) era, the number of devices carried by the communication system will reach tens of billions, and it is necessary to provide wider signal coverage and higher-speed and lower-latency data transmission. Millimeter Wave (mmWave) communication, due to its large bandwidth, can still meet the requirements of high data rate. At the same time, a large

number of Multiple-Input Multiple-Output (MIMO) technologies [1-3] can improve the system capacity and spectrum utilization in 5G wireless communication systems and compensate for the propagation losses. Large Scale millimeter Wave Multiple Input Multiple Output System (mmWave MIMO) deploys massive antennas in the Base Stations (BSs), which not only improves the ability to multiplex spectrum resources among multiple users, but also because of its powerful capabilities and its strong anti-interference ability, it significantly improves the data transmission rate and becomes the key technology of 5G wireless communication system [4-5]. However, due to the limited physical space and high-power consumption in the millimeter-wave massive MIMO system, to simplify the complexity of the system and keep the cost as low as possible, the number of radio frequency chains is usually relatively reduced to increase the number of antennas, which, to a certain extent, increases the system's reliability [6]. Communication quality presents challenges. The channel state information of a communication system directly reflects the communication quality of a system. That is why the research significance of the channel estimation of this system is increasing.

In [7], an adaptive channel estimation algorithm was designed using channel sparsity. The structural sparsity in the angular domain was exploited in [8] to calculate the uplink in multiple user mmWave massive MIMO wideband channels. In [9], a channel estimation method for mmWave high-quality MIMO Orthogonal Frequency-Division Multiplexing (OFDM) systems based on low precision adc was proposed. For mmWave analog downlink, a low-rank tensor decomposition was proposed for channel parameter estimation of angle, delay and fading coefficients. Instead of directly estimating mmWave MIMO channels, in [10], a hybrid analog-digital structure was studied based on the proposed singular subspace estimation method.

In recent years, deep learning has an increasingly broad research prospect [11]. In the field of wireless communication, its powerful data processing ability and learning ability can reach or even surpass the performance of traditional communication algorithms when solving various problems in wireless communication [12]. In dealing with the channel estimation problem, the deep learning method has powerful feature extraction ability and flexible network structure, and can obtain complex CSI through its excellent learning ability without establishing a well-defined mathematical model. It is of great help to improve the efficiency

and accuracy of channel estimation, and this research direction has become a new trend in current research.

In [13], a DNN framework was introduced for Direction of Arrival (DOA) estimation. Using the complex channel DOA and gain information, the channel was estimated, and the mean square error property of the channel DOA was evaluated. A DL-based super-resolution DOA estimation method was proposed in [14]. The work used DNN for offline learning and online deployment process. The learning mechanism effectively learnt the characteristics and spatial structure of wireless channels to achieve channel estimation. In [15], a DL-based multi-cell interference-limited massive MIMO system channel estimation method was proposed. The estimator adopted a specially designed DNN based on the Deep Image Prior (DIP) network. The received signal was denoised and then subjected to conventional Least Squares (LS) estimation. Authors of paper [16] proposed a channel estimation based on Spatial Frequency CNN (SF-CNN), which utilized spatial and frequency correlations to simultaneously feed the damaged channel matrix at adjacent subcarriers into the CNN. Then the original method was extended by exploiting the temporal correlation in the temporal computation channel to further improve the computational accuracy, and a Spatiotemporal Convolutional Neural Network (SFT-CNN) was proposed and conducted further research on the newly proposed network structure. The channel was estimated separately using a memory channel estimation module, Spatial Pilot Reduced CNN (SPR-CNN). The model reduced pilot loss to some extent. Reference [17] introduced the denoising network DnCNN to denoise the channel matrix image, and the performance of the network was better than the algorithm based on compressed sensing.

The conventional pilot-based channel estimation method usually produces pilot pollution, which usually performs poorly in more practical and complex channels, which reduces the accuracy of channel estimation and affects the communication quality of the system [18]. And using the traditional convolutional neural network method for training, it is easy to fall into the local optimum, and if the number of network layers is deepened, the problem of degradation is very likely to occur.

In view of this, the deep learning method used in this paper can effectively avoid the pollution of pilot signals, solve problems such as network degradation, and use a method similar to image denoising to estimate the channel according to the channel characteristics. Since millimeter-wave massive MIMO systems are easily affected by noise factors, to

improve the accuracy of channel estimation, this paper proposes a channel estimation method based on deep learning, namely Attention-ResUNet. U-Net [19] is employed as the base network. Since U-Net is a complete convolutional structure designed for image processing, it preserves pixel-level details at different resolutions by adding skip connections. Therefore, adopting U-Net has a major impact on improving details, where information at different scales can be preserved. First of all, to solve the problem of performance dropping down fully with the increase of the number of network layers and the problem of less feature extraction encountered by the traditional neural network channel estimation method, this paper uses the residual block to replace the module in the original U-Net network. Secondly, in order to improve the convergence speed and generalization ability of the overall system model and avoid falling into local optimum, Batch Normalization (BN) layer and dropout are added to the network. Finally, the attention mechanism is combined to enhance the noise characteristics and perform feature fusion to extract noise.

This paper is organized as follows: Related work is presented in Section 2. The model proposed in this paper has been introduced in Section III. The dataset and simulation results are discussed in Section IV. Finally, the conclusions and future work arrangements are given in the fifth section.

2. Related Work

In this paper, a millimeter-Wave Massive MIMO system as shown in Figure 1 is built, where the number of antennas and Radio Frequency (RF) chains of the transmitter are N_T and N_T^{RF} , respectively. The quantity of antennas and the amount of Radio Frequency chains of the receiver are N_R , N_R^{RF} , respectively. In order to reduce the number of RF links at the receiving end and the transmitting end and reduce the loss, a hybrid structure of phase shifters is used and a sea of antennas are connected. Therefore, $N_T \gg N_T^{RF}, N_R \gg N_R^{RF}$.

In the delay domain, in line with the reference [14], the $N_T \times N_R$ channel matrix between receiver and transmitter can be expressed as:

$$\mathbf{H}(\tau) = \sqrt{\frac{N_T N_R}{L}} \sum_{l=1}^L \alpha_l \delta(\tau - \tau_l) \mathbf{a}_R(\varphi_l) \mathbf{a}_T^H(\phi_l) \quad (1)$$

Among them, L is the number of principal paths, α_l and τ_l are the propagation gain and postpone of the l^{th} path, separately, φ_l and ϕ_l are the arrival and departure azimuths of the receiver and transmitter. Regarding a Uniform Linear Array (ULA), the corresponding answer vector can be denoted as:

$$a_R(\varphi_l) = \frac{1}{\sqrt{N_R}} [1, e^{-j2\pi \frac{d}{\lambda} \sin(\varphi_l)}, \dots, e^{-j2\pi \frac{d}{\lambda} (N_R-1) \sin(\varphi_l)}]_T \quad (2)$$

$$a_T(\phi_l) = \frac{1}{\sqrt{N_T}} [1, e^{-j2\pi \frac{d}{\lambda} \sin(\phi_l)}, \dots, e^{-j2\pi \frac{d}{\lambda} (N_T-1) \sin(\phi_l)}]_T \quad (3)$$

where, d and λ represent the distances between contiguous aerials and the carrier airways. In the light of the model, the frequency domain channel of the k^{th} subcarrier in OFDM can be expressed as:

$$H_k = \sqrt{\frac{N_T N_R}{L}} \sum_{l=1}^L \alpha_l e^{-j2\pi \tau_l f_s \frac{k}{K}} a_R(\varphi_l) a_T^H(\phi_l) \quad (4)$$

where f_s is the sampling rate, and K is the amount of OFDM subcarriers. In order to estimate the above-mentioned channel matrix H_k , the number of radio frequency chains of the transmitter is controlled so that only one of the beams is reserved on each channel for transmission of pilot frequencies. On the other hand, for the receiver part, the received pilots are combined by steering all radio frequency chains associated with different beams. Specifically, the transmitter uses the M_T beamforming vector $f_{k,u} \in \mathbb{C}^{N_T \times 1}, u = 1, \dots, M_T$. Corresponding to the transmitted pilot signal of each beamforming vector $f_{k,u}$, the receiver uses the M_R combination vector $w_{k,v} \in \mathbb{C}^{N_R \times 1}, v = 1, \dots, M_R$ to process them.

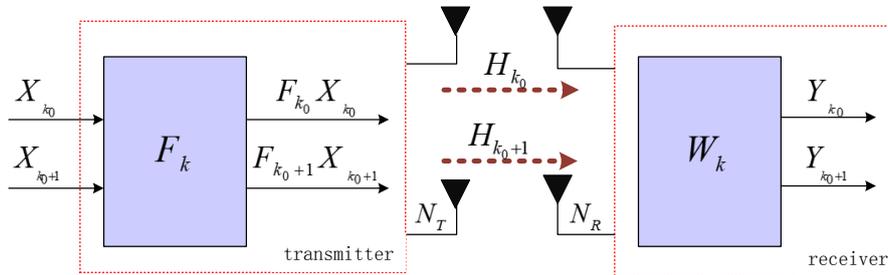


Figure 1. Structural representation of mmWave MIMO-OFDM system

Since the receiver is equipped with an $N_R^{RF} (< M_R)$ radio chain, it can only use the N_R^{RF} combining vector in channel usage. If the receiver uses all M_R combined vectors to process a beamforming vector carrying pilots, the desired channel can be expressed as $\left[\frac{M_R}{N_R^{RF}} \right]$. Therefore, the total channel processing all beamforming vectors is $\left[\frac{M_R}{N_R^{RF}} \right]$, and this pilot transmission process can capture the dominant path in the mmWave channel [20]. Then the pilot signal matrix associated with the k^{th} subcarrier at the baseband of the receiver can be written as:

$$Y_k = W_k^H H_k F_k X_k + \tilde{N}_k \quad (5)$$

where, $w_k = [w_{k,1} \cdots, w_{k,M_R}]$ and $F_k = [f_{k,1} \cdots, f_{k,M_T}]$ are the combining and beamforming matrices, and X_k is an $M_T \times M_T$ diagonal matrix. $\tilde{N}_k = W_k^H N_k$ represents the effective noise after the combination, and N_k is the additive white Gaussian noise before the combination.

For this, pilot interposition is deliberated in the frequency domain or the time domain. According to the estimated channel, an interpolation method can be used to obtain a channel without pilot positions. Obviously, the accuracy of the interpolation depends on the accuracy of the estimated channel and the variation of the channel. Therefore, this paper uses the deep learning method to improve the channel estimation accuracy under the pilot condition, so as to provide ideas for further research in the future.

3. Attention-ResUnet based channel estimation

3.1 Main Framework

The overall structure of the neural network model Attention-ResUnet used in this paper (shown in Figure 2), consists of the encoding path on the left and the decoding path on the right.

Generally speaking, the number of layers of the network is usually deepened hoping that the performance of the deeper network will be better than that of the shallower network, or hoping that their performance is at least equal. However, unrestrictedly deepening the number of network layers suffers from severe degradation problems. Therefore, at each layer,

using the residual module to transmit information can build a deeper neural network. And it can solve the degradation problem very well. It improves the interdependence between channels while reducing computational cost. The proposed ResUNet architecture in this paper consists of a three-encoder block and three decoder blocks. As can be clearly seen from Figure 2, in the encoder part, a residual block is employed for each block and each module block contains batch normalization layer, ReLU activation layer and convolution layer. The batch normalization layer effectively accelerates the convergence rate of the network, improves the generalization ability of the model, and can accelerate the convergence rate of the network, thereby improving the network performance.

Hence, the number of convolutional layers in the residual block exhibit a crucial impact on the whole network. A large number of convolutional layers will cause the network to be bigger, and there may be risks such as memory overflow. Therefore, two convolutional layers are selected in this model to guarantee the basic property of the network.

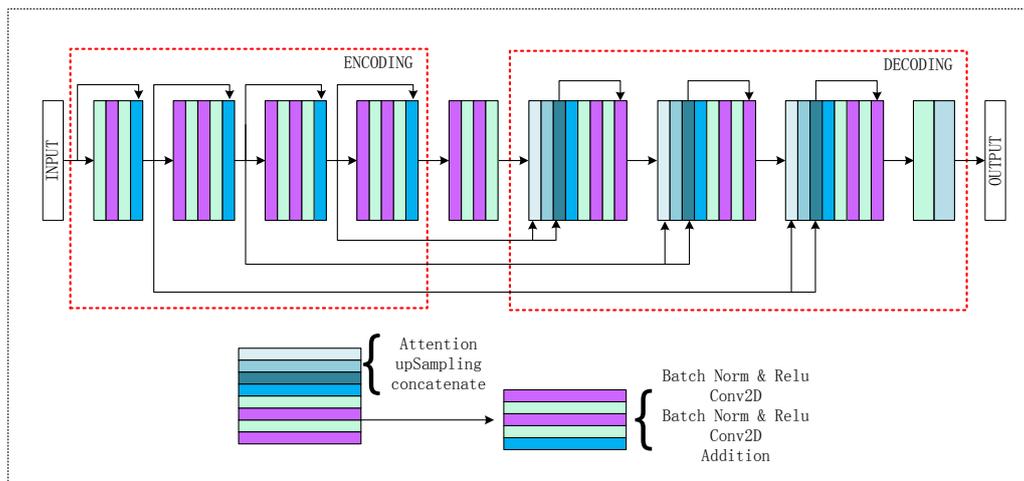


Figure 2. Overall structure diagram

Furthermore, in the input and output parts of the encoder, a map is employed to connect. And on the first convolutional layer of the encoder block, a hierarchical convolutional layer is adopted to reduce the spatial dimension of the feature map by half. Accordingly, the decoder section is also structured as described above. However, unlike the encoder, a soft-attention module is employed to improve features before each module in the decoder part. After that, the next step is to upsample from the nearest neighbors of the lower-level feature maps and concatenate the features of the corresponding encoder parts. Also, to

avoid the problem of mode collapse, the output value of the generator is normalized to $[-1,1]$ using a hyperbolic tangent (tanh) activation function. A concise description of the residual [21] unit and attention mechanism module is given in 3.2.

The design of the overall structure draws on the means of image processing and considers the task of channel estimation at the same time. The image denoising method is used to extract features from noise, and the neural network is used for training and testing to finally achieve channel estimation. For the system mentioned in this article, $N_T=32, N_R=16$ is considered as a typical example. The real part and the imaginary part of the complex channel matrix that is initially estimated are separated to obtain four 16×32 real-valued matrices. Then the values are entered in the network architecture used in this article. The noise feature extraction is performed in the encoder part, and the noise extraction is realized by feature fusion in the decoder part. Finally, a 16×32 complex-valued estimated channel matrix is output. Experiments show that it has good channel estimation performance.

3.2 Residual unit and attention module

The structure of the residual unit is shown in Figure 3. In the residual network, the most important thing is that it proposes a concept similar to fast connection. That is, by skipping other network layers, the input results are directly added to the output tasks. The following formula can be used as a visual representation of the residual network:

$$H(x) = x + F(x) \quad (6)$$

where, $H(x)$ is the mapping of the bottom layer, x is the input result, and $F(x)$ is the output result of the hidden layer in the network.

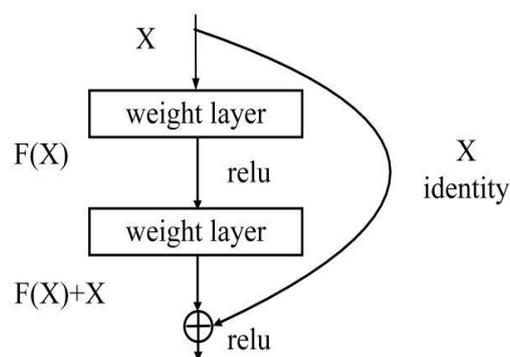


Figure 3. Residual block

Compared with other neural network models, the residual unit can add the output of many convolution blocks to the feature extraction task of the next convolution block, and effectively reduce the parameters used in training to a certain extent. In the traditional convolutional neural network, the amount of network layers is continuously increased, and the negative effects such as error and time loss gradually become prominent. However, the use of residual network can solve the above problems. Compared with other networks, the residual network structure is relatively simple, and it uses relatively few training parameters, which reduces the training time to a certain extent. At the same time, it also solves the problem that the performance of the network decreases with the increase of the number of layers.

ResUNet uses full pre-activated residual units. Due to the above advantages, this paper adopts the model architecture of ResUNet. Meanwhile, attention mechanisms are most popular in Natural Language Processing (NLP) [22]. Through the attention mechanism, the neural network can quickly extract effective information from a large amount of information and improve the efficiency. The reason for adopting the attention mechanism is that its structure is simple, its applicability is strong, and it can improve the ability of feature extraction on the basis of the original network, and further improve the performance of the system.

4. Results and Discussion

4.1 Dataset Preparation and Evaluation Indicators

To measure the channel estimation performance [24], the Normalized Mean Square Error (NMSE) employed to evaluate the estimation mass is defined as :

$$NMSE = E\{\|\hat{H} - H\|_2^2 / \|\hat{H}\|_2^2\} \quad (7)$$

In the formula: H is the channel matrix estimated by the model, and the smaller the NMSE, the better the estimation performance.

The dataset used in this paper is generated based on the 15-channel model published by 3rd Generation Partnership Project (3GPP) TR38.901 [23]. Channel state information is trained and estimated through a network model using an NVIDIA GeForce GTX1080Ti GPU under the tensorflow framework. The parameter settings are shown in Table 1. The number of

samples is selected to be 100000, of which 75% are used for the training data set, 10% are used for the validation data, and 15% are used for the test data. Finally, this paper compares and analyzes the proposed algorithm with LS, MMSE, CNN and ResUNet methods.

Table 1. Main parameters of system simulation

Parameter	Value
Carrier Frequency	30GHz
Sampling Rate	100MHz
Number of Main Paths	3
Number of Subcarriers	128
Optimizer	Adam
Epochs	300
Learning Rate	0.00003
Dropout	0.2
Batch Size	32
Scaling Constant	2
SNR Limits	-10dB-20dB

4.2 Simulation Analysis

First, the neural network is trained under different signal-to-noise ratio conditions based on the generated dataset. The specific process is to generate a channel data set according to the channel model of (3GPP) TR38.901 version 15, and then these data are used to generate pilot signals received in different signal-to-noise ratios, which are used to train the neural network to obtain the corresponding signal-to-noise ratio.

Figure 4 compares the loss of each network model under different iterations between CNN, ResUNet and the Attention-RseUnet method proposed in this paper. By setting the same network parameters, under different iteration times, it is better than the optimization based on the attention mechanism module. When extracting features, it plays a major role in the features that need attention and ignores the unimportant features. The network model mentioned in this paper loses performance. It outperforms the other two model methods.

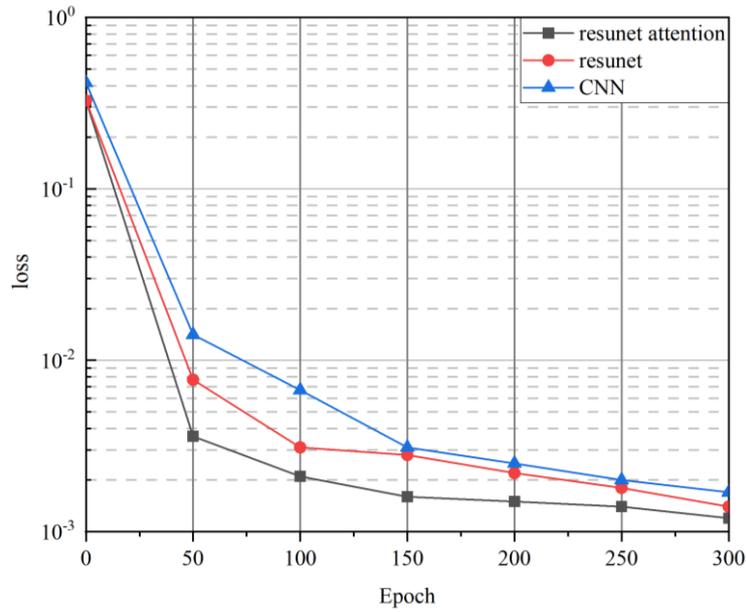


Figure 4. The loss of each network model under different iterations

Figure 4 compares the NMSE performance of the four methods such as ResUNet, CNN, LS, MMSE and the Attention-ResUnet method in this paper at different signal-to-noise ratios, that is, from -10dB to 20dB. Among them, LS and MMSE are traditional channel estimation algorithms. The estimation performance of the LS algorithm is the worst, and the MMSE algorithm has a certain improvement over the LS algorithm.

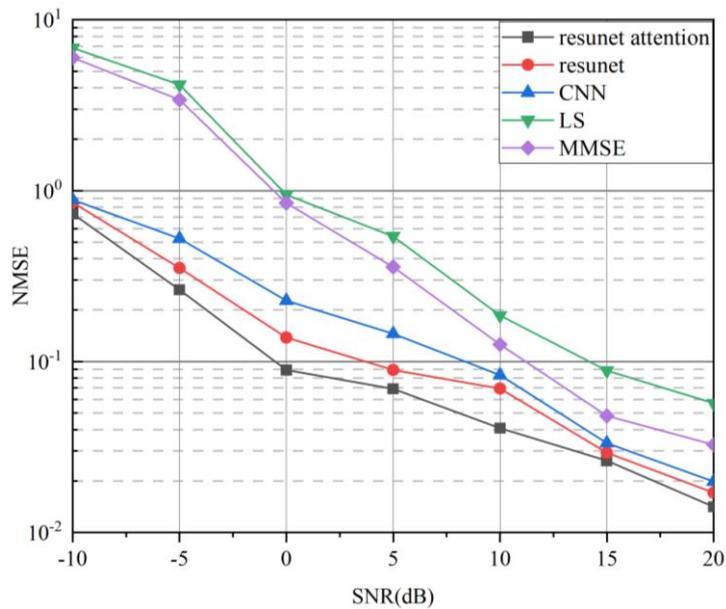


Figure 5. NMSE curves of the proposed method and other methods

For the clear performance of Figure 4, the estimation performance of the method proposed in this paper is improved by about 0.96 dB on average compared with the ResUNet and CNN methods. When the signal-to-noise ratio is -10~5dB, the estimation performance of the ResUNet and CNN methods is improved by about 0.23~0.51dB on average; in the case of 6~20 dB, the channel estimation performance based on Attention-ResUNet is improved by about 0.43~0.68 dB on average. Since the Attention-ResUNet network model adds an attention mechanism module to the training and learning of the samples, it shows better performance in noise extraction. Under the same signal-to-noise ratio, the channel estimation accuracy based on Attention-ResUNet is obtained. The average boost is about 0.25 dB.

However, in practical scenarios, the number L of main paths may vary. So the robustness of the proposed method is tested under different numbers of main paths. As shown in Figure 5, the performance of the method proposed in this paper is compared when $L=1, 2, 3,$ and 4 .

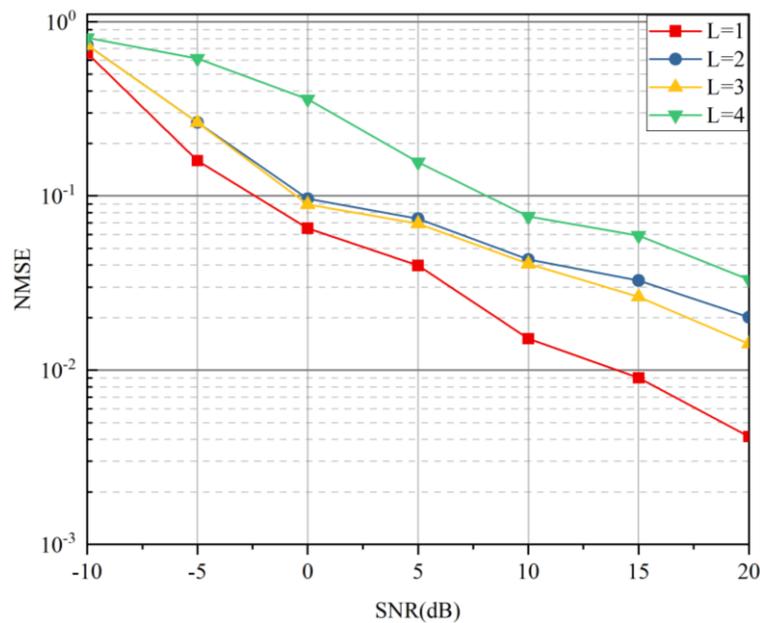


Figure 6. Performance curves for different numbers of primary paths.

Among them, $L=3$ as the criterion for comparison is the same as the training result shown in Figure 4. When $L = 1$, the performance is better than the standard method, which is due to the reduction in the number of main paths, which significantly reduces the structural complexity of the system, which propitious denoising. When $L=2$, the performance is basically the same as the baseline, but slightly degrades. Finally, the performance drops

significantly when $L=4$. In the process of training, when the number of main paths is set to 3, its neural network can automatically learn the channels when $L=1, 2$, thus simulating the real environment to a certain extent. Training with $L=3$ shows good robustness. However, when $L=4$, it changes the overall structure of the channel due to the increase in the number of paths and make the complexity grow linearly, which leads to the decrease of system performance.

5. Conclusion

In this paper, the Attention-ResUNet neural network fused with attention mechanism is applied to channel estimation for mmWave Massive MIMO. The generated channel matrix is regarded as an image to denoise the image by enhancing the spatial pixel features of the image through the attention module. The experimental results clearly show that in the channel estimation task, the deep learning pattern can notably increase the channel estimation property and improve the estimation accuracy to a certain extent. The next research direction is to combine the real environment and in-depth analysis of the channel system model, employing a new deep learning method, combining it with image processing and integrating it into the task of channel estimation to improve the robustness and accuracy of channel estimation.

References

- [1] Neumann, D., Wiese, T., & Utschick, W. (2018). Learning the MMSE channel estimator. *IEEE Transactions on Signal Processing*, 66(11), 2905-2917.
- [2] Bagadi, K. P., & Das, S. (2010). MIMO-OFDM channel estimation using pilot carries. *International Journal of computer applications*, 2(3), 81-88.
- [3] Guo, Z., & Nilsson, P. (2006). Algorithm and implementation of the K-best sphere decoding for MIMO detection. *IEEE Journal on selected areas in communications*, 24(3), 491-503.
- [4] Zhang, T. C., Wen, C. K., Jin, S., & Jiang, T. (2016). Mixed-ADC massive MIMO detectors: Performance analysis and design optimization. *IEEE transactions on wireless communications*, 15(11), 7738-7752.
- [5] Xiang, L., Liu, Y., Van Luong, T., Maunder, R. G., Yang, L. L., & Hanzo, L. (2020). Deep-learning-aided joint channel estimation and data detection for spatial modulation. *IEEE Access*, 8, 191910-191919.

- [6] Smys, S., Joy Iong Zong Chen, and Subarna Shakya. "Survey on neural network architectures with deep learning." *Journal of Soft Computing Paradigm (JSCP)* 2, no. 03 (2020): 186-194.
- [7] Alkhateeb, A., El Ayach, O., Leus, G., & Heath, R. W. (2014). Channel estimation and hybrid precoding for millimeter wave cellular systems. *IEEE journal of selected topics in signal processing*, 8(5), 831-846.
- [8] Gao, Z., Hu, C., Dai, L., & Wang, Z. (2016). Channel estimation for millimeter-wave massive MIMO with hybrid precoding over frequency-selective fading channels. *IEEE Communications Letters*, 20(6), 1259-1262.
- [9] Wang, Y., Xu, W., Zhang, H., & You, X. (2018). Wideband mmWave channel estimation for hybrid massive MIMO with low-precision ADCs. *IEEE Wireless Communications Letters*, 8(1), 285-288.
- [10] Ghauch, H., Kim, T., Bengtsson, M., & Skoglund, M. (2016). Subspace estimation and decomposition for large millimeter-wave MIMO systems. *IEEE Journal of Selected Topics in Signal Processing*, 10(3), 528-542.
- [11] Shakya, Subarna, and Lalitpur Nepal Pulchowk. "The robust routing protocol with authentication for wireless adhoc networks." *Journal of ISMAC* 2, no. 02 (2020): 83-95.
- [12] Qin, Z., Ye, H., Li, G. Y., & Juang, B. H. F. (2019). Deep learning in physical layer communications. *IEEE Wireless Communications*, 26(2), 93-99.
- [13] Ravindran, S., & Jose, R. (2019, July). Direction of arrival and channel estimation using machine learning for multiple input multiple output system. In *2019 International Conference on Communication and Electronics Systems (ICCES)* (pp. 1327-1330). IEEE.
- [14] Huang, H., Gui, G., Sari, H., & Adachi, F. (2018, August). Deep learning for super-resolution DOA estimation in massive MIMO systems. In *2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)* (pp. 1-5). IEEE.
- [15] Balevi, E., Doshi, A., & Andrews, J. G. (2020). Massive MIMO channel estimation with an untrained deep neural network. *IEEE Transactions on Wireless Communications*, 19(3), 2079-2090.
- [16] Dong, P., Zhang, H., Li, G. Y., Gaspar, I. S., & NaderiAlizadeh, N. (2019). Deep CNN-based channel estimation for mmWave massive MIMO systems. *IEEE Journal of Selected Topics in Signal Processing*, 13(5), 989-1000.

- [17] Ma, W., Qi, C., Zhang, Z., & Cheng, J. (2019, October). Deep learning for compressed sensing based channel estimation in millimeter wave massive mimo. In 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP) (pp. 1-6). IEEE.
- [18] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
- [19] Hussana Johar, R. B., and B. R. Sujatha. "Orthogonal Frequency Division Multiplexing-Multiple Input Multiple Output Channel Estimation for Rayleigh and Rician Channel Models." In International Conference on Inventive Computation Technologies, pp. 414-422. Springer, Cham, 2019.
- [20] Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer, Cham.
- [21] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
- [22] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30.
- [23] 3GPP. (2018). Study on channel model for frequencies from 0.5 to 100 GHz. 3rd Generation Partnership Project (3GPP), Tech. Rep., 38.
- [24] Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1125-1134).

Author's biography

Zhang Miyuan is currently enrolled in a Postgraduate degree program in Liaoning University of Technology, Liaoning Province, China. Major in information and communication engineering, mainly researching mobile communication and artificial intelligence. He is currently working on mmWave Massive MIMO systems.

Cai Xibiao, professor at Liaoning University of Technology, Jinzhou, Liaoning Province, whose main research interests are wireless communication and pattern recognition.

Li Yangyang is currently enrolled in a Postgraduate degree program in Liaoning University of Technology, Liaoning Province, China. Major in Electronics and Communication Engineering, mainly studies the theory and application of signal and information processing. He is currently working on various algorithms for recommender systems.

Zhang Yan is currently enrolled in a Postgraduate degree program in Liaoning University of Technology, Liaoning Province, China. Majoring in Power Electronics and Power Transmission with specific study on Photovoltaic Power Generation and Artificial Intelligence. He was awarded Bachelor of Electrical Engineering and Automation with First-Class Honours from Xi'an Polytechnic University, Shaanxi Province, China. He is currently working on various algorithms for Photovoltaic Power Generation Systems.