

Deep Neural Network-Based Channel Estimation Scheme in Massive MIMO Systems

Shuyu Lu*

College of Design and Engineering, National University of Singapore, Singapore 119077

* e1352460@u.nus.edu

Abstract. Channel estimation is one of the most essential technologies of wireless communication, as well as necessary indicators to measure the system's quality. In recent years, the combination of channel estimation and deep learning techniques has raised wide attention and become one of the most popular research directions of machine learning applications in the wireless communication area. However, in wireless communication systems such as massive MIMO, it's too complicated to take traditional channel estimation methods with shortcomings like insufficient precision or increased cost. With the combination of deep neural networks (DDN) and the least squares (LS) method, this paper focuses on the deep learning-based channel estimation for massive MIMO systems. Compared with traditional algorithms such as LS or minimum mean-square error method, the loss function of the results is significantly reduced while simulating for the same analog channel. The problem of lack of precision has been improved efficiently and the performance has been improved substantially, which can prove the adequacy of the design of the channel estimator.

Keywords: Massive MIMO; deep learning; channel estimation; deep neural network.

1. Introduction

During recent years, with the rapid development of wireless communication technologies and continuous improvement of performance, the change and substitution of traditional methods is becoming increasingly important. The expansion of coverage, the explosion of information and the increase in the number of users and environmental noises all improve the requirements on measurements of various parts in wireless communication systems [1]. The limitations of some traditional measurements also appear, which makes it more and more important to find more efficient, convenient and rapid methods to substitute.

To explore the detailed application and performance enhancement of deep learning model in channel estimation, it's necessary to specify the challenges and limitations traditional method are faced with in wireless communication systems, especially the massive multi-input multi-output (MIMO) systems. Mainly because of the pilot's contamination and environmental noises, the channel estimation in massive MIMO networks is quite complicated. Some traditional matrix operations such as matrix inversion are too complex to realize in terms of calculation [2]. Moreover, considering the insufficient precision and increasing cost, methods such as least squares (LS) and minimum mean-square error (MMSE) estimation are inappropriate, including the reproducibility of large numbers of samples and much higher complexity than other application scenarios [3].

The detailed application of deep learning in massive MIMO systems has become one of the most popular research directions in wireless communication and achieved corresponding progress and results. Currently, deep learning-based channel estimation often uses deep neural networks (DNN) to design the estimators. Combined with other techniques can merit the advantages of making the estimators perform better, compensating for the regular shortcomings of a DNN background [4].

Literature published in 2019 has proved that deep learning-based channel estimation solution, which is better than the traditional method, focuses on the case that the pilot's length is greater than the antennas for massive MIMO systems. It can be mainly divided into two stages called pilot-aided estimation and data-aided estimation which are both deep learning-based. The former stage can be consisted of a two-layer neural network (TNN) and the DNN, while the latter one can be achieved with another DNN [5].

As an important technology of wireless communication, traditional MIMO OFDM may be affected by the influence of nonlinear distortions of power amplifier (PA), reducing the accuracy and performance of estimation of receivers. Literature in 2021 has proposed a receiver consisted of LS estimation and aided with zero-forcing (ZF) algorithm. The simulation results proved that the model can significantly improve the bit error rate and demonstrate robustness to distortions of different levels [6].

Moreover, focusing on MIMO systems with received signal-to-noise ratio (SNR) feedback, relevant literature in 2022 has also provided corresponding solutions. The literature set two scenarios as quasi-static block fading and time-varying fading. The former scenario can construct an autoencoder with a convolutional neural network (CNN). The latter one can develop totally new channel estimation scheme combining CNN with a recurrent neural network (RNN). Simultaneously, it can be trained with generative adversarial networks (GAN) to provide enough samples, solving the problem of data limitations [7].

Traditional approximate message passing (AMP) algorithm can solve the problem of sparse signal recovery for millimeter-wave massive MIMO systems, while the DNN can achieve the advanced learning approximate message passing (LAMP) algorithm. To enhance the precision, literature in 2020 has proposed an improved algorithm based on a prior-aided Gaussian mixture LAMP (GM-LAMP), with theoretical calculations and verification, the estimation accuracy has significantly raised [8].

The research object of this paper is the deep learning-based channel estimation for massive MIMO systems. The complete research process includes three major stages. The first is the confirmation of the specific research direction and the application area. Secondly, it's the decision on the algorithm and model to be re-appeared by a literature review about domestic and international research status. Eventually, it's important to tap into valuable and strange application scenarios based on the verification of the algorithm's accuracy.

2. Methodology

This paper mainly focuses on channel estimation algorithms for massive MIMO systems based on the DNN, and the algorithm and model taken mainly refer to the literature published in 2020. The system mainly uses the signals that have been noise-filtered and conducts channel estimation on this basis. The characteristic of the DNN is the complexity of the networks which require many parameters to be trained. Therefore, through the adjustment of the neural network parameters, the channel estimation can be achieved through an untrained DNN, enabling the network to set parameters without pre-training and decreasing the parameters from millions to thousands, which has a certain realization value and significance [3]. Moreover, one of the key points of the method in this paper is the needless fundamental knowledge about channel estimation and only needs to extract relevant information and characteristics from the received signal. On this basis, this method widely broadens the application scenarios and the channel types that can be applied. Meanwhile, it also reduces the thresholds and conditions to construct the channel estimators [9].

The deep learning-based channel estimator consists of two parts, firstly, the noise in the received signal can be filtered with a pre-designed DNN, and the prior information can also be gained to mitigate the environment interference and pilot contamination. On this basis, the LS algorithm can conduct corresponding channel estimation to the filtered signal. In summary, the fundamental logic is very similar to LS method-based channel estimation. However, the traditional problems of accuracy limitations and calculation complexity can be improved and solved through the substitution of the original signal directly received with the filtered signal after the DNN [3].

Figure 1 demonstrated the detailed and fundamental design logic of the channel estimator. The main features of the model in this paper is to combine the low complexity of LS estimators and the noise filtering ability of the DNN constructure in one estimator. Therefore, the estimator can achieve the eventual performance of MMSE algorithm that is commonly applied to massive MIMO systems

with a simpler approach. Moreover, the necessity of pre-training model can also reduce the parameters' amount involved in the design process, decreasing the calculation sophistication at the same time.

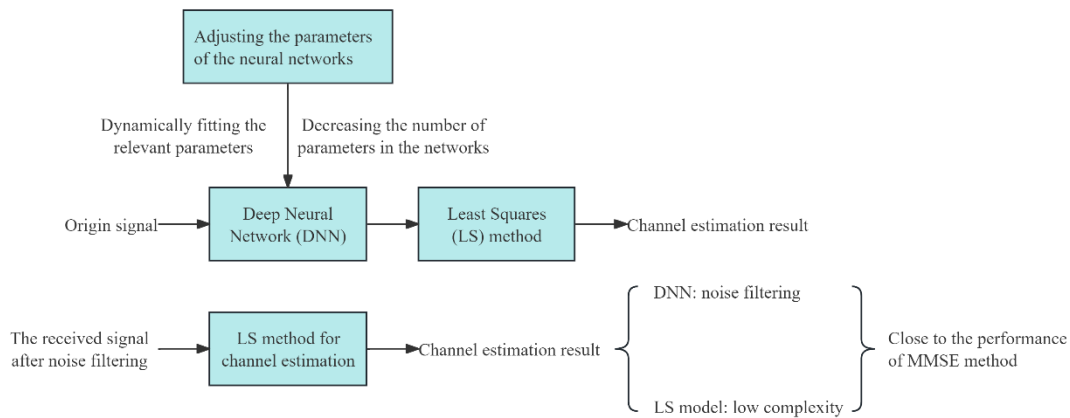


Fig. 1 The fundamental constructure and major characteristic of estimator design

3. Results and Discussion

The simulation of the estimator in this paper is mainly constructed on the Jupyter Notebook platform, aided by the Python and MATLAB language and software. The MATLAB software mainly provides the simulation basis, generating simulated channel and interference matrices for the following signal processing and channel estimation operations. The Pycharm software is mainly utilized for the import of related function libraries and the definition of relevant functions which may be repeatedly used later in the major function. Moreover, this part includes the definition, construction and final output of the neural networks. On this basis, the Jupyter Notebook is the platform on which the main program is executed. The pre-processing of the signal, the import of the generated channel and defined functions, and the eventual channel estimation and other operations are all completed here and derive the corresponding results. Besides, the plotting of the system performance and the presentation of relevant parameters will also be demonstrated during this part.

Taking published literature as a reference, the former research utilized two Nvidia GeForce GTX 2070 GPUs to accelerate [3]. Considering the limited of hardware devices, this paper substituted it with one Nvidia GeForce GTX 1650 to speed up. Although the calculation consumption may be a departure from the previous one, the accuracy and performance of the result will not be influenced by this variance. Besides, during the design of the DNN definition, the estimator mainly uses Adam optimization and early stopping to prevent the overfitting problem, calculating the corresponding epochs and weights. Here the learning rate during the optimization is defined as 0.01 [3].

The variation of the loss function with the changes of the epochs is one of the significant simulation results, as figure 2 to figure 5 shows. Here the k value represents the number of channels in every hidden layer of the neural networks. It's clear that the loss function for different k values and different SNR conditions basically decreases with the increases of the epochs and stays constant eventually. Figure 2, figure 3, figure 4, and figure 5 respectively symbolize the simulation scenarios where k equals to 64, 32, 16 and 8. Besides, each figure includes five different curves between the mean square error (MSE) and the number of epochs, which represent different SNR conditions as 0dB, 5dB, 10dB, 15dB and 20dB. Observing the changes in the curves, the loss function will rise up again with the increase in the epochs, representing the degradation in the model performance when the SNR is relatively lower, and the number of epochs is higher than on other occasions.

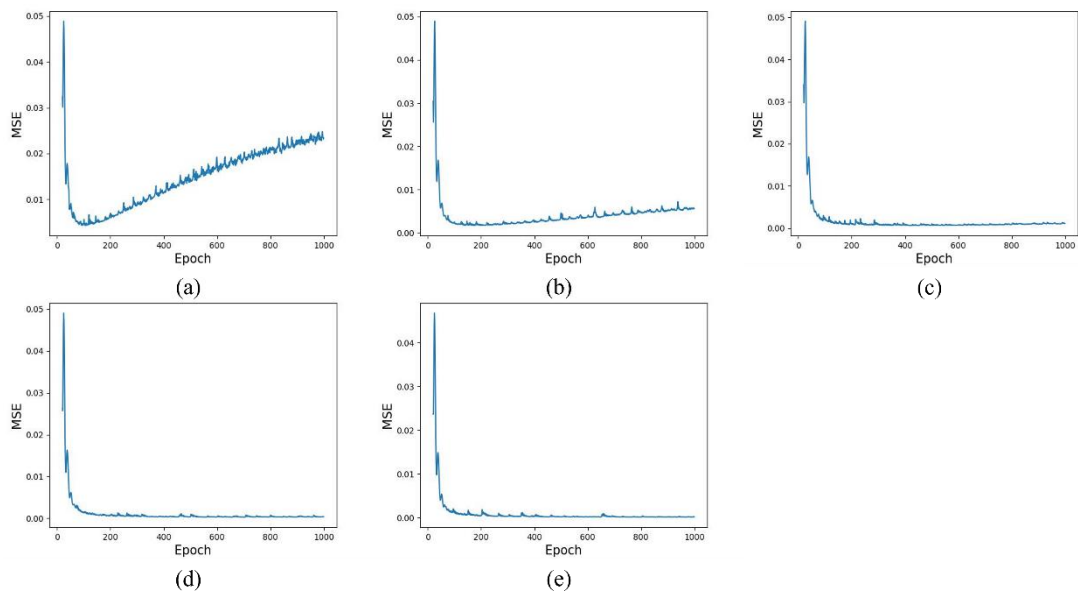


Fig. 2 The variation of the loss function with the changes of the epochs ($k = 64$)

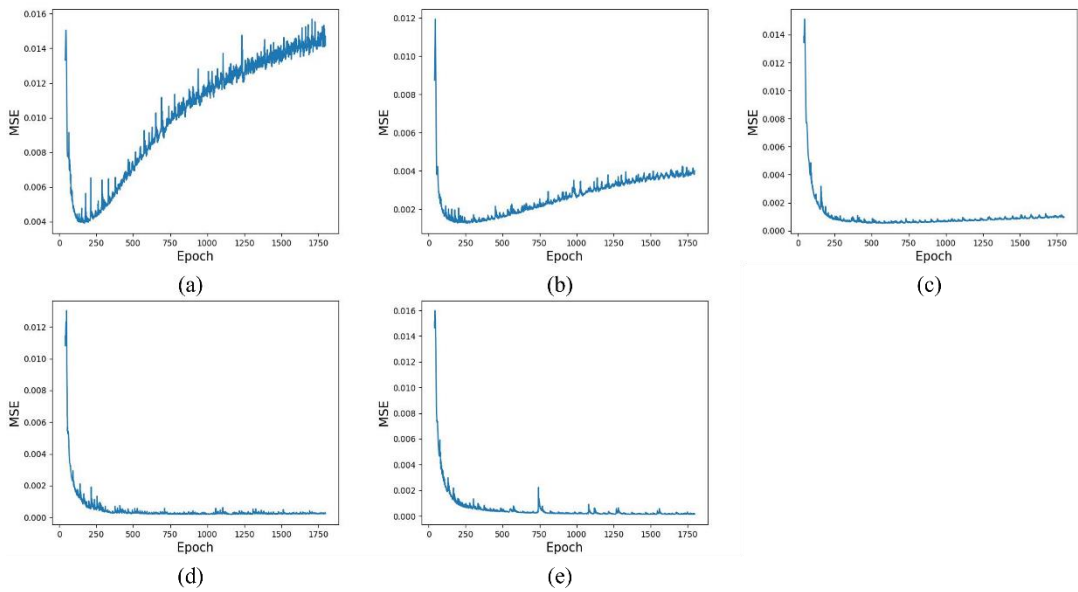


Fig. 3 The variation of the loss function with the changes of the epochs ($k = 32$)

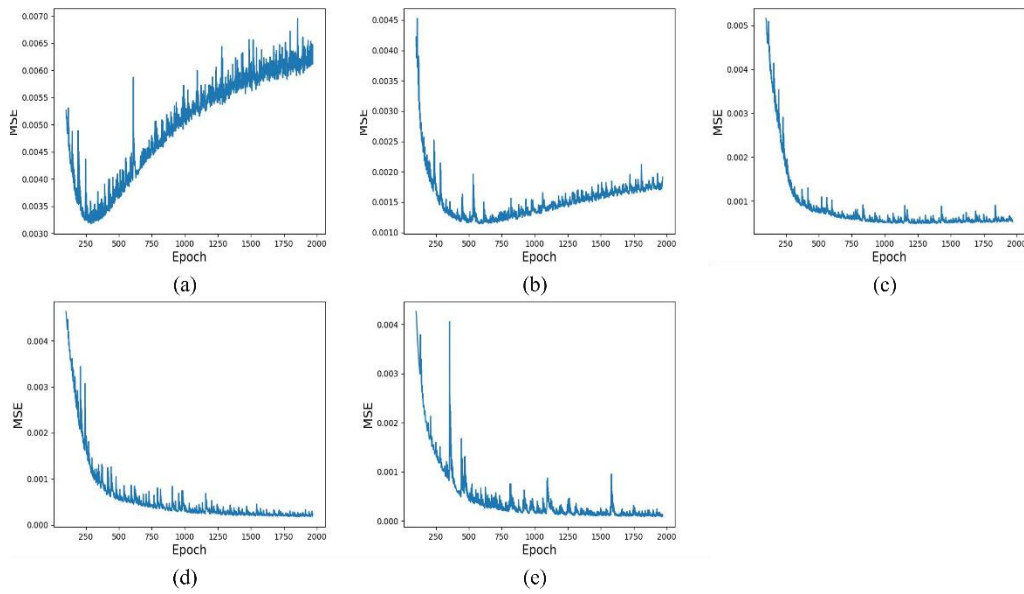


Fig. 4 The variation of the loss function with the changes of the epochs ($k = 16$)

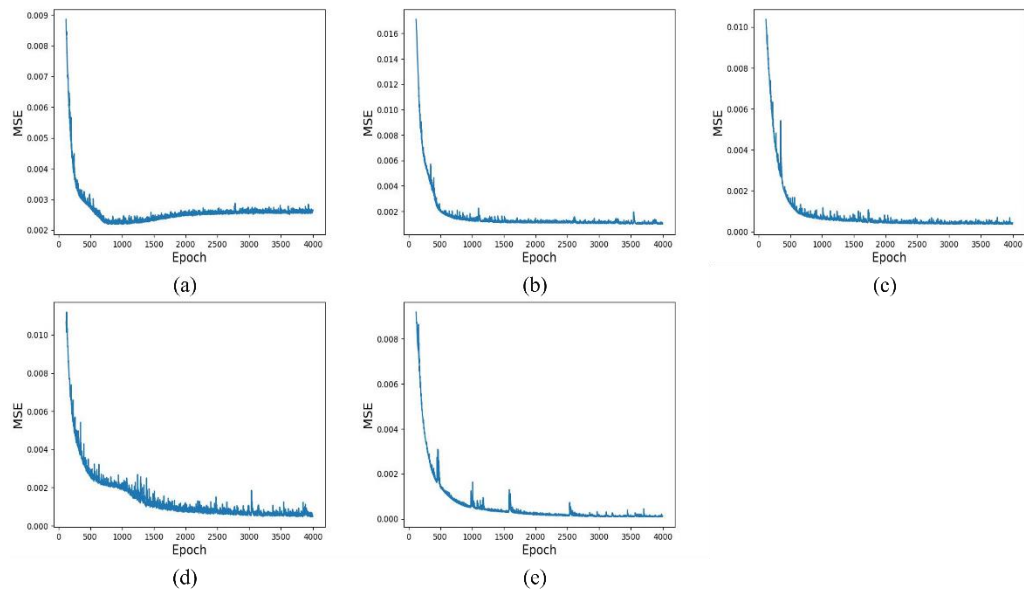


Fig. 5 The variation of the loss function with the changes of the epochs ($k = 8$)

As the table 1 shown, the eventual performance of the model and the comparison with traditional methods can refer to the difference in MSE under the same condition of SNR. The lower MSE, the better the model performed. Although there are slight differences between different k values, the overall performance is better than the traditional methods in the same scenario. Especially compared to LS method, the MSE significantly decreases, symbolizing the enhancement of accuracy.

Table 1. Different MSE values under the same SNR with various channel estimation methods

Channel estimation method	MSE value under different conditions of SNR				
	0dB	5dB	10dB	15dB	20dB
LS	0.1159	0.0367	0.0116	0.0037	0.0012
MMSE	0.3484	0.1101	0.0348	0.0110	0.0035
Deep learning-based channel estimator under different k values					
$k=8$	0.00219	0.00098	0.00036	0.00047	0.00009
$k=16$	0.00318	0.00114	0.00048	0.00017	0.00009
$k=32$	0.00391	0.00127	0.00053	0.00018	0.00013
$k=64$	0.00429	0.00170	0.00065	0.00028	0.00012

As figure 6 shown, the curves are mainly consisted of five different SNR conditions including 0dB, 5dB, 10dB, 15dB and 20dB. The four different k values are equal to 8, 16, 32, and 64 respectively. Comparing the variations in the MSE with the changes in the SNR between different k values, which represent the channel numbers in every hidden layer of the neural network, it can be concluded that when the SNR value and k value are both small, the MSE value is also low, and the performance is better. However, when the SNR value increases, the performance under different k values converges and is considerably close to each other. Changing the channel numbers can cause the estimator to perform differently under various SNR conditions, but the results all outperform the traditional methods, which can prove the effectiveness of the estimator design in this paper.

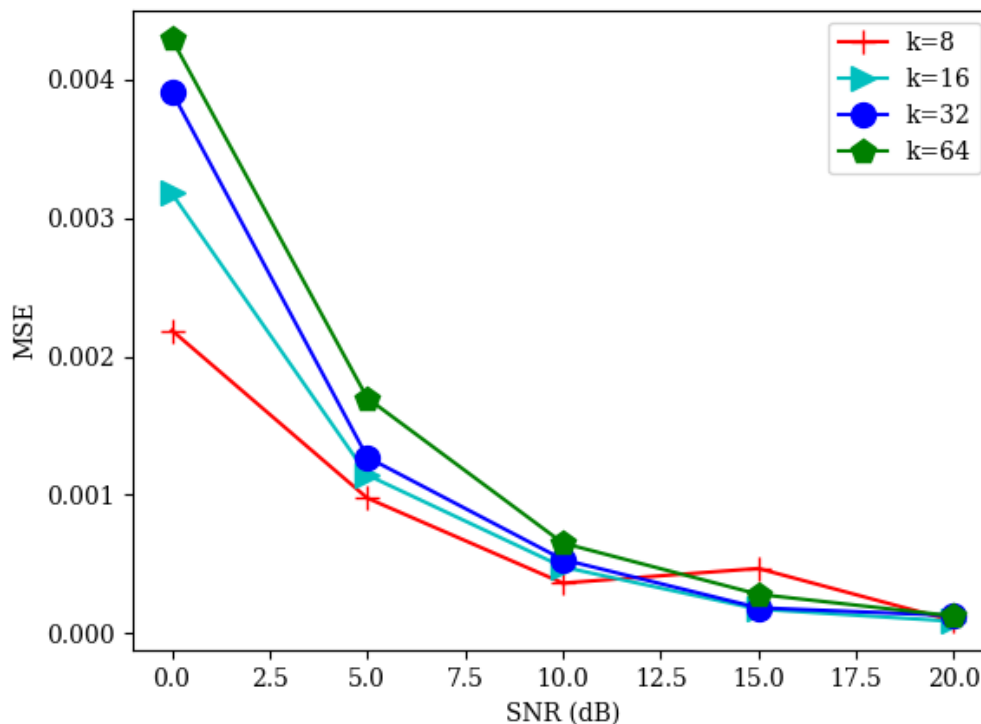


Fig. 6 The curves between the MSE value and SNR under different k values

Based on the algorithm and estimator in this paper, broad applications can be considered as well as wider innovations. Firstly, the expansion of the scope of application is essential. Considering that the research scenarios and applied channel types can be very broad, the past literature has conducted similar simulations and testing, focusing on the Extended Pedestrian A (EPA) model and Kronecker channel model. According to the past literature, the simulation results between these two channel types are very similar to each other that they can be referred to each other [3]. Therefore, the estimator

can also be applied to other different kinds of channel models on this basis to get quite different results. For example, the Extended Vehicular A (EVA) model and the Extended Typical Urban (ETU) model both can be generated in further simulations with similar methods and platforms. By observing the variations of loss functions and other performance indicators, it can be measured that whether the system and estimator still performs well in some specific application scenarios as the past results.

The next key point is the innovation of the optimization algorithm. The optimization method in this paper is mainly utilizing the adaptive moment estimation (Adam) algorithm, which is a kind of traditional gradient descent estimator around deep learning and has been improved in recent years' relevant research [10]. It can be considered that the Adam optimization can be substituted with batch gradient descent (BGD), mini-batch gradient descent (MBGD), stochastic gradient descent (SGD) and other common deep learning-based optimization algorithms and models. These models can be compared with each other to find a better solution. The Adam algorithm is a method of stochastic optimization. It can adjust the learning rate automatically, making the estimator does not require training. Other optimization methods also have their advantages. The stability of BGD method, the efficiency of SGD method and other valuable benefits all deserve to be considered. On this basis, comparing these methods and considering the final performance may come out with a more appropriate selection.

Eventually, the innovation in the application scenarios is also important and worth considering about. The major applicable background of the estimator in this paper is the massive MIMO systems to achieve the function of channel estimation. Based on this, further consideration for other communication systems may be valuable, such as the channel estimation for the millimeter-wave (MMW) radar, the OFDM signal, the cellular network and other relevant calculations. Besides, the scope of the application and combination subjects can also be further expanded. By combining it with other fields such as mathematics, physics and relevant medicine research may make great contributions to the development of those areas and future research. Moreover, through the conversion of related constructs and components, the fundamental logic and algorithms can be further applied to other scenarios, such as the signal processing, the signal restoration and so on to improve the system performance.

4. Conclusion

The algorithm of this paper can be re-appeared normally and get corresponding results. Although the simulation results only demonstrate the fundamental preparation work and parts of the performance of the designed estimators, but the accuracy can be proved through relevant derivation of formula and calculations. Besides, compared with traditional channel estimation methods, the improvement in accuracy and the decrease in loss function is significantly observed. However, the lack of the simulation results and the relatively narrow simulation environment scope both make contributions to the slight lack of reliability. Moreover, the monolithic optimized algorithm and application scenarios should also be improved in the future research.

The deep learning-based estimator can make up for the problems of precision or calculation complexity effectively. Through the connection of the DNN and traditional channel estimation algorithms and the combination of the advantages of both, the estimator can efficiently bridge the gap of channel estimation in some specific application scenarios. The research in deep learning-based estimators apparently make significant contributions to the application of deep learning in channel estimation, even the application of machine learning in wireless communication. Moreover, it also provides more possibilities for the future developments in relevant areas.

Certainly, the design and application of the estimator in this paper still has considerable shortcomings. There is no doubt that problems include the narrowness of application scenarios and the limitations of optimization algorithms which have been mentioned. These can make the components of the estimator still changeable and have the space to be improved. Many questions still have the space to be solved. The first one is how to improve the ability of the estimator to suppress

the environment noise. Besides, the way can be considered to reduce loss function indicators to improve the performance in low SNR scenarios. Moreover, how to conduct further enhancement of system performance through other deep learning algorithms can also be optimized. These are all areas and directions that deserve further research in the future.

References

- [1] Dai L, Jiao R, Adachi F, et al. Deep learning for wireless communications: An emerging interdisciplinary paradigm. *IEEE Wireless Communications*, 2020, 27(4): 133-139.
- [2] Belgiovine M, Sankhe K, Bocanegra C, et al. Deep learning at the edge for channel estimation in beyond-5G massive MIMO. *IEEE Wireless Communications*, 2021, 28(2): 19-25.
- [3] Balevi E, Doshi A, Andrews J G. Massive MIMO channel estimation with an untrained deep neural network. *IEEE Transactions on Wireless Communications*, 2020, 19(3): 2079-2090.
- [4] Ma X, Gao Z. Data-driven deep learning to design pilot and channel estimator for massive MIMO. *IEEE Transactions on Vehicular Technology*, 2020, 69(5): 5677-5682.
- [5] Chun C J, Kang J M, Kim I M. Deep learning-based channel estimation for massive MIMO systems. *IEEE Wireless Communications Letters*, 2019, 8(4): 1228-1231.
- [6] Xu L, Gao F, Zhang W, et al. Model aided deep learning based MIMO OFDM receiver with nonlinear power amplifier//2021 IEEE Wireless Communications and Networking Conference (WCNC). IEEE, 2021: 1-6.
- [7] Kang J M, Chun C J, Kim I M. Deep learning based channel estimation for MIMO systems with received SNR feedback. *IEEE Access*, 2020, 8: 121162-121181.
- [8] Wei X, Hu C, Dai L. Deep learning for beam-space channel estimation in millimeter-wave massive MIMO systems. *IEEE Transactions on Communications*, 2020, 69(1): 182-193.
- [9] Hu Q, Gao F, Zhang H, et al. Deep learning for channel estimation: Interpretation, performance, and comparison. *IEEE Transactions on Wireless Communications*, 2020, 20(4): 2398-2412.
- [10] Zhang Z. Improved adam optimizer for deep neural networks//2018 IEEE/ACM 26th international symposium on quality of service (IWQoS). Ieee, 2018: 1-2.