Data Driven Channel Estimation in Massive Multiple-Input Multiple-Output (MIMO) Systems using Deep Learning Algorithm

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Abstract- Channel estimation in massive multiple-input multiple-output (MIMO) systems is a challenging task. Existing deep learning approaches, which aim to learn the mapping from input signals to target channels, often struggle to accurately estimate channel state information (CSI). In this paper, we approach the problem by treating the quantized received measurements as a low-resolution image and apply deep learning-based image super-resolution techniques to reconstruct the channel. Specifically, we leverage a state-of-the-art convolutional neural network (CNN) framework for channel estimation. This framework processes the quantized received measurements while preserving abundant low-frequency information through skip connections. To address the gradient dispersion problem in the estimator, we introduce dense connections within the residual blocks to maximize information flow between layers. Additionally, the local channel features extracted from different residual blocks are retained through multi-path feature fusion. Simulation results demonstrate that the proposed scheme outperforms both traditional methods and existing deep learning approaches, particularly in low signal-to-noise ratio (SNR) scenarios.

Keywords - Massive MIMO, Channel Estimation, Deep Learning, CNN

INTRODUCTION

The advancement of wireless technology needs noise free and accurate data communication. noise free and accurate data communication increases the spectral efficiency and energy efficiency of communication systems. the improves efficiency of communication systems achieve by using application of massive multiple input multiple output (MIMO) [1-2]. The massive MMIO systems equipped large scale of antenna in both sides transmitter and receivers. The high dimension of antenna face of challenges of accurate channel estimation [3-4]. The non-accurate channel estimation degraded the quality of service of wireless communication. Traditional channel estimation methods include Least Squares (LS) and Minimum Mean-Square Error (MMSE) approaches. In these pilot-based methods, the channel response (CR) is first determined at the pilot symbols, followed by the estimation of the CR at the data symbols. The LS estimator, which operates without relying on any statistical knowledge of the channel, is computationally efficient but tends to suffer from a high mean-square error (MSE). On the other hand, the MMSE estimator leverages the second-order statistics of the channel to minimize the MSE, generally resulting in superior performance but at the cost of increased computational complexity. Recently several channel estimation approaches are employed based on neural network and deep learning algorithm. the deep learning algorithms mapping the problem of non-linearity of signals and improves the performance of channel estimation. The deep neural network (DNN) is recognized as a promising structure well-suited for wireless channels. In practice, DNNs have been successfully integrated into communication systems, effectively bridging the gap between these systems and real-world environments. Studies have demonstrated that DNN-based OFDM receivers exhibit high reliability in simulations. Researchers have also incorporated neural networks into traditional algorithms, enhancing the stability of their systems. However, despite these positive outcomes, existing systems have limitations, as they rely on independent block-type pilots, making them less adaptable to time-variant environments. Therefore, there remains significant potential for improvement in DNN-based signal processing schemes. Despite of several approach of channel estimation still problems are remained. Now for the performance improvements we motivated for the channel estimation in massive MIMO systems. in [9] proposed DL-based OFDM receiver, named RecNet which is the combination of channel estimation neural network and signal detection neural network. Focusing on estimating the channel matrix in multiple antenna scenarios, our channel estimation (CE) module is designed to estimate the time-frequency response of a frequency-selective and fast time-variant channel model. In the 2D (time-frequency) channel matrix, only the channel response at the pilot positions is initially known. The proposed CE-NN then estimates the remaining channel response. The output of the CE-NN provides a complete channel response, which is subsequently used for equalizing the received signals, distinguishing it from end-to-end deep learning-based systems like [10]. Finally, the original symbols are recovered from the equalized signals using a detection neural network (NN). The main contribution of this paper are presented as follows: An efficient channel estimation for massive MIMO based on deep learning algorithm. Reduces training errors of existing neural network model Enhance robustness of proposed algorithm in terms of SNR. The rest of paper organized as in section II related works, in sections III methodology of channel estimation, in section IV describes experimental results and finally conclude in section V.

II. RELATED WORK

The incremental advancements in deep learning algorithms have significantly enhanced the performance of channel estimation in massive MIMO systems. Recently, several deep learning-based channel estimation algorithms have been proposed. This section describes some of these newly developed algorithms. In [1], a DL-based channel estimation method for LS-Error-Correction was proposed, outperforming MMSE with reduced complexity. In [2], a genetic algorithm for mapping in non-symmetric constellations was introduced, applying media-based modulation for enhanced reliability. The study also investigated USTLD in a three-antenna MIMO configuration and developed a high-density M-QAM-Labeling-Mapper. In [3], a data-driven deep learning approach for pilot signals and channel estimation was presented, showcasing superiority over compressive sensing methods. In [4], lens antenna arrays were explored for energy-efficient hybrid precoding, and a prior-aided Gaussian mixture LAMP network was proposed for beam space channel estimation. In [5], the focus was on low-cost ML-based channel estimation with 2D antenna panels, proposing Universal Training to enhance Turbo-AI's robustness. In [6], RecNet, a DL-based OFDM receiver, was introduced, along with a low-complexity CNN-based channel estimator and signal detection neural network. Competitive accuracy was demonstrated under low SNR conditions. In [7], an adaptive DL-based channel estimation scheme was proposed, outperforming LMMSE and exhibiting robustness for high SNR estimation errors. In [8], a new DNN-based channel estimator with mixed training for changing scenarios was presented, highlighting limitations in UWA scenarios. In [9], a DL-based joint channel estimation and feedback framework for FDD massive MIMO was introduced, analyzing network performance. In [10], a neural network-based estimator derived from the 3GPP channel model was showcased, demonstrating optimal performance in mmWave environments. In [11], DL techniques were integrated for accurate channel estimation in massive MIMO, utilizing RF channel characteristics. Future research directions were identified, and estimation barriers were highlighted. In [12], massive MIMO channel sparsity was exploited for blind channel estimation, proposing a DL-assisted technique with a denoising CNN for improved virtual pilot estimation. In [13], a VAE-based channel estimation framework was proposed, analyzing variants and practical approaches for training and testing with noisy data. In [14], a model-driven DL algorithm for joint activity detection and channel estimation was introduced, focusing on massive grant-free random access in 6G cellular IoT. In [15], a robust DNN for dynamically changing UWOC environments was proposed, introducing a joint CESD that exploits online classification for time-varying channels. In [16], an adaptive system model and the Watterson channel model were adopted for simulation, considering four types of channel quality and proposing cooperative decision-making based on neural networks. In [17], compressed sensing theory was introduced to MIMO channel estimation, proposing DL-based schemes to reduce delay and improve accuracy. In [18], a compressed sensing approach for high-dimensional wireless channel estimation was presented, optimizing input to a deep generative network for improved channel reconstruction without a priori knowledge. In [19], HF channels with narrow bandwidth allocation were explored, establishing relationships between received data and the estimated circulant channel matrix, and modeling spatial correlation matrices. In [20], dual-wideband effects for mmWave massive MIMO systems were considered, transforming channels into spatial-frequency-wideband models and employing specially designed hybrid beamforming schemes.

III. METHODOLOGY

This section describes proposed algorithms of deep learning-based channel estimation. The processing of algorithm depicts in figure (1). The proposed algorithm provides end-to-end training using convolutional neural network (CNN). The Dense-Net architecture effectively addresses the vanishing gradient problem commonly associated with the excessive layers in typical CNN networks. Moreover, Dense-Net requires fewer network parameters compared to the Residual Network (Res-Net) architecture. We will demonstrate that the proposed algorithm outperforms the state-of-the-art deep learning-based algorithm in channel estimation. In addition to the performance improvement, the proposed algorithm features a deeper network structure that can learn high-level features with fewer total parameters[10]

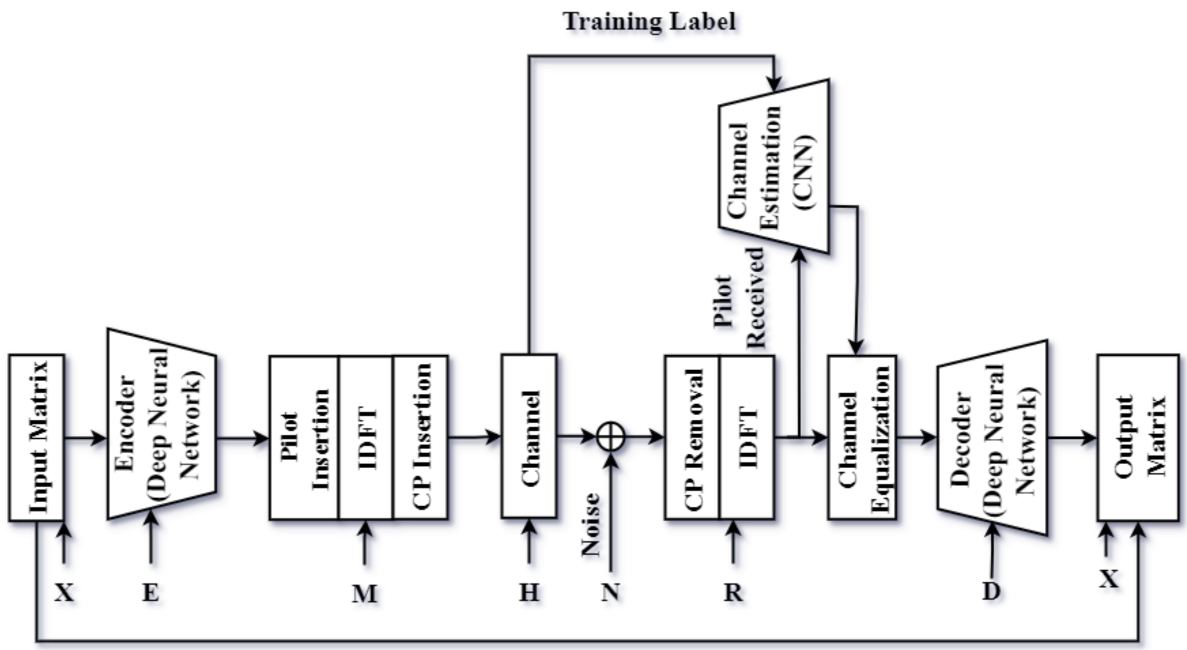

Figure 1 process model of training of channel estimation

The proposed hybrid learning is resolving issue of feature mapping. the processing of model mapped feature of dataset of channel matrix, and search all features approach as non-linear. The proposed model employed rectified linear active function for the training of the networks. The ReLU function describes as[15]

$$f_{ReLU(x)} = max(0, x)\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Here x defines the argument of the function. Also consider O and xin to be the output of the network and the input of the learning , the expression can write as

$$O = f(x_{in}, w) = f^{(n-1)}(f^{(n-2)}(\ldots.f^{1}(x_{in}))), \ldots\ldots\ldots(2)$$

Where n and W are defined as the number of layers of the network and the weight of the network respectively.

Processing of CNN

1. The input of network is featuring vector F_m and precoding matrix P_m
2. After the processing of feature vector and other parameters employe firefly algorithm. the employed firefly algorithm removes local interference and improve the process of feature mapping.
3. The layer of convolutional network 64 different 4 X 4X1 filters and 1 stride produces feature map follows ReLU.
4. Employed the feature constraints for next layer for the selection of distant features. The fitness of selection is $D \sum_{m=1}^{M} |p_m| \leq F_m$
5. The layer of fully connected to process of feature factors. The total numbers of neurons is 256.

6. The output of FC layer is proceeded in 3X3X1 filter of convolutional layers filter and stride 1
7. The maximum pooling of network filter is 3X3X1
8. The total number of convolutional layers is 10
9. Finally estimates optimal preceded matrix P_m
10. Predict features as normal and disease.
11. Exit
12. Table 1 parameters value of CNN network

Algorithm	Parameter	Values
CNN	Layer	10
	Activation function	ReLU
	Optimizer	FA
	Loss	Binary cross entropy
	Epochs	200
	Validation _split	2
	Batch size	500

IV. EXPERIMENTAL ANALYSIS

To validate the performance of proposed algorithm of channel estimation, using the MIMO system model mentioned in the description in section III. The process of simulation uses MATLAB software with version (R2018a). The system configuration is windows 10 with 16 GB RAM. The simulation process has undergone with the following parameters given in table-2[]19,20

Parameters	Values
MIMO	4 *4
FFT size	256
Cyclic prefix	24
Types of modulation	16-QAM
Noise model	Gaussian Noise
NN architecture	TLN
Number of hidden	2-3-5
Window Length	40 symbols
Hidden size	40*2(2 for Bi-direction)
Activation function	Tanh for hidden layers &Relu for hidden layersLoss function
Train SNR	20dB
Test SNR	5,10,15,20,25dB
Train number	100000
Validation number	10000

Table 2 lists the simulation parameters for the validation of channel estimation algorithms. The mentioned parameters have been certain dedicated values to estimate the performance of channels such as MIMO, FFT size, cyclic prefix, types of modulation, noise model and train number, and validation number of proposed algorithm.

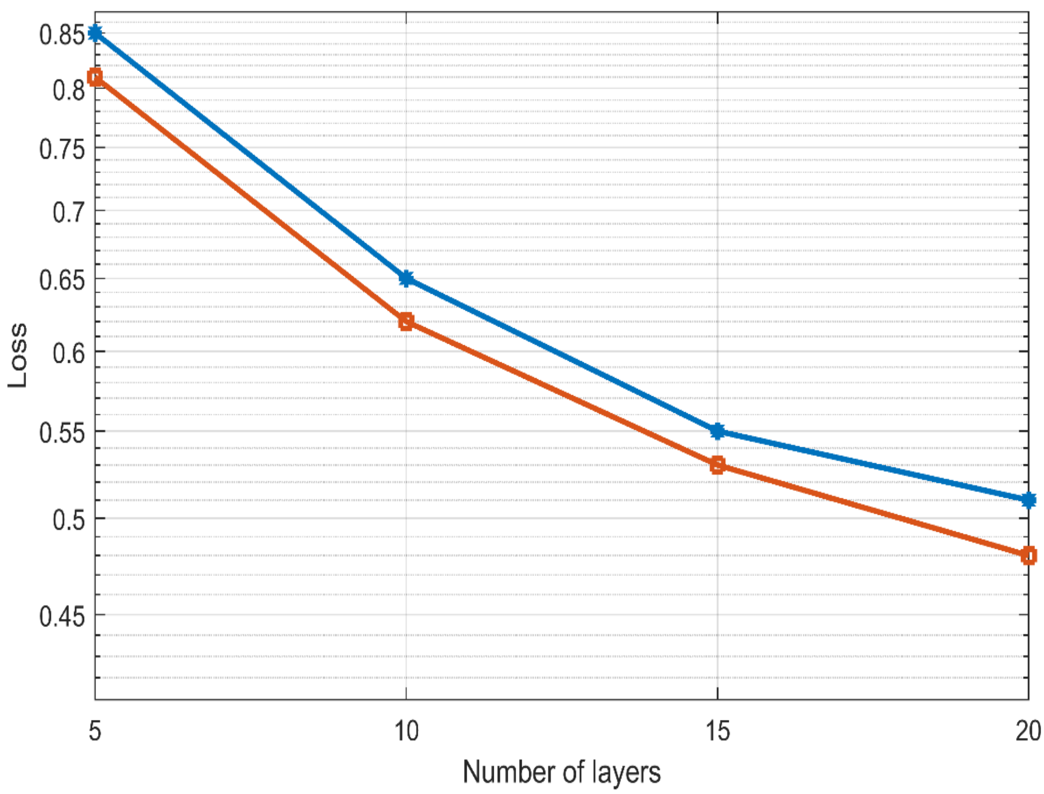

Figure: 2 Performance analysis of loss and number of layers.

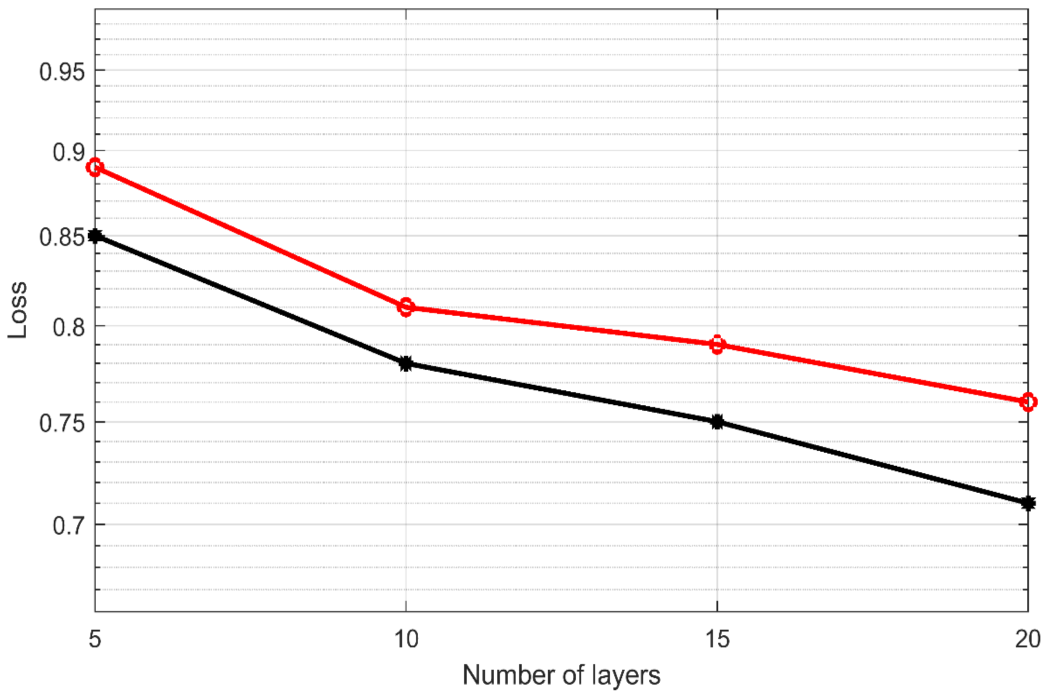

Figure: 3 performance analysis of loss and number of layers.

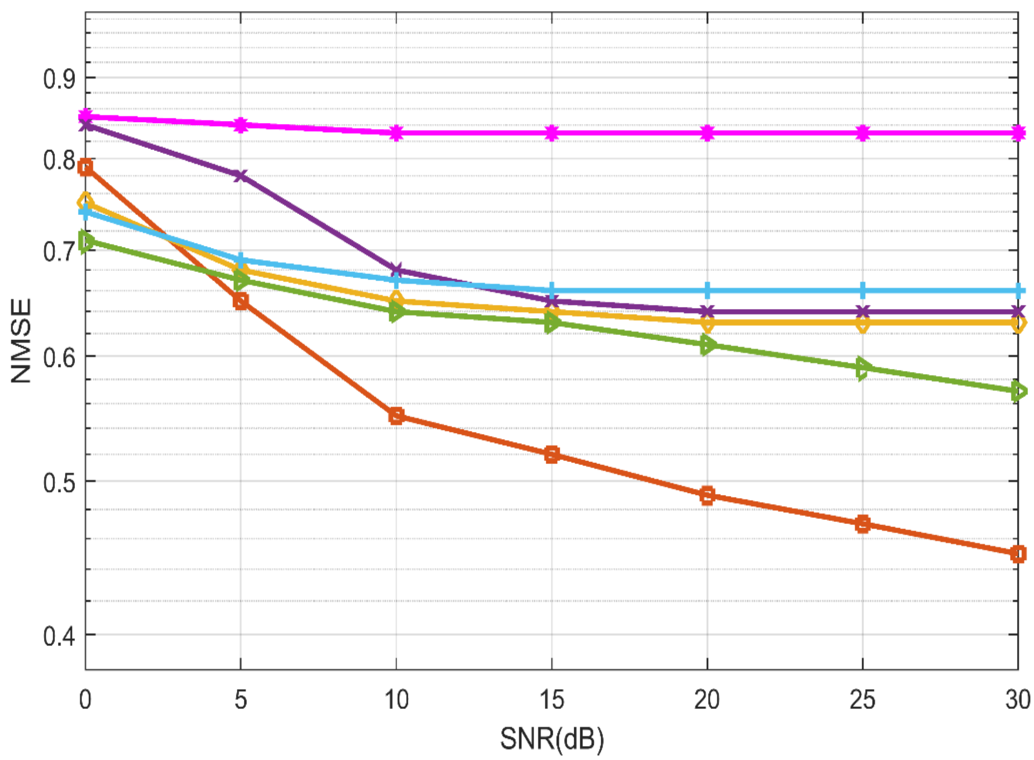

Figure: 4 performance analysis of NMSE and SNR (dB).

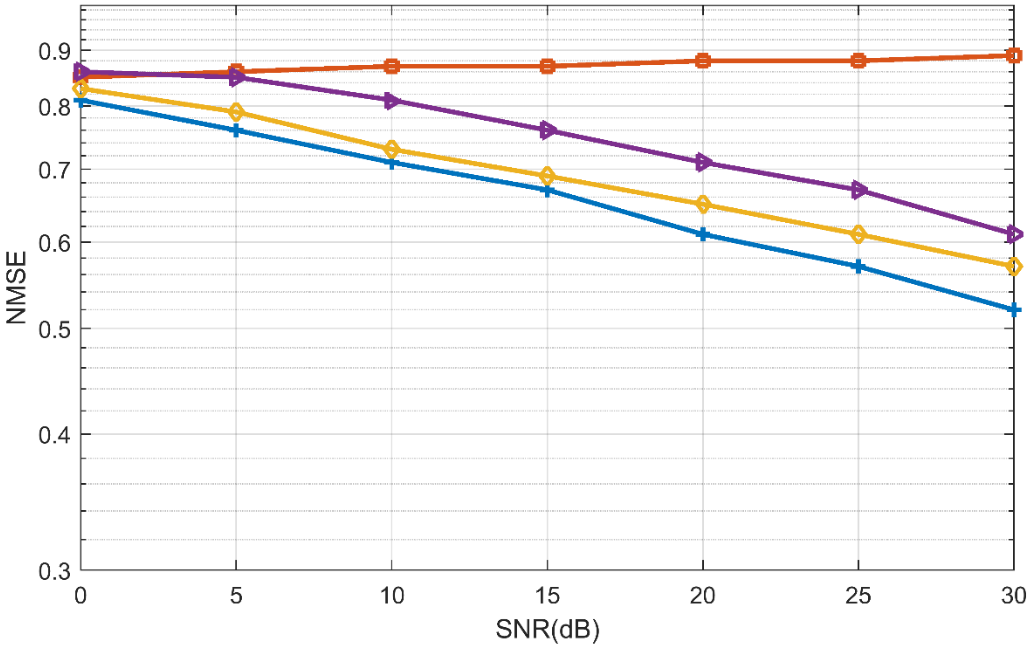

Figure: 5 Performance analysis of NMSE and SNR (dB).

V. CONCLUSION & FUTURE WORK

In this paper, we propose a deep learning-based channel estimation system for challenging massive MIMO scenarios, utilizing CNN layers to enable end-to-end learning. The proposed learning-based filter is particularly well-suited for communication systems where obtaining an accurate channel model is either impractical or impossible, extending beyond just wireless communication. Our autoencoder is designed with multiple CNN layers to learn complex signal representations for optimal transmissions, requiring fewer parameters compared to fully connected (FC) layers. Additionally, the proposed CNN architecture easily converges to optimal solutions during training, as shown in Fig. 1. The Dense-Net architecture addresses the traditional challenges of CNNs, such as vanishing gradients and excessive parameters, through dense connections and feature multiplexing. In slow fading channels, the proposed channel estimator can estimate channel impulse responses (CIRs) with near-perfect accuracy. In fast fading channels, the proposed estimator outperforms existing DL-based algorithms while maintaining lower computational complexity.

REFERENCE

[1]. Gizzini, Abdul Karim, Marwa Chafii, Ahmad Nimr, and Gerhard Fettweis. "Enhancing least square channel estimation using deep learning." In 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), pp. 1-5. IEEE, 2020.

[2]. Mthethwa, Bhekisizwe, and Hongjun Xu. "Deep learning-based wireless channel estimation for MIMO uncoded space-time labeling diversity." IEEE Access 8 (2020): 224608-224620.

[3]. Ma, Xisuo, and Zhen Gao. "Data-driven deep learning to design pilot and channel estimator for massive MIMO." IEEE Transactions on Vehicular Technology 69, no. 5 (2020): 5677-5682.

[4]. Wei, Xiuhong, Chen Hu, and Linglong Dai. "Deep learning for beamspace channel estimation in millimeter-wave massive MIMO systems." IEEE Transactions on Communications 69, no. 1 (2020): 182-193.

[5]. Chen, Yejian, Jafar Mohammadi, Stefan Wesemann, and Thorsten Wild. "Turbo-AI: Iterative Machine Learning Based Channel Estimation for 2D Massive Arrays." arXiv preprint arXiv:2011.03521 (2020).

[6]. Liu, Changjiang, and Tughrul Arslan. "RecNet: Deep learning-based OFDM receiver with semi-blind channel estimation." In 2020 IEEE International Symposium on Circuits and Systems (ISCAS), pp. 1-4. IEEE, 2020.

[7]. Gizzini, Abdul Karim, Marwa Chafii, Ahmad Nimr, and Gerhard Fettweis. "Adaptive channel

estimation based on deep learning." In 2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall), pp. 1-5. IEEE, 2020.

[8]. Zhou, Mingzhang, Junfeng Wang, Haixin Sun, Jie Qi, Xiao Feng, and Hamada Esmaiel. "A novel DNN based channel estimator for underwater acoustic communications with IM-OFDM." In 2020 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), pp. 1-6. IEEE, 2020.

[9]. Chen, Tong, Jiajia Guo, Chao-Kai Wen, Shi Jin, Geoffrey Ye Li, Xin Wang, and Xiaolin Hou. "Deep learning for joint channel estimation and feedback in massive MIMO systems." arXiv preprint arXiv:2011.07242 (2020).

[10]. Turan, Nurettin, and Wolfgang Utschick. "Reproducible evaluation of neural network based channel estimators and predictors using a generic dataset." In WSA 2020; 24th International ITG Workshop on Smart Antennas, pp. 1-6. VDE, 2020.

[11]. Liu, Zhenyu, Lin Zhang, and Zhi Ding. "Overcoming the channel estimation barrier in massive MIMO communication via deep learning." IEEE Wireless Communications 27, no. 5 (2020): 104-111.

[12]. Sabeti, Parna, Arman Farhang, Irene Macaluso, Nicola Marchetti, and Linda Doyle. "Blind channel estimation for massive mimo: A deep learning assisted approach." In ICC 2020-2020 IEEE International Conference on Communications (ICC), pp. 1-6. IEEE, 2020.

[13]. Baur, Michael, Benedikt Fesl, Michael Koller, and Wolfgang Utschick. "Variational Autoencoder Leveraged MMSE Channel Estimation." arXiv preprint arXiv:2205.05345 (2022).

[14]. Qiang, Yiyang, Xiaodan Shao, and Xiaoming Chen. "A model-driven deep learning algorithm for joint activity detection and channel estimation." IEEE Communications Letters 24, no. 11 (2020): 2508-2512.

[15]. Lu, Huaiyin, Ming Jiang, and Julian Cheng. "Deep learning aided robust joint channel classification, channel estimation, and signal detection for underwater optical communication." IEEE transactions on communications 69, no. 4 (2020): 2290-2303.

[16]. Zhou, Yaru, Yu Wang, Guan Gui, Haris Gacanin, and Hikmet Sari. "Deep learning-based channel quality estimation in adaptive shortwave communication systems." In 2020 International Conference on Wireless Communications and Signal Processing (WCSP), pp. 363-368. IEEE, 2020.

[17]. Huang, Xiao, and Sicong Liu. "Massive mimo channel estimation for vehicular communications: A deep learning based approach." In 2020 IEEE International Conference on Communications Workshops (ICC Workshops), pp. 1-6. IEEE, 2020.

[18]. Balevi, Eren, Akash Doshi, Ajil Jalal, Alexandros Dimakis, and Jeffrey G. Andrews. "High dimensional channel estimation using deep generative networks." IEEE Journal on Selected Areas in Communications 39, no. 1 (2020): 18-30.

[19]. Wang, Zhiyong, Fangling Pu, Xiaoshi Yang, Ning Chen, Yongmin Shuai, and Rui Yang. "Online LSTM-based channel estimation for HF MIMO SC-FDE system." IEEE Access 8 (2020): 131005-131020.

[20]. Lin, Yuxing, Shi Jin, Michail Matthaiou, and Xiaohu You. "Tensor-based channel estimation for millimeter wave MIMO-OFDM with dual-wideband effects." IEEE Transactions on Communications 68, no. 7 (2020): 4218-4232.