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Deep Learning Aided 5G Channel Estimation

Dr. M. Vijaya Lakshmi[1], B. Shashitha[2], B. Alekhya[3], Clementina Rithika[4], CH. Bhavana[5]
[1]*Assistant Prof ETE, GNITS, Hyderabad, India*
[2, 3, 4, 5]*B.Tech, GNITS, ETE Department, Hyderabad, India*

Abstract: ***Wireless communications involves the transfer of voiceand data without a cable or wires. It uses orthogonal frequency-division multiplexing, also known as a multicarrier transmission technique. In multiple input multiple output (MIMO) wireless communication (4G and 5G technologies), channel estimation is crucial. Multiple antennas are used at both the transmit and receive sides of a MIMO system to increase spectral efficiency and reliability.***

In 5G channel estimation is performed to improve the accuracy of the received signal. Least-squares estimation is a cheap method with relatively large channel estimationerrors, but it is supported in this work by using a new channel estimation method that leverages deep learning. LS (least squares) and MMSE (minimum mean squared error) are two popular traditional approaches to channel estimation, but deep learning provides much more accurate results than previous channel estimation methods.

Keywords: OFDM, LS, MMSE, DL

I. INTRODUCTION

Fifth generation (5G) wireless technology was developed to accommodate the exponential increase in wireless data traffic and communication reliability. To overcome frequency selective fading in multipath propagation environments, OFDM (Orthogonal Frequency Division Multiplexing) technology is a natural success in existing networks. As a result, this method improves spectral efficiency compared to single-carrier approaches. Pilot symbols known to the transmitter and receiver are typically used for channel estimation. Depending on different deployment scenarios, 5G system pilot symbols can have different structures. Least-squares (LS) estimation is one of the traditional techniques for channel estimation with minimal computational effort, as it does not require prior knowledge of the statistical channel information.

However, in the context of many applications, this estimation method gives relatively poor results. As an alternative, a minimum mean squared error (MMSE) estimation approach was developed to reduce the average channel estimation error. However, the MMSE estimation approach is significantly more computationally complex as it requires channel statistical data, especially the mean and covariance matrices. DNN (deep neural network) models with two different architectures are used for frequency selective fading channel estimation in 5G MIMO OFDM systems. The effectiveness of the proposed deep learning-assisted channel estimation is then evaluated using two different receiver velocity-based scenarios. The performance of DNN-based channel estimation is compared with that of conventional LS and linear MMSE (LMMSE) in terms of mean squared error (MSE) and bit error rate (BER) versus signal-to-noise ratio (SNR) criteria. Estimate.

II. METHODOLOGY

Adaptive systems, called neural networks, also known as artificial neural networks, learn using nodes, or neurons, interconnected in a layered structure similar to the human brain. Neural networks can be trained to recognize patterns, classify data, and predict future events by learning from data. Neural networks abstract their inputs in layers. Similar to how the human brain recognizes patterns in sounds and images, it can be trained using different instances. Its behavior is determined by the connections between components and the weight or strength of these connections.

As long as there is no inter-carrier interference, each sub-carrier is represented as an independent channel and orthogonality between sub-carriers is maintained. Orthogonality allows each subcarrier component of the signal to be represented as the Hadamard product of the channel frequency response at the transmitted signal and the subcarrier as

$$y_b(t) = \sum_{a=1}^{NT} h_{a,b}(t) \odot X_a(t) + n_b(t)$$

where n_b (t), $h_{a,b}$ (t) ,and x_a(t) are the noise, channel, and Fourier transforms of the signal, except when working in the frequency domain.

Block Diagram

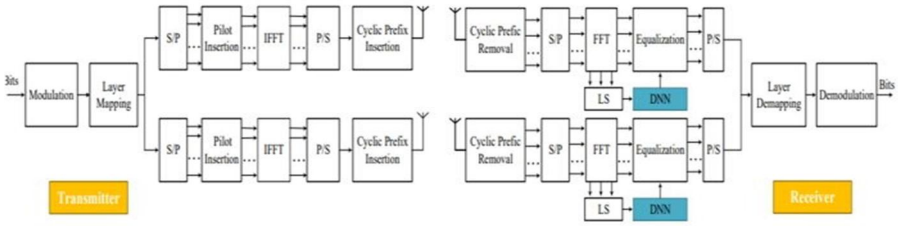


Fig 1.1: DNN structure used for channel estimation

A. DNN-Aided Channel Estimation

To overcome the aforementioned problems of LS and LMMSE estimation, DNN-based estimation is proposed toreduce the MSE between the channel estimate derived by LS estimation and the actual channel. The figure shows the structure of the proposed DNN-based estimation.

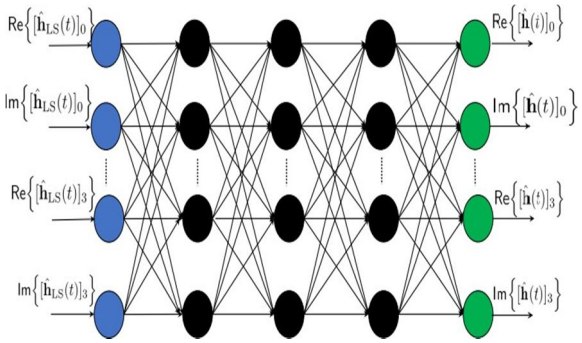


Fig 5.2: DNN structure for channel estimation

The organizational structure of the proposed DNN structure includes input layer, hidden layer and output layer. DNN may have a secret level tone. However, the proposed DNN structure for the MIMO-OFDM system under consideration consists of three hidden layers, each containing many neurons. Specifically, a neuron, which isa type of arithmetic unit, performs the following calculations

$$o = f(z) = f(\sum_{i=1}^{M} w_i x_i + b)$$

where M indicates number of inputs to the neuron forwhich x_i is the i-th input (i = 1, . . . , M);
w_i is the i-th weight corresponding to the i-th input; o isthe output of the neuron and b represents the bias.
f(.) is called as an activation function
which is used to classify the nonlinearity of the data.

To minimize MSE, DNN-based estimation learns realchannel information using the channel estimate obtained by LS estimation as input, and defines the realization of the input to the training process as:

$$I_{nt} = \{Re\{[\hat{H}_{LS}(t)]_0\}, Im\{[\hat{H}_{LS}(t)]_0\}, \ldots . \{Re\{[\hat{H}_{LS}(t)]_3\}, \{Im\{[\hat{H}_{LS}(t)]_3\}$$

where the real and imaginary parts of the complex numberare given by Re and Im, respectively, and the superscript n denotes the nth realization. Here is the output of the neural network:

$$O_{nt} = \{Re\{[\hat{H}(t)]_0\}, Im\{[\hat{H}(t)]_0\}, \ldots . Re\{[\hat{H}(t)_3\}, \{Im\{[\hat{H}(t)]_3\}$$

Where $\hat{h}(n)$ represents the output of the neural network at realization n. To handle complex numbers in neural networks, the above equation divides thechannel estimate into real and imaginary domains. Assignments are handled individually by the learning process.

The original transmitted data and received signal are recorded as training data. The data received from the data block and pilot block are the inputs to the deep learning model. The model is trained to reduce discrepancies betweenthe submitted data and the neural network output. There arevarious ways to show the difference.

$$L = \frac{1}{N}\sum_{k}(\hat{X}(k) - X(k))^2$$

where L is the loss, X(k) is the monitoring message forthis scenario, X ̂(k) is the prediction, and X(k) is the set of transmitted symbols. A DNN model consists of three layers,one of which is the hidden layer. Each layer has 16, 10, and4 neurons, respectively. The input numbers correspond to thesum of the real and imaginary sections of the two OFDM blocks containing transmitted symbols and pilots. Group andpredict all 16 bits of the transmitted data using a single, independently trained model. The predictions are then addedto produce the output.

Dataset is divided in to 3 sample sets.\

- Training: These are presented to the network duringtraining and adjusted according to errors.
- Tests do not affect network performance, so they are areliable indicator of network performance during and after training.
- Validation: Used to assess how well the network is generalizing and stop training if it stops improving.

There are several ways to split the data, but the default method allocates 70% of the data for training, 15% forvalidation, and 15% for testing.

III. RESULTS AND DISCUSSIONS

A. BER VS SNR for Deep Learning Channel Estimation

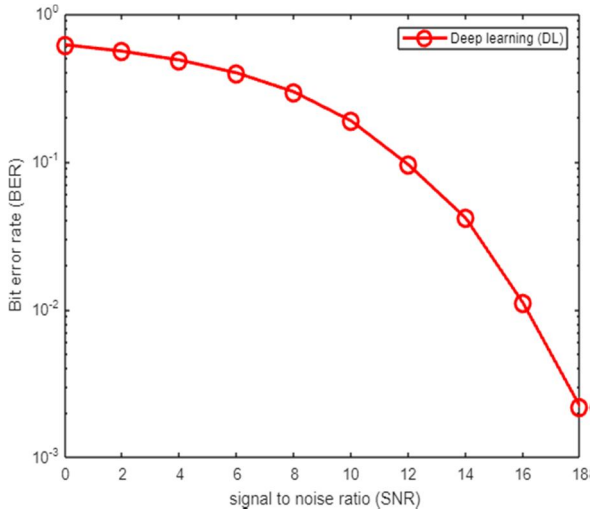


Fig 3.2 BER VS SNR of DL

SNR (DB)	BER
2	0.5613
6	0.4065
10	0.1853
14	0.0376

Table 3.1 BER VS SNR of DL

B. Simulation Parameters

PARAMETERS	VALUES
Cyclic Prefix	64
Type of Modulation	QPSK
Mini-Batch Size	8
Maximum Number of epoches	300
Maximum Doppler Frequency	200HZ

Table 3.2 simulation parameters of DL

BER vs. SNR for DL channel estimation shows that higher SNR is needed to get better BER, because BER value decreases as SNR increases. The lower the BER value, the better the communication.

C. BER VS SNR Comparison

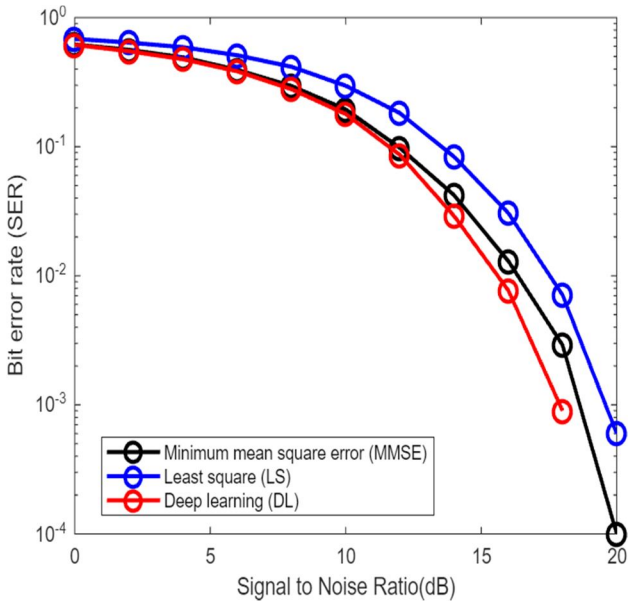


Fig 3.2 BER VS SNR OF LS, MMSE and DL

SNR (DB)	2	6	10	14
BER(LS)	0.6444	0.5169	0.2923	0.0839
BER(DL)	0.5613	0.4065	0.1853	0.0376
BER(MMSE)	0.5511	0.3826	0.1716	0.0293

Table 3.3 BER VS SNR OF LS, MMSE and DL

Simulations were performed and the results were compared with traditional LS and LMMSE estimations using bit error rate (BER) versus signal-to-noise ratio (SNR) as a measure. Each method of channel estimation steadily decreases the BER as the SNR increases. In both cases, the LS estimation gives the worst BER performance because no statistical channel information is considered when estimating the channel. In contrast, LMMSE estimation uses the mean and covariance matrices, resulting in better BER performance than LS estimation. The proposed deep learning algorithm provides the best MSE performance especially at low and medium SNR values.

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IV. CONCLUSION

When training the proposed DNN-based channel estimation method, the relevant full channel and least-squares channel estimation are used. By applying a QPSK modulation scheme, the performance of a given estimate is compared with traditional LS and LMMSE estimates in terms of channel estimation error and BER as a function of SNR level. With a correct understanding of the channel characteristics, we find that the proposed DNN-based estimation has good advantagesin terms of minimizing the channel estimation error.

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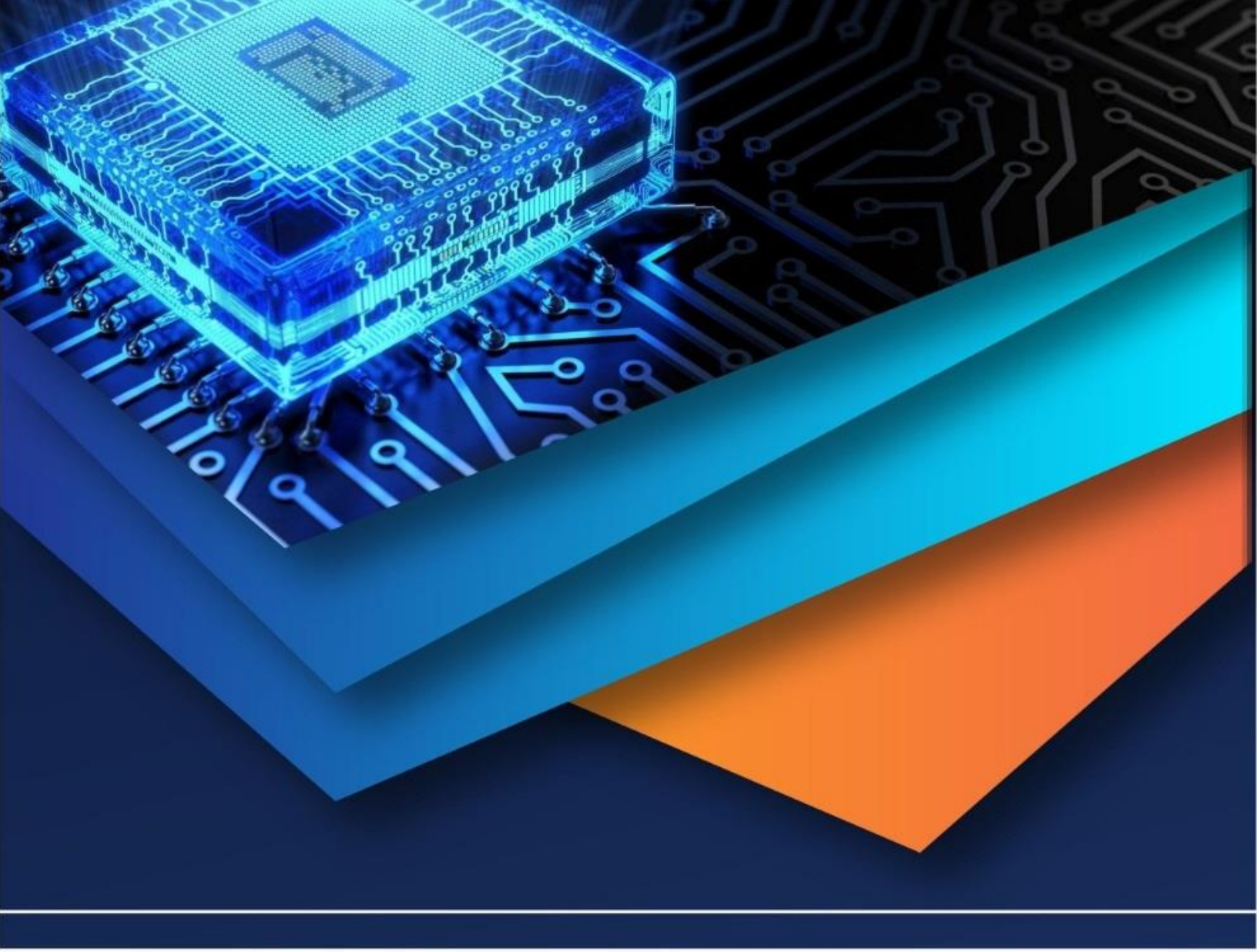
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