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A Deep Learning Aided Massive-MIMO-OFDM Channel Estimation

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ABSTRACT:-Massive Multiple-Input Multiple-Output (massive MIMO) system relies on channelstate information (CSI) feedback to perform precoding and achieve performance gain in frequency division duplex (FDD) networks. However, transmission of massive MIMO system is subject to excessive feedback overhead. In this paper, we propose a Deep Learning (DL) approach-based channel estimation technique to enhance the performance of massive MIMO system. This technique is used to enhance recovery quality and improve trade-off between compression ratio (CR) and complexity of massive MIMO system. The proposed technique is based upon using the Channel State Information Network combined with gated recurrent unit (CsiNet-GRU). Moreover, the dropout method is used in the proposed technique to reduce overfitting during the learning process. The simulation results demonstrate that the proposed CsiNet-GRU technique results in a significant improvement in performance when compared with existing techniques used in conjunction with massive MIMO systems.

KEYWORDS:- massive MIMO, OFDM, 5G-New Radio, Channel estimation, Deep learning.

I. INTRODUCTION

The fifth generation (5G) wireless communications networks have a lot of novel requirements, such as the high system capacity with respect to the fourth generation (4G) networks, wide frequency range (Covering through millimeter wave (mmWave) bands), increased data rate, ultra-low latency, reducedenergy, and low cost [1]. Massive MIMO system was found very promising to be utilized in 5G systems to achieve its requirements. In addition, using massive MIMO systems brought new challenges on channel modeling [2]. It is quite notable that one of the performance bounds of 5G, like any other communication system, is determined by channel characteristics. Therefore, an accurate channel model plays an important role in designing, evaluating, and developing wireless communication systems. Massive MIMO channel state information (CSI) feedback techniques were devised in order to get more accurate and dynamic estimate of channel parameters, as compared with other channel models such as ITU-R IMT-2020, COST 2100 and the IEEE 802.11 ay models [3]. Artificial intelligence (AI) approaches were investigated in 5G systems to facilitate processing the signal received by massive MIMO antennas for the purpose of acquiring accurate channel estimation [4]. In this respect, a number of deep learning methods were proposed, with a variety of adopted algorithms. Compressive Sensing (CS) using the spatial and temporal correlation of CSI was used to obtain channel information with acceptable accuracy under substantially reduced feedback load [5]. Least Absolute Shrinkage and Selection Operator (LASSO) L1-solver [6] and Approximate Message- Passing (AMP) [7], were used CS to estimate channel parameters.

In [8], the authors utilized deep learning technology in massive MIMO to develop a CSI system, which was based upon using sensing and recovery network. The proposed network estimated the channel structure from training samples, and was called (CsiNet).

In addition, several algorithms using Auto-encoder CsiNet arrangement which utilized few neural network (NN) layers were proposed in order to reduce the channel state information (CSI) feedback and perform recovery with high degree of accuracy [9]. The authors in [10] adopted a simple and efficient approach to reduce the overhead of downlink channel estimation and feedback using linear regression (LR) and support vector regression (SVR) in machine learning.

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Our contribution in this paper, we introduced a technique based on Deep Learning approach that can enhance the accuracy of channel estimation to improve the performance of massive MIMO utilized in 5G systems. The proposed technique is a modification of the DL-based channel stateinformation (CSI) feedback network as adopted in frequency division duplex (FDD) for massive (MIMO) system which was introduced in [9]. Gated Recurrent Unit (GRU) network is introduced to the system in order to increase the accuracy of CSI. In addition, the Dropout method is used to reduce the overfitting during the training processes. The performance of the proposed technique is investigated and compared to other similar techniques available in literature. The rest of the paper is organized as follows: - section 2 describes the utilized system model, section 3. Describes the proposed channel state information gated recurrent unitwith the use of the Dropout method. Section 4 gives the simulation results and analysis and finally section 5 gives the conclusion of the paper.

II. SYSTEM MODEL

This section deals with the methodology used by us to do the channel estimation. Here, we use deep learning techniques to perform channel estimation. For example, by viewing the resource grid as a 2-D image, we can turn the problem of channel estimation into an image processing problem, similar to denoising or super-resolution, where CNNs are effective.

3.1 Neural Network Formation

Using Matlab's 5G Toolbox, we can customize and generate standard-compliant waveforms and channel models to use as training data. UsingMatlab's Deep Learning Toolbox, we use this training data to train a channel estimation CNN. This paper shows how to generate such training data and how to train a channel estimation CNN. The work also shows how to use the channel estimation CNN to process images that contain linearly interpolated received pilot symbols. The work concludes by visualizing the results of the neural network channel estimator in comparison to practical and perfect estimators. Figure 1 represents the methodology that are being used to simulate the work in this paper.

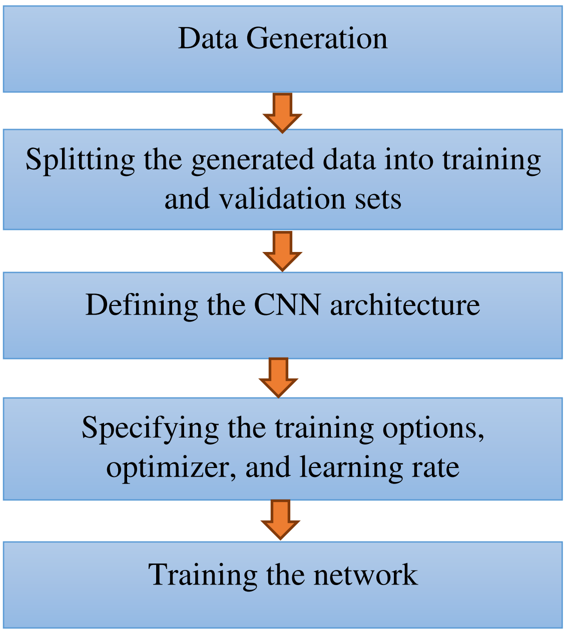

Fig. 1: Deep learning based MIMO-OFDM channel estimation flow chart

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In this work, The DM-RS symbols in the grid are used for channel estimation. This example does not transmit any data, therefore, the resource grid does not include any PDSCH symbols. To flush the channel content, append zeros at the end of the transmitted waveform. These zeros take into account any delay introduced in the channel, such as multipath and implementation delay. The number of zeros depends on the sampling rate, delay profile, and delay spread. Send data through the TDL channel model. Add additive white Gaussian noise (AWGN) to the received time-domain waveform. To take into account sampling rate, normalize the noise power. The SNR is defined per resource element (RE) for each receive antenna (3GPP TS 38.101-4). For an explanation of the SNR definition that this example uses, see SNR Definition Used in Link Simulations. Perform perfect synchronization. To find the strongest multipath component, use the information provided by the channel. OFDM-demodulate the received data to recreate the resource grid. Figure 2 represents the flow diagram of deep learning based MIMO-OFDM channel estimation.

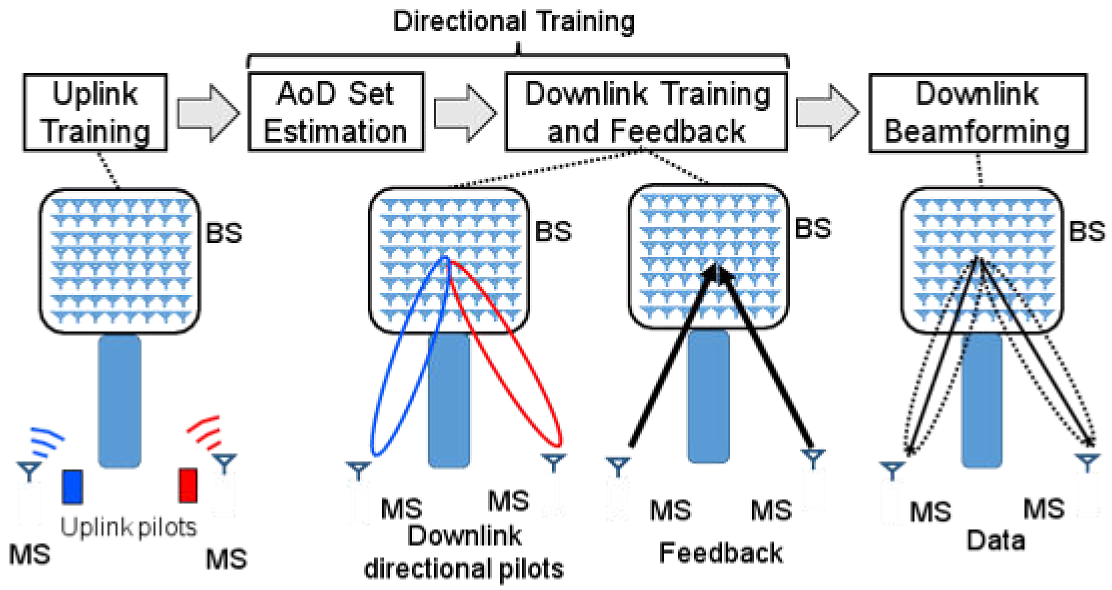

Fig. 2: Flow diagram DL based MIMO-OFDM channel estimation process

Data generation is set to produce 256 training examples or training data sets. This amount of data is sufficient to train a functional channel estimation network on a CPU in a reasonable time. For comparison, the pretrained model is based on 16,384 training examples.

3.1.1 Dataset Generation

Training data of the CNN model has a fixed size dimensionality, the network can only accept 612-by-14-by-1 grids, i.e. 612 subcarriers, 14 OFDM symbols and 1 antenna. Therefore, the model can only operate on a fixed bandwidth allocation, cyclic prefix length, and a single receive antenna.

The CNN treats the resource grids as 2-D images, hence each element of the grid must be a real number. In a channel estimation scenario, the resource grids have complex data. Therefore, the real and imaginary parts of these grids are input separately to the CNN. In this example, the training data is converted from a complex 612-by-14 matrix into a real-valued 612-by-14-by-2 matrix, where the third dimension denotes the real and imaginary components. Because ywe have to input the real and imaginary grids into the neural network separately when making predictions, the example converts the training data into 4-D arrays of the form 612-by-14-by-1-by-2N, where N is the number of training examples.

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3.1.2 Neural Network structure

The designed neural network is an 11 layer deep convolutional neural network (CNN). Table 3.1 represents the layered structure of the proposed CNN. It consists of repeated convolution layer followed by ReLu activation function and the output layer is the regression output layer. The input layer of the proposed system is an imageinput layer that takes the 612x14x1 received pilot symbols as input and makes them available to the higher layer for further processing. After being convoluted using CNN layer for five times the output features are then fed to a regression output layer. This regressionoutput layer is then estimates the value of the channel coefficients. The image 3 represents the internal structure of the proposed CNN with various number of the trainable parameters along with number of various input output parameters.

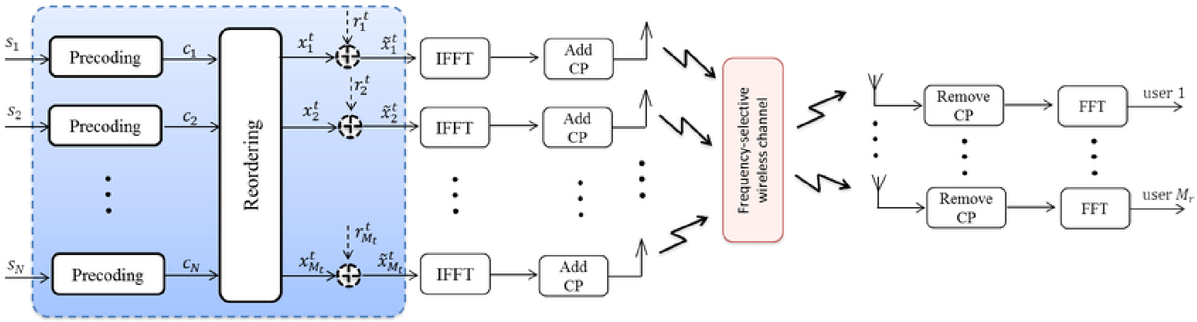

Figure 3: Layering structure of the proposed5G channel estimator

III. Result and Discussion

After successful implementation, we have tested the proposed method using software simulation. For software simulation, we have used Matlab environment with deep learning and 5G toolboxes. For clearity and to show the effectiveness of the work, we have compared the obtained result with some standard OFDM MIMO channel estimation schemes. Here we perform and compare the results of perfect, practical, and neural network estimations of the same channel model. To perform perfect channel estimation, use the nrPerfectChannelEstimateMatlab function using the value of the path gains provided by the channel. To perform practical channel estimation, use the nrChannelEstimate function from Matlab 5G toolbox. This function will estimate the channel with taking into account some standard errors and noises during the transmission. To perform channel estimation using the neural network, we must interpolate the received grid. Then split the interpolated image into its real and imaginary parts and input these images together into the neural network as a single batch. Use the predict (Deep Learning Toolbox) function to make predictions on the real and imaginary images. Finally, concatenate and transform the results back into complex data. Fig. 3 represents the training statistics of the proposed neural network. From this figure, it is clear that the training completes in 5 epochs and we get a validation accuracy of 16.168. The total training time taken by the network while being trained is 3 minutes and 56 seconds.

A. Bit Error Rate (BER) performance

Fig. 4 represents the bit error rate vs SNR for a transmitter-receiver system having the proposed model as a channel estimation method with some other channel estimation methods such as Least Square Estimate (LSE) method and theoretical method. Here the DNN based our approach shows similar BER than the theoretical method.

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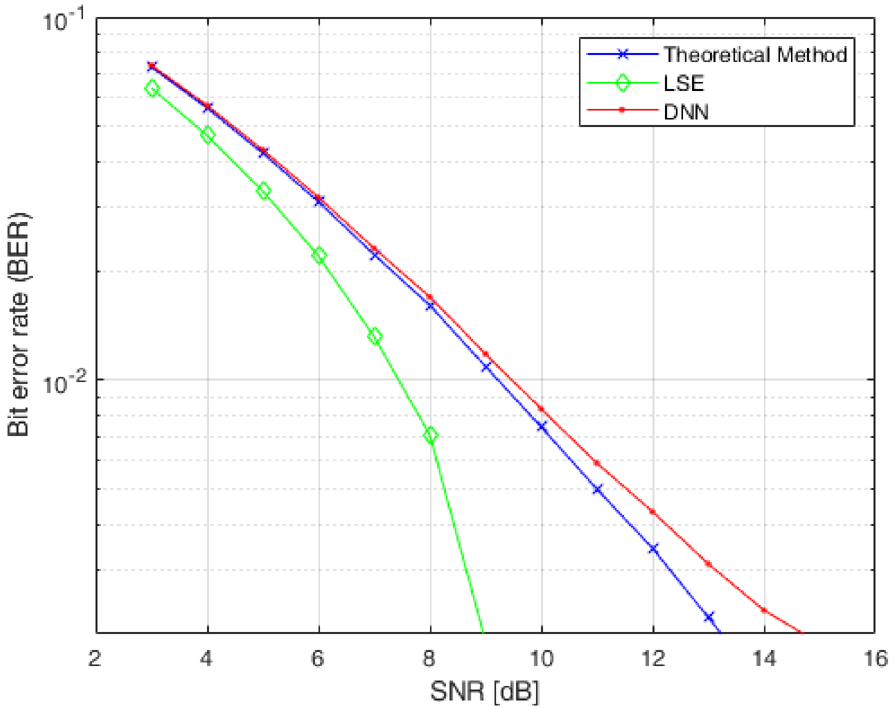

Fig. 4 Bit error rate vs SNR for channel estimation with the proposed method as well as some conventional methods.

B. Error Performance

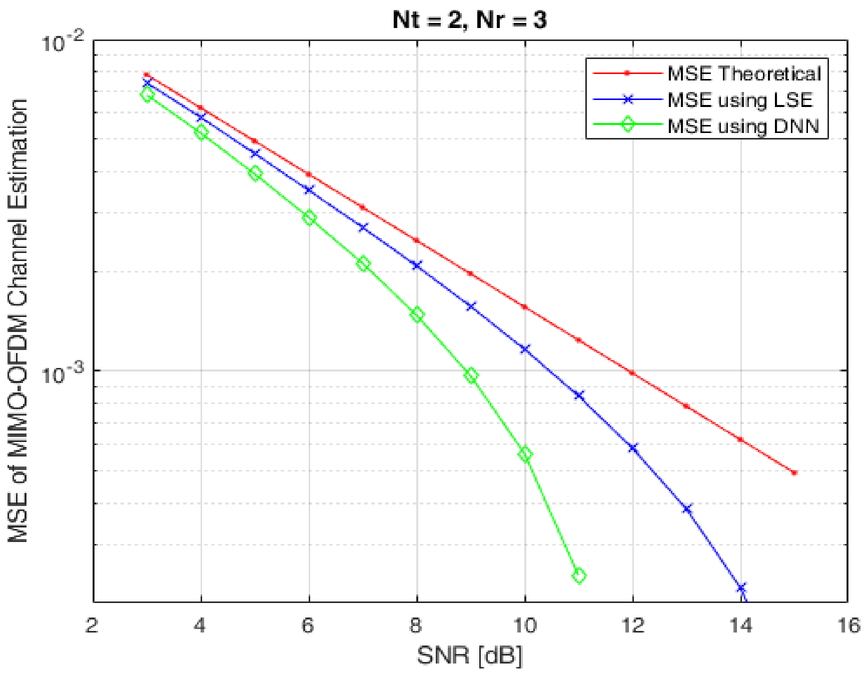

Fig. 5: Mean square error (MSE) while estimating channel vs SNR for proposed method as well as other channel estimation methods.

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Fig. 5 represents the Mean square error (MSE) while estimating channel vs SNR for proposed method as well as other channel estimation methods. From this figure. It is clear that we are getting the minimum mean square error for the channel estimation using the proposed DNN based channel estimation method.

IV. CONCLUSION

In this paper, we proposed a channel state information (CSI) feedback network by extending the DLbasedCsiNet technique to incorporate GRUs and making use of the Dropout method. The GRU layers were used to extend the CsiNet decoders for time correlation extraction and final reconstruction of CSI, whereas the Dropout method was used to reduce the overfitting of the channel modeling. The proposed CsiNet-GRU technique achieved the lowest NMSE, the best cosine similarity coefficient and the best accuracy as compared to other CS-based and CSI-based techniques. However, the introduction of the GRUs layers had increased the complexity, with the subsequent expected increase in the run time. Thus, the proposed technique allows for the tradeoffbetween accuracy and run timeparameters in designing massive MIMO utilized in conjunction with FDD networks.

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