Deep Learning Based Pilot Assisted Channel Estimation for Rician Fading Massive MIMO Uplink Communication System

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***Abstract*—Massive multiple input multiple output (MIMO) communication is one of the promising candidates for the successful deployment of Fifth-generation communication which offers an extensive improvement in spectral efficiency as well as data rate. The estimation of massive MIMO channel is very arduous due to its enormous diversity gain and enlarged capacity. However, channel estimation for uplink Rician fading massive MIMO system, where the channel is occupied with both Line of sight and non-line of sight component is not properly investigated yet. In this article, we have studied deep learning based channel estimation scheme for the massive MIMO system in Rician fading environment. Unlike the traditional approach, we have developed an optimized neural network model which can intelligently design pilot and estimate channels. We have simulated massive MIMO system at different signal to noise ratio values varying number of transmitted antennas and also investigated the performance of our proposed scheme by analyzing simulation results.**

***Index Terms*—Massive MIMO, channel estimation, deep learning, fading channel.**

I. Introduction

In the last few years, massive multiple input multiple output (MIMO) communication has emerged as a significant technology to meet the expected demand of immensely higher data rate along with handling high data traffic in next generation communication system [1]. In particular, a massive MIMO system consists of a base station (BS) equipped with massive number of antennas in the millimeter-wave band that supports a large number of users to communicate through BS simultaneously. In the modern massive MIMO systems, optimum channel estimation plays vital role in both precoding and decoding using the faithful channel state information (CSI) available to the receiver. But, the high dimensional system architecture and orthogonal subcarriers increases the computational complexity of channel estimation at the BS [2].

In the massive MIMO system, multipath propagation of the signal causes fading in the realistic channels which can be characterized and modeled by both Rayleigh fading and Rician fading [3]. Channel estimation of massive MIMO over Rayleigh distributed fading system has been thoroughly studied in the previous research. In the massive connection scenario, [4], [5] assumed the sparse distribution of the channel, and exploited an approximate message passing (AMP) algorithm to detect active users in Rayleigh fading channels. But Rayleigh fading channel model does not take into account the deterministic line-of-sight (LOS) component while LOS component can be dominant than random non-line-of-sight (NLOS) component in open areas and cellular environments [6], [7]. Therefore, massive MIMO systems over a Rician fading channel model represents the real propagation scenario. As a result, channel estimation of Massive MIMO with Rician fading channels has gained a lot research interest recently.

However, the common approach of the channel estimation for the massive MIMO is designed based on least square (LS) and minimum mean-square error (MMSE) methods [8], [9]. But in that traditional approaches, the pilot length is assumed to be larger than the antennas at the base station. But, this assumption in the fading channel makes the system computationally expensive and low spectral efficient. Therefore, it has now become paramount task to develop channel estimation method without that assumption. Based on the current approaches, it is very challenging to develop an effective channel estimator.

Recently with the development of machine learning and deep learning (DL) approaches, these techniques are extensively using in the wireless communication for symbol detection and unfolding projected gradient descent [10]. Besides, it has been reported that deep learning based approaches notably deep neural network (DNN) is more robust in channel estimation than the conventional methods [11]. The authors have demonstrated the ability of DNN to learn the characteristics of wireless channels and have shown results of DNN based channel estimation for the first time in [11]. In the context of massive MIMO channel estimation, a sparse recovery algorithm named denoising based approximate message passing (DAMP) has been proposed in [12]. Deep learning based two stage channel estimation scheme has been investigated in [13]. Investigation of deep learning based massive MIMO channel estimation with pilot contamination has been described in [14]. To circumvent the challenge in estimating of massive MIMO

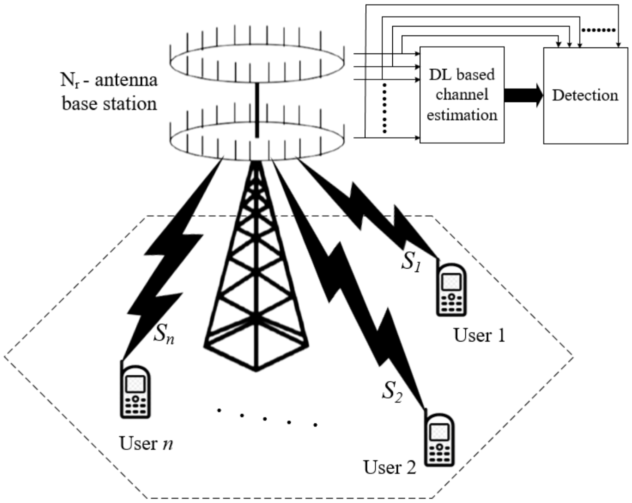

Fig. 1. An uplink massive MIMO system model.

with Rician fading channel, we have focused on deep learning based model to design an effective channel estimator. In this article, we have proposed a scheme consisting of two deep neural network: one for pilot to design pilot sequence and another one is for channel estimation. The rest of this article is organized as follows. In Section II, the system model for a uplink massive MIMO has been demonstrated. DL based pilot assisted channel estimation method has been discussed in Section III. Simulation results have been demonstrated in the Section IV and finally conclusions are drawn in section V.

II. System Model

In the study, we have considered a single cell uplink massive MIMO system as depicted in Fig. 1, where the BS is equipped with N_r $(N_r \gg 1)$ antennas to serve N_t $(N_t \gg 1)$ independent and single-antenna users in the same time frequency resource. The uplink channel matrix is represented by $\mathbf{G} = \{g_{11}, g_{12}, ..., g_{mn}\} \; \epsilon \; C^{N_r \times N_t}$, where $m \; \epsilon \; N_t$ and $n \; \epsilon \; N_r$. Considering multipath propagation effects and pathloss, the Rician fading massive MIMO channel model is formulated as [15],

$$\mathbf{G} = \mathbf{H}\mathbf{D}^{\frac{1}{2}}$$

where $\mathbf{H}$ is denoted as $N_t \times N_r$ multipath fading effect and $\mathbf{D} = \{\beta_1, \beta_2, ..., \beta_n\}$ is represented as $N_t \times N_t$ diagonal matrix. Each nth entry of this diagonal matrix includes pathloss and shadowing effect. Since, in the Rician fading channel model, $\mathbf{H}$ consists of two components: deterministic component corresponding to LOS signals and random component taking account NLOS signals, $\mathbf{H}$ is defined as

$$\mathbf{H} = \bar{\mathbf{H}}\left\{\omega(\omega + \mathbf{I_n})^{-\frac{1}{2}}\right\} + \mathbf{H_r}\left\{(\omega + \mathbf{I_n})^{-\frac{1}{2}}\right\}$$

where ω is $N_t \times N_t$ diagonal matrix that includes each entry K_n as Rician factor of each user. Besides $\bar{H}, H_r \; \epsilon \; \mathbf{C}^{\mathbf{N_r \times N_t}}$ denotes deterministic component and random LOS component,

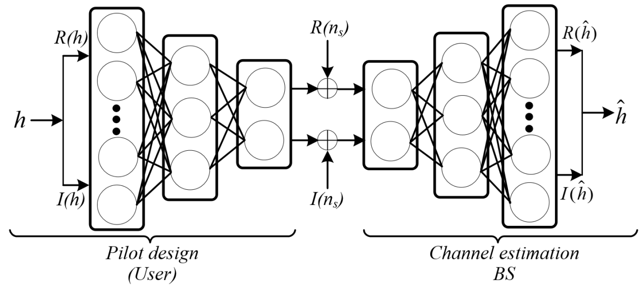

Fig. 2. DL based pilot assisted channel estimation framework.

respectively. The deterministic component depends on antenna spacing, wave length, arrival of angle of nth user. Now, let T_s be the time slots within a coherence fading block and $\mathbf{S} \; \epsilon \; \mathbf{C}^{\mathbf{N_t \times T_s}}$ be the transmitted pilot to the BS, then the received pilot signal $Y_s \; \epsilon \; \mathbf{C}^{\mathbf{N_t \times T_s}}$ is given by

$$\mathbf{Y_s} = \sqrt{\mathbf{p_u}} \; \mathbf{HS} + \mathcal{N}_\mathbf{s}$$

where p_u is uplink transmission power and $\mathcal{N}_s \; \epsilon \; \mathbf{C}\mathcal{N}(\mathbf{0}, \sigma^\mathbf{2})$ represents noise matrix. To represent in more convenient vector form, the received signal can be rewritten as

$$y_\mathbf{s} = \sqrt{\mathbf{p_u}} \; hs^T + n_\mathbf{s}$$

Now, the channel is estimated at the receiver side by the information of y_s and the pilot s and the estimated channel is denoted as $\hat{h_s} = F(y_s; s)$, where $F(.)$ is non linear channel estimator. So, the problem of minimizing the mean squared error (MSE) can be formulated as [16]

$$\min_{S, F(.)} E\left[\left\| h_s - \hat{h_s} \right\|^2\right]$$

III. DL Based Pilot Assisted Channel Estimation

In this stage, the aim is to find optimized non linear channel estimator $F(.)$ through DL. The structure of the DL based channel estimator is shown in Fig. 2. In order to design the pilot s, we have used a three layer neural network (NN) to which the input is h excluding the noise. The layer of NN has been compressed during propagation from user to BS using auto encoding technique. Then, the entire received signal y_s can be represented as the summation of the output of auto encoder and noise n_s. Using this output, a decoder acquires an initial coarse channel by increasing the neuron number along with stacking additional NN layer to refine the channel. From the perspective of encoder and decoder, the estimated channels can be reformulated as

$$\hat{h_s} = f_{de}\left(Q\left(f_{en}(h_s; \Theta_{en})\right); \Theta_{de}\right)$$

where $f_{en(.)}$ and $f_{de(.)}$ denote the compression and reconstruction operations at the user end and the BS respectively; Θ_{en} and Θ_{de} is the weight matrix of NN to determine $\mathbf{S}$ and $\mathbf{H}$; and $Q()$ represents the quantization operation. The entire process has been optimized using an end-to-end approach to minimize the loss function MSE of the channel estimation. Thus, the original signal has been reconstructed at the BS terminal from the optimized NN.

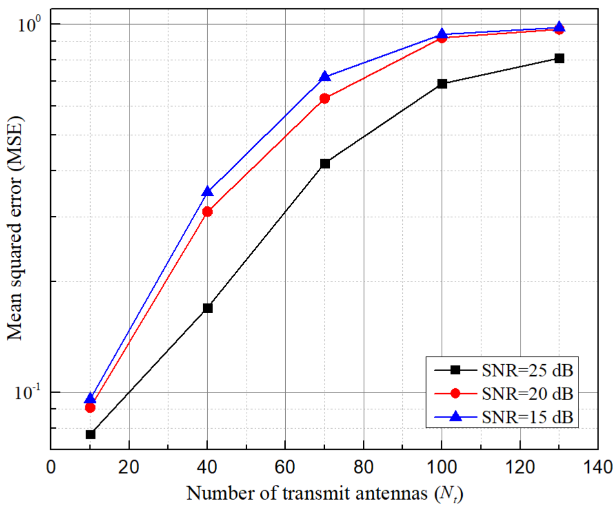

Fig. 3. MSE versus number of transmit antennas (M) of the proposed scheme.

IV. Result and Discussion

To evaluate the performance of our proposed scheme, we have simulated a massive MIMO system in the python environment. At each node of all hidden layers, we have used the rectified linear unit (ReLU) activation function. 100 epoch was set during the training phase of the neural network. However, the number of transmitted antennas were varied from 20 to 140 at different signal to noise ration (SNR) values, i.e. 25 dB, 20 dB, 15 dB to measure the MSE and optimize the NN. For all of the SNR values, the MSE values lie within 1 to .08. It is appeared that when SNR value is low, MSE value is high and vice-versa for higher SNR value. Since higher SNR values indicates lower noise effect in the signal, low MSE value during training have been achieved.

V. Conclusion

In this paper, pilot assisted DL based channel estimation has been demonstrated for the massive MIMO with Rician fading system. The proposed method includes compression and reconstruction operation to determine channel response along with artificial pilot design. The simulation results depict the performance of the proposed scheme. It ensures the efficacy of DL based approach for massive MIMO systems in Rician fading environments.

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