Deep Learning Approach for Improving Spectral Efficiency in mmWave Hybrid Beamforming Systems

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***Abstract*—Hybrid beamformer design plays an important role in millimeter wave multiple input multiple output systems. In this paper, we propose a deep learning (DL) neural network for hybrid precoders and combiners to improve spectral efficiency. With the received signal and channel matrix as the input, the proposed DL network estimates the beamformer matrix as output. The proposed DL approach does not require prior knowledge such as angle features and channel information. Thus, it provides improved spectral efficiency compared to non-DL approaches.**

***Index Terms*—Hybrid beamforming, millimeter wave, deep learning**

I. Introduction

Hybrid beamforming is one of the most essential topics on the millimeter wave (mmWave) multiple input multiple output (MIMO) systems being used in mobile systems [1], [2]. Thus, research has to be done regarding a beamformer with robust performance in a variety of scenarios. In other words, beamforming techniques should be adaptable to as many scenarios as possible that are changed by the evironmental factors such as the position of transmitter/receiver, clutter distribution, and beam steering angle. A lot of research has been carried out to propose hybrid beamformer designs. For example, a greedy-based approach [3] that uses the projection of the residual matrix and orthogonal matching pursuit (OMP) was proposed. These kinds of beamforming techniques select the analog precoder and combiners using transmit and receive array responses. These non deep learning (DL)-based algorithms require the background knowledge of the direction of arrival (DOA) and direction of departure (DOD) angle. The hybrid beamformers are proposed to solve these kinds of minimization problems and to estimate the beamforming matrix by extracting phase features. However, the hybrid beamformer techniques have some critical challenges such as the optimal solution and the complexity problem.

To overcome the above challenges, many researchers proposed the DL-based approaches. These techniques for the hybrid beamforming have several advantages such as reducing time for processing, higher performance, and low computational complexity. Therefore, many researches are focused on the DL-based techniques for the mmWave MIMO system such as DL-based channel estimation [4], [5], [6], beamforming matrix, DOA estimation, DOD estimation, and beam selection [7]. Long *et al.* [7] proposed a sub-optimum algorithm that uses support vector machines (SVMs) for beamforming matrix estimation and antenna selection. Furthermore, hybrid beamforming using the DL neural network was proposed by Huang *et al.* [8]. Their hybrid beamformer design is based on joint precoder and combiner consideration for massive MIMO systems [3]. Huang *et al.* [8] proposed a multi-layer perceptron-based network architecture that does not extract the features from the input data [9].

In this paper, we propose a DL-based approach to estimate the channel, precoder, and combiner matrices. The neural network architecture estimates the beamformer matrix at the output by training datasets composed of received signals and channel matrices. We generate dataset with channel matrices and noises in several different scenarios for the robust performance of the system. As a result, we can select the best input-output pairs by using the estimated beamforming matrices. The DL-based approach can provide higher performance of spectral efficiency and less computation complexity. Furthermore, it does not require any background information such as angle information to achieve robustness in practical environmental scenarios.

After this introduction, the rest of this paper is organized as follows: Section II introduces the mmWave transceiver architecture with hybrid beamformers and channel model for this research. The proposed DL approach and dataset generation process are discribed in Section III. Section IV provides experimented simulation results. Finally, Section V presents the conclusion of this paper.

II. System Model

In this section, N_T is the number of transmit antennas for the multiuser mmWave MIMO communication system and N_R is the number of receive antenna in user side. N_S is the number of transmit data streams. The basestation (BS) has N_T^{RF} number of baseband beamformers $\mathbf{F}_{BB} \in \mathbb{C}^{N_T^{RF} \times N_T}$ and analog beamformers $\mathbf{F}_{RF} \in \mathbb{C}^{N_T \times N_T^{RF}}$. The transmitted signal can be represented as $\mathbf{x} = \mathbf{F}_{RF}\mathbf{F}_{BB}\mathbf{s}$ where $\mathbf{s} \in \mathbb{C}^{N_S}$ is the

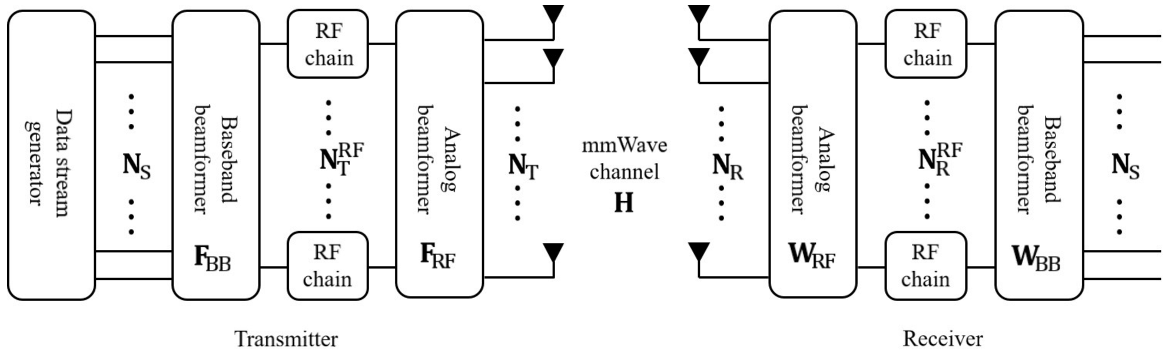

Fig. 1. Block diagram of mmWave transceiver architecture with hybrid beamformers.

N_S size of complex symbol vector. We represent the received signal at the receive N_R antennas as

$$\mathbf{y} = \sqrt{\rho}\mathbf{H}\mathbf{F}_{RF}\mathbf{F}_{BB}\mathbf{s} + \mathbf{n} \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N_R}$. $\mathbf{n} \in \mathbb{C}^{N_R}$ represents the additive white Gaussian noise (AWGN), ρ is the average received power and $\mathbf{H} \in \mathbb{C}^{N_R \times N_T}$ is the channel matrix [10] represented as

$$\mathbf{H} = \gamma \sum_{i=1}^{N_c} \sum_{j=1}^{N_{path}} \alpha_{ij} g_R(\Theta_R^{(ij)}) g_T(\Theta_T^{(ij)}) \mathbf{a}_R(\Theta_R^{(ij)}) \mathbf{a}_T(\Theta_T^{(ij)}) \tag{2}$$

where $\Theta_R^{(ij)} = (\phi_R^{(ij)}, \theta_R^{(ij)})$ and $\Theta_R^{(ij)} = (\phi_R^{(ij)}, \theta_R^{(ij)})$ are the angle of arrivals (AOAs) and angle of departures (AODs) respectively. ϕ is the angular parameter of azimuth angle and θ is the elevation angle, respectively. α_{ij} is the complex channel gain that is related to the ith clutter parameters N_c and the jth multipath N_{path}. $\mathbf{a}_R(\Theta_R^{(ij)})$ and $\mathbf{a}_T(\Theta_T^{(ij)})$ are steering vectors in size of $N_R \times 1$ and $N_T \times 1$. They represent the array response at the both sides of the system, respectively. The steering vector $\mathbf{a}_R(\Theta_R^{(ij)})$ can be represented as

$$\Big[\mathbf{a}_R(\Theta_R^{(ij)})\Big]_n = \exp\Big\{ -\frac{2\pi}{\lambda} \mathbf{p}_n^T \mathbf{r}(\Theta_R^{(ij)}) \Big\} \tag{3}$$

where the position matrix $\mathbf{p}_n = [x_n, y_n, z_n]^T$ denotes the nth receive antenna in the Cartesian coordinate system. The position matrix in the spherical coordinate system is $\mathbf{r}(\Theta_R^{(ij)}) = \big[\sin(\phi_R^{(ij)})\cos(\theta_R^{(ij)}), \sin(\phi_R^{(ij)})\sin((\theta_R^{(ij)})), \cos((\theta_R^{(ij)}))\big]^T$. The transmit steering vector $\mathbf{a}_T(\Theta_T^{(ij)})$ can be represented as same as $\mathbf{a}_R(\Theta_R^{(ij)})$.

The received signal that is passed by analog combiners and baseband combiners can be represented as $\tilde{\mathbf{y}} = \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{y}$, i.e.,

$$\tilde{\mathbf{y}} = \sqrt{\rho}\mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{H}\mathbf{F}_{RF}\mathbf{F}_{BB}\mathbf{s} + \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{n} \tag{4}$$

where $\mathbf{W}_{RF} \in \mathbb{C}^{N_R \times N_R^{RF}}$ and $\mathbf{W}_{BB} \in \mathbb{C}^{N_R^{RF} \times N_S}$ are the analog combiner and the baseband combiner respectively. Finally, we can represent the spectral efficiency [11] as

$$\begin{aligned} R = \log_2 \big(\big| \mathbf{I}_{N_S} + \frac{\rho}{N_S} \mathbf{\Lambda}_n^{-1} \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{H}\mathbf{F}_{RF}\mathbf{F}_{BB} \\ \times \mathbf{F}_{BB}^H \mathbf{F}_{RF}^H \mathbf{H}^H \mathbf{W}_{RF}^H \mathbf{W}_{BB}^H \big| \big) \end{aligned} \tag{5}$$

where $\mathbf{\Lambda}_n = \sigma_n^2 \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{W}_{RF} \mathbf{W}_{BB} \in \mathbb{C}^{N_S \times N_S}$ represents the noise in the form of covariance matrix. Therefore, the goal of this paper is to estimate the hybrid beamformers $\mathbf{F}_{RF}, \mathbf{W}_{RF}, \mathbf{F}_{BB}$, and $\mathbf{W}_{RF}$ that maximize the spectral efficiency.

III. LEARNING-BASED HYBRID BEAMFORMER DESIGN

We propose a DL network for DL-based channel estimation in hybrid beamformer design. In the data generation process, we generate and label the training dataset. The final goal is to estimate the beamforming matrices $\mathbf{F}$ and $\mathbf{W}$ using received signal $\tilde{\mathbf{y}}$ and channel matrix $\mathbf{H}$. To train the proposed network, we realize 100 different scenarios and generate the channel matrices. For each realization, we also add noise to the dataset, hence the signal-to-noise ratio level [12] is defined by

$$\mathrm{SNR} = 20\log_{10} \Bigg\{ \frac{\big|\big[\mathbf{H}\big]_{i,j}\big|^2}{\sigma^2} \Bigg\} \ \big[\mathrm{dB}\big] \tag{6}$$

where $\big[\mathbf{H}\big]_{i,j}$ denotes the channel matrix in the propagation path of ith scatter and jth multipath. The input $\mathbf{X}_1$ of the first stage is the received signal $\tilde{\mathbf{y}}$ as follows:

$$\begin{aligned} \big[\big[\mathbf{X}_1\big]_{:,:,1}\big] &= \big|\big[\tilde{\mathbf{y}}\big]_{i,j}\big| \\ \big[\big[\mathbf{X}_1\big]_{:,:,2}\big] &= \mathrm{Re}\left(\big[\tilde{\mathbf{y}}\big]_{i,j}\right) \\ \big[\big[\mathbf{X}_1\big]_{:,:,3}\big] &= \mathrm{Im}\left(\big[\tilde{\mathbf{y}}\big]_{i,j}\right) \end{aligned} \tag{7}$$

As the size of $\mathbf{X}_1$ is $N_R \times N_T \times 3$, $\big[\mathbf{X}_1\big]_{:,:,1}$ denotes the first channel of input data $\mathbf{X}_1$. Given that the first stage network is trained by the output $\mathbf{y}$ and the channel matrix $\mathbf{H}_{\text{in}}$ Re and Im denote the real and imaginary part of the following complex value.

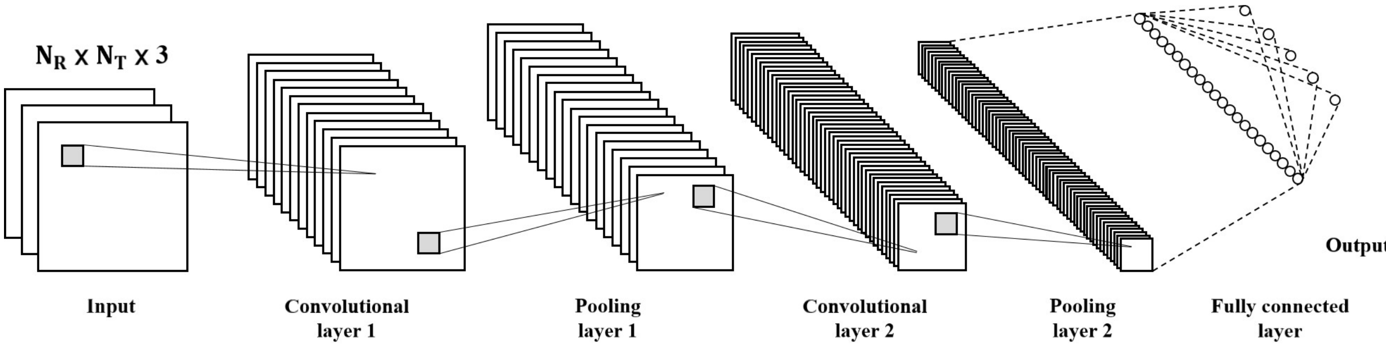

Fig. 2. Proposed network architecture for training dataset.

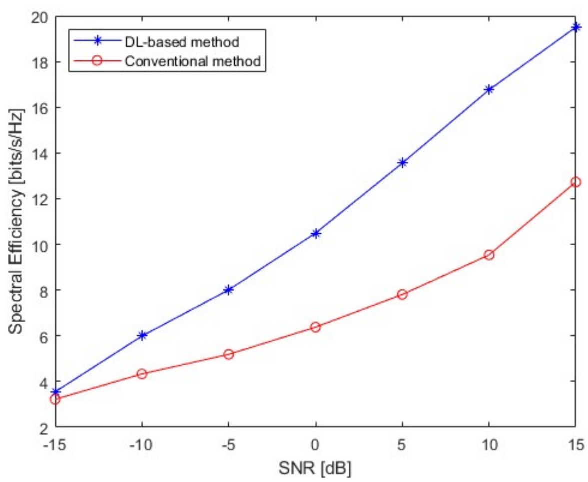

Fig. 3. Spectral efficiency comparison between proposed DL-based approach and OMP algorithm.

In the second stage, our proposed network receives the output of the first stage as input. The output label for the second stage $\mathbf{Z}$ is

$$\mathbf{Z} = \left[\mathbf{Z}_{RF}^{T},\ \mathbf{Z}_{BB}^{T}\right]^{T} \tag{8}$$

$$\mathbf{Z}_{RF} = \left[\text{vec}\{\angle\mathbf{F}_{\text{RF}}\}^{T},\ \text{vec}\{\angle\mathbf{W}_{\text{RF}}\}^{T}\right] \tag{9}$$

$$\begin{aligned}\mathbf{Z}_{\text{BB}} =& \left[\text{vec}\{\text{Re}\left(\mathbf{F}_{\text{BB}}\right)\}^{T},\ \text{vec}\{\text{Im}\left(\mathbf{F}_{\text{BB}}\right)\}^{T},\right.\\ & \left.\text{vec}\{\text{Re}\left(\mathbf{W}_{\text{BB}}\right)\}^{T},\ \text{vec}\{\text{Im}\left(\mathbf{W}_{\text{BB}}\right)\}^{T}\right]\end{aligned} \tag{10}$$

and the hybrid beamformers $\mathbf{F}_{RF}, \mathbf{W}_{RF}, \mathbf{F}_{BB}$, and $\mathbf{W}_{RF}$ are the outputs. The proposed network is presented in Fig.2. The network architecture has input size of $\mathbf{X}_1$ is $N_R \times N_T \times 3$. It comprises the convolutional neural network layers and fully connected layers. The pooling layers are also utlized after the convolutional layers and the output layer is the regression. The hyperparamete in each layer and unit are tuned and fixed so that the spectral efficiency performance can be achieved.

To train the proposed network, we generate channel matrix, received signal and additive noise in different scenarios as part of the dataset so that the proposed DL network shows robustness against the imperfect data and channel matrix.

IV. Simulation and Result

We experimented the performance of the proposed DL-based hybrid beamforming and compared it with the non DL-based technique, the orthogonal matching pursuit [3]. It is one of the non DL-based state-of-the-art techniques where the analog precoder and combiners are selected from a transmit and receive array responses. We use the uniform square arrays with $N_R = N_T = 24$ antennas. The channel environment matrix is modeled with $N_c = 5$, transmit and receive angles from each side which is selected randomly in the range of angle $\left[-60°, 60°\right]$. The proposed network is trained and updated with a learning rate of 0.005 and a mini-batch size of 500 for 200 epochs. To train the proposed network, the training dataset is composed of 70% of generated data and 30% are selected as the validation dataset.

The DL-based approach decides the analog beamformers precisely by maximizing the spectral efficiency from the candidates of the precoder-combiner sets. The OMP has degrading performance than the DL-based approach due to the decision problem that is unable to select the best array responses.

V. Conclusion

In this paper, a DL-based hybrid beamforming was proposed for the estimation of channel, precoder, and combiners matrix for the mmWave MIMO systems. We showed that the proposed learning approach provided higher spectral efficiency as compared to the OMP algorithm. In addition, the pretrained DL-based hybrid beamformer showed robust performance in the different channel scenarios which are corrupted by noise.

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