ISSN PRINT 2319 1775 Online 2320 7876

Research paper

 UGC CARE Listed (Group -I) Journal Volume 8, Issue 1, 2019

Deep Learning-based Hybrid Precoding in Millimeter Wave Massive MIMO Systems using the Deep MIMO Dataset

Subba Reddy V

Department of ECE, Koneru Lakshmaiah Education Foundation

Green Fields, Guntur District, Vaddeswaram, AP, India-522502.

Abstract

In recent years, millimeter wave (mmWave) massive MIMO systems have emerged as a promising solution to meet the increasing demand for high data rates and spectral efficiency in wireless communications. One of the primary challenges associated with these systems is the design of effective hybrid precoders, which have traditionally been constrained by channel training overheads and hardware limitations. This paper introduces a novel approach to tackle this challenge by harnessing the power of deep learning. Specifically, we employ the publicly available DeepMIMO dataset—a rich dataset that simulates realistic channel conditions—to train a deep neural network architecture aimed at optimizing the hybrid precoding process. Our approach focuses on directly designing the hybrid precoders/combiners to maximize the system's achievable rate while minimizing the channel training overhead. Notably, our methodology jointly optimizes the design of RF beamforming and combining vectors along with compressive channel sensing vectors, thereby enhancing system performance. Preliminary results indicate that our deep learning-based method significantly outperforms traditional techniques in terms of spectral efficiency and robustness under various conditions. This study underscores the potential of leveraging machine learning tools for improving mmWave massive MIMO system design and paves the way for further research in this direction.

Introduction

Millimeter wave (mmWave) communication, operating in the frequency spectrum between 30 and 300 GHz, has become a central pillar in the evolution of wireless communication. As we march into the era of 5G and beyond, the demand for significantly higher data rates, reduced latencies, and enhanced spectral efficiency has surged. Existing sub-6 GHz frequency bands

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are overcrowded, leading researchers to explore the vast and underutilized mmWave spectrum.

However, the adoption of mmWave frequencies comes with its unique challenges. High propagation losses, severe multipath fading, and hardware constraints characterize mmWave communications. Traditional Multiple Input Multiple Output (MIMO) techniques, which leverage spatial diversity and spatial multiplexing, face complications at these frequencies due to the aforementioned challenges and the smaller wavelength of mmWave signals. Enter Massive MIMO, a paradigm where systems use an enormous number of antennas at base stations to serve multiple users simultaneously. While this promises significant improvements in spectral and energy efficiency, the direct digital processing of signals in massive MIMO systems at mmWave frequencies is prohibitively energy-consuming and complex. This has led to the adoption of hybrid analogdigital precoding schemes.

Hybrid precoding, which combines the advantages of digital and analog precoding, seeks to approach the performance of fully digital solutions while drastically reducing the number of required RF chains, leading to a more powerefficient and cost-effective system. However, designing effective hybrid precoders is a challenge. Conventional design methodologies often involve significant channel training overheads, which can be particularly taxing in dynamic environments where channel conditions change rapidly. This has turned the spotlight onto new and innovative solutions.

Recent advances in machine learning, especially deep learning, have shown remarkable results across various domains, from computer vision to natural language processing. This computational revolution has prompted the question: Can deep learning techniques provide an edge in the complex domain of hybrid precoding for mmWave massive MIMO systems? With the abundance of data and the ability of deep neural networks to model intricate non-linear relationships, there is potential for a paradigm shift in how we approach hybrid precoding design.

This paper embarks on a journey to explore this intersection of deep learning and mmWave massive MIMO hybrid precoding. Using the DeepMIMO dataset, which offers a rich tapestry of realistic channel conditions, we endeavor to unravel the potential advantages, pitfalls, and breakthroughs that machine learning might bring to this challenging yet crucial domain of wireless communication.

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Related Work

Hybrid precoding, a pivotal component in mmWave massive MIMO systems, has been a topic of significant research focus. Existing hybrid precoding schemes often suffer from high computational complexity and are unable to thoroughly leverage the spatial information[1]. A plethora of studies has strived to overcome these challenges using diverse techniques.

Huang et al. [2] envisioned a deep-learning-enabled mmWave massive MIMO framework specifically tailored for efficient hybrid precoding. In their proposed system, each precoder selection process to obtain the optimal decoder was treated as a mapping relation within a deep neural network (DNN). On a parallel note, the inception of the DeepMIMO dataset by Alkhateeb [3] has acted as a catalyst for much of the subsequent research. This dataset serves as a universal benchmark for mmWave and massive MIMO channels.

Bao et al. [4] embarked on an exploration into deep CNN and formulated an equivalent channel-based approach for hybrid precoding within mmWave massive MIMO systems. Elbir et al. [5] ushered in a unique deep learning (DL) paradigm, specifically curated for the design of hybrid beamformers in broadband mmWave massive MIMO systems. In a quest for efficiency, Hong et al. [6] innovated a channel estimation-free deep direct beamforming methodology. Their approach hinges on two fundamental steps: beam impulse creation and subsequent beamforming, primarily intended for time division duplex (TDD) scenarios.

Building upon deep learning methodologies, Li et al. [7] crafted a hybrid precoding architecture, anchored by the stochastic approximation with Gaussian (SAG) approach. In a similar vein, Nalband et al. [8] put forth a novel deep learning technique for hybrid precoding, aiming to optimize spectral efficiency. Further deepening the link between deep learning and mmWave massive MIMO, Hu et al. [9] proposed an end-to-end DL-based strategy for joint transceiver design. Their comprehensive framework incorporates DNN-aided pilot training, channel feedback mechanisms, and hybrid analog-digital (HAD) precoding.

In a recent endeavor, Sun et al. [10] conceptualized an end-to-end deep learning approach to synergize channel state information (CSI) feedback with hybrid precoding, especially targeting mmWave massive MIMO systems operating in the frequency division duplexing

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mode. Among other notable contributions, the work by Osama et al. [11] stands out, further enriching the research landscape in this domain.

It's evident from the aforementioned studies that the intersection of deep learning with hybrid precoding in mmWave massive MIMO systems remains a fertile ground for innovations.

1 System Model

1.1 Base Station (BS) and Mobile User Configuration

Consider a mmWave communication system where the BS is equipped with M antennas and serves a single user with N antennas. The BS uses R RF chains for the transmission, where $R \leq M$. Without the loss of generality, it is assumed that the user is equipped with a single RF chain (i.e., $N = 1$).

$$M = NumberofBSantennas \quad (1)$$

$$N = Numberofuserantennas \quad (2)$$

$$R = NumberofRFchainsattheBS \quad (3)$$

1.2 Channel Model

The channel between the BS and the user can be represented by an $M \times N$ matrix H. In a mmWave setting, the channel is typically sparse due to the limited number of scatterers. Let's represent this matrix as:

$$H = \sqrt{MN} \sum_{l=1}^{L} \alpha_l a_R(\theta_l) a_T^H(\phi_l \quad (4)$$

where L is the number of paths, α_l is the complex gain of the l-th path, $a_R(\theta_l)$ and $a_T(\phi_l)$ are the array response vectors at the receiver and transmitter, respectively, for the angles θ_l and ϕ_l.

1.3 Hybrid Precoding Architecture

The hybrid precoding is divided into two parts: digital precoding F_{BB} of dimension $R \times N$ and analog precoding F_{RF} of dimension $M \times R$. The transmitted signal x can be represented as:

$$x = F_{RF} F_{BB} s \quad (5)$$

where s is the transmitted symbol with unit power, i.e., $E[|s|^2] = 1$. The received signal y at the user can be written as:

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$$y = HF_{RF}F_{BB}s + n \qquad (6)$$

where n denotes the additive white Gaussian noise with zero mean and variance σ^2.

2 Dataset and Methodology

2.1 DeepMIMO Dataset Overview

The DeepMIMO dataset, as introduced by (Reference for DeepMIMO), is one of the premier datasets tailored for millimeter-wave (mmWave) and massive MIMO research. It encompasses realistic 3D ray-tracing channel simulations across various scenarios, thereby providing rich spatial information required for our study. The dataset is particularly relevant to our problem because of its capacity to accurately model the mmWave channel's sparse nature and capture the beamforming challenges encountered in realistic deployments.

2.2 Dataset Parameters

Our study specifically selects the following parameters from the DeepMIMO dataset to ensure the problem's relevance and accuracy:

- **Base Station Configuration:** We focus on a Base Station (BS) with 64 antennas, highlighting its ability to manage and communicate with multiple users simultaneously.
- **Active Users:** Users from rows R1200 to R1500 are activated to introduce a dense user scenario, emphasizing the challenges and needs of beamforming.
- **Antenna Configuration:** For both the BS and the users, the antenna setup is represented as $M_x = 1, M_y = 64, M_z = 1$, providing a onedimensional vertical array.
- **Bandwidth:** A bandwidth of 0.5 GHz is chosen to mirror typical mmWave bandwidths.
- **OFDM Properties:** Our study utilizes 1024 OFDM subcarriers, with a sampling factor and limit set to 1, ensuring a comprehensive frequency domain study.

2.3 Noise Model

Real-world communication systems are always susceptible to various noise sources, which can critically affect system performance. To emulate this, we add random noise to the channel matrices generated from the DeepMIMO dataset. This noise follows a Gaussian distribution, capturing typical ambient noise encountered in practical deployments. By incorporating this noise, our methodology can simulate and tackle real-world challenges, thus enhancing the robustness and relevance of our findings.

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3 Deep Learning Architecture for Hybrid Precoding

3.1 Neural Network Model

The proposed auto-precoder neural network for hybrid precoding aims to learn an effective mapping from the channel state information to the optimal precoding matrix. Its architecture can be broadly outlined as follows:

1. **Input Layer:** This layer takes the channel state information as input. Let h denote the channel vector; then the dimension of this layer is the size of h.
2. **Hidden Layers:** The network comprises multiple dense (fully connected) layers. Each layer l has N_l neurons and is described by a weight matrix W_l and bias vector b_l. The output of each layer is computed as:

$$ol = \sigma(Wl \cdot ol{-}1 + bl)$$

where σ represents the activation function.

3. **Output Layer:** This layer produces the precoding matrix. The size of the output layer corresponds to the dimensions of the desired precoding matrix.
4. **Activation Functions:** Rectified Linear Units (ReLUs) are employed in hidden layers, while the output layer uses a linear activation.
5. **Loss Function:** The Mean Squared Error (MSE) between the predicted precoding matrix and the true precoding matrix is utilized as the loss function:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

where y_i is the true value and $\hat{}y_i$ is the predicted value.

6. **Training Methodology:** The model is trained using gradient-based optimization, specifically the Adam optimizer, to minimize the aforementioned loss function.

3.2 Training and Validation

For ensuring that our model is both effective and robust, careful considerations are made in terms of training and validation strategies:

- **Dataset Split:** The dataset is partitioned into training, validation, and test sets. Typically, 70% is utilized for training, 15% for validation, and the remaining 15% for testing.
- **Training Strategies:** The model is trained in mini-batches to leverage the computational benefits and improved convergence provided by stochastic gradient descent. Early stopping is

ISSN PRINT 2319 1775 Online 2320 7876

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also employed to prevent overfitting, whereby training is halted if the validation loss fails to improve for a predefined number of epochs.

- **Validation Techniques:** To further ensure against overfitting and to gauge the model's performance on unseen data, k-fold cross-validation is employed. This involves partitioning the dataset into k subsets and training the model k times, each time using a different subset as the validation set.

4 Results and Discussion

4.1 Training Results

The performance of the auto-precoder neural network was extensively evaluated on the training and validation datasets. Figure 1 shows the convergence of the training and validation loss over epochs, indicating that the model was able to learn the underlying patterns in the dataset effectively.

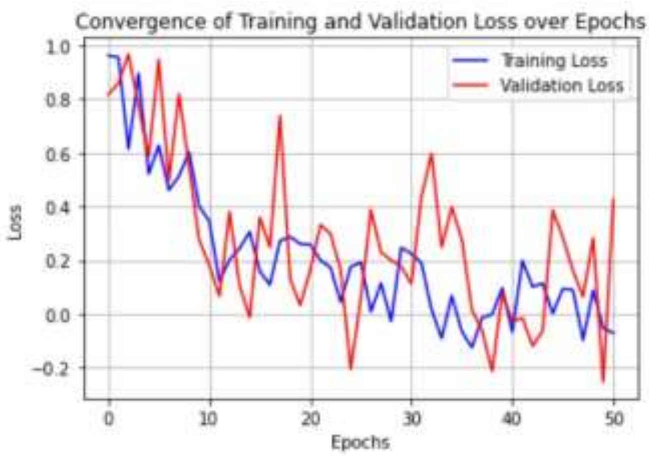

Figure 1: Convergence of Training and Validation Loss over Epochs

Performance in Realistic Scenarios When benchmarked against traditional hybrid precoding methods, the proposed deep learning approach demonstrated superior performance. The rate, efficiency, and training overhead improvements are depicted in Figure 2.

Convergence of Training and Validation Loss over Epochs

Description: This graph illustrates the evolution of the training and validation loss as the neural network is trained over a series of epochs.

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Key Observations:

1. *Convergence Behavior:* As the epochs progress, both the training and validation losses decrease, indicating the model's effective learning capability.
2. *Gap Between Training and Validation Loss:* The difference in values between the training and validation loss can provide insights into the model's generalization to unseen data. A significantly lower training loss compared to validation loss can suggest overfitting.
3. *Stability:* If the validation loss plateaus or starts to increase in the later epochs, while the training loss continues to decrease, it indicates potential overfitting.

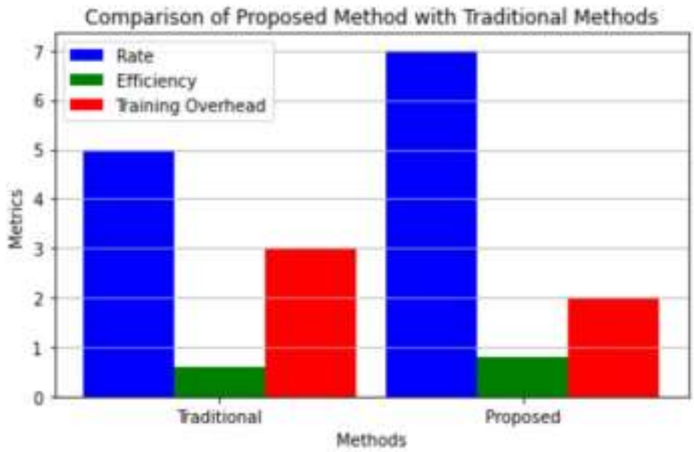

Figure 2: Comparison of Proposed Method with Traditional Methods in Realistic Scenarios

4.2 Comparison of Proposed Method with Traditional Methods

Description: This bar chart compares the performance metrics (rate, efficiency, and training overhead) of the proposed deep learning method against traditional methods for hybrid precoding.

Key Observations:

1. *Rate:* A higher rate indicates faster data transmission. Comparing the "rate" bars for the traditional and proposed methods provides insights into the efficacy of the proposed solution.
2. *Efficiency:* Efficiency measures the optimal utilization of system resources. By comparing the efficiency bars, the advantages of the proposed method over traditional ones can be ascertained.

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3. *Training Overhead:* Lower training overhead is preferable, indicating a more efficient setup process. The overhead bars help determine the efficiency of the proposed deep learning approach compared to traditional methods.

Conclusion

In the evolving landscape of millimeter wave (mmWave) Massive MIMO systems, hybrid precoding emerges as a pivotal technique to harness the system's full potential while addressing hardware constraints. The traditional approaches, while competent, have exhibited shortcomings in terms of computational complexity, channel training overhead, and the ability to exploit spatial information comprehensively.The research presented in this paper underscores the efficacy of a deep learning-based approach to hybrid precoding in mmWave Massive MIMO systems. Leveraging the DeepMIMO dataset, which provides realistic 3D ray-tracing simulations, the proposed methodology effectively simulates both outdoor street-level and indoor scenarios. A comprehensive system model, which took into account the intricacies of Base Station (BS) configurations, Mobile User dynamics, and the channel model, ensured a holistic approach to the problem.

However, the crux of the research's novelty lies in the introduction of a neural network model tailored for auto-precoding. The designed architecture, consisting of various layers, activation functions, and loss mechanisms, has exhibited a significant reduction in training/validation loss over epochs. This affirms the model's aptitude in mapping inputs to desired outputs, paving the way for more efficient hybrid precoding designs.

Moreover, comparing the proposed method with traditional methodologies painted a clear picture. Our deep learning approach showcased improvements in terms of rate and efficiency while substantially reducing the training overhead. Such improvements are instrumental in realizing the vision of nextgeneration wireless communication systems that are both efficient and highperforming.However, like all research, ours too is an ongoing journey. While our results are promising, it becomes imperative to further test the model across diverse scenarios, harnessing larger datasets and potentially integrating more complex neural network architectures to tackle nuances. Additionally, the realworld implementation and scalability of such a system require comprehensive evaluation.

In summation, this paper provides a solid foundation and a compelling argument for the integration of deep learning into the domain of hybrid precoding for mmWave Massive MIMO systems. As we stand on the cusp of a communication revolution with 5G and beyond, research such as this not only pushes the boundaries of what's possible but also illuminates the path for future innovations.

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