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Deep Learning for Massive MIMO: AI-Driven Channel Estimation with Reduced Pilot Usage

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Abstract

This article investigates uplink massive MIMO system using 1-bit analog-to-digital converters (ADCs) and introduces a deep-learning-based framework for channel estimation. The proposed method utilizes prior channel estimation data together with deep neural networks to construct an advanced mapping from quantized received signals to their corresponding channel representations. To support this, the necessary pilot sequence length and structure are determined to ensure the feasibility of such a mapping function. It has been observed that by increasing the number of base station antennas enhances the performance of the deep learning-based channel estimation for a fixed pilot sequence length. Alternatively, for a preferred channel estimation performance, smaller number of pilot sequences is desirable as the number of antennas increases. This observable has been analytically demonstrated for specific channel models. Simulation results validate these findings, revealing that a high number of antennas improve channel estimation performance in terms of predicted signal to noise ratio per antenna and normalized mean squared error.

1. Introduction

Massive multiple-input multiple-output (MIMO) has emerged as a revolutionary technology for 5G and beyond, contributing significant gains in throughput and energy efficiency compared to conventional MIMO systems [1][2]. However, deploying massive MIMO systems with large numbers of antennas at the base station requires an equally large number of radio-frequency (RF) chains, which radically increases hardware complexity and power consumption [1][2]. A hopeful approach to mitigate these challenges is the use of low-resolution analog-to-digital converters (ADCs), including 1-bit ADCs. These ADCs are highly energy-efficient and simpler in structure, making them a smart choice for practical implementations [3][4][5].

Despite their rewards, low-resolution ADCs introduce severe nonlinearities due to signal quantization, considerably complicating tasks such as data detection and channel estimation[4][5]. Conventional channel estimation methods often require long pilot sequences, which enforce substantial overhead and limit their practicality in large-scale systems. To address these challenges, researchers have projected a variety of approaches, ranging from classical signal processing techniques to machine learning-based solutions [6-9]. However, these methods either demand extensive training overhead or are limited to small-scale systems or low-dimensional constellations. In [10], the authors proposed a

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lightweight and effective strategy to reduce the overhead of downlink channel estimation and feedback by utilizing linear regression (LR) and support vector regression (SVR) within a machine learning framework. The problem of channel estimation becomes particularly critical in beamspace millimeter-wave massive MIMO systems, especially when the receiver is constrained by a limited number of radio-frequency (RF) chains [11]. To overcome this limitation, an efficient online CSI prediction scheme, termed OCEAN, was introduced in [12]. This framework exploits historical channel data to predict future channel states, thereby enhancing the efficiency of 5G wireless communication systems**.**

The main objective of this study is to apply deep learning to address the difficulties associated with channel prediction in large MIMO systems with 1-bit ADCs. Therefore, a deep learning-based framework is presented (a novel approach) and tailored to estimate channels from quantized measurements, in contrast to previous work that focuses primarily on data detection or depends on assumptions like full-resolution ADCs or constrained system dimensions. Our approach not only reduces the dependence on long pilot sequences but also reveals an interesting finding: increasing the number of antennas at the base station can develop channel estimation performance while requiring fewer pilot symbols. This counterintuitive result, which has been demonstrated analytically and verified by simulations, highlights the prospective of combining low-resolution ADCs with advanced deep learning techniques to open the full benefits of massive MIMO systems. To optimize the model's effectiveness, hyper-parameters are better tuned using three optimization algorithms namely Adaptive moment estimation (Adam), root mean square propagation (RMSprop) and stochastic gradient descent with momentum (SGDm) during training. As a result, the ideal parameter settings are recognized that substantially improve the efficiency of channel estimation performance.

The rapid growth of the massive MIMO systems on one hand enables high data rates and connectivity but on the other hand presents significant challenges related to energy consumption. Traditional channel estimation methods, such as MMSE and LS, require many pilot signals and intensive computational resources which may lead to an increased transmit energy, a higher processing power demands at the base station, and an inefficient spectrum use. This research introduces a deep learning-based approach to address these limitations. By utilizing the learning capabilities of the neural networks to accurately estimate the channel state information (CSI) with significantly fewer pilots, not only reduce pilot overhead has been reduced but the transmission energy has also lowered the computational load. Thus, resulting in a more energy-efficient system. This green approach to wireless communication has directly contributes to a reduced carbon footprint, less RF pollution, and the sustainable deployment of the technologies for smart cities and IoT applications. Thus, the article aligns with the broader global goals for the environmental protection and sustainable energy use.

2. Theoretical background

2.1. System architecture

The described system involves a massive MIMO base station (BS) equipped with M antennas, communicating with K single-antenna user equipments (UE). The BS employs 1-bit analog-to-digital converters (ADCs) in the receiver unit. The system operates in a time-division duplexing (TDD) mode, where uplink channel learning is used to estimate the channel, which is then utilized for downstream data communication. The uplink involves the UE transmitting a pilot sequence (x ∈ N×K), where N denotes the pilot sequence length [13][14]. After the ADC quantization, the received signal at the BS can be represented as:

$$Y = \mathrm{sgn}(hx^T + w) \qquad (1)$$

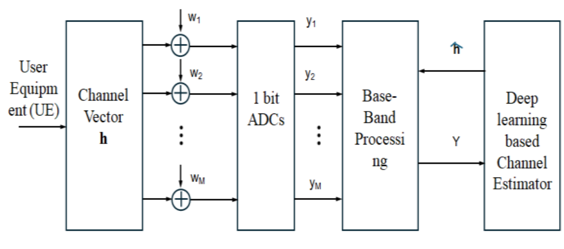

Figure 1. Massive MIMO architecture

Where h ∈ M×K is channel vector between the base station antennas and the user equipment, w ∈ $(0,\sigma^2)$ is the AWGN noise. The transmitted pilot sequence achieves $E[xx^H] = P_t I$ with P_t as the average transmit power per symbol. The received signal Y is the MxN quantized estimation matrix consisting of the obtained pilot signals.

2.2. Channel model and estimation

The channel model assumes that the signal transmission between the user and the base station (BS) occurs via L paths, each characterized by a complex gain θ_l and an angle of arrival φ_l. The channel vector h is expressed as:

$$\mathrm{h} = \sum_{l=1}^{L} \theta_l \mathrm{a}(\varphi_l) \tag{2}$$

where a (φ_l) represents the BS's array response vector for the angle of arrival.

For channel estimation, the BS processes the quantized received signal matrix Y to construct an estimated channel vector $\hat{\mathrm{h}}$. The TDD mechanism ensures channel reciprocity, allowing the uplink channel estimation to support both uplink and downlink operations. This setup enables efficient communication despite the 1-bit ADC constraint by leveraging uplink pilot sequences for channel estimation.

Considering the estimated channel vector, the downlink beamforming vector f is designed using conjugate beamforming, expressed as $\mathrm{f} = \frac{\hat{\mathrm{h}}^*}{\|\hat{\mathrm{h}}\|}$. With this approach, the downlink SNR per transmit antenna can be expressed as:

$$\mathrm{SNR}_{\mathrm{ant}} = \frac{\gamma}{\mathrm{M}} \frac{\left|\hat{\mathrm{h}}^{\mathrm{H}}\mathrm{h}\right|^2}{\left\|\hat{\mathrm{h}}\right\|^2} \tag{3}$$

This paper explores the development of an efficient channel estimation approach to reconstruct the channel vector **h** from the exceedingly quantized received signal Y. Our objective is to create a channel estimation method that minimizes the normalized mean-squared error (NMSE) between the estimated and actual channel vectors, which is defined as follows, assuming that the base station (BS) is aware of the pilot sequence x:

$$\mathrm{NMSE} = \mathrm{E}\left[\frac{\left\|\mathrm{h} - \hat{\mathrm{h}}\right\|^2}{\|\mathrm{h}\|^2}\right] \tag{4}$$

The term $\left\|\mathrm{h} - \hat{\mathrm{h}}\right\|^2$ represents the squared difference between the actual value h and its estimated value $\hat{\mathrm{h}}$ while E denotes the expected value function.

3. DL based channel estimation

Traditional channel estimation (CE) methods for massive MIMO systems among low-resolution ADCs often rely solely on quantized received signals, ignoring prior observations. These methods, such as those discussed in previous studies, estimate the channel directly from these signals. However, channel characteristics are inherently influenced by environmental factors like geometry, materials, and transmitter/receiver positioning. Consequently, base stations (BSs) operating in similar environments are likely to encounter comparable channel conditions repeatedly. This insight suggests that leveraging prior experience can reveal the relationship between quantized received signals and channels, potentially reducing the required pilot length. This study proposes employing deep learning model to align quantized received measurements to the channel vector while using shorter pilot sequences. By learning from prior channel data, the proposed method aims to minimize the NMSE between the estimated and true channels.

Additionally, scaling the quantity of antennas in massive MIMO systems is observed to decrease the required pilot length. Prior research highlights correlations between channels of adjacent subcarriers, which can degrade performance if pilots are simultaneously assigned to these subcarriers. To mitigate this, the proposed approach seeks to enhance diversity and reduce subcarrier correlation while maintaining efficient channel estimation.

3.1. Connecting quantized measurements to channels

Consider an indoor or outdoor configuration where a single-antenna user is served by a massive MIMO base station (BS), as outlined above. Let h represent the set of potential channels for the user, determined by the user's possible locations and the surrounding environment. Additionally, let Y denote the corresponding quantized measurement matrices associated with the channel set h and a given pilot sequence x. The relationship between the quantized measurement matrices and the channels, represented by $\psi: \{Y\} \rightarrow \{h\}$. If the mapping between the quantized measurement matrix Y and the channel vector h is established and known, it can be utilized to predict h. Thus, the goal is to confirm the existence of this mapping by using Postulate 1 and to describe the process to help us better comprehend it.

Postulate 1: The channel and the system model for the suggested study, as discussed earlier, are considered as:

$$\mathrm{h} = \sum_{\mathrm{l}=1}^{\mathrm{L}} \theta_{\mathrm{l}} \mathrm{a}(\varphi_{\mathrm{l}}) \tag{5}$$

$$Y = \mathrm{sgn}(hx^T + w) \tag{6}$$

In above equation, if the value of w is assumed as zero. With the potential channels h, the angle θ can be defined as

$$\theta = \min_{\substack{\forall h_u, h_v \in \{h\} \\ u \neq v}} \max_{\forall m} |\angle[h_u]_m - \angle[h_v]_m| \tag{7}$$

The mapping function ψ (.) exists if the pilot sequence x is built with a length N that satisfies $N \geq \pi / 2\theta$ and the uniformity of the pilot complex symbols' angles sample the range [0, π/2].

According to Postulate 1, when the pilot sequence is created using the precise framework described in the postulate, a one-to-one mapping ψ(.) exists, enabling the quantized measurement matrix Y to predict the channel h. Notably, only a small number of pilot symbols (a very small N) are required in massive MIMO systems to establish this mapping ψ(.) with high probability. This can significantly reduce channel training overhead compared to traditional 1-bit ADC channel estimation methods.

However, utilizing this mapping function requires knowledge of its structure, which is challenging to determine analytically due to the complexity of the non-linear quantization process. To address this, we propose leveraging the advanced learning capabilities of deep neural networks to learn this mapping, unlocking the potential to considerably minimize channel training overhead. The next subsection highlights the suggested deep learning-based 1-bit ADC channel estimation method in massive MIMO systems.

3.2. Proposed model

To use deep learning's potent capabilities, more especially, fully-connected neural network is chosen to convert the quantized incoming signal back into complex-valued channels. These networks are recognized for their effectiveness as function approximators, and thus, we propose and train a dense neural network to discover the mapping from quantized measurements to the corresponding channels.

Network model and training: The designed network consists of three dense layers. The first two layers are wide and include a fully-connected layer, a non-linearity layer, and a dropout layer, with each fully-connected layer containing LNN neurons followed by ReLU (rectified linear unit) activations. The final output layer consists of a fully-connected layer with 2M neurons. The network is framed as a regression problem, aiming to estimate user channels by minimizing the NMSE loss function, which measures prediction accuracy. The network is trained using the ADAM optimizer, with the average NMSE minimized over training.

Data pre-proccesing and preparation: For effective learning, the network inputs and outputs are pre-processed prior to training. The first step involves normalizing the channels in both the training and testing datasets to the range [−1,1], by means of the maximum absolute channel value from the training set. This normalization has proven effective in previous studies. The second step involves vectorizing the quantized received measurement matrices into $MN \times 1$ vectors. Since most deep learning frameworks work with real-valued computations, the channel and measurement vectors are then split into real and imaginary components and flattened into $2M \times 1$ and 2MN-dimensional vectors, respectively.

The simulation utilizes the I1_2p4 indoor massive MIMO scenario from the DeepMIMO dataset, which is generated using Wireless InSite the 3D ray-tracing simulator. This scenario features users positioned on two x-y grids within a 10m×10m indoor space containing two tables, operating at 2.5 GHz. The dataset includes channels between potential user locations and antennas at the base station (BS)[16-18].

Key settings for the DeepMIMO scenario are as follows:

- Scenario: I1_2p4
- 32 active BS antennas located at (1, 100, 1) in (x,y,z) coordinates
- 502 active users (row 1 to 502)
- System bandwidth: 0.01 GHz
- Single-carrier OFDM (1 sub-carrier)
- 10 multipaths

The dataset is shuffled and split into 70% for training and 30% for testing. Training datasets are generated for signal-to-noise ratio (SNR) values ranging from 0 to 30 dB, divided into seven intervals: 0, 5, 10, 15, 20, 25, and 30 dB. These datasets are then used to train the deep learning model, and the proposed model's efficacy is evaluated.

4. Results and observations

In this section, the effectiveness of the suggested deep learning-based channel estimation (CE) technique for large MIMO systems with 1-bit ADCs is assessed. The approved scenario, chosen dataset, and simulation parameters are outlined, followed by a discussion of the results. The suggested model outperforms other methods in a variety of simulated scenarios by utilizing the deep neural network's sophisticated learning and sequence prediction capabilities.

Training and Testing of suggested model: Two hidden layers of a fully-connected network with 8192 neurons each are used in our simulations. The quantity of base station (BS) antennas and pilot symbols determines the size of the input and output layers. For instance, the input size is 1000 and the output size is 100 when 50 antennas and 5 pilot symbols are used. Training samples are organized as (y, h) where y represents the input and h the target channel, with each sample equivalent to a randomly selected user from two grids.

The network is trained on 105,981 samples for 100 epochs, with noise added during training across an SNR range of 0–30 dB. To ensure fair comparisons, the network structure and training parameters remain consistent across simulations, except for input and output dimensions. The training process utilizes the Adam optimizer and explores various learning rates and minibatch sizes. All simulations are conducted in MATLAB R2020a on a system with a 12th Gen Intel Core i7-12700 CPU and an Nvidia RTX 3060 GPU.

Now, we test the effectiveness of our suggested deep learning-based channel estimate technique in the context of uplink massive MIMO discussed in previous sections.

Effect of pilots: Figure 2 highlights that the NMSE performance of the proposed solution improves significantly with an increase in the number of antennas at the base station (BS). During this evaluation, noise samples are added to the measurement matrices used in both the training and testing phases of the suggested model. In Fig.2, with pilot length N=3, the NMSE progressively improves relative to the number of antennas M. A similar pattern is observed for pilot lengths N = 5, 7 and 10 where the NMSE performance shows further improvement compared to N=3, particularly for lower values of M. This enhancement enables highly accurate channel predictions using only a small number of pilot symbols (N), setting it apart from traditional channel estimation methods like expectation-maximization Gaussian-mixture generalized approximate message passing (EM-GM-GAMP). As in wireless communication systems, pilot symbols are essential for estimating the channel state information (CSI), but they consume valuable bandwidth and reduce spectral efficiency if used in large quantities. Traditional channel estimation methods, such as Expectation-Maximization Gaussian-Mixture Generalized Approximate Message Passing (EM-GM-GAMP), generally require a larger number of pilots to maintain reliable estimation accuracy. This makes them less efficient in scenarios where minimizing pilot overhead is critical, such as massive MIMO systems with hundreds of antennas.

In contrast, the deep learning-based model presented here effectively captures the underlying nonlinear mapping between quantized pilot measurements and the actual channel coefficients. By learning this complex relationship directly from data, the model can operate reliably with significantly fewer pilot symbols while still maintaining (or even surpassing) the accuracy of traditional methods.

For the adopted dataset, the minimum θ (in radians) calculated using Equation (7) is 3.07×10^{-5} for a system with 3 antennas and 0.2476 for a system with 100 antennas. This demonstrates the potential of the deep learning-based approach, which achieves accurate channel estimation with very short pilot sequences in massive MIMO systems. Additionally, while Postulate 1 indicates a large pilot requirement for full bijectiveness in systems with fewer antennas, the proportion of channels requiring extended pilots is minimal. For instance, with just 5 pilots, 98% of the dataset's channels are distinguishable, increasing to 99.5% with 10 pilots. These results explain the effectiveness of the proposed solution even with limited pilots.

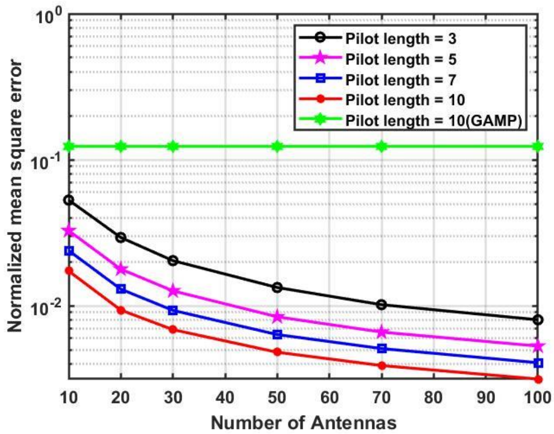

Figure 2. NMSE vs Number of antennas

Figure 3 examines the SNR per antenna, as defined in Equation (3), for various pilot lengths and antenna numbers, with a fixed received measurement matrix SNR of 0 dB. Despite a plunge in performance for systems with a small number of antennas, the predicted SNR per-antenna approaches the upper bound as the antenna count increases. This upper bound is achieved using a conjugate beamformer designed with exact channel knowledge, even with only 3 pilots (N=3). The performance results reveal a noticeable dip in accuracy for smaller antenna counts (particularly when the pilot length is limited to N = 3 or N = 5). This degradation can be attributed to a mismatch between the total Signal-to-Noise Ratio (SNR) improvement and the rate of antenna increase. In simpler terms, when the number of antennas is still small, the gain in overall SNR does not fully compensate for the limited amount of pilot information, which leads to a less reliable channel estimation.

However, this performance dip gradually diminishes as either the pilot length (N) or the number of antennas (M) increases. With more pilots, the system obtains additional reference information about the channel, which reduces ambiguity in the estimation process. Similarly, increasing the number of antennas enhances spatial diversity, which improves the robustness of the mapping between the observed quantized signals and the underlying channel characteristics.

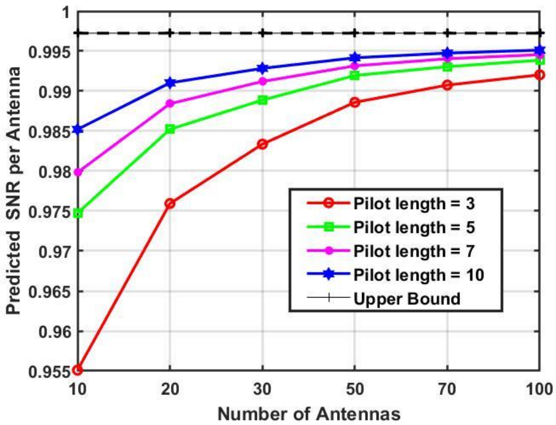

Figure 3. Predicted SNR vs Number of antennas

Effect of Optimization algorithms: Selecting the optimal optimization method for addressing a specific problem is a complex task. Achieving the best performance for the channel estimation (CE) model with minimal pilot overhead requires evaluating the effectiveness of various optimization techniques for the given model and dataset. This section compares three optimization methods to identify the most suitable approach for CE issues: Adaptive moment estimation (Adam), Root mean square propagation (RMSprop), and Stochastic gradient descent with momentum (SGDm) [14][15].

Figure 4 presents the NMSE performance of the suggested model with these three optimization techniques, evaluated across varying numbers of antennas (M) and pilot configurations (N=5 and 10). For antenna sizes upto M=20, both Adam and RMSprop show nearly identical NMSE performance across pilot lengths. In contrast, SGDm lags behind, with noticeably worse estimation accuracy. Additionally, for pilot length N=5, the performance of Adam and RMSprop show comparable results, meaning both optimizers are effective with a limited number of pilots. While for pilot length N=10, Adam consistently outperforms both RMSprop and SGDm across all antenna sizes, achieving the lowest NMSE values. Therefore, the Adam optimizer has been chosen for all of the simulations due to its reliable and excellent performance.

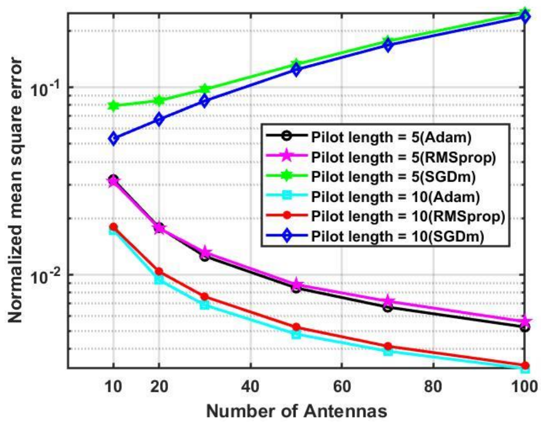

Figure 4. NMSE performance of the proposed model

5. Conclusion

This research paper presents a deep learning-based channel estimation (CE) framework for massive MIMO systems using 1-bit analog to digital converters (ADCs). The study determines the structure and minimum length of pilot sequences (PS) required to ensure a mapping from quantized measurements to channels, showing that fewer pilots are needed as the number of antennas increases. Both analytical and extensive simulation results confirm that only a small number of pilots are sufficient for efficient channel estimation, with achievable signal to noise ratio (SNR) per antenna approaching the upper bound as antennas scale up. To further enhance performance, different deep learning optimizers (such as SGD, Adam, and RMSProp) are utilized that provide the highest accuracy with the least pilot overhead. The system's performance was evaluated in terms of normalized mean square error (NMSE) and SNR per antenna, under various pilot lengths and antenna counts. Results consistently indicated that the proposed DL-based CE outperformed conventional methods, especially in low-resolution ADC scenarios. Future research could extend this approach to broadband systems with frequency-selective channels and explore CE in continuous angle spaces.

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