One-Bit Multi-User Massive MIMO Channel Estimation using Conditional Generative Adversarial Networks (cGAN)

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Publicly accessible code is available at:
https://github.com/anuj3509/Multi-User-Massive-MIMO-Channel-Estimation-using-cGAN

Abstract

Accurately estimating wireless channels poses a significant challenge, especially in massive multiple-input multiple-output (MIMO) systems utilizing low-resolution analog-to-digital converters (ADCs).

Traditional deep learning (DL) methods, which aim to understand the relationship between input data and actual channel conditions, encounter difficulties in precisely reconstructing channel matrices due to inadequately explored and formulated loss functions.

The report emphasises on employing conditional generative adversarial networks (cGANs) for producing authentic channel estimations through the adversarial training of two deep learning models. With cGANs, the models not only grasp the transformation from quantized received signals to actual channel matrices but also dynamically adjust to select the most suitable loss function for effective network training.

Introduction

While Massive MIMO technology is pivotal for enhancing capacity and spectrum utilization within 5G wireless communication systems, current implementations often rely on high-resolution analog-to-digital converters (ADCs), resulting in elevated power consumption and hardware complexity. To address these drawbacks, there is growing interest in exploring massive MIMO systems equipped with one-bit ADCs as a more efficient alternative. However, accurately estimating channels amidst heavily quantized signals from low-resolution ADCs remains a challenge.

In this report, we examine a solution using conditional generative adversarial networks (cGANs) to train two networks adversarially. The cGAN framework learns signal-to-matrix mapping and dynamically adjusts loss functions for optimal training. This architecture includes a generator network with skip connections and a discriminator network for quality assessment. Through adversarial training, the generator aims to create channel matrices that deceive the discriminator, facilitating realistic channel estimation.

Modelled Architecture

In our study, we investigate a massive MIMO system operating within a single cell, employing one-bit ADCs. The system comprises K users with single-antenna setups and a base station (BS) equipped with M antennas. Each antenna at the BS utilizes two one-bit ADCs. The channel characteristics between the BS and users are modeled using precise ray-tracing data obtained from Remcom Wireless InSite. This software enables the computation of detailed channel properties for each BS-user pair across various channel paths.

To estimate the channels accurately, the BS utilizes pilot signals transmitted by the users. In this process K users transmit pilot sequences simultaneously, each sequence having a length of T, to the BS. Subsequently, the BS receives the signal Y, which undergoes one-bit quantization.

System Model

In our project, we explore a single-cell massive MIMO system featuring one-bit analog-to-digital converters (ADCs) at a base station (BS) equipped with multiple antennas. The system accommodates several single-antenna users, each connected to the BS through various channel paths. The channel characteristics between the BS and each user are meticulously simulated using accurate ray-tracing data from Remcom Wireless InSite. This simulation includes detailed computations of azimuth and elevation angles of departure (AoDs) and arrival (AoAs), as well as the phase, received power, and propagation delay for each channel path associated with a user.

To model the channel between the BS and each user, we employ a channel vector, $\mathbf{h}_k$, constructed by summing the contributions from each channel path. This is given by:

$$\mathbf{h}_k = \sum_{l=1}^{L} \omega_l \cdot \mathbf{a}(\beta^k_{azi}, \beta^k_{aod})$$

where L is the total number of channel paths, ω_l represents the complex gain for path l, and $\mathbf{a}(\beta_{k,azi}, \beta_{k,aod})$ denotes the array response of the BS.

The complex gain, ω_l, incorporates the path's power and phase shifts, calculated as:

$$\omega_l = \sqrt{\frac{P_{k,l}}{K}} e^{j(\phi_{k,l} + 2\pi \frac{k}{K} \lambda_{k,l} B)}$$

The array response, $\mathbf{a}$, is structured as: $\mathrm{a}(\beta^k_{azi}, \beta^k_{aod}) = [1, e^{jkd \cdot \sin(\beta^k_{aod}) \cos(\beta^d_{azi})}, \ldots, e^{jkd(M-1) \cdot \sin(\beta^k_{aod}) \cos(\beta^k_{azi})}]^T$

where B is the system bandwidth and d is the antenna spacing.

The complete channel matrix $\mathbf{H}$ for all K users is represented as:

$$\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_K]$$

with dimensions $\mathbf{H} \in C^{M \times K}$. We visualize this channel matrix by plotting the real component of a 64 × 32 matrix (representing 64 BS antennas and 32 users), where the color scale on the accompanying colorbar reflects the data values within the matrix.

Estimating Channel

Channel estimation at the base station (BS) is achieved using pilot signals transmitted by K users. Each user sends a unique orthogonal pilot sequence of length τ, allowing simultaneous transmissions. The BS receives these signals and performs one-bit quantization, represented as:

$$Y = sgn(H\Phi + N)$$

where Y is the quantized signal matrix with dimensions $M \times \tau$, Φ is the matrix of orthogonal pilot sequences from the users with dimensions $K \times \tau$, and N is a noise matrix following a Gaussian distribution.

The quantization process uses the signum function, applied element-wise to both the real and imaginary parts of the signal. This results in a quantized output where each element of Y can take one of four possible complex values: $\{1+j, 1-j, -1+j, -1-j\}$, reflecting a very low-resolution measurement of the channel.

Our goal is to recover the channel matrix H from these quantized observations Y and the known pilot sequences Φ. To achieve this, we utilize a conditional Generative Adversarial Network (cGAN) model, which provides a more accurate and robust estimation of the realistic channel matrix by leveraging the capabilities of adversarial deep learning models.

Channel Estimation via cGAN

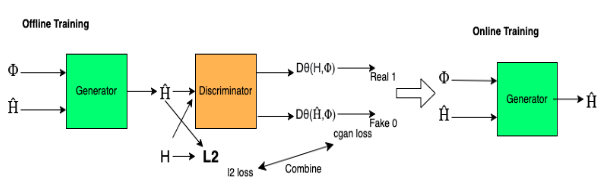

Figure 1: cGAN approach.

In our study, we approach channel estimation as an image-to-image translation task. We represent the received signal Y, the pilot sequence Φ, and the channel matrix H as two-channel images, capturing their real and imaginary components. Our goal is to convert low-resolution, quantized signals Y into a high-resolution channel matrix H.

To achieve this, we employ a conditional Generative Adversarial Network (cGAN). In the cGAN framework, both the generator and discriminator are conditioned on inputs—the received signals and pilot sequences. This allows the generator to accurately estimate the channel matrix from the quantized signal Y and Φ, while the discriminator distinguishes between 'real' (true channel matrix and pilot sequence) and 'fake' (estimated channel matrix and pilot sequence) data pairs.

Using the trained generator, we can accurately estimate channel matrices from new instances of received signals and pilot sequences, enhancing resolution and accuracy compared to the original quantized observations.

Objective Function

The objective of the cGAN is to make the generator synthesize channel matrices $\hat{H}$ that are realistic enough to deceive the discriminator, while the discriminator aims to distinguish between real and synthesized channel matrices effectively. This optimization process involves a Generative Adversarial Network (GAN) loss function:

$$\mathcal{L}_{GAN}(G_\psi, D_\theta, Y, H, \Phi) = E[\log D_\theta(H, \Phi)] +$$
$$\mathrm{E}[\log(1 - D_\theta(G_\psi(Y, \Phi)))] \quad (1)$$

Here, G_ψ represents the generator parameterized by ψ, which synthesizes the channel matrix $\hat{H}$ (i.e., $G_\psi(Y, \Phi)$) to resemble the ground-truth H, and D_θ is the discriminator parameterized by θ, aiming to differentiate between the generated channel matrix $\hat{H}$ and the real channel matrix H. Thus, G_ψ minimizes the GAN loss against the adversarial D_θ to maximize it:

$$\min_\psi \max_\theta \mathcal{L}_{GAN}(G_\psi, D_\theta, Y, H, \Phi) \quad (2)$$

To ensure proper optimization of the generator, we also include an $\mathcal{L}_2$ loss to the GAN loss:

$$\mathcal{L}_2 = E[||H - G_\psi(Y, \Phi)||^2] \quad (3)$$

Thus, the final objective function is defined as:

$$\min_\psi \max_\theta (\mathcal{L}_{GAN}(G_\psi, D_\theta, Y, H, \Phi) + \mathcal{L}_2) \quad (4)$$

Network Architecture

In this implementation, the generator employs the U-Net architecture, which is particularly effective for image-related tasks. This configuration features a series of upsampling and convolutional layers, organized into three encoder blocks and four decoder blocks. Each block incorporates instance normalization and LeakyReLU activation, enhancing convergence and maintaining detail across various scales. U-Net is characterized by its skip connections, which link the outputs of encoder and decoder blocks to preserve fine details.

The discriminator utilizes a convolutional patch architecture, focusing on small, detailed sections of the input to assess authenticity. This approach allows for a more nuanced analysis, improving the discriminator's effectiveness in distinguishing between real and generated outputs, thereby optimizing the model's performance for channel estimation tasks.

Results and Discussion

In this section, we test the cGAN Channel Estimation model by altering various hyper-parameters in different scenarios.

Generating Dataset

Channel Generation was facilitated by Remcom Wireless InSite ray-tracing using an already available executable scenario. Loading this scenario and running it in MATLAB, an indoor sub-6G massive MIMO system was formulated which operates at 2.5 GHz. Four channel datasets are generated with varying numbers of base station (BS) antennas, mainly $M = 64$, $M = 128$, $M = 192$, and $M = 256$, while the number of users is fixed at $K = 32$. All other parameters are set to default values, with the antenna spacing equal to half the wavelength, a bandwidth of 0.01 GHz, and the number of multipaths set to $L = 10$.

Additionally, four channel datasets are generated, each containing 4200 channel matrices H with dimensions of 64×32, 128×32, 192×32, and 256×32, respectively. Corresponding datasets of received signals are generated based on the channel matrix datasets and pilot sequences using one-bit quantization. On top of that, noise with varying signal-to-noise ratios (SNRs) is added to the received signals. To train the proposed conditional Generative Adversarial Network (cGAN) model, both the generator and the discriminator utilize the MSProp algorithm with learning rates of 2×10^{-4} and 2×10^{-5}, respectively.

Loss Metrics

We use the normalized mean-squared error (NMSE) to quantify the disparity between the estimated matrix $\hat{H}$ and the actual channel matrix H. NMSE is calculated as follows:

$$NMSE = 10\log_{10}\left(E\left[\frac{\|H-\hat{H}\|^2}{\|H\|^2}\right]\right)$$

where $\|\cdot\|$ denotes the matrix norm and E represents the expectation. The result is then converted to decibels by applying $10\log_{10}$ to obtain the NMSE values.

Performance Analysis

We tested the cGAN model for channel estimation on different scenarios by varying the number of antennas at the base station and by altering the SNR of the noise added. After every epoch in the training loop, we receive an output image which contains the input image, the targeted output and the predicted output for channel estimation.

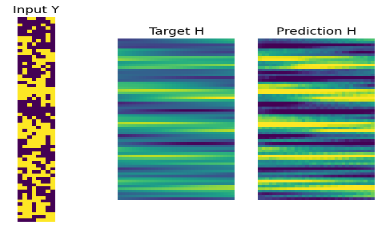

Figure 2: Output after each training epoch

Final plots displaying the variations in average normalised mean squared error vs. evolving SNR at each set of antennas are displayed below.

From the various plots above, we observe that using 64 antennas at the base station performs marginally better compared to other antenna configurations. Increasing the number of antennas in the transmitter (Tx) array leads to higher data rates. While adding more antennas to a base station in MIMO systems can improve capacity and spectral efficiency, there are several downsides:

- Power Sharing and Interference: Adding more antennas can lead to diminishing gains and eventually losses due to power sharing and interference between users.
- Increased Hardware Complexity: Accommodating more antennas requires a significant amount of hardware to be packed into a limited space.
- Temperature Issues: The addition of more antennas can result in increased power dissipation, leading to temperature concerns.

The cGAN-based approach has been compared with other existing methodologies such as U-Net, CNN, and MLP-based approaches for channel estimation. The comparison of predicted channel estimations is illustrated in Figure 7.

In [1], the cGAN approach was compared with three other deep learning methods: U-Net, regular CNN, and MLP. All models had the same number of layers and were trained under identical conditions. The U-Net result demonstrated the difference between the cGAN approach and conventional training using L2 loss. The results of regular CNN and MLP also highlighted the performance difference without the cGAN structure and the U-Net architecture.

Visually comparing the performance improvements gained by the cGAN approach, we observed that the images of the ground truth channel and the cGAN-generated channel were very similar, with the cGAN effectively capturing finer details (Figure 7b). However, for U-Net, the result was somewhat blurry (Figure 7c). Similarly, regular CNN and MLP also produced fuzzy channel results (Figure 7d and 7e). The cGAN architecture, on the other hand, is capable of producing more realistic results. These comparisons are cited from [1].

From our study, we found that incorporating more antennas can increase the average normalized mean squared error at some points. However, implementing MIMO systems with a higher number of antennas at the base station can be challenging due to the complex signal processing involved, which typically demands significant computational power.

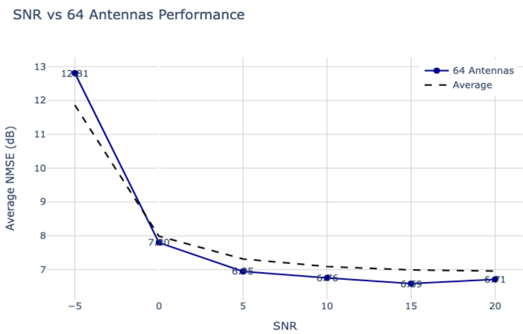

Figure 3: SNR vs. Average NMSE for 64 BS Antennas

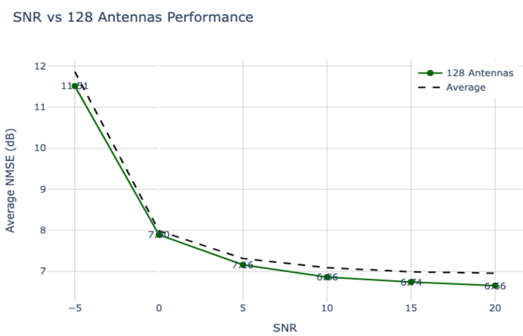

Figure 4: SNR vs. Average NMSE for 128 BS Antennas

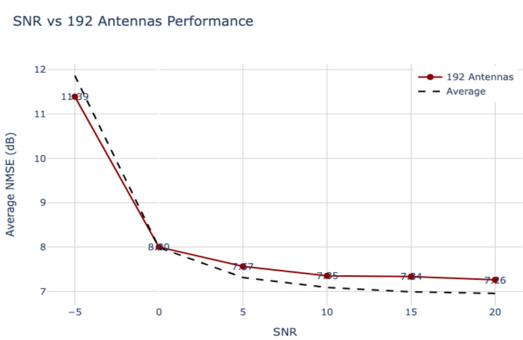

Figure 5: SNR vs. Average NMSE for 192 BS Antennas

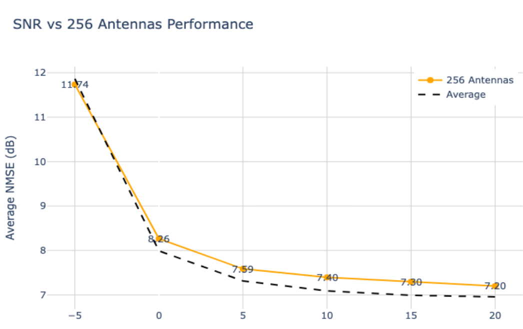

Figure 6: SNR vs. Average NMSE for 256 BS Antennas

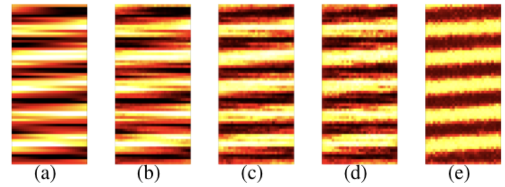

Figure 7: Visualization of estimated channels with different methods. (a) Groundtruth (b) cGAN result (c) U-Net result (d) CNN result (e) MLP result

Conclusion

Throughout this project, we successfully recreated and demonstrated the capabilities of cGAN based approach for One-Bit Multi-User Massive MIMO Channel Estimation. We observed that this model performs significantly better than other channel estimation methodologies used in conjunction with U-Net, CNN or MLP. Especially at lower SNRs, cGAN based approach has gains improved by several dB when compared to other reported methodologies.

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