FFDNet Based Channel Estimation for Multiuser Massive MIMO System with One-Bit ADCs

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***Abstract*—Low-resolution analog-to-digital converters (ADCs) in massive multiple-input multiple-output (m-MIMO) systems offer significant throughput increase for wireless communication. The low-resolution ADC part limits the performance of the transceiver, especially estimating the channels from highly quantized measurements. Mapping from quantized received signals to channel is very challenging. Since the channel response has the characteristic of sparsity, we have leveraged a fast and flexible denoising convolutional neural network (FFDNet) based channel estimation scheme for the m-MIMO system with one-bit ADCs treating the channel matrix as a 2D natural image in this letter. FFDNet can effectively learn from sufficiently large training datasets and is exploited to estimate the channel in the m-MIMO system equipped with one-bit ADCs. We have investigated the exhibited performance of the FFDNet based channel estimation through simulation results. A significantly reduced normalized mean square error has been achieved in our proposed scheme.**

***Index Terms*—FFDNet, massive MIMO, channel estimation, one-bit ADC, deep learning.**

I. INTRODUCTION

Massive multiple-input multiple-output (m-MIMO) enables the deployment of the base station (BS) equipped with a large number of antenna arrays to ensure the reusing of spectrum resources among multiple users as well as to significantly improve the data transmission rate [1]. However, such benefits turn impractical due to the usage of high-resolution (e.g., 8-12 bits) analog-to-digital converters (ADCs). Having high resolution ADCs in the system leads to high hardware costs and power consumption. Therefore, low resolution ADCs (e.g., one-bit) at the receivers have been considered as a promising solution because of its capability of drastically reducing the power consumption and cost of the m-MIMO systems [2]. The vast potential of one-bit ADCs in m-MIMO systems has attracted significant global attention in the last few years and continues to do so [3].

However, it is extremely challenging to design efficient channel estimation techniques and obtain accurate channel estimation due to the highly quantized measurements accompanied by one-bit ADCs. Accurate prior channel state information (CSI) along with statistical properties of the channel is required for the conventional channel estimation techniques [4]. But, it turns out arduous to manage those prior CSI and statistical properties when the number of transmitters and receivers is very large especially in the case of m-MIMO systems [5]. Though compressed sensing based techniques are very effective in this case, but utilization of non-linear optimization algorithms increases the complexity while having inadequate performances [6]. Therefore, the feasibility of using these techniques for the one-bit ADCs in m-MIMO systems is decreasing on a large scale.

Recently, the adoption of deep learning (DL) algorithms has been demonstrated to be effective for designing channel estimator and have achieved substantial success. Yang *et. al.* [7] studied multilayers perceptron's (MLPs) to learn the uplink to downlink channel mapping in m-MIMO systems. But, MLPs show very poor performances in case of a small amount of data or highly complicated data. A comparison among the estimation performance of DL approaches to generalized approximate message passing (GAMP) in m-MIMO with non-ideal one-bit ADCs depicted in [8]. The simulation results substantiate the robustness of DL approaches to ADC impairments than GAMP approaches. In [9], a DL based channel estimation framework for one-bit m-MIMO has been demonstrated. The authors observed that fewer pilots are required for the same channel estimation performance when more antennas are employed. Balevi and Andrews *et. al.* [10] have proposed a two-stage estimation scheme for one-bit massive MIMO by exploiting deep neural networks as well as convolutional neural network. They have obtained 5-10dB gain in channel estimation. To process the average of multiple pilot signal segments, the authors have proposed a segment-average based one-bit massive MIMO channel estimation scheme that utilizes a deep neural network (DNN) in [11]. Their proposed scheme outperforms conventional linear channel estimators. DNN as an autoencoder has been utilized to optimize the training signal for few-bit massive MIMO in [12]. Compared with Bussgang-based linear minimum mean squared error channel estimator, their scheme has shown more efficacy. The exploitation of generative adversarial network (GAN) to estimate channels from compressed pilot measurements for one-bit massive MIMO has achieved superior performance over sparse signal recovery methods [13].

However, investigations are being conducted on using deep convolutional neural network (CNN) for channel estimation currently considering the sparsity features of the channel matrix of m-MIMO systems [14]-[18]. Besides, the changes between adjacent elements in the channel are very subtle. Hence, the channel matrix can be treated as two-dimensional (2D) noise-free natural image [19]. Based on the abovementioned analyses, it is feasible to utilize the CNN based image denoising network to design an efficient channel estimator for the m-MIMO systems equipped with one-bit ADCs. However, the state-of-the-art CNN based image denoising methods are tailored to specific noise levels, and they work well when the noise is in the trained image. This limits the flexibility and efficiency of the conventional CNN based image denoiser in the practical channel estimation [20].

To overcome the aforementioned drawbacks, we have proposed a fast and flexible denoising convolutional neural network (FFDNet) for the channel estimation in one-bit ADCs equipped multiuser m-MIMO systems. Both denoising performance and computation efficiency have increased the superiority of FFDNet over other state-of-the-art CNN based denoiser. Moreover, FFDNet is very efficient in denoising effectively and flexibly 2D images that are corrupted by additive white Gaussian noise (AWGN). Therefore, it has been considered as promising to apply for realizing the channel estimation into the one-bit ADCs equipped multiuser m-MIMO systems. To this end, we have investigated the performance of exploiting FFDNet for channel estimation demonstrating the simulation results.

II. System Model

Consider a single cell one-bit ADCs equipped multiuser m-MIMO system as depicted in Fig. 1, where we have the BS which is equipped with N_r $(N_r \gg 1)$ antennas and N_t $(N_t \gg 1)$ single antenna equipped users. Each antenna includes two one-bit ADCs for the real and imaginary parts, respectively. The channel is assumed to be Rayleigh block-fading channel which stays constant for T channel uses. If N_t users transmit pilot sequence with length of τ to the BS simultaneously, the received pilot signal $\mathbf{Y} \in \mathbf{C}^{\mathbf{N_r} \times \tau}$ is given by

$$\mathbf{Y} = \sqrt{\rho}\, \mathbf{HS} + \mathcal{N} \tag{1}$$

where ρ is the signal to noise ratio (SNR) during pilot transmission, the channel matrix $\mathbf{H}$ of N_t users is $[\mathbf{h_1}, \mathbf{h_2}, \mathbf{h_3}, ..., \mathbf{h_{N_t}}]$ with the dimension of $\mathbf{H} \in \mathbf{C}^{\mathbf{N_r} \times \mathbf{N_t}}$, and $\mathbf{S}$ is mutually orthogonal pilot sequence from N_t users with the dimension of $\mathbf{S} \in \mathbf{C}^{\mathbf{N_t} \times \tau}$. The entries of $\mathbf{H}$ are independent and $\mathbf{C}\mathcal{N}(\mathbf{0}, \mathbf{1})$ distributed. Furthermore, $\mathcal{N}$ is also independent and $\mathbf{C}\mathcal{N}\left(\mathbf{0}, \sigma^{\mathbf{2}}\right)$ distributed, stands for AWGN. The real and the imaginary components of the received signal at each antenna are quantized separately using a one-bit ADC and are represented by the values from the set $\{1+j, 1-j, -1+j, -1-j\}$.

Now, the objective of this letter is to recovery the channel matrix $\hat{\mathbf{H}}$ using the trained FFDNet. A noisy channel image corrupted by AWGN with noise level σ is fed into the trained FFDNet as input. The trained FFDNet gives output a noise free channel image.

III. FFDNet Model

A. Network Architecture

As shown in Fig. 2, the first layer of FFDNet is a reversible downsampling process which takes input noisy channel image

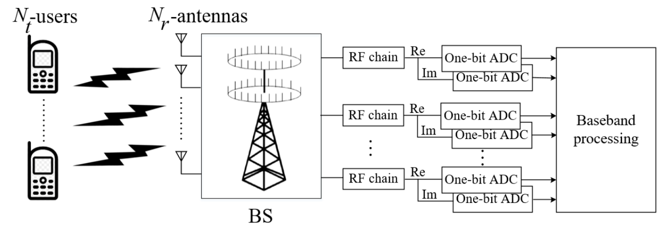

Fig. 1. Diagram of multiuser m-MIMO system with one-bit ADCs.

y of size $N_r \times N_t$. This layer reshapes the noisy channel image y into four downsampled sub-images with size $\frac{N_r}{2} \times \frac{N_t}{2} \times 4$. The downsampling process can significantly improve the training speed without reducing the modeling ability. After the operation of downsampling, a tunable noise level map with the noise level σ along with the downsampled sub-images to establish $\widetilde{y}$ with a size $\frac{N_r}{2} \times \frac{N_t}{2} \times (4+1)$ as the input of the CNN model. The CNN model comprises three types of layers, such as "Conv+ReLU" with a size $(3 \times 3 \times 64)$, "Conv+BN+ReLU" with a size $(3 \times 3 \times 64)$, and "Conv" with a size $(3 \times 3 \times 64)$. The first layer of the CNN model is "Conv+ReLU" where rectified linear units (ReLU) adds non-linearity to the convoluted output. Middle layers of the CNN model consist of "Conv+BN+ReLU" where BN is added to normalize the layers. "Conv" is used as last layer to regenerate the denoised subimages which leads to reconstruction of denoised channel image $\widetilde{x}$ in turn. Moreover, after each convolution, zero-padding is employed to guarantee that the size of the feature maps is not changed.

B. Objective Function

The objective of the FFDNet is to generate denoised image $\widetilde{x}$, which is implicitly defined by [20]

$$\widetilde{x} = \mathcal{F}(y, \mathbf{M}, \lambda; \theta)$$

where the noise level map is denoted as $\mathbf{M}$, θ is the trainable parameter of CNN model, and λ is used to control the balance between the data fidelity term and the regularization term. But in FFDNet, all the elements of $\mathbf{M}$ is tunable. As a result, the parameter λ can be neglected. Then, the objective function can be rewritten as

$$\widetilde{x} = \mathcal{F}(y, \mathbf{M}; \theta)$$

In order to train the FFDNet, we have acquired noise free 2D channel matrix implementing the multiuser m-MIMO system with one-bit ADCs where the length of pilot sequence τ was chosen 8. Then AWGN noise was added to the noise free channel image. In order to keep the balance between complexity and performance, the depth of the network is set as 15. Finally, to optimize the FFDNet during the network training, the loss function is expressed as

$$\mathcal{L}(\theta) = \frac{1}{2N} \sum_{1}^{N} \left\| \mathcal{F}(y, \mathbf{M}; \theta) - x \right\|^2$$

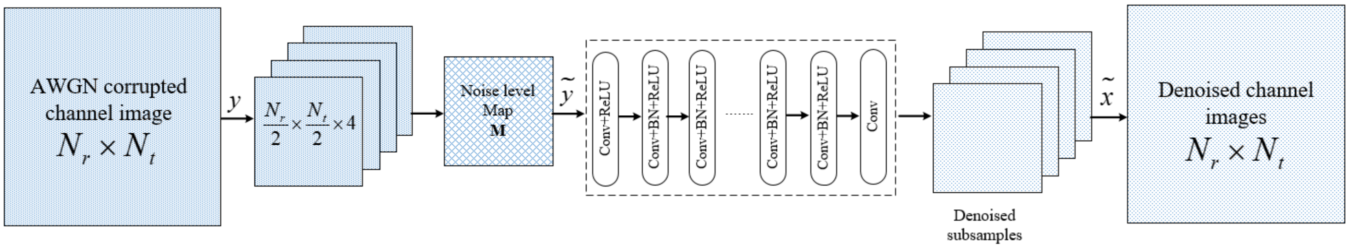

Fig. 2. FFDNet architecture.

IV. Simulation Results

To evaluate the performance of our proposed scheme, we have simulated a multiuser m-MIMO systems with one-bit ADCs in "Matlab 2020b" and generated channel matrices varying the number of antennas N_r at BS, such as 128, 192, 256 as well as for different SNR values ranging from -10dB to 10dB. The number of user N_t was kept fixed to 64. Meanwhile,we have added noise level from 2 to 10 to evaluate peak signal to noise ratio (PSNR) performance on channel estimation achieved with FFDNet. Besides, to calculate the the difference between the estimated channel matrix $\hat{\mathbf{H}}$ and the real channel matrix $\mathbf{H}$, we have utilized normalized mean square (NMSE). NMSE is defined as follows

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

After having the datasets, we have divided the datasets into training, testing and validation sets by the ratios of 70%, 20%, and 10%, respectively. All the training and testing programs have been performed in anaconda python 3.7 on a system equipped with 3.80 GHz CPU, 256 GB RAM, and a single NVIDIA Quadro RTX 6000 GPU. To optimize the model, we have used "Adam" optimizer. After training the FFDNet, the network is tested to evaluate noise level sensitivity under different number of antennas at BS. Fig. 3 elucidates the PSNR performance under different noise levels. For a specific noise level map, PSNR value started to decrease rapidly when the number of receiver increases. At noise level 10, the network has achieved 42.08dB PSNR for 256 number of N_r. The observed PSNR value is lower when the N_r is 128 at noise level 10. This is because when the size of transceiver array increases, the channel matrix acquires more obvious sparsity.

In Fig. 4, we have depicted the achieved NMSE varying noise levels. For all combination of the transceiver arrays, the NMSE have started increasing with the increasing of noise levels. Since PSNR performance is better for higher number of the receiver array, large transceiver array tends to achieve low NMSE in the channel estimation task. The maximum NMSE is 4.41dB for the N_r of 128 at noise level 25 and the minimum NMSE is 1.65dB for the N_r of 256 at the input noise level 5.

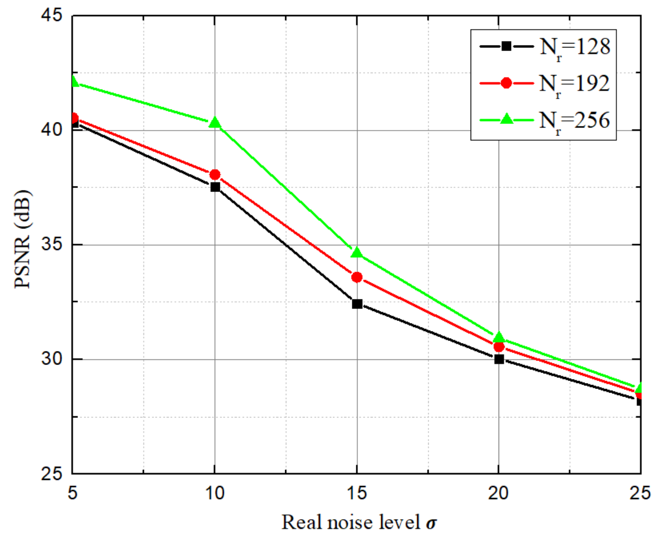

Fig. 3. The PSNR performance of channel estimation.

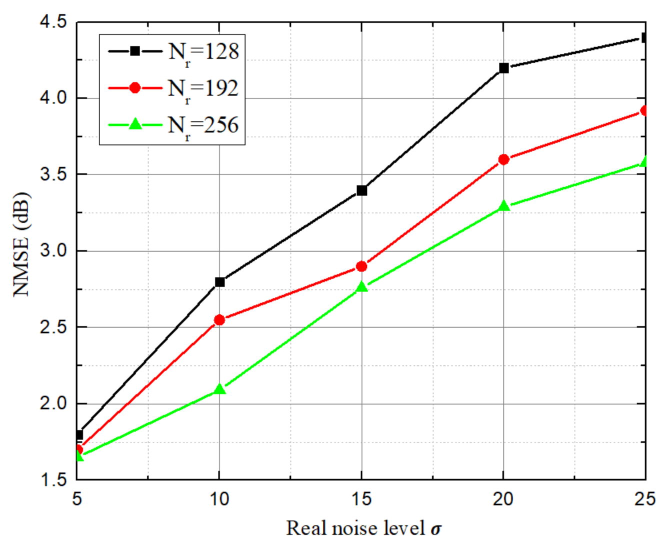

Fig. 4. Performance of NMSE with different number of antennas N_r at BS.

V. Conclusion

In this paper, we have proposed FFDNet for channel estimation in the one-bit ADCs equipped multiuser m-MIMO system. The channel matrix is treated as 2D noise free image considering the sparsity. The trained FFDNet takes the AWGN corrupted noisy image and removes noise to realize the channel. The detail of network architecture and training method for the FFDNet have been demonstrated. The simulation results have also been presented to evaluate the performance. The overall results validate the superiority of FFDNet in channel estimation as well as can be exploited to enhance the existing channel estimation performance significantly of multiuser m-MIMO system with one bit ADCs.

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