Deep Channel Learning For Large Intelligent Surfaces Aided mm-Wave Massive MIMO Systems

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Abstract—This letter presents the first work introducing a deep learning (DL) framework for channel estimation in large intelligent surface (LIS) assisted massive MIMO (multiple-input multiple-output) systems. A twin convolutional neural network (CNN) architecture is designed and it is fed with the received pilot signals to estimate both direct and cascaded channels. In a multi-user scenario, each user has access to the CNN to estimate its own channel. The performance of the proposed DL approach is evaluated and compared with state-of-the-art DL-based techniques and its superior performance is demonstrated.

Index Terms—Deep learning, channel estimation, large intelligent surfaces, massive MIMO.

I. INTRODUCTION

The massive MIMO (multiple-input multiple-output) architecture has been suggested as a promising technology for fifth generation (5G) communications systems by providing high spectral efficiency exploiting high spatial multiplexing gains [1]. However, its proposed marriage with millimeter wave (mm-Wave) transmission comes with the expensive cost of energy consumption and hardware complexity, even if hybrid beamforming is employed [1], [2]. Recently, large intelligent surface (LIS) (also known as reflective intelligent surface) technology has been proposed as a promising solution with low cost and hardware complexity [3]. An LIS is an electromagnetic 2-D surface that is composed of large number of passive reconfigurable reflecting elements which are fabricated from meta-materials [4].

LIS includes a programmable meta-surface which can be controlled via external signals such as backhaul control link from the base station (BS). Hence, real-time manipulation of the reflected phase and magnitude becomes possible. This property allows us to use LIS in wireless communications as a reflecting surface between the BS and the users to improve the received signal energy, expanding the coverage as well as reducing the interference [5]. While LIS can provide low-cost and simplistic architecture, it brings a difficulty it includes two wireless channels between the BS and user, one being the direct channel and another one is the cascaded channel between the BS and the users through LIS [6]–[9].

Regarding channel estimation in LIS, a transmission protocol has been proposed in [6] for orthogonal frequency division multiplexing, while [7] proposed a sparse matrix factorization approach. Moreover, a dual ascent-based estimation has been considered in [8]. Apart from the conventional approaches [6]–[8], deep learning (DL) techniques can also be useful for channel estimation since DL has a promising capability and has gained much interest recently (see [10] and references therein). Especially, for LIS-assisted massive MIMO, DL has been applied for signal detection [11] and the reflected beamformer design, e.g., [9]. To the best of our knowledge, this is the first work studying DL for channel estimation in an LIS scenario.

In this letter, we propose a DL approach for channel estimation in a LIS-assisted mm-Wave massive MIMO systems. In the proposed DL framework, we design a twin convolutional neural network (CNN) for the estimation of direct (BS-user) and cascaded (BS-LIS-user) channels and assume that each user has access to the deep network to estimate its own channel. The CNN is fed with the received pilot signals and it constructs a non-linear relationship between the received signals and the channel data. The deep network is trained with several channel realizations to obtain a robust estimation performance. In the prediction stage, a test data, which is separately generated than the training data, is used to validate the performance. Finally, we show that the proposed DL framework achieves reasonable channel estimation accuracy and outperforms the existing DL-based techniques [10], [12].

Fig. 1. An LIS-assisted mm-Wave massive MIMO scenario.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider an LIS-aided mm-Wave massive MIMO system as shown in Fig. 1. We assume that the BS has $M$ antennas to serve $K$ single-antenna users with the assistance of LIS which is composed of $L$ passive reflecting elements. In LIS-assisted communication scheme, each LIS element introduces a phase shift onto the incoming signal from the BS. The phase of each LIS element can be adjusted through the PIN diodes which are controlled by the LIS-controller connected to the BS over the backhaul link [8], [13].
The BS transmits $K$ data symbols $s_k \in C$ by using a baseband precoder $F = [f_1, \ldots, f_K] \in C^{M \times K}$. Hence, the downlink $M \times 1$ transmitted signal becomes $s = \sum_{k=1}^{K} \sqrt{\gamma_k} f_k s_k$, where $\gamma_k$ denotes the allocated power at the $k$-th user. The transmitted signal is received from the $k$-user with two components, one of which is through the direct path from the BS and the another one is through the LIS. The received signal from the $k$-th user can be given by

$$y_k = (h_{D,k}^H + h_{A,k}^H \Psi^H \mathbf{H}^H) s + n_k,$$

where $n_k \sim CN(0, \sigma_n^2)$ and $h_{D,k} \in C^M$ denotes the direct channel between the BS and the $k$-th user. The vector $h_{A,k} \in C^L$ expresses the LIS-assisted channel between the LIS and the $k$-th user. $\Psi \in C^{L \times L}$ is a diagonal matrix whose diagonal entries are the phase-only components $\phi_1, \ldots, \phi_L$ representing the phase shift introduced by the LIS elements, i.e., $\Psi = \text{diag}\{\exp(j\phi_1), \ldots, \exp(j\phi_L)\}$. Finally, the channel between the LIS and the BS is represented by $\mathbf{H} \in C^{M \times L}$.

In mm-Wave transmission, the channel can be represented by the Saleh-Valenzuela (SV) model where a geometric channel model is adopted with limited scattering [6], [13]. Hence, we assume that the mm-Wave channels, i.e., $h_{D,k}, h_{A,k}$, and $H$, include the contributions of $N_D, N_A$, and $N_H$ paths, respectively. Thus, we can represent the channels $h_{D,k}$ and $h_{A,k}$ as $h_{D,k} = \sqrt{\frac{M}{N_D}} \sum_{n=1}^{N_D} a_{D,k}^{(n)} e^{j\omega n} \Psi^H \mathbf{A}^H_{D,k}$, and $h_{A,k} = \sqrt{\frac{M}{N_{A}}} \sum_{n=1}^{N_{A}} a_{A,k}^{(n)} e^{j\omega n} \Psi^H \mathbf{A}^H_{A,k}$, where $a_{D,k}^{(n)}$, $a_{A,k}^{(n)}$ and $\{\theta^{(n)}_{A,k}, \theta^{(n)}_{D,k}\}$ are the complex channel gains and received path angles for the corresponding channels, respectively. $a_{D}(\theta)$ and $a_{A}(\theta)$ are $M \times 1$ and $L \times 1$ steering vectors of the path angles as $a_{D}(\theta) = \frac{1}{\sqrt{M}} [e^{j\omega_1}, \ldots, e^{j\omega_{M-1}}]^T$, $a_{A}(\theta) = \frac{1}{\sqrt{L}} [e^{j\omega_{L}}, \ldots, e^{j\omega_{L-1}}]^T$ where $\omega_n = n \frac{2\pi}{\lambda} \sin(\theta)$ and $\lambda$ is the wavelength. Further, the mm-Wave channel between the BS and the LIS is given by

$$H = \sqrt{\frac{ML}{N_H}} \sum_{n=1}^{N_H} a_{BS}^{(n)} a_{LIS}^{(n)} \Psi^H \mathbf{A}^H_{LIS}(\theta^{(n)}_{LIS}),$$

where $a_{BS}^{(n)} \in C$ denotes the complex gain and $\{\theta^{(n)}_{BS}, \theta^{(n)}_{LIS}\}$ are the angle-of-departure (AOD) and angle-of-arrival (AOA) angles of the paths, respectively. $a_{BS}(\theta) \in C^M$ and $a_{LIS}(\theta) \in C^L$ are the steering vectors. Let $G_k \in C^{M \times L}$ be the cascaded channel matrix between the BS and the $k$-user as $G_k = H \Gamma_k$ where $\Gamma_k = \text{diag}\{h_{A,k}\}$. Then, we can write $H \Psi h_{A,k} = G_k \psi_k$, for which we have $\Psi = \text{diag}\{\psi_k\}$.

In this work, our aim is to estimate the direct and cascaded channels $\{h_{D,k}, G_k\}$ in downlink transmission. In this case, we assume that each user feeds the received pilot signals to the deep network (henceforth, called ChannelNet) to estimate its own channel.

III. CHANNEL ESTIMATION VIA DEEP LEARNING

The proposed DL framework uses the received pilot signals as input to estimate the direct and cascaded channels.

A. Labeling: Channel Data

Consider the downlink scenario where the BS transmits the orthogonal pilot signals $x_p \in C^M$, one at a single coherence time $\tau$, with $p = 1, \ldots, P$ and $P \geq M$. Hence, the total number of channel uses to estimate the direct channel is $P$, whereas for the cascaded channel estimation, it is $LP$. The received signal at the $k$-th user can be given by

$$y_k = (h_{D,k}^H + \psi^H G_k^H) X + n_k,$$

where $X = [x_1, \ldots, x_P] \in C^{M \times P}$ is the pilot signal matrix while $y_k = [y_{k,1}, \ldots, y_{k,P}]$ and $n_k = [n_{k,1}, \ldots, n_{k,P}]$ are $1 \times P$ row vectors and $n_k \sim CN(0, \sigma_n^2 1_P)$. We assume that the pilot training has two phases: direct channel estimation (i.e., $h_{D,k}$) and the cascaded channel estimation (i.e., $G_k$). In phase I, we assume that all of the LIS elements are turned off, i.e., $\psi = 0_L$, by using the BS backhaul link. Then, the received baseband signal at the $k$-th user becomes

$$y_{D}^{(k)} = h_{D,k}^H X + n_{D,k}.$$

Here, the direct channel $h_{D,k}$ is selected as the label of the deep network with the corresponding input data of $y_{D}^{(k)}$. Once $h_{D,k}$, being the estimated channel, is obtained, in the second phase of the training stage, the cascaded channel $G_k$ can be estimated by transmitting pilot symbols when each of the LIS elements is turned on by one. In this case, the BS sends a request to LIS via the micro-controller device in the backhaul link to turn on a single LIS element at a time. The cascade channel estimation stage is composed of $L$ frames. In each frame, $P$ pilot signals are transmitted. For the $l$-th frame, the reflect beamforming vector becomes $\psi_l^{(l)} = [0, \ldots, 0, \psi_l^{(l)}, 0, \ldots, 0]^T$ where $\psi_l^{(l)} = 1$ and the received signal from the cascaded channel at the $k$-th user becomes

$$y_{C}^{(k,l)} = (G_k^H + g_{k,l}^H) X + n_{k,l},$$

where $Y_{C}^{(k,l)} = [y_{C,k,1}^{(k,l)}, \ldots, y_{C,k,P}^{(k,l)}]$ and $n_{k,l} = [n_{k,1}^{(l)}, \ldots, n_{k,P}^{(l)}]$ are $1 \times P$ row vectors. In $g_{k,l}$, $g_{k,l}$ represents the $l$-th column of $G_k$ as $g_{k,l} = G_k \psi^{(l)}$. Then the least-squares (LS) estimate of $g_{k,l}$ becomes

$$\hat{g}_{k,l} = y_{C}^{(k,l)} X^H (XX^H)^{-1} - h_{D,k}^H.$$

By using $h_{D,k}$, $\hat{g}$ can be solved for $l = 1, \ldots, L$. Then, we can construct the estimated cascaded matrix as $G_k = [\hat{g}_{k,1}, \ldots, \hat{g}_{k,L}]$. 

![Fig. 2. Proposed deep network architecture.](image)
Algorithm 1 Training data generation for ChannelNet.

**Input:** $K$, $U$, $V$, $X$, $\psi$, SNR, SNR$_h$, SNR$_G$.

1. **Output:** Training datasets $D_{\text{DC}}$ and $D_{\text{CC}}$.
2. Initialize with $t = 1$ and the dataset length is $T = UVK$.
3. For $1 \leq v \leq V$ do
   4. For $1 \leq u \leq U$ do
      5. Initialize $h_{D,k}(v)$ and $G_k(v)$, $\forall k$.
      6. For $1 \leq u \leq U$ do
         7. $h_{D,k}(v)_i,j \sim \mathcal{CN}(|h_{D,k}(v)|_i,j, \sigma_k^2)$, $\forall k$.
         8. $G_k(v)_i,j \sim \mathcal{CN}(|G_k(v)|_i,j, \sigma_k^2)$, $\forall k$.
      9. For $1 \leq k \leq K$ do
         10. Using $h_{D,k}(v)$ and $g_{k,u}(v)$, generate $y_D^{(k,u)}$ and $y_C^{(k,u)}$
            from (4) and (5).
         11. Using $y_D^{(k,u)}$ and $y_C^{(k,u)}$, define $X_{\text{DC}}(t)$ and $X_C^{(t)}$.
      12. $t \leftarrow t + 1$.
      13. End for $k$.
      14. End for $u$.
   15. End for $v$.
   16. Construct the datasets as $D_{\text{DC}}$ and $D_{\text{CC}}$.

B. Input Design: Received Pilots

The deep network accepts the received signals as input at the preamble stage. As a result, the input-output pairs become $\{y_D^{(k)}, I_{D,k}\}$ and $\{y_C^{(k)}, G_{k}\}$ for direct and cascaded channel estimation, respectively. In the use of only real/imaginary components is still possible, it is shown in [13-17] that the use of “three-channel” data ameliorates the performance by enriching the features inherited in the input data. Let us define the input of the deep network as $X_{\text{DC}}$ and $X_{\text{CC}}$ for the direct and cascaded channel, respectively. Then, $X_{\text{DC}}$ is a $M \times M \times 3$ real-valued “three-channel” matrix, each of which is of size $M = \sqrt{M}$. In order to benefit from 2-D convolutional filters, we construct the matrix quantity $X_{\text{DC}}$ from the vector $y_D^{(k)}$ by partitioning $y_D^{(k)}$ into $\sqrt{M}$ subvectors and put them into $\sqrt{M}$ columns. In particular, for the first and the second “channels” of $X_{\text{DC}}$, we have vec$\{X_{\text{DC}}\}_1 = \text{Re}\{y_D^{(k)}\}$ and vec$\{X_{\text{DC}}\}_2 = \text{Im}\{y_D^{(k)}\}$. Finally, the third “channel” is denoted by the element-wise absolute value of $y_D^{(k)}$ as vec$\{X_{\text{DC}}\}_3 = |y_D^{(k)}|$. Similarly, we can define $X_{\text{CC}}$ as an $L \times M \times 3$ real-valued matrix and we have vec$\{X_{\text{CC}}\}_1 = \text{Re}\{y_k\}$, vec$\{X_{\text{CC}}\}_2 = \text{Im}\{y_k\}$ and vec$\{X_{\text{CC}}\}_3 = |y_k|$ where $Y_k = \{y_C^{(k,d)}, \ldots, y_C^{(k,L)}\}^T$ is an $L \times M$ matrix composed of the received pilot signals. The output of the deep network is vectorized form of the channel matrices, i.e., $z_{\text{DC}} = [\text{Re}(I_{D,k})]_1, \text{Im}(I_{D,k})]_1$ and $z_{\text{CC}} = [\text{Re}(\text{vec}(G_k))]_1, \text{Im}(\text{vec}(G_k))]_1$ which are $2M \times 1$ and $2M \times 1$ vectors, respectively. The training data can be obtained by generating the input-output pairs for several realizations, as described in Algorithm 1.

C. Network Architectures and Training

ChannelNet composed of two identical CNNs, each of which is composed of 9 layers as illustrated in Fig. 2. The first layer is the input layer which accepts the received pilot signals. Since the same network is used for both direct and cascaded channels, the size of the input differs as described in Section III-B. The framework with comparison to the state-of-the-art DL-based approaches such as MLP [12] and SF-CNN [10].

Fig. 3. Channel estimation NMSE with respect to SNR.

IV. NumerICAL Simulations

In this part, we evaluate the performance of the proposed ChannelNet framework with comparison to the state-of-the-art DL-based approaches such as MLP [12] and SF-CNN [10]. Throughout the simulations, we select $P = M = 64$, $L = 100$, and $K = 8$. The physical environment is modeled with $N_D = N_A = N_H = 10$ paths, where the direction of users are uniform randomly drawn from the interval $[-\pi, \pi]$. To train the network, we generate different channel scenarios for $U = 100$, $V = 500$ and $K = 8$. During training, three signal-to-noise ratio (SNR) levels are used to improve the robustness, i.e., SNR$\in \{10, 20, 30\}$ dB. In addition, synthetic noise is added to the labels with SNR$_h$ = SNR$_G$ = $\sqrt{M}$ is assumed to be an integer value. If not, a rectangular $X_{\text{DC}}$ can always be constructed without affecting the network training.
SNR on the pilot data $X$, i.e., $\text{SNR}_X$ when $\text{SNR}=0$ dB. We observe that all of the algorithms require at least $\text{SNR}_X \geq 20$ dB to provide a reasonable NMSE performance and the proposed DL approach has the superior performance among all.

V. SUMMARY

We proposed a DL-based channel estimation technique for LIS-assisted massive MIMO systems. In the proposed scheme, each user has an identical deep network which is fed by the received pilot signals to effectively estimate the direct and the cascaded channels. We have shown that the proposed channel estimation approach provides less NMSE and more robust performance against the deviations in the pilot data.

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