Channel Estimation with DnCNN in Massive MISO LEO Satellite Systems

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***Abstract*—In low Earth orbit (LEO) satellite communication systems, obtaining accurate channel state information (CSI) is crucial for achieving high performance. Least squares (LS) channel estimation is a simple conventional channel estimation scheme, but it does not account for compensating for channel estimation errors. In this paper, we propose a channel estimation scheme with a machine learning-based denoising network for massive multiple-input single-output LEO satellite communication systems. Our proposed scheme uses a denoising convolutional neural network to reduce channel estimation errors from the LS estimator. The numerical results demonstrate that our proposed machine learning-based denoising network effectively improves the accuracy of the estimated channel from the LS channel estimator.**

***Index Terms*—Low earth-orbit (LEO) satellite communications, channel estimation, denoising convolutional neural network (DnCNN), massive MISO, machine learning (ML).**

I. Introduction

Low Earth-Orbit (LEO) satellite communication systems are considered a key technology for providing global service coverage in the next generation of wireless communication systems. However, accurately estimating the channel state information (CSI) in LEO satellite communication systems is a challenging task due to many factors such as the long propagation delay and the high mobility [1-2]. While least squares (LS) channel estimation is a simple conventional channel estimation scheme, it does not consider the compensation of channel estimation errors. To reduce the errors in the estimated channel, various techniques, such as machine learning, have been explored. Deep neural networks (DNNs) and convolutional neural networks (CNNs) are commonly used machine learning models for mitigating channel estimation errors. Image denoising machine learning models can also be applied to wireless channel estimation to denoise the estimated channel. However, since wireless channels have complex values, research is underway to modify the structure of image denoising machine learning models to fit wireless channels [3-4]. A promising machine learning model for image denoising in wireless channels is the denoising convolutional neural network (DnCNN), which is considered an important technology in image denoising [3]. In this paper, we propose a channel estimation scheme with a machine learning-based denoising network in massive multiple-input single-output (MISO) LEO satellite communication systems. Our proposed scheme uses a DnCNN to denoise estimated channels from an LS estimator. We evaluate our proposed scheme and show that our machine learning-based denoising network can effectively enhance the accuracy of the estimated channel from the LS estimator.

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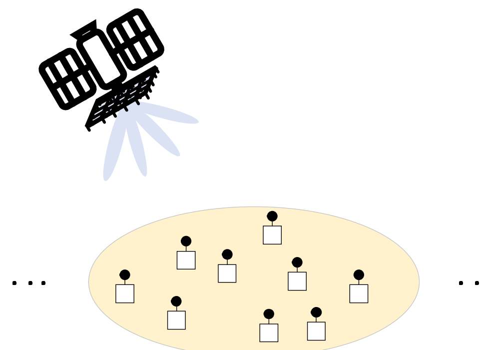

Fig. 1. System model.

II. System Model

Our system model is illustrated in Fig. 1. We consider a massive multiple-input single-output (MISO) low earth-orbit (LEO) satellite communication system. The satellite is equipped with $N_x \times N_y$ uniform planar array (UPA) antennas, where N_x and N_y are the numbers of antennas on the x-axis and the y-axis, respectively.

The satellite serves a single user among the total K single-antenna users within its coverage area in the LEO satellite. Assuming that the carrier frequency is f, the received signal by the satellite from the user k at the time instance t can be modeled by

$$\mathbf{y}_k(t,f) = \mathbf{h}_k(t,f)x_k + \mathbf{n}_k, \tag{1}$$

where $\mathbf{h}_k(t,f) \in \mathbb{C}^{N_x N_y \times 1}$ represents a channel vector from the user k to the satellite, and x_k is the transmitted signal from the user k. Also, $\mathbf{n}_k \in \mathbb{C}^{N_x N_y \times 1}$ is a circularly symmetric complex Gaussian noise at the user k with zero mean and variance σ^2, i.e., $\mathbf{n}_k \sim \mathcal{CN}(0, \sigma^2 \mathbf{I})$. In LEO satellite communication systems, the channel $\mathbf{h}_k(t,f)$ can be expressed with two terms as follows:

$$\mathbf{h}_k(t,f) = \mathbf{h}_k^{\mathtt{LoS}}(t,f) + \mathbf{h}_k^{\mathtt{NLoS}}(t,f), \tag{2}$$

where $\mathbf{h}_k^{\mathtt{LoS}}(t,f) \in \mathbb{C}^{N_x N_y \times 1}$ and $\mathbf{h}_k^{\mathtt{NLoS}}(t,f) \in \mathbb{C}^{N_x N_y \times 1}$ are a line-of-sight (LoS) channel component and a non-line-of-sight (NLoS) channel component, respectively. With the UPA antenna structure, the LoS and the NLoS terms become

$$\begin{aligned}\mathbf{h}_k^{\mathtt{LoS}}(t,f) = &\sqrt{\frac{r_k}{r_k+1}} m_k \exp\left(j2\pi(f_k^{\mathtt{D,LoS}} t - f\tau_k^{\mathtt{LoS}})\right) \\ &\times \mathbf{v}_k(\theta_k^{\mathtt{LoS}}, \phi_k^{\mathtt{LoS}}) \end{aligned} \tag{3}$$

$$\begin{aligned}\mathbf{h}_k^{\mathtt{NLoS}}(t,f) = &\sqrt{\frac{1}{r_k+1}} \sqrt{\frac{1}{L_k}} \sum_{l=1}^{L_k} m_{k,l} \Big\{ \exp\Big(j2\pi(f_{k,l}^{\mathtt{D,NLoS}} t \\ &- f\tau_{k,l}^{\mathtt{NLoS}})\Big) \mathbf{v}_k(\theta_{k,l}^{\mathtt{NLoS}}, \phi_{k,l}^{\mathtt{NLoS}}) \Big\}, \end{aligned} \tag{4}$$

where $r_k \in [0,1]$ is the Rician factor. Also, m_k and $m_{k,l}$ respectively are the complex-valued channel magnitude of the LoS at the user k and the complex-valued channel magnitude of the lth NLoS at the user k. In (3) and (4), $\tau_k^{\mathtt{LoS}}$ and $\tau_{k,l}^{\mathtt{NLoS}}$ are the propagation delay in LoS component and the propagation delay in NLoS component, respectively. Also, $f_k^{\mathtt{D,LoS}}$ and $f_{k,l}^{\mathtt{D,NLoS}}$ represent the relativistic Doppler shift that arises from the movement of both the satellite and the user k in the LoS path and the relativistic Doppler shift that arise from the movement of both the satellite and the user k in the lth NLoS path, respectively. In (4), L_k denotes the number of NLoS paths to the user k. Moreover, in (3) and (4), $\theta_k^{\mathtt{LoS}}$ and $\theta_{k,l}^{\mathtt{NLoS}}$ are the angles of the horizontal of the LoS path and the angles of the horizontal of the lth NLoS path, respectively, and $\phi_k^{\mathtt{LoS}}$ and $\phi_{k,l}^{\mathtt{NLoS}}$ are the vertical directions of the LoS path and the vertical directions of the lth NLoS path, respectively. Therefore, $\mathbf{v}_k(\theta,\phi)$ is the array response vector of the user k, which can be expressed as follows:

$$\mathbf{v}_k(\theta,\phi) = \mathbf{v}_{k,x}(\theta,\phi) \otimes \mathbf{v}_{k,y}(\theta,\phi), \tag{5}$$

where

$$\mathbf{v}_{k,x}(\theta,\phi) \triangleq \sqrt{\frac{1}{N_x}}[1, \exp(-j\vartheta), \dots, \exp(-j(N_x-1)\vartheta)]$$

$$\mathbf{v}_{k,y}(\theta,\phi) \triangleq \sqrt{\frac{1}{N_y}}[1, \exp(-j\vartheta), \dots, \exp(-j(N_y-1)\vartheta)].$$

In the equations above, $\otimes$ represents the Kronecker product, and $\vartheta \triangleq \frac{2\pi d f}{c} \cos\theta \sin\phi$ consists of the antenna spacing d and the speed of light c.

Now, we consider the received pilot signal by the satellite. We denote by $\mathbf{p}_k \in \mathbb{C}^{1 \times N_p}$ the pilot signal from the user k, which is length N_p time symbols such that $\|\mathbf{p}_k\|^2 = 1$, and $\mathbf{p}_i \neq \mathbf{p}_j$ whenever $i \neq j$. Also, for analytical tractability, we assume that the channel $\mathbf{h}_k(t,f)$ is maintained during N_p symbols. Let $\mathbf{Y} \in \mathbb{C}^{N_x N_y \times N_p}$ be the concatenated received signal at the satellite for the user k's pilot transmission. Then, we have

$$\mathbf{Y}_k = \mathbf{h}_k(t,f) \otimes \mathbf{p}_k + \mathbf{N}_k, \tag{6}$$

where $\mathbf{N}_k \in \mathbb{C}^{N_x N_y \times N_p}$ is the concatenated noise signal during the pilot reception. We can obtain the downlink channel by using the conventional least squares (LS) channel estimator. The user k's channel obtained with the LS estimator at the LEO satellite becomes

$$\begin{aligned}\hat{\mathbf{h}}_k^{LS}(t,f) &= \mathbf{Y}_k \mathbf{p}_k^{\dagger} (\mathbf{p}_k \mathbf{p}_k^{\dagger})^{-1} \\ &= \mathbf{Y}_k \mathbf{p}_k^{\dagger} \\ &= \mathbf{h}_k(t,f) + \tilde{\mathbf{n}}_k, \end{aligned} \tag{7}$$

where $\tilde{\mathbf{n}}_k \triangleq \mathbf{N}_k \mathbf{p}_k^{\dagger}$ is the channel estimation error for the user k's channel obtained with the LS estimator. The conventional LS channel estimation scheme does not consider the compensation of the channel estimation errors, so we mitigate the channel estimation error by using the machine learning-based denoising network.

III. Proposed channel estimation with DnCNN

In this section, we explain our proposed channel estimation scheme that reduces the channel estimation error from the LS estimator by using the DnCNN.

A. Basic idea

Fig. 2 illustrates our proposed channel estimation scheme, which aims to eliminate the estimation error present in the channel obtained from the LS estimator on the received signal by using the DnCNN. Therefore, this approach is similar to removing noises present in an image, where DnCNN estimates the channel estimation error $\tilde{\mathbf{n}}_k$ by extracting the features of the channel estimation error $\tilde{\mathbf{n}}_k$ present in the channel obtained using LS estimator $\hat{\mathbf{h}}_k^{LS}(t,f)$. Thus, the channel obtained using the proposed channel estimation scheme is represented as follows:

$$\hat{\mathbf{h}}_k(t,f) = \hat{\mathbf{h}}_k^{LS}(t,f) - \hat{\mathbf{n}}_k, \tag{8}$$

where $\hat{\mathbf{n}}_k$ is the estimation error obtained using DnCNN.

B. Structure of our proposed channel estimation with DnCNN

The proposed machine learning-based denoising model consists of a total of three layers, including an input layer and an output layer. In between the input and the output layers, there are 15 repeated convolutional layers. The input layer employs 64 filters of size $3 \times 3 \times 1$ to generate 64 feature maps, and the output layer adopts 1 filter of size $3 \times 3 \times 64$ to reconstruct the channel matrix. Also, each of the repeated convolutional layers uses 64 filters of size $3 \times 3 \times 64$. In particular, the repeated convolutional layer employs batch normalization (BN) to enhance the learning speed and improve the overall performance. The activation function used here

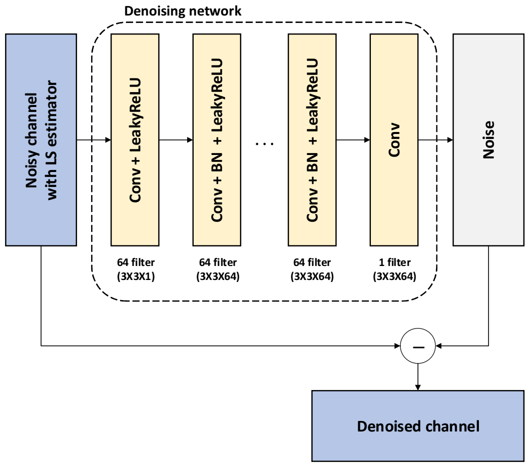

Fig. 2. The proposed channel estimation scheme with DnCNN.

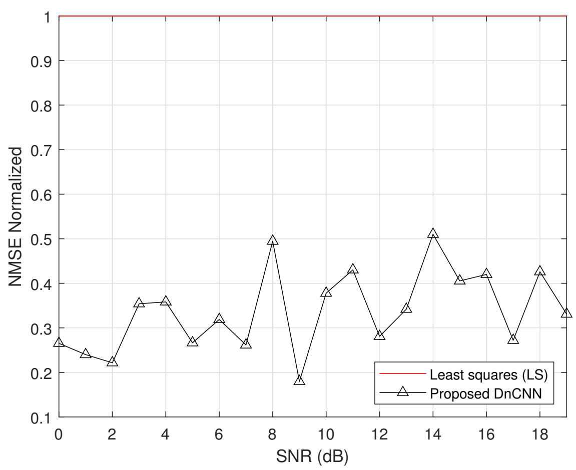

Fig. 3. The NMSE result of DnCNN normalized with the NMSE result of LS.

is the Leaky Rectified Linear Unit (LeakyReLU) function, represented by

$$f(x) = max(\alpha x, x). \tag{9}$$

The classic DnCNN model utilizes the Rectified Linear Unit (ReLU) function as the activation function. However, since the estimation error has a real value, we use the LeakyReLU as the activation function to cover a real value of the channel estimation error from the LS estimator.

IV. Numerical Results

In this section, we evaluate our proposed channel estimation scheme. First, we consider that the value of α at the LeakyReLU function is 0.1. Also, the satellite has 5×5 UPA antenna, and the Rician factors in all user channels are the same with a value of $r_k = 10dB$. Also, we assume that all users have five NLoS paths and that the angles of the horizontal θ, and the vertical directions ϕ of each user's LoS path follow uniformly distributed values in the $[-1, 1]$ range, respectively. Additionally, the evaluation environment is assumed to be completely free of delays and Doppler shifts. To evaluate the performance of our proposed DnCNN model, we compare the normalized mean square error (NMSE) obtained from the channel estimation using only the LS estimator and the NMSE obtained from the channel estimation using both the LS estimator and our proposed DnCNN together. The NMSE used for the evaluation is defined as follows

$$\text{NMSE} = \mathbb{E}\left[\frac{\|\mathbf{h}_k(t,f) - \mathsf{h}\|^2}{\|\mathbf{h}_k(t,f)\|^2}\right], \tag{10}$$

where h denotes the estimated channel with each scheme such that $\mathsf{h} \in \{\hat{\mathbf{h}}_k^{LS}(t,f), \hat{\mathbf{h}}_k(t,f)\}$. We consider that the pilot signal transmitted by each user has unit power, so the signal-to-noise ratio (SNR) can be calculated by

$$\text{SNR} = \frac{1}{\sigma^2}. \tag{11}$$

Fig. 3 shows that the NMSE with our proposed channel estimation scheme with DnCNN normalized with the NMSE result of the LS estimator. As we can see in Fig. 3, the proposed DnCNN model outperforms at low SNR as well as at high SNR.

V. Conclusion

In this paper, we proposed a channel estimation scheme with a machine learning-based denoising network to refine estimated channels from an LS estimator in massive MISO LEO satellite communication systems. In particular, we reduce the channel estimation error from an LS estimator by using DnCNN, which is used to image denoising. Also, we propose a modified DnCNN model that uses the LeakyReLU activation function instead of the ReLU activation function. In numerical results, we showed that our proposed channel estimation scheme with DnCNN can effectively increase the accuracy of the estimated channel from the LS channel estimator.

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