An Improved Deep Learning Network for IRS-Aided Communication with a Residual Carrier Frequency Offset

Muhammad Awais, Mubasher Ahmed Khan, and Yun Hee Kim
Dept. of Electronics and Information Convergence Engineering, Kyung Hee University
{mawais, mubasher, yheekim}@khu.ac.kr

Abstract

This paper aims to provide an accurate cascaded channel estimation method for wireless communication assisted by intelligent reflecting surface (IRS) in the presence of nonlinear residual carrier frequency offset (CFO) impairments at the receiver. A deep denoising network is employed to obtain an estimator outperforming the conventional model for the cascaded IRS channel.

Ⅰ. Introduction

Intelligent reflecting surface (IRS) is a promising but a key challenge in achieving the full potential of IRS is the acquiring of accurate channel state information (CSI) which becomes more challenging in the presence of nonlinear impairments. In our previous work in [1], we considered residual CFO impairments in estimating CSI but an improved network can be used to enhance performance. Our previously enhanced convolutional deep residual network (ECDRN) [2] to estimate CSI was optimized for nonlinear power amplification. However, ECDRN has not been deployed for other nonlinear impairments therefore, in this paper, we aim to utilize ECDRN in presence of CFO impairments at the receiver and compare performance with traditional methods.

Ⅱ. Signal Model

A MISO communication system model as presented in [1] consisting of a M base station (BS) antennas and N IRS elements is considered. Single user transmits T pilot symbols for estimation of CSI. therefore received signal at the BS without distortion for the lth time can be written as

$$\boldsymbol{y}_l = \boldsymbol{G}\ \mathrm{diag}(\boldsymbol{f})\boldsymbol{\phi}_l + \boldsymbol{w}_l, \qquad l = 1,2,\cdots,N \tag{1}$$

where $\boldsymbol{G}$ is the BS-IRS channel, and $\boldsymbol{f}$ is the IRS-user channel, $\boldsymbol{w}_l \in (0, \sigma^2 \boldsymbol{I}_M)$ is the AWGN noise, and $\boldsymbol{\phi}_l = \left[e^{j2\pi\theta_{l,1}},\ldots,e^{j2\pi\theta_{l,N}}\right]^T$ is the phase shift vector at the lth training time. We consider a residual CFO $\epsilon \in [-\Delta, \Delta]$ impairments in $\boldsymbol{y}_l$, then our signal becomes

$$\hat{\boldsymbol{y}}_l = e^{j2\pi\epsilon(l-1)}\boldsymbol{G}\ \mathrm{diag}(\boldsymbol{f})\boldsymbol{\phi}_l + \boldsymbol{w}_l, \tag{2}$$

Writing equation (2) in matrix form we get

$$\boldsymbol{Y} = (\boldsymbol{\Xi}(\epsilon) \circ \boldsymbol{H})\boldsymbol{\Phi} + \boldsymbol{W} \tag{3}$$

where $\boldsymbol{\Xi} = [1\ e^{j2\pi\epsilon}\ \cdots\ e^{j2\pi(T-1)\epsilon}] \otimes 1_{M\times 1}$, $\boldsymbol{H} = \boldsymbol{G}\,\mathrm{diag}(\boldsymbol{f})$ is the cascaded channel, $\boldsymbol{\Phi} = [\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots, \boldsymbol{\phi}_N]$ are the orthogonal phase shift matrices subject to $\boldsymbol{\Phi}\boldsymbol{\Phi}^H = \boldsymbol{I}_T$, and $\boldsymbol{W} \in C^{M\times T}$ is the noise matrix. The least square (LS) estimator of the channel is given by

$$\widehat{\boldsymbol{H}}_{ls} = \boldsymbol{Y}\boldsymbol{\Phi}^H(\boldsymbol{\Phi}\boldsymbol{\Phi}^H)^{-1}. \tag{4}$$

Ⅲ. Deep Learning Network Based Channel Estimation

We apply our proposed ECDRN [2] which consists of D residual blocks (RBs). The input to the ECDRN network is the LS estimate with dimensions $N_x \times N_y$ from Eq. (4) with the real and imaginary parts as different input channels. The input is first passed through a 2D convolution (Conv2D) layer followed by ReLU activation. It is then forwarded to RBs connected in series. Each RB consists of two Conv2D followed by batch normalization (BN) and ReLU and one last Conv2D layer. The output of this last Conv2D layer is subtracted from the input of the RB and output of each RB is forwarded to the next RB as input. The ECDRN network is trained to minimize the loss function $L(\Theta)$ for the training data set $\left\{(\boldsymbol{H}^{(i)}, \widehat{\boldsymbol{H}}_{ls}^{(i)})\right\}_{i=1}^{S_t}$ defined by the mean square error (MSE) as

$$L(\Omega) = \frac{1}{S_t}\sum_{i=1}^{S_t}\left\|\boldsymbol{H}^{(i)} - F(\widehat{\boldsymbol{H}}_{ls}^{(i)};\Omega)\right\|^2 \tag{5}$$

where Ω are the learning parameters and S_t is total training samples.

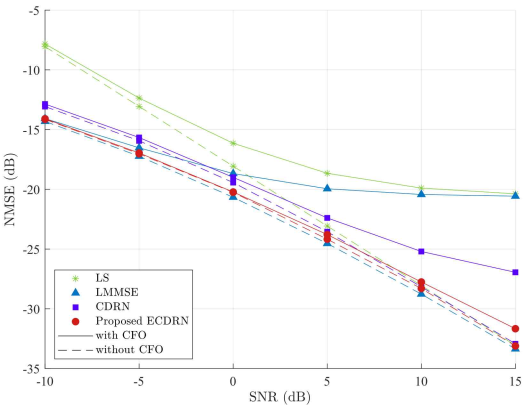

Fig. 1. Normalized MSE of the channel estimates vs SNR

The proposed ECDRN network has been tested against different parameters. to obtain the optimal performance and as in Fig. 1 has shown improvement compared to the LS, linear minimum mean square error (LMMSE), and original CDRN in presence of CFO.

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References

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