Deep Denoising Channel Estimation for IRS-Aided Communication with a Receiver Nonlinearity

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Abstract

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

Ⅰ. Introduction

Intelligent reflecting surface (IRS) has been shown to be a key enabling technology for beyond 5G communications [1]. To properly realize the gain promised by IRS, it is imperative to obtain complete and accurate channel state information (CSI). Presence of noise and nonlinearity at the receiver makes acquisition of this information a non-trivial task. The authors in [2] have employed a CNN-based deep residual network (CDRN) to estimate the cascaded channel of a user to IRS and IRS to base station (BS) with a carrier frequency offset at the receiver. This paper extends the work to improve the used deep learning network and cope with the effect of nonlinear power amplification (PA) at the receiver.

Ⅱ. Signal Model and Channel Estimation

A MISO communication network as presented in [2] is considered. The cascaded channel is estimated using pilot symbols transmitted by user for T times. The received signals at the BS for the lth time without distortion can be written as

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

where $\boldsymbol{G}$ is the IRS to BS channel, and $\boldsymbol{f}$ is the user to IRS Channel, $\boldsymbol{w}_l$ is the AWGN noise vector, and $\boldsymbol{\phi}_l = \left[e^{j2\pi\theta_{l,1}},...,e^{j2\pi\theta_{l,N}}\right]^T$ is the phase shift vector at the lth training time. This signal in matrix form is given by

$$\boldsymbol{Y} = \boldsymbol{H}\boldsymbol{\Phi} + \boldsymbol{W} \tag{2}$$

where $\boldsymbol{\Phi} = \{\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, ..., \boldsymbol{\phi}_T\}, T \ge N$ are the orthogonal phase shift vectors, $\boldsymbol{H} = \boldsymbol{G}\,\mathrm{diag}(\boldsymbol{f})$ is the cascaded channel and $\boldsymbol{W}$ is the noise matrix. Due to the presence of PA at the receiver, the received signal becomes

$$[\boldsymbol{Z}]_{nm} = f_{dist}([\boldsymbol{H}\boldsymbol{\Phi} + \boldsymbol{W}]_{nm}) \tag{3}$$

where the $f_{dist}(x)$ is implemented for each element and is defined by

$$f_{dist}(x) = x\left(1 + \left(\frac{x}{x_{sat}}\right)^{2\omega}\right)^{-\frac{1}{2\omega}} \tag{4}$$

where ω is the smoothing factor between linear and saturation areas and x_{sat} is the level of saturation of the inputs. The least square (LS) estimator $\widehat{\boldsymbol{H}}_{ls}$ of the cascaded channel is

$$\widehat{\boldsymbol{H}}_{ls} = \boldsymbol{Z}\boldsymbol{\Phi}^H(\boldsymbol{\Phi}\boldsymbol{\Phi}^H)^{-1} \tag{5}$$

As $\boldsymbol{\Phi}$ is orthogonal, it results in $\boldsymbol{\Phi}\boldsymbol{\Phi}^H = \boldsymbol{I}_N$.

Ⅲ. Denoising Based Channel Estimation

The authors in [2] applied a CDRN to estimate the channel. We apply our Enhanced CDRN (ECDRN) shown in Fig. 1 that consists of D residual blocks (RBs). The input to the network is the noisy LS estimate in Eq (5) with the real and imaginary parts as two input channels for the ECDRN. The input is first passed through a convolution layer followed by ReLU activation. It is then processed by D subsequent RBs. Each RB consists of two subsequent 2D convolutional layers each followed by Batch Normalization (BN) and ReLU and one final 2D convolution layer. The output of this last Conv2D layer is subtracted from the input of the RB and the result is passed on to the next RB as input. The network is trained to minimize the loss function $L(\boldsymbol{\Theta})$ for the training data set $\left\{(\boldsymbol{H}^{(i)}, \widehat{\boldsymbol{H}}_{ls}^{(i)})\right\}_{i=1}^{I_t}$ defined by the mean square error (MSE) as

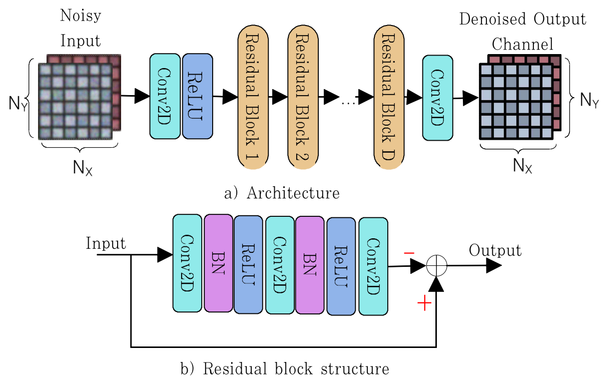

Fig. 1. Enhanced CDRN network architecture with residual blocks

$$L(\boldsymbol{\Theta}) = \frac{1}{I_t}\sum_{i=1}^{I_t}\left\|\boldsymbol{H}^{(i)} - D(\widehat{\boldsymbol{H}}_{ls}^{(i)}; \boldsymbol{\Theta})\right\|^2 \tag{6}$$

where $\boldsymbol{\Theta}$ are the learning parameters. The network has been tested against different number of layers and feature maps to obtain the most optimal performance and has shown improvement compared to the original CDRN.

Acknowledgements

This work was supported by the Ministry of Science and ICT, South Korea, in part through the National Research Foundation of Korea (NRF) under Grant NRF-2021R1A2C1005869 and in part through the Institute for Information & Communications Technology Planning & Evaluation (IITP) under the Information Technology Research Center Support Program under Grant IITP-2021-0-02046.

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