Online Adaptive Channel Denoising Methods for MIMO-OFDM Systems

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MIMO-OFDM 시스템을 위한 온라인 적응형 채널 잡음 제거 방법

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Abstract

This paper presents online adaptive channel denoising methods for multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems. To facilitate channel denoising that matches with current channel environments, we develop an online training data generation technique by leveraging data-aided channel estimation. We then propose two approaches, adaptive filter (2D Wiener filter and extreme learning machine) and deep learning (denoising neural network with a hybrid training strategy) are proposed for channel denoising. Using simulations, we demonstrate the superiority of the proposed channel denoising methods in mitigating channel estimation errors.

Ⅰ. Introduction

Multiple-input multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) communication is one of the core technologies in modern wireless standards. A key requirement for maximizing the performance is accurate channel state information at a receiver (CSIR). To meet this requirement, 5G adopts channel estimation based on demodulation-reference signal (DM-RS), inserted in a partial set of resource elements. Unfortunately, channel estimation error is inevitable not only due to a limited number of DM-RSs but also from channel selectivity in both time and frequency domain. A representative approach for mitigating channel estimation errors in the DM-RS channel estimation is to denoise channel estimates by utilizing time-frequency channel correlations. Most conventional channel denoising methods require prior knowledge about time-frequency channel correlations [1] or sufficient training data that matches true channel distributions [2]. These requirements, however, may not be met in practical communication systems due to the highly unpredictable and diverse nature of wireless channel environments. To address these limitations, in this work, we propose online adaptive channel denoising methods that can learn about the current channel environment based on online training data. To this end, we develop a practical strategy to generate online training data with the aid of data-aided channel estimation. We then propose two approaches, adaptive filter and deep learning, to design channel denoising methods utilizing online training data.

Ⅱ. Proposed Method

We consider a MIMO-OFDM system with N_t transmit antennas and N_r receive antennas. Information bits are mapped to a symbol vector $\mathbf{x}[n,k] \in \mathcal{X}^{N_t}$ where $\mathcal{X}$ is a constellation set and transmit symbol power is normalized such that $\mathbb{E}[|x_i[n,k]|^2] = 1$. The received symbol vector at the k-th subcarrier of the n-th OFDM symbol is given by

$$\mathbf{y}[n,k] = \mathbf{H}[n,k]\mathbf{x}[n,k] + \mathbf{v}[n,k], \quad (1)$$

where $\mathbf{H}[n,k] \in \mathbb{C}^{N_r \times N_t}$ is a channel frequency response (CFR) matrix and $\mathbf{v}[n,k] \sim \mathcal{CN}(0, \sigma^2\mathbf{I})$ is a circularly symmetric complex Gaussian noise with variance σ^2. A typical channel estimation method involves two procedures: estimating the CFRs where the DM-RSs are located and then interpolating the estimated CFRs for the remaining locations. Since the number of DM-RSs is limited, the channel estimate determined using the DM-RSs is *noisy*. We focus on denoising these noisy channel estimates through the development of online adaptive channel denoising methods.

ⅰ. Generating Online Training Data

A key to designing online adaptive channel denoising methods is to generate online training data that not only captures the distributions of initial channel estimation errors but also provides knowledge about time-frequency domain channel correlations for the current channel environment. However, obtaining perfect knowledge of true CFRs, which serve as *labels* for online training data, is unfeasible at the receiver. To overcome this challenge, we leverage data-aided channel estimation, which improves channel estimation performance by utilizing detected data symbols as additional DM-RSs. Motivated by the fact that data-aided channel estimation provides *high-quality* channel estimates, we utilize these estimates as true labels for online training data.

ⅱ. Channel Denoising Methods

We propose two channel denoising methods based on 2D Wiener filter and extreme learning machine approaches. The common strategy of these methods is to determine a denoise channel estimate as a linear or non-linear combination of the adjacent noisy estimates in a pre-defined time-frequency window. Let $\hat{\mathbf{h}}[n,k] = [\hat{h}[n-p,k-q],\cdots,\hat{h}[n,k]]^T$ be a vector that consists of the noisy estimates adjacent to target CFR $\hat{h}[n,k]$, where $\hat{h}[n,k]$ be the (r,t)-th entry of $\mathbf{H}[n,k]$. In the Wiener filter-based method, we aim at minimizing the MSE by solving the following problem:

$$\boldsymbol{\alpha} = \text{argmin}_{\boldsymbol{\alpha}} \mathbb{E}[|h[n,k] - \boldsymbol{\alpha}^T \hat{\mathbf{h}}[n,k]|^2]. \quad (2)$$

Then the Wiener filter coefficient is given by

$$\boldsymbol{\alpha}^T = \boldsymbol{\theta}\boldsymbol{\Phi}^{-1}, \quad (3)$$

where $\boldsymbol{\theta} = \mathbb{E}[h[n,k]\hat{\mathbf{h}}^{\mathrm{H}}[n,k]]$ is a cross-covariance vector and $\boldsymbol{\Phi} = \mathbb{E}[\hat{\mathbf{h}}[n,k]\hat{\mathbf{h}}^{\mathrm{H}}[n,k]]$ is an auto-covariance matrix. We empirically compute both $\boldsymbol{\theta}$ and $\boldsymbol{\Phi}$ using the online training data. For ELM-based method, approximating zero error between the output and the target implies that $\sum_{j=1}^{N} ||\sum_{i=1}^{\tilde{N}} \beta_i \left(\mathbf{w}_i^T\hat{\mathbf{h}}_j + b_i\right) - \bar{h}_j|| = 0$, then the output of ELM with $\tilde{N}$ hidden nodes and activation function $g(\cdot)$ is given by

$$\sum_{i=1}^{\tilde{N}} \beta_i g\left(\mathbf{w}_i^T\hat{\mathbf{h}}_j + b_i\right) = \bar{h}_j,\ j = 1,\ldots,N, \quad (4)$$

where $\mathbf{w}_i$ is the weight vector, which connects the i-th hidden node to the input nodes, β_i is the weight connecting the i-th hidden node and the output nodes, and b_i is the bias of the i-th hidden node. Then the equation (4) with N samples can be written as $\mathbf{L}\boldsymbol{\beta} = \bar{\mathbf{h}}_{tr}$. Training an ELM is equivalent to seeking a least squares solution, denoted as $\hat{\boldsymbol{\beta}}$ is given by

$$\hat{\boldsymbol{\beta}} = \mathbf{L}^{\dagger}\bar{\mathbf{h}}_{tr} \quad (5)$$

where $\mathbf{L}^{\dagger}$ is pseudo inverse of $\mathbf{L}$. In the proposed method with the deep learning approach, we employ a denoising neural network called DnCNN. The input to DnCNN consists of the entire set of noisy channel estimates $\hat{\mathbf{H}}$, while the output is the denoised channel estimates $\bar{\mathbf{H}}$ with the same dimensions as the input. The denoising operation is expressed as

$$\bar{\mathbf{H}} = f(\hat{\mathbf{H}};\theta_{DL}) \quad (6)$$

where $f(\cdot)$ is the DnCNN function and θ_{DL} is the set of parameters for DnCNN. To train DnCNN, we adopt a hybrid training strategy, which involves offline and online training phases. During the offline training phase, we consider various channel environments to train the deep learning model for channel denoising in general environments. In the online training phase, we update DnCNN using the online training data generated during the training period, enabling online adaptation of DnCNN based on the current channel environments. The MSE loss function is utilized in both training phases.

In simulation, we consider a MIMO-OFDM system with 3.5GHz center frequency, 15-kHz subcarrier spacing, and 1024 subcarriers. We assume that $N_t = 2$, $N_r = 64$, and 4-QAM symbol mapping. The training period set as $T = \{5, 10\}$ slots in the time domain. Channel impulse responses are modeled as Rayleigh fading channels with a specific power delay profile. To model time-varying channels, the Gauss-Markov process is adopted with a temporal correlation coefficient. For the proposed adaptive filters, the size of the time-frequency window is set to (3×3). For offline training of DnCNN, data samples are generated from the following three scenarios: (PDP, Rx speed)∈{(EPA,3), (EVA,120), (ETU,300)}. The linear MMSE method is employed for both DM-RS channel estimation and symbol data detection.

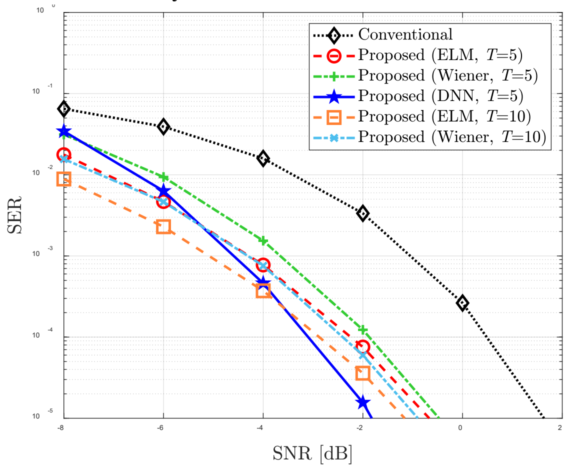

Fig. 1. SER comparison between the proposed channel denoising and conventional channel estimation methods

Fig. 1 compared the performance of the proposed channel denoising methods and conventional channel estimation method under EPA with the Rx speed of 3km/h. The figure shows that all the proposed methods significantly enhance the detection performance compared to the conventional method by providing more accurate channel estimates through channel denoising. Both adaptive filter-based methods exhibit similar performance, and their performance increases with longer training periods. The deep learning-based method provides an additional performance gain over the adaptive filter-based methods, demonstrating the effectiveness of DnCNN trained with our hybrid training strategy.

Ⅲ. Conclusion

In this paper, we have presented online adaptive channel denoising methods for MIMO-OFDM systems in doubly selective channels. Our objective is to design channel denoising methods that match the current channel environments. To this end, we have developed an online training data generation technique that employs data-aided channel estimates as labels. Then, we have designed channel denoising methods to utilize the online training data based on either adaptive filters or deep learning. Through simulation, it has been proven that the proposed channel denoising methods significantly enhance the performance of conventional DM-RS-based channel estimation.

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