Time-Domain Equalizer Using Neural Network Without Known Training Signals for OFDM Systems Without CP

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1. Introduction

Recently, machine learning has been applied to various problems in wireless physical layer [1]. In [2], an extreme learning machine (ELM)-based signal detector for OFDM systems has been proposed. The ELM-based detector is designed by online training using the received samples obtained through only a current channel. It is reported that the detector is superior to the deep neural network (DNN)-detector in [3] designed by pre-training using samples generated by a channel model. However, the ELM-detector requires to transmit enormous known signals for online training. In this article, we propose a novel time-domain equalizer (TEQ) using an online-trained neural network (NN) for OFDM systems without cyclic prefix (CP). Unlike [2], the proposed TEQ requires no transmission of known signals for online training.

2. Proposed Time-Domain Equalizer

We consider an OFDM system with *N* subcarriers. Data symbols s_k are grouped into a data block $\mathbf{s}_n \in \mathbb{C}^N$. At the transmitter with a single antenna, a time-domain signal of the *n*th block obtained by *N*-point inverse discrete Fourier transform (IDFT) of \mathbf{s}_n is transmitted, $\mathbf{x}_n = \mathbf{F}^H \mathbf{s}_n = [x_{nN} \ x_{nN-1} \ \cdots \ x_{nN-(N-1)}]^T \in \mathbb{C}^N$ where **F** is the DFT matrix. We assume that the desired signal is x_{k-d} , where *d* is an arbitrary decision delay.

At the receiver with N_r antennas, the proposed TEQ uses L_w successive received samples $\mathbf{r}_k = \mathbf{h}_d x_{k-d} + \check{\mathbf{H}}\check{\mathbf{x}}_k + \mathbf{n}_k \in \mathbb{C}^{N_r L_w}$, where \mathbf{h}_d is the (d + 1)th column vector of the current channel matrix $\mathbf{H} \in \mathbb{C}^{N_r L_w \times (L_w + L_h)}$, $\check{\mathbf{H}}$ is a matrix removed \mathbf{h}_d from \mathbf{H} , $\check{\mathbf{x}}_k$ is a transmitted signal vector, \mathbf{n}_k is a Gaussian noise vector. The purpose of the proposed TEQ is to detect x_{k-d} from \mathbf{r}_k by suppressing interference and noise components. This article assumes that the receiver obtains \mathbf{H} by blind channel estimation.

In the proposed TEQ, the input signal \mathbf{r}_k is processed in two parts. First, the maximum ratio combining is performed as $u_k = \mathbf{h}_d^H \mathbf{r}_k = \|\mathbf{h}_d\|^2 x_{k-d} + \mathbf{h}_d^H \check{\mathbf{H}} \check{\mathbf{x}}_k + \mathbf{h}_d^H \mathbf{n}_k$. Second, the desired signal is removed as $\check{\mathbf{r}}_k = \mathbf{H}_d^\perp \mathbf{r}_k = \mathbf{H}_d^\perp \check{\mathbf{H}} \check{\mathbf{x}}_k + \mathbf{H}_d^\perp \mathbf{n}_k$, where $\mathbf{H}_d^\perp = \mathbf{I}_{N_r L w} - \mathbf{h}_d \mathbf{h}_d^H / \|\mathbf{h}_d\|^2$ is orthogonal to \mathbf{h}_d , and \mathbf{I} is the identity matrix. Then the processed signal $\check{\mathbf{r}}_k$ is fed into a NN $F(\cdot)$ with adjustable parameters \mathbf{w} . The output of NN is $z_k = F(\check{\mathbf{r}}_k; \mathbf{w})$. The TEQ output is given by $y_k = u_k - z_k$, and $\tilde{y}_k = y_k / \|\mathbf{h}_d\|^2$ are grouped into a block $\tilde{\mathbf{y}}_n$. Finally, DFT



is applied, and the estimated block \hat{s}_n can be obtained by the hard-decision of $\tilde{\mathbf{Y}}_n = \mathbf{F} \tilde{\mathbf{y}}_n$.

Note that the desired signal in y_k is never affected by NN because z_k contains only the interference and noise components. Thus, the NN is trained by minimizing $J(\mathbf{w}) = |y_k|^2$, and the TEQ can suppress interference and noise while the desired signal component is kept unchanged. In the proposed TEQ, no known training signals are required to train the NN.

3. Simulation Result

In the simulation, the order of the CIR was $L_h = 8$, N = 64, $N_r = 2$, $L_w = 45$, and $d = \lfloor (L_w + L_h)/2 \rfloor$. We used a NN with three full-connected layers, and the activation function is ReLU. The optimizer was the Adam optimizer with the learning rate of 5×10^{-5} . Figure 1 shows the BER performance as a function of the number of training blocks, where SNR is 40 dB. Unlike a constrained linear MMSE-TEQ, the BER of the proposed TEQ decreases without known training signals as the number of training blocks increases. The computational complexities per block required by the proposed TEQ, [3], and [2] are about 1×10^7 , 3×10^6 , and 3×10^5 real multiplications, respectively.

4. Conclusion

We proposed a novel TEQ using NN without known signals for online training for OFDM systems without CP.

References

- Q. Mao, et al., "Deep Learning for Intelligent Wireless ...," IEEE Commun. Survey Tuts., vol. 20, no. 4, pp. 2595–2621, Jun. 2018.
- [2] J. Liu, et al., "Online Extreme Learning Machine-Based ...," IEEE Commun. Lett., vol. 23, no. 7, pp. 1276–1279, Jul. 2019.
- [3] H. Ye, et al., "Power of Deep Learning ...," IEEE Wireless Commun. Lett., vol. 7, no. 1, pp. 114–117, Feb. 2018.

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