Computationally Efficient Pre-Distortion based on Adaptive Partitioning Neural Network in Underwater Visible Light Communication

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Abstract: We proposed a computationally efficient pre-distortion scheme based on adaptive partitioning neural network to mitigate nonlinear impairments in high-speed UVLC system. We demonstrated a 56.3% computational complexity reduction in 2.85Gbit/s 64QAM-CAP UVLC system. © 2022 The Author(s)

1. Introduction

Underwater exploration has always been an extreme temptation for human worldwide. Underwater visible light communication (UVLC) technique with blue-green visible light (450~550nm) has drawn growing attention in recent years, as it has the unparalleled potentials of providing higher speed and lower latency [1]. Advanced modulation formats such as carrierless amplitude and phase modulation (CAP) with M-order quadrature amplitude modulation (M-QAM) have also been utilized to enhance UVLC system performance [2]. Nonetheless, maintaining high-speed UVLC system is still challenging. Both the rapid attenuation effect from the harsh underwater channel and the nonlinear response from the imperfect optoelectronic components (including the light source, electrical amplifier, photodetector, etc.), would seriously degenerate the system performance. To alleviate these detrimental effects, digital pre-distortion algorithms have been proposed. The traditional lookup table (LUT) algorithm has the limitations of geometrically increasing computational complexity when high-order modulation formats are considered [3]. Recently, neural network (NN) has been demonstrated to be an attractive solution for nonlinear distortion mitigation in optical communication [4]. Several NN based pre-distortion schemes at transmitter have been applied to boost the system performance improvements [5, 6]. However, one deficiency of using NNs is that their huge computational budgets would limit their application scenarios, especially in resource-constrained system.

In this paper, we proposed and demonstrated a computationally efficient pre-distortion scheme based on adaptive constellation partitioning complex-valued neural network (PD-PCVNN). The method is inspired by the prior understanding about the nonlinear response of UVLC system, which is that the symbols locating in the outer region of the constellation suffer far more nonlinear distortion than those locating in the inner region [7]. Therefore, we separate the transmitted symbols in constellation into two partitions according to the levels of distortion at receiver adaptively, and pre-distort two partitions by two small-size neural networks. Finally, a 64QAM-CAP UVLC system utilizing PD-PCVNN based pre-distorter with up to 56.3% computational complexity reduction and BER below the 7% hard-decision forward error correction (HD-FEC) limit of 3.8×10^{-3} at 2.85Gbit/s are experimentally demonstrated, strongly verifying the feasibility of the proposed computationally efficient pre-distortion scheme.

2. Principle

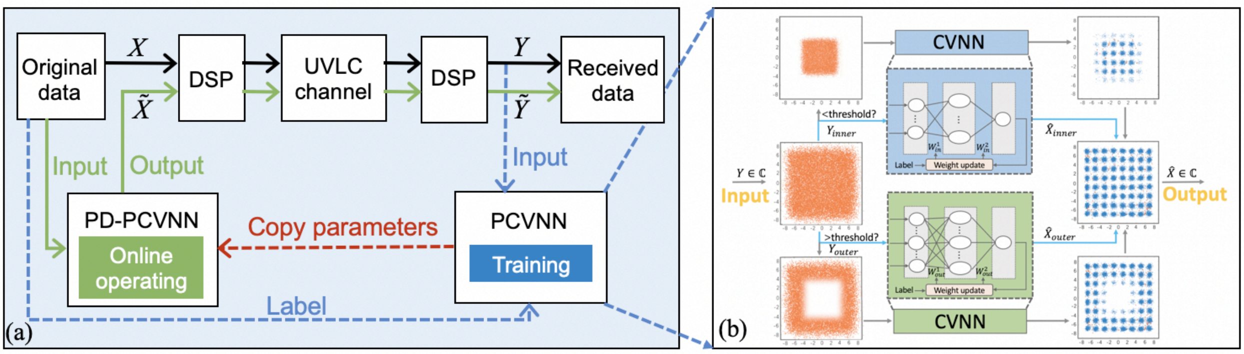

Fig. 1. Schematic diagram of the proposed method. (a) pipeline of PD-PCVNN based pre-distortion scheme. (b) diagram of constellation partition of PCVNN.

The schematic diagram of the proposed method is illustrated in Fig.1. We depict in Fig.1(a) the pipeline of PD-PCVNN based pre-distortion scheme, including the training phase and the online operation phase. In the training phase, our previous proposed post-equalizer PCVNN [7] is used to learn the inverse channel response, as shown in the Fig.1(b). The input of PCVNN is the received QAM symbol sequences $Y=[y_1,y_2,\cdots,y_n]$. Then the received QAM symbols are separated into two partitions according to their locations in constellation by a threshold with rectangular shape. The value of threshold is adaptively determined by the level of nonlinear distortion after linear equalization. After that, the two partitions are sent into two different complex-valued NNs as there are real and imaginary components for QAM symbols. Complex ReLU activation function is used to activate the complex-valued layers. The loss function is the mean square error (MSE) of the modulus of error vector between the predicted output and the original signal. The back propagation process based on the principle of complex chain rule is performed for tuning the networks.

Then the trained hyperparameters of PCVNN are copied at the trasmitter to build the pre-distored PCVNN (PD-PCVNN). Subsequently, the original QAM symbols $x(n)$ are sent into the PD-PCVNN to obtain the pre-distorted symbols $\hat{x}(n)$. It is worth to note that imcomplete pre-distortion has better performance gain than complete pre-distortion [8]. The final output of the pre-distorted symbols are expressed as

$$\tilde{x}(n)=x(n)+w\times(\hat{x}(n)-x(n)) \tag{1}$$

where w is the weighting parameter to control the level of pre-distortion. Then the pre-distorted symbols are prepared for transmitting though the UVLC system.

3. Experimental setup

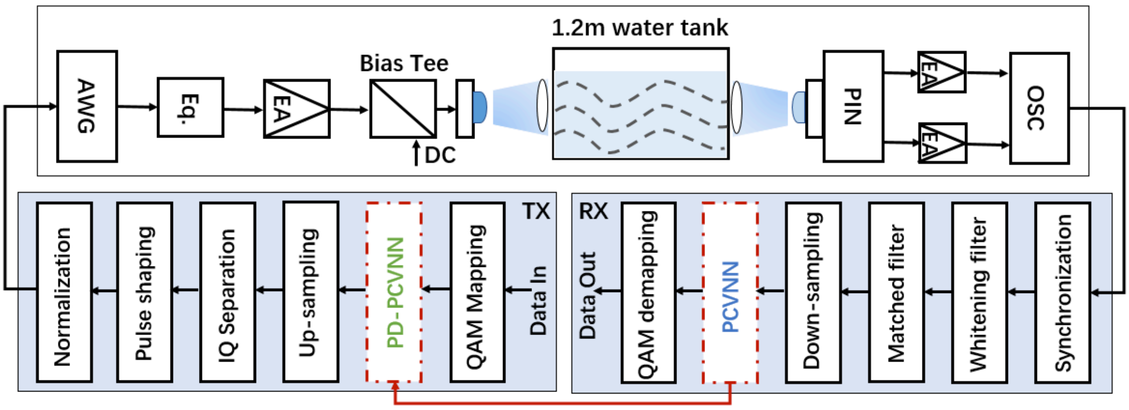

Fig. 2. Experimental setup of UVLC system with pre-distortion.

Figure 2 illustrates the block diagram of the PD-PCVNN based UVLC system in our experiments. At the transmitter, the original binary signal is firstly mapped to 64QAM symbols. Then the symbols are pre-distorted by the trained PD-PCVNN. After four times of up-sampling, the pre-distorted symbols are up-converted by pulse shaping filters to obtain CAP signal. Subsequently, the normalized offline generated signal is sent to the arbitrary waveform generator (AWG). Then after through a fixed pre-equalization circuit and electrical amplifier circuit, the electrical signal is coupled with bias current through bias tee to drive the blue LED.

After 1.2m water tank transmission, the light signal arrives at the receiver. A commercial PIN is used to convert the light signal into electrical signal. The received electrical signal is sampled by the oscilloscope (OSC) and sent for further offline DSP processing. The received signal is synchronized first and processed with a LMS based linear filter. Then the signal is down-sampled to 1 sample per symbol after the matched filtering and down-conversion. Afterwards, we enter the training phase and train the PCVNN with processed data. The network structure for equalizing the received symbols located in the inner constellation contains 21 input taps, 8 neurons in the hidden layer and 1 output neuron. Whereas, the network structure for equalizing the outer symbols has 23 input taps, 25 neurons in the hidden layer and 1 output neurons. As a contrary, when using a traditional CVNN, the optimized structure contains 25 input taps, 45 nodes in hidden layer and 1 output node by trail. Finally, the received signal is de-mapped to binary data and bit error rate (BER) is calculated to evaluate the system performance.

4. Results and discussion

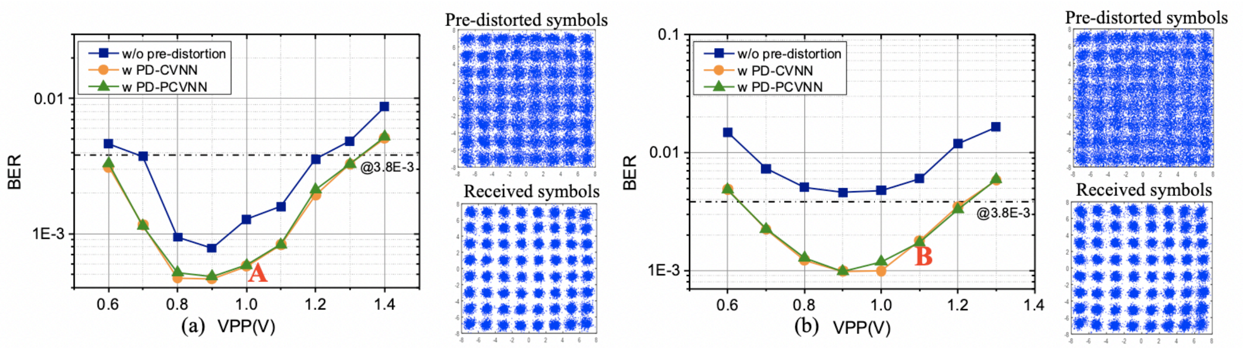

Fig. 3. BER versus different Vpp with data rates of (a) 2.7Gbps and (b) 2.85Gbps.

In this section, we compare the performance of PD-PCVNN and PD-CVNN to validate the computational efficiency of the proposed scheme. Since the training sessions of networks are done, the networks are ready to pre-distort the original symbols. The parameter w in Eq.1 are set to 0.2 in the following experiments. In Fig.3, we illustrate BER with different Vpp at two different data rates. Higher data rate would bring more distortion. Therefore, the partition threshold in is set at 5 for 2.7Gbps case and 4 for 2.85Gbps case, respectively. It is observed that PD-PCVNN achieves similar performance compared with PD-CVNN at both data rates. We also show the constellations of the original symbols pre-distorted by PD-PCVNN and the received symbols after transmission.

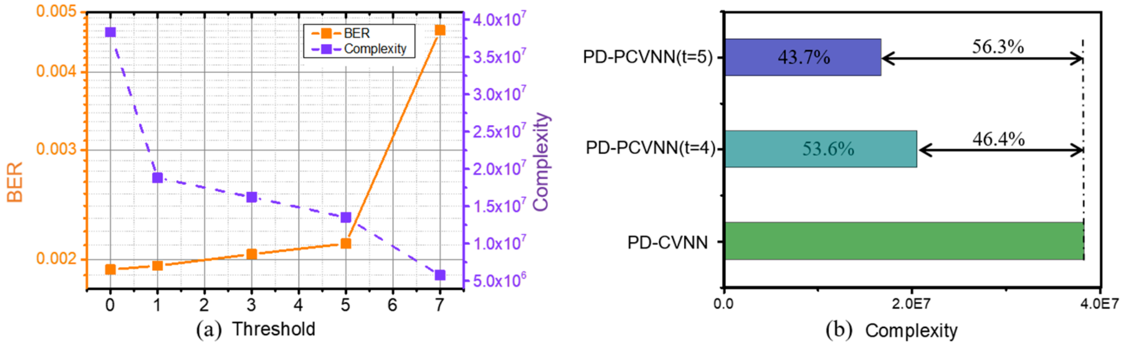

Fig. 4. (a) BER and complexity versus different thresholds. (b) Complexity comparison of PD-PCVNN and PD-CVNN.

We next analysis the reasonability of partitioning network for pre-distortion. In Fig.4 (a), we show the BER and complexity versus different thresholds of PD-PCVNN at 2.7Gbps with 1.2Vpp. We also provide the computational complexity by counting the number of multiplication operations. As the threshold increases, more symbols are divided into the inner partitions, causing a reduction of the total computation complexity. Meanwhile, smaller network size means that it has limited ability to learn the inverse channel response, which may leads to higher BER. However, we see that the BER performance changes slowly before threshold arrives at 5, while the complexity decreases rapidly. Therefore, by properly setting the threshold of PD-PVCNN, we successfully reduce the computational complexity without deteriorating the system accuracy. We further compare the computational complexity of PD-PCVNN and PD-CVNN in Fig.4 (b). PD-PCVNN reaches a complexity reduction of 46.4% and 56.3% when the threshold is set at 4 and 5, which can greatly enhance the practicability of pre-distortion scheme.

5. Conclusion

A computationally efficient pre-distortion scheme based on adaptive constellation partitioning neural network to mitigate nonlinear distortion is proposed for high-speed UVLC system. The proposed method can maintain system performance while reduce the total complexity by up to 53.6% of traditional pre-distortion network.

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6. References

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