Learning-Assisted Receiver for ACO-OFDM with Device Imperfections

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***Abstract*—Visible light communication (VLC) has been regarded as an emerging technology to satisfy the ever-increasing demand of ultra-high-speed wireless communications. To guarantee the transmission efficiency, asymmetrically clipped optical-orthogonal frequency division multiplexing (ACO-OFDM) has been adopted. However, adversely effected by the device imperfections, which include the nonlinearity of light emitting diode and low-resolution quantization of analog-to-digital converter, the demodulation performance of ACO-OFDM receiver is limited. To tackle this problem, a learning-assisted receiver is designed, where convolutional neural network (CNN) is adopted to demodulate the received signal with distortion. More specifically, the received signal before fast Fourier transform (FFT) is input into the convolutional layer, which is helpful to exploit the signal feature even under device imperfections. Then, the demodulation is modeled as a classification problem, where the output of CNN is the demodulation likelihood information. Simulation results show that our proposed CNN can recovery information from the distorted signal, and improves the demodulation performance significantly.**

***Index Terms*—Visible light communication, ACO-OFDM, device imperfections, convolutional neural network**

I. Introduction

With the ever-increasing growth of ultra-high data throughout demand, visible light communication (VLC) has been regarded as a potential technique to provide abundant bandwidth over unlicensed spectrum [1]. Benefited from its cost efficiency, anti-electromagnetic interference, environment friendliness, and high security, VLC shows to be a promising supplement to the conventional radio frequency (RF) wireless communication in the upcoming sixth generation (6G) [2], [3]. Typically, a VLC system consists of a photo detector (PD) and light emitting diode (LED), which are typically used as the receiver and transmitters, respectively.

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Nevertheless, in an LED-based VLC system, the modulation bandwidth is typically limited, which requires a more efficient modulation technique to provide higher spectrum efficiency [4]. To satisfy such requirements, orthogonal frequency division multiplexing (OFDM) has been introduced into VLC system, which include DC-biased optical OFDM (DCO-OFDM) [5], asymmetrically clipped optical OFDM (ACO-OFDM), and so on [6]. In particular, the above OFDM modulation schemes can effectively improve communication rate and reduce intersymbol interference, thus improving the transmission performance of VLC significantly. Moreover, by clipping noise that appears only on the even subcarriers and is orthogonal to the desired signal, ACO-OFDM shows to be more power-efficient when compared to OFDM with DC offset [6].

Due to the high peak to average power ratio (PAPR) of OFDM modulation, the ACO-OFDM is sensitive to the inherent nonlinearity of LED [7]. Especially, when high-order modulation is adopted, the performance caused by nonlinearity cannot be ignored. To solve this problem, compensation methods such as pre-distortion and post-distortion have been proposed to improve the transmission performance. For example, a post-distortion method was proposed in [8], where a memory polynomial with memory elimination scheme were proposed to suppress the memory and nonlinearity effect, respectively. In [9], a pre-distortion scheme is proposed, which utilizes the inverse characteristic of LED nonlinearity to eliminate the nonlinear effect of LED at the transmitter. Although the above

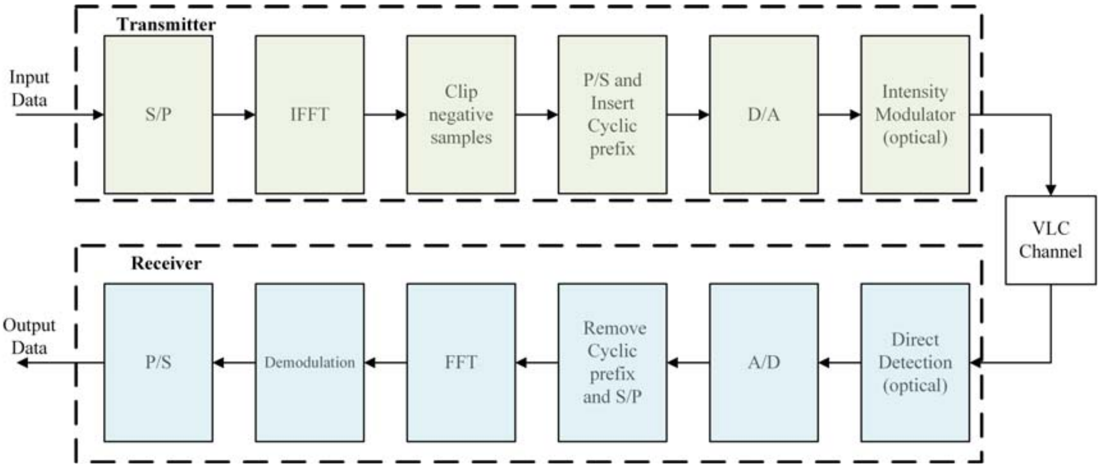

Fig. 1. Illustration of ACO-OFDM system with conventional receiver.

compensation methods can improve the system performance, it is critical to identify the characteristic of the LED, which is computationally complicated. Besides, due to the ultra-high data rate of VLC, the quantization resolution of PD is limited, which will deteriorate the received signal obviously. As such, the low-resolution quantization turns to be another issue to ACO-OFDM, which will also degrade the transmission performance. Both the distortion caused by LED nonlinearity and low-resolution quantization are nonlinear, which make the ACO-OFDM signals in practice hard to handle.

Benefited from its superiority in handling intractable problem, deep learning has been introduced into communication system to improve its performance. For example, many works concerning deep learning-based demodulation have been done, where deep learning is utilized to recover the information accurately in the presence of the device imperfections. In [10], a deep learning based Terahertz receiver was proposed, where reliable demodulation can be realized when single-bit analog-to-digital converter (ADC) is utilized. In [11], a deep learning based demodulator for non-orthogonal multiple access (NOMA)-VLC, which can compensate signal and recovery information jointly, thus improving the system performance significantly. Obviously, deep learning is potential to recovery the information from the distorted received signal, which motives us to use it to demodulate the ACO-OFDM signal suffered from LED nonlinearity and low-resolution quantization.

Against this background, a learning-assisted receiver is proposed to improve the demodulation performance in the presence of device imperfections. In particular, to handle to received signal, convolutional neural network (CNN) is deployed in our considered receiver, which can be improve the system performance observably. Simulation results demonstrate the superior performance of our proposed learning-assisted receiver, which can provide a better demodulation performance in the presence of LED nonlinearity and low-resolution quantization.

II. System Model

We consider an ACO-OFDM communication system shown in Fig1, where a single LED transmits information to a single PD. Assume that the M-ary quadrature amplitude modulation (M-QAM) symbols are transmitted and $X(k)$ represents the symbol on the k-th carrier, where $k \in \{1, 2, \cdots, N\}$ with N denoting the total number of subcarriers. With the help of inverse fast Fourier transform (IFFT) block, the transmitted signal can be expressed as

$$x(n) = \sum_{k=0}^{N-1} X(k) e^{j\frac{2\pi kn}{N}}. \tag{1}$$

More specially, based on the design principle of ACO-OFDM signal, the even subcarriers will be pdded with null, i.e., $X(0) = X(2) = \cdots = 0$. Meanwhile, the signals on odd subcarriers are required to satisfy Hermitian symmetry, where $X(k) = X^*(N-k)$ with $(\cdot)^*$ denoting the complex conjugation operation.

Then, the signal is clipped o to generate a unipolar ACO-OFDM signal $x_{\text{ACO}}(n)$ before transmission, where the negative signal will be zeroed out, given by

$$x_{\text{ACO}}(n) = \begin{cases} x(n), & x(n) \geq 0 \\ 0, & x(n) < 0 \end{cases}.$$

Before transmission, the cyclic prefix (CP) is added to act as a guard interval to avoid inter-symbol interference. Finally, the ACO-OFDM signal is loaded on the LED by intensity modulator to emit the optical signal.

At the receiver of VLC systems, a PD is utilized for photoelectric conversion. After analog-to-digital conversion and CP removal, the received signal on the k-th subcarrier in frequency domain can be presented as

$$Y(k) = H(k)X(k) + W(k), \tag{2}$$

where $W(k)$ is the additive white Gaussian noise (AWGN) with zero mean and the variance σ_W^2, $H(k)$ is the channel

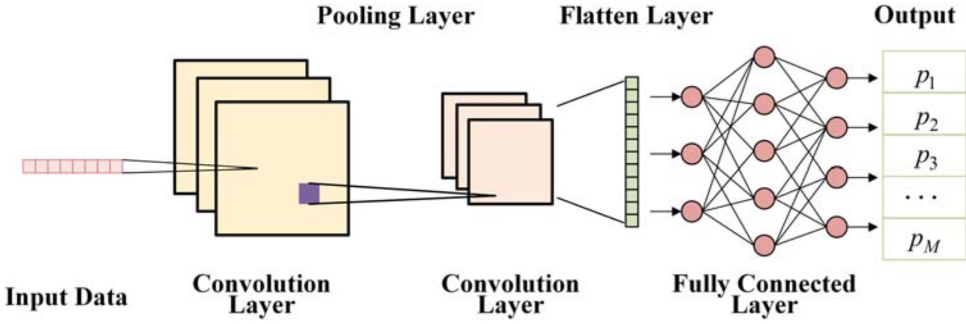

Fig. 2. Structure of the learning-assisted ACO-OFDM receiver.

frequency response (CFR) corresponding to the k-th subcarrier.

Typically, the LED suffers from the adverse effect of nonlinear distortion, which deteriorates the performance of our considered ACO-VLC communications. To depict the effect of LED nonlinearity, the odd order memoryless polynomial model, which is a general model of nonlinear distortion, is adopted. Accordingly, the transmitted signal related to the modulated signal $x_{\text{ACO}}(n)$ can be expressed as

$$s(n) = \sum_{l=1}^{L} \alpha_{2l-1} x_{\text{ACO}}(n) |x_{\text{ACO}}(n)|^{2(l-1)}, \tag{3}$$

where $2L-1$ is the order of nonlinearity, α_{2l-1} are the model parameters, and $|\cdot|$ represents the absolute value.

In addition to LED nonlinearity, quantization distortion caused by low-resolution ADC is another issue to be considered, which will make the received signal deteriorated seriously, given by

$$q(n) = \mathcal{Q}(y(n)), \tag{4}$$

where $\mathcal{Q}(\cdot)$ is the quantization process.

Typically, with the help of maximum likelihood (ML) detection, the information can be recovered from the received signal. However, effected by LED nonlinearity and low-resolution quantization, the demodulation performance will be limited since $q(n)$ is different from $x_{\text{ACO}}(n)$. To this end, it is critical to find a solution that can demodulate the received signal under device imperfections.

III. Learning-Assisted Receiver

In this section, we will detail our considered CNN-based receiver, where the basis of CNN and the architecture of our considered receiver will be provided, which has been shown in Fig.2.

A. Convolutional Neural Network

Benefited from its outstanding performance in extracting features, CNN is particularly efficient for recognition and classifications. Typically, the CNN consists of several components, namely, convolutional layer, pooling layer, flatten layer, fully connected layer, etc. The functions of each layers are summarized as follows.

- The convolutional layer performs a convolution operation, which can be applied to filter the input data to create feature maps that summarize the features in the data.
- The pooling layers can reduce the dimensions of the feature maps, which can make the scale of features invariant, thus reducing the required computational complexity.
- The flatten layer reorganize the out of its above layer, which enables the output of convolutional layer can be directly connected with the fully connected layer.
- In addition, the fully connected layer, where each node is connected to all the nodes of the previous layer, can be used to synthesize the features extracted from the previous layers.

More specifically, the output of the k-th feature map in the t-th convolutional layer can be presented as

$$\mathbf{y}_k^t = \mathcal{B}(\mathbf{W}_{c,k}^t * \mathbf{C}^{t-1} + b_{c,k}^t), \tag{5}$$

where $\mathbf{C}^{t-1}$ represents the input from the $t-1$ convolutional layer, and $*$ denotes the convolution operation. $\mathbf{W}_{c,k}^t$ and $b_{c,k}^t$ are the k-th convolution kernel in the t-th convolutional layer and its corresponding bias, respectively. $\mathcal{B}$ is the batch normalization (BN) operation, which can accelerate convergence and avoid overfitting, given by

$$\mathcal{B}(y) = \xi \frac{x - \mathbb{E}(y)}{\sqrt{\text{Var}(y) + \epsilon}} + \lambda, \tag{6}$$

where $\mathbb{E}(\cdot)$ and $\text{Var}(\cdot)$ represent the expectation and variance operation, respectively, ξ is scale factor, λ is offset factor, and ϵ is a small value.

To introduce linearity into the network, activation function is utilized to handle the output of convolutional layer. For our considered CNN, rectified linear unit (ReLU) function is selected as the activation function of convolutional layer, which is given by

$$\text{ReLU}(x) = \max(x, 0). \tag{7}$$

Accordingly, the output of the t-th convolutional layer can be presented as $\mathbf{C}^t = [\text{ReLU}(\mathbf{y}_1^t), \cdots, \text{ReLU}(\mathbf{y}_{n_t}^t)]$ with

n_t denoting the number of convolution kernels in the t-th convolution layer.

As for the pooling layer, a two-dimensional max pooling layer is selected to perform the downsampling operation, which is realized by dividing the input into rectangular pooling regions and then computing the maximum of each region. In particular, the max pooling layer can realize faster convergence rate by selecting superior invariant features, thus improving generalization performance significantly [12].

When the feature of the input data is obtained by the convolutional layer and pooling layer, a fully connected layer is utilized to handle the output of pooling layer to obtain the required result. Different from the convolutional layer, the output of the i-th layer of fully connected layer is given by

$$\mathbf{y}_i = f(\mathbf{W}_{f,i}\mathbf{y}_{i-1} + b_{f,i}), \tag{8}$$

where $\mathbf{W}_{f,i}$ and $b_{f,i}$ denote the weight matrix and bias of the i-th layer of fully connected layer, respectively. $f(\cdot)$ denotes the activation function.

B. Proposed Learning-Assisted Receiver

Our proposed learning-assisted ACO-OFDM receiver is shown in Fig.2, which is based on CNN. To demodulate the received signal, the input of CNN is the received signal and the output is the demodulation likelihood information. As such, the size of CNN output is M.

More specifically, to exploit the signal feature even under device imperfections, the received signal before fast Fourier transform (FFT) operation is input the convolutional layer, which can avoid the effect of device imperfections be ignored during the signal conversion process. To this end, the signals on all subcarriers are input into the CNN jointly.

In addition, to demodulate the received signal accurately, the demodulation is modeled as a classification problem. Accordingly, the softmax is selected as the activation function of the output layer of fully connected layer, which can generate classification probability of the received symbol belonging to each modulation category. Typically, the softmax function is given by

$$\mathrm{softmax}(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_M \exp(z_j)}. \tag{9}$$

Based on the above process, we can obtain the likelihood information of the received signal. Next, the category of current received signal can be determined, which is the one with the largest likelihood information among the outputs of fully connected layer, given by

$$m^* = \underset{m=1,2,\cdots,M}{\mathrm{argmax}} \ p_m. \tag{10}$$

Moreover, to train the CNN-based receiver efficiently with satisfied speed and stability of the training, Adam method in [13] is used to train the network.

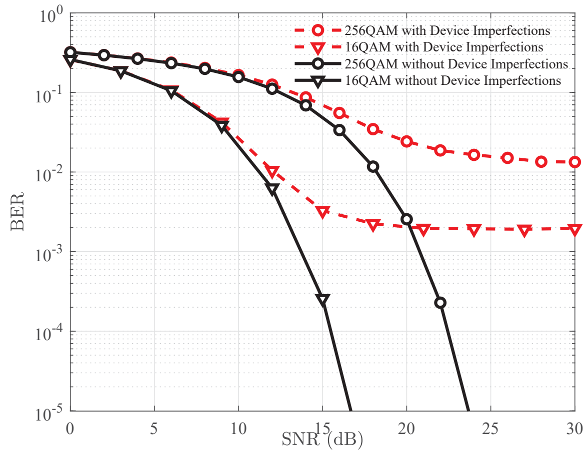

Fig. 3. Performance comparison of different modulations with and without device imperfections.

IV. Simulation Results

In this section, we present the simulation results to verify the effectiveness of our proposed learning-assisted ACO-OFDM receiver in the presence of device imperfections. More specifically, we assume that the toatl number of subcarrier is N =32 and the length of guard interval is 32. Besides, 10^6 samples are utilized to train the CNN, where the number of convolutional layers is 2 and the convolutional kernel of the two convolutional layers are 16 and 32, respectively.

Firstly, Fig.3 presents the bit error rate (BER) performance of different modulations with/without device imperfections, where we plot both the . As we can see, the BER performance decrease as the order of modulation increases. Besides, when the system suffers from device imperfections, the performance degrades significantly regardless of the modulation order, where performance floors of both 16QAM and 256QAM can be observed. Finally, the modulation scheme with higher modulation order will suffer from the device imperfections more obviously.

As we can see from Fig. 4, the performance of our proposed learning-assisted receiver is the same as the conventional receiver when there exists no device imperfections. When the device imperfections are taken into consideration, the BER performance of ACO-OFDM degrades significantly regardless of the type of receiver. In particular, there exists a performance floor, which indicates that the LED nonlinearity and low-resolution quantization will lead to irreparable performance loss. However, benefitted from the outstanding processing ability of CNN to nonlinear distortions, the performance of our proposed learning-assisted receiver outperforms the conventional receiver. In particular, a lower performance floor can be realized by the learning-assisted receiver when compared to the conventional receiver, thus verifying the effectiveness of our proposed receiver.

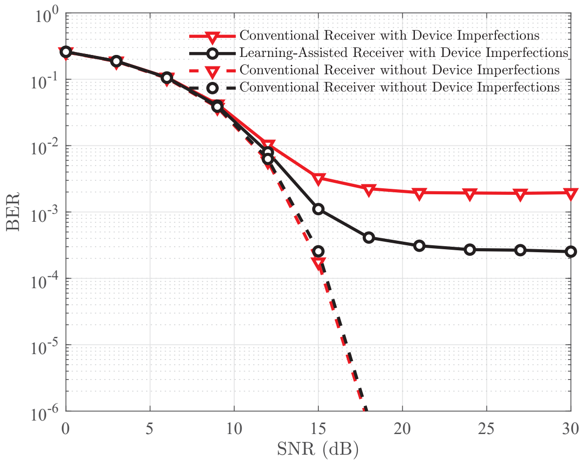

Fig. 4. Performance comparison of conventional receiver and learning-assisted receiver.

V. Conclusion

In this paper, a learning-assisted ACO-OFDM receiver was proposed, which utilizes a CNN to demodulate the received information. Specifically, we first analyzed the device imperfections including LED nonlinearity and low-resolution quantization, which shows the challenge of demodulation in the presence of device imperfections. Then, our proposed learning-assisted ACO-OFDM receiver was proposed, which relies on the feature extraction ability of CNN. To exploit the signal feature even under device imperfections, the received signal before FFT operation is input into the convolutional layer. Moreover, to demodulate the information accurately, the demodulation is regarded as classification problem. The simulation results demonstrate the superiority of our learning-assisted ACO-OFDM receiver, which shows a lower performance floor when compared to the conventional receiver.

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