Optical Fiber Communication System with Intelligent Joint Source-Channel Coded Modulation

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***Abstract*—We propose a new point-to-point optical fiber communication system based on intelligent joint source-channel coded modulation. The experimental results show that the proposed system achieves higher information compression and greater tolerance to optical link impairments.**

***Keywords*—Optical fiber communication, deep learning, joint source channel coded modulation.**

I. INTRODUCTION

As an essential part of the global communication infrastructure, optical fiber communication carries most of the global data traffic in modern society [1]. With the increasing demand for high-bandwidth devices such as cloud devices, VR, AR and surveillance cameras, the point-to-point data transmission is highly desired. According to Shannon's separation theorem [2], the traditional point-to-point optical fiber communication (T-OFC) separately applies source coding and channel coding to achieve system optimality. However, in practical scenarios where the source or channel distributions are non-ergodic, the joint source channel coding (JSCC) is known to outperform the separate scheme [3]. Meanwhile, the T-OFC systems attempt to minimize bit or symbol errors and ignore the meaning behind digital bits, producing a lot of redundant information in transmission, which could not best fit the information source and the optical physical channel. In order to enhance point-to-point data transmission and realize a better interaction between information source and optical physical channel, there is an urgent need for a novel point-to-point optical fiber communication structure based on joint design.

In this paper, we propose a novel point-to-point optical fiber communication structure for image transmission, which applies deep neural networks (DNN) for joint source-channel coded modulation (JSCCM-OFC). The proposed structure pursues high information source fidelity instead of low bit error rate, making it possible for higher information transmission capacity under fixed communication bandwidth. The characteristic enables the JSCCM-OFC to be deployed in many emerging applications, such as remote monitoring. We conduct experiments over IM-DD transmission system using the proposed structure compared with the T-OFC with PAM8 and PAM4 modulation formats. The results show the proposed JSCCM-OFC achieves higher information compression and greater tolerance to additive white gaussian noise, modulation nonlinearity and bandwidth limit.

II. JOINT SOURCE-CHANNEL CODED MODULATION

Considering natural images contain abundant visual features according to human comprehension, we establish the JSCCM-OFC system to deliver the underlying meaning of images. We adopt DNN for the JSCCM, inspired by its impressive performance in computer vision tasks [4-5]. By utilizing DNN to construct the JSCCM, a concise optical communication structure is realized, which directly generates discrete symbols with continuous amplitude for transmission.

The JSCCM network is designed to remove the redundancies of the input image, thus information compression is realized. As shown in Figure 1(a), in the JSCCM, residual convolution (ResConv) [6] module is utilized for feature extraction. The dual attention (DA) [7] module is applied to guide the network to focus on effective features, while the feature attention (FA) [8] module is implemented to lead the network to protect significant features against optical channel noise. The last mapping layer (ML) is designed for data compression. The joint demodulation and decoding (JDD) network is constructed with a symmetrical structure, which could reconstruct the

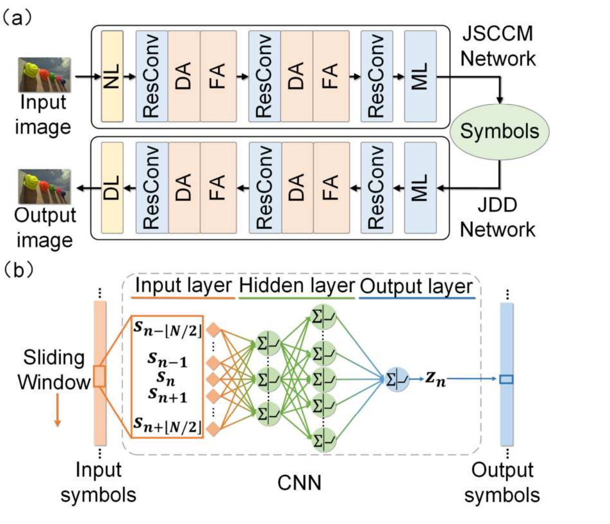

Fig. 1. (a) Structure of the JSCCM-JDD network, NL: normalization layer, DL: denormalization layer. (b) Details of the CNN equalizer.

RGB image with the received symbols. A CNN equalizer is designed before the JDD, whose details are shown in Figure 1(b). The input layer contains 121 input symbols. The other three layers which are followed by nonlinear activation function contain 5, 11, 1 neurons, respectively. By inputting 121 symbols within the convolution window into the CNN, one equalized symbol is obtained. After sliding the window, all symbols are equalized.

III. SOURCE AND PHYSICAL LAYER INTERACTION

To further improve the transmission performance, joint optimization (JO) is employed to promote the adaptability of the JDD network to the real optical channel environment. The details of the JO strategy are illustrated in Figure 2. The received symbols include training images and testing images. After equalization, the training images are sent into the JDD network for parameter updating to achieve better decoding performance.

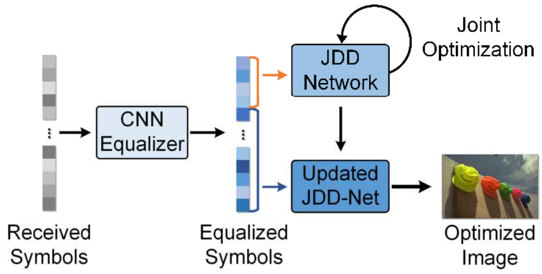

Fig. 2. Details of the JO process.

IV. EXPERIMENTS AND RESULTS

The experimental setup of the optical transmission system is depicted in Figure 3. At the transmitter, the output symbols of the JSCCM network are processed by resampling and a square-root-raised cosine filter. Then digital pre-emphasis is adopted. The signals are then sent to the arbitrary waveform generator (AWG). The electrical analog signals generated by the AWG are amplified by a linear broadband amplifier. Then the electrical signals are modulated into optical signals by a Mach-Zehnder modulator (MZM). In B2B transmission, a variable optical attenuator (VOA) is utilized to control the receiver optical power (ROP). When evaluating the tolerance to peak-to-peak values and baud rates of the RF signals, the ROP is set as 0 and −4 dBm, respectively. In fiber transmission, the input fiber optical power and ROP are both 0 dBm, with the control of the VOA and erbium-doped fiber amplifier (EDFA). At the receiver, the optical signals are converted into electrical signals by the photodetector (PD). The received electrical signals are sampled using the digital sampling oscilloscope (DSO). After that, the digital signals are sent into the receiver network for decoding.

The JSCCM network and JDD network are trained on cifar10 dataset [9] under AWGN channel before deployment. The loss function is mean square error (MSE), which is expressed as:

$$MSE = \frac{1}{B}\sum_{i=1}^{B}\left\|O_i - I_i\right\|_2^2 \qquad (1)$$

where B is the batch size, O_i is the output image and I_i is the input image.

For implementation of the T-OFC systems, we select the JPEG [10] and JPEG2000 [11] (JP2K) for source coding. The 2/3 LDPC is applied for channel coding. The 61-tap feed forward equalization (FFE) is used for equalization. PAM4 and PAM8 are used as the modulation formats.

To test the generalization of the JSCCM system, we select an image captured by a mobile phone for transmission, instead of open-source image datasets. Through the JSCCM network, the test image is mapped into a discrete-time analog symbol sequence with a length of 34,368, and the value of each symbol is normalized to $[-1,1]$. The data rate of this JSCCM-OFC system is up to 8.73×10^5 images/s. As for the traditional methods, when PAM8 is applied, we adjust the compression ratio of JPEG and JP2K to keep the data rate equivalent to that of the JSCCM-OFC system. When PAM4 is applied, the data rate is a third lower at 5.82×10^5 images/s.

For performance evaluation, the peak signal-to-noise ratio (PSNR) and structural similarity index matrix (SSIM) [12] between the received and transmitted images are calculated. Figure 4(a) shows the PSNR and SSIM according to the ROPs in the different optical communication systems. The experimental results illustrate that the JSCCM-OFC system is more robust to channel noise, and its performance can be further improved with JO. The "cliff" effect occurs when the ROP is −5 dBm for PAM8 and −10 dBm for PAM4, while acceptable reconstruction performance can still be achieved in the JSCCM-OFC system. By setting a 20-dB PSNR as the standard, the receiver sensitivity is increased by approximately 10 dB in the JSCCM-OFC system compared with the T-OFC system at the same transmission rate and by approximately 5 dB at 1.5 times faster transmission rate. Figure 4(b) shows the recovered images at the receiver in the ROPs of 0 and −13 dBm with the JSCCM and the JP2K+LDPC+PAM4, respectively. When the ROP is 0 dBm, the JSCCM-OFC system provides a higher transmission fidelity compared with the traditional structure. When the ROP is −13 dBm, the image could not be recovered in the T-OFC system. A PSNR greater than 20 dB and a SSIM greater than 0.7 are still achieved in the JSCCM-OFC system. The details of the image could be recognized according to human comprehension.

Figure 5(a) shows the tolerance to modulation nonlinearity, which indicates that the JSCCM-OFC system is more robust to the nonlinear noise induced by optical modulator. Figure 5(b) shows the tolerance to the bandwidth

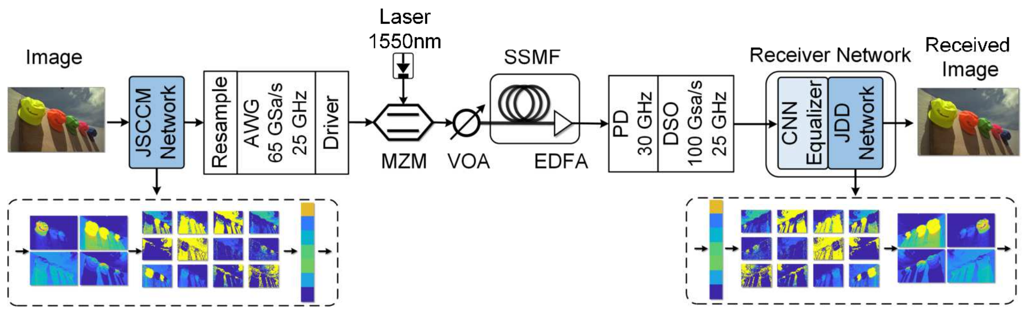

Fig. 3. Experimental system of the JSCCM-OFC.

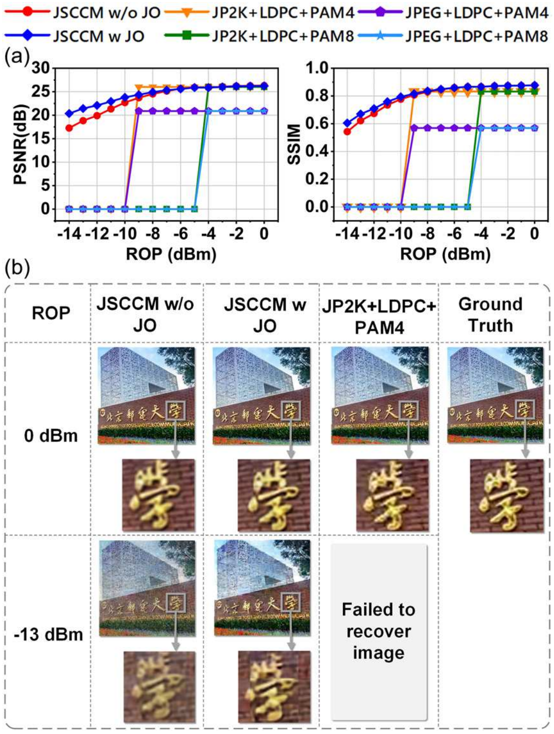

Fig. 4. (a) Experimental results with respect to the ROP. (b) Recovered images when the ROPs are 0 and −13 dBm.

limit. The JSCCM-OFC system enabled the transmission of 64 Gbaud, whereas the PAM4 and PAM8 transmissions could only achieve up to 56 and 46 Gbaud, respectively. Figure 5(c) shows the tolerance to transmission distance. Without special CD compensation, the PAM4 and PAM8 transmission systems can reliably transmit the image within 20 km, whereas the JSCCM-OFC system can transmit the same image over 80 km without severe degradation.

V. CONCLUSION

In this paper, we propose the JSCCM-OFC system for image transmission, which could realize higher data compression and robustness against optical link impairments. We experimentally demonstrate the JSCCM-OFC in IM-DD transmission system. The results show that the JSCCM-OFC achieves significant improvement compared with the traditional structure, especially in low ROP region and high optical link impairments regimes. Moreover, the cliff-like performance degradation is avoided by applying the JSCCM. With the JO strategy, the transmission performance can be further improved, implying the JDD network can be adapted to the physical channel state.

ACKNOWLEDGEMENTS

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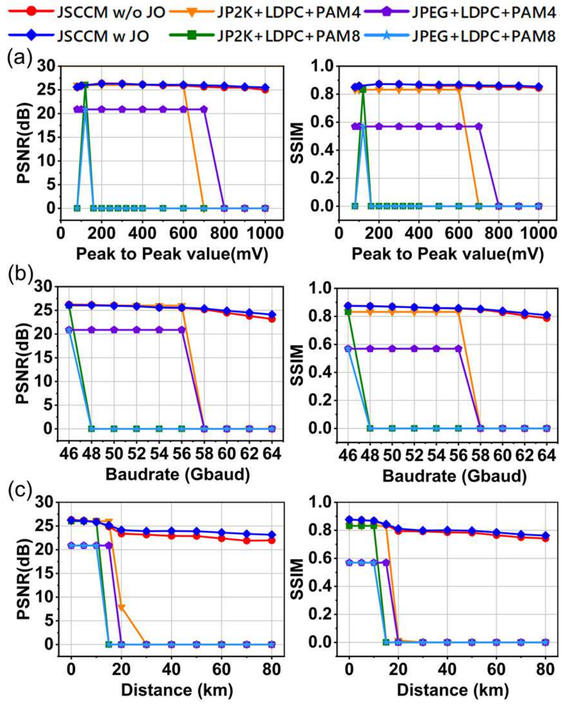

Fig. 5. Experimental results with respect to (a) peak-to-peak value, (b) baud rate, and (c) transmission distance.

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