An Autoencoder-based Transceiver for UAV-to-Ground Free Space Optical Communication

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***Abstract*—An end-to-end autoencoder-based transceiver for UAV-to-ground free space optical communication is proposed. Simulation results show ~12dB improvement compared to the PPM transmitter and ~51.3% reduction of decoder's running-time compared to the maximum likelihood receiver.**

Keywords—autoencoder, UAV-to-ground, free space optical communication

I. INTRODUCTION

With the increasing demand for large bandwidth and high transmission rate, free space optical (FSO) communication has gained significant attention due to the advantages of high data rate, large information capacity, license free spectrum and high channel security over the wireless radio frequency communication technology [1]. In recent years, unmanned aerial vehicle (UAV) has attracted increasing attention because of its agility and scalability and the FSO-UAV based communication has emerged as the promising direction that can be utilized to develop space-earth integration networks [2]. However, the UAV optical link is limited owing to the atmospheric turbulence, which causes intensity fluctuation, beam wandering and beam broadening. The amplitude of the optical signal is sensitive to the random variations which will particularly deteriorate the performance in the intensity modulation/direct detection (IM/DD) system.

Recently, deep learning technique has been applied in the field of communication. Deep neural networks (DNN) are frequently utilized for optimization in a specific block or function. Besides, an end-to-end transceiver consisting of transmitter, receiver and communication channel can be constructed and optimized forming an autoencoder (AE) [3]. AE can be generally trained by gradient-based deep learning algorithms in the condition of loss function. Compared with the block-based module, the entire components in the communication chain can be trained, analyzed and optimized simultaneously. In FSO communication, AE design has been applied in terrestrial links for constellation shaping, channel estimation and signal detection to mitigate the atmospheric turbulence [4].

In this paper, a data-driven end-to-end transceiver based on DNN is proposed to alleviate atmospheric turbulence. We concentrate on UAV-to-ground FSO communication links especially in long-range and strong atmospheric turbulent scene. We establish the end-to-end AE in an IM/DD system with two-stage deep learning training scheme. Simulation results show that the bit error rate (BER) of the proposed transceiver can reach below the 7% hard-decision forward error correction (HD-FEC) threshold at signal-to-noise ratio (SNR) of approximately 22dB and under strong atmospheric turbulence with maximum Rytov variance 3.5. Our proposed transceiver is approximately 12dB superior to the system with pulse position modulation (PPM) transmitter. Besides, ~51.3% of the decoder's running-time is reduced compared with maximum likelihood (ML) receiver without the need for perfect channel state information (CSI).

II. PRINCIPLE OF THE PROPOSED AUTOENCODER-BASED TRANSCEIVER

The DNN can be applied as the function approximator and the *K*-layer feed-forward DNN can map an input vector s_0 into an output vector $s_k = f_{DNN}(s_0)$ in the form:

$$s_k = \alpha_k(W_k s_{k-1} + b_k),\ \ k = 1,\ldots,K \tag{1}$$

The sets of parameters denoted as $\theta_k = \{W_k, b_k\}$ are the trainable variables during each training iteration, α_k is the activation function. In the proposed transceiver, DNN acts as the encoder for the *M*-ary message in the transmitter and the decoder in the receiver. The dimension of the code is denoted as (n, k), where n is the number of bits in a symbol and $k = \log_2 M$.

The deep learning training is proposed in two stages. In

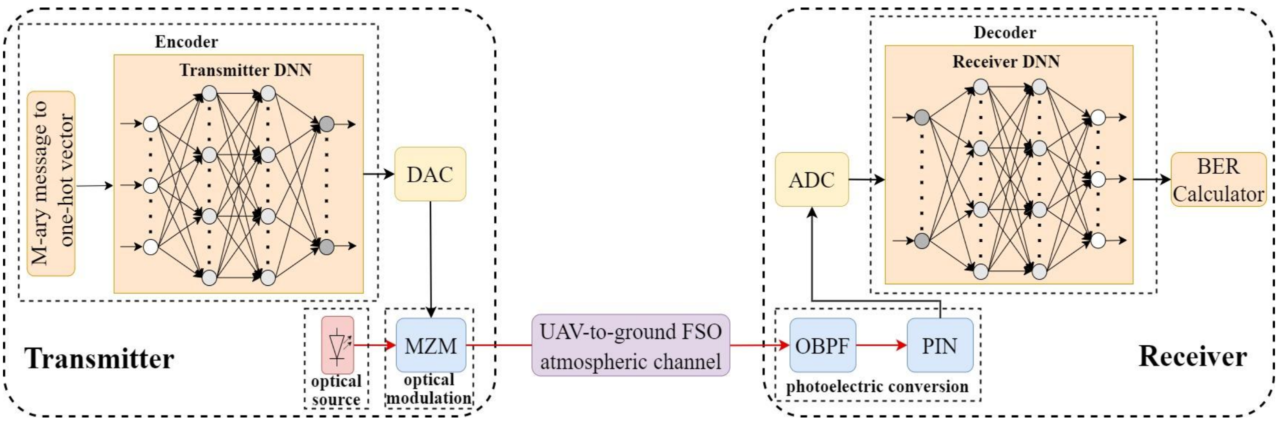


Fig.1. Schematic diagram of the UAV-to-ground FSO communication system based on DNN.

the first stage, pre-training is applied to train the sets of parameters in the transmitter DNN denoted as θ_e to achieve the maximal codewords separation with loss function:

$$L_e(\theta_e) \triangleq [n/2 - d_{min}(\theta_e)]^2 \tag{2}$$

The second stage is the end-to-end supervised training. The state-of-the-art Adam optimizer algorithm and cross-entropy loss function is applied in the second training stage. Symbol error rate (SER) can be reduced through the two-stage deep learning training. Since the same bit mapping strategy is applied, better BER performance can be obtained by minimizing SER.

As we focus on the UAV-to-ground FSO communication system in long distance and strong turbulence, the main limiting factor in the IM/DD system is the atmospheric turbulent effect. In addition, the signal is affected by noise, mainly owing to thermal noise in the receiver and shot noise caused by the background radiation. Considering x as one transmitted signal and y as one received signal, FSO channel model is [5]:

$$y = \eta H x + noise \tag{3}$$

Where *noise* indicates the additive white Gaussian noise (AWGN) with zero mean and variance σ_N^2, H is atmospheric turbulence intensity, η is responsivity of the positive intrinsic negative (PIN) photodiode. Gamma-Gamma distribution is applied as the fading effect because it highly fits the characteristics of the moderate and strong atmospheric turbulence. Scintillation of the optical signal is determined by the Rytov variance σ_R^2, which can represent the strength of the atmospheric turbulence.

III. Simulation Results and Discussions

In this paper, our scheme is simulated and validated using deep learning library TensorFlow. The schematic diagram of the proposed IM/DD UAV-to-ground FSO communication system is depicted in Fig. 1. At the transmitter, a continuous wave laser at 1550nm can provide an optical carrier signal to a Mach-Zehnder modulator (MZM) with 40GHz bandwidth modulated by the transmitter DNN. After the optical band pass filter (OBPF), the optical signal is converted into electric signal by PIN. The digital signal is obtained to the receiver DNN after analog-to-digital converter (ADC). We assume photodetector responsivity η is 1 A/W and the launch power is adjusted from -10dBm to 15dBm. The 16-ary message is firstly converted into the one-hot vector and then passes through the transmitter DNN. Besides, a constraint layer is applied at the output layer of the transmitter DNN to ensure hardware physical characteristic. We use AE (12, 4) to indicate the proposed autoencoder-based transceiver with the encoding scheme n = 12 and k = 4. In the end-to-end training process, the AE is trained on a set of 2^{14} randomly generated input messages, corresponding to 2000 iterations of the optimization algorithm. The test phase is performed separately with the set of different 2^{18} random messages. The AE is trained with Rytov variance $\sigma_R^2 = 3.5$, where UAV can work at the altitude of about 20km and in strong atmospheric turbulent scene.

In Fig. 2(a)-(b), we compare the BER performance of the proposed AE (12, 4) with different encoding dimensions. BER is analyzed in strong atmospheric turbulence with Rytov variance 3.5 in Fig. 2(a). AE (4, 4) will achieve error floor at approximately 10^{-1} at about 20dB. The proposed AE

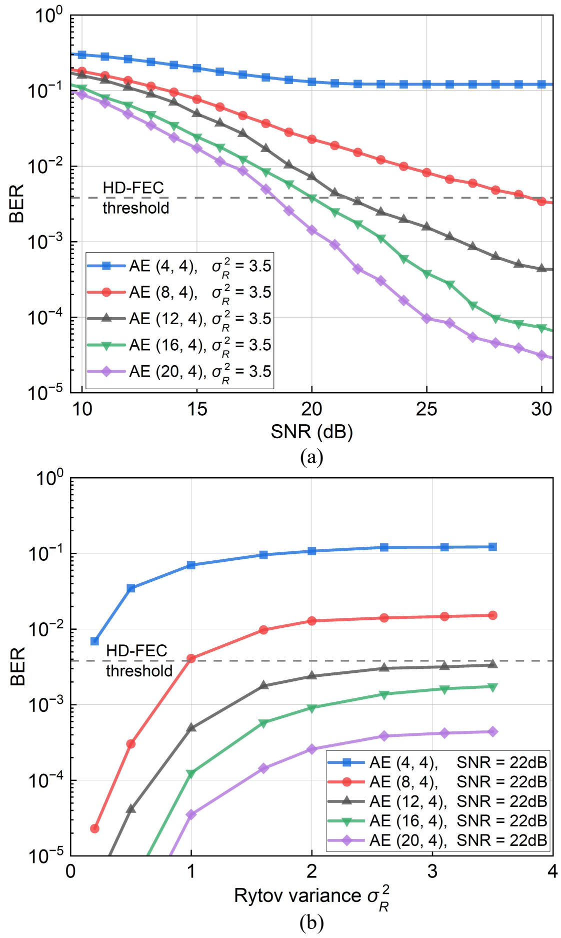
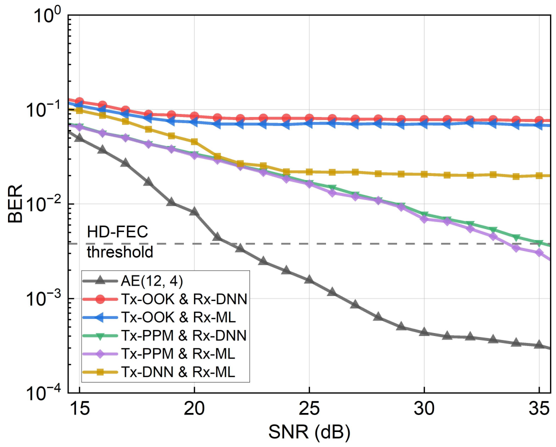


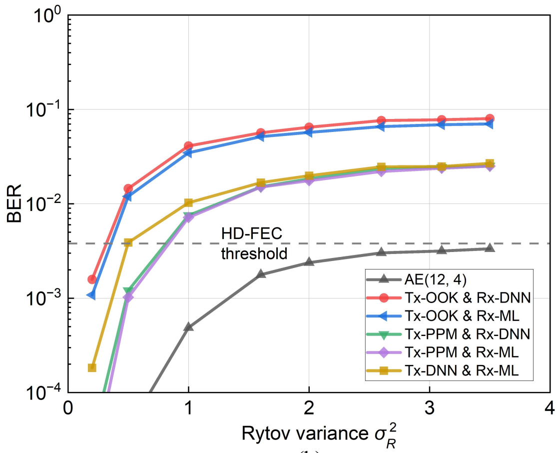
Fig. 2. BER comparison of the proposed AE (12, 4) with different encoding dimension against (a) SNR and (b) Rytov variance.

(12, 4) can achieve the HD-FEC threshold at about 22dB, which is 6dB superior to AE (8, 4) scheme but is 2dB and 3dB inferior to AE (16, 4) and AE (20, 4) schemes. Though the transmission power can be saved with the increase of n, the coding efficiency will decrease which will particularly affect the transmission effectiveness. In Fig. 2(b), AE is tested with fixed 22dB in different turbulent channel. The more bits are used in a symbol, the lower error floor will be obtained since the differentiation between the codewords is increased and the distorted symbol can retain more features of the transmitted symbol. AE (12, 4), AE (16, 4) and AE (20, 4) schemes can satisfy the HD-FEC threshold when Rytov variance is within 3.5. Moreover, AE (12, 4) is selected as our proposed scheme because it has the highest transmission efficiency while meeting the requirement of transmission accuracy.

As is shown in Fig. 3(a)-(b), the proposed data-driven AE (12, 4) with DNN transmitter and DNN receiver is compared with the 16-ary schemes (i) On-off keying (OOK) transmitter - DNN receiver, (ii) OOK transmitter - ML receiver, (iii) PPM transmitter - DNN receiver, (iv) PPM transmitter - ML receiver and (v) DNN transmitter - ML receiver. The schemes with OOK transmitter show the worst BER performance which will encounter 7×10^{-2} error floor with Rytov variance 3.5 shown in Fig. 3(a). Our proposed AE (12, 4) is approximately 12dB superior to the schemes with PPM transmitter. This is mainly due to the role of channel coding by the transmitter DNN through two-stage deep learning training. In Fig. 3(b), only our proposed transceiver AE (12,4)



(a)



(b)

Fig. 3. BER comparison of the proposed AE (12, 4) against (a) SNR and (b) Rytov variance with (i) OOK transmitter - DNN receiver, (ii) OOK transmitter - ML receiver, (iii) PPM transmitter - DNN receiver, (iv) PPM transmitter - ML receiver and (v) DNN transmitter - ML receiver.

can satisfy the HD-FEC threshold as long as Rytov variance is no more than 3.5 tested at 22dB. Unlike the schemes with OOK transmitter or PPM transmitter, in the schemes with DNN transmitter, the BER performance of ML receiver is significantly worse than DNN receiver because every bit in the symbol is processed separately in the ML receiver while decoding and compensation are implemented simultaneously in the DNN receiver. Therefore, symbol differentiation can be better distinguished. Besides, we compare the decoding time between the DNN receiver and the ML receiver with the (12, 4) encoding dimension. We find that about 0.374s is used for DNN decoder and 0.768s is used for ML decoder so that ~51.3% of the decoder's running-time can be reduced with DNN receiver without the need for perfect CSI.

IV. Conclusion

An end-to-end autoencoder-based transceiver with two-stage deep learning training scheme is proposed for UAV-to-ground IM/DD FSO communication to mitigate atmospheric turbulence. Simulation result show that our proposed AE (12, 4) can reach the HD-FEC threshold at 22dB with maximum Rytov variance 3.5. Our proposed transceiver shows approximately 12dB improvement compared to the PPM transmitter and 51.3% reduction in decoder's running-time compared to the ML receiver.

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References

[1] M. A. Khalighi, and M. Uysal, "Survey on Free Space Optical Communication: A Communication Theory Perspective", IEEE Commun. Surv. & Tutor., vol. 16, no. 4, 2014, pp. 2231-2258.

[2] C. Abou-Rjeily, G. Kaddoum, and G. K. Karaginnidis, "Ground-to-Air FSO Communications: when High Data Rate Communication Meets Efficient Energy Harvesting with Simple Designs", Opt. Express, vol. 27, no. 23, 2019, pp. 34079-34092.

[3] B. Karanov et al., "End-to-End Deep Learning of Optical Fiber Communications", J. of Lightwave Technol., vol. 36, no. 20, 2018, pp. 4843-4855.

[4] M. A. Amirabadi, M. H. Kahaei, S. A. Nezamalhosseini, and V.T. Vakili, "Deep Learning for Channel Estimation in FSO Communication System", Opt. Commun., vol. 459, 2020, pp. 124989.

[5] H. Kaushal, and V. K. Jain, "Optical Communication in Space: Challenges and Mitigation Techniques", IEEE Commun. Surv. & Tutor., vol. 19, no. 1, 2017, pp. 57-96.