Deep Learning-Based End-to-End Bit-Wise Autoencoder for G-Band Fiber-Terahertz Integrated DFT-S-OFDM Communication System

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Abstract: We proposed and experimentally demonstrated a bit-wise end-to-end deep-learning-based autoencoder for a fiber-THz integrated DFT-S-OFDM communication system at 209 GHz. More than 5.5-dB sensitivity gain is achieved compared with traditional DFT-S-OFDM system at 50Gbps. © 2023 The Author(s)

1. Introduction

Terahertz (THz) band communication provides excellent potential for a plethora of applications and services. It is a promising pillar technology to satisfy the demands of an intelligent information society in sixth-generation (6G) radio-access networks (RAN) [1]. One step forward, orthogonal frequency division multiplexing (OFDM) is also widely applied in 6G-oriented joint communication and sensing systems to manage efficiently the scarce spectrum resource [2][3]. Since the OFDM signals have a high peak-to-average power ratio (PAPR), the linear amplified output after the amplifiers has a low power efficiency in the THz band [4], seriously deteriorating the communication performance and coverage range. Thus, the transmitted waveform needs to be well-designed to maximize the power efficiency for the THz transmitters. Recently, the discrete Fourier transform spread OFDM (DFT-S-OFDM) schemes have been studied to effectively manage the high PAPR of OFDM waveform for THz communication systems [3][4]. However, the DFT-S-OFDM schemes also suffer from nonlinear distortion (NLD) induced by saturated amplifiers, which limits the improvements from high-order modulation formats in increasing the spectral efficiency and network capacity. Furthermore, the additional inverse discrete Fourier transform at the receiver induces noise spreading effect, which spreads the noise over the entire sub-band and causes the DFT-S-OFDM signal more sensitive to noise distribution [5]. As another pillar technology in 6G, artificial intelligence (AI) shows superiority in improving the performance of communication systems with an end-to-end (E2E) optimization [6][7]. In THz communication systems, the deep-learning-based E2E optimization has the potential to enhance the robustness and performance of the DFT-S-OFDM scheme to combat NLD and noise spreading effects.

In this paper, we proposed and experimentally demonstrated a deep-learning-based bit-wise autoencoder that optimizes DFT-S-OFDM signal for fiber-THz integrated communication system at 209 GHz. Within the artificial neural network (ANN) autoencoder, the transmitter ANN (T-ANN) encodes bits sequence into complex symbols whose constellation location is redistributed to achieve improved robustness to the intersymbol interference (ISI) and NLD of the THz channel model. In the 209 GHz fiber-THz integrated transmission experiment, the optimized DFT-S-OFDM signal with 32-ary bits-to-symbol mapping achieves significant superiority over the conventional 32-ary quadrature amplitude modulation (32-QAM) DFT-S-OFDM signal. Over 5.5 dB sensitivity gain and 3 Gbps data-rate improvement can be achieved at the 20% soft-decision forward error correction (SD-FEC) threshold of 2E-2.

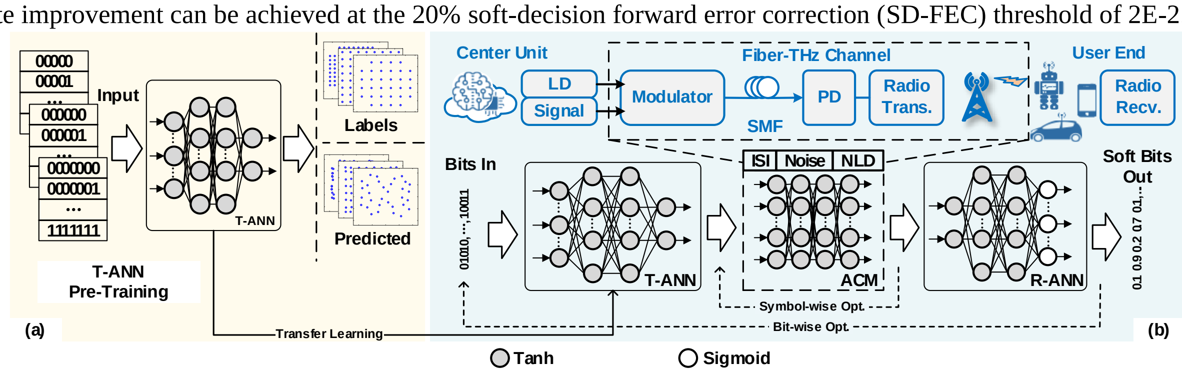

Fig. 1 (a) T-ANN pre-training process; (b) Diagram of the bit-wise E2E optimization framework.

2. Principles

The training process of the bit-wise E2E optimization framework can be separated into two phases. In the first phase, as shown in Fig. 1(a), a 2-layer fully connected T-ANN with *tanh* activate functions is roughly pre-trained with the classic QAM mapping rules so that the weights of the T-ANN can be adjusted to a suboptimal value. By applying the transfer learning technique, the weights of the pre-trained T-ANN are used to initialize the T-ANN in the autoencoder network, which helps to speed up the convergence of the autoencoder training process. To train an M-ary bits-to-symbol mapping, the T-ANN is fed with $\log_2(M)$ bits data and outputs a 2-dimension symbol. Next, a 2-layer fully connected ANN is trained with the data acquired in the real fiber-THz integrated communication system to model the THz channel characteristics including ISI, NLD, and noise power. The gradient propagation between the T-ANN and receiver ANN (R-ANN) is subsequently handled by the trained ANN-based channel model (ACM).

In the second phase, as shown in Fig. 1(b), the autoencoder consists of the pre-trained T-ANN, the ACM, and the R-ANN. The weights of the trained ACM are fixed to impose channel impairments on the T-ANN encoded symbols. The T-ANN learns to adjust the symbol distribution so that each symbol suffers less noise-spreading influence from adjacent symbols in the DFT-S OFDM demodulation process and becomes more resistant to channel impairments. A symbol-level loss function guides this symbol-wise optimization on the T-ANN. The symbol-level loss function calculates the negative value of the minimum pair-wise distance of M different symbols and uses the gradient to update the weights of T-ANN so that it can pull the two nearest symbols away. At the receiver side, the R-ANN decodes the distorted 2-dimension symbols into their corresponding bits after two fully connected hidden layers. The activate functions of the hidden layers and output layer are respectively *tanh* and *sigmoid*. Since the output value of *sigmoid* ranges from 0 to 1, the output of the R-ANN is a soft-bits sequence that indicates how confident the R-ANN is about its decisions. We utilize the binary cross entropy as the bit-level loss function on the R-ANN's output (also the autoencoder's output). The gradients of bit-level loss enable bit-wise optimization on the T-ANN and R-ANN so that they can approach the optimal Gray coding and decoding. After the bit-wise and symbol-wise optimization, the T-ANN and R-ANN can generate a robust bits-to-symbol mapping rule and an effective decoding mechanism, respectively.

3. Experiment and Discussions

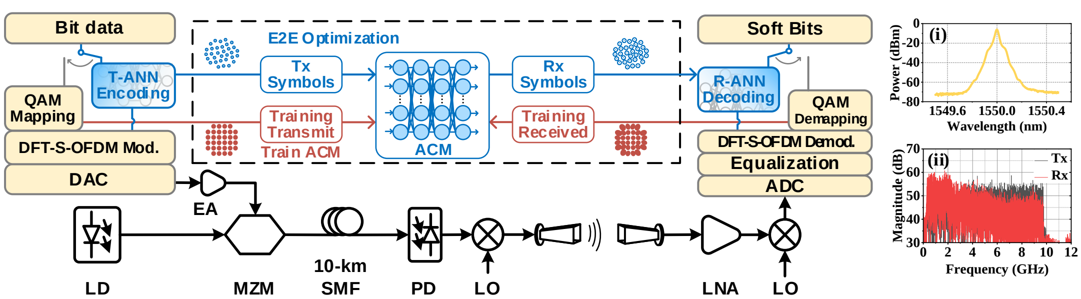

Fig. 2 Experimental setup of the fiber-THz integrated E2E optimized DFT-S-OFDM communication system, (i) is the optical spectrum of the received signal at the photodiode (PD), (ii) is the spectrum of the transmitted (Tx) and received (Rx) signal.

Fig. 2 shows the experimental setup of the fiber-THz integrated E2E optimized DFT-S-OFDM communication system at 209 GHz, together with the DSP blocks and extra visualizations of the signals. The optimized 32-ary bits-to-symbol DFT-S-OFDM signal is generated from the bit data by the T-ANNs, through DFT-S OFDM modulation, added with cyclic prefix, 6× upsampling, and sent to a 60 GSa/s digital-to-analog converter (DAC). After an electrical amplifier (EA), the electrical signal is modulated by the Mach-Zehnder modulator (MZM) with a laser diode (LD) operating at 1550 nm. After 10 km single mode fiber (SMF) transmission, the optical signal is detected by a PD. Fig. 2(a) shows the optical spectrum of the PD input signal. Then, the intermediate frequency signal is up-converted into a THz-wave signal at 209 GHz via a 2nd-order harmonic mixer with a 104.5 GHz local oscillator (LO) generated by an 8x frequency multiplier from 13.1 GHz. A pair of horn antennas are employed for 1-m wireless transmission. The THz-wave signal received is amplified by a low-noise-amplifier (LNA), then recovered to the IF signal by the 2-order harmonic of the 104.5 GHz LO. Finally, the output signal is captured by an 80 GSa/s real-time analog-to-digital converter (ADC). The received spectrum is Fig. 2(b) and the signal is equalized by a feed-forward equalizer (FFE), DFT-S OFDM demodulated, and decoded by the R-ANN. In our experiment, we make a hard decision on the output soft-bits from the R-ANN for simplicity, deciding that soft-bits over 0.5 are "1" and those lower than 0.5 are "0". We choose the conventional grid 32-QAM DFT-S-OFDM signal as the baseline. The baseline applies the same DSPs as the E2E-optimized DFT-S-OFDM scheme.

Fig. 3(a) shows the learning curve of the autoencoder network. As the training epoch goes on, subsets (i)-(iv) show the adjustment in the learned bits-to-symbol mapping rule. Fig. 3(b) is the final converged mapping rule. The T-ANN achieves a near Gray coding on the 32-ary complex symbols which helps minimize the R-ANN decoding bit errors. Fig. 3(c) shows the bit-error-ratio (BER) performance of the fiber-THz integrated system versus the received optical power (ROP) of the PD when the DAC output signal amplitude (Vpp) is 0.3 V. Under the 20% SD-FEC threshold, the E2E optimized scheme realizes 5.5 dB PD sensitivity improvement over the conventional grid 32-QAM DFT-S-OFDM baseline scheme in the 10-km fiber-THz channel. The back-to-back (BtB) and wireless integrated case act a similar performance to the 10-km fiber-wireless integrated case. The E2E optimized constellation in Fig. 3(vi) suggests significant noise resistance than the constellation of the baseline scheme in Fig. 3(v). Fig. 3(d) displays the variation of the system BER as the Vpp increases. We find strong noise effects in Fig. 3(vii) when Vpp is lower than 0.2 V. The E2E optimized symbols distribution realizes better performance under low signal-to-noise (SNR) conditions. Owing to the nonlinear impairments from the amplifiers, the performance penalty becomes severe as the Vpp increases over 0.3 V. Comparing Fig. 3 (viii) and (ix), NLD in the red boxed area will seriously affect the symbol detection of the baseline, while the E2E optimized one suffers less. Fig. 3(e) further shows the BER performances of the two schemes as the transmission bit rate increases. The E2E optimized DFT-S-OFDM signal achieves over 54 Gbps transmission speed under the 20% SD-FEC threshold, 3 Gbps higher than the baseline. The E2E optimized scheme shows better resistance to NLD and noise spreading effects than conventional DFT-S-OFDM signals.

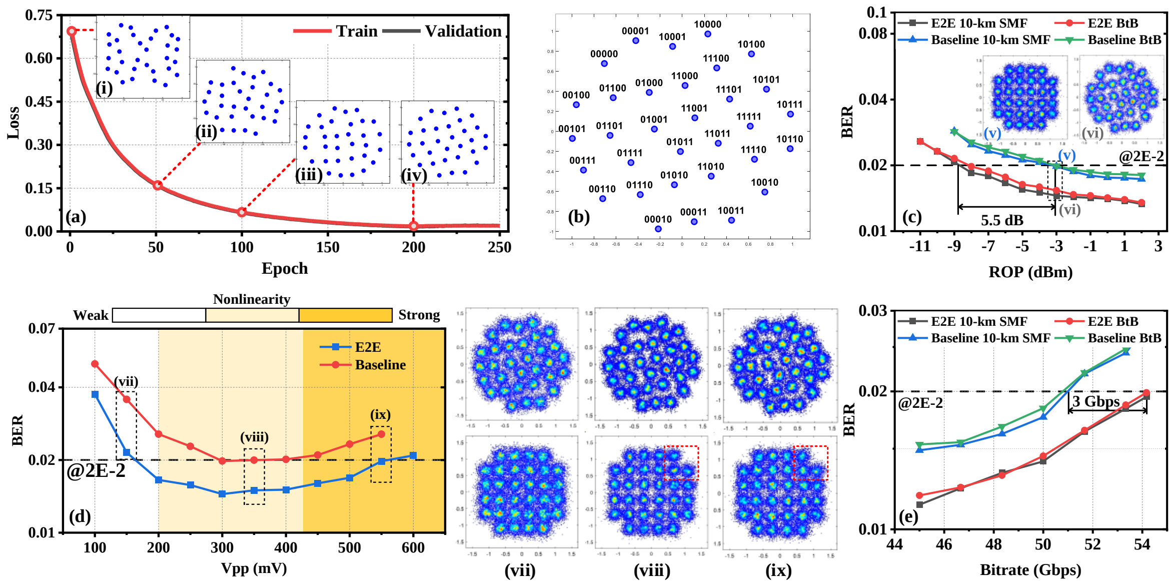

Fig. 3 (a) The learning curve of the autoencoder network; (b) The learned bits-to-symbol mapping rule; (c) The BER of the fiber-THz integrated system with different (c) ROP, (d) Vpp, and (e) Bitrate.

4. Conclusion

A novel deep-learning-based E2E bit-wise autoencoder is proposed to optimize the DFT-S-OFDM signal for the fiber-THz integrated system at 209 GHz. The T-ANN and R-ANN are jointly trained in the autoencoder network to combat the NLD and noise-spreading effect of the DFT-S-OFDM signal. The T-ANN achieves a near-optimal bits-to-symbol mapping while the R-ANN can effectively decode the distorted received symbols into soft bits. In our experiment, the E2E optimized signal shows strong resistance to NLD, realizes 5.5 dB sensitivity improvement than the baseline, and over 54 Gbps transmission speed under the 20% SD-FEC threshold in just 10-GHz bandwidth.

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