End-to-End Optimization and Equalization based on Deep-Learning for Fiber-Terahertz Integrated Communication System at 209 GHz

Yaxuan Li
Key Laboratory of EMW Information (of Fudan University)
Shanghai, China
19307130295@fudan.edu.cn

Junlian Jia
Key Laboratory of EMW Information (of Fudan University)
Shanghai, China
jljia20@fudan.edu.cn

Zhongya Li
Key Laboratory of EMW Information (of Fudan University)
Shanghai, China
20210720074@fudan.edu.cn

Jianyang Shi
Key Laboratory of EMW Information (of Fudan University)
Shanghai, China
jy_shi@fudan.edu.cn

Nan Chi
Key Laboratory of EMW Information (of Fudan University)
Shanghai, China
nanchi@fudan.edu.cn

Junwen Zhang
Key Laboratory of EMW Information (of Fudan University)
Shanghai, China
junwenzhang@fudan.edu.cn

***Abstract*—We proposed and experimentally demonstrated a bit-wise end-to-end autoencoder with post-equalization function for optimization based on deep learning in a fiber-THz integrated communication system at 209 GHz. Using this method, we achieved a higher transmission speed of 4 Gbps and a sensitivity gain of 1 dB compared to the conventional 32-QAM single-carrier signal.**

Keywords—fiber-terahertz, end-to-end learning, AI.

I. Introduction

The development of emerging communication services such as cloud computing, the Internet of Things, 4K/8K ultra-high-definition video, 3D games, or virtual reality/augmented reality (VR/AR) has led to the increased potential and advantages of terahertz (THz) band communication in numerous application scenarios. THz communication has become a key technology in the sixth-generation (6G) radio-access network (RAN) to meet the high throughput demand [1]. Single-carrier modulation (SCM) with high-roder QAMs is an effective modulation scheme with a low peak-to-average power ratio (PAPR) compared with OFDM signals for fiber-THz integrated systems [2]. Although SCM signals suffer less from system nonlinear distortion (NLD) than multi-carrier modulation methods, nonlinear effects and inter-symbol interference (ISI) are still the main factors limiting communication distance and quality. Fortunately, NLD and ISI can be optimized. Artificial intelligence (AI), another key technology of 6G, has shown more promising effects than traditional methods in end-to-end optimization to improve communication system performance [3-6]. Applying end-to-end optimization and equalization based on deep learning in fiber-THz integrated systems has been proved to be an effective metnod to mitegate the impariments caused by NLD and ISI [6].

In this paper, we proposed and experimentally demonstrated a bit-wise end-to-end (E2E) autoencoder framework to optimize and equalize SCM signals based on deep-learning for a fiber-THz integrated communication system at 209 GHz. The framework includes a transmitter artificial neural network (T-ANN) that encodes the bit sequence into complex symbols, a symbol-level data-driven artificial neural network-based channel model (ACM), and a receiver artificial neural network (R-ANN). In the experimental system, we achieved almost a 1 dB sensitivity gain and over 4 Gbps data-rate improvement over the traditional 32-ary quadrature amplitude modulation (32-QAM) SCM signal at the 20% soft-decision forward error correction (SD-FEC) threshold of 2E-2. Additionally, the

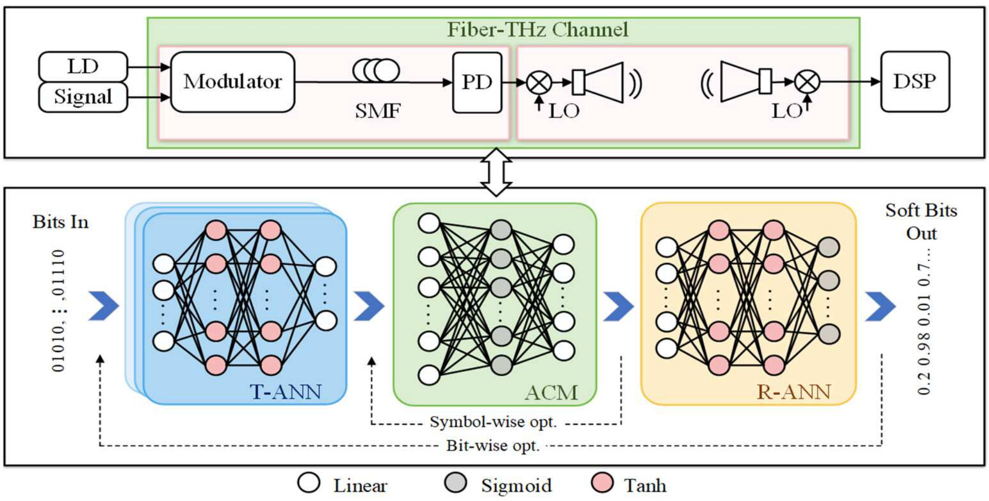

Fig. 1 Diagram of the bit-wise E2E optimization and equalization framework.

optimization and equalization enabled the system to operate within a larger dynamic range of driving voltages.

II. Principles

The bit-wise E2E optimization framework shown in Fig. 1 consists of the T-ANN, ACM, and R-ANN. In the training process, we first train the symbol-level multiple input multiple output ACM using the sampled data from the real system. The transmit symbols are fed to the ACM input, and the corresponding receive symbols are labeled. The trained ACM can model the real system's channel nonlinearity and partial ISI. We fix the ACM weights and place it between T-ANN and R-ANN to simulate signal damage as closely as possible through real channels.

Then, we roughly pre-train T-ANN to accelerate the convergence of the autoencoder training process. T-ANN is a fully connected network with two hidden layers and the nonlinear activation function tanh. The input of T-ANN is M bits of data, which will be encoded to output constellation 2-dimensional coordinates of complex symbols. The output symbols of T-ANN are then fed into the ACM and decoded by R-ANN. R-ANN is a fully connected network with two hidden layers, multiple symbol inputs, and M soft bits output. The activation functions of the hidden layers and the output layer are tanh and sigmoid, respectively. R-ANN can perform soft decoding while performing symbol-level post equalization, and the output value indicates its decoding. Due to the design of the multiple input single output structure and the activation function of the output layer with a range of 0-1, R-ANN can perform both symbol-to-bit soft decoding and symbol-level equalization.

Finally, we train T-ANN and R-ANN. Because the entire autoencoder framework is differentiable, both symbol-level and bit-level gradients can be successfully backpropagated. The symbol-level loss considers the minimum distance and maximum power of symbols after ACM. The update of T-ANN weights would pull the two nearest symbols away while limiting the maximum power. The bit-level loss is a classical binary cross-entropy (BCE) that allows T-ANN and R-ANN to perform bit-level optimization. After training, T-ANN can generate a robust 2^M*-ary* bit-to-symbol mapping rule that resists system channel damage, while R-ANN is an effective receiver symbol equalizer and decoder.

III. Experiment and Discussions

Figure 2 illustrates the experimental setup and details of the digital signal processing (DSP) for a fiber-THz integrated communication system optimized and equalized for end-to-end transmission at 209 GHz. The loaded bits are first encoded into symbols using either QAM mapping or T-ANN and then sent to a 60-GSa/s arbitrary waveform generator (AWG) after single-carrier modulation. The electrical signal amplified by an electrical amplifier (EA) drives a Mach-Zehnder modulator (MZM), where a continuous-wave (CW) light generated by a laser diode (LD) at 1550 nm is fed into the MZM. The optical signal is transmitted through a 10 km standard single mode optical fiber (SMF) and detected by a photodiode (PD). The 209-GHz local oscillator (LO) is generated by a 2-order harmonic mixer with 104.5 GHz created by an 8-time frequency multiplier from a base frequency of 13.06 GHz. The THz signal is transmitted wirelessly via a pair of horn antennas for a distance of 1 meter. The received wireless signal is first amplified by a low-noise amplifier (LNA), then down-converted to an intermediate frequency (IF) signal by 209-GHz LO. Finally, it is amplified and sampled by an 80-GSa/s digital real-time oscilloscope (OSC). The signal is equalized in the time domain and demodulated using CAP, and is then decoded using either 32-QAM de-mapping or R-ANN. In the following results, the soft bits output from R-ANN are subjected to a hard decision (using a threshold of 0.5) to calculate the bit-error-ratio (BER) and compare the transmission performance with the standard 32-QAM signal.

Figure 3(a) displays the loss learning curve for symbol-level loss and bit-level loss during autoencoder training. Fig. 3(b) illustrates the BER of the two schemes as the transmission bit rate increases. The E2E optimized signal achieves 4-Gbps higher transmission speed than the grid 32-QAM signal from 54 to 58 Gbps. These results demonstrate that the E2E optimization framework has superior resistance and robustness to NLD and ISI of CAP signals in fiber-THz integrated communication systems. Fig. 3(c) is the BER performance of the fiber-THz integrated system as a function of PD received optical power (ROP) at 60 Gbps. Under each ROP condition, the optimized working point (minimum BER) for the system when adjusting the peak-to-peak voltage (Vpp) of the AWG output signal is selected. In the case of 10-km SMF and back-to-back (BtB) transmission, E2E optimized

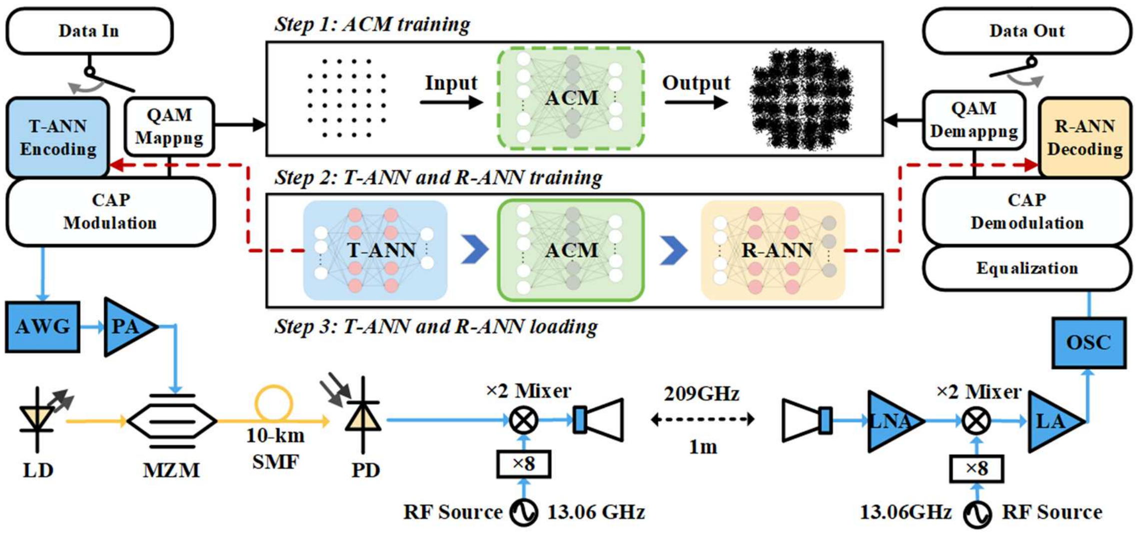

Fig. 2 Experimental setup of the fiber-THz integrated E2E optimized CAP communication system.

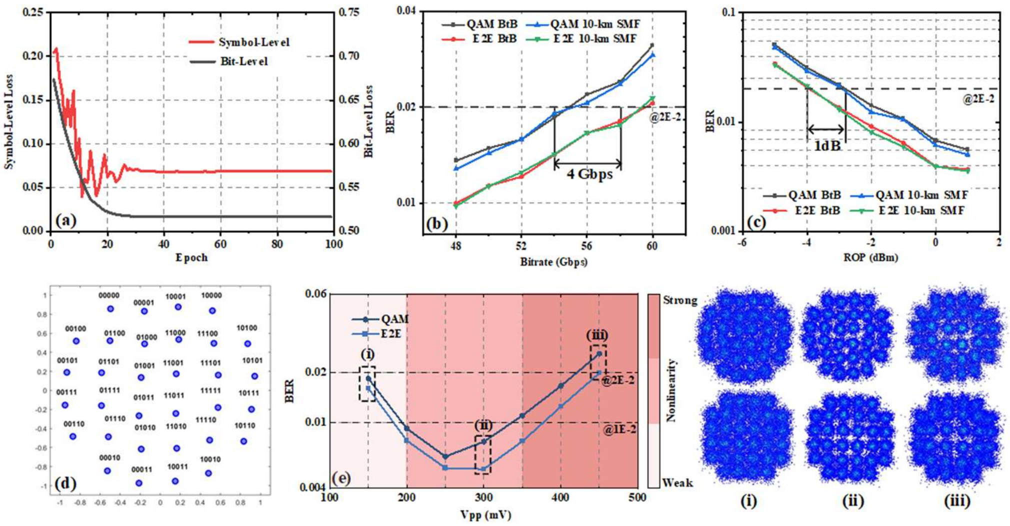

Fig. 3 (a) The iteration losses; the BER performance of the fiber-THz integrated system with different (b) Bitrate, (c) ROP; (d) The learned bits-to-symbol mapping constellation, and (e) the BER performances of different QAMs versus the driving signal Vpp.

scheme realizes a PD sensitivity improvement of about 1 dB over traditional grid 32-QAM under the 20% SD-FEC threshold.

The resulting T-ANN 32-ary bit-to-symbol mapping rule is presented in Fig. 3(d). The optimized constellation is similar to Gray coding, where neighboring symbols differ by only one bit, minimizing bit errors when the same symbol errors occur. Though the mapping may seem irregular, it is tailored for the system and is the optimal solution due to ACM learning from the real system NLD and ISI, which highlights the advantages of E2E optimization. Fig. 3(e) shows in detail the change curve of the system BER performance with driving signal voltage in Vpp, and the illustrations display the E2E optimization constellation and grid 32QAM constellation affected by system channel damage under linear, weak nonlinear, and strong nonlinear conditions. From the results, this optimization method enables the communication system to work in a larger range of Vpp. When Vpp is lower than 200 mV, low signal-to-noise ratio (SNR) is the key factor affecting performance, and E2E optimization results do not significantly improve but still better than grid 32-QAM. With the increase of Vpp, the nonlinearity of the amplifiers and MZM is severe. The constellation points of grid 32-QAM are severely distorted, appearing as the outward stretching of the inner and middle constellation points and the restricted inward compression of the outer constellation points, which seriously affects system performance. However, cause the E2E optimization pre-distort the symbols for NLD, the receiving constellation is relatively uniform. Combined with R-ANN decoding, it exhibits excellent anti nonlinear and ISI performance. The insets (i) to (iii) show the constellations of the E2E optimized and traditional grid 32-QAM signals.

IV. Conclusion

In this paper, we propose a novel E2E optimization and equalization framework based on deep learning for the fiber-THz integrated system using SCM modulation. Our framework enables deep learning to assist in system design and estimation by modeling the nonlinearity and ISI in the real system and using them in the autoencoder training. The T-ANN achieves bit-to-symbol mapping while the R-ANN effectively equalizes and decodes received symbols into soft bits. In our experiment, we achieved over 1-dB sensitivity gain and over 4-Gbps data-rate improvement over the traditional grid 32-QAM signal at the 20% soft-decision forward error correction (SD-FEC) threshold of 2E-2. The proposed scheme offers a promising solution for 6G fiber-THz communication systems by significantly improving overall performance.

Acknowledgment

This work is partially supported by National Natural Science Foundation of China (62235005,62171137 and 61925104), Natural Science Foundation of Shanghai (21ZR1408700), and the Major Key Project PCL. The work is also supported by the Shanghai Engineering Research Center of Low-Earth-Orbit Satellite Communication and Applications, and Shanghai Collaborative Innovation Center of Low-Earth-Orbit Satellite Communication Technology.

References

[1] X. You et al., “Towards 6G wireless communication networks: Vision, enabling technologies, and new paradigm shifts,” Science China Information Sciences, vol. 64, no. 1, pp. 1-74, 2021.

[2] J. Zhang, J. Yu, N. Chi, F. Li and X. Li, “Experimental demonstration of 24-Gb/s CAP-64QAM radio-over-fiber system over 40-GHz mm-wave fiber-wireless transmission,” Opt. Express, vol. 21, no. 22, pp. 26888-26895, 2013.

[3] B. Karanov et al., “End-to-end deep learning of optical fiber communications,” J. Lightwave Technol., vol. 36, no. 20, pp. 4843-4855, 2018.

[4] T. O’shea, and J. Hoydis, “An introduction to deep learning for the physical layer,” IEEE Trans. Cognit. Commun. Networking, vol. 3, no. 4, pp. 563-575, 2017.

[5] Z. Li et al., “Deep learning based end-to-end visible light communication with an in-band channel modeling strategy,” Opt. Express, vol. 30, no. 16, pp. 28905-28921, 2022.

[6] Z. Li et al., "Two-dimensional end-to-end deep learning autoencoder in G-Band fiber-Terahertz integrated transmission for 6G RAN."2022 27th OptoElectronics and Communications Conference (OECC) and 2022 International Conference on Photonics in Switching and Computing (PSC), pp. 01-03, 2022.