Channel modeling with one-stage conditional generative adversarial network for fiber optic communication system

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ABSTRACT

Effective channel modeling is essential for optimizing and designing modern communication systems. It is especially significant for the next generation of communication systems, which are anticipated to revolutionize data transmission methods. Existing methods for channel modeling, particularly those based on deep learning, suffer from high training complexity and slow deployment, making them less viable for real-time applications. Addressing these challenges, we propose a novel wave-to-wave-level modeling strategy utilizing a one-stage conditional generation countermeasure network (OSCGAN). This method is specifically tailored for a 20G Baud IM/DD optical fiber communication system. Our approach significantly reduces training complexity and expedites the deployment process. We experimentally demonstrate that our model not only achieves lower computational overhead but also maintains higher accuracy across various channel conditions. This advancement presents a promising solution for efficiently deploying advanced communication systems while ensuring robust and accurate performance in diverse operational environments. Through this innovative approach, our study contributes to the field by providing a feasible and efficient alternative for channel modeling in high-speed communication systems

Keywords: Optical fiber communication, channel modeling, OSCGAN

1. INTRODUCTION

Channel modeling is crucial for comprehending signal propagation mechanisms, vital for accurately characterizing channels and optimizing reliable communication systems[1-4]. In end-to-end systems, channel modeling facilitates gradient backpropagation, optimizing transceiver performance from transmitter to receiver[5-8]. Given its versatility, neural network approaches have become increasingly prevalent in channel modeling tasks. Several neural network architectures have been employed for this purpose, including heterogeneous neural networks[9], long short-term memory networks (LSTM)[10], and conditional generative adversarial neural networks (CGAN)[11]. Each of these models has its strengths, with CGAN, in particular, demonstrating exceptional generative capabilities, making it highly suitable for modeling in optical fiber communication systems. CGAN's success in these applications can be attributed to its ability to effectively simulate complex channel conditions and behaviors. Despite these advancements, Traditional CGANs employ a labor-intensive two-stage training process, where the generator and discriminator undergo iterative competitive training. This process, while effective, leads to significant increases in training complexity and computational demand. The iterative nature of the training also introduces challenges in achieving convergence, thereby potentially limiting the practical deployment of CGAN in real-world environments. This complexity underscores the need for more streamlined training methodologies that maintain the effectiveness of the model while reducing the computational overhead.

This study proposes and validates a novel channel emulator based on one-stage conditional generative adversarial networks (OSCGAN) for optical fiber communication system. Our experimental findings demonstrate that OSCGAN emulator surpasses conventional model, achieving a 50% reduction in complexity and a 10% increase in modeling accuracy.

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2. PRINCIPLES

The architecture of the OSCGAN emulator, as illustrated in Figure 1, comprises a generator and a discriminator, both featuring an input layer, two hidden layers, and an output layer. The generator models the channel to generate the emulated signal, while the discriminator compares the emulated signal with the real data. First, the condition vector C and real signal Y for training the OSCGAN emulator are constructed based on the signals sent and received by the IM/DD optical fiber communication system. Then, the condition vector C and the noise vector Z are then concatenated to form the input vector for the generator. Third, the input vector passes through two hidden layers to capture signal features. A $Relu$ activation function is embedded after each hidden layer, and the feature vector is nonlinearly fitted through the $Relu$ activation function. Then the vectors output by the two hidden layers are input to the output layer to output the simulated signal $\hat{Y}$ generated by the generator, as shown in equation (1).

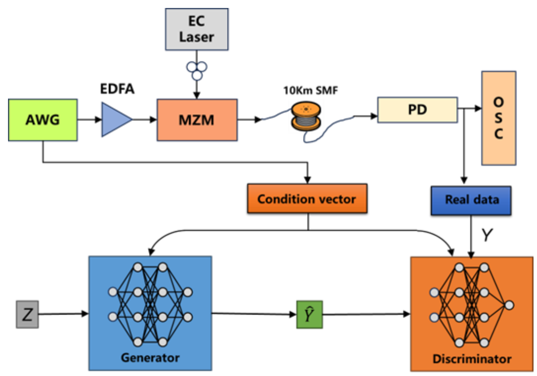

Figure 1. The architecture of the OSCGAN emulator for communication system.

$$\hat{Y} = W_3\left(Relu\left(W_2(Relu(W_1(C+Z)+b_1)+b_2)\right)\right)+b_3 \quad (1)$$

where $W_1^{'}$, $W_2^{'}$ and $W_3^{'}$ represent the weights of the discriminator, and $b_1^{'}$, $b_2^{'}$ and $b_3^{'}$ represent the bias of the discriminator. Fourth, the real data Y and the corresponding emulated signal $\hat{Y}$ are concatenated with the condition vector C, to serve as the input vector for the discriminator. Fifth, the input vector of the discriminator is sequentially calculated through hidden layers and output layer to obtain the similarity P between $\hat{Y}$ and Y, as shown in equation (2).

$$P = W_3^{'}\left(Relu\left(W_2^{'}(Relu(W_1^{'}(\hat{Y}+Y+C)+b_1^{'})+b_2^{'})\right)\right)+b_3^{'} \quad (2)$$

where $W_1^{'}$, $W_2^{'}$ and $W_3^{'}$ represent the weights of the discriminator, and $b_1^{'}$, $b_2^{'}$ and $b_3^{'}$ represent the bias of the discriminator.

The loss function of the traditional two-stage CGAN is shown in equation (3).

$$\min_G \max_D E[\log D(Y \mid C)] + E[\log(1 - D(G(Z \mid C))] \quad (3)$$

where C denotes the condition vector and Y denotes the real signal. D denotes the discriminator and G denotes the generator. $G(Z \mid C)$ denotes the simulated signal generated by the generator. To simplify, the objective can be split into separate losses for D and G as outlined below:

$$L_D = -\log D(Y \mid C) - \log(1 - D(G(Z \mid C))) \quad (4)$$

$$L_G = \log(1 - D(G(Z \mid C))) \quad (5)$$

Both L_D and L_G share the same adversarial term involving $\log(1 - D(G(Z \mid C))$. Hence, we just need to multiply the gradient of L_D by -1 to get the gradient of L_G from L_D. This allows L_D to be used for updating L_G's parameters, which are determined during L_D's training process. This approach streamlines CGAN training from two stages to one.

The OSCGAN emulator applies a one-stage loss function to compute the discrepancy between the $\hat{Y}$ and Y. The Adam algorithm is then used to update the (W, b). During testing, the trained model is evaluated using a test dataset, and the $\hat{Y}$ is compared against the Y to compute the NMSE. Equation (5) outlines the NMSE calculation, where N refers to the symbol' number.

$$NMSE = \frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{N} Y_i^2} \tag{6}$$

The OSCGAN emulator employs the same adversarial term in the loss functions of both the generator and discriminator. This allows for the generator's gradient to be derived during the discriminator's training phase, thereby consolidating the conventional two-stage training approach into a single-stage process. This one-stage strategy can effectively improve the efficiency of channel modeling of communication system.

3. EXPERIMENTAL SETUP

Figure 2 illustrates the experimental setup of the communication system. At the transmitter, the CAP-32 modulated signal is fed into an arbitrary waveform generator (AWG) to generate the transmission signal. A laser at 1550nm generates the optical carrier, which is modulated by the electrical signal using a Mach-Zehnder modulator (MZM). Subsequently, the modulated signal is transmitted over a 10 km standard mode fiber (SMF) and detected by a photodetector (PD). The signal is digitized by a real-time digital-to-analog converter (DAC), processed using a constant modulus algorithm (CMA), and remodulated for decoding. Data gathered from both the transmitter and receiver, along with received optical power (ROP) levels, are utilized for training and evaluation. The reception data of real channel are selected as benchmarks, with both the traditional CGAN and OSCGAN models used for comparison. To assess the performance of the OSCGAN emulator for the 10 km SMF IM/DD optical system, NMSE and training complexity evaluations were conducted on the 20G Baud CAP-32 IM/DD transmission. Figures 3(a) and 3(b) display the NMSE and training complexity outcomes across various ROP levels.

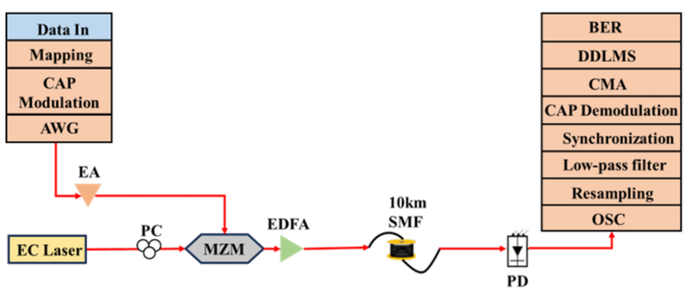

Figure 2. The experimental setup of communication system.

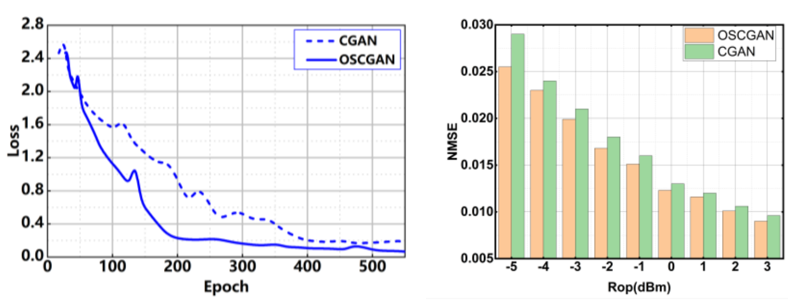

Figure 3. The experimental results 20G Baud CAP-32 IM/DD optical communication system. (a): Training complexity; (b) NMSE under different ROPs.

It is evident that the OSCGAN emulator outperforms the CGAN emulator. Across varying levels of received optical power (ROP), OSCGAN achieves lower NMSE and reduced training complexity compared to CGAN. In particular, the modeling accuracy of the OSCGAN emulator is increased by up to 10% at ROP of 0dBm, and the training complexity is reduced by 50%. This confirms that the OSCGAN emulator has great application prospects in channel modeling of communication system.

4. CONCLUSION

This paper proposes an OSCGAN emulator for communication system. The experimental findings indicate that OSCGAN emulator surpasses the traditional CGAN emulator, achieving a 10% increase in modeling accuracy and a 50% reduction in training complexity. This shows that the OSCGAN emulator has great potential in channel modeling of IM/DD optical fiber communication system.

REFERENCES

[1] Zhang, J. and District, B. H., "The interdisciplinary research of big data and wireless channel: a cluster-nuclei based channel model," China Communications, (2016).

[2] Xu, Q., Gao, R., Cheng, Z., et al., "End-to-end learning strategy based on a frequency domain feature decoupling network emulator with joint probabilistic shaping and equalization for a 300-Gbit/s OAM mode division multiplexing transmission," Opt. Express 32, 13809-13824 (2024).

[3] Xu, Q., Gao, R., Chang, H., et al., "Bayesian generative adversarial network emulator based end-to-end learning strategy of the probabilistic shaping for OAM mode division multiplexing IM/DD transmission," Opt. Express 31, 40508-40524 (2023).

[4] Li, Z., Shi, J., Zhao, Y., Li, G., Chen, J., Zhang, J. and Chi, N., "Deep learning based end-to-end visible light communication with an in-band channel modeling strategy," Opt. Express 30, 28905-28921 (2022).

[5] Timothy, O. and Hoydis, J., "An introduction to deep learning for the physical layer," IEEE Transactions on Cognitive Communications and Networking 3(4), 563-575 (2017).

[6] Maximilian, S., Aoudia, F. and Hoydis, J., "Joint learning of geometric and probabilistic constellation shaping," 2019 IEEE Globecom Workshops (GC Wkshps), (2019).

[7] Aref, V. and Chagnon, M., "End-to-end learning of joint geometric and probabilistic constellation shaping," in Optical Fiber Communication Conference (OFC) 2022, (Optica Publishing Group, 2022), W4I.3 (2022).

[8] Karanov, B., Chagnon, M., Thouin, F., et al., "End-to-end deep learning of optical fiber communications," Journal of Lightwave Technology 36(20), 4843-4855 (2018).

[9] Zhao, Y., Zou, P., Yu, W., et al., "Two tributaries heterogeneous neural network based channel emulator for underwater visible light communication systems," Optics Express 27(16), 22532-22541 (2019).

[10] Wang, D., Song, Y., Li, J., et al., "Data-driven optical fiber channel modeling: A deep learning approach," Journal of Lightwave Technology, 38(17), 4730-4743 (2020).

[11] Yang, H., Niu, Z., Xiao, S., et al., "Fast and accurate optical fiber channel modeling using generative adversarial network," Journal of Lightwave Technology, 39(5), 1322-1333 (2020).