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End-to-End Learning for Chromatic Dispersion Compensation in Optical Fiber Communication

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***Abstract*—In this Letter, we investigate the chromatic dispersion compensation problem in optical fiber communication. An end-to-end autoencoder (AE) is proposed to replace the transceiver of the traditional intensity modulation direct detection system. To deal with the obstructed gradient return problem in end-to-end transmission, we introduce a generative adversarial network to simulate the channel transmission process and employ a square-law detector for incoherent detection to reduce the complexity. Simulation results show that the BER of the proposed system can be significantly cut down compared with the conventional electric domain compensation algorithms.**

***Index Terms*—Chromatic dispersion compensation, end-to-end learning, generative adversarial network, optical fiber communication.**

I. Introduction

Optical fiber communication has always occupied a significant position in the communication field due to its large capacity and reliable long transmission distance. In high-speed optical communication systems, chromatic dispersion is the main factor that limits the propagation distance and the transmission accuracy of optical signals. The chromatic dispersion is caused by the different speeds of light at different frequencies in the optical fiber. As the transmission distance increases, it will continue to accumulate in the optical network, causing pulse broadening and severe inter-symbol interference [1] [2]. Therefore, it is imperative to develop efficient chromatic dispersion compensation methods. In this Letter, we investigate the chromatic dispersion compensation problem in the intensity modulation and direct detection (IMDD) system, which is widely deployed in practical optical networks.

In the IMDD system, dispersion compensation technology is mainly divided into optical domain compensation and electrical domain compensation. The optical domain dispersion compensation schemes use optical components to compensate for single-mode fiber dispersion, such as dispersion compensation fiber and chirped apodized fiber Bragg grating. Dispersion compensation fiber is a device with a negative dispersion coefficient, which cancels out the positive dispersion coefficient of a single-mode fiber [3]. The principle of fiber Bragg grating compensation is to reflect the long-wavelength and short-wavelength components of the light at the start and end of the fiber grating, respectively, which compresses the broadened pulse caused by dispersion [4]. Different from the optical domain compensation, the electrical domain dispersion compensation preprocesses or equalizes the electrical signals to restore the signal distortion. In [5], a digital signal processing module at the transmitter is introduced to perform dispersion compensation iteratively under amplitude constrained or phase constrained scenarios. In [6], a feed forward equalizer based on the least mean square (LMS) algorithm is developed to equalize the signals after photoelectric conversion at the receiver. In [7], a maximum likelihood sequence estimation (MLSE) module is proposed to compensate for residual signal impairments after a feedforward equalizer. In [8], the authors propose a neural network to perform nonlinear equalization on the photoelectric conversion signals at the receiver. In [9] [10], the fiber dispersion and nonlinear distortion are addressed by a physics-based machine learning model, which begins with the fact that numerically solving the nonlinear Schrödinger equation has essentially the same functional form as deep multi-layer neural networks.

Generally speaking, the optical domain dispersion compensation can highly improve system performance but is costly due to additional optical components; the electrical domain compensation is generally convenient to implement, however, its effect is not ideal in practice. In this Letter, we propose a novel electrical domain compensation scheme, end-to-end autoencoder (AE), to process the chromatic dispersion in optical fiber communication, which can enable global optimization of the IMDD system significantly. To solve the obstructed gradient return problem in end-to-end transmission, we also develop a generative adversarial network (GAN) to simulate the fiber channel transmission process. In addition, we use a square-law detector in the end-to-end network for incoherent detection to ensure effective signal transmission while reducing the complexity of the receiver.

The rest of this paper is organized as follows: In Section II, we describe the GAN-based channel model. In Section III, the end-to-end AE architecture is illustrated in detail. In Section IV, we present simulation results, as well as discussions. Conclusions are drawn in Section V.

II. GAN-based channel model

Gradient back-propagation is indispensable for the training of a deep learning neural network, however, the channel transfer function in practical scenarios is extremely complex and cannot even be modeled with a well-defined mathematical formula. Therefore, we use the GAN model to simulate the

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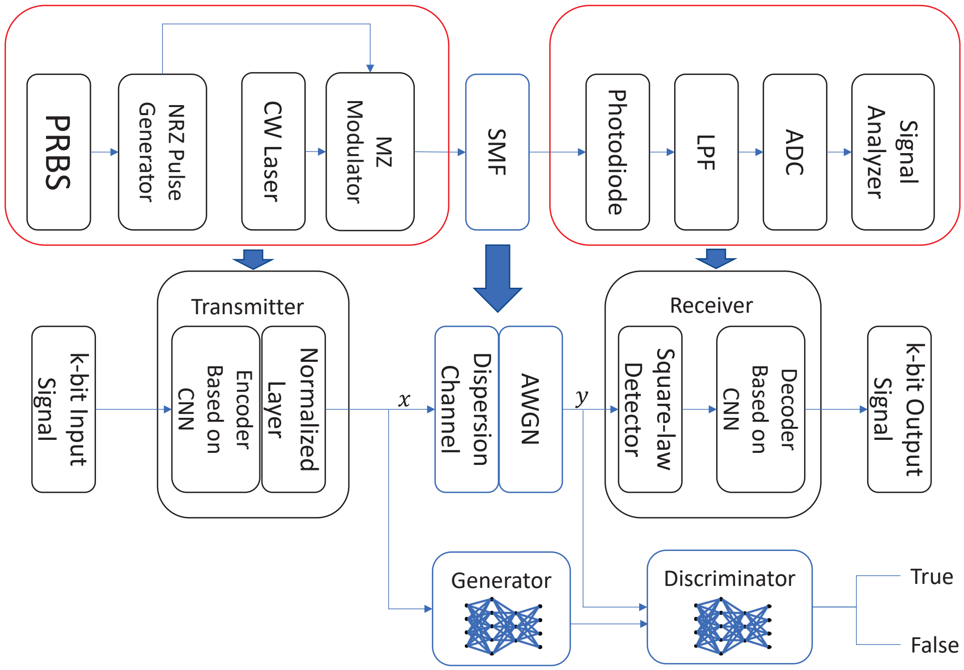

Fig. 1. Schematic diagram of end-to-end optical fiber communication system based on GAN.

output distribution of the considered fiber channel. The GAN is a typical generative model learning [11]. Different from identification model learning, the target of generative model learning is to approximate a certain mapping relationship so that the input data are mapped to a specified spatial distribution. This kind of learning can be regarded as a process of mathematical modeling, which obtains internal laws through feature extraction of the observation data to get a mathematical model of the real world problem. A typical GAN is composed of a generator and a discriminator. The former learns a specific mapping relationship and outputs a specified spatial distribution; the latter distinguishes whether the data come from real space or the distribution simulated by the generator. In the process of learning, the generator continuously improves the ability of spoofing discriminator while the discriminator continuously improves the discriminating ability. Through such an adversarial learning process, the generator finally learns the specified mathematical model while the discriminator provides confidence in the output distribution of the generator.

As shown in Fig. 1, in the IMDD optical communication system, the transmitter signal is transmitted into the generator and the single-mode fiber, whose outputs are connected to the discriminator. We first use a loss function to measure the difference between the generator and the discriminator, and calculate the gradient to optimize the GAN. The generator finally learns the transfer function of the channel after several iterations of optimization. Then we perform gradient backhaul through the generator to optimize the parameters of the encoder. Table I shows the GAN architecture, where the generator is composed of four convolutional layers and the discriminator consists of three convolutional layers and one fully connected (FC) layer.

TABLE I
GAN STRUCTURE

Layer type	Filters	Kernel Size	Activation Function
Conv. layer 1	128	25	Leaky ReLU
Conv. layer 2	64	15	Leaky ReLU
Conv. layer 3	16	15	Leaky ReLU
Conv. layer 4	2	15	Linear
Conv. layer 1	128	25	ReLU
Conv. layer 2	64	15	ReLU
Conv. layer 3	16	15	ReLU
FC layer	4	15	ReLU

III. END-TO-END AE STRUCTURE

The AE is a typical unsupervised learning model with two network structure parts – an encoder and a decoder [12]. The encoder is forced to extract important features to achieve data dimensionality reduction by limiting the network structure, such as reducing the number of neurons in the hidden layer. The decoder performs a reverse process, where the output approximates the original input data by reconstructing the output characteristics of the encoder. In other words, the output label is the original input feature, so the AE is also regarded as a self-supervised learning model. AE can extract more important features by constraining the network structure. With these merits, it is widely used in the fields of data denoising and dimensionality reduction. In this Letter, we adopt the AE to realize an end-to-end transmission system. Compared with the traditional physical layer structure based on continuous modules, the end-to-end system has the advantages of simpler design ideas and global optimization. The encoder is used as a transmitter to learn functions such as modulation and precoding through training while the decoder is taken as a

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receiver to decode and demodulate the received signals to restore the input signals. As shown in Fig. 1, k-bit original signal is modulated by the encoder to obtain the transmitted signal x, which is sent to the dispersion channel and the generator. Then the received signal y is restored to the original signal by the decoder. We employ a cross-entropy function of the output data and the original input data to calculate the loss to update the encoder and decoder. Meanwhile, the GAN is trained according to the process discussed in Section II. Due to the prior assumption that the dispersion channel gradient return is blocked, we perform gradient backpropagation through the generator network to optimize the encoder. It is worth noting that the training process is not completed independently although the AE and the GAN are relatively independent. In each iteration, the end-to-end network and the GAN-based channel model need to cooperate with each other and be updated gradually. Table II shows the AE network architecture, where the encoder is composed of three convolutional layers and one normalization layer while the decoder is composed of nine convolutional layers.

At the receiver, incoherent detection is performed by a square-law detector, which has the advantages of simple circuiting and detection of small signals. A double frequency signal is obtained by squaring during the demodulation process. In this way, the phase information of the signal is lost during the detection process, which will cause relatively large nonlinear distortion. The purpose of our experiment is to explore how to ensure the effective transmission of signals while maintaining low complexity at the receiver in the end-to-end system. In order to meet the requirement of gradient return, we set the square-law detector as a layer in the network, as shown in Fig. 2. The square-law detector consists of two connected layers: The first layer realizes the square of signals; the second layer realizes the superposition of adjacent neurons.

TABLE II
AE STRUCTURE

Layer type	**Filters**	**Kernel Size**	**Activation Function**
Conv. layer 1	128	35	ReLU
Conv. layer 2	16	35	ReLU
Conv. layer 3	8	25	ReLU
Norm. layer	1	10	Linear
Conv. layer 1	256	35	ReLU
Conv. layer 2	64	35	ReLU
Conv. layer 3	64	35	ReLU
Conv. layer 4	64	35	ReLU
Conv. layer 5	16	25	ReLU
Conv. layer 6	16	25	ReLU
Conv. layer 7	16	25	ReLU
Conv. layer 8	4	20	ReLU
Conv. layer 9	1	10	Sigmoid

IV. Simulation Results

We compare the performance of our proposed end-to-end system for dispersion compensation with two electrical domain dispersion compensation algorithms: The least mean square algorithm which equalizes the signals after photoelectric conversion at the receiver [6]; the maximum likelihood sequence estimation module which compensates for residual signal damage after LMS equalization [7].

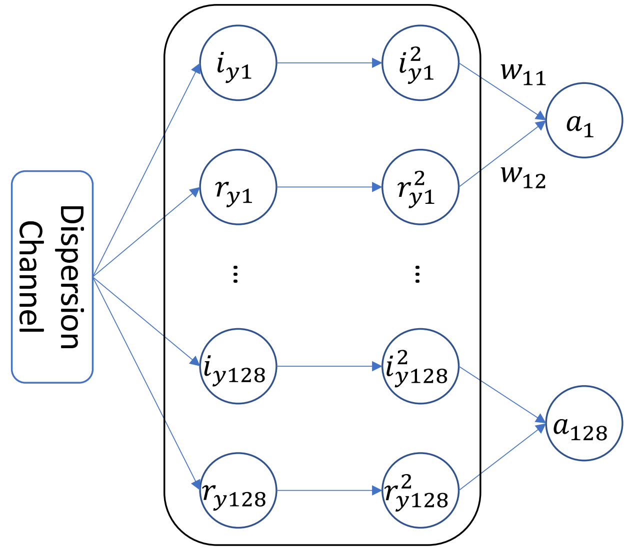

Fig. 2. The layer structure of the square-law detector.

Consider a 20km single-mode fiber with a dispersion coefficient of 16.75ps/nm/km. We adopt a laser with a frequency of 193.1THz and a line width of 19MHz, and the system transmission rate is 25Gbps. The sizes of the training set and the test set are set to 2×10^5 and 5×10^2, respectively. Both block length and batch size are set to 128. In each training epoch, the size of input dataset is set as $[2\times10^5, 128, 1]$. Similarly, we use a dataset of size $[5\times10^2, 128, 1]$ as the test set for the network. The learning rates of the AE network and the GAN are set to 3×10^{-4} and 1×10^{-5}, respectively. The training times for both the transmitter and the receiver increase by 200 after each training, and the number of iterations is 64. The parameters are summarized in Table III. We adopt a variable signal-to-noise ratio (SNR) training method, where the SNR of each training is randomly selected from $[0, 10, 20, 30]$dB.

TABLE III
SIMULATION PARAMETERS

Parameter	**Value**
Length of fiber	20km
Transmission rate	25Gbps
Frequency of laser	193.1THz
Line width of laser	19MHz
Dispersion coefficient	16.75ps/nm/km
Training set size	2×10^5
Test set size	5×10^2
Block length	128
Batch size	128
Learning rate of AE	3×10^{-4}
Learning rate of GAN	1×10^{-5}
Number of iterations	64

Fig. 3 shows the bit error rate (BER) as a function of SNR for three dispersion compensation schemes. As we can see, the BER of the system decreases with increasing SNR. Compared with the other two dispersion compensation algorithms, the performance of our proposed end-to-end (E2E) system-based dispersion compensation scheme is greatly improved.

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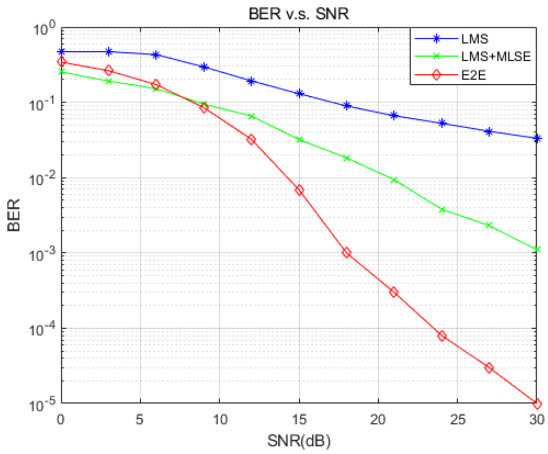

Fig. 3. BER as a function of SNR for three dispersion compensation schemes.

Specifically, when the SNR is 30dB, the BER of the proposed end-to-end system is reduced to 10^{-5}. However, we can see that the proposed algorithm performs slightly worse than the joint compensation based on LMS and MLSE in low SNR range. This is because the system noise is relatively large in low SNR range, and the neural network with a given dataset needs to learn the noise information while learning the mapping relationship between input and output. As the SNR increases, the influence of noise gradually decreases and the neural network can effectively learn the mapping relationship between input and output, so the performance of the end-to-end system is significantly improved.

We also compare the execution time of the algorithms. The complexity of the joint compensation algorithm based on LMS and MLSE is $O(n)$. When the input data size is 10^3 and 10^4, the average execution time of the algorithm is $24.79ms$ and $685.08ms$ with 16G RAM on Intel Core i7-9700 CPU, respectively. The complexity of our trained end-to-end network at the execution stage is a constant $O(1)$ which is independent of the problem size. The average execution time of our proposed method is $5.52ms$ on the same computing platform, which is much less than that of the two electrical domain dispersion compensation schemes.

V. Conclusion

In this paper, we investigated the dispersion compensation problem in IMDD optical fiber communication systems. We proposed an end-to-end system architecture to achieve global optimization, where a generative adversarial network is developed to simulate the channel transmission model efficiently. A square-law detector is employed to implement incoherent detection to reduce the complexity of the receiver. Experimental results show that our proposed end-to-end dispersion compensation scheme can significantly reduce the BER of the IMDD optical fiber communication systems compared with other two ones.

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