MIMO-GRU for Fiber Nonlinearity Equalization in 880Gbit/s Long-distance Transmission System

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***Abstract*—We propose a nonlinear equalizer which has multi-input multi-output structure of gated recurrent unit (GRU) neural network. The complexity of the proposed scheme is only 1.2% of DBP algorithm with equal equalization effects.**

Keywords—nonlinear equalization, neural network, optical fiber communication systems

I. INTRODUCTION

In recent years, the rapid growth of traffic makes coherent optical communication systems have higher information rate, longer transmission distance and higher launch power [1]. However, the capacity of optical fiber systems is further limited by optical nonlinearity, which is caused by the interaction between the Kerr effect of increased launch power and the amplified spontaneous emission noise of the amplifier [2].

Early nonlinear equalization techniques included digital back-propagation (DBP) [3], Volterra series based nonlinear equalizer [4], perturbation-based nonlinear equalization [5] and so on. These algorithms need to obtain the dynamic parameters of optical fiber links, and have high computational complexity. The nonlinear equalization scheme which uses neural network to learn the features between the data without obtaining the parameters of optical fiber link has attracted wide attention. Different types of nonlinear equalizer based on neural networks have achieved good results, such as convolutional neural networks (CNN) [6] and recurrent neural networks (RNN) [7], deep neural networks (DNN) [8]. As an optimized RNN model, GRU retain the advantages of RNN in better feature extraction in time sequence, and solve the problem of gradient explosion of RNN model.

In this paper, we propose a multi-input multi-output (MIMO) structure based on GRU neural network to achieve nonlinear equalization of coherent optical communication systems over multi-channel, high baud rate and long distance. We set up a dual polarization (DP) 16QAM, 110GBaud, 1600km coherent optical transmission simulation system. The numerical simulation results show that the nonlinear equalizer we proposed can efficiently compensate for the intra-channel nonlinearity and the inter-channel nonlinearity. Compared with linear compensation, nonlinear equalization based on MIMO-GRU improves the range of single-channel and multi-channel launch power by 2.2dBm 0.7dBm and 0.55dBm, respectively.

II. THE PRINCIPLE OF MIMO-GRU NEURAL NETWORK

A. Principle of GRU

Its interior consists of three parts, reset gate r_t, update gate z_t and candidate memory $\hat{h_t}$ [9]. The output h_t of the current moment is determined by the input x_t of the current moment and the information h_{t-1} retained at the previous moment. The internal calculation process of the GRU is shown in Eq. (1).

$$\begin{aligned} r_t &= \sigma\left(W_r \cdot [x_t, h_{t-1}] + b_r\right) \\ z_t &= \sigma\left(W_z \cdot [x_t, h_{t-1}] + b_z\right) \\ h_t^{\hat{}} &= \tanh\left(W_h \cdot [x_t, r_t \odot h_{t-1}] + b_h\right) \\ h_t &= \left(1 - z_t\right) \odot h_{t-1} + z_t \odot h_t^{\hat{}} \end{aligned} \tag{1}$$

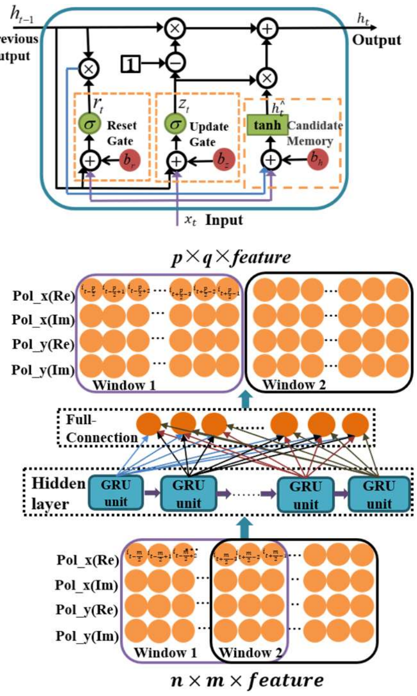
Where W_r, W_z, W_h represents the weight matrix and b_r, b_z, b_h represents the bias vector, σ is the logistic sigmoid function, tanh represents the hyperbolic tangent activation function, $\odot$ operator represents the element-wise product.

B. Architecture of the MIMO Based GRU

The multi-input multi-output structure of GRU is shown in Fig.1(b). First, the data with nonlinear damage are converted into format like n × m × feature as input, where n represents the batch of input data, m represents the length of the input data, and the feature with the value of 4 represents the real and imaginary parts of the data in each polarization state. Then, the data are sent to the hidden layer composed of GRUs to learn and extract the features of the data themselves and between the data. After that, the feature relationships of the data are transferred to the fully connected layer, which integrates and classifies the data. Finally, the data with nonlinear equalization are out in the format of p × q × feature, where p represents the batch of output data, q represents the length of output data, and the feature is still 4.

For MIMO structure implementation, we use the sliding window method. The length of the sliding window on the input side is the same as the length of the data input into the neural network, both of which are m. For each sliding window, we select the index of any moment t from $x_{t-\frac{m}{2}}$ to $x_{t+\frac{m}{2}-1}$ as input. Similarly, the index of our output data are from $y_{t-\frac{p}{2}}$ to $y_{t+\frac{p}{2}-1}$. Considering the characteristics of nonlinear effect, the current symbol is affected by adjacent symbols. Therefore, the input window length is longer than the output window length to better equalize the influence of nonlinear effects. Here, we take the number of input data m=32, the number of output data q=16, the number of hidden units H=16, and the length of sliding window is 16.

(a)



(b)

Fig. 1. (a) Internal structure of GRU (b) Architecture of nonlinear equalization scheme based on MIMO-GRU

C. Complexity analysis

In this section, we analyze and compare the complexity of three algorithms, MIMO-GRU, Bi-directional Long Short-Term Memory (Bi-LSTM) and DBP, which is measured by the number of real multiplications per bit (RMPB). DBP algorithm uses distributed Fourier method to invert Manakov equation which is followed in the transmission process of DP optical fiber communication system. For data of length *N*, the calculation complexity of DBP algorithm is shown in Eq. (2).

$$C_{DBP} = (2N\log_2 n_{FFT} + N)\times 4\times n_s \times N_{step} \times N_{span} \tag{2}$$

where n_{FFT} represents the size of FFT, n_s represents the number of samples, N_{step} represents the number of steps per span, and N_{span} represents the number of spans.

Bi-LSTM is also a neural network structure improved by RNN. For data of length *N*, the calculation complexity of Bi-LSTM algorithm is shown in Eq. (3).

$$C_{Bi-LSTM} = 2N[4(IH + H^2) + 3H + HO] \tag{3}$$

For data of length *N*, the computational complexity of our proposed based on MIMO-GRU model is shown in Eq. (4)

$$C_{MIMO\text{-}GRU} = (3\times(IH + H^2 + H) + HO)\times N / O \times 4 \tag{4}$$

where *I* represents the number of input data, *H* represents the number of hidden units, *O* represents the number of output data.

III. Result And Analysis

The simulation platform is shown in Fig. 2. We set one channel and three channels at the transmitting. In the case of three channels, the launch power of adjacent channels is 3dBm higher than that of the central channel of interest to simulate the multi-channel cases. To clearly demonstrate the inter-channel nonlinearity, the channel spacing is set 120GHz and 150GHz respectively, and the roll-down factor is 0.1. The wavelength of the channel of interest is 1550.12nm. We choose standard single-mode fiber (SSMF) for transmission. There are 20 spans, each span length is 80km. Other parameters in the SSMF fiber are set as follows, attenuation factor $\alpha = 0.2\text{dB/km}$, second order dispersion $\beta_2 = 17ps/nm/km$, fibre nonlinear coefficient $\gamma = 1.3\text{W/km}$. At the end of each span, an Erbium-doped fiber amplifier (EDFA) is used to amplify the attenuated launch power, and the noise figure of EDFA is set to 5dB.

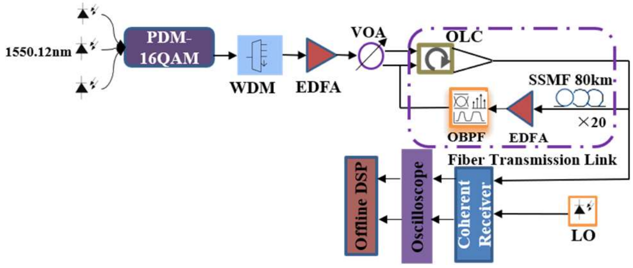


Fig. 2. Setup of simulation platform for coherent communication system

At the receiver, we use offline digital signal processing (DSP) to process the data subjected to both linear damage and nonlinear damage during transmission. The detailed DSP process is shown in Fig. 3. It consists of amplitude normalization, chromatic dispersion compensation (CDC), constant modulus algorithm (CMA) equalization, carrier phase estimation (CPE) based on blind phase search, nonlinear equalizer based on MIMO-GRU neural network, 16QAM demapping and bit error ratio (BER) calculation.

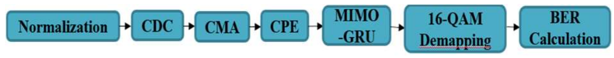


Fig. 3. Offline DSP processing flow of the receiving side

After linear compensation, 60% of the data are sent to the neural networks as training data, and other 40% data are as testing data. The network is trained by minimizing the mean square error (MSE) loss with the back-propagation algorithm and Adam optimizer. The learning rate is 0.005. Finally, the BER is calculated by error counting based on the test data. The system performance is evaluated according to the Q-factor:

$$Q = 20log_{10}(\sqrt{2}erfc^{-1}(2BER)) \tag{5}$$

The equalization effects of the proposed scheme are compared with DBP and Bi-LSTM based equalizer in single channel and multiple channels system, the results are shown in Fig. 4. Fig. 4(a) shows the result for the single channel system, where our proposed equalizer based on MIMO-GRU is better than the DBP with 8 steps per span (simplified as DBP-8sps) at the left side of the optimal power point, indicating that it can balance the influence of nonlinearity that may be introduced by the transmitter. With the increase of power, its equalization performance is slightly lower than DBP-8sps, but has a great improvement compared with CDC.

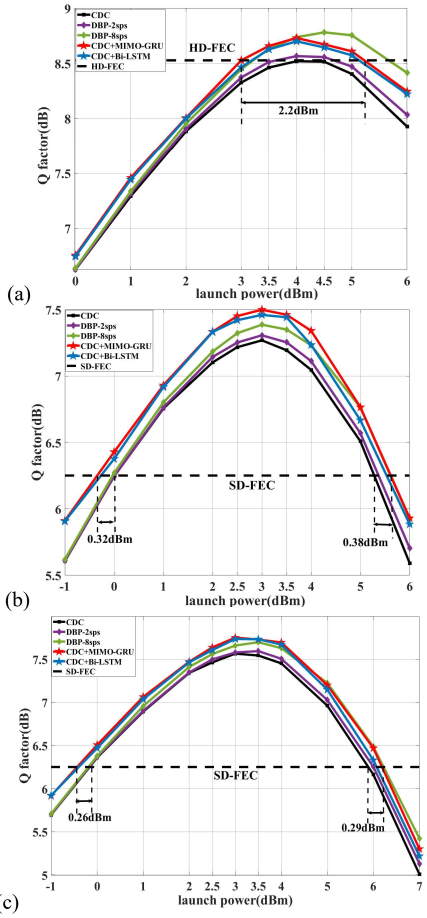


Fig. 4. Q factor performance at different launch power (a) Single channel (b) Multi-channel with channel spacing 120GHz (c) Multi-channel with channel spacing 150GHz

Fig. 4(b) and Fig. 4 (c) show the equalization effects of the nonlinear equalization scheme based on MIMO-GRU for multiple channels with different channel spacing. For the 120GHz channel spacing system, the range of launch power is increased by 0.7dBm and the compensation effect is better than DBP-8sps; For 150GHz channel spacing, the range of launch power is increased by 0.55dBm and its compensation effect is close to that of DBP-8sps. The better equalization effect for the smaller channel spacing reflects that the designed equalizer can equalize the nonlinear damage from Cross-phase Modulation (XPM) effectively. Fig. 5 compares the performance of Q factor and the amount of RMPB for different nonlinear equalization schemes, where the system is multiple channels with 120GHz channel spacing and 4dBm input launch power. The results show that, our proposed MIMO-GRU based equalizer has the similar performance with DBP-8sps and Bi-LSTM based equalizer, while whose computational complexity is much lower than the other equalization methods, the RMPB of the MIMO-GRU scheme only is 1.2% of DBP-8sps and 10.2% of Bi-LSTM.

IV. Conclusion

In this paper, a neural network with MIMO structure based on GRU is proposed to equalize fiber nonlinearity. Coherent optical communication systems with a transmission rate of more than 800Gbit/s and a transmission distance of 1600km are constructed to verify the performance of the proposed nonlinear equalization scheme in single channel and multiple channels, respectively. The results show that, whether in the single-channel system or multiple channels, the MIMO-GRU based nonlinear equalizer both appears the performance improvement, and has the similar equalization effects with DBP-8sps and Bi-LSTM based equalizer. However, compared with DBP-8sps and Bi-LSTM based equalizer, the computation complexity of the MIMO-GRU based equalizer is much lower. This indicates that our proposed nonlinear equalizer is more accessible to practice.

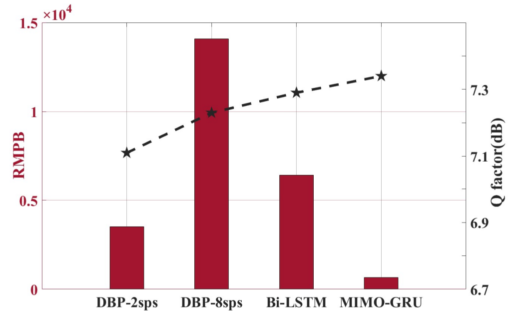


Fig. 5. PMBR times and Q factors of different nonlinear equalization schemes

Acknowledgment

This work was funded by the National Natural Science Foundation of China (No. 62171048, No. 62071065, No. 62075015)

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