High-efficient Equalizer based on the simplified Deep Neural Network for 56Gb/s/λ PAM-4 in C-band 10G DML-based Short reach system

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Abstract—We demonstrate a superior DNN equalizer to improve performance of DML-based short-distance optical transmission systems. The corresponding results show that this scheme can achieve low bit-error-rate in C-band and exhibit excellent nonlinear suppression capabilities.

I. Introduction

Recently, to meet the unabated demand for mobile and cloud services, the short-distance optical fiber communication systems especially for optical fiber access networks and data centers would usher in large-scale development, which will inevitably lead to an increase in construction and deployment costs. Consequently, owing to its simple structure and low system cost, the intensity modulation direct detection (IM-DD) based on low-bandwidth and directly modulated laser (DML) [1,2] is considered as one of the most promising solution for the short reach systems. And, the high-speed PAM-4 modulation format especially for the DML-based one has been as attractive technique for its inherent advantages, such as easy to generate and process signals, low cost, high power, simple structure, et al. Whereas, the chirp induced by DML, the low-devices and fiber chromatic dispersion would result in serve inter-symbol interference (ISI) waveform distortion and eye skew, thereby reducing system sensitivity. So, the digital signal processing schemes have been presented to respectively deal with these problems. Thereinto, the decision feedback equalizer (DFE) [3], feedforward equalizer (FFE) [4] and other machine learning methods [4,5] have been proposed to compensate for the ISI caused by the bandwidth limitation and fiber chromatic dispersion, while the distortion induced by DML chirp were not involved. Apart from this, the schemes combined Volterra filters with DFE/FFE were utilized to suppress nonlinear effects caused by DML chirp and restore signals [6,7]. This method has the limited performance improvement and needed higher taps and the nonlinear items of Volterra, which would increase the complexity of DSP. At the same time, this cannot simultaneously process the hybrid limitation bandwidth, fiber chromatic dispersion and chirp problems.

To the end, a simple DNN-based nonlinear equalizer (DNNE) is proposed to mitigate the hybrid the linearity nonlinearity penalties from a DML in a PAM-4 modulated short reach optical transmission system. For this scheme, the Adam algorithm is utilized to update the coefficients, and by utilizing the Dropout to delete some neurons with a certain probability, the DNNE can be significantly simplified, therefore reducing the complexity of the training model and prevent overfitting. A 56Gb/s per wavelength PAM-4 signal-based optical transmission system over single mode fiber (SMF) is constructed to verify our scheme. The corresponding results show that, the DNNE can achieve a receiver sensitivity of −10dBm at a bit-error rate (BER) of 4.26×10^{-4} and exhibit excellent nonlinear capabilities.

II. Principle of DNN-based Equalizer

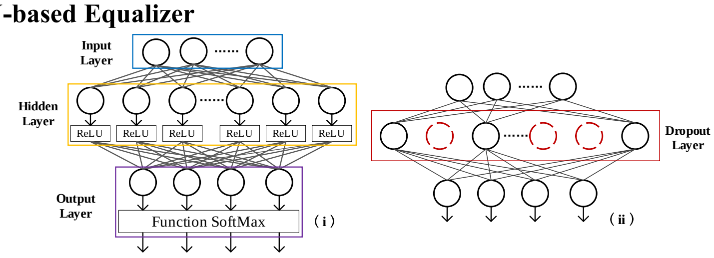

Fig. 1. Schematic diagram of (i)common DNN classification (ii)the simplified DNN with Dropout layer

As a nonlinear model, the Deep neural network (DNN) can implement multiple classification tasks. By dividing the location of different layers, as shown in Fig.1(i), the neural network layer inside DNN includes input layer, hidden layer and output layer, and the layers are fully connected. The relationship between output *Z(x)* and input *x* can be expressed as Eq (1),

$$Z_i^k(x) = f\left(\sum_{n=1}^{N} \omega_{in}^k \, x_n^{k-1} + b_i^k\right) \quad (1)$$

where k, n and i are the index of the layer, features, and neurons respectively, and ω is the weight coefficient, b is the bias term. N is the feature dimension of the input data. In our scheme, the input features consisted of the present sample, (N-1)/2 pre-data, and (N-1)/2 post-data. The function $f(\cdot)$ represents the activation functions, and the use of ReLU in the input and hidden layer which can improve the nonlinearity of the system and accelerate the convergence speed. As for the output layer, the SoftMax is used to further the numerical processing. And, its output characterizes the relative probability between different categories, which can be used to identify the 4 levels of the PAM-4 signals.

To update the weight coefficients and biases, Adam algorithm is used [4], which updates the weight coefficients by calculating the adaptive parameter learning rate based on the first order moments of the gradient and taking advantage of the second order moments of the gradient (ie, uncentered variance). In addition, Adam speeds up the convergence speed by momentum combined with adaptive learning rate. In the t-th iteration, the Adam algorithm updates the weight coefficients using the Eq (2),

$$\omega_t = \omega_{t-1} - \theta \times \frac{\widehat{m}_t}{(\sqrt{\widehat{v}_t}+\epsilon)} \tag{2}$$

where θ is the step size; $\widehat{m}_t$ and $\widehat{v}_t$ are the first-order and the second order moment estimation of the gradient respectively; ϵ is a parameter used to prevent zero-division error.

Additionally, to reduce the complexity of the training process, a Dropout layer is employed in this equalizer for simplifying the DNN. Dropout refers to randomly removing some hidden layer neurons from the fully connected network with a certain probability when training a batch of data (the dotted line in Fig.1(ii) shows the temporarily deleted neurons). Moreover, with the aid of this Dropout layer operation, the overfitting of this equalization can be prevented from reducing the neurons connections in hidden layer. Based on these steps, the simplified network is used for fit the training data and update the parameters iteratively. To further illustrate this point, taking the "Dropout ratio" equaling to 0.5 for example, approximately 50% of the neuron values are set to zero. In the testing phase, the weight coefficient needs to be multiplied by the probability p to scale, which can express as Eq (3),

$$\omega_{test}^{i} = pW^{i} \tag{3}$$

where p is the probability of removing neurons, W^i is the coefficient of i-th neuron. It is effective to improve the generalization of the model by using the Dropout, and a more concise network can be found from the original DNN.

III. Simulation and Results

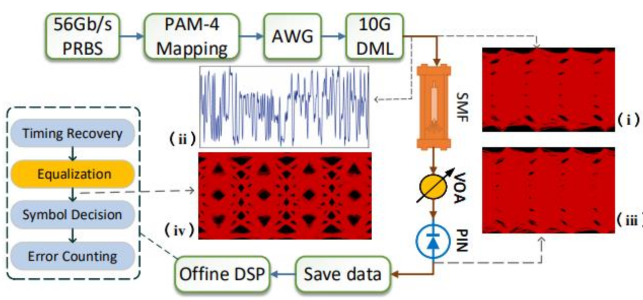

Fig. 2. Simulation Setup (i)eye diagram after DML; (ii) PAM-4 signal after DML; (iii)eye diagram at the receiver; (iv)eye diagram after equalization

As shown in Fig.2, the DML based IM-DD transmission simulation system is conducted to prove the validity of the proposed scheme by combing the MATLAB module and the commercially available software OptiSystem 13.0. Here, to emulate the real experiment system, the system devices and parameters are precisely adjusted. At the transmitter, the bitstreams generated by a pseudo-random bit sequence (PBRS 2^{17}-1) are mapped into PAM-4 symbols at a rate of 56Gb/s. Then, these signals are used to drive DML in C-band (10GHz bandwidth, ~10dBm output power), where the electrical signals are directly loaded into the gain region of the laser cavity to complete the electro-optical conversion. Changes in current will alter the optical frequency, which will lead to signal distortion and blurry eye diagrams at the receiver, as shown in Fig.2. (i), (ii), and (iii). After single mode fiber (SMF) transmission, the PAM-4 optical signals are injected into a variable optical attenuator (VOA), and then the signals are detected by positive intrinsic-negative (PIN). Finally, by capture the data and the DSP processing to recover the original symbols including timing recovery, equalization, symbol decision and error calculations.

To demonstrate the effectiveness of the DNNE, we compare its BER performance with 3-rd Vol-FFE/DFE. The convergence curves for the number of taps at the received optical power (ROP) of -9 dBm is given in Fig3(i), in which

Vol-FFE/DFE reflects the taps used in the first order, and the number of second and third order taps are (5,5) and (7,5) respectively. It is observed that more than 51 taps are needed to achieve convergence in Vol-DFE/FFE. In contract, the convergence performance of the DNNE is better, only 31 taps are sufficient. This will effectively reduce the complexity and cost of system.

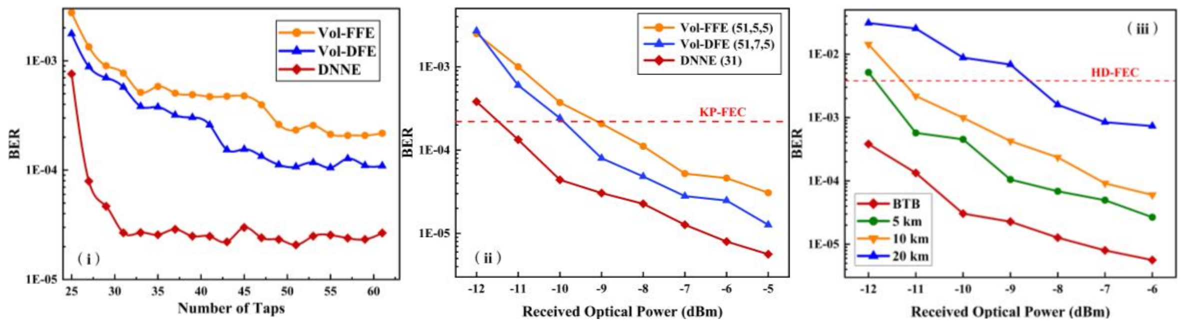

Fig.3. BER performance (i) convergence curves of the number of taps at -9dBm; (ii) different ROP with Vol-FFE/DFE and DNNE; (iii) different lengths of SMF with DNNE

Comprehensive consideration of complexity and performance, we set the numbers of taps as Vol-FFE (51,5,5), Vol-DFE (51,7,5) and DNNE (31). To verity the advantage of the DNNE, the BER performances under different ROP are given in Fig3(ii). It can be obviously observed that DNNE always outperforms the Vol-FFE/DFE. Additionally, DNNE can achieve a ~2dB sensitivity improvement at least under KP4-FEC threshold(BER = 2.2×10^{-4}).

Finally, the BER performances of DNNE under different lengths of SMF is used for further testing. The BER curves of PAM-4 signal after 5km, 10km and 20km transmission under the ROP of -9dBm are shown in Fig.3(iii). Signal distortion mainly comes from nonlinear interference caused by optical fiber dispersion and frequency chirp after SMF transmission. The system performance through different SMF propagations can reach the HD-FEC threshold (BER = 3.8×10^{-3}) when DNNE was used. Obviously, DNNE can achieve the short-distance DML-based optical transmission systems.

IV. Conclusions

In this work, we proposed and verified the effectiveness of deep neural network for reducing signal distortion of 56Gb/s/λ PAM-4 data with DML. Compared with previous nonlinear equalizers, DNNE can obtain lower BER and improve the receiver sensitivity by more than 2dB, which provides a high-efficiency solution for improving the performance of short-distance optical communication systems based DML.

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