56 Gbps IM/DD PON based on 10G-Class Optical Devices with 29 dB Loss Budget Enabled by Machine Learning

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Abstract: We demonstrate 56Gbps PAM4 PON transmission over 25km SSMF using 10G-class DML and APD with 6 GHz 3-dB bandwidth. 29 dB loss budget is achieved by a novel equalization technique based on convolutional neural network.

OCIS codes: (060.2330) Fiber optics communications; (060.2360) Fiber optics links and subsystems; (060.4510) Optical communications

1. Introduction

In recent years, the fast development of 4K/8K high resolution video streaming and the increasing holdings of mobile devices have put forward increasing demand for high bandwidth access networks. Now the 100G-EPON standard is being discussed in IEEE 802.3ca Task Force which is intended to reuse the existing infrastructure of 10G-EPON and scale up to 4×25 Gbps. While this has been done fairly satisfactory in previous work [1], the challenge for 50 Gbps per wavelength transmission have been raised with the demand for still reusing 10G-EPON optics. Due to the ultra-limited bandwidth, it is nearly impossible to directly transmit 50 Gb/s NRZ with 10G-class devices, which makes 25GBd four level pulse amplitude modulation (PAM4) a reasonable choice. However, there are still limitations which come from two aspects: severe inter symbol interference (ISI) caused by the limited bandwidth and the nonlinearity of the optical devices. Therefore, digital signal processing (DSP) is introduced to solve these problems which mainly focus on pre- and post-equalization. Algorithms like feed-forward equalization (FFE), volterra nonlinear equalization (VNE) and maximum likelihood sequence estimation (MLSE) have been used to achieve 50 Gbps PAM4 transmission based on 10G-class optics [2,3]. However, FFE and VNE may encounter problem of limited performance boost when increasing the input sequence length, which is caused by the simple model structure of these equalizers. Machine learning and neural network have become very popular these years and shown its strength especially in the domain of computer vision and machine translation. Thus, neural network comes into view of optical communities with more layers, more intrinsic inter-layer relationship, and usually, higher capability of equalization. Several previous papers have been utilizing neural network to improve system performance. Some of them use neural network as an assistance to other algorithms [4], while some others directly use it as an equalizer [5-7], but it does not seem to have much improvement on system performance, which bring some doubt on the efficiency of neural network as a channel equalizer. However, the common point of these papers is that they all use simple feed-forward fully-connected shallow structure, which nearly disappears in the mainstream machine learning society. A much more powerful tool, convolutional neural network (CNN), is now widely used in the domain of computer vision and also the key for AlphaGo to defeat various professional Go players [8]. CNN have also shown its powerful capability in optical performance monitoring [9].

In this paper, we propose a CNN-based equalization technique which is inspired by the most classic hand-written digit recognition CNN, LeNet5 [10], and experimentally demonstrate 56 Gbps PAM4 IM/DD PON transmission over 25km standard single mode fiber (SSMF) based on 10G-class directly modulated laser (DML) and avalanche photodiode (APD) with a total 3-dB end-to-end bandwidth of 6 GHz, achieving 29 dB loss budget, therefore supporting PR30 link loss budget.

2. Principle of Convolutional Neural Network based Equalizer

The motivation of using CNN instead of multi-layer fully-connected neural network comes from its local pattern extraction capability, in which the stack of convolutional layers acts as multi-channel nonlinear learned local pattern detector that is exactly the capability to overcome the ISI and device nonlinearity.

The most important building block of CNN is the convolutional layer. It performs the convolutional operation upon the input unit to form the output, which is actually cross correlation operation with slide window and sharing parameters. The convolutional layer can be designed to filter 1D, 2D and 3D input, whose structures are shown in Fig. 1(a). Another often used layer is the linear layer, which is also called fully connected layer. Such kind of layer is like the multiple output FFE, in which the input unit is weighted and summed for each output unit, whose structure can be found in Fig. 1(b). Apart from these parametered layers, there are also nonlinear activation layers, which is used to provide the nonlinearity of the network. These layers contain the activation function which is applied to input element-wisely. The most widely used 3 kinds of activation functions are Sigmoid, Rectified Linear Unit (ReLU) and Softmax, which are expressed as following:

$$Sigmoid(x)=\frac{1}{1+e^{x}},\ ReLU(x)=max(0,x),\ Softmax(x)=\frac{e^{x}}{\sum_{i}e^{x_i}} \tag{1}$$

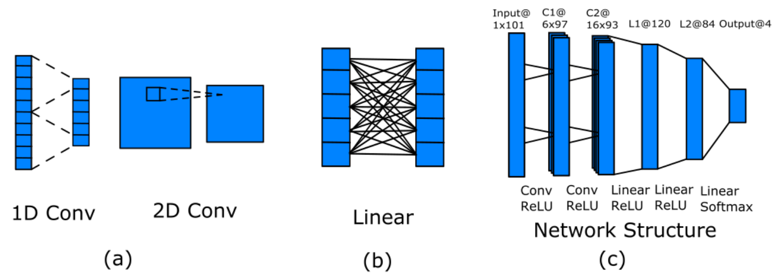

Fig. 1 (a) the structure of convolutional layer (3D version is emitted) (b) the structure of linear layer (c) the network structure of the whole CNN-based equalizer

The structure of the proposed CNN-based equalizer is shown in Fig. 1(c). The whole equalizer is symbol-spaced, of which the input is a time-domain window with length of 101 symbols. The first two layers are 1D convolutional layers with one input channel to six output and six input to 16 output each, both of which have a sliding window size of five and are followed by a nonlinear activation layer of ReLU, which is preferred over Sigmoid because of its fast-training characteristic. After the convolutional layers, the output is unrolled and fed into three consecutive linear layers with 1688 input to 120 output, 120 input to 84 output and 84 input to four output respectively. The first two linear layers are followed by a ReLU layer while the third is followed by Softmax layer, whose four output units denote the four PAM4 symbols. When training, the cross entropy loss of the output is calculated, the loss is back-propagated and the parameters are updated according to the mini-batch gradient descent rule with a batch size of 128. In case of over-fitting, the dropout regularization mechanism is also applied, which makes the hidden unit of the network be removed randomly with a probability of 0.1. The dropout mechanism, which is only activated when training, forces the network to be simple while stays efficient and thus the generalization capability of the network is increased. The whole dataset contains ten independent $2^{15}-1$ pseudorandom-binary-sequences (PRBS15) while the train dataset contains six sequences with around 200k PAM4 symbols, and the cross validation and test dataset contain two each. The train dataset is used to train the model, while the model hyper-parameter and structure tuning are performed according to the performance upon both train and cross validation dataset. The final BER result comes from the performance of model on the test dataset in order to keep the generalization of the model.

3. Experimental setup & results

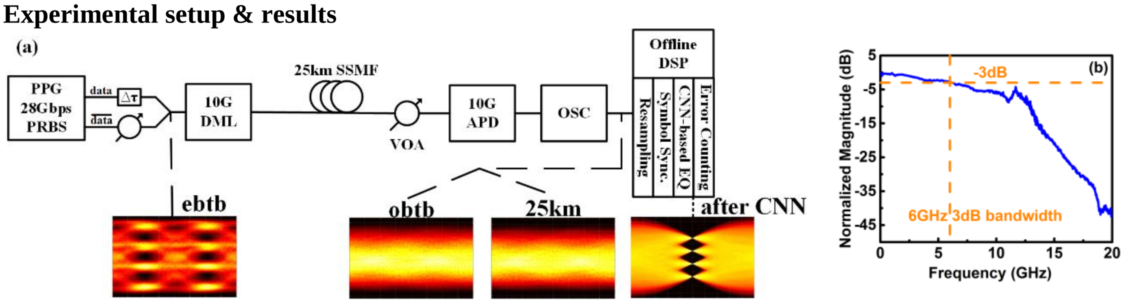

Fig. 2 (a) experimental setup and DSP flow chart (b) channel frequency response

Figure 2(a) shows the experimental setup of proposed 56 Gbps PAM4 IM/DD PON system. At transmitter side, two 28 Gbps PRBS15 NRZ sequences with phase shift of π are generated by Keysight N4960A pulse pattern generator (PPG), of which one is attenuated by 3dB and the other one is delayed by a phase shifter for some symbols. Then the two NRZ signals are added by a power divider to form a 56 Gbps PAM4 signal. The PAM4 signal is then modulated from electronic to optical domain using a 10G-class O-band DML, which is converted back to electronic signal with a 10G-class APD after 25km SSMF transmission. The total 3-dB channel bandwidth is 6 GHz, which is shown in Fig. 2(b). In order to improve the link loss budget, the output power of DML is set to 10 dBm, which is usually in the nonlinear region of the modulation curve of DML and bring much nonlinearity which degrades the signal quality severely. The eye diagrams of electronic back-to-back, optical back-to-back and 25km transmission can also be found in Fig. 2.

After the optical-electronic conversion of APD, the received signal is sampled by a LeCroy digital sample oscilloscope (DSO) with 30-GHz bandwidth and 80-GSa/s sample rate. Then the sampled digital signal is offline-processed with MATLAB and Python. The DSP flow chart is also shown in Fig. 2(a). The sampled signal is first resampled to one sample per symbol, and then the transmitted PRBS15 sequence is extracted from the raw resampled signal. After symbol synchronization, the sequences are gathered together to form a whole dataset and used to train the CNN-based equalizer of which the detail has been discussed above. Finally, bit error rate is counted based on the output of the equalizer.

To investigate the performance of the proposed CNN-based equalizer, we compare direct-decision, FFE, volterra equalizer and CNN-based equalizer and evaluate their BER performance on 56 Gbps PAM4 transmission of both optical back-to-back and 25km SSMF transmission, which is shown in Fig. 3(a) & (b). The FFE taps are 51, 101 and 151, while the configuration of volterra equalizer are (121, 21, 0) and (121, 21, 5), corresponding to the length of first, second and third order kernel. For both optical back-to-back and 25km SSMF transmission, the final results come very close for all FFE and volterra equalizers, which are better than direct-decision. The proposed CNN-based equalizer has a significantly improvement on the system performance, which enables the under-FEC transmission with a sensitivity of -19.2 dBm, and there is no penalty after 25km fiber transmission. Due to the limit number of symbol in test dataset, the lowest BER that can be measured is 7.62e-6, under which the BER cannot be measured correctly due to the limited data sequence length. Considering the 10 dBm output optical power of DML, the total link loss budget achieves 29.2 dB, which can support PR30 link loss budget. In addition, we also test the 10Gbps NRZ transmission performance of APD with 10G-class MZM for reference, of which the result is shown in Fig. 3(c). The APD in our system has a receiver sensitivity of -26 dBm for BER=3.8e-3 and -21.2 dBm for BER=1e-9.

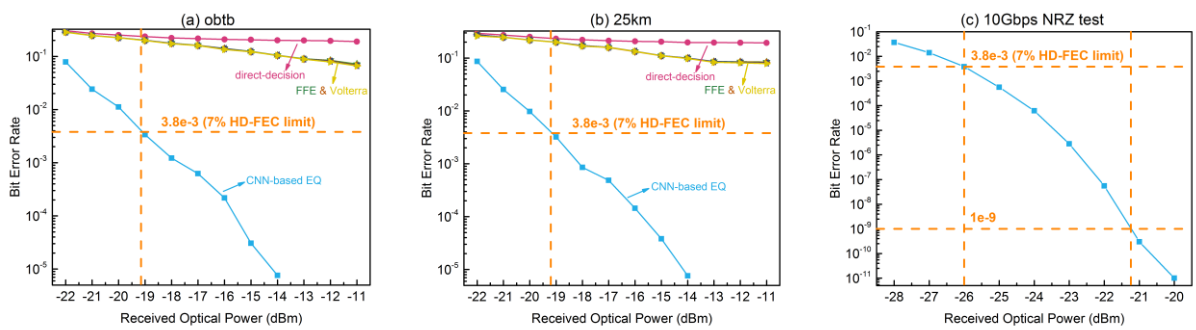

Fig. 3 Comparison of different equalization algorithms on BER performance of 56Gbps PAM4 for (a) Optical back-to-back and (b) 25km SSMF transmission. (c) 10Gbps NRZ test for APD performance evaluation

4. Conclusions

We propose a new equalization technique based on CNN in order to overcome the limitation of ISI and nonlinearity when reusing existing 10G-class optics in next generation passive optical networks. With the help of this specially designed CNN-based equalizer, we successfully achieve 56 Gbps PAM4 IM/DD transmission with 10G-class devices of a total 6 GHz 3-dB channel bandwidth under the conditions of both back-to-back and 25km SSMF. The receiver sensitivity is -19.2 dBm, which makes a total link loss budget of 29 dB. By comparing the performance of the proposed CNN-based equalizer with linear feed-forward equalizer and nonlinear volterra equalizer, we find the proposed equalizer can significantly improve system performance. Have proven its success in the domain of computer vision and machine translation, we believe neural network and machine learning can also shine a light on optical access networks and optical interconnections.

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