Multi-Symbol Output Long Short-Term Memory Neural Network Equalizer For 200+ Gbps IM/DD System

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Abstract *We propose a single-lane 212Gbps IM/DD PAM-4 system with a novel Multi-Symbol Output LSTM equalizer that performs much better than FFE&VNE and single-symbol output LSTM, and reduces complexity by 49.85% at the same time, and achieves similar performance with Bi-directional LSTM with around 1/4 complexity.*

Introduction

With the growing demand of bandwidth and the development of deep learning, machine learning based equalization has been a hot topic in optical communication area. A lot of studies have shown that artificial neural network (ANN) can be a promising solution for nonlinear equalization tasks[1]–[6].

In order to further improve the performance, many works have focused on improving the structure of neural network equalizers. Deep neural networks (DNN)[7]–[9], convolution neural networks (CNN)[10], recurrent neural networks (RNN)[11],[12] and long short-term memory networks (LSTM)[13],[14] have been applied to multiple fiber-optic nonlinear equalization tasks. However, signal processing tasks are different from image/speech area. Slide window method is used in most existing NN-based equalizers, and those windows are the input of the NN models. Adjacent windows have a large amount of the same data, but the input is different from each other in image recognition tasks. Calculating similar inputs brings more complexity. Therefore, it's important to make neural networks better serve Digital Signal Processing (DSP) tasks.

In this paper, we proposed a novel NN equalization technique, which reduces the complexity of NN-based equalizers by increasing the output symbols. We experimentally demonstrated a 212Gbit/s IM/DD PAM-4 system using C-band EML transmitters and used multi-symbol output (MSO) LSTM for equalization. Results show that the proposed MSO-LSTM performs much better than Forward-Feedback Equalization & Volterra Nonlinear Equalization (FFE&VNE) and Single-Symbol Output (SSO) LSTM, and achieves similar performance with recently proposed Bi-directional LSTM[14] with only around 1/4 complexity.

Long Short-Term Memory Network (LSTM)

Long short-term memory (LSTM) neural network, is a special kind of RNN, which solves the problem of gradient disappearance and gradient explosion in long sequence training. The excellent features of LSTM make it ideal for digital signal processing tasks in communication systems. We proposed an equalizer based on LSTM at receiver end, and used it for equalizing PAM-4 signals in our system.

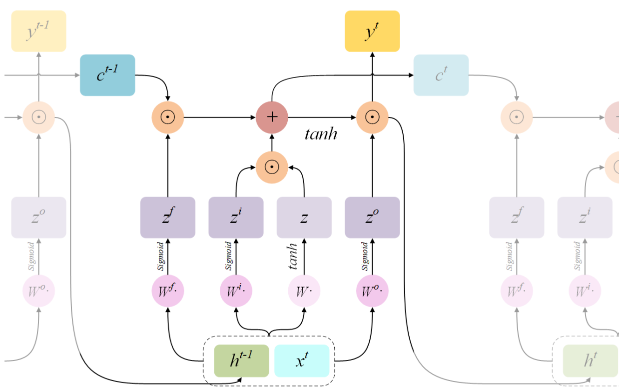

Fig. 1: The architecture of LSTM

Fig.1 shows the structure of LSTM, in which z stores the weighted input data, and z_f, z_i and z_o refer to the gating states that control the network to forget, to selectively memorize, and to output, respectively.

While doing equalization jobs, LSTM adopts signals block as input data, trying to calculate signal intensity or symbol in target position. In offline training, the whole data is first divided into training set and test set, and only training set participates in the weight update of the model. The test set is only used to evaluate the performance, so that the result is assured to be without overfitting.

The total calculation amount can be expressed by $4(n_e + n_h) \cdot n_h \cdot n_s$, in which n_e denotes the length of input data, n_h denotes the number of neurons in the hidden layer (in z^f, z^i, z, z^o, respectively), and n_s denotes the number of groups of input data, which means the number of slide windows in the signal sequence.

Multi-Symbol Output NN-based Equalization

The aim of using multi-symbol output instead of single-symbol output is to reuse the same input signal block and reduce useless calculation, and to increase the information carried by training labels and decrease the length of training sequence. The output symbols share the input taps. The amount of output symbols only affects the complexity of the output layer, while the main structure of NN never changes. The number of sliding windows is inversely related to the number of output symbols.

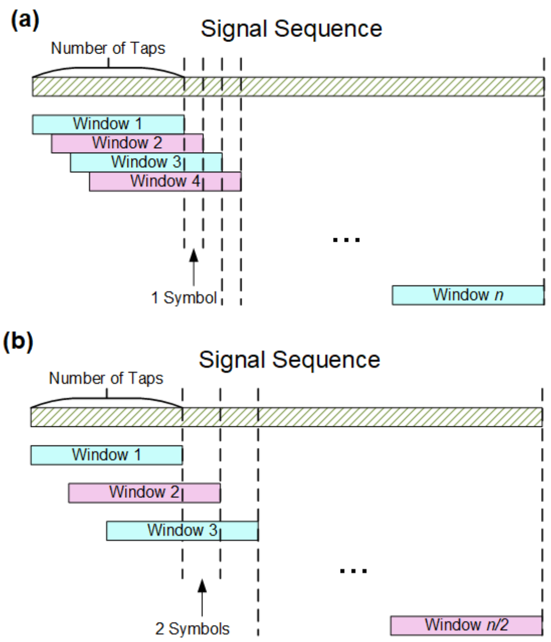

Fig. 2: The slide window scheme of (a) traditional single-symbol output NN-based equalizers (b) the proposed multi-symbol output neural network

The schemes of the slide window process in SSO-NN equalization and the proposed multi-symbol output NN are shown in Fig.2. It can be seen that the number of sliding windows n_s is reduced by half when the output symbol is 2. After being processed by LSTM, the data is flattened and feed into full-connected network, and multi-symbol output can be achieved by increasing the length of the output layer and encoding the output symbols of the network.

When using cross entropy as loss function for equalization and decision, the linear increase in the output symbol results in an exponential increase in the length of the output layer. For PAM4 signals, there are 16 combinations of the two symbols. Moreover, the more edged the output symbol is in the sequence, the fewer effective taps the symbol corresponds to. Therefore, there is trade-off in choosing the number of output symbols. If NN is only used in equalization but not decision, Mean square error can be the loss function, and the length of output layer then equals to the output symbols.

In this paper, we demonstrated a 2-symbol ouput LSTM neural network, which has an output layer of 16 instead of 4. The training label varies from 0 to 15, which refers to symbol '00', '01', ..., etc. The schematic diagram is shown in Fig.3(c), in which $n_e = 300$ is the length of input signal, n_{h1} refers to the number of LSTM units, n_{h2} refers to the length of the linear FC layer. The activation function we chose is *Sigmoid* and the loss function is cross entropy.

Experimental Setup

The experimental setup of the proposed 212-Gb/s/λ PAM-4 IM/DD System is shown in Fig.3(a). On the Tx side, 106-Gbaud PAM-4 signals are generated by a digital-to-analog converter (DAC) working at 106-GSa/s with the 3-dB bandwidth of 40 GHz. An EML with 3-dB bandwidth of 40 GHz and a center wavelength of 1550 nm is operated at 25Â℃. The 106-Gbaud PAM-4 signal from DAC is amplified by an electrical amplifier (EA) before driving the EML. Then, the 106-Gbaud PAM-4 optical signals are transmitted back-to-back and over 1km Non-Zero Dispersion-Shifted Fiber (NZDSF) (GVD of 2ps/nm/km) with an average loss of 0.25 dB/km. Considering that the baudrate of the signal is very high, we use NZDSF instead of regular standard fiber such as SMF-28 to reduce fiber dispersion effect. An EDFA preamplifier is used at the ONU before direct detection by a PIN PD. A variable optical attenuator (VOA) is applied to adjust the received optical power (ROP) for sensitivity measurement to test the system performance. On the Rx side, the signal is detected by a 70 GHz PD and amplified by a 60 GHz EA, and then captured by a 160-GSa/s oscilloscope with 63-GHz bandwidth and processed by offline DSP with Python. The workflow of offline DSP on Rx is shown in Fig.3(e).

Results and Discussion

To get best parameters of the LSTM equalizer, we tested different numbers of n_{h1} and n_{h2} in Fig.3(c) in 212Gb/s 1km transmission with -1 dBm received optical power. The results are shown in Fig.4.

According to Fig.4, we picked the best $n_{h1} = 300$, $n_{h2} = 200$, and designed SSO-LSTM, SSO-Bi-LSTM and the proposed MSO-LSTM based on these parameters. To investigate the performance of the proposed MSO-LSTM, we compared FFE$\&$VNE, SSO-LSTM, SSO-Bi-LSTM and MSO-LSTM by evaluating the BER performances of those Equalization techniques on 212 Gbps PAM4 transmission of both optical back-to-back and 1km NZDSF transmission.

It can be seen that the proposed MSO-LSTM performs better than both FFE/VNE and SSO-LSTM, and similar with SSO-Bi-LSTM. By encoding the output symbols, more information is brought. Therefore,

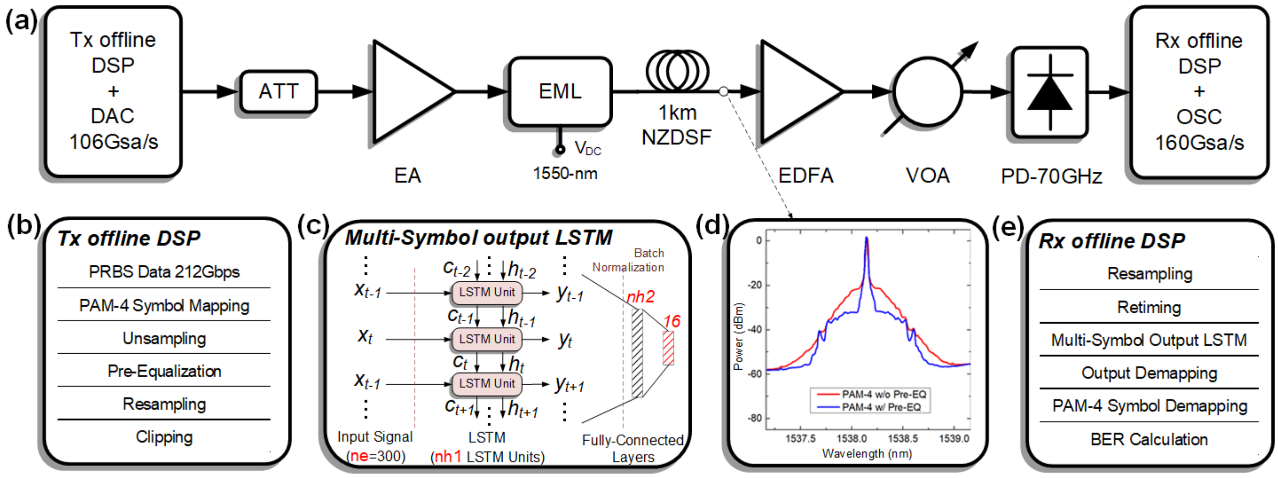

Fig. 3: (a) the experimental setup of the 212-Gb/s/λ PAM-4 IM/DD system (b) the workflow of offline DSP on Tx (c) the schematic of the proposed multi-symbol output LSTM (d) the optical spectra of 106 Gbaud PAM4 signal with and without pre-equalization (e) the workflow of offline DSP on Rx

Numbers of hidden 2 \ Numbers of hidden 1	50	100	150	200	250	300
50	0.0247	0.0253	0.0249	0.027	0.0268	0.0255
100	0.0095	0.0086	0.0102	0.0099	0.0105	0.0112
150	0.0048	0.005	0.0042	0.0056	0.0057	0.0061
200	0.0029	0.0019	0.0021	0.0027	0.0027	0.0029
250	0.0011	0.0014	0.0016	0.0014	0.0023	0.002
300	0.0012	0.0009	0.0008	0.0008	0.0014	0.0014

Fig. 4: The heat map of BER performance obtained by LSTM-Eq. with different parameters

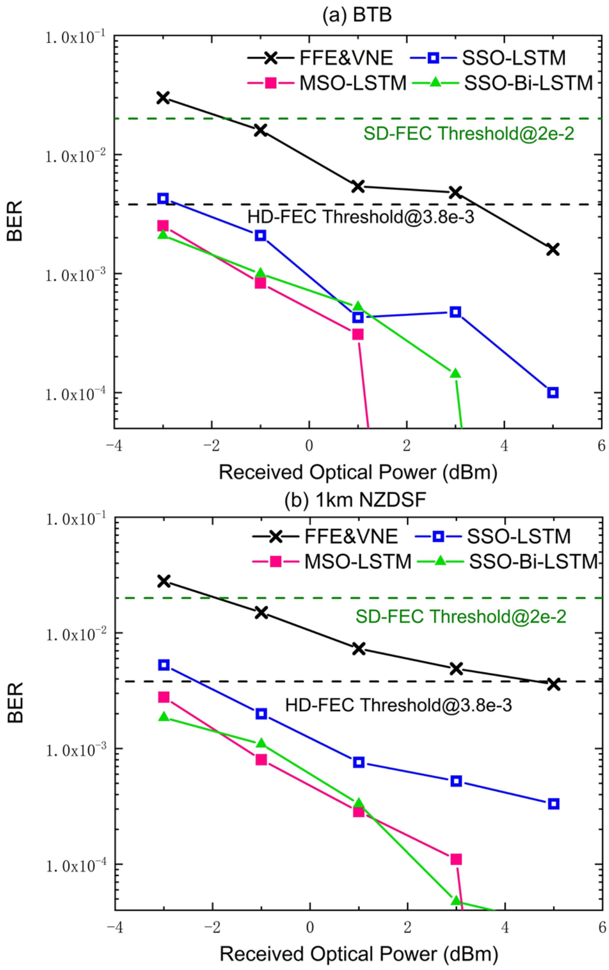

Fig. 5: BER performance of 212Gbps PAM4. (a) back-to-back, (b) after 1km NZDSF transmission.

the cross entropy loss would reflect more information, and the LSTM NN is better trained. 1dB gain is achieved comparing to SSO-LSTM equalization.

We also compared the complexity of single-symbol output LSTM and the proposed multi-symbol output LSTM. We calculated Multiply-ACCumulate operation (MACC) for both SSO-LSTM, SSO-Bi-LSTM and MSO-LSTM. When $n_e = 300$, $n_h = n_{h1} = 300$ and $n_{h2} = 200$, SSO-LSTM has an operation of $4(n_e + n_h) \cdot n_h + n_h \cdot n_{h2} + n_{h2} \cdot 4 = 780800$ MACC per symbol, Bi-SSO-LSTM has an operation of $2 \times 4(n_e + n_h) \cdot n_h + 2n_h \cdot n_{h2} + n_{h2} \cdot 4 = 1560800$ MACC per symbol, and MSO-LSTM has an operation of $[4(n_e+n_h) \cdot n_h + n_h \cdot n_{h2} + n_{h2} \cdot 16]/2 = 391600$ MACC per symbol. It means we can save up to 49.85$\%$ complexity comparing to SSO-LSTM, and 74.91$\%$ comparing to Bi-SSO-LSTM. The parameters are chosen in search for extreme performance. When using the algorithm in real time systems, parameter selection needs to be more cost-effective.

Conclusions

We propose a new structure for neural network-based equalizers that can gain performance and reduce complexity. We successfully achieve 212 Gbps PAM4 IM/DD transmission under the conditions of both back-to-back and 1km NZDSF with MSO-LSTM for DSP at Rx end. By comparing the performance of the proposed MSO-LSTM equalizer with SSO-LSTM equalizer, Bi-SSO-LSTM equalizer and Volterra nonlinear equalizer, we find the proposed equalizer can improve system performance and reduce complexity by 49.85$\%$. Our work is not limited to LSTM, and the design of multi-symbol output can be applied to most NN-based equalization algorithms at Rx end. We believe next generation AI based equalization algorithms will be more powerful and more suitable for DSP tasks. *This work was partially supported in part by Chinese National key R&D projects under grant number 2018YFB1801703.*

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