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Low Complexity Joint Neural Network Equalizer in a 248 Gbit/s VSB PS-PAM8 IM/DD Transmission System

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Abstract *We propose a novel joint neural network equalizer in a 248 Gbit/s VSB PS-PAM8 transmission system at the C-band. The proposed joint neural network equalizer outperforms the conventional neural network equalizer with significant MACC calculation complexity deduction.*

Introduction

Driven by the consistently increasing data traffic demand, the solutions for the high-speed data-interconnect (DCI) will be essential for the future optical network. To support next-generation 800G or even 1.6T data connection, the single line bitrate beyond 200 Gbit/s will be the top priority [1-5]. However, the transmission distance for the intensity modulation and direct detection (IM/DD) system beyond 200 Gbit/s at the C-band is limited to less than 2 km standard single mode fiber (SSMF) due to the selective frequency fading and severe nonlinear impairments [6-7]. Therefore, advanced digital signal processing (DSP) algorithms are required for enhancing system performance.

With the rapid development of machine learning technology, neural networks (NN) have been widely adopted as nonlinear equalizers in IM/DD systems [8-10]. However, the conventional NNs have relatively weak performance on compensating for linear impairments due to the nonlinear activation function and sophisticated nonlinear structure. Therefore, the mixed linear and nonlinear impairments are compensated by the DSP consisting of the feedforward equalizer (FFE) and the NN equalizer or the relatively complex NN equalizer with extended memory depth in previous work [11-13]. The former leads to front-end DSP-induced impairments and high delay due to the cascaded DSP structure, and the latter suffers excessive computational complexity. We have proposed a joint neural network (JNN) equalizer consisting of a linear forward-path (LP) and a nonlinear forward-path (NLP) in parallel to decouple the linear and nonlinear impairments compensation in the NN equalizer. The decoupling method significantly reduces the nonlinear taps while improving the equalization performance. The novel joint network structure provides a solid solution for the low complexity and high-performance NN structure design.

In this paper, it is the first time to achieve the vestigial sideband (VSB) IM/DD transmission system beyond 200 Gbit/s at the C-band. With the PS technique and JNN equalizer, 92 GBaud PS-PAM8 signals transmitted over 10 km SSMF meet the normalized generalized mutual information (NGMI) threshold at 0.88 for 20% soft-decision forward error correction (SD-FEC). Compared with the conventional NN equalizer, the JNN equalizer improves the receiver sensitivity with only 25.63% multiply-accumulate operation (MACC) calculation complexity.

Joint Neural Network Equalizer Principle

The principle and structure of the JNN are depicted in Fig. 1. The JNN consists of two parallel paths: the LP and NLP. The input vector x_{LP} of LP consists of L_{LP} symbols. It should be noted that all the nonlinear factors are excluded by the LP to enhance linear fitting ability. The activation function of the LP is the proportional function $y = kx$, which is appropriate for compensating linear impairments. The factor k controls the proportion of LP output in the final JNN output, which is not negligible for the combination of the LP and NLP. Meanwhile, given the combination law of convolution, no hidden layer is required in the LP. The forward calculation of the LP can be expressed as:

$$\begin{cases} y_{LP} = f_l(w_{LP} * x_{LP}) \\ f_l = kx \end{cases} \tag{2}$$

Here, x_{LP} denotes the input symbol sequence.

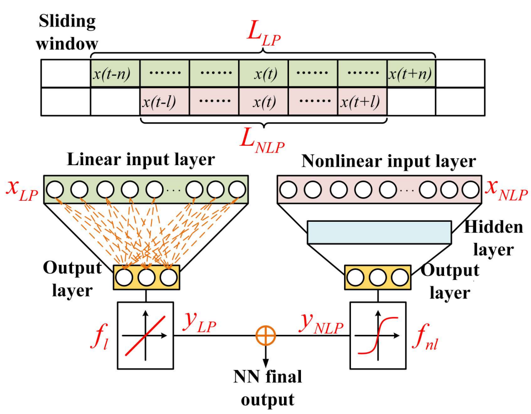

Fig. 1: The diagram of the layer structure of JNN.

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w_{LP} represents the weights of the LP. f_l and y_{lp} are the linear activation function and the output of the LP. Compared with the LP, the NLP contains the additional hidden layer to provide the high-order nonlinear fitting capability. The hidden layer of the NLP can be the fully connected layer, convolution layer, or recurrent layer. Here, the long short-term memory (LSTM) layer is selected in this experiment. As the variant of the recurrent neural network (RNN), the LSTM layer stores the information of the current moment and the previous moment in the cell state, which solves the gradient explosion and vanishment problem. Significantly, the output of the NLP is activated by a designed nonlinear function to enhance the ability of nonlinear fitting. The sigmoid function is chosen here to avoid information loss.

The output of the LP and NLP is added to get the final output, which represents the recovered PAM symbol. While training, the mean square error (MSE) loss of the JNN output is calculated and fed back to adjust the weights to get convergence. In summary, the two parallel paths are effectively combined to compensate for linear and nonlinear impairments.

Experimental Setup

The experimental setup is demonstrated in Fig. 2(a). At the transmitter side (Tx), the external cavity laser (ECL) operating at 1550 nm generates the continuous wave. The 14.5 dBm C-band light wave is injected into an intensity modulator (IM) with 40 GHz 3-dB bandwidth driven by the 92 Gbaud PAM electrical signals. The electrical signals are generated by the 92 GSa/s arbitrary waveform generator (AWG) and amplified by an electrical amplifier. After the 10 km SSMF transmission, the signals are amplified by an Erbium-doped fiber amplifier (EDFA). Meanwhile, a tunable optical filter (TOF) with 0.8 nm bandwidth is employed to generate optical VSB signals. The optical spectra of the optical signal before and after the TOF are depicted in Fig. 2(i). The optical power is attenuated by the attenuator to weaken nonlinear effects. At the receiver side (Rx), the optical signals are detected by a photodiode (PD) with 70 GHz 3-dB bandwidth. The detected electrical signals are amplified by an electrical amplifier with 22 dB gain and then captured by a 256 GSa/s digital oscilloscope with 59 GHz 3-dB bandwidth for offline DSP.

The block diagrams of DSP employed at the Tx and Rx are shown in Fig. 2(b). The origin binary bitstream is mapped into uniformly distributed PAM4 or probability shaping (PS) PAM8 symbols. The PS symbols follow the Maxwell-Boltzmann distribution. The entropy of PS-PAM8 symbols is set as 2.7 bits/symbol. The PAM symbols are oversampled to 2 Sa/symbol for the following shaping and pre-equalization (Pre-Eq). A 128-tap root raised cosine filter with a 0.05 roll-off factor is adopted to realize Nyquist shaping. After that, a Pre-Eq filter is applied to pre-compensate the impairments induced by the bandwidth limitation. The weights of the Pre-Eq filter are obtained from the 53-tap T/2-spaced CMA equalizer at the Rx. Finally, the electrical PAM symbols are resampled to 1 Sa/symbol. At the Rx, two NN equalizers are considered and compared in two DSP options. In both DSP options, the captured PAM symbols are resampled to 1 Sa/symbol at first. The retiming algorithm is applied to mitigate the sampling offset. The Kramers-Kronig (KK) scheme is adopted to mitigate the signal-signal beating interference (SSBI) of the received VSB symbols. However, due to the high carrier-to-signal ratio of the transmitted signals, the KK scheme shows limited performance improvement.

In the DSP *Opt. 1*, the JNN equalizer is adopted to compensate for impairments. As for the structure of the JNN equalizer, the LP consists of an input layer, an output layer, and a linear activation function. Meanwhile, the NLP consists of an input layer, an LSTM layer as the hidden layer, an output layer, and a nonlinear activation function. The length of the input symbol sequence for LP and NLP is set as 153 and 15, respectively. The number of neurons in the LSTM layer of JNN is set as 31. The value of the control

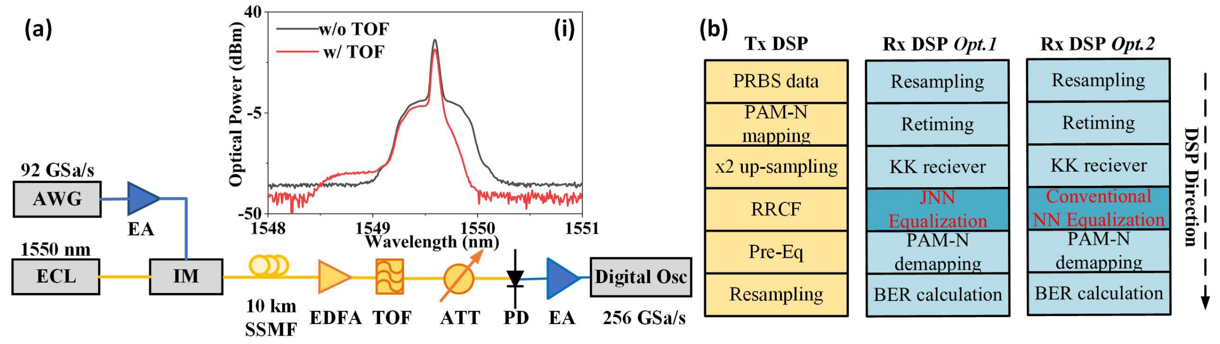

Fig.2: (a) The diagram of the experimenta setup. (b) The block diagram of DSP. Inset: (i) The optical spectra before and after TOF.

factor k is set as 1.6. In the DSP *Opt. 2*, the conventional NN equalizer is adopted as the baseline model, which consists of an input layer, an LSTM hidden layer, and an output layer. The number of the input symbols and neurons are set as 153 and 31 to be consistent with the JNN equalizer for fair comparison. The details of the NN equalizers are presented in Tab. 1.

Tab. 1: Hyperparameters of the NN equalizers

Parameter	Value
Gradient optimizer	Adam
Epoch	35
Batch size	80
Initialization strategy	Gaussian
Loss function	MSE loss

Experimental results and discussions

The NGMI curves versus the received optical power for 92 GBaud VSB PAM4 and PS-PAM8 signals transmitted over 10 km SSMF are demonstrated in Fig. 3. The NGMI is generally regarded as an accurate indicator to measure the performance of uniformly distributed and PS signals. Compared with the JNN equalizer, the conventional NN equalizer shows limited performance gain. With the JNN equalizer, the PAM4 and PS-PAM8 signals meet the NGMI threshold when the received optical power is -0.1 dBm and 2.5 dBm, respectively. The probability distribution of the recovered PS-PAM8 signals with the JNN or conventional NN equalizer is depicted in Fig. 3.

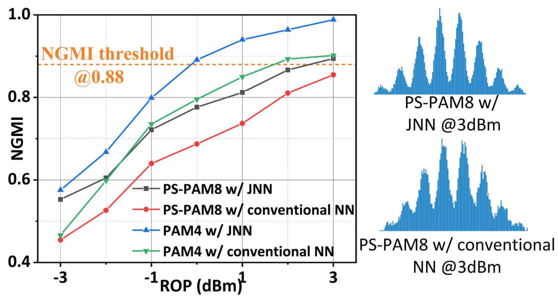

Fig. 3: NGMI curves versus received optical power of PAM4 and PS-PAM8 signals with the JNN or conventional NN.

To further investigate the performance improvement brought by the parallel structure of the JNN equalizer, the performance of the JNN with or without the LP is compared in Fig. 4. The LP significantly improves the performance of the JNN equalizer. The decoupling mechanism of linear and nonlinear impairments compensation in the NN equalizer improves the compensation ability of linear impairments while mitigating the interference of linear damage to nonlinear equalization. The constellation diagrams of the recovered PAM4 and PS-PAM8 signals with the LP in the JNN equalizer is depicted in Fig. 4.

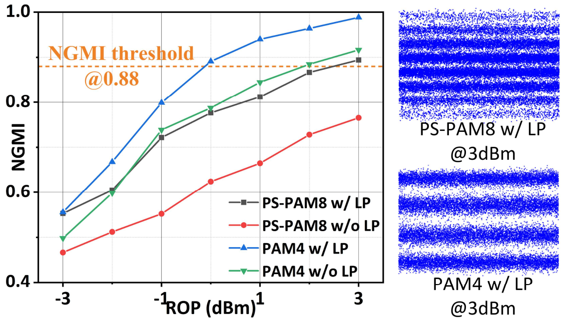

Fig. 4: NGMI curves versus received optical power of PAM4 and PS-PAM8 signals with or without the LP.

As for the computational complexity, the MACC is adopted as a measurement indicator. The MACC refers to the times of multiple-add operation, which determines the cost of hardware resources. The MACC complexity of the output layer and LSTM layer in the NN equalizers is expressed as:

$$\begin{aligned} C_{LSTM\ layer} &= 4 \times n_H \times (n_I + n_H) \\ C_{Output\ layer} &= n_H \times n_O \end{aligned} \tag{2}$$

According to the structure of the JNN and conventional NN equalizer, the MACC calculation complexity of these two NN equalizers is 5857 and 22847, respectively. Compared with the conventional NN equalizer, the proposed JNN equalizer performs better with only 25.63% MACC calculation complexity.

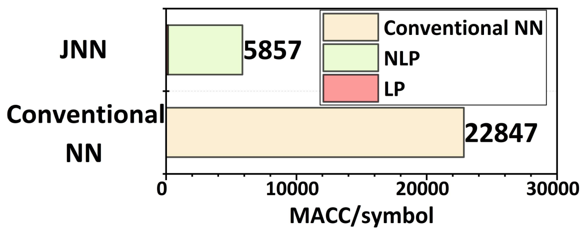

Fig. 5: The MACC complexity per symbol of the DSP.

Conclusions

In this paper, we propose a JNN equalizer in a VSB IM/DD system beyond 200 Gbit/s/λ at the C-band. The proposed novel JNN equalizer decouples the linear and nonlinear impairments compensation in the NN equalizer to improve equalization performance with the 74.37% MACC calculation complexity reduction.

Acknowledgments

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