SCIENCE CHINA
Information Sciences

• LETTER •

April 2024, Vol. 67, Iss. 4, 149301:1–149301:2
https://doi.org/10.1007/s11432-023-3947-8

Linear shallow neural network to accelerate transmitter dispersion eye closure quaternary (TDECQ) assessment

Junjiang XIANG[1], Zejun CHEN[1], Yijun CHENG[2], Hailin YANG[1], Xuancheng HUO[1], Meng XIANG[1,3,4], Gai ZHOU[1], Yuwen QIN[1,3,4] & Songnian FU[1,3,4*]

[1]*Institute of Advanced Photonics Technology, School of Information Engineering, Guangdong University of Technology, Guangzhou* 510006*, China;*
[2]*School of Optical and Electronic Information, Huazhong University of Science and Technology, Wuhan* 430074*, China;*
[3]*Key Laboratory of Photonic Technology for Integrated Sensing and Communication, Ministry of Education of China, Guangdong University of Technology, Guangzhou* 510006*, China;*
[4]*Guangdong Provincial Key Laboratory of Information Photonics Technology, Guangdong University of Technology, Guangzhou* 510006*, China*

Received 28 August 2023/Revised 13 December 2023/Accepted 26 January 2024/Published online 21 March 2024

To support the ever-emerging capacity requirement of datacenter interconnection (DCI) applications, transmitter dispersion eye closure quaternary (TDECQ) has been proposed by IEEE802.3 standard [1], which is specifically employed for the four-level pulse amplitude modulation (PAM-4) signals. However, the traditional scheme of TDECQ assessment needs several iterative operations, leading to an enhanced computation complexity. Therefore, the intelligent TDECQ assessment with both high accuracy and low implementation complexity has attracted worldwide research interests. Meanwhile, deep learning (DL) is widely investigated in optical communication systems [2], which can reduce the operation complexity and maintenance cost. For example, a two-dimensional convolutional neural network (2D-CNN) based on the rectified linear unit (ReLU) as the nonlinear activation function (NAF), together with three feature extraction layers and one regression layer, has been proposed for accelerating the TDECQ assessment, when the eye-diagram of 25 Gbaud PAM-4 signals is used as the 2D-CNN input. The mean absolute error (MAE) of 0.13 dB is experimentally reported, when the TEDCQ range is from 1.9 to 5 dB [3]. However, the computation complexity of deep neural networks (DNNs) hinders their applications. Therefore, it is ideally desired to simplify the involvement of NAF and reduce the number of neural units.

In the current submission, a linear shallow neural network (L-SNN) is proposed to accelerate the TDECQ assessment. Since the L-SNN only consists of input and output neural units, we can realize a minimalist neural network (NN) without the use of hidden layer and NAF, for the ease of precise and fast TDECQ assessment. Our experimental results of 25 and 50 Gbaud PAM-4 optical signals indicate that the MAE is below the standard threshold of 0.25 dB over a TDECQ range of 1.5–4.0 dB.

Operation principle of L-SNN. Since amplitude histograms (AHs) are utilized as the NN input in this study, the TDECQ value of each AH is calculated by the traditional TDECQ assessment scheme recommended by the IEEE standard to obtain the correct label. Meanwhile, a traditional DNN is equipped with the input layer, hidden layer, and output layer. Especially, the NAF is indispensable. Generally, DNN can be described as

$$\boldsymbol{H}^1 = \mathrm{NAF}(\boldsymbol{W}^1 \times \boldsymbol{X} + \boldsymbol{b}^1), \tag{1}$$

$$\boldsymbol{Y} = \boldsymbol{W}^2 \times \boldsymbol{H}^1 + \boldsymbol{b}^2, \tag{2}$$

where $\boldsymbol{X}$ is the input matrix with a size of $1 \times D$. $\boldsymbol{W}^i$ is an $n^{i-1} \times n^i$ weight matrix, which provides a linear connection from the $(i-1)$th layer to the ith layer. n^i denotes the neuron numbers of the ith layer. $\boldsymbol{b}^i$ is the bias for each layer. $\boldsymbol{H}^1$ represents the output value of the first hidden layer, and $\boldsymbol{Y}$ is the prediction result. $\mathrm{NAF}(\cdot)$ indicates the used NAF.

Generally, the NAF is used to identify complex nonlinear relationships between the input data and output task. However, as for the application of optical communication, it is worth thinking about the necessity of the NAF. The commonly-used NAFs can be divided into two categories, including saturated activation functions and unsaturated activation functions. Those unsaturated activation functions include ReLU and Swish, which can be analytically divided into linear factors and nonlinear factors. When the input data is positive, the NAF is approximately a linear function. Since the obtained dataset from optical communication applications has no negative value, it is reasonable to replace the unsaturated activation functions with the linear activation function (LAF). Meanwhile, both Tanh and Sigmoid are widely used as the saturated activation function. When the NAF is satisfied with Taylor theorem [4], Sigmoid is used to decompose as an example. We can identify that, the saturated activation function can also be divided into

* Corresponding author (email: songnian@gdut.edu.cn)

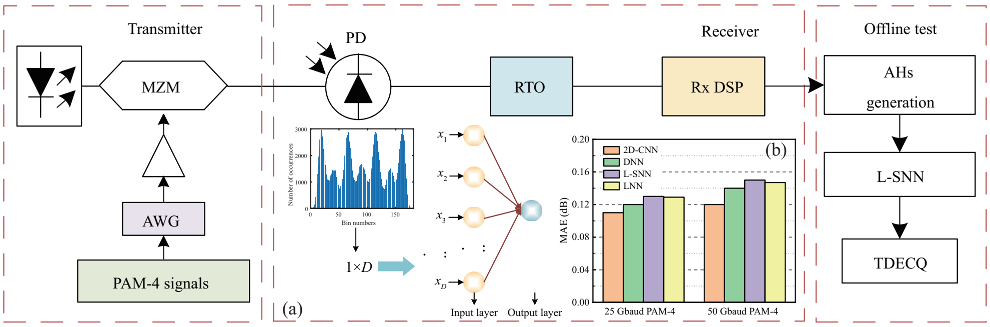

Figure 1 (Color online) Experimental setup of TDECQ assessment. (a) Structure of L-SNN; (b) compared results.

the linear factor and the nonlinear factor shown as

$$\mathrm{Sigmoid}(x) = \frac{1}{1+\mathrm{e}^{-x}} = \underbrace{\frac{1}{2}+\frac{1}{4}x}_{\text{linear factor}} + \underbrace{\cdots + R_n}_{\text{nonlinear factor}}, \quad (3)$$

where $R_n = o[x^n]$ is the higher-order term. The saturated activation function approaches a constant under the saturated state, and it can be approximated by a linear function under the un-saturated state. Therefore, the potential application of LAF in the field of optical communication is promising.

When all NAFs are removed, a linear neural network (LNN) is developed with the linear connection. Then, the DNN can be reconfigured as

$$\begin{aligned} \boldsymbol{Y} &= \boldsymbol{W}^2(\boldsymbol{W}^1 \times \boldsymbol{X} + \boldsymbol{b}^1) + \boldsymbol{b}^2 \\ &= \underbrace{\boldsymbol{W}^2 \times \boldsymbol{W}^1}_{\text{weights}} \times \boldsymbol{X} + \underbrace{\boldsymbol{W}^2 \times \boldsymbol{b}^1 + \boldsymbol{b}^2}_{\text{bias}} = \underbrace{\boldsymbol{W}}_{\text{weights}} \times \boldsymbol{X} + \underbrace{\boldsymbol{b}}_{\text{bias}}. \end{aligned} \quad (4)$$

Next, L-SNN is further developed, without the use of hidden layers and NAFs, as shown in Figure 1(a). Since the used AH as input is optimized with 210 bins, the input neural unit of L-SNN is 210, while the output neural unit of L-SNN is 1.

Experimental setup and results. The experimental setup of TDECQ assessment is schematically shown in Figure 1. At the transmitter (Tx), electrical 25/50 Gbaud PAM-4 signals based on short stress pattern random quaternary (SSPRQ) pattern are generated by arbitrary waveform generator (AWG, Keysight M8194A) having a sampling rate of 120 GSa/s. A root-raised cosine (RRC) filter with a roll-off factor of 0.1 is used, before the corresponding digital signals are loaded into AWG. After being amplified by an electrical amplifier with a gain of 18 dB and a 3 dB bandwidth of 67 GHz, the electrical signals are used to drive the Mach-Zehnder modulator (MZM) (FUJITSU FTM7938EZ) with a 3 dB bandwidth of 40 GHz, leading to the successful generation of 25 and 50 Gbaud PAM-4 optical signals. At the receiver (Rx), a photodetector (PD) (Finisar XPDV3120R-VF-FP) with 3 dB bandwidth of 70 GHz is used to realize the optical-to-electrical conversion. The output electrical signals are digitalized by the real-time oscilloscope (RTO, LECROY LabMaster 10-59Zi-A) with a sampling rate of 160 GSa/s. Then the received PAM-4 signals are used to generate each AH with 30000 sampling points as the L-SNN input. All AHs labeled with variable TDECQ values are collected by varying the MZM bias. Next, 67% of those AHs are used for training, while 37% of those AHs are used for testing. Initially, we carried out a performance comparison among 2D-CNN, DNN, LNN, and the proposed L-SNN. Figure 1(b) shows the experimental TDECQ assessment results of 25 and 50 Gbaud PAM-4 optical signals, respectively. Although the MAE values of 2D-CNN and DNN-enabled assessment schemes are better than those of L-SNN-enabled schemes, the implementation of 2D-CNN and DNN requires a lot of hardware resources. The MAE values of L-SNN enabled assessment for 25 and 50 Gbaud PAM-4 optical signals are 0.13 and 0.15 dB, respectively, over a TDECQ range of 1.5–4.0 dB. In particular, the L-SNN-enabled scheme can reach the accuracy threshold recommended by IEEE standard [5]. Although the MAE performance is almost the same for both LNN and L-SNN, the used number of multiplications is only 210 for the L-SNN, which is almost two orders of magnitude smaller than that of LNN.

Conclusion. We have demonstrated a data-driven TDECQ assessment scheme based on L-SNN. In comparison with existing DL-based schemes, the proposed L-SNN can achieve the lowest computation complexity with only 210 multiplications. The MAE of the L-SNN scheme for 25 and 50 Gbaud PAM-4 optical signals is experimentally verified to be 0.13 and 0.15 dB, respectively, over the TDECQ range of 1.5–4.0 dB, which has reached the accuracy threshold of 0.25 dB recommended by the IEEE standard.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant No. 62025502) and Guangdong Introducing Innovative and Entrepreneurial Teams of the Pearl River Talent Recruitment Program (Grant No. 2021ZT09X044).

Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 IEEE Standard for Ethernet. Amendment 10: Media Access Control Parameters, Physical Layers, and Management Parameters for 200 Gb/s and 400 Gb/s Operation. 802.3bs-2017. https://ieeexplore.ieee.org/servlet/opac?punumber=8207823

2 Khan F N, Fan Q R, Lu C, et al. An optical communication's perspective on machine learning and its applications. J Lightwave Technol, 2019, 37: 493–516

3 Varughese S, Garon D A, Melgar A, et al. Accelerating TDECQ assessments using convolutional neural networks. In: Proceedings of the Optical Fiber Communications Conference and Exhibition (OFC), 2020

4 Guan X, Yang Y, Li J J, et al. Mind the remainder: Taylor's theorem view on recurrent neural networks. IEEE Trans Neural Netw Learn Syst, 2022, 33: 1507–1519

5 Varughese S, Melgar A, Thomas V A, et al. Accelerating assessments of optical components using machine learning: TDECQ as demonstrated example. J Lightwave Technol, 2021, 39: 64–72