Mixed-Precision Integer-Arithmetic-Only Neural Network-Based Equalizers for DML-Based Short-Reach IM/DD Systems

Zhaopeng Xu[(1)], Honglin Ji[(1)], Yu Yang[(1)], Gang Qiao[(1)], Qi Wu[(1,2)], Jia Li[(1)], Weiqi Lu[(3)], Lulu Liu[(1)], Shangcheng Wang[(1)], Jinlong Wei[(1)], Zhixue He[(1)], Weisheng Hu[(1,2)], and William Shieh[(3)]

[(1)] Peng Cheng Laboratory, Shenzhen 518055, China, xuzhp@pcl.ac.cn
[(2)] State Key Lab of Advanced Optical Communication Systems and Networks, Shanghai Jiao Tong University, Shanghai 200240, China
[(3)] School of Engineering, Westlake University, Hangzhou 310024, China

Abstract *We propose mixed-precision integer-arithmetic-only NNs for low-complexity equalization in a 50-Gb/s 25-km DML-based PAM4 IM/DD link based on input neuron partitioning. The proposed scheme avoids floating-point weight operations and saves 26.3% memory at a minimum NN size compared with fixed-precision quantization counterpart without degrading BER. ©2023 The Author(s)*

Introduction

Driven by the ever-growing Internet traffic in recent years, there is an increasing demand for scale and capacity in data centers. Due to the simple structure and low cost, intensity-modulated direct detection (IM/DD) systems dominate short-reach applications such as data center interconnects [1,2]. However, IM/DD systems can only acquire the intensity information, which gives rise to nonlinear signal distortion due to the interaction of linear impairments such as chromatic dispersion (CD) with the square-law detection [3,4]. The interplay of CD and the frequency chirp of cost-effective lasers such as directly-modulated lasers (DMLs) can also severely degrade the quality of received signals. As such, it is important to adopt efficient equalization techniques in IM/DD links in order to achieve a desired performance.

Various neural networks (NNs) have been proposed as efficient equalizers in IM/DD systems [5-16]. They are shown to outperform traditional methods with the help of the layered signal processing structure and the nonlinear activation function in each layer. Despite the excellent performance, an important drawback lies in the complexity of NN-based equalizers especially when real-time implementation is considered. To relax the complexity requirements, a number of approaches such as pruning and multi-task learning are proposed [17-20]. The number of multiplications needed for equalizing a received symbol can be decreased, taking advantage of efficient design of NN architectures. However, the above-mentioned NN-based equalizers are all based on floating-point (FP) data type, which requires as many as 32 or 64 bits to storage each weight/bias and performs FP multiplications. Quantization of FP-NNs can be an alternative method to lower the complexity requirement in a different dimension, where preliminary investigations for IMDD systems have been made on the FPGA implementation of NNs with only fixed bit representation [21,22].

In this work, we propose mixed-precision integer-quantized NNs for equalization in IM/DD links which squeeze more bits to further reduce the multiplication complexity and the memory needed for storage of NN parameters. The integer-arithmetic-only NNs no longer require any FP operations, and the precision partitioning operation provides adaptive bit representation for different weights and biases. We experimentally demonstrate a C-band 50-Gb/s 25-km DML-based pulse amplitude modulation (PAM)-4 IM/DD system, and find that NN-based equalizers are quite robust to precision loss. A fixed 12-bit NN and a mixed 6/12-bit NN are shown to maintain the bit-error-rate (BER) performance achieved by the FP-NN. Compared with fixed-precision quantization, the proposed mixed-precision scheme saves at least 26.3% memory for NN storage, which is promising towards hardware-efficient NN implementation.

Mixed-Precision Integer-Quantized NN-Based Equalizer

The schematic of the proposed mixed-precision

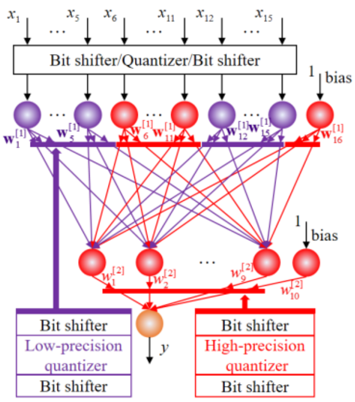

Fig. 1: Schematic of a 2-layer mixed-precision integer-quantized NN.

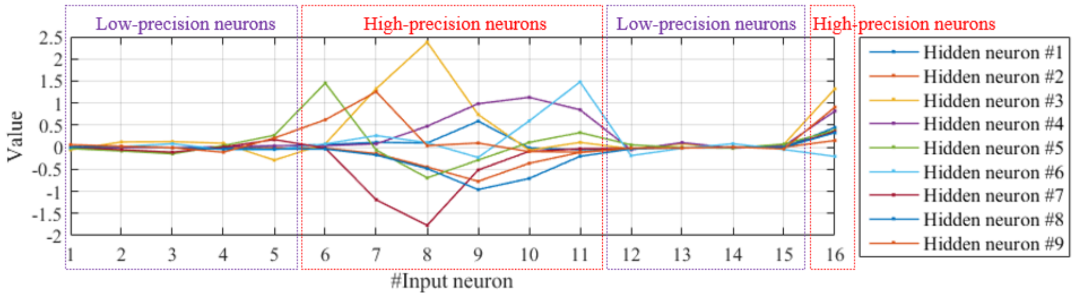

Fig. 2: Weight values of different input neurons.

integer-quantized NN is illustrated in Fig. 1. Here we only present a 2-layer feedforward NN (15 inputs, 9 hidden neurons, and 1 output), however the key idea of mixed quantization can be easily generalized to deeper NNs or other NN variants. The NN inputs, weights, and biases (regarded as weights of an extra neuron with unit input in Fig. 1) are passed through bit-shifters, quantizers, and matched bit-shifters for integer data type operation. Different from fixed-precision quantization that using the same quantizers for all the NN parameters, for the mixed-precision scheme, the quantizers are separated into different categories. Fig. 2 presents a typical input-hidden weight value of a well-trained NN with 15 inputs, 9 hidden neurons, and 1 output shown in our previous work [9]. It can be observed that the middle input neurons are associated with weights with larger values, while the side neurons are connected with little weights (The weights of the 16th input neuron refer to the biases, which are of significance). As such, the weights can be classified into different categories accordingly. Only two categories, namely low- and high- precision are selected here for the sake of simplicity. The precision classification process matches the trained weight value that is related to the order of input neurons, which is straightforward in principle and easy to operate.

As shown in Fig. 1, the i -th input and its associated weights are denoted by x_i $(i=0,1,\cdots 15)$ and $\mathbf{w}_i^{[1]} \in \mathbb{R}^9$ $(i=0,1,\cdots 16)$, respectively. The weight of the i -th hidden neuron is represented by $w_i^{[2]}$ $(i=0,1,\cdots 10)$, and the only one output is denoted by y. The input and hidden weight matrices after mixed-precision quantization, denoted by $\mathbf{W}_Q^{[1]}$ and $\mathbf{W}_Q^{[2]}$, can be expressed as

$$\mathbf{W}_Q^{[1]} = [Q_L([\mathbf{w}_1^{[1]}, \mathbf{w}_2^{[1]}, \cdots \mathbf{w}_5^{[1]}]), Q_H([\mathbf{w}_6^{[1]}, \mathbf{w}_7^{[1]}, \cdots \mathbf{w}_{11}^{[1]}]), Q_L([\mathbf{w}_{12}^{[1]}, \mathbf{w}_{13}^{[1]}, \cdots \mathbf{w}_{15}^{[1]}]), Q_H(\mathbf{w}_{16}^{[1]})], \quad (1)$$

$$\mathbf{W}_Q^{[2]} = Q_H([w_1^{[2]}, w_2^{[2]}, \cdots w_{10}^{[2]}]), \quad (2)$$

where $Q_L(\cdot)$ and $Q_H(\cdot)$ represent low- and high-precision quantization respectively. The inputs also need to go through the quantization process to keep the entire arithmetic integer and we select the high-precision quantizer to uphold the input resolution. The input vector after quantization, denoted by $\mathbf{x}_Q$, is expressed as

$$\mathbf{x}_Q = [Q_H(x_1, x_2, \cdots x_{15}), 1]^T, \quad (3)$$

where the superscript T denotes transpose. Assuming the activation function of the hidden and the output layer is denoted by $f^{[1]}$ and $f^{[2]}$, the inference, namely the equalization step of the mixed quantized NN, is given by

$$y = f^{[2]}\left[\mathbf{W}_Q^{[2]}[f^{[1]}(\mathbf{W}_Q^{[1]}\mathbf{x}_Q)^T, 1]^T\right]. \quad (4)$$

Note that the overall quantization process is operated in a simple post-training manner without the need of retraining. One may conduct iterative training to further improve performance if the training complexity can be totally ignored.

Experimental Setup

The experimental setup of the C-band DML-based IM/DD link is presented in Fig. 3. The transmitter consists of an arbitrary waveform generator (AWG, Keysight M8196A) an electronic amplifier (EA) with 17 dB gain, and a 16-GHz DML. The DML is biased at 55 mA and the output power is 9.5 dBm. A root raised cosine (RRC) filter with a roll-off factor of 0.1 is used for pulse shaping. 25-km single-mode fiber is used for transmission.

At the receiver, a variable optical attenuator (VOA) is used to control the received optical power (ROP). The signal is detected by a 43-GHz photodetector (PD) and captured by a digital storage oscilloscope (DSO, DSA-X 93304Q). The received signal is downsampled to 1 Sa/symbol for fixed/mixed quantized NN-based

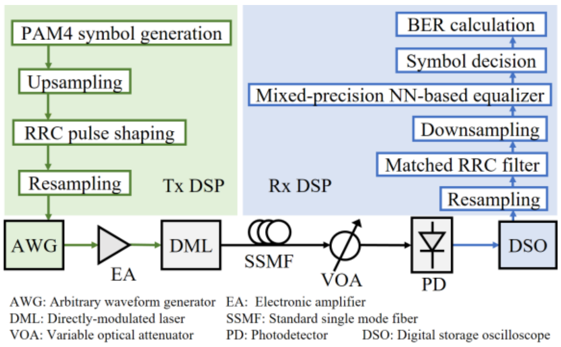

Fig. 3: Experimental setup of a DML-based short-reach IM/DD System.

equalization. 15 inputs and 9 hidden neurons are selected to minimize the NN size while achieving the lowest BER [9], and there is no overstatement of quantization performance at this minimum NN size compared with quantization of over-parameterized NN-based equalizers. Tanh is employed as the activation function of the hidden layer. 20000 symbols are used for training while another 1.2 million symbols are used for inference and BER calculation.

Results and Discussions

We highlight the advantage of the proposed mixed-precision by plotting the BER as a relationship of the number of quantized bits, shown in Fig. 4. The ROP is set at -1 dBm. To keep the BER of FP-NN, fixed-precision NN quantization can only support as low as 12 bits. However, a great portion of weights can actually have even lower resolution. When performing weight partition and quantize only the low-precision part, the number of bits can be pushed to only 6 without any BER penalty. These weights are of less significance to the entire equalizer, and as such less bits can be used to represent them. On the other hand, if we keep the bits for low-precision neurons and only quantize the high-precision ones, the BER performance shows almost no difference compared with fixed-precision quantization. This suggests the high-precision weights contribute the most to the NN, while keeping the resolution of the low-precision

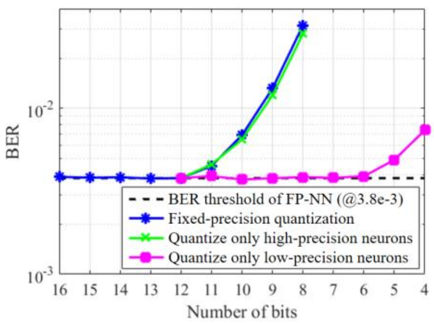

Fig. 4: BER versus number of bits using different NN quantization approaches.

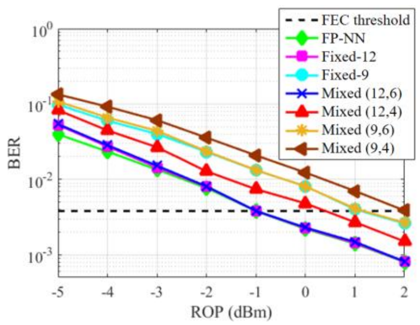

Fig. 5: BER versus ROP employing fixed or mixed quantized NN-based equalizers. (h,l) denotes the h high-precision and l low-precision bits for the mixed schemes.

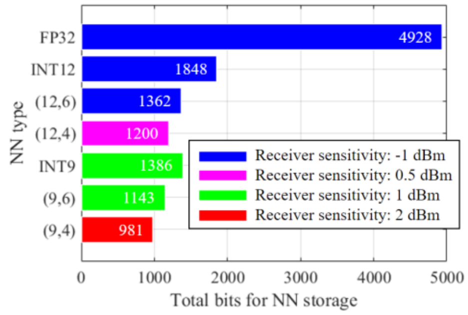

Fig. 6: Total bits needed for parameter storage of different types of quantized NNs.

does not make much sense.

Fig. 5 shows the BER versus ROP under different types of fixed or mixed quantized NNs. We use (h,l) to denote the h high-precision bits and l low-precision bits for the mixed schemes. As expected, the fixed 12-bit and the mixed (12,6) NNs present similar receiver sensitivity compared with FP-NN, which is around -1 dBm when the BER is below the 7% hard-decision forward error correction (HD-FEC) threshold. Further decrease of the quantized bits will degrade the performance, however, the sensitivity gap is still at an acceptable level. The required ROP for mixed (12,4), fixed 9-bit/mixed (9,6), and mixed (9,4) NNs are about 0.5 dBm, 1 dBm, and 2 dBm, respectively.

The total bits required for parameter storage for the employed quantized NNs are given in Fig. 6. Again we can see that the inference of FP-NN can be carried out using integer-only arithmetic. Only 1848 bits (fixed 12-bit) or even 1362 bits (mixed (12,6)) is now needed instead of 4928 bits to store 32-bit FP-NN. Compared with fixed-precision quantization, the proposed mixed-precision approach reduces the memory by about 26.3% without any performance loss. If the receiver sensitivity is relaxed to 2 dBm, the total bits for mixed-quantization NN storage are less than 1000, making it a promising candidate for real-time receiver design.

Conclusions

Hardware-efficient mixed-precision NN-based equalizers are proposed and verified in a 50-Gb/s 25-km DML-based IM/DD system. Different resolutions are determined based on manoeuvrable input neuron partitioning. Compared with quantizing the NN with the same number of bits, more than 26.3% memory can be saved by using mixed-precision NN-based equalizers without degrading BER performance. The proposed scheme consumes much less hardware resources, which paves the way to make NN-based equalizers more feasible for practical implementation.

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