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Low-Complexity Multi-symbol Output Complex-Valued Neural Network for Nonlinear Equalization in 100G Coherent Photonic-assisted W-band Fiber-wireless Integrated Communication

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Abstract *A low-complexity multi-symbol complex-valued NN nonlinear-equalizer is proposed and experimentally demonstrated in coherent photonics-assisted MMW communication. Effective nonlinear compensation is demonstrated for 100Gbps 16-QAM photonic-assisted W-band signal after fiber-wireless integrated transmission, while the computational complexity is reduced by up to 78.1% compared with single-output NN.*

Introduction

The six-generation mobile network (6G) is expected to delivery 100x higher-speed and 1000x more capacity compared with 5G, based on higher frequency spectrum to millimeter-wave (MMW) and advanced signal processing technologies [1]. Photonic-assisted MMW fibre-wireless integration is one of the key technologies that enables ultra-high-speed access and also seamless ultra-dense coverage with current fiber networks [2]. In these systems, advanced equalization schemes are generally applied to overcome the nonlinear impairments when operating at 100G and beyond high-speeds [3].

As artificial intelligence (AI) has become one of the cornerstones of 6G, neural networks (NN) has attracted more and more research interests in recent years thanks to its superior performance in channel impairment equalizations [4]. However, the computation complexity of NN is still one of the challenges for future practical applications [5]. Many studies have been done for relevant analyses of various kinds of NN in terms of computational complexity [5-7]. Additionally, simplification of NN equalizers have also been proposed to reduce the computational complexity, by using multi-symbol output NN equalizer [8,9]. However, both [8] and [9] is focused directly-detected (IM/DD) systems, where real signals are equalized. For photonic-assisted MMW communication based on coherent optics, study of simplified NN with multi-symbol outputs on complex-valued signals is desirable.

In this paper, we propose and experimentally demonstrate a low-complexity NN nonlinear equalization in coherent photonics-assisted MMW fiber-wireless integrated system. A multi-task, complex-valued NN is proposed with multiple outputs for computation complexity reduction. We study the performances of the complex-valued NN network with 1, 2, 4, and 8 outputs in the 100Gbps 16-QAM photonic-assisted W-band signal after fiber-wireless integrated transmission, as well as the required training process in each case. The maximum decrease of computational complexity reaches to 78.1% compared with single-output NN.

Principle

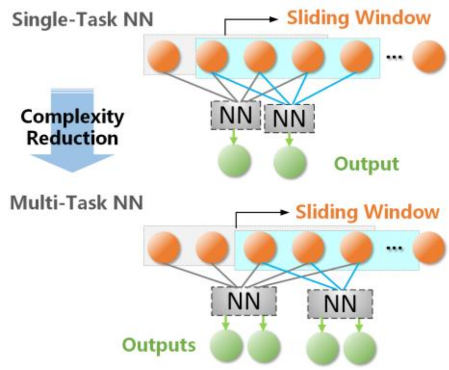

Fig. 1: Single-task and multi-task NN with single-symbol output and multi-symbol outputs, respectively.

The comparison of single-task and multi-task NN with single-symbol output and multi-symbol output is shown in Fig.1, respectively. It can be seen that a basic NN structure includes three layers, namely an input layer, a hidden layer and an output layer. The input layer is related to the input symbol sequence. A sliding window (determined by the channel memory) controls the number of input symbols as the window slides. The hidden layer helps improve the performance together with a risk of increasing complexity. Given that information conveyed by weights in the NN corresponding with the current symbol may be still useful to the next symbol [8], we can apply the NN structure which is used for a single symbol equalization to equalize multiple symbols so that the computation complexity per symbol task can be greatly reduced.

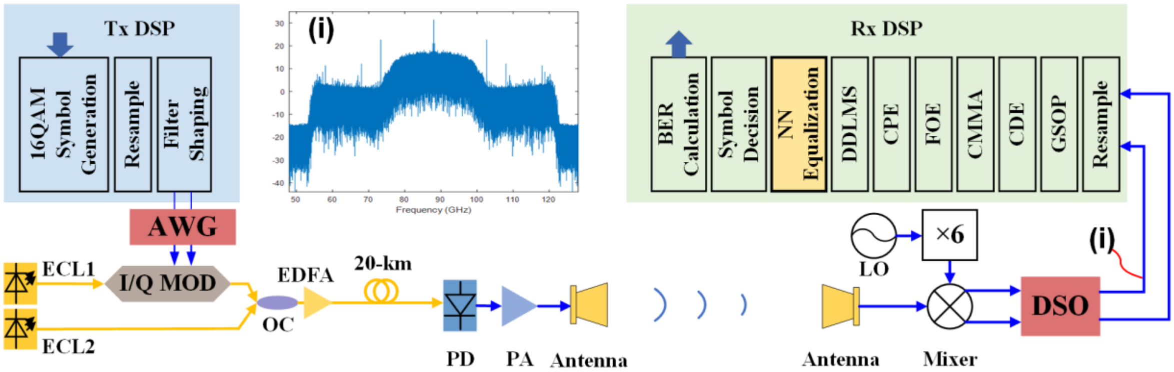

Fig. 1: Experimental setup of multi-symbol output NN equalization in coherent photonic-assisted W-band fiber-wireless transmission system and the spectrum of the signal before NN equalization.

Experimental setup

Fig.2 shows the experimental setup. On the transmitter (Tx) side, offline DSP firstly prepares the data to be transmitted in the system. A 16 QAM symbol signal is generated. After resampling and filter shaping, the signals are sent into an arbitrary waveform generator (AWG), which modulates the optical signal from an external cavity laser (ECL) via an I/Q modulator. The modulated signal and its unmodulated counterpart with 100-GHz frequency-spacing are coupled into the optical coupler (OC). After the transmission of fibers, the optical signal is captured by a photodetector (PD) and converted to a W-band signal with center-frequency around 100 GHz. A sequence of power amplifier (PA) and attenuator (ATT) is set to adjust the power of the signal. Then it is transmitted by the antenna on the Tx side. The corresponding antenna on the receiver (Rx) side collects the signal after its transmission through the free space of 1 m. A local oscillator signal with the frequency of 100GHz generated by x6 frequency multiplier, together with the received signal, are sent into an I/Q mixer to down-convert the signal and separate the in-phase component and the orthogonal component for the digital storage oscilloscope (DSO). The signal received by the DSO should be processed after a series of offline DSP including resampling, chromatic dispersion equalization (CDE), least mean square (LMS), etc. The digitalized signal is the input symbol sequence for complex-valued NN equalization. The output symbols of NN are decided according to mapping, and finally, the bit error rate (BER) can be calculated.

The further details of the multi-task complex-valued NN structure are depicted in Fig.3. The top layer represents the input symbol sequence and the center symbol is the current one to be deduced. Due to the nonlinear impairment, the past symbols and proceeding ones should also be considered. Firstly, every symbol should be separated into real and imaginary parts. Then, the data in the sliding window are processed for equalization. What we get from the output layer is the real and imaginary parts of the predicted symbol. Converting the 1×2 vector into the complex symbol is the last step in the complete NN.

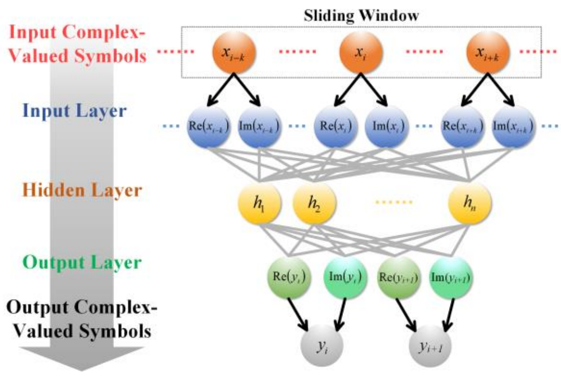

Fig. 3: The detailed structure of complex-valued NN with multiple outputs.

Our NN model has been trained in Python. The number of nodes of the hidden layer is 20. The BER decreases when the length of input symbols grows, which means that the system has a channel memory. The optimal length of the sliding window for single-symbol output NN is 19 according to a series of trials, in which the BER doesn't decrease when the length exceeds 19. As for multi-symbol output NN, the length is set to 19 + n (the number of outputs) to avoid missing the relevant information of multiple symbols. We set the number of outputs as 2^n for ease of processing, which is 2,4, and 8. Hence the length of input symbols is 21, 23, and 27 respectively.

The training epochs are changed to maintain the performance of NN with different outputs. The batch size is fixed to 256 and there are 32768 symbols to be processed in total. 70% of them are for training while 30% of them are for testing.

Results and discussion

Fig.4 shows the performance of NN equalization.

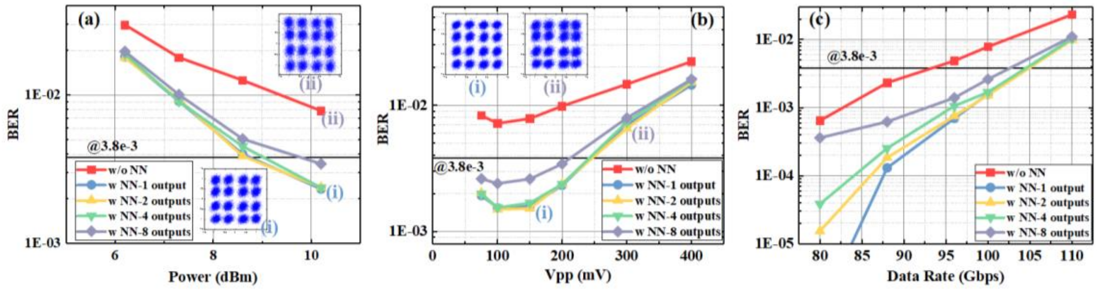

Fig. 4: The performance of NNs. (a) BER v.s. RoP. (i) and (ii) are the constellations after NN with 2 outputs and without NN. (b) BER v.s. Vpp. (i) and (ii) are the constellations after NN with 2 outputs at 150mV and 300mV. (c) BER versus data rates.

Fig.4(a) shows the relationship between received optical power (ROP) and BER. We measure the optical power sent to the PD and find that the performance gets worse when the optical power becomes lower. Without NN equalization, the signal BER is all above the 7% forward error correction (FEC) threshold of 3.8e^{-3}. The NN with one output helps improve the performance when ROP reaches 10.2dBm. The NN with 2-symbol and 4-symbol output are without exception, showing similar performance with the former. The BER performance under NN with 8-symbol output is slightly worse than the 1/2/4 outputs. (i) and (ii) of Fig.4(a) show the constellations of the signal after the NN equalization with 2 outputs and without the NN equalization respectively.

Fig.4(b) shows the relationship between Vpp and BER, indicating the optimal working point at the Vpp of 100mV. Without the NN equalization, the performance gets worse when the Vpp is either lower or higher. With the NN nonlinear equalization, the optimal working point of the Vpp increases to 150mV. It can be seen that the BER for NN with 1, 2, and 4 outputs are nearly the same. Similarly, the performance of NN with 8 outputs is slightly worse.

Fig.4(c) shows the relationship between the data rate and BER. The BER gets worse when the data rate becomes higher and the maximum rate for this system can reach less than 90Gbps under the threshold of 7% FEC without the NN equalization. With single-output NN equalization, the rate increases to about 100Gbps and so do the NN with 2 outputs and 4 outputs. However, in the region of lower data rates, there are obvious differences among the three schemes. NN with 8 outputs can also reach the rate of 100Gbps with slightly worse BER.

Finally, the computational complexities of different schemes are shown in Fig.5. In terms of the structure of the NN, the complexity is mainly decided by the multiplications per symbol of real-time implementation [8], which involves the length of input symbols, the nodes of the hidden layer and the number of outputs. We gradually increase the epochs to maintain the performance when the number of outputs grows. The training needs 30/50/100/180 epochs for NN with 1/2/4/8 outputs. In terms of the process of training NN, the computation becomes more complex. But once the whole model is trained successfully, the following equalization don't need extra training. We have found that the maximum decrease of computational complexity could reach 78.1% when the NN has 8 outputs under the condition of maintaining the similar performance.

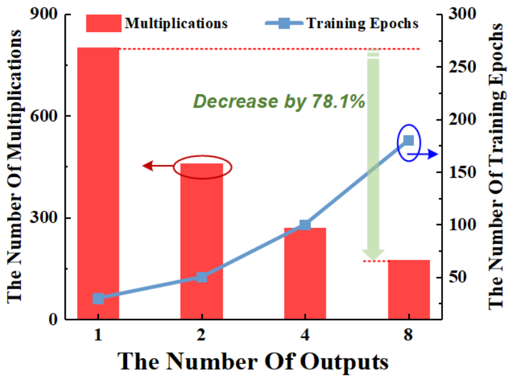

Fig. 5: The relationship of multiplications per symbol and training epochs when the number of outputs changes.

Conclusions

A low-complexity complex-valued multi-task NN nonlinear equalization is proposed and experimentally demonstrated for coherent photonics-assisted MMW fiber-wireless integrated system. We study the performances of the complex-valued NN network with 1, 2, 4, and 8 outputs in the 100Gbps 16-QAM photonic-assisted W-band signal after fiber-wireless integrated transmission. Compared with signals without NN equalization, the improved BER performances of multi-task NN are confirmed, while the maximum decrease of computational complexity reaches to 78.1% compared with single-task NN.

Acknowledgements

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References

[1] Francesco Testa, Mark T. Wade, Mikael Lostedt, Fabio Cavaliere, Marco Romagnoli, and Vladimir Stojanović, "Optical Interconnects for Future Advanced Antenna Systems: Architectures, Requirements and Technologies," *Journal of Lightwave Technology*, vol. 40, no. 2, pp.393-403, 2022. **DOI:** 10.1109/JLT.2021.3113999

[2] Feng Lu, Lin Cheng, Mu Xu, Jing Wang, Shuyi Shen, and Gee-Kung Chang, "Orthogonal and Sparse Chirp Division Multiplexing for MMW Fiber-Wireless Integrated Systems," *IEEE Photonics Technology Letters,* vol. 29, no. 16, pp. 1316-1319, 2017. **DOI:** 10.1109/LPT.2017.2722001

[3] Syed Tajammul Ahmad and K. Pradeep Kumar, "RBF Neural Network Nonlinear Equalizer for 100G 16-QAM Coherent Optical System," presented at International Conference on Microwave and Photonics, Dhanbad, India, 2018. **DOI:** 10.1109/ICMAP.2018.8354579

[4] Diego Fernando Carrera, Cesar Vargas-Rosales, Noe M. Yungaicela-Naula,and Leyre Azpilicueta, "Comparative Study of Artificial Neural Network Based Channel Equalization Methods for mmWave Communications," *IEEE Access,* vol. 9, pp. 41678-41687, 2021. **DOI:** 10.1109/ACCESS.2021.3065337

[5] Stavros Deligiannidis, Charis Mesaritakis, and Adonis Bogris, "Performance and Complexity Analysis of Bi-Directional Recurrent Neural Network Models Versus Volterra Nonlinear Equalizers in Digital Coherent Systems," *Journal of Lightwave Technology*, vol. 39, no. 18, pp. 5791-5798, 2021. **DOI:** 10.1109/JLT.2021.3092415.

[6] Pedro J. Freire, Yevhenii Osadchuk, Bernhard Spinnler, Antonio Napoli, Wolfgang Schairer, Nelson Costa, Jaroslaw E. Prilepsky, and Sergei K. Turitsyn, "Performance Versus Complexity Study of Neural Network Equalizers in Coherent Optical Systems," *Journal of Lightwave Technology*, vol. 39, no. 19, pp. 6085–6096, 2021. **DOI:** 10.1109/JLT.2021.3096286

[7] Zhaopeng Xu, Chuanbowen Sun, Tonghui Ji, Jonathan H. Manton, and William Shieh, "Computational Complexity Comparison of Feedforward/Radial Basis Function/Recurrent Neural Network-based Equalizer for a 50-Gb/s PAM4 Direct-detection Optical Link," *Optics Express*, vol. 27, no. 25, pp. 36953–36964, 2019. **DOI:** 10.1364/OE.27.036953

[8] Zhaopeng Xu, Shuangyu Dong, Jonathan H. Manton and William Shieh, "Low-Complexity Multi-Task Learning Aided Neural Networks for Equalization in Short-Reach Optical Interconnects," *Journal of Lightwave Technology*, vol. 40, no. 1, pp.45-54, 2022. **DOI:** 10.1109/JLT.2021.3117687

[9] Bohan Sang, Jiao Zhang, Chen Wang, Miao Kong, Yuxuan Tan, Li Zhao, Wen Zhou, Dongdong Shang, Yamin Zhu, Hong Yi and Jianjun Yu, "Multi-Symbol Output Long Short-Term Memory Neural Network Equalizer For 200+ Gbps IM/DD System," presented at European Conference on Optical Communication, Bordeaux, France, 2021. **DOI:** 10.1109/ECOC52684.2021.9606010