Experimental Demonstration of Optical Modulation Format Identification Using SOI-based Photonic Reservoir

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Abstract: We experimentally show modulation format identification of optical signals using silicon-on-insulator (SOI) photonic-integrated-circuit-based reservoir. After 100-km SSMF transmission, we achieve identification of 32 GBd 4QAM, 16QAM, 32QAM and 64QAM signals with up to ~97% accuracy. ©2023 The Author(s)

1. Introduction

Artificial neural networks (NNs) are proving repeatedly to have the capability to solve key telecommunication network issues in a more energy-efficient manner than current solutions based on von Neumann architectures [1]. For their part, photonic NNs present additional benefits regarding latency compared to their digital domain counterparts. In particular, reservoir computing can achieve high performances while maintaining a reduced complexity and with high-speed when trained for a particular task [2]. Currently, ultra-fast energy-efficient network monitoring and telemetry have become essential for future autonomous networks in the framework of green information communication technologies. Towards these goals, leveraging cost-effective and smaller footprint benefits of planar waveguides (e.g., silicon) for photonic reservoir computing is considered as a new computing paradigm for future optical networks.

In this paper, we present experimental investigations and evaluation of a silicon-on-insulator (SOI) based neuromorphic photonic reservoir (NeuroPIC) that is capable of identifying among different optical modulation formats. Our investigated NeuroPIC was fabricated using AMO's nanophotonics SOI platform, available as foundry offering [3]. We trained, validated and tested our modulation format identification (MFI) network using 32 GBd single-polarization data for four different quadrature-amplitude-modulation formats (i.e., 4QAM, 16QAM, 32QAM and 64QAM). In our evaluations, the NeuroPIC is placed after up to 100-km standard single-mode fiber (SSMF) link, and we successfully show identification of the modulation formats with high accuracy. According to our knowledge, this is the first experimental demonstration of optical MFI using a PIC-based photonic reservoir.

2. Experimental Setup

Fig. 1 depicts the experimental setup of the NeuroPIC in a system testbed. The 32 GBd single-polarization signals were generated by modulating a 1550 nm continuous wave (CW) from an external cavity laser (ECL) using a $LiNbO_3$ IQ modulator (IQ MOD), driven by a two-channel digital-to-analog converter (DAC, 64 GS/s, 8-bit) via a pair of driver amplifiers. For each of the four modulation formats, five different scenarios were evaluated, namely; one back-to-back (b2b), plus transmission over four different SSMF link scenarios corresponding to 20 km, 60 km, 80 km and 100 km. Each of the transmission links presents a unique level of polarization mode dispersion (PMD) and chromatic dispersion (CD) to test the robustness of the NeuroPIC for MFI. The signals were then amplified using Erbium-doped fiber amplifiers (EDFAs), and the out-of-band amplified spontaneous emission (ASE) noise filtered using an optical band pass filter (OBPF). A 20-dB optical splitter was used to enable a reference signal monitoring on an optical spectrum analyzer (OSA). After equal splitting, we employed fiber arrays for coupling the optical signals into and out of the photonic reservoir, via its 16 input- and 16 output-grating couplers. The input power at each grating was +4.4 dBm. We optimized the output signals by adjusting the polarization controller (PC) located at the input of the NeuroPIC. Our fabricated photonic reservoir is based on recurrent neural network (RNN) with fix inter-node connections, and with no activation functions inside the network. The reservoir topology implemented was first reported in Ref. [4] and was also the chosen architecture for our previous work based on numerical simulation for MFI [5]. Our SOI-based NeuroPIC is made up of 3×3 multimode interference couplers (MMI) and delay lines as building blocks. Two of the six connections of the MMI served as input and output to the MMI whereas the remaining four connections are looped to the neighboring four MMIs via delay lines. After

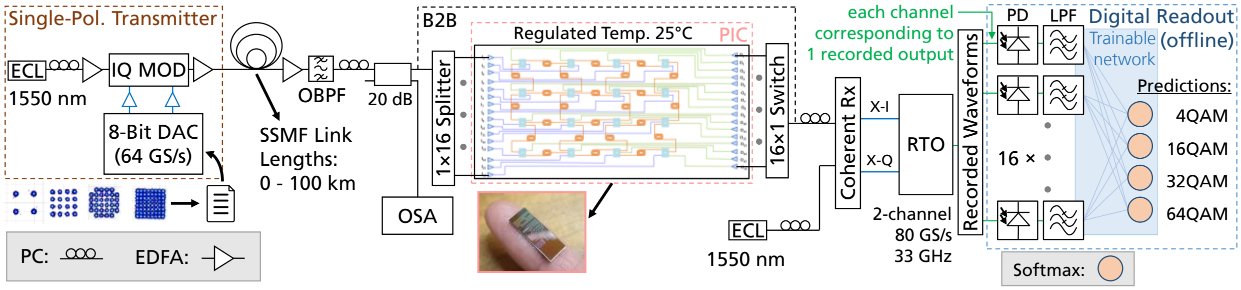

Fig. 1: Representation of the experimental setup showing the single-polarization transmitter capable of generating QAM formats, the SSMF transmission link, the PIC-based photonic reservoir, a 90° hybrid receiver and a digital readout for training and MFI predictions. The inset shows a picture of the fabricated SOI-based NeuroPIC.

interferences of the optical signals in the reservoir, the output signals were collected via a 16×1 optical switch placed after the output fiber arrays.

The selected output signal of the reservoir was detected using a 90° hybrid receiver, and sampled with an analog-to-digital converter (ADC, 33 GHz, 80 GS/s). Note that the temperature of the NeuroPIC was kept at 25°C (above room temperature) throughout our measurements. Each test sequences of the recorded data signal consisted of ~4 million symbols, which were transmitted using 3 shots for each measurement, making the total number of symbols in the dataset of over 240 million. A trigger signal was used to synchronize the transmitter and the receiver, which allowed us to record each output of the reservoir separately and then align them in time domain digitally. After the receiver, we intentionally added additive white Gaussian noise (AWGN) to the digital signals to test the efficiency of MFI of the NeuroPIC under noisy conditions, before normalizing the signals at the input of the digital readout.

Our implemented digital readout consisted of 16 photodiodes (PDs, one for each output of the reservoir), a layer with digital filters (to emulate practical photodiodes) and a *Softmax* function layer with four outputs. Each output of the *Softmax* layer corresponded to a particular modulation format to be predicted. The connection between these two layers represents the simplest possible multiclass classifier with only 64 weights to be trained. The down sampling was performed together with the finite impulse response (FIR) low-pass filter (LPF), where for every 320 received samples, one single data point was generated. As expected, the cutoff frequency of the digital filter played a critical role during down sampling of the data and the subsequent accuracy of the format identification. In our previous work, we showed that high cutoff frequencies have a negative impact on the prediction accuracy [5]. We implemented the readout using Pytorch [6] and Scikit-learn framework [7]. The offline training incorporated the recorded output signals from the NeuroPIC with a cross-validation scheme, in which the dataset was divided into 10 stratified folds. 80% of the total dataset was used for training, while 10% was used for validation and 10% for testing. As optimizer, we chose Adam [8] and both the learning rate and the weight decay were set to 0.001. The training was performed for 100 epochs. The modulation format corresponding to output node containing the highest value was chosen as the MFI prediction.

3. Results and Discussions

To evaluate the prediction accuracy of the NeuroPIC for different transmission lengths and for different noise levels, we initially performed measurements with the NeuroPIC in a b2b scenario (i.e., without a transmission link) as a benchmark. We then trained the readout using this data and achieve a prediction accuracy of 100%. Subsequently, we repeated the same experiment with increasingly longer SSMF links and recorded the performance. We then started adding complex AWGN to the digitized complex fields such that each recorded output had a specified optical signal-to-noise ratio (OSNR). Each of these scenarios presented a unique level of PMD and CD for each distinct OSNR level. For the training of the readout, the data was split into 10 stratified folds and the results of the prediction accuracy and the corresponding standard deviations are shown in Table 1. Splitting the dataset into longer sequences usually translates into more accurate predictions, but also represents longer training times and a reduction the predictions resolution. With lower OSNR levels, the accuracy of the predictions started to drop as seen in Fig. 2. On the right part of the Table 1 we can see, that for longer links and lower OSNR levels, the standard deviation of the prediction accuracy tends to increase. By achieving high prediction accuracy using lower filter cutoff frequencies, we demonstrate that low speed PDs could be used for such MFI task as an alternative to high cost receivers. The overall results do not show any bias towards any particular modulation format and all formats present a similar

Table 1. Prediction accuracy results over all the measured scenarios and OSNR levels. The MFI was trained and tested using 10 stratified folds and their average results are shown in this table.

	Prediction Accuracy					Standard Deviation				
Length / OSNR	b2b	20 km	60 km	80 km	100 km	b2b	20 km	60 km	80 km	100 km
12 dB	100%	100%	100%	100%	97.32%	0	0	0	0	1.464
8 dB	99.69%	99.40%	99.92%	98.97%	96.10%	0.187	0.216	0.132	1.105	2.170
7 dB	99.50%	98.90%	99.61%	98.95%	97.16%	0.283	0.216	0.768	0.445	1.870
5 dB	98.17%	97.34%	98.89%	93.27%	89.30%	0.763	0.723	0.486	0.903	7.228
2 dB	94.02%	93.53%	93.80%	92.79%	87.41%	1.408	0.551	0.758	1.053	3.027

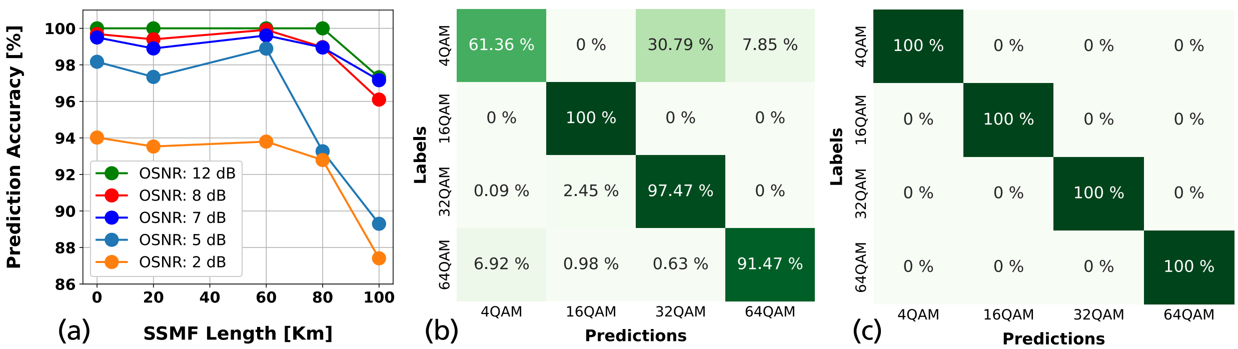

Fig. 2: (a) Impact of the fiber length and receiver OSNR on the prediction accuracy. Confusion matrix with the predictions precision corresponding to each modulation format of the (b) 100-km fiber length scenario at 2 dB OSNR (worst case), and (c) b2b (without transmission link) at 12 dB OSNR (best case).

prediction precision. In agreement to the results from our previous work, it appears that some level of PMD and CD at the receiver can actually help the MFI. Increased dispersion levels will translate into an increased inter-symbol interference, which itself can be beneficial for the performance of the NeuroPIC as was explained in our previous work [5].

4. Conclusions

We have experimentally shown a neural network consisting of a photonic integrated circuit based neuromorphic reservoir (NeuroPIC) and a simplified digital readout. Our NeuroPIC can correctly identify among four different higher-order optical modulation formats. Specifically, 4QAM, 16QAM, 32QAM and 64QAM signals with a symbol rate of 32 GBd were identified with very high accuracy after transmissions of up to 100 km. However, the prediction accuracy of the NeuroPIC was observed to decrease for lower OSNR levels. In our future works, we plan to adapt our photonic reservoir to dual-polarization applications scenarios related to network monitoring and telemetry in autonomous networks.

5. Acknowledgments

Funded by the German Federal Ministry of Education and Research (BMBF) under the CELTIC-NEXT AI-NET-PROTECT project with grants 16KIS1281, 16KIS1291, 16KIS1301, and under 6G-RIC project with grants 16KISK020K and 16KISK030.

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