

Optical Neural Network and Reservoir Computing for Optical Fiber Communications

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1. Introduction

- Nonlinear effects in optical fibers are one of the major limiting factor for optical ** communications [1].
- State of art for nonlinear mitigation:
 - > Nonlinearity mitigation through digital signal processing [2]

3. Feedforward optical neural network

Artificial neural network (ANN) with one hidden layer and linear output units can approximate arbitrary well any continuous function with sufficient number of neurons in the hidden layer [4]. Layer k

(b

(a)

- Optical phase conjugation [1]
- Nonlinear frequency division multiplexing [3]

High implementation cost Full knowledge of the optical parameters

- Machine learning •••
 - Broad area of application
 - Very well-know for classification problems
 - \succ Early stages for optical communications [4]
 - Applications with central processing units are suboptimal in terms of speed and power efficiency [5]
- Alternatively, optical neural network can be suitable to mitigate linear and nonlinear optical impairments
 - Reservoir computing [6, 7]
 - > Feedforward optical neural network (ONN) [5]

2. Reservoir Computing



(a) General schematic of an ANN. (b) Building blocks for an ONN.

- In order to implement any ANN with optical components, two different ••• structures are needed [5]:
 - \succ optical nonlinear unit (ONU)
 - \succ optical interference unit (OIU)
 - □ Any N x N unitary matrix can be implemented using optical beam splitters (variable reflectivity) or Mach-Zehnder interferometer [9].
 - Any matrix can be factorized using the singular-value decomposition:

Unitary matrices Generic matrix $A = U \Sigma V$

Rectangular diagonal matrix with non-negative numbers (optical attenuators)

Chromatic dispersion (CD) and nonlinearities induced by Kerr effect are timedependent impairments.

Challenging task to overcome in a common machine learning architecture where there no memory is considered (typically)

- Recurrent neural networks mitigates time-dependent impairments with the aid of recurrent connections
 - Universal approximators [8]
 - **Difficulty to train**
- In turn, reservoir computing simplifies the train process by leaving the ** hidden layer (reservoir) untrained.

Hidden layer (Reservoir) Input layer Output layer



General schematic of a reservoir computing. The blue arrows are the only weights trained.

4. Simulations





5. Conclusions

- Reservoir computing: Leaving the reservoir untrained is a great benefit for hardware implementation [10]
- By applying a nonlinear transformation, the input space will be mapped to a ** higher-dimensional space, resulting in a dimensionality expansion that might be linear separable.
- Forward optical neural network: Speed and power consumption can be ••• significantly improved with an optical implementation of an ANN [5]

References

[1] A. D. Ellis et al Adv. Opt. Photonics, vol. 9, no. 3, p. 429, 2017.

[2] E. Ip. Journal of Lightwave Technology. vol. 28, no. 6, pp. 939–951, 2010.

[3] S. K. Turitsyn et al., Optica, vol. 4, no. 3, p. 307, 2017.

[4] F. Musumeci et al., pp. 1–21, 2018.

[5] Y. Shen, N. C. Harris, D. Englund, and M. Soljacic, Nat. Photonics, pp. 1–2, 2018.

[6] H. Jaeger, GMD - Ger. Natl. Res. Cent. Inf. Technol., no. 148, pp. 1–47, 2001. [7] W. Maass, T. Natschlager, and H. Markram, Neural Comput., vol. 14, no. 11, pp. 2531–2560, 2002. [8] K. Funahashi and Y. Nakamura, Neural Networks, vol. 6, pp. 801–806, 1993. [9] M. Reck, A. Zeilinger, H. J. Bernstein, and P. Bertani, Physical Review Letters, vol. 73, no. 1, pp. 58–61, 1994. [10] G. Van Der Sande, D. Brunner, and M. C. Soriano, De Gruyter, vol. 6, no. 3, pp. 561–576, 2017.

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