# Reservoir computing with nonlinear optical media

**Tiago D. Ferreira**, Nuno A. Silva, Duarte Silva, Carla C. Rosa, Ariel Guerreiro

INESC TEC – Centre for Applied Photonics and Faculty of Sciences, University of Porto

**Abstract:** Reservoir computing is a versatile approach for implementing physically Recurrent Neural networks which take advantage of a reservoir, consisting of a set of interconnected neurons with temporal dynamics, whose weights and biases are fixed and do not need to be optimized. Instead, the training takes place only at the output layer towards a specific task. One important requirement for these systems to work is nonlinearity, which in optical setups is usually obtained via the saturation of the detection device. In this work, we explore a distinct approach using a photorefractive crystal as the source of the nonlinearity in the reservoir. Furthermore, by leveraging on the time response of the photorefractive media, one can also have the temporal interaction required for such architecture. If we space out in time the propagation of different states, the temporal interaction is lost, and the system can work as an extreme learning machine. This corresponds to a physical implementation of a Feed-Forward Neural Network with a single hidden layer and fixed random weights and biases. Some preliminary results are presented and discussed.

## Introduction

Reservoir computing consists in propagating data through a set of interconnected neurons with randomly fixed weights and biases [1]. This randomness in the reservoir assures that the data at the output is projected to a high-dimensionally space, where it is easy to train a model to realize a certain task. An essential aspect of the reservoir is the interaction with previous states. If this temporal aspect is lost, the system becomes an extreme learning machine [2]. Although simple, the propagation through the reservoir is still computationally demanding. Currently, the goal is to physically implement the reservoir by using light passing through a medium capable of projecting the input into a high-dimensionally output space. This way, it is only necessary to encode the information on light and measure the output. The model is then easily trained.

## Lorentz model

To explore the capacity of a photorefractive crystal to work as a reservoir computer, we consider the Lorentz model [1]

$$\dot{x} = 10(y-x),\ \dot{y} = x(28-z) - y,\ \dot{z} = xy - 8z/3. \qquad (1)$$

## Reservoir computing scheme

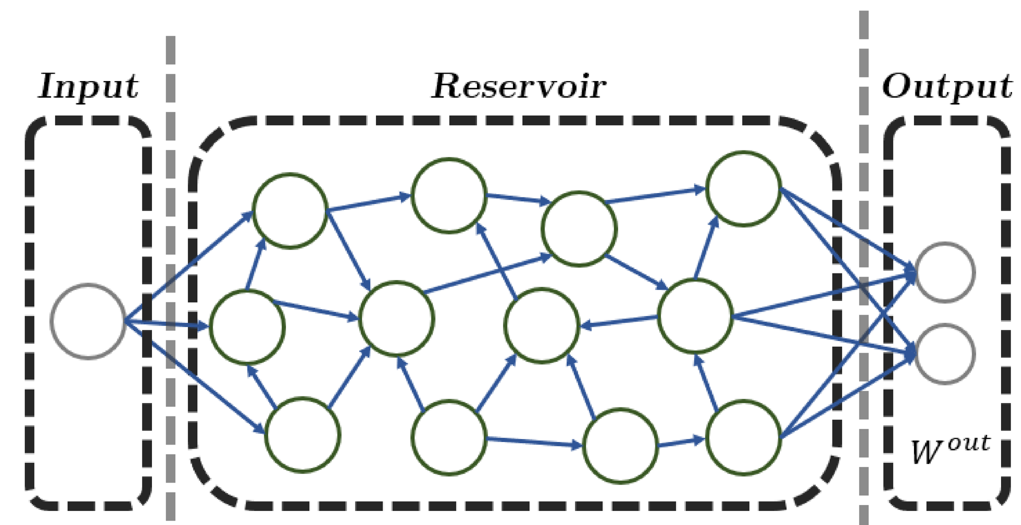


**Figure 1** – Schematic representation of a Reservoir Computer.

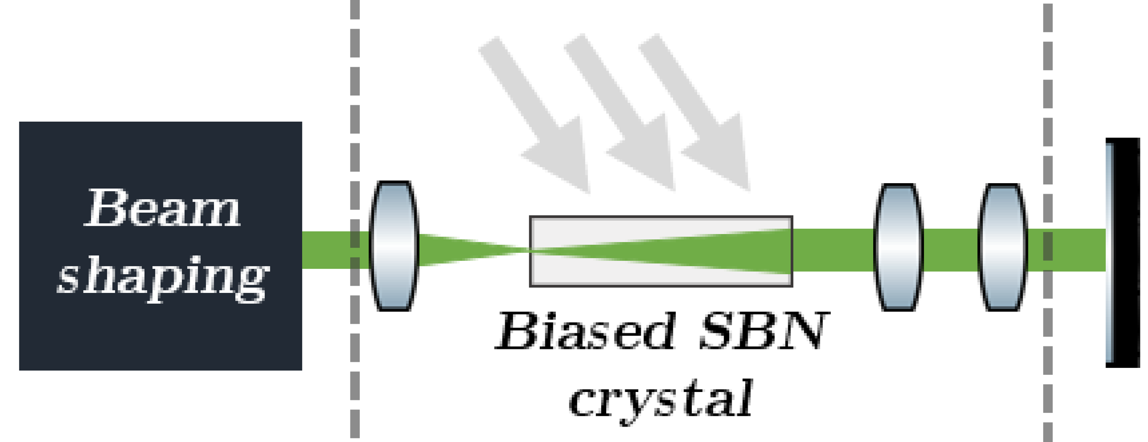


**Figure 2** – Physical implementation of the reservoir. In this setup, the reservoir is composed by a lens that focuses the light beam at the entrance of the crystal and by the beam propagation inside the nonlinear crystal.

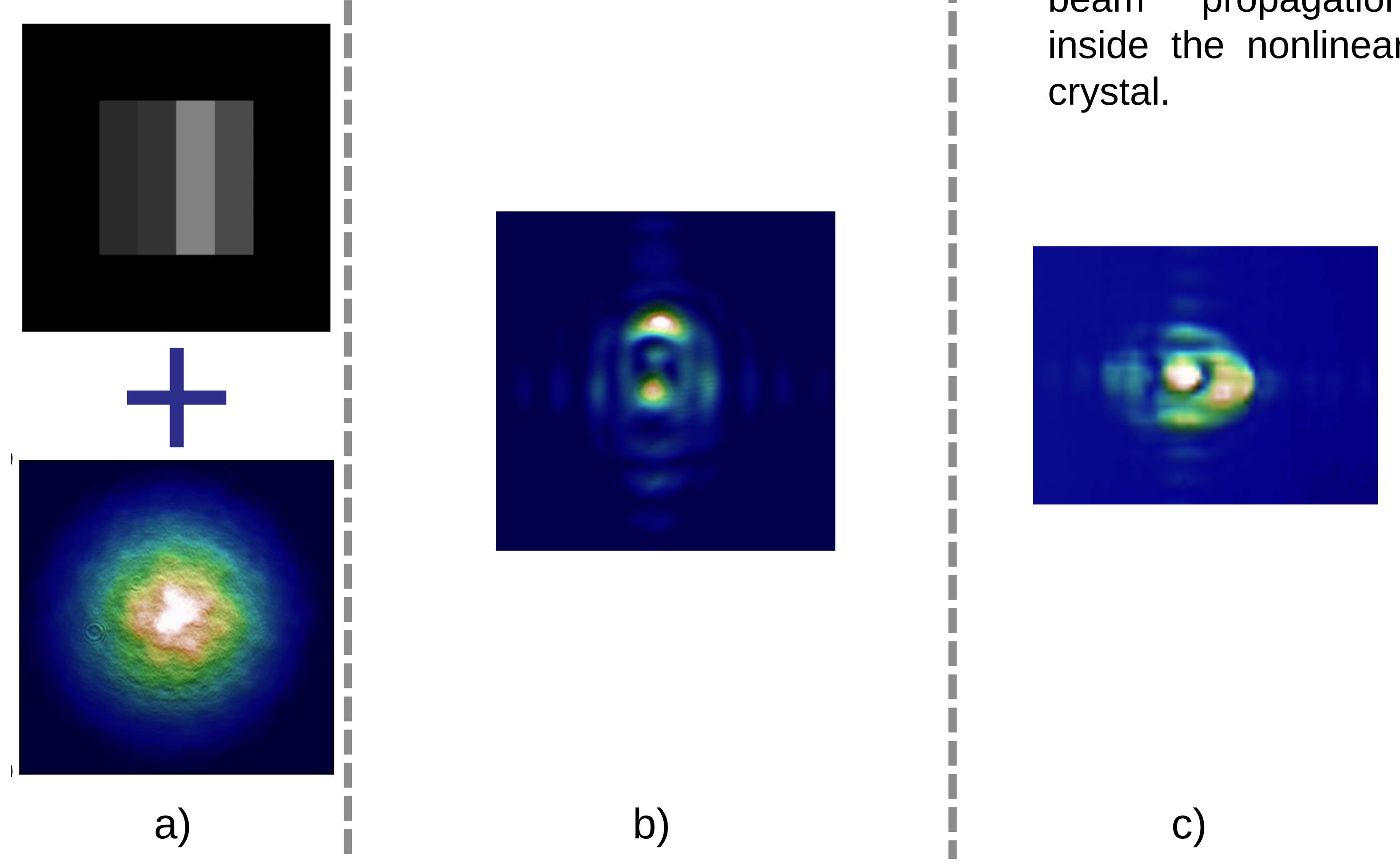


**Figure 3** – The experimental implementation consist first in codifying the information in the phase of a Gaussian beam - a). This beam is focused on the entrance of the nonlinear crystal – b). The output is imaged into a CMOs camera, and the data is downscaled, with each pixel corresponding to an output channel –c).

## Preliminary Experimental Results - Forecasting

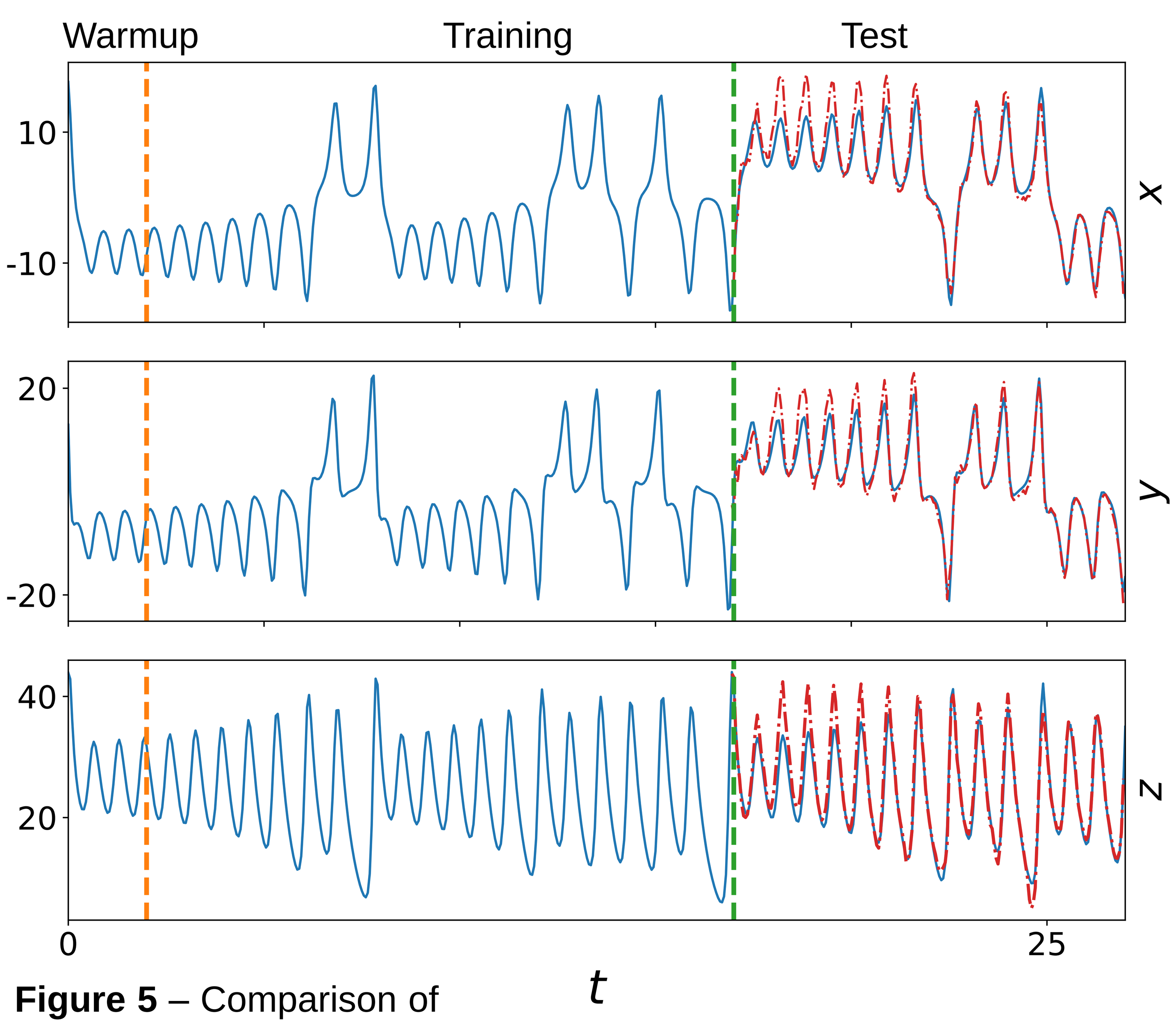


**Figure 4** – Experimental results to test the capacity of our system to learn the Lorentz model, equation (1). We begin with a warmup phase followed by a training phase. In this phase, a model is trained and applied to the test phase. The red point-dashed curve is the prediction of the model. The Lorentz model was integrated using the parameters of [1].

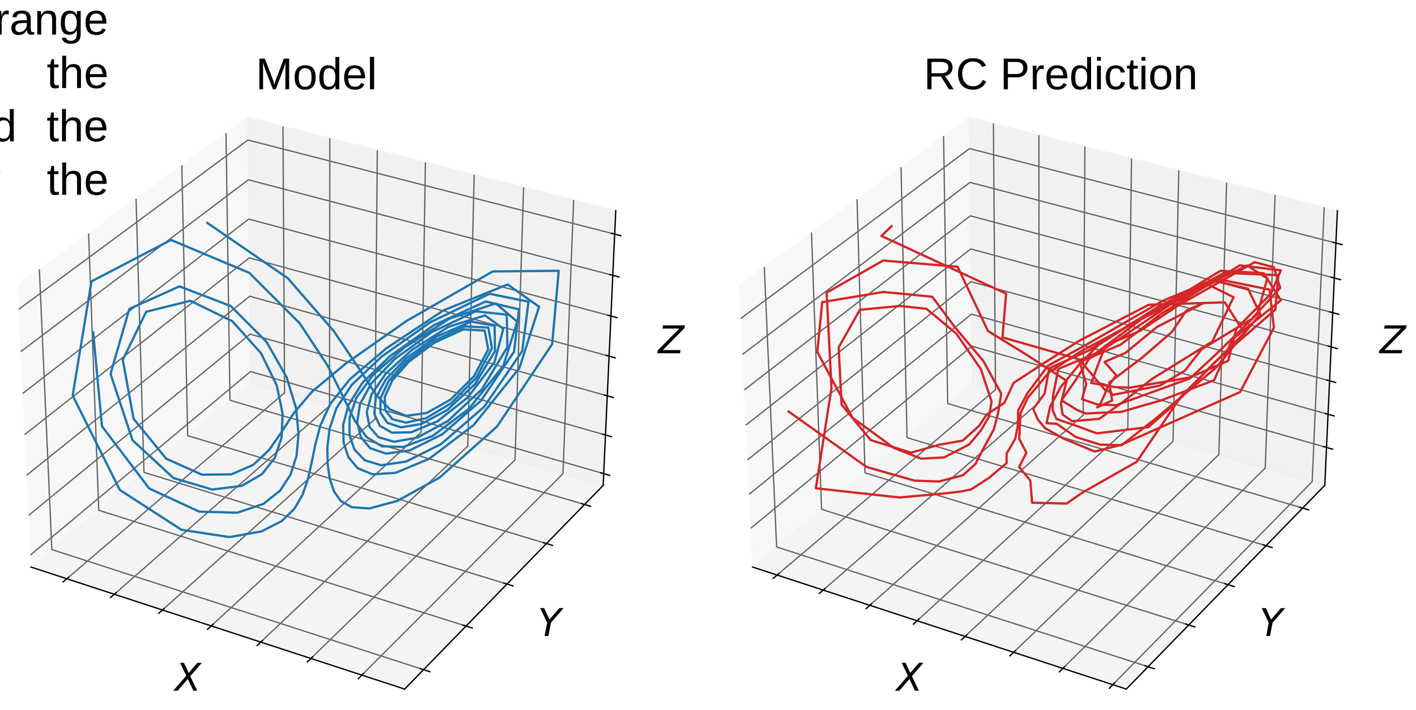


**Figure 5** – Comparison of the Lorentz strange attractor for the theoretical data and the data predicted by the model.

## Preliminary Experimental Results – Physical Twin

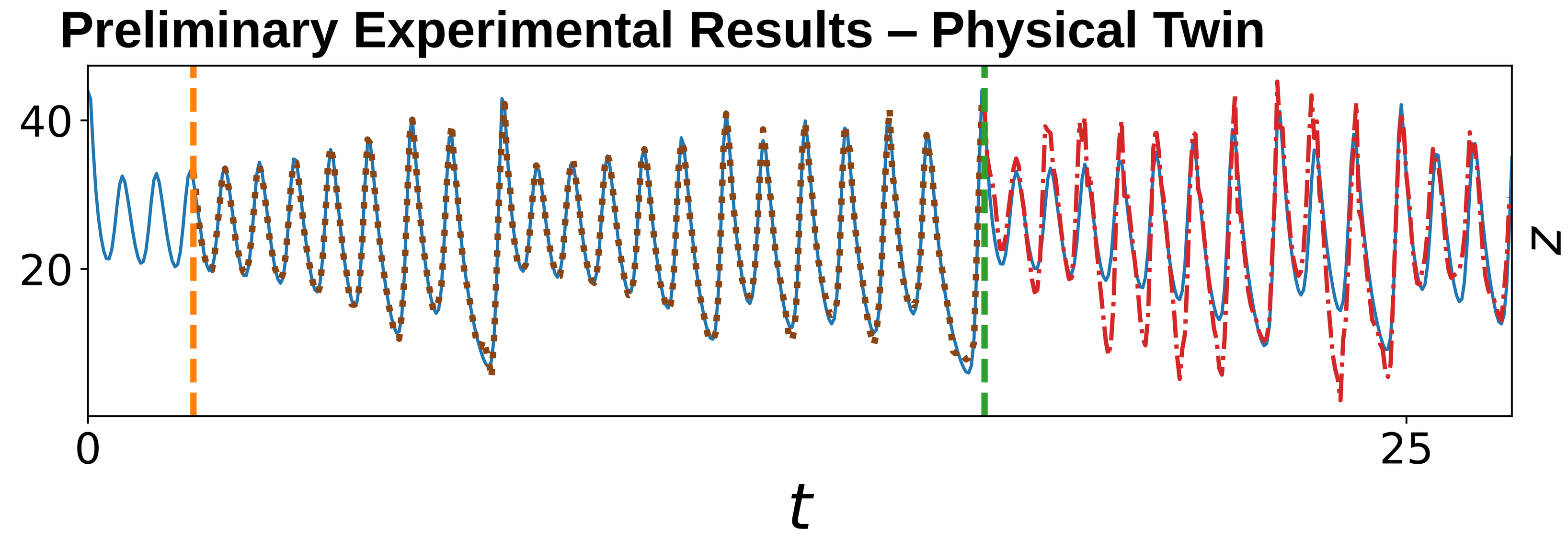


**Figure 6** – Experimental results for testing the capacity of the system to infer the next z step. During the training, the system is fed with x, y and z values. In the testing phase, only the x and y are given, and model predicts the z value. The brown points correspond to the prediction of the training model for the training data and the red point-dashed curve is the system prediction.

## Conclusions

- The preliminary results suggest that light propagating in a photorefractive crystal can be used as a reservoir computer.
- It is necessary to explore in more detail the temporal and nonlinear response of the system to optimize the performance of the Reservoir computer.

### References

**[1]** Daniel J. Gauthier, Erik Bollt, Aaron Griffith and Wendson A. S. Barbosa. "Next generation reservoir computing". Nat Commun 12, 5564 (2021). https://doi.org/10.1038/s41467-021-25801-2

**[2]** G.Huang, Q. Zhu, and C. Siew. "Extreme learning machine: a new learning scheme of feedforward neural networks". IEEE International Joint Conference on Neural Networks. (2016) 10.1109/IJCNN.2004.1380068

### Acknowledgements

This work is financed by National Funds through the Portuguese funding agency, FCT - Fundação para a Ciência e a Tecnologia, within project UIDB/50014/2020. T.D.F. is supported by Fundação para a Ciência e a Tecnologia through Grant No. SFRH/BD/145119/2019. N.A.S. also acknowledges the financial support of the project "Quantum Fluids of Light in Hot Atomic Vapors", supported by FCT in collaboration with the Ministry of Education, Science and Technological Development of the Republic of Serbia.