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Machine learning-assisted extreme events forecasting in Kerr ring resonators

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Abstract. Predicting complex nonlinear dynamical systems has been even more urgent because of the emergence of extreme events such as earthquakes, volcanic eruptions, extreme weather events (lightning, hurricanes/cyclones, blizzards, tornadoes), and giant oceanic rogue waves, to mention a few. The recent milestones in the machine learning framework offer a new prospect in this area. For a high dimensional chaotic system, increasing the system's size causes an augmentation of the complexity and, finally, the size of the artificial neural network. Here, we propose a new supervised machine learning strategy to locally forecast bursts occurring in the turbulent regime of a fiber ring cavity.

1 Introduction

Since the dawn of physics, predicting relevant events has been fundamental, particularly the prediction of eclipses, movements of celestial bodies, and catastrophic events such as storms, earthquakes, pandemics have attracted the attention of humanity. The emergence of calculus and differential equations in mechanics was a substantive step in predicting events and a deterministic vision of the nature surrounding us. However, the many-body problem, which is deterministic, leads to the difficulty of predicting due to the exponential sensitivity to differences in initial conditions (chaos). The inability to predict is the norm and not an exception for field models, which exhibit complex behaviors such as turbulence, spatiotemporal chaos, and intermittence. Hence, despite having adequate deterministic models at times, the prediction of catastrophic events such as storms, economic crises, pandemics, volcanic eruptions, fires, and earthquakes is not currently within reach. In this work, we show that machine learning algorithms opens a new breach in the prediction of high-dimensional chaotic systems. Machine learning can find hidden correlations in data that are exploited to perform model-free forecasting of spatiotemporal chaos [1, 2]. Many of the strategies try to model full extended dynamical system, making them unsuitable to partially observed systems. A critical limitation for full-size forecasting is the extensive nature of the systems under study. We propose a triggerable model-free prediction protocol using the information owing map. The exponential decay scale of the entropy transfer allows us to define the local subdomains and detect the structures that carry the system's information. The network's performance is tested with experimental data originating from a passive resonator operating in a chaotic spatiotemporal regime. We detect precursors and then forecast their complex future dynamics with our previously trained network. Allowing us to predict not only *when* and *where* extreme events will appear but also *what* is coming [3].

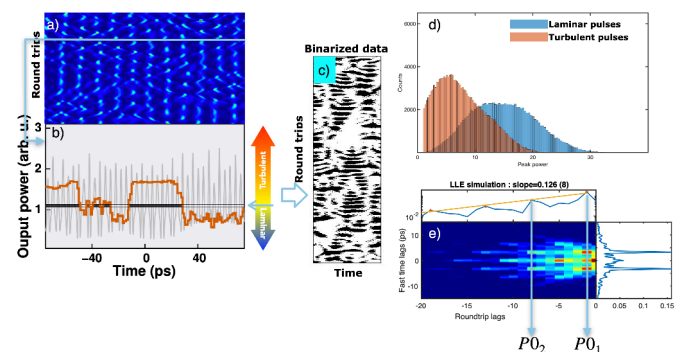


Figure 1. a) Illustration of complex spatiotemporal dynamics of observed far from the threshold of a fiber ring cavity in monostable regime. b) Example of binarization process and the obtained result. c) d) Statistics of the pulses according to their location in a laminar (blue) or turbulent (red) domain. e) Information transfer map computed from the complex evolution.

2 Dynamical system and methodology

2.1 The system

The playground of our study is a synchronous pumped fiber ring cavity. This system is the prototype system resonant energy injection in a nonlinear system. Kerr frequency combs, cavity solitons, modulational instability are examples of dynamics that can be observed in this systems. It is also one of dissipative systems that have been shown to exhibit extreme events induced by extensive or spatiotemporal chaos [4]. An advantage of the Kerr ring cavity is that it is very well described by a partial differential equation known in nonlinear optics as the Lugiato-Lefever equation [4, 5], which in its dimensionless form reads:

$$\frac{\partial \psi}{\partial t} = S - (1 + i\Delta)\psi - i\eta \frac{\partial^2 \psi}{\partial \tau^2} + i|\psi|^2 \psi. \quad (1)$$

Let's considering a fiber of length L , with a group velocity β_2 , and a nonlinear Kerr parameter γ . Assuming that after a

cavity round trip, the losses are given by α , the accumulated linear phase shift is Φ_0 and the amplitude of the pump is E_i , the dimensionless parameters read: $S = 2E_i \sqrt{\gamma L / \alpha^3}$, $\psi = A \sqrt{\gamma L / \alpha}$, $t = \alpha T / T_R = \alpha m$, $\tau = T / T_n$ ($T_n = \sqrt{|\beta_2 L| / (2\alpha)}$), and the detuning $\Delta = (2k\pi - \Phi_0) / \alpha$. The integer m gives the roundtrip number and the coefficient $\eta = \pm 1$ is the sign of the group velocity dispersion term. The configuration of our setup gives $\alpha = 0.20$, $\Delta = 1.1$ and $T_n \approx 1.1$ ps. Setting the normalized pump power to $S^2 = 4.9$ we can observe the dynamics shown in Fig. 1a).

2.2 The methodology

Using the analogy with hydrodynamics, we can reduce the complex dynamics observed in Fig. 1a) in term succession of laminar and turbulent regimes. Our methodology can be summarized as follows :

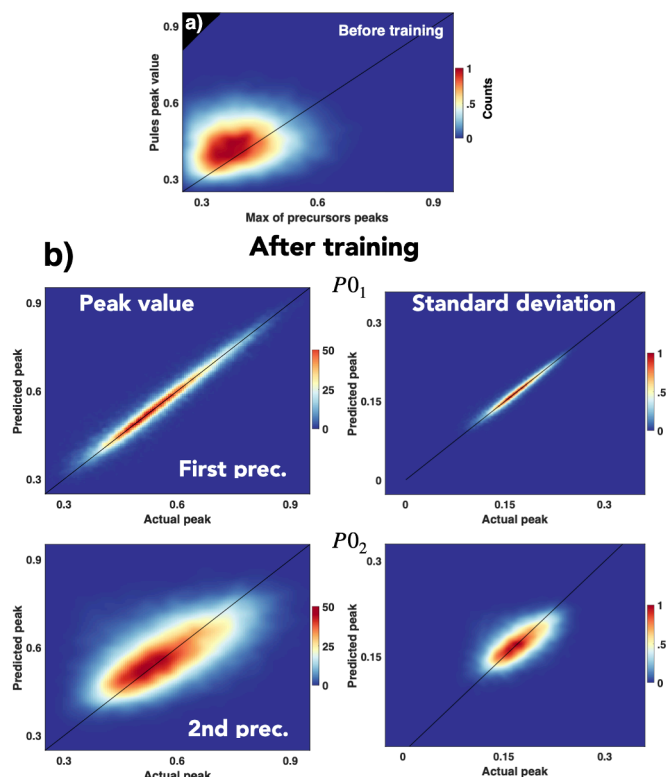


Figure 2. Correlation maps before (a) and after the training (b) for the first and second precursors.

1. Run an average process we obtain the red profile of Fig. 1b)
2. Choosing a threshold above which the region is turbulent and laminar below, we obtained a binarized evolution as shown in Fig. 1c).
3. Detect all the pulses and tag them as laminar or turbulent according their location in the binarized evolution. After the previous steps, we can see that the largest pulses are laying in laminar regions (see Fig. 1d)).

4. Compute the information transfer map to determine how the past (Round trip lag) of a given position (Fast time lag) carries information up to the present. The results of this calculation are shown in Fig. 1e). It appears that a peak in the present mostly shares information with specific round trips in the past. We called these position the precursor locations.
5. We can then detect the precursors associated to each pulse and create a set of pulse-precursors paires. Next, we split this set in training and test data samples. Then, the training sample is used to feed a sequence to sequence forecasting artificial neural network.

3 Results and conclusion

We have taken advantage of the apparent causality to make an association precursors-pulses. Knowing when and where the bursts may emerge, a fair question is "What is coming?". On the other hand, as shown in Figure 2a), no correlation can be found between the profile (amplitude and size) of the precursors of the corresponding pulse. However, using the pulses/precursors pairs to perform supervised learning with a recurrent neural network, we have obtained a high correlated map between the actual observation and the prediction, as can be seen in Figure 2b). As our strategy deals with intrinsic characteristic quantities of the dynamical behavior, the pre-trained network can trigger the forecasting even for a more extensive system, provided that all the other parameters are the same.

To conclude, we show that turbulence-induced pulses can be forecasted on demand using a strategy based on supervised machine learning process. We illustrate it experimental from data originating from a passive fiber cavity operating in a highly chaotic regime. This strategy is made possible by the presence of precursors around the location of pulses.

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