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Machine learning for ultrafast nonlinear fibre photonics

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ABSTRACT

We provide an overview of our latest advances in the application of machine learning methods to ultrafast nonlinear fibre optics. We establish that neural networks are capable of accurately forecasting the temporal and spectral properties of optical signals that are obtained after propagation in the focusing or defocusing regimes of nonlinearity. Machine learning is also efficient in addressing the related inverse problem as well as providing insights into the underlying physical process. In addition, we illustrate the use of evolutionary algorithms to access and optimise complex nonlinear dynamics of ultrafast fibre lasers.

Keywords: machine-learning, ultrafast nonlinear optics, nonlinear fiber photonics.

1. INTRODUCTION

Recent years have seen the rapid growth of the field of smart photonics where the deployment of machine-learning strategies is the key to enhance the performance and expand the functionality of optical systems [1]. Ultrafast photonics areas where the promise of machine learning is being realised include the design and operation of pulsed lasers, and the characterisation and control of ultrafast propagation dynamics [2]. Here, we review our recent results in the field by providing several examples of advances enabled by machine-learning tools such as neural networks (NNs) and evolutionary algorithms (EAs).

First, we describe the use of a supervised feedforward NN paradigm to solve the direct and inverse problems relating to nonlinear pulse shaping in optical fibres, bypassing the need for direct numerical solution of the governing propagation model, i.e. the nonlinear Schrödinger equation (NLSE) or its extensions. Further, we present the use of a NN to obtain new insights into the longitudinal temporal and spectral evolutions of periodic signals made of equally frequency-spaced components. Finally, we discuss the possibility of using EAs to perform search and optimisation of non-stationary regimes of fibre lasers.

2. MACHINE LEARNING FOR NONLINEAR PULSE SHAPING

Propagation of light in single-mode optical fibers is governed by the NLSE including dispersion and Kerr nonlinearity, to which it is also possible to add the effects of losses or gain. This equation, usually solved numerically by the split-step Fourier algorithm [3], leads to a very large panel of dynamics such as soliton pulse compression, self-similar temporal and spectral broadening, wave-breaking, and spectral narrowing, amongst others. The resulting output properties are highly dependent on the initial pulse properties (peak power, temporal duration, chirp and waveform) as well as the fiber parameters (value and regime of dispersion, fiber length, nonlinear/gain/loss coefficients) so that obtaining a full picture of the output landscape can be very demanding in terms of computational resources.

In that context, we have shown that feedforward NNs, after convenient training, can offer a very efficient substitute to the split-step Fourier algorithm [4]. As can be seen on Fig. 1 for two initial chirped pulses, the network accurately predicts the temporal and spectral intensity profiles of the pulses that form upon nonlinear propagation in fibres with both anomalous and normal dispersion. This data-driven approach reduces the computational time by two orders of magnitude and the network can accommodate to and maintain high accuracy for a wide dynamic range of system parameters. The use of NNs is not restricted to the NLSE framework, and benefits have also been evidenced for the prediction of supercontinuum properties with spectral extent spanning several hundreds of nanometres, and with strong pulse instabilities [5, 6].

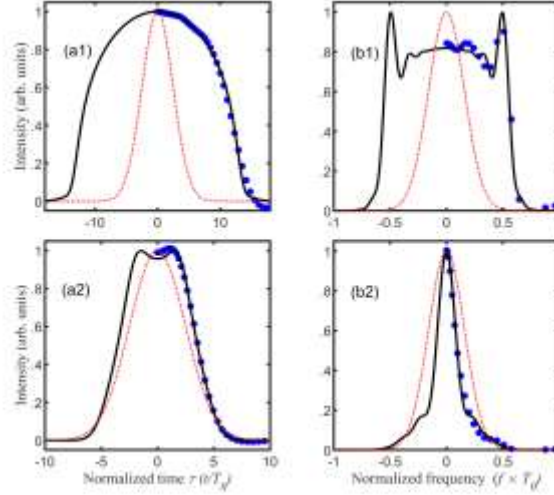


Figure 1. Reconstruction of the temporal and spectral properties (subpanels 1 and 2 respectively) for an initially chirped pulse. (a) Results for a Gaussian pulse after propagation in a normal dispersion fibre with the normalised length $\xi = 2.5$, normalised power $N = 2.8$, and normalised chirp parameter $C = -2.42$, (b) Results obtained with $\xi = 2.2$, $N = 2$ and $C = 2.42$. The predictions of the NN (blue circles) are compared with the results given by the NLSE (black curves) and with the initial properties of the pulse (dashed red line).

We have also applied NNs to help solve the inverse problem which is a much more complex task [7]: we have demonstrated the ability of the NN to determine the nonlinear propagation properties from the pulses observed at the fibre output, and to classify the output pulses according to the initial pulse shape [4]. We have also expanded our analysis to the case of pulse propagation in the presence of distributed gain or loss, with a special focus on the generation of self-similar parabolic pulses [8].

In addition to effectively solving forward and inverse mapping problems, recently developed data-science techniques offer new insights to understand the interaction dynamics between Kerr nonlinearity and dispersion. Indeed, the data-driven dominant balance approach [9] provides convenient means to automate the identification of which particular physical processes drive propagation in different regimes, a task usually performed using intuition and comparison with asymptotic limits [10]. The technique has been successfully applied to complex cases such as noise-driven spontaneous modulation instability where extreme events emerge.

3. MACHINE LEARNING FOR FOUR WAVE MIXING AND SPECTRAL COMB GENERATION

We have also explored the use of machine learning to study four-wave mixing interactions involved in the temporal and spectral evolutions of periodic signals made of equally frequency-spaced components. In the case of degenerate four-wave mixing, the dynamics can be reconstructed by taking advantage of the combination of experimental measurements together with supervised machine-learning strategies [11]. The training dataset consists of power-dependent spectral phase and amplitude recorded at the output of a short fibre segment for various initial conditions. A NN is shown to be able to accurately predict the nonlinear dynamics over tens of kilometres, and to retrieve the main features of the phase space topology including multiple Fermi–Pasta–Ulam recurrence cycles and the system separatrix boundary.

Based on numerical simulations, we have also demonstrated that data-driven discovery using sparse regression can be used to extract the governing differential equation model of the ideal four-wave mixing process [12]: sparse regression successfully recovers the underlying physical model, fully capturing the dynamical landscape on both sides of the system separatrix starting from a reduced set of trajectories.

When the process of four-wave mixing cascades, the interactions between the numerous spectral lines of the comb spectrum become more complex. We have deployed a supervised machine-learning model based on a NN to predict the temporal and spectral reshaping of a simple sinusoidal modulation into a pulse train [13]. Both normal and anomalous second-order dispersion regimes of the fibre are studied, and the speed of the neural network is leveraged to probe the space of input parameters for the generation of custom combs or the occurrence of significant temporal or spectral focusing. Figure 2 shows some examples of the accuracy and ability of such a NN to find appropriate conditions to generate on-demand temporal or spectral profiles.

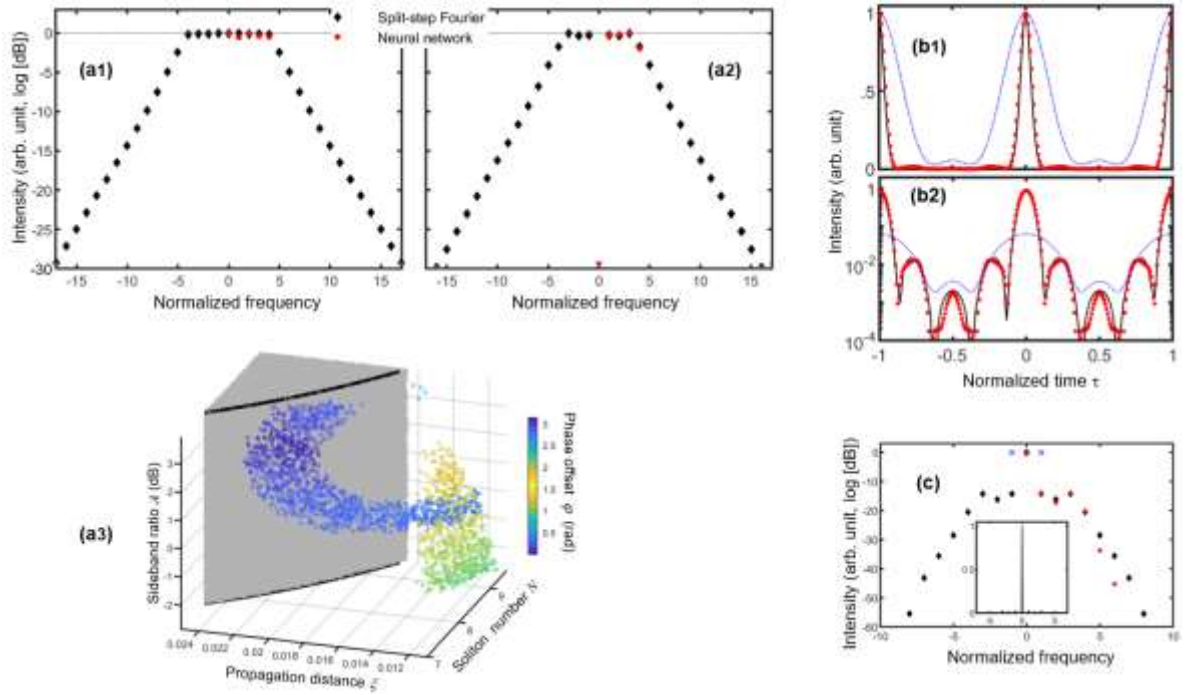


Figure 2. Various examples of the use of NNs. (a) Generation of on-demand frequency combs in an anomalously dispersive fibre: (a1,a2) Combs composed of 9 spectral lines of equal amplitude and 6 spectral lines of equal amplitude, respectively, but with the center component canceled; (a3) Regions of the input parameter space for the formation of high flatness combs. (b) Temporal focusing in an anomalously dispersive fibre: generation of a pulse train with the highest peak power relative to the average power (linear and logarithmic scales in panels 1 and 2, respectively). (c) Spectrum generated during spectral focusing in a normally dispersive fibre. The NN predictions (red circles) are compared to the results of the NLSE numerical simulations (diamonds or black lines). Also shown are the initial conditions (blue crosses).

4. MACHINE LEARNING FOR FIBER LASERS

Machine-learning techniques have not only been very successful in the study of passive propagation in a fibre segment, they have also been widely used in the context of the dynamics of fibre lasers [14]. For instance, NN-based algorithms have been used as surrogate model solvers to predict the output properties of the laser [15, 16]. Another area of AI investigation stimulating great enthusiasm is the implementation of EAs to experimentally help automatically target the stationary pulse state of an ultrafast laser [17]. Yet, controlling non-stationary regimes was an open issue as such regimes exhibit a fast evolutionary behavior, requiring dedicated real-time measurement tools for their detection.

We have demonstrated the possibility of using EAs to perform search and optimisation of the breathing-soliton regime in a fibre laser [18]. Through exploration of the nonlinear cavity dynamics, which can be accessed by automated control of the nonlinear-polarisation-evolution transfer function, we show that composite merit functions, derived from specific features of the radio-frequency spectrum of the laser output, permit to achieve various self-starting pulsating regimes in the laser, including single breathers with controllable breathing ratio and period, and breather molecular complexes with a controllable number of elementary constituents. Benefiting from this reliable tool, we have demonstrated that the generated frequency-locked pulsating states were governed by a Farey tree hierarchy and followed the structure of a devil's staircase [19]. We have also experimentally implemented EAs to explore regimes that were even further away from stationary operation such as noise-like emission [20] or generation of spectral extreme events [21].

5. CONCLUSIONS

The use of machine-learning tools has increased exponentially in recent years and continues to grow at a sustained pace. Here, we have provided an overview of some of our contributions made to the field over the past years, on the use of artificial NNs, the implementation of EAs, and the exploration of new algorithms disclosing, from data analysis, new perspectives on the physical understanding or modelling of the governing nonlinear

dynamics. All these results demonstrate that suitably trained NNs can greatly help in the characterisation and inverse-engineering of fiber-based shaping systems by providing immediate and sufficiently accurate solutions. EAs open novel opportunities for the experimental exploration of highly dynamic, non-stationary operating regimes of ultrafast lasers.

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REFERENCES

- [1] P. Freire, E. Manuylovich, J. E. Prilepsky, and S. K. Turitsyn, "Artificial neural networks for photonic applications—from algorithms to implementation: tutorial," *Adv. Opt. Photon.*, vol. 15, no. 3, pp. 739-834, 2023.
- [2] G. Genty, L. Salmela, J. M. Dudley, D. Brunner, A. Kokhanovskiy, S. Kobtsev, and S. K. Turitsyn, "Machine learning and applications in ultrafast photonics," *Nat. Photon.*, vol. 15, pp. 91-101, 2021.
- [3] G. P. Agrawal, *Nonlinear Fiber Optics, Sixth Edition*. San Francisco, CA: Academic Press, 2019.
- [4] S. Boscolo and C. Finot, "Artificial neural networks for nonlinear pulse shaping in optical fibers," *Opt. Laser Technol.*, vol. 131, p. 106439, 2020.
- [5] L. Salmela, N. Tspinakis, A. Foi, C. Billet, J. M. Dudley, and G. Genty, "Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent neural network," *Nature Machine Intelligence*, vol. 3, no. 4, pp. 344-354, 2021.
- [6] M. Mabed, L. Salmela, A. Ermolaev, C. Finot, G. Genty, and J. M. Dudley, "Neural network analysis of unstable temporal intensity peaks in continuous wave modulation instability," *Opt. Commun.*, vol. 541, p. 129570, 2023.
- [7] C. Finot, I. Gukov, K. Hammani, and S. Boscolo, "Nonlinear sculpturing of optical pulses with normally dispersive fiber-based devices," *Opt. Fiber Technol.*, vol. 45, pp. 306-312, 2018.
- [8] S. Boscolo, J. M. Dudley, and C. Finot, "Modelling self-similar parabolic pulses in optical fibres with a neural network," *Results in Optics*, vol. 3, p. 100066, 2021.
- [9] J. L. Callahan, J. V. Koch, B. W. Brunton, J. N. Kutz, and S. L. Brunton, "Learning dominant physical processes with data-driven balance models," *Nat. Commun.*, vol. 12, no. 1, p. 1016, 2021.
- [10] A. V. Ermolaev, M. Mabed, C. Finot, G. Genty, and J. M. Dudley, "Analysis of interaction dynamics and rogue wave localization in modulation instability using data-driven dominant balance," *Sci. Rep.*, vol. 13, no. 1, p. 10462, 2023.
- [11] A. Sheveleva, P. Colman, J. M. Dudley, and C. Finot, "Phase space topology of four-wave mixing reconstructed by a neural network," *Opt. Lett.*, vol. 47, no. 22, pp. 6317-6320, 2022.
- [12] A. V. Ermolaev, A. Sheveleva, G. Genty, C. Finot, and J. M. Dudley, "Data-driven model discovery of ideal four-wave mixing in nonlinear fibre optics," *Sci. Rep.*, vol. 12, no. 1, pp. 1-11, 2022.
- [13] S. Boscolo, J. M. Dudley, and C. Finot, "Predicting nonlinear reshaping of periodic signals in optical fibre with a neural network," *Opt. Commun.*, vol. 542, p. 129563, 2023.
- [14] Q. Ma and H. Yu, "Artificial Intelligence-Enabled Mode-Locked Fiber Laser: A Review," *Nanomanufacturing and Metrology*, vol. 6, no. 1, p. 36, 2023.
- [15] S. Boscolo, C. Finot, I. Gukov, and S. K. Turitsyn, "Performance analysis of dual-pump nonlinear amplifying loop mirror mode-locked all-fibre laser," *Laser Phys. Lett.*, vol. 16, no. 6, p. 065105, 2019.
- [16] M. Mabed, F. Meng, L. Salmela, C. Finot, G. Genty, and J. M. Dudley, "Machine learning analysis of instabilities in noise-like pulse lasers," *Opt. Express*, vol. 30, no. 9, pp. 15060-15072, 2022.
- [17] U. Andral, J. Buguet, R. Si Fodil, F. Amrani, F. Billard, E. Hertz, and P. Grelu, "Toward an autsetting mode-locked fiber laser cavity," *J. Opt. Soc. Am. B*, vol. 33, no. 5, pp. 825-833, 2016.
- [18] X. Wu, J. Peng, S. Boscolo, Y. Zhang, C. Finot, and H. Zeng, "Intelligent Breathing Soliton Generation in Ultrafast Fiber Lasers," *Laser Photonics Rev.*, vol. 16, no. 2, p. 2100191, 2021.
- [19] X. Wu, Y. Zhang, J. Peng, S. Boscolo, C. Finot, and H. Zeng, "Farey tree and devil's staircase of frequency-locked breathers in ultrafast lasers," *Nat. Commun.*, vol. 13, no. 1, p. 5784, 2022.
- [20] C. Lapre, F. Meng, M. Hary, C. Finot, G. Genty, and J. M. Dudley, "Genetic algorithm optimization of broadband operation in a noise-like pulse fiber laser," *Sci. Rep.*, vol. 13, no. 1, p. 1865, 2023.
- [21] X. Wu, Y. Zhang, J. Peng, S. Boscolo, C. Finot, and H. Zeng, "Control of spectral extreme events in ultrafast fiber lasers by a genetic algorithm," *Laser Photonics Rev.*, p. 2200470, 2023.