

Predicting frequency comb structure in nonlinear optical fibre using a neural network

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Abstract. We deploy a neural network to predict the spectro-temporal evolution of simple sinusoidal temporal modulations upon propagation in a nonlinear dispersive fibre. Thanks to the speed of the neural network, we can efficiently scan the input parameter space for the generation of on-demand frequency combs or the occurrence of substantial spectral/temporal focusing.

1 Introduction

The application of machine learning approaches in photonics for characterising and controlling ultrafast propagation dynamics has attracted increasing interest in recent years [1]. Neural networks (NNs) have been successfully introduced as an effective tool for substituting the nonlinear Schrödinger equation (NLSE) in modelling the reshaping of ultrashort pulses that results from nonlinear propagation in a dispersive optical fibre [2,3] or for predicting the generation of optical supercontinua [4]. The fibre Kerr nonlinearity will also affect the propagation of a continuous wave modulated at a certain frequency, which will experience an energy exchange between the spectral lines that make up its spectrum as well as a change in the relative phase between the frequency components. The emergence of new, evenly spaced frequency components will give rise to a frequency comb, whereas significant temporal domain reshaping will occur, typically producing pulse trains with extremely high repetition rates [5]. In this contribution, we describe how we have developed and trained a NN [6] that enables us to predict the longitudinal spectro-temporal evolution of periodic waveforms in a fibre. Both the normal and anomalous regimes of dispersion of the fibre are explored to synthesise on-demand frequency combs or detect the occurrence of significant spectral or temporal focusing, and the remarkable speed of the NN is exploited to scan the space of input parameters.

2 Methods

This work focuses on the nonlinear propagation of two types of periodic waveforms that have already been studied in the context of linear shaping [7]: a continuous wave modulated at a frequency f_m which produces an optical spectrum with a central component and two symmetrically located sidebands, and a wave whose

spectrum is made up of four spectral lines without any continuous background. The data from numerical simulations of the NLSE based on the standard split-step Fourier technique is used to train the NN and verify its predictions. We employ a feedforward NN including three hidden layers and applying the Bayesian regularisation back propagation method. The NN learns the NLSE model from an ensemble of hundreds of thousand simulation data (real and imaginary parts of the spectral field) for the anomalous or normal dispersion regime of the fibre, corresponding to randomly chosen combinations of the input parameters: amplitude ratio A of the central frequency component of the optical spectrum to the lateral sidebands, spectral phase offset φ of the sidebands relative to the central component, normalised propagation length ζ , and soliton-order number N .

After training, the NN is tested on a distinct ensemble of tens of million data not used in the training stage. The speed of the trained NN is its greatest asset: in less than a minute, it can accurately predict the output properties of this large data set. Therefore, it can explore the whole 4D input parameter space for the best parameter sets that fulfil given targets without being trapped in local optima.

3 Performance examples

Some examples of the NN's performance are illustrated in Figure 1. In panels (a1) and (a2), the NN was tasked with determining the input parameters that enable the formation of optical spectra made of nine spectral lines of equal intensity and of six spectral lines of equal intensity but with the central component suppressed, respectively, when a three-frequency component initial condition is used at the input of an anomalously dispersive fibre. The NN predictions are in good agreement with the results of the NLSE model. The scatter plot in panel (a3) evidences the existence of two distinct regions in the input parameter

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space that can support the formation of highly flat frequency combs. Moreover, we can see that flat combs can be achieved starting from lateral sidebands with either lower or higher intensity in comparison to the central component.

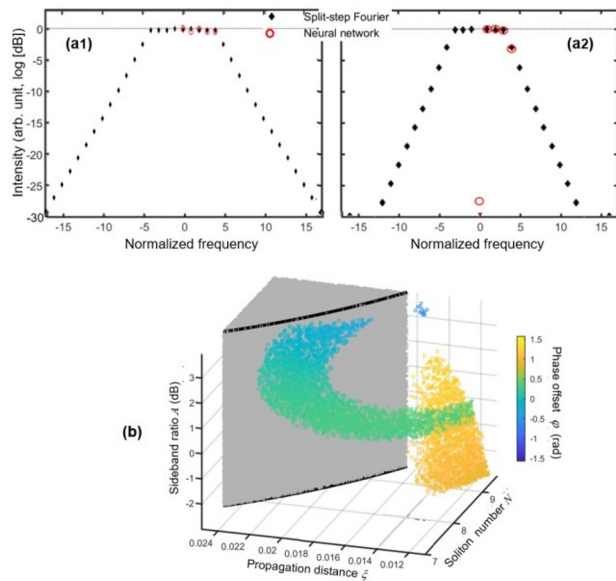


Fig. 1. Generation of on-demand frequency combs in an anomalously dispersive fibre: (a1, a2) Combs consisting of 9 spectral lines of equal amplitude and of 6 spectral lines of equal amplitude but with the central component cancelled, respectively. (b) Regions in the input parameter space that enable the formation of high-flatness combs.

As our NN accounts for both the spectral intensity and phase of the generated comb, it is straightforward to reconstruct the temporal properties of the corresponding pulse train. For the pulse train in panel (a) of Fig. 2, the NN was prompted to probe the input parameter space for the pulse train with the largest ratio of the pulse peak power to the average power. Even when plotted on a logarithmic scale, the temporal profile of the compressed waveform predicted by the NN shows excellent agreement with that obtained from NLSE simulation. Additionally, we have verified that the NN is capable of accurately reconstructing the initial waveform's longitudinal temporal evolution. The findings depicted in panel (b) of Fig. 2 relate to the spectral focusing that typically occurs in a normally dispersive fibre. The NN was able to determine a combination of spectral phase and propagation parameters resulting in remarkable inverse four-wave mixing starting from three spectral lines of equal amplitude. At the output of the fibre, the main frequency component contains more than 80% of the total energy, whereas the neighbouring frequency components' intensities are more than 15 dB lower. Further results, including the synthesis of customised frequency combs and optical undular bores [8] in the normal dispersion propagation regime, will be discussed at the conference.

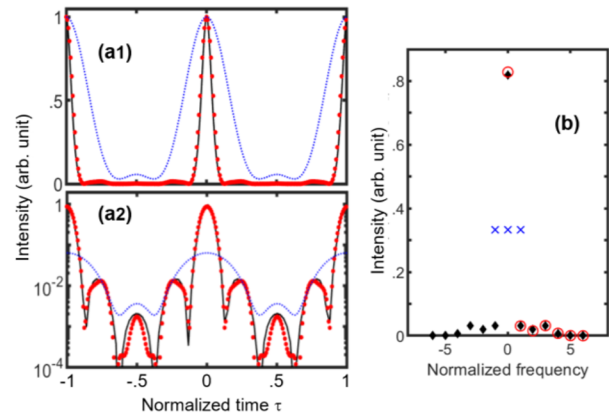


Fig. 2. (a) Temporal focusing in an anomalously dispersive fibre: generation of a pulse train with the highest pulse peak power relative to the average power (plotted on linear and logarithmic scales in panels 1 and 2, respectively). (b) Spectral focusing in a normally dispersive fibre: generated optical spectrum. The predictions from the NN (red circles) are compared with the results of NLSE numerical simulations (black diamonds or lines). Also shown are the initial conditions at the fibre input (blue crosses or lines).

4 Conclusions

We have shown that, starting from periodic wave initial conditions with three or four frequency components, a trained NN can identify the input system parameters needed to produce on-demand target frequency combs in a nonlinear optical fibre. The accurate prediction of the longitudinal evolutions of the wave intensity profiles in the time and frequency domains by the NN for both the anomalous and normal dispersion regimes of the fibre has enabled the replication of the processes of ultrashort pulse formation, spectral compression and undular bores that are involved in the NLSE.

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