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Modelling Nonlinear Propagation of Periodic Waveforms in Optical Fibre with a Neural Network

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Abstract: We deploy a neural network to predict the spectro-temporal evolution of a periodic waveform upon nonlinear fibre propagation and demonstrate efficient probing of the input-parameter space for on-demand comb generation or significant spectral/temporal focusing occurrence. © 2022 The Author(s)

1. Introduction

Recent years have seen a growing interest in applying the techniques of machine learning to optical systems and, particularly, for the characterisation and control of ultrafast propagation dynamics [1]. We have successfully introduced the use of neural networks (NNs) as an efficient tool for substituting the nonlinear Schrödinger equation (NLSE) in the modelling of the shaping of ultrashort pulses that occurs upon nonlinear propagation in an optical fibre [2,3] or for predicting the generation of optical supercontinua [4]. The fibre nonlinearity does not only affect the propagation of ultrashort pulses, but also a continuous wave modulated at some frequency will experience an energy exchange between the spectral lines making up its spectrum along with a change in the relative phase between the frequency components. New equally spaced frequency components will emerge giving rise to a frequency comb, while significant reshaping will take place in the time domain, generally leading to very high repetition rate pulse trains [5]. In this paper, we implement a NN to predict the spectro-temporal evolution of a periodic waveform in a fibre [6]. Both the normal and anomalous second-order dispersion regimes of the fibre are studied, and the speed of the NN is leveraged to probe the space of input parameters for the generation of on-demand target combs or the occurrence of significant temporal or spectral focusing.

2. Methods, Results and Discussion

The general problem studied in this work is the nonlinear propagation of two types of periodic waveforms, which have already been investigated in the context of linear shaping [7]: a continuous wave modulated at the frequency f_m , yielding an optical spectrum made of a central component and two sidebands at $\pm f_m$, and a wave whose spectrum consists of four spectral lines without any continuous background. The data from numerical simulations of the NLSE based on the standard split-step Fourier algorithm is used to train a NN and validate its predictions. We employ a feedforward NN relying on the Bayesian regularisation back propagation algorithm and including three hidden layers. The NN learns the NLSE model from an ensemble of hundreds of thousands simulation data (real and imaginary parts of the spectral field) for the anomalous or normal dispersion regime of the fibre and corresponding to randomly chosen combinations of 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 ξ , 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 step. The strength of the trained NN lies in its speed: in less than one minute, it can predict the output features of this large data set with high accuracy. Therefore, it can search the full 4D input parameter space for the optimum parameter sets meeting given targets without being trapped in local optima.

Figure 1 illustrates some examples of the NN's performance. In panels (a1) and (a2), the NN was asked to identify the input parameters that enable the formation of optical spectra made of nine spectral lines of equal intensity and of six equal intensity spectral lines 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 predictions from the NN show good agreement with the results of the NLSE model. The scatter plot in panel (a3) highlights the existence of two distinct regions in the space of input parameters that support the formation of highly flat frequency combs. We also see that it is possible to achieve a flat comb starting from both lower and higher intensity lateral sidebands as compared with the central component. As our NN accounts for both the spectral intensity and phase features of the generated comb, it is straightforward to reconstruct the temporal properties of the corresponding pulse train. In panel (b), the NN was asked to probe the input parameter space for the pulse train with the highest ratio of the pulse peak power to the average power. The temporal profile of the compressed waveform predicted by the NN is once again in very good

agreement with that obtained from NLSE simulation, even when plotted on a logarithmic scale. We have also verified that the NN can efficiently reconstruct the longitudinal temporal evolution of the initial waveform. The results shown in panel (c) refer to the process of spectral focusing taking place in a normally dispersive fibre. Starting from three spectral lines of equal amplitude, the NN was able to identify a combination of spectral phase and propagation parameters leading to a remarkable inverse four-wave mixing. More than 80% of the total energy is concentrated in the central frequency component whereas the intensity level of the neighbouring components is more than 15dB lower. Further results including the generation of customised frequency combs and of optical undular bores [8] in the normal dispersion regime will be presented at the conference.

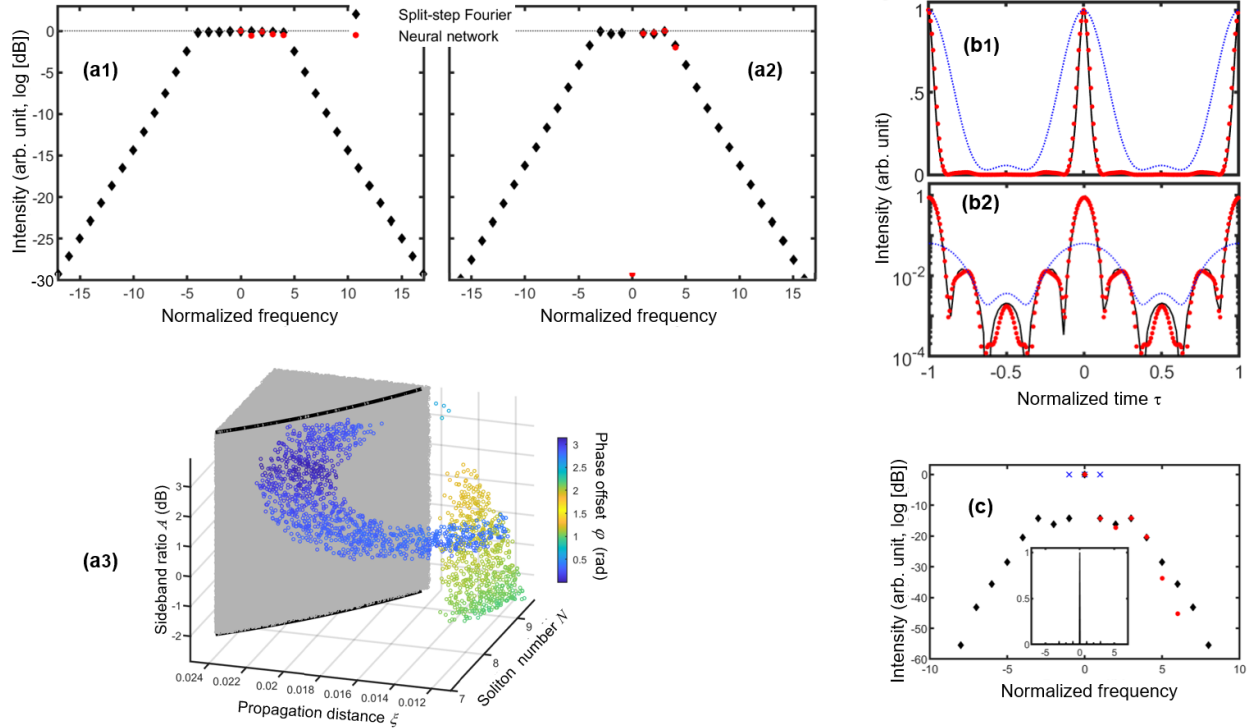


Fig. 1. Various examples of use of the NN. (a) Generation of on-demand frequency combs in an anomalously dispersive fibre: (a1,a2) combs consisting of 9 spectral lines of equal amplitude and of 6 spectral lines of equal amplitude but with the central component cancelled, respectively; (a3) Regions in the input parameter space that enable the formation of high-flatness combs. (b) 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). (c) 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).

3. Conclusion

We have demonstrated the ability of a trained NN to identify the input system parameters that are required to generate on-demand target frequency combs in a nonlinear optical fibre starting from periodic wave initial conditions with three or four frequency components. 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 replication of the processes of ultrashort pulse formation, spectral compression and undular bores that are involved in the NLSE.

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