DEEP LEARNING BASED CLASSIFICATION OF HIGH INTENSITY LIGHT PATTERNS IN PHOTOREFRACTIVE CRYSTALS

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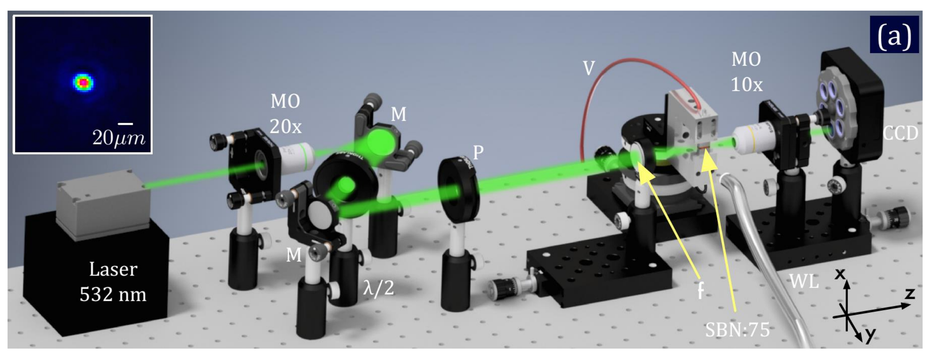
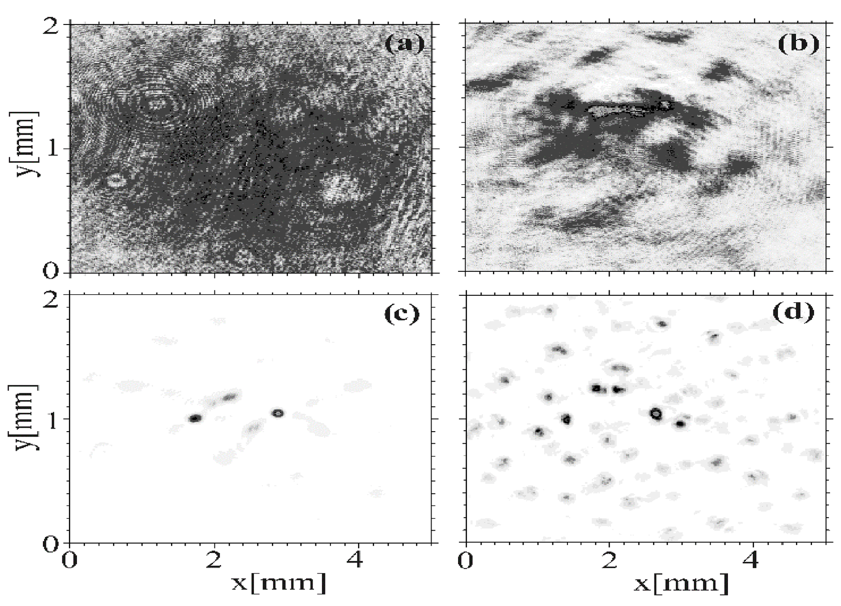
Rogue waves (RWs) or extreme events have been in the focus of interest in diverse fields of science since the middle of the last century [1]. Here, we establish a new scheme for identification and classification of high intensity events generated by the propagation of light through a photorefractive SBN crystal [2]. Speckling and soliton-like patterns are among these events which are the inevitable consequence of the development of modulation instability. We implement the convolution neural network method to relate experimental data of light intensity distribution and corresponding numerical profiles. The accuracy of detection of speckles reaches maximum value of 100%, while the accuracy of solitons and caustic detection is above 97%. These performances are promising for the creation of neural network based routines for prediction of extreme events in wave media.

RWs are rare, highly intense, spatially localized and temporally transient structures in complex systems (oceans, optics, biological systems, mater waves, social sciences). We explored their appearance in a SBN photorefractive crystal and found a variety of output light intensity patterns [2].

Experimental setup



Output intensity profiles



* White and black color corresponds to the lowest and highest intensity, respectively (grayscale form 0 (min) to 255 (max intensity))

Classes of output profiles/regimes:
(a) Dispersion-like (no RWs)
(b) Caustic-like
(c) Soliton-like
(d) Speckling

Model equation of the light propagation through the crystal with local saturable nonlinear term [3]:

$$i\frac{\partial}{\partial z}\psi(x,y,z)+\beta\left(\frac{\partial^2}{\partial x^2}+\frac{\partial^2}{\partial y^2}\right)\psi(x,y,z)-g\frac{\psi(x,y,z)}{1+|\psi(x,y,z)|^2}=0$$

Ψ(x,y,z) - the envelope of the electric field, x and y - transverse crystal sample lengths, z the propagation coordinate and g - nonlinear parameter. The initial conditions and the external voltage→ related to g.

The light experiences different regimes, corresponding to those identified at the output crystal facet in the experiment.

Goal: ***To implement the convolution neural network (CNN) [4] to previously obtained experimental and numerical data for distinguishing regimes with different types of high intensity events.***

CNN architecture and training

Q: Why deep learning (DL)?

A: Standard statistical methods and measures are related to the determination of the RW threshold by criteria based on the observation - approximate and not unique. The DL offers a tool for going beyond these limits.

The key: Representative and well balanced dataset to allow to choose optimal NN architecture and to read and interpret decision results.

Our network architecture: 3-stage feature extractor along with a fully connected multi-layer perceptron (MLP) [5]

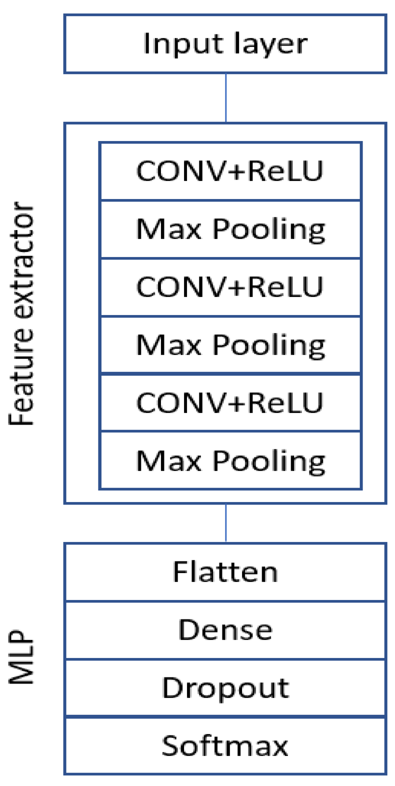


Table 1. The details of the optimal network architecture; b denotes mini-batch size.

Layer type	Output shape	# of parameters	Kernel size	Stride/dropout rate	Activation
Input	(b,512,512,1)	0	-	-	-
CONV	(b,508,508,32)	832	5x5	1	ReLU
MaxPolling	(b,127,127,32)	0	4x4	4	-
CONV	(b,123,123,64)	51264	5x5	1	ReLU
MaxPolling	(b,30,30,64)	0	4x4	4	-
CONV	(b,26,26,64)	102464	5x5	1	ReLU
MaxPolling	(b,13,13,64)	0	2x2	2	-
Flatten	(b,10816)	0	-	-	-
Dense	(b,1024)	11076608	-	-	ReLU
Dropout	(b,1024)	0	-	0.4	-
Dense	(b,4)	4100	-	-	softmax

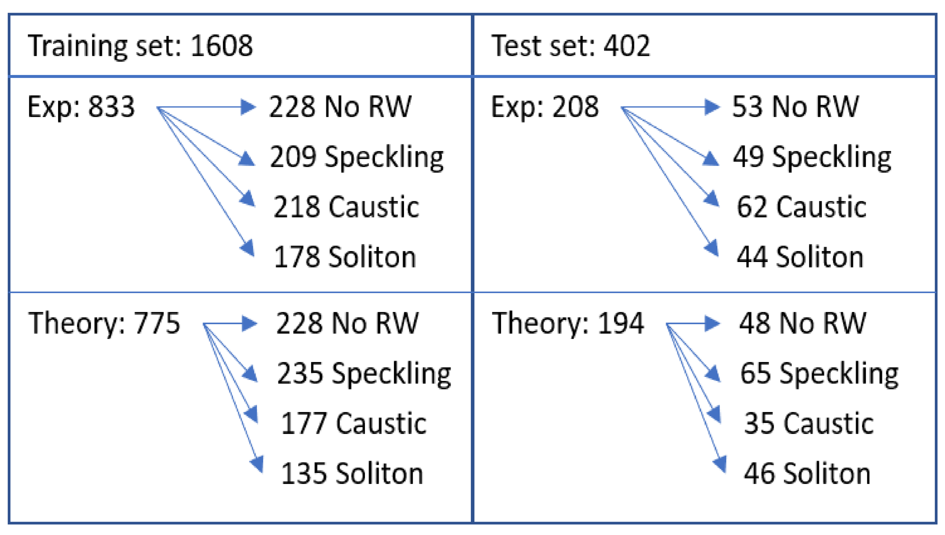
Sample set: 1041 (experimental) and 969 (numerically) generated intensity profiles

Numerical datasets → Training set (80%), Testing set (20%) → The architecture design, model hyperparameters, evaluation (10-fold cross-validation)

Experimental datasets → Training set (80%), Testing set (20%)

Numerical + Experimental datasets → Training set (80%), Testing set (20%)

* Each class is more or less equally represented in the sample set *



Scheme of the dataset content

Results

NN classification performances: class accuracy (Acc), sensitivity (Sen), specificity (Spec):

$$Acc=\frac{TP+TN}{TP+TN+FP+FN}\qquad Sen=\frac{TP}{TP+FN}\qquad Spec=\frac{TN}{TN+FP}$$

TP, TN, FP and FN - true positives, true negatives, false positives and false negatives

Training set overall Acc for optimal CNN architecture (Table 1):

Theoretical (**97.55 ± 1.41**) %; Experimental (**99.76 ± 0.76**) % ;Combined (**98.69 ± 1.19**) % (mean ± standard deviation of 10 fold cross-validation).

The same network is used for evaluating the network performances on the blindfolded test sets of experimental and theoretical data separately as well as combined.

Table 2. Model performances evaluated on the blindfolded test dataset – confusion matrices:

Theory		Predicted			
		noRW	speckling	caustic	soliton
TRUE	noRW	48	0	0	0
	speckling	0	65	0	0
	caustic	0	0	35	0
	Soliton	0	0	12	34

Experimental		Predicted			
		noRW	speckling	caustic	soliton
TRUE	noRW	52	0	1	0
	speckling	0	49	0	0
	caustic	0	0	62	0
	Soliton	0	0	0	44

Theory & Experimental		Predicted			
		noRW	speckling	caustic	soliton
TRUE	noRW	100	0	1	0
	speckling	0	114	0	0
	caustic	0	0	97	0
	Soliton	0	0	9	81

Best approach: CNN analysis on the mix of both experimental and theoretical datasets

Table 3. Performance metrics of the test datasets (%):

Metrics test set	Theory	Experiment	Theory & experiment
Overall Acc	93.81	99.52	97.51
Acc no RW	100.00	99.52	99.75
Acc speckling	100.00	100.00	100.00
Acc caustic	93.81	99.52	97.51
Acc soliton	93.81	100.00	97.76
Sen no RW	100.00	98.11	99.01
Sen speckling	100.00	100.00	100.00
Sen caustic	100.00	100.00	100.00
Sen soliton	73.91	100.00	90.00
Spe no RW	100.00	100.00	100.00
Spe speckling	100.00	100.00	100.00
Spe caustic	92.45	99.32	96.72
Spe soliton	100.00	100.00	100.00

- ***This research is as a step ahead towards the implementation of deep learning methods for the investigation and prediction of the extreme events.***
- ***The CNN architecture consisting of the 3-stage feature extractor and a fully connected multi-layer perceptron is applied in order to classify different high intensity profiles generated experimentally and numerically***
- ***The model performances are evaluated on the blindfolded test set***
- ***CNN based detector and classifier has satisfying performances***

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