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Deep Learning assisted Recognition of Perfect Optical Vortices through Astigmatic Transformed Speckle Patterns

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Abstract: We present a deep learning model that recognizes Perfect Optical Vortices through their astigmatic transformed speckle patterns in the presence of Gaussian White Noise with an accuracy of $> 97\%$ for SNR of 0dB.

1. Introduction

The optical vortices carry phase singularity with helical phase front due to Orbital Angular momentum (OAM). They are extensively studied and widely used due to their orthogonality property. The optical vortices are described by their topological charge, l which takes an integer value. Due to modal dependency, the size of the optical vortex increases with the magnitude of l. This problem is more prominent while launching the optical modes in the fiber and trapping particles using optical tweezers. This issue is resolved by introducing the perfect optical vortices (POVs) that have the same ring radius for all optical vortices [1]. All these POVs are intensity degenerate modes as they have identical intensity patterns and hence it is impossible to measure their charge by simply looking at them. Here, we present a speckle-based Convolutional Neural Network (CNN) for the recognition of intensity degenerate POVs. In general, the proposed method is also applicable for the classification of any class of intensity degenerate modes. The speckles used for the recognition task are astigmatic transformed by performing a one-dimensional Fourier Transform. The speckle-based CNN and Wavelet Scattering Network have been demonstrated to be more robust against noise [2–5]. We train and evaluate the network by the inclusion of very high Gaussian White Noise (GWN) to show the robustness of our model.

2. Theory

Mathematically, the POVs with adjustable ring diameter can be expressed by the Fourier transform of Bessel beams [1]. Experimentally it is impossible to realize an ideal Bessel beam but one can always generate Bessel – Gauss (BG) beam. One can obtain the complex field amplitude of POV by taking the Fourier transform of the BG beams. The complex field amplitude of POV of order l with ring width $2w_r$ and radius r_r is represented as

$$PV_l(r,\phi) = i^{l-1}\frac{w_g}{w_r}\exp(il\phi)\exp\left(-\frac{r^2+r_r^2}{w_r^2}\right)I_l\left(\frac{2rr_r}{w_r^2}\right) \quad \textbf{(1)}$$

where, I_l is the lth order modified Bessel function of the first kind, w_g is the beam waist of the Gaussian beam that is used to confine the Bessel beam. The astigmatic transformed speckle fields of POV modes are generated by first multiplying the complex field amplitude of POV modes (Eq. (1)) with the random phase mask, ϕ_R having uniformly distributed phase values between 0 and 2π and then taking its one-dimensional Fourier Transform ($\mathcal{F}_{1D}$) as,

$$U_{sc}(\boldsymbol{r}) = \mathcal{F}_{1D}\{PV_l(r,\phi)e^{i\phi_R(\boldsymbol{r})}\} \quad \textbf{(2)}$$

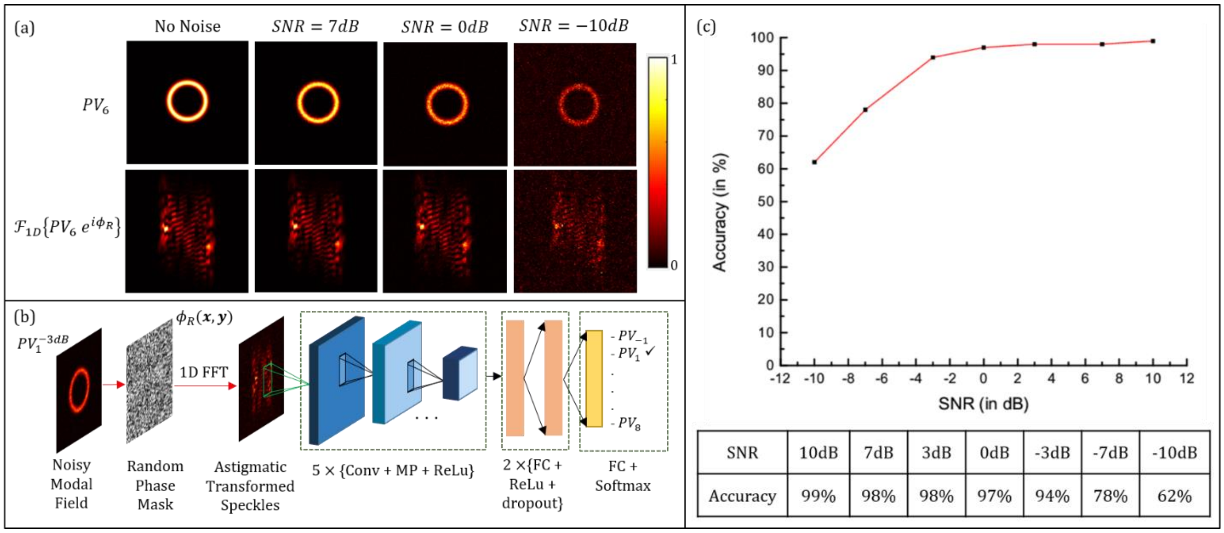
The corresponding intensity images of speckle fields are obtained by multiplying the speckle field (Eq. (2)) with its complex conjugate:

$$I_{sc}(\boldsymbol{r}) = U_{sc}(\boldsymbol{r})U_{sc}^*(\boldsymbol{r}) \quad \textbf{(3)}$$

The GWN is added to modes to simulate real-life experimental scenarios and to add robustness. The GWN is quantified by specifying SNR in dB. Fig. 1(a) shows the intensity distributions of POV with and without GWN and their respective astigmatic transformed far-field speckle patterns.

3. Speckle-learned CNN Network

We have generated data and trained the network for sixteen different POV modes with $l = \pm 1$ to ± 8. We have generated a total of eight datasets, one with no GWN and the rest seven with seven different noise levels ranging from 0.1 to 10 times the input signal power. The SNR values used for generating these seven datasets are 10dB, 7dB, 3dB, 0dB, -3dB, -7dB, and -10dB. Each dataset has 2000 images of each POV mode with an image size of $227 \times 227 \times 3$



SNR	10dB	7dB	3dB	0dB	-3dB	-7dB	-10dB
Accuracy	99%	98%	98%	97%	94%	78%	62%

Fig. 1. (a) Intensity images of direct mode and astigmatic transformed speckle patterns of PV_6 mode. (b) Workflow to train the CNN for the recognition of POVs through their astigmatic transformed speckles. (c) Test accuracies for a model trained under different noise levels.

pixels. Instead of training from scratch, we utilize a pre-trained network, "Alexnet" which is well known for its accuracy and moderate computational load. This is a faster way of training the model as Alexnet has already learned a lot of features when it is trained for more than a million images of 1000 classes. We only change the number of neurons in the last layer to 16 while retaining all the weights and biases learned by the network. These weights and biases are not frozen and are updated during the training. For training the network, we have used the "Stochastic Gradient Descent with Momentum" algorithm with a constant learning rate of 0.0001 and momentum of 0.9. The network is trained on 80% of images in the datasets and the rest 20% of images are used for evaluating the network. Fig. 1(b) shows the workflow for training the speckle-based CNN model for the recognition of POV modes. We have obtained an accuracy of $> 99\%$ for the network trained on POV modes without any noise and the accuracy decreases with the increase in the noise level. Fig 1(c) shows the test accuracy of networks trained under various noise levels.

4. Summary and Conclusion

In conclusion, we have presented a speckle-learned deep learning model for the recognition of intensity degenerate POV modes. The network is trained and evaluated on the astigmatic transformed far-field intensity speckle images of the sixteen POV modes. Experimentally, the astigmatic transformed far-field intensity speckle images can be easily generated by using a cylindrical lens. The main idea behind this technique is to break the symmetry in speckle distributions of degenerate modes by astigmatic transformation and hence any other intensity degenerate modes (LG and Superposition modes) having identical direct intensity profiles due to complex conjugate phases can be distinguished using this method. For the ideal case i.e. in the absence of any noise, the network can recognize the modes with an accuracy $> 99\%$. For robustness, we have also trained the network in the presence of seven different levels of GWN. The results show that the network performs well and can recognize POV modes with an accuracy of $> 97\%$ even when the noise is the same as that of the signal. Thus, we believe that this speckle-based recognition technique is powerful enough to recognize any intensity degenerate mode by lifting alignment constraints and the need for capturing the complete modal field.

5. References

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