The compensation of atmospheric turbulence for vortex beam based on deep learning

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ABSTRACT

Beam propagation in free space will inevitably be disturbed by atmospheric turbulence (AT). In this paper, deep convolutional neural network (CNN) is used to extract the phase information of Gaussian beam. Through the training, the loss function value decreases from about 0.04 to less than 0.005, and the loss on the test set also decreases to about 0.005, and the phase information is extracted successfully. The phase information of Gaussian beam under turbulent conditions is extracted by CNN network to compensate the transmission of vortex beam under turbulent conditions. From the research, it is found that extracting turbulent phase through CNN network and compensating vortex beam with the extracted phase can effectively suppress OAM mode expansion caused by AT disturbance.

Keywords: Deep learning, vortex beam, AT, distortion compensation

1. INTRODUCTION

The vortex beam is a hollow beam carrying orbital angular momentum (OAM) with a helical wavefront structure [1]. The transmission of information by vortex beams can improve the channel capacity. When the vortex beam is vertically incident to the center of the rotating target, the rotational Doppler effect will be produced, which changes the frequency of the scattered light, and can be used to measure the target speed. At present, vortex beams have been widely used in optical communication, optical measurement and other fields [2]. In the process of practical application, the vortex beam will be interfered by AT and other factors, which will distort the wavefront of the beam and cause the quality of the beam to decline [3]. There are many methods to suppress AT interference, the traditional methods include Gerchberg-Saxton (GS) algorithm [4-5], stochastic-parallel-gradient-descent (SPGD) algorithm [6-7], etc. These algorithms have been widely used in the field of laser atmospheric transmission compensation. But the traditional iterative compensation algorithm has no memory, and every time the compensation needs to be iterated, which greatly reduces the efficiency of compensation. In addition, GS algorithm and SPGD algorithm will also have the problem of falling into the local minimum value, so that the correction effect can not reach the best.

In recent years, the rise of deep learning has provided a new scheme for AT compensation [8]. Deep neural network mimics the working mode of the brain, which has a very good feature extraction ability [9-11]. The AT compensation scheme based on deep learning even shows faster and more accurate correction ability than the adaptive optical system. At present, many researchers have applied deep learning to the optical field. Liu et al. [12] designed a CNN model, which learns the mapping relationship between input intensity distribution and turbulent phase. After trained by a large number of samples, the CNN model can predict the equivalent turbulent phase screen accurately, including untrained turbulent phase screen. The input of the CNN model structure is the original Gaussian beam and the intensity distribution affected by AT, and the AT phase screen is output after passing through the CNN network. However, this scheme does not compensate and analyze the vortex beam's AT transmission, which is not conducive to the subsequent application of vortex beam.

In order to compensate for the vortex beam, this paper built a CNN network to extract the phase of the Gaussian beam. Then used the Gaussian beam obtain the AT phase screen, and used the obtained turbulent phase screen to compensate the vortex beam. In the process of building CNN network for training, the intensity distribution images of Gaussian beams disturbed by turbulence and standard Gaussian beams are used as the input of CNN network, and the equivalent phase screen of AT is used as the label to train CNN network. Through multiple rounds of training on a large number of data sets, the loss function of CNN network on both training set and test set has decreased to a certain extent. In free

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Fourth International Conference on Advanced Optics and Photonics Research in Engineering (AOPR 2024),
edited by Koichi Shimizu, Yufei Ma, Proc. of SPIE Vol. 13260, 1326005 . · doi: 10.1117/12.3045123

space, the turbulence intensity is not constant, so three turbulence intensity data sets are generated for training. Finally, when the transmission distance is 1000m, the phase information obtained by Gaussian beam is used to compensate the vortex beam, and the mode purity of the vortex beam is improved.

2. THE THEORY OF AT

To study AT by numerical simulation, it is important to construct a suitable phase screen to reflect the change of refractive index of AT. There are two main methods for constructing the phase screen of AT, one is the power spectrum inversion method [13-15], and the other is the use of Zernike polynomial expansion to represent the wavefront phase [16-17].

The power spectrum inversion method uses a pair of complex Gaussian random matrices to filter the power spectrum. The phase representation formula is

$$\varphi(x,y)=\sum_{n=-\infty}^{+\infty}\sum_{m=-\infty}^{+\infty}h(f_{xn},f_{ym})\sqrt{\phi(f_{xn},f_{ym})\Delta f_{xn}\Delta f_{ym}} \times\exp[i2\pi(f_{xn}x+f_{ym}y)] \tag{1}$$

The AT power spectrum used in this paper is Kolmogorov spectrum [18]:

$$\phi_{\varphi}(f_{xn},f_{ym})=0.023r_0^{-5/3}(f_{xn}^2+f_{ym}^2)^{-11/6} \tag{2}$$

Where r_0 is the coherence length of AT.

$$r_0=0.185\left[\lambda^2\Big/\int_z^{z+\Delta z}C_n^2(z)dz\right]^{3/5} \tag{3}$$

C_n^2 represents the structural constant of the intensity of AT over the transmission path, and λ is the wavelength.

Figure 1 (a), (c) and (e) shows the intensity distribution image of the vortex beam transmitted through the AT phase screen for 1000m, and the turbulence intensity is respectively $C_n^2=1\times10^{-14}m^{-2/3}$, $C_n^2=5\times10^{-14}m^{-2/3}$, $C_n^2=1\times10^{-13}m^{-2/3}$. The vortex beams used in this paper are all coherent synthetic vortex beams, which are generated by Gaussian beam array.

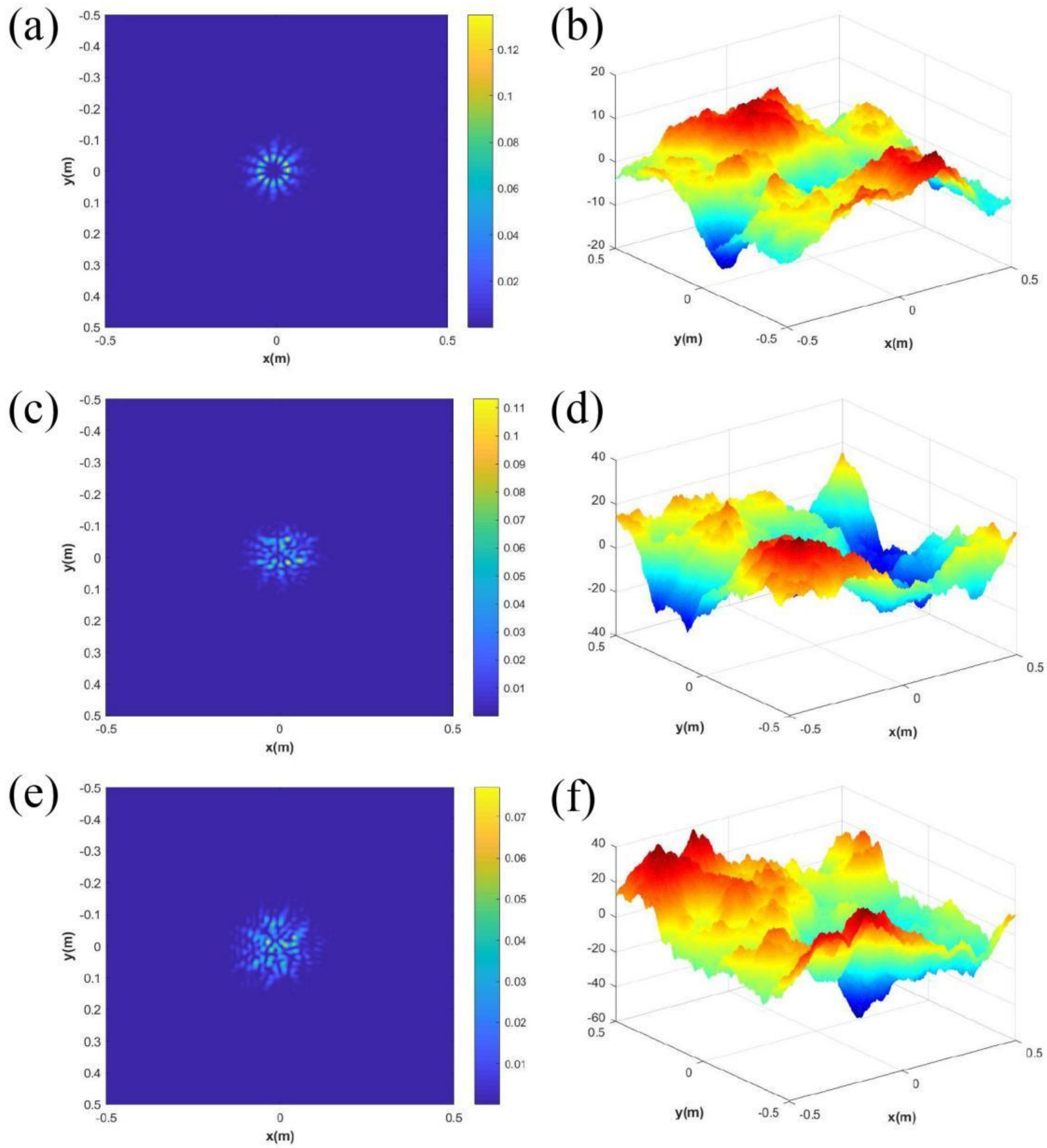

Figure 1 Intensity distribution image of transmitted beam under the influence of turbulence of different intensity and corresponding turbulence phase screen. (a) (b) $C_n^2 = 1 \times 10^{-14} m^{-2/3}$; (c) (d) $C_n^2 = 5 \times 10^{-14} m^{-2/3}$; (e) (f) $C_n^2 = 1 \times 10^{-13} m^{-2/3}$.

3. AT PHASE EXTRACTION AND WAVEFRONT DISTORTION COMPENSATION

In order to analyze the effect of CNN network on coherent vortex beams, the turbulent phase carried by Gaussian beams is extracted by CNN network. The AT affecting beam transmission can be equivalent to a turbulent phase screen, which can be extracted from the turbulent spot image by using the neural network. The core of CNN network feature extraction is to use convolution check images for feature extraction. Shallow convolution kernel will extract shallow feature, while deep convolution kernel will extract abstract deep feature. During the training process, the gradient descent algorithm updates the parameters of the convolution kernel according to the error, and the back propagation algorithm propagates the error from the deep layer to the shallow layer. These two algorithms can be used to optimize the parameters of the network and reduce the loss function.

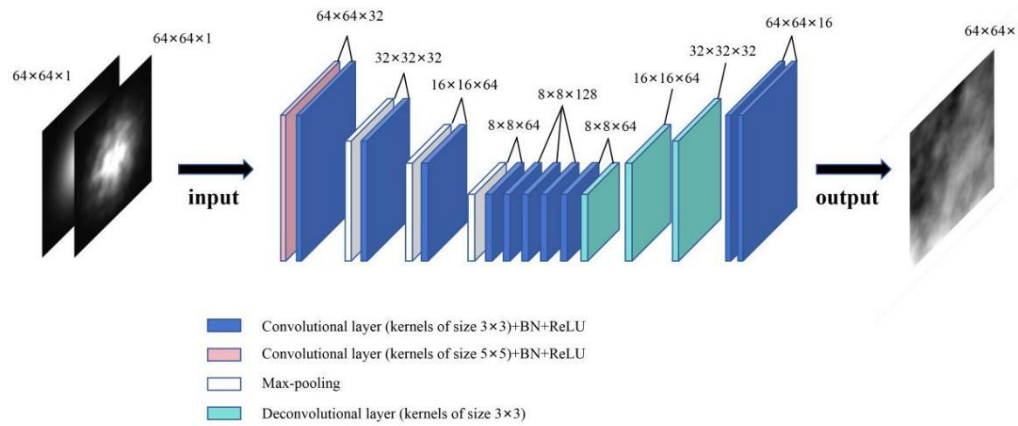

Figure 2. Structure of CNN.

The neural network model we used is shown in Figure 2. In order to ensure certain image clarity and reduce the time complexity of the network as much as possible, the pixel value size of 64×64 is adopted in both images. Too large a pixel value will greatly increase the training time of the network, while too small a pixel value will also cause the image to be unclear. The output of CNN network is the equivalent phase screen of AT, and the pixel value size is also 64×64, which is normalized to [0,1] through appropriate normalization factors. During training, 50000 sets of data are generated as the training set, 1000 sets of data as the test set.

In this paper, a data set is generated when the transmission distance is z=20m, and the turbulent phase is extracted from the distorted Gaussian beam intensity distribution image by using CNN network. When the turbulence intensity is $C_n^2 = 1 \times 10^{-14} m^{-2/3}$, the changes of the loss function of the training set and the test set are shown in Figure 3. From the change curve of the loss function, we can find that the neural network has a poor fitting to the training set data at this time, and the predicted phase screen has a large gap with the actual phase screen. With the continuous training, the value of the training set loss function decreases from 0.04 to about 0.0005, indicating that the network parameters are continuously optimized during the training process. The verification set loss function also gradually decreases with the progress of training, which proves that the ability of the CNN network is good.

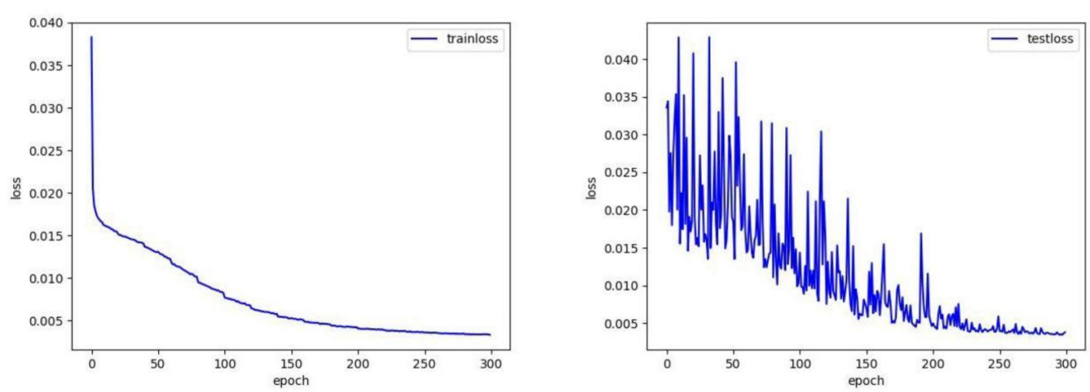

Figure 3. Change of loss function in training set and test set.

The vortex beam has phase singularity, and the center light intensity of the beam is zero, so the vortex beam is not suitable for establishing mapping relationship with the phase screen. However, when Gaussian beam and vortex beam are coaxial transmitted through AT, the wavefront distortion of Gaussian beam and vortex beam is the same. Therefore, we can obtain the phase information of AT through the distorted Gaussian beam, and then the turbulent phase information can be used to compensate the vortex light field. After the turbulent phase screen is extracted, a conjugate phase can be loaded to compensate the beam.

In the actual application of vortex beam, the transmission distance of vortex beam often reaches kilometer level. In order to make the compensation of vortex beams more practical, the training data set of CNN network was updated, and the transmission distance was set to 1000m. The data sets were generated and trained respectively under the turbulence intensity of $C_n^2 = 1\times10^{-14} m^{-2/3}$ and $C_n^2 = 5\times10^{-14} m^{-2/3}$, and then the training was carried out. The trained CNN network was used for the AT compensation of vortex beams. It should be noted that in the training process, the distorted Gaussian beam intensity distribution image is still used as the network input, and the phase information is extracted through the distorted Gaussian beam during compensation, and then the extracted phase is used to compensate the vortex beam.

After compensation by using conjugate phases, the distorted spots of the vortex beam become more uniform, as shown in Figure 4. In addition to the distortion of beam intensity, AT will also lead to the distortion of wavefront phase. As the beam travels, the initial OAM mode is difficult to distinguish. The effect of compensation can be seen by comparing the mode purity spectra of vortex beams. Figure 5 shows the changes of mode purity spectra before and after vortex beam compensation under three turbulence intensities. From the figure, we can easily find that after compensating the conjugate phase, the crosstalk problem of vortex beam mode is obviously improved, and the energy of plus or minus 6 order mode is greatly improved.

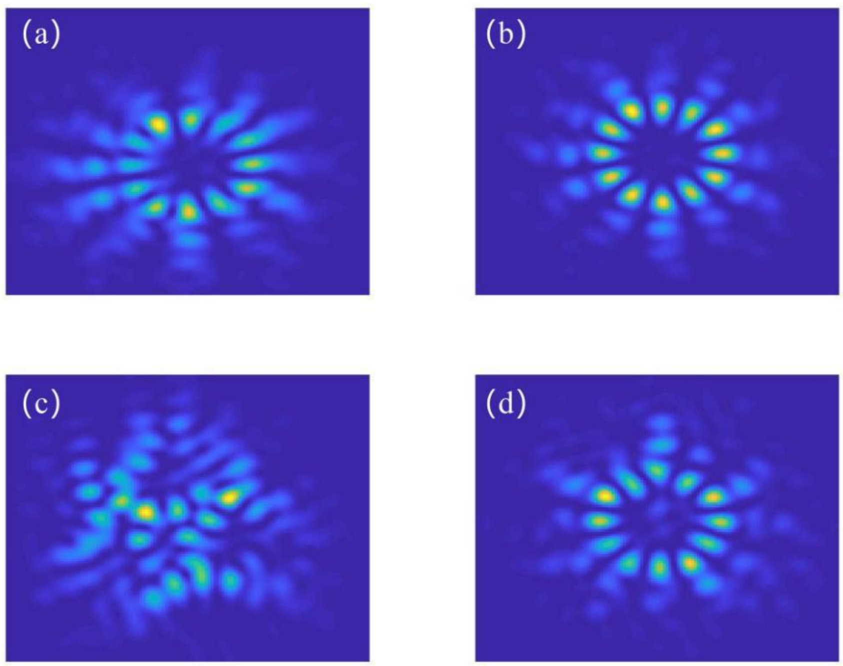

Figure 4. The change of the intensity distribution image of the vortex beam before and after compensation. (a) (b) $C_n^2 = 1 \times 10^{-14}\mathrm{m}^{-2/3}$; (c) (d) $C_n^2 = 5 \times 10^{-14}\mathrm{m}^{-2/3}$.

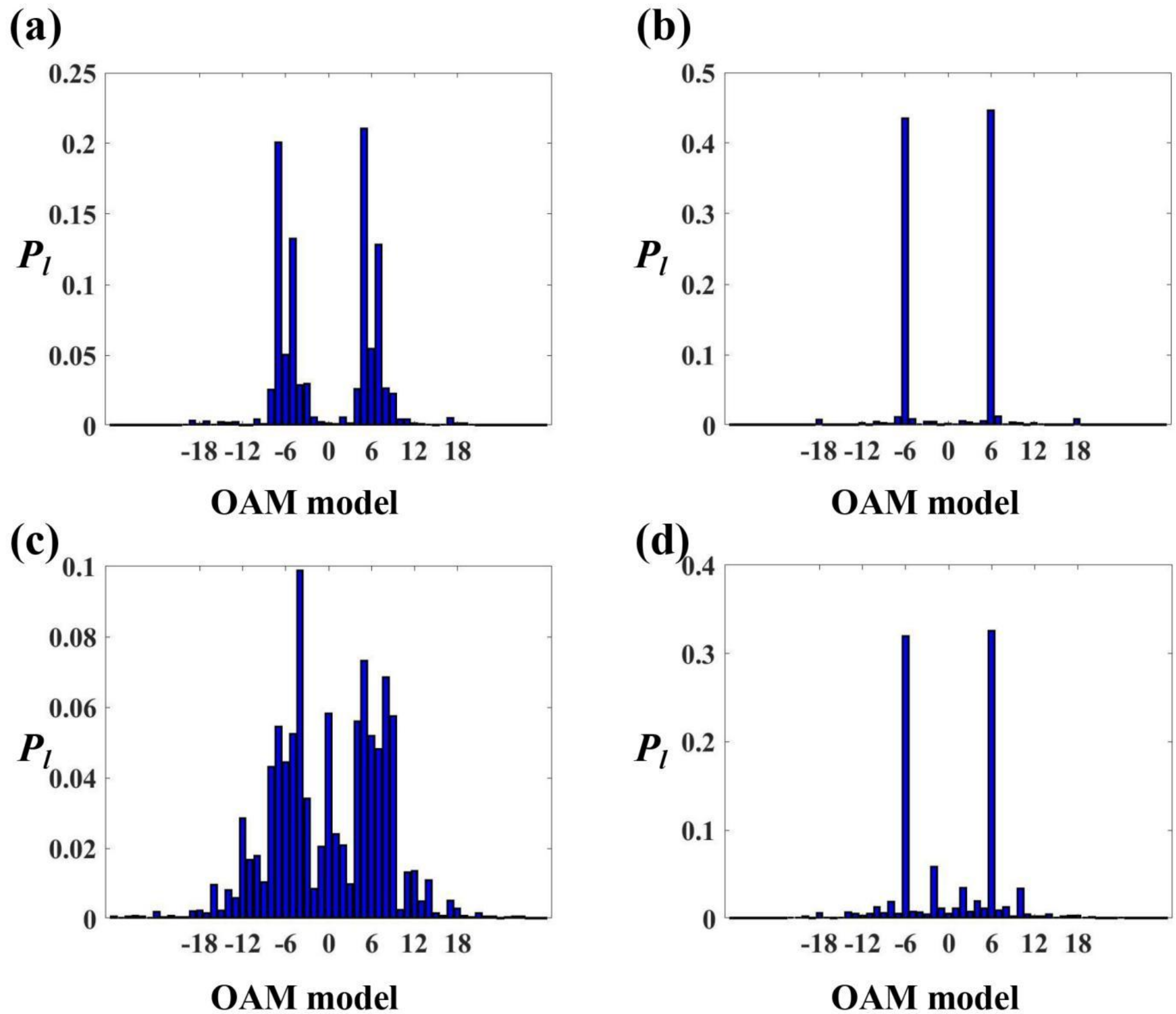

Figure 5. The change of the mode purity of the vortex beam before and after compensation.

4. CONCLUSIONS

In this paper, the phase of Gaussian beam is extracted through CNN network, and the phase features are extracted from the distorted Gaussian beam spot image by using the excellent feature extraction ability of CNN network, and the extracted phase information is used to compensate the vortex beam. After training a large number of data sets, the CNN network can predict the test set very well, and the phase distribution of the predicted phase screen is similar to the real phase screen. The phase screen extracted by Gaussian beam is used to compensate the vortex beam. The mode purity and intensity distribution of the vortex beam before and after compensation are compared. It is found that the beam quality of the beam is obviously improved after compensation. The deep learning method is used to compensate the AT aberration, which has the advantage of fast speed and does not require repeated iterative training. With the development of deep learning and continuous upgrading of computer equipment such as GPU, the use of deep learning method to compensate AT is expected to obtain better compensation effect, so this method has a good development prospect.

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