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基于深度学习的复合贝塞尔高斯光束大气湍流效应补偿

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摘要 相位失真是实现涡旋光束轨道角动量复用技术实际应用的主要挑战之一。本文提出了一种基于深度学习的复合贝塞尔高斯涡旋光束大气湍流效应补偿方法，以提高模态分离与检测准确度。设计的网络通过学习不同轨道角动量下畸变光束强度分布与湍流相位之间的映射关系，具备了适应未知湍流环境的泛化能力，可以有效地预测等效湍流相位屏。仿真结果表明，复合贝塞尔高斯光束在不同湍流强度下传输 1000 m 并经过相位补偿后，光强相关系数可提高至 0.97 以上；在强湍流下传输 1500 m 并经相位补偿后，拓扑荷数为 10 的模式纯度从 2.43% 提高至 64.07%。该方法对畸变光束具有更强的特征提取能力，在快速准确预测等效湍流相位屏方面具有良好的泛化能力，有助于提高未来轨道角动量复用技术的可靠性。

关键词 光通信；复合贝塞尔高斯光束；大气湍流；深度学习；相位补偿

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1 引 言

涡旋光束具有 $l\hbar$ 的轨道角动量（OAM）[1]，其中：l 为拓扑荷数，一般取整数，也可以为分数；$\hbar$ 为普朗克常数。由于 l 的取值多样性以及不同 OAM 之间的正交性，利用 OAM 复用技术能显著提高信道容量和频谱利用率。然而，由于大气湍流扰动，涡旋光的传输质量不可避免地遭受各种影响，如螺旋相位失真和 OAM 模式间串扰等，因此传输信息会出现错误接收和解调困难。鉴于此，在传统的涡旋光通信系统中，通常需要建立畸变相位补偿机制。

理论和实验研究表明，自适应光学补偿系统[2-3]能有效改善 OAM 信号在大气湍流中的传输特性，提高信号的传输质量[4-7]。然而，自适应光学方法需要进行多次迭代，所需硬件昂贵且结构复杂。近年来，随着人工智能的快速发展，机器学习[8-12]被应用于光通信等诸多领域。2019 年，马慧敏等[13]从失真的强度图像中提取特征，然后通过神经网络获得了相应的泽尼克系数。2020 年，徐启伟等[14]基于深度卷积神经网络快速准确地提取到了光束传输 20 m 时的湍流相位。2020 年，熊文杰等[15]将光束传输距离提升至 50 m，从标准涡旋光束和畸变涡旋光束强度分布中提取出了湍流信息，并恢复出其畸变。2022 年，赵杰等[16]将相位畸变的叠加涡旋光束光强图输入深度多分支补偿网络，得到前 10 阶泽尼克系数，进而拟合出大气湍流补偿屏。

为了更好地对长距离传输后的复合涡旋光束的相位进行补偿，笔者基于深度学习方法，结合残差网络与特征金字塔思想，设计了相位提取网络，并用该网络进行了大气湍流相位的提取。该网络将畸变光强图作为输入，通过对其特征进行学习，输出预测的等效湍流相位，然后将其反相位通过空间光调制器（SLM）加载到接收到的复合贝塞尔高斯涡旋光束上进行大气湍流效应补偿。在不同的湍流情况下，复合贝塞尔光束经过补偿后光强相关系数、模态纯度均得到很大提高。

2 理论基础

2.1 复合贝塞尔光束在大气湍流中的传输

本文主要研究复合贝塞尔高斯（BG）光束的叠加过程与特性。将束腰半径相等、拓扑荷数不同的两束 BG 光束同轴叠加，其复振幅[17]表达式为

$$U(r,\theta)=\sum_{l=N_1}^{N_2}\mathrm{J}_l(a_{\mathrm{B}}r)\exp\left(-\frac{r^2}{w_{\mathrm{g}}^2}\right)\exp(-\mathrm{i}l\theta),\quad(1)$$

式中：l 为拓扑荷数；$\mathrm{J}_l(\cdot)$ 为第一类贝塞尔函数；a_{B} 为宽度参数；w_{g} 指输入激光的高斯束腰半径；r、θ 分别为极坐标中的径向参数和角向参数。

大气湍流在高空中具有明显的各向异性，因此笔者在 non-Kolmogorov 湍流模型的基础上引入了各向异性系数[18]，见式（2）。

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$$\Phi_n(\kappa)=A(\alpha)C_n^2\mu^2\frac{\exp\left\{-\left[\mu^2(\kappa_x^2+\kappa_y^2)+\kappa_z^2\right]/\kappa_l^2\right\}}{\left[\mu^2(\kappa_x^2+\kappa_y^2)+\kappa_z^2+\kappa_0^2\right]^{\alpha/2}},\quad 3<\alpha<4, \tag{2}$$

其中，

$$A(\alpha)=\frac{\Gamma(\alpha-1)}{4\pi^2}\sin\left[\frac{\pi}{2}(\alpha-3)\right], \tag{3}$$

$$C_n^2(h)=C_n^2(0)\exp(-h/100)+8.148\times10^{-56}v^2h^{10}\exp(-h/1000)+2.7\times10^{-16}\exp(-h/1500), \tag{4}$$

式中：$\kappa_0=4\pi/L_0$，L_0为湍流的外尺度；$\kappa_l=c(\alpha)/l_0$，$c(\alpha)=\left[\pi A(\alpha)\Gamma\left(\frac{-\alpha+3}{2}\right)\left(\frac{-\alpha+3}{3}\right)\right]^{\frac{1}{\alpha-5}}$，$l_0$为湍流的内尺度；$\mu$为大气湍流各向异性系数；$\alpha$为non-Kolmogorov湍流功率谱指数，其范围为$3<\alpha<4$；$\Gamma(\cdot)$为伽马函数；κ_x、κ_y、κ_z分别为空间波数在x、y、z方向上的分量；C_n^2表示湍流折射率结构常数，随空间高度变化而变化[19]；h为高度(m)；v为均方根风速(m/s)。

笔者在构建相位屏过程中考虑了大气湍流的内外尺度。在实际的大气湍流信道中，湍流外尺度是随高度变化的[20]，其表达式为

$$L_0(h)=\begin{cases}\dfrac{1}{2}\left\{\dfrac{4}{1+\left[(h-8500)/2500\right]^2}+\dfrac{5}{1+\left[(h-7500)/2000\right]^2}\right\}, & h>2000\ \mathrm{m}\\ 1.552, & h\leqslant 2000\ \mathrm{m}\end{cases}。 \tag{5}$$

本文基于相位屏方法模拟了复合BG涡旋光束在大气湍流中传输的强度分布，传输过程如图1所示。从图1中可以看出，由于湍流效应，光束的光强发生随机起伏。

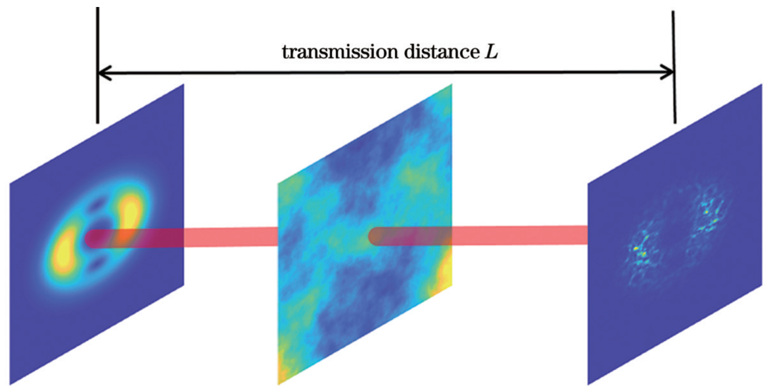


图1　复合BG光束在大气湍流中传输

Fig. 1　Composite BG beam propagation in atmospheric turbulence

2.2　相位提取网络

2.2.1　网络设计

卷积神经网络以其对图像出色的特征提取能力，被广泛应用于图像处理中。鉴于此，笔者基于卷积神经网络设计了相位提取网络(PhaNet)，用于提取大气湍流相位，如图2所示。PhaNet模型包括7层卷积层、4层残差层、6层反卷积层、3层特征融合层。

为了可以清晰地接收到更大范围的涡旋光束，将512×512的光强图像输入到网络中，建立畸变光强图像与湍流相位之间的映射关系。为了提升模型的鲁棒性，实现不同距离以及不同湍流强度下的预测，对该网络进行以下设计：1)采用7次卷积操作进行下采样，扩大感受野，增强网络对不同尺度湍流特征的提取能力。2)设计分支残差结构模块，对输入的特征图分两部分进行特征提取。其中，1×1卷积对输入的特征图进行降维操作，3×3卷积对输入的特征图进行特征提取与升维操作，使用两层结构可以在不增加梯度计算的情况下减少模型的推理时间。3)将分支残差模块放置在下采样之后，以消除卷积操作的随机性，减小由网络加深带来的信息损失的影响，从而增强网络的特征提取能力。4)将反卷积后的模块与分支残差模块中提取到的语义信息融合，提高网络对不同传输距离下畸变光束的特征提取能力。5)输出层采用饱和非线性激活函数Tanh，以提高网络的预测性能；隐藏层采用非饱和线性激活函数LeakReLU，以避免神经元死亡以及某些像素点过大或过小，同时可使网络的收敛速度更快。

2.2.2　网络性能

笔者基于大气湍流相位屏方法模拟了96000幅

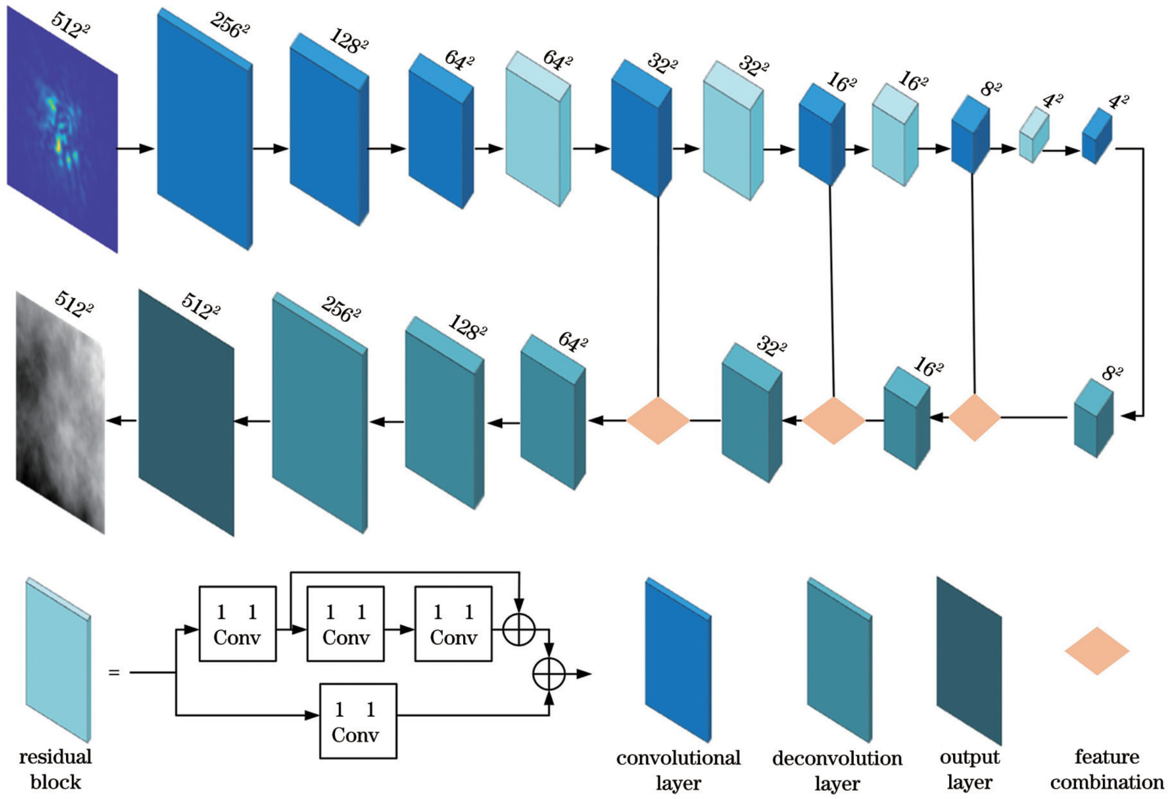


图 2　PhaNet模型

Fig. 2　PhaNet model

BG光束在大气湍流中传输1000 m的强度图像，其中，训练集中有80000幅图像，测试集中有16000幅图像，共24类。模拟时设置了3种湍流强度（5×10^{-13}、1×10^{-13}、5×10^{-14} $\mathrm{m}^{-2/3}$）和8种拓扑荷数组（l_1，l_2），$l_1=\{-4,-3,-2,-1,1,2,3,4\}$，$|l_2|>4$。输入网络的图像参数如下：接收屏像素为512×512，传输距离为1000 m，湍流内外尺度分别为$l_0=0.0001$ m和$L_0=50$ m，光束束腰为0.02 m，宽度参数为50 m^{-1}，波长为1550 nm。网络训练参数如下：迭代次数Epoch为5000，批大小为200，学习率为0.01。

收敛速度与损失值是判断网络模型鲁棒性的最重要指标。上述数据在PhaNet模型中的收敛曲线如图3所示。从图3中可以看出：损失曲线呈快速收敛的趋势，迭代至100次左右时损失值明显下降；迭代至1000次时，损失值降到0.0348409；迭代至4000次时，损失曲线已趋于稳定，损失值为0.00957521。证明了PhaNet模型具有较高的预测性能。

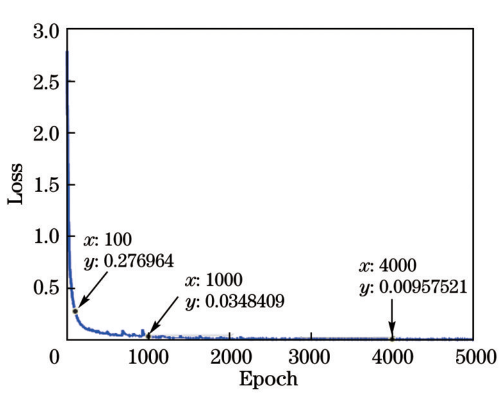


图 3　训练集损失曲线

Fig. 3　Training set loss curve

3　大气湍流效应补偿

3.1　大气湍流屏预测

笔者将影响光束相位畸变的大气湍流等效为大气湍流相位屏。基于本文提出的PhaNet模型预测的大气湍流相位屏如图4所示（传输距离为1000 m）。图4中，第一行是模拟的不同湍流强度下的湍流相位屏，第二行是不同湍流强度下PhaNet模型预测的湍流相位屏，取反作为光束的补偿相位；第三行是模拟湍流相位屏与预测湍流相位屏之差。从图4中可以看出，在三种湍流强度下，预测湍流相位屏与真实湍流相位屏之差很小，其均方差分别为0.0577、0.0427、0.0369，各像素点差值不超过1.5。可见，在不同的湍流强度下，PhaNet模型均具有很强的预测能力，鲁棒性较好。

3.2　畸变相位的补偿

为了进一步验证基于PhaNet模型的大气湍流效应补偿技术的可行性，笔者设计了大气湍流效应补偿系统的物理模型，如图5所示。在复合BG光束传播路径中插入随机相位屏模拟信道中大气湍流的影响；畸变光束通过BS分束器，其中的反射光束经过遮挡板

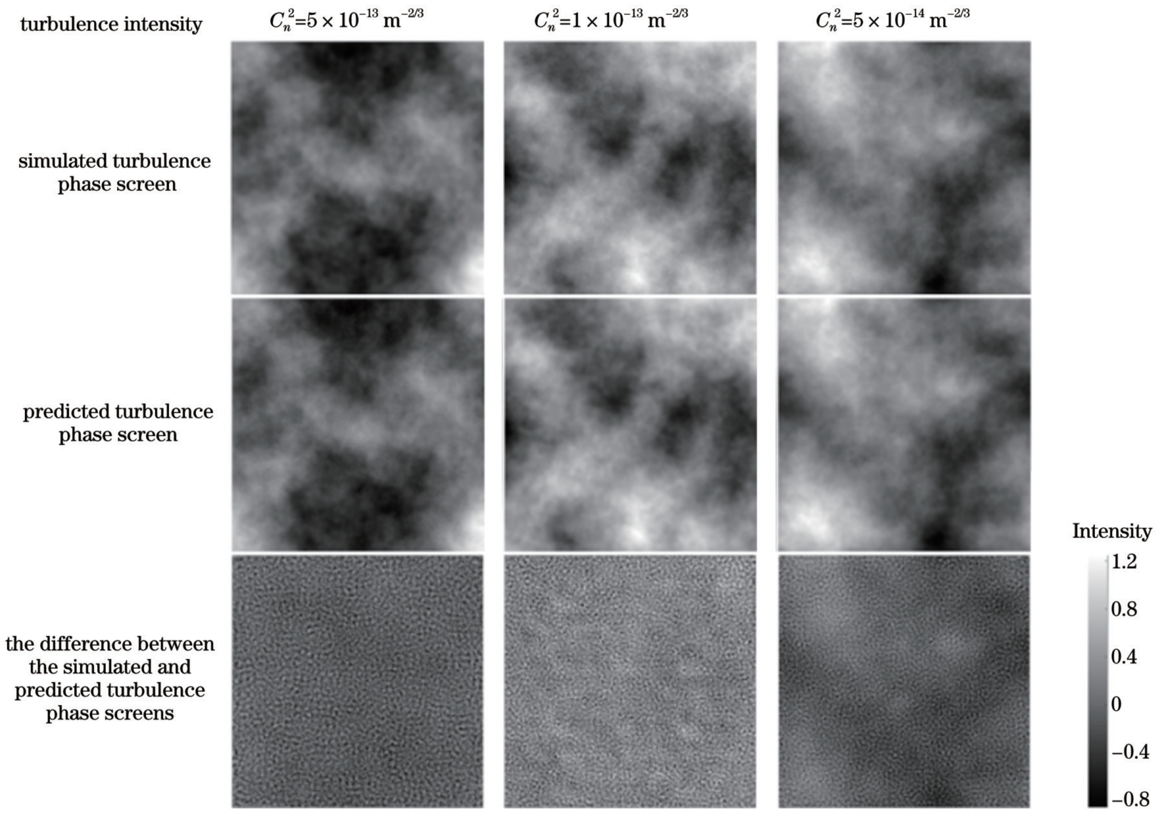


图 4 不同湍流强度下的模拟湍流相位屏与预测湍流相位屏

Fig. 4 Simulated and predicted turbulence phase screens under different turbulence intensities

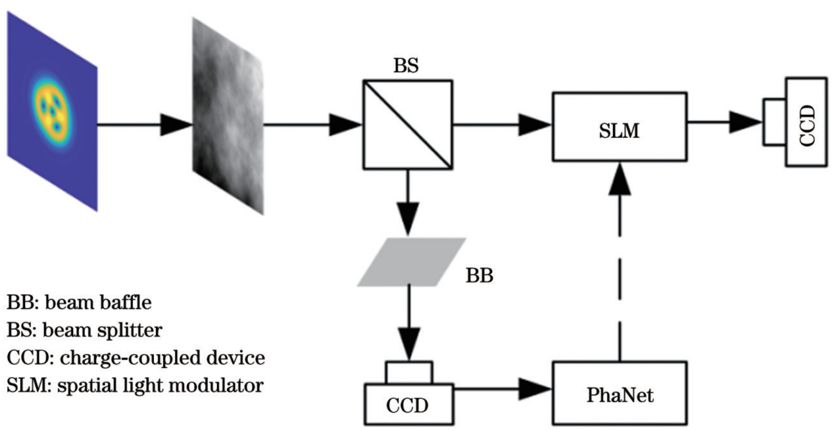


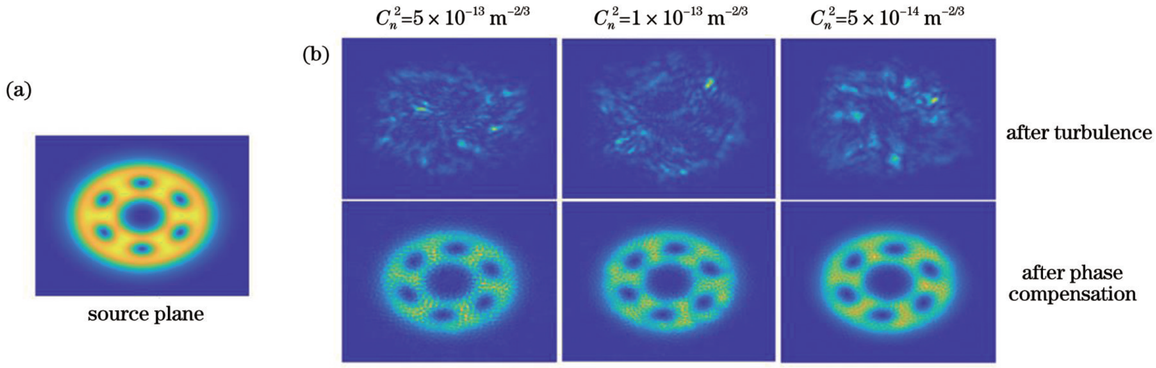
图 5 畸变光束补偿模型图

Fig. 5 Distortion beam compensation model diagram

BB，拓扑荷数 l 较小的强度图像被 CCD 相机捕获；将扭曲的光强分布图输入 PhaNet 模型中即可提取湍流信息，将湍流信息取反加载至 SLM。经过 BS 分束器之后的另一束（透射）光束通过 SLM 实现大气湍流效应补偿。

接下来研究复合 BG 光束在不同湍流强度下传输不同距离后的大气湍流效应补偿，使用模式纯度、光强相关系数对补偿效果进行评估。图 6 是复合 BG 光束在不同湍流强度下传输 1000 m 后的相位补偿与未补偿对比图。从图 6(b)可以看出：随着湍流强度增加，复合 BG 光束相位的波动范围增大，光强弥散更加明显，已失去原来的图像特征；经过相位补偿后，复合 BG 光束的湍流扰动大幅度减小，强度分布呈现原来的图像特征。从图 6(c)可以看出：从强湍流到弱湍流，l_1=4 的模式纯度分别从 3.41%、3.54%、4.61% 补偿提高到 30.70%、31.21%、31.35%，l_2=10 的模式纯度分别从 6.09%、6.23%、6.30% 补偿提高到 64.68%、65.45%、66.53%。从图 6(d)可以看出：l_2=10 与不同拓扑荷 l_1 复合后的光束的光强相关系数分别从 0.4199、0.4596、0.5281 提高到 0.97 以上。

图 7 是复合 BG 光束在 $C_n^2=1\times10^{-13}\ \mathrm{m}^{-2/3}$ 大气湍流中传输不同距离后的校正情况。从图 7(a)、(b)



(c)

Turbulence intensity /m$^{-2/3}$	Mode purity /%			
	l_1=4 after turbulence	l_2=10 after turbulence	l_1=4 after phase compensation	l_2=10 phase compensation
5×10^{-13}	3.41	6.09	30.70	64.68
1×10^{-13}	3.54	6.23	31.21	65.45
5×10^{-14}	4.61	6.30	31.35	66.53

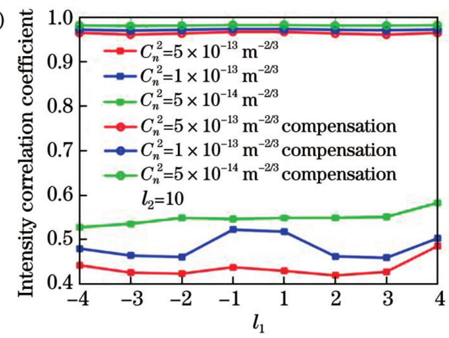
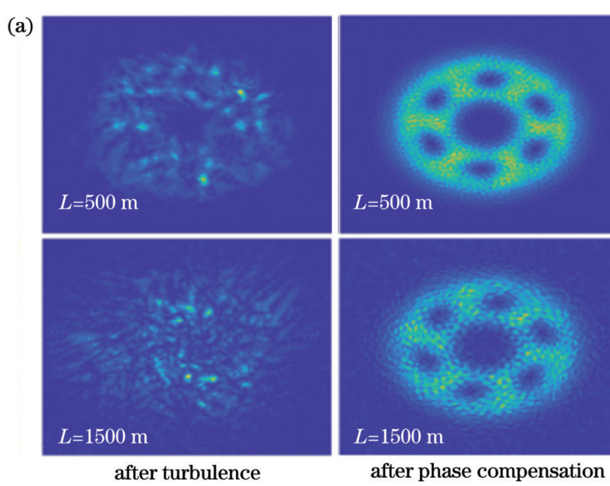


图 6 复合 BG 光束在不同湍流强度下传输 1000 m 的相位补偿与未补偿对比。(a)源平面复合光束;(b)光强对比;(c)模式纯度对比;(d)光强相关系数对比

Fig. 6 Compensated and uncompensated phases comparison of the composite BG beam propagating 1000 m under different turbulence intensities. (a) Source plane composite beam; (b) beam intensity contrast diagram; (c) mode purity comparison; (d) beam intensity correlation coefficient comparison



(b)

Transmission distance /m	Mode purity /%			
	l_1=4 after turbulence	l_2=10 after turbulence	l_1=4 after phase compensation	l_2=10 phase compensation
500	4.31	6.30	31.37	65.72
1500	3.50	2.43	30.55	64.07

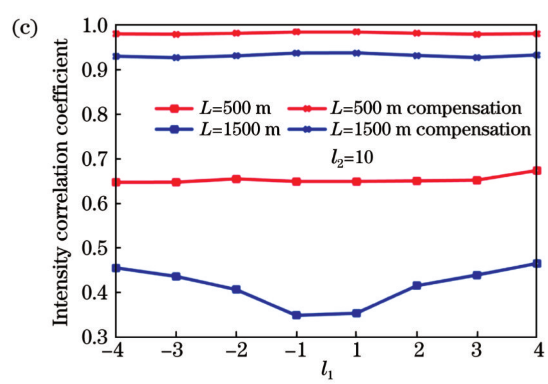


图 7 复合 BG 光束在大气湍流下传输不同距离的相位补偿与未补偿对比图。(a)光强对比;(b)模式纯度对比;(c)光强相关系数对比

Fig. 7 Compensated and uncompensated phases comparison of the composite BG beam propagating different distances in atmospheric turbulence. (a) Beam intensity contrast diagram; (b) mode purity comparison; (c) beam intensity correlation coefficient comparison

可以看出，在相同的条件下，随着传输距离增加，光束弥散愈发严重，经过补偿，光强图像得到明显改善。随着传输距离 L 从 500 m 增加到 1500 m，l_1=4 的模式纯度分别从 4.31%、3.50% 补偿至 31.37%、30.55%，l_2=10 的模式纯度分别从 6.30%、2.43% 补偿至 65.72%、64.07%，l_2=10 与不同拓扑荷 l_1 复合的光束的光强相关系数分别从 0.6477、0.3495 校正到 0.9794、0.9268。

4 结 论

采用设计的 PhaNet 模型实现了对复合 BG 光束大气湍流效应的补偿。通过对接收的畸变光束强度分布进行特征提取，构建畸变光强图像与湍流相位之间的映射关系，有效地预测了影响光束的湍流相位，实现了湍流环境下对不同 OAM 态复合 BG 光束畸变相位的补偿。分析了不同湍流强度、传输距离下 PhaNet 模型对复合 BG 畸变光束的补偿效果。研究结果表明，复合 BG 光束在不同湍流强度下传输 1000 m 的光强相关系数可提高至 0.97 以上，在强湍流中传输 1500 m 的光强相关系数可校正至 0.92 以上。本文所设计的网络模型的补偿效果较好，可以在很大程度上提高涡旋光通信的可靠性。

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Atmospheric Turbulence Compensation Based on Deep Learning to Correct Distorted Composite Bessel-Gaussian Beam

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Abstract

Objective Atmospheric turbulence (AT) severely affects the transmission of vortex beams (VBs) transmitted in the atmosphere. Wavefront distortion, coherence destruction, and orthogonality destruction of multiplexed VBs are the main effects of AT, which directly increase crosstalk among channels and reduce communication performance. To improve the robustness of optical orbital angular momentum (OAM) communications, considerable efforts have been made to effectively compensate for the phase distortion of VBs. The adaptive optical method is widely used but requires multiple iterations and complicated hardware that is not affordable or easily operated by most researchers, causing tremendous difficulties for further study. Recently, taking advantage of powerful signal processing techniques, deep learning has been widely used in many fields such as image classification and optical communication, providing researchers with a new approach for addressing these problems. In this study, we propose a novel method of AT compensation based on a deep learning method to effectively correct the distorted composite Bessel-Gaussian (BG) vortex beam and improve the robustness of OAM multiplexing communication.

Methods Using a deep learning method, we designed a new model called the phase extraction network (PhaNet), which combines a residual network with a feature pyramid for AT phase extraction (Fig. 2). The PhaNet model can automatically learn the mapping relationship between the intensity distribution of the distorted beam and the turbulence phase under different orbital angular momenta. It contains seven convolutional layers, four residual layers, six deconvolution layers, and three feature fusion layers. A total of 96000 images of BG vortex beam intensity with a specified turbulence range were randomly generated, 80000 of which were used as training data, with the remaining 16000 serving as test data. Following training with the loads of the studied samples, the PhaNet model was used to directly predict AT phase screens based on the intensity distribution of the distorted composite BG vortex beam. The turbulence phase can be compensated by loading a reverse-predicted phase into the received composite BG vortex beam. We then used the AT compensation system as a physical model (Fig. 5) to study the AT effect compensation of a composite BG vortex beam by mode purity and intensity correlation coefficient under different conditions of turbulence intensities and distances.

Results and Discussions To predict the entire turbulence phase, we successfully constructed the PhaNet model, which requires the intensity distribution of the distorted beam as input. Comparison results (Fig. 3) show that in the 21-layer structure, the mean loss significantly decreases, whereas the iterations show an inverse trend. When the number of iterations is 4000, the training loss reaches a plateau at 0.00957521. Therefore, to ensure the effectiveness of the predicted results in the PhaNet model, we chose 80000 training data and 4000 iterations as the training conditions. If better prediction performance is required, the amount of training data or number of iterations must be further increased. However, increasing the number of input samples increases the computational cost and lengthens the prediction time. To verify the generalization ability of the PhaNet model, we used the previously trained model to perform turbulence compensation for the composite BG beam propagating under different conditions by changing the parameters of turbulence (Fig. 6) and distances (Fig. 7), and we then analyzed the mode purity and intensity correlation coefficient. Under the conditions in which the topological charges $l_1=4$ and $l_2=10$ propagate from strong to weak turbulence and the composite BG beam has a 1000 m transmitting distance, the mode purity of $l_1=4$ increases by approximately tenfold, from 3.41%, 3.54%, and 4.61% to 30.70%, 31.21%, and 31.35%, respectively, after compensation. Simultaneously, the mode purity of $l_2=10$ shows a similar trend, increasing remarkably from 6.09%, 6.23%, and 6.30% to 64.68%, 65.45%, and 66.53%, respectively, after compensation. In addition, the beam intensity correlation coefficient of $l_2=10$ combined with different topological charges l_1 increases from 0.4199, 0.4596, and 0.5281 to 0.97 and greater. The mode purity of the composite BG beam ($l_1=4$ and $l_2=10$) at a propagation distance of 1500 m in strong turbulence are 3.50% and 2.43% respectively, which can be improved to 30.55% and 64.07%, respectively, after compensation. The beam intensity correlation coefficient of $l_2=10$ combined with different topological charges l_1 increases from 0.6477 and 0.3495 to 0.9794 and 0.9268, respectively.

Conclusions We propose an AT compensation scheme for a composite BG vortex beam based on a phase extraction network. The compensation effect of the phase extraction network on a distorted composite BG vortex beam under different turbulence intensities and propagation distances is numerically analyzed. The results show that after phase compensation, when the composite BG vortex beam propagates 1000 m under different turbulence intensities, the intensity correlation coefficient can be increased to greater than 0.97, whereas the intensity correlation coefficient is improved to 0.9268 when the transmission distance increases to 1500 m under strong turbulence. These results show that the PhaNet model possesses a good generalization ability for quickly and accurately predicting the equivalent turbulent phase screen, even in unknown turbulence environments, and thus has great potential for improving the performance of OAM communication.

Key words optics communications; composite Bessel-Gaussian beam; atmospheric turbulence; deep learning; phase compensation