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Venugopal Raskatla, Vijay Kumar, "Deep learning assisted OAM modes demultiplexing," Proc. SPIE 12126, Fifteenth International Conference on Correlation Optics, 121260A (20 December 2021); doi: 10.1117/12.2615170

Event: Fifteenth International Conference on Correlation Optics, 2021, Chernivtsi, Ukraine

Deep Learning assisted OAM modes demultiplexing

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ABSTRACT

Orbital angular momentum (OAM) beams have the potential to increase the information-carrying capacity because of the extra degrees of freedom associated with them. Traditional methods for mode detection and de-multiplexing are complex and require expensive optical hardware. We propose a very simple and cost effective deep learning based model for demultiplexing OAM modes at the receiver. In this method we have used a random phase mask of known inhomogeneity to generate a scattered field of OAM mode and the intensity images of these scattered field are used as an input to the Convolutional Neural Network. The model is trained for various Laguerre-Gaussian (LG_{pl}) modes carrying OAM with $p = 0$ and $l = 1,2,3,4,5,6,7,8$. The model is tested for various set of images and the overall accuracy of each dataset is >99%. To demonstrate the proof of concept we simulated an experiment to generate the speckle field at the receiver of optical communication system for demultiplexing OAM modes and decoding the 3-bit information.

Keywords: Optical Communication, OAM beams, Deep Learning, Speckles, Singular optics.

1. INTRODUCTION

Beams carrying Orbital Angular Momentum (OAM) are extensively studied due to their wide applications. They are used in areas such as Optical trapping[1,2], microscopy and imaging[3], quantum entanglement[4] and quantum information processing. Due to extra degree of freedom, the OAM beams are extensively used in optical communication to enhance the bandwidth and information carrying capacity[5-7]. The traditional methods for generating and identifying these OAM beams are very complex and the optical components required are also expensive. The OAM beams can be generated using spiral phase plate, computer generated hologram, mode conversion, etc., whereas for their detection interferometer and diffraction based methods, mode sorting methods are used. Since these methods require the precise alignment, the accuracy of mode detection is less. Also fidelity is limited by the presence of noises as they introduces additional phase resulting in hybrid modes. To overcome these difficulties machine learning and deep learning approaches has been demonstrated which loosen the constrain of alignment by using intensity images of the received field[8-10]. The machine learning models deployed for demultiplexing in optical communication also reduces the need of physical components reducing the cost of system. Even though these machine leaning and deep learning based models are simple and cost effective, they are noise limited. In case of free space optical communication system, the noises introduced in the transmitted beam due to atmospheric turbulence results in intermodal cross talks and reduces the fidelity and accuracy of the mode detection.

To overcome this problem we propose a speckle field based deep learning model for OAM modes demultiplexing for free space optical communication. In this method we use a random phase mask to generate a scattered field of the received OAM beams. The intensity images of the scattered field are captured and used for training deep learning model. To train the deep learning model we use Alexnet, a pre-trained network. We have chosen Alexnet because of its moderate computational power and high accuracy. This method (also known as Transfer learning) of utilizing the pre-trained network faster and more efficient than training the network from scratch. To build a 3 bit information demultiplexing model, we modify the last layer of Alexnet to classify 8 (2^3) different OAM modes by retaining the weights and biases learned by the network. The results shows that our model is able to classify the modes with an overall accuracy > 99%. In addition to noise and alignment free, implementing this model discards the need of capturing of whole field. Also a small region of the scattered field having sufficient number of speckles in enough for identifying the mode as the speckles in the field have local correlation.

Fifteenth International Conference on Correlation Optics, edited
by Oleg V. Angelsky, Proc. of SPIE Vol. 12126, 121260A

2. ORBITAL ANGULAR MOMENTUM BEAMS

For complex scalar field, $U(\boldsymbol{r})$, the scalar Helmholtz equation is given as

$$\nabla^2 U(\boldsymbol{r}) + k^2 U(\boldsymbol{r}) = 0 \tag{1}$$

For a field propagating along z-axis the $U(r)$ can be approximated as

$$U(\boldsymbol{r}) = u(\boldsymbol{r}) e^{ikz} \tag{2}$$

where, $u(\boldsymbol{r})$ is the slowly varying function of z.

By substituting equation (2) in equation (1), we get,

$$\nabla^2 u(\boldsymbol{r}) + 2ik \frac{\partial u(\boldsymbol{r})}{\partial z} = 0$$

If $u(\boldsymbol{r})$ is a slowly varying function of z then the resulting equation is the paraxial wave equation describing the wave propagating tightly along z axis and is given as

$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + 2ik \frac{\partial u}{\partial z} = 0 \tag{3}$$

The most obvious solution of this paraxial wave equation is the shape invariant Gaussian beams which retain their Gaussian profile while propagating along z direction, These Gaussian beams are expressed as

$$u_G(\boldsymbol{r}) = A_0 e^{i\Phi z} \left[\frac{1}{\sqrt{1 + z^2/z_0^2}} e^{ik(x^2+y^2)/2R(z)} \right] e^{-(x^2+y^2)/w^2(z)}$$

where, $R(z) = z + z_0^2/z$, the wavefront curvature of the beam

$w(z) = w_0\sqrt{1 + z^2/z_0^2}$, the effective width of the beam as a function of z,

$\Phi(z) = \arctan(z/z_0)$, Gouy phase shift

$A_0 = \sqrt{I_0}$, Amplitude

$z_0 = \pi w_0^2/\lambda$, Rayleigh range

Working in different coordinate systems gives rise to different shape invariant beams carrying OAM. For example in Hermite – Gauss beams are the solution of equation (3) in Cartesian coordinate system whereas family of Laguerre – Gauss beams carrying optical vortices are the solutions in cylindrical coordinate system.

For $A_0 = 1$, the expression for Laguerre – Gauss beams is given as

$$u_{pl}(\boldsymbol{r}) = \frac{2p!}{\sqrt{\pi w_0^2 (p + |l|)!}} \left(\frac{\sqrt{2}\rho}{w(z)} \right)^{|l|} L_p^{|l|} \left(\frac{2\rho^2}{w^2(z)} \right) e^{il\Phi} u_G(\boldsymbol{r}) e^{-i(2p+|l|)\Phi(z)}$$

where, p is non-negative integer, l is integer and $L_p^{|l|}$ is an associated Laguerre function of order p and l. Here p is termed as radial mode index and l as azimuthal mode index.

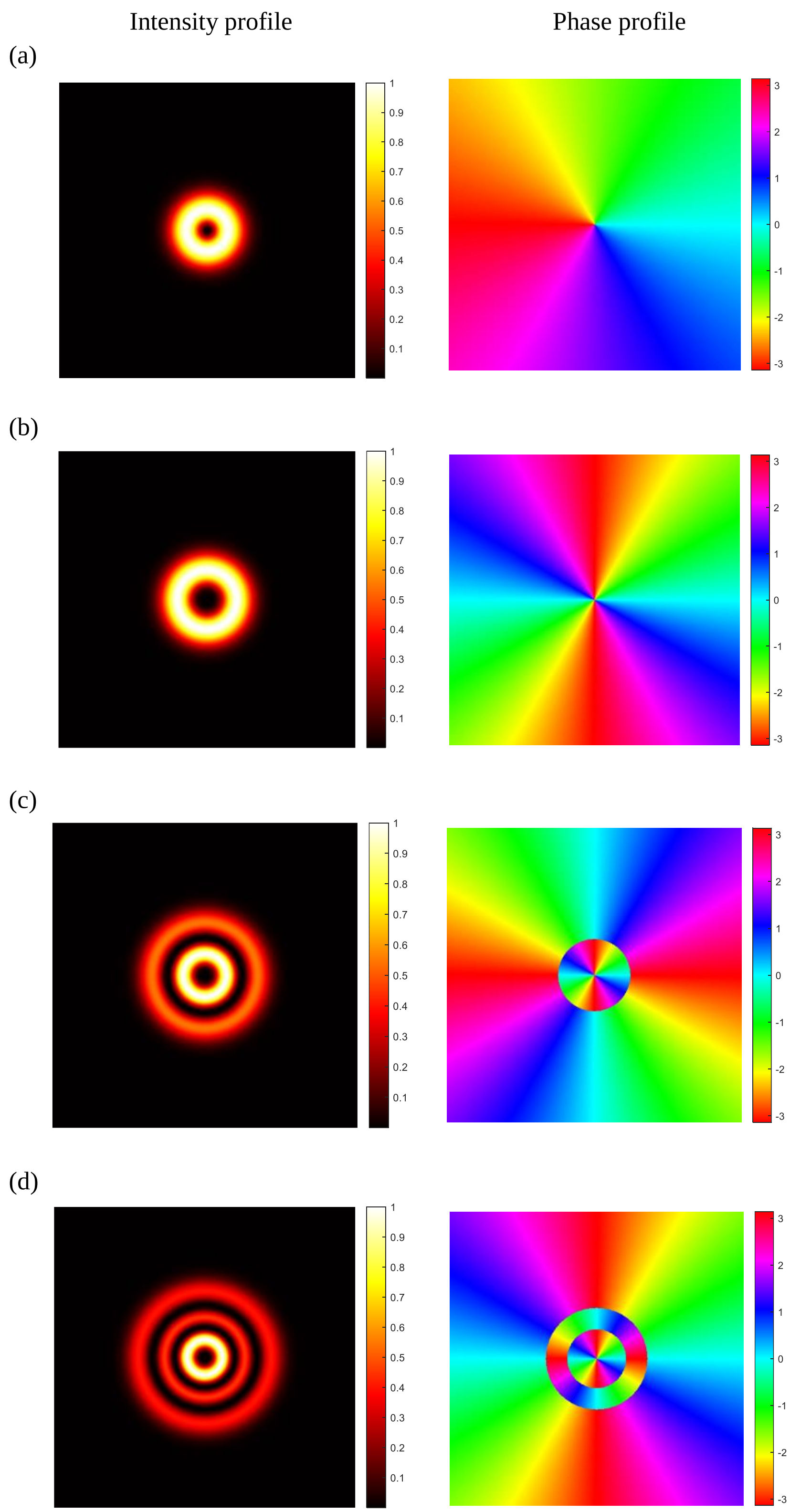

Figure 1. The intensity and phase profiles of LG beams. (a) $\boldsymbol{p = 0, l = 1}$, (b) $\boldsymbol{p = 0, l = 2}$, (c) $\boldsymbol{p = 1, l = 2}$, (d) $\boldsymbol{p = 2, l = 2}$. The phase ranges from $-\boldsymbol{\pi}$ to $\boldsymbol{\pi}$. At each dark ring the phase jumps by $\boldsymbol{\pi}$ and these dark rings are the phase singularities in the field.

3. PROPOSED EXPERIMENTAL SET UP FOR GENERATING SCATTERED FIELD

We have used a Spatial Light Modulator (SLM) to generate different OAM modes by displaying the binary phase hologram of desired mode. A He-Ne laser ($\lambda = 632nm$) is illuminated on SLM and the reflected beams from the SLM carries the desired OAM. A ground glass of known inhomogeneity is used to generate a scattered field for a given OAM mode. The ground glass acts as random phase mask and introduces the random phase in the incident OAM beams and hence generating the speckle field. This speckle field is captured using a CCD and the intensity images are used for further classification of beams. The 8 OAM beams with $p = 0$ and $l = 1,2,3,4,6,7,8$ are generated to build a 3 bit demultiplexing model.

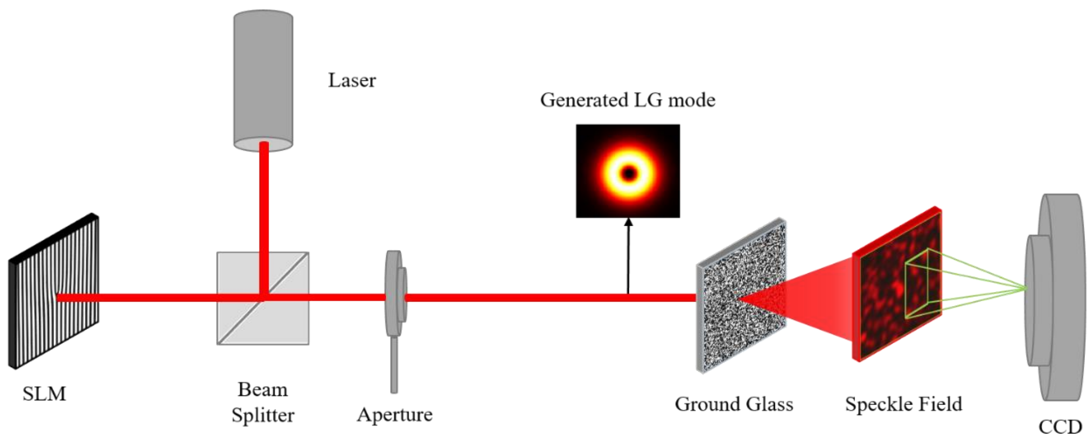

Figure 2. Schematic of experimental arrangement to capture speckle field of LG modes. Ground glass is used as random phase mask for generating speckle field.

4. DEEP LEARNING

Inspired from the structure of human brain, deep learning is a self-learning method developed for learning from large data. Deep learning is essentially a neural network that mimic the human brain to identify, classify, and describe the input data or objects. In the deep learning the features are automatically learned during the training. Convolutional Neural Network (CNN), a type of neural network uses convolution operator for extracting the features by convolving filters with input images. The initial layers of CNN extract the low level features whereas the deeper layers extract high level features. In addition to convolution layers, non-linear activation function such as ReLU and pooling layers are also added for effective learning. To combine all these features fully connected layers are used. At the end softmax layer and classification layers are used to predict the class of the input data.

The deep learning models require huge data and large computational power. To avoid this problem we can use the pre-trained networks which were trained for similar data. By modifying the last layers and retaining the weights and biases we can utilize the power of trained networks. It is the fastest and efficient way of training. Networks such as Alexnet, Resnet, VGG-16 can be used for training data for classification task as these have learned lots of feature during training. They have good accuracy and moderate computational power.

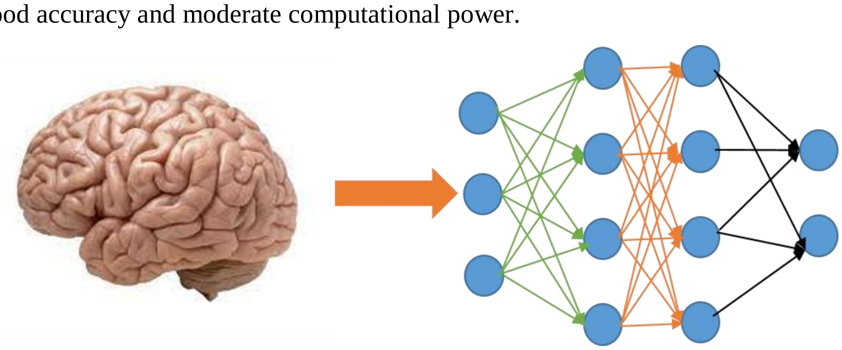

Figure 3. Neural network attempt to mimic the human brain

5. DEEP LEARNING BASED MODEL FOR OAM MODE DEMULTIPLEXING

In order to build a 3 bit demultiplexing model we utilize the Alexnet. The Alexnet is already trained for 1000 classes over 1.2 million images, hence it has learned lot of features in terms of weights and biases. We can use this weights and biases to train our model instead of training from scratch. Training in this way requires less computational power and less number of data compared to training from scratch. Alexnet has 5 convolution layers and 3 fully connected layers. It accepts images of size $227 \times 227 \times 3$ and hence we will preprocess our data to this size. The last layers gives the probabilities of 1000 classes, thus, we modify the number of neurons in the last layer to 8 as we have only 8 OAM modes. Table 1 shows the detailed architecture of modified Alexnet network. In the network the convolution layers are followed by number of non-linear activation layers and pooling layers to reduce the number of parameters by performing down sampling. The images of the scattered field captured are fed to this network for training and testing the model. We have trained the network over an 800 images and tested it for various datasets. We have used “The Stochastic Gradient Descent with Momentum (SGDM) optimizer to train the network with learning rate of 0.0001 and 30 maximum epochs. We have achieved an overall accuracy > 99% for each dataset.

Table 1. Alexnet Architecture modified for training 8 classes of LG Beam

Layer Name	No. of filters	Filter size	Stride	Padding	Size of feature map	Activation Function
data	-	-	-	-	$227 \times 227 \times 3$	-
conv1	96	11×11	4	-	$55 \times 55 \times 96$	MP + ReLu
conv2	256	5×5	1	2	$27 \times 27 \times 256$	MP + ReLu
conv3	384	3×3	1	1	$13 \times 13 \times 384$	ReLu
conv4	384	3×3	1	1	$13 \times 13 \times 384$	ReLu
conv5	256	3×3	1	1	$13 \times 13 \times 256$	MP + ReLu
fc6	4096	-	-	-	$1 \times 1 \times 4096$	ReLU + Dropout
fc7	4096	-	-	-	$1 \times 1 \times 4096$	ReLU + Dropout
fc8	8	-	-	-	$1 \times 1 \times 8$	Softmax

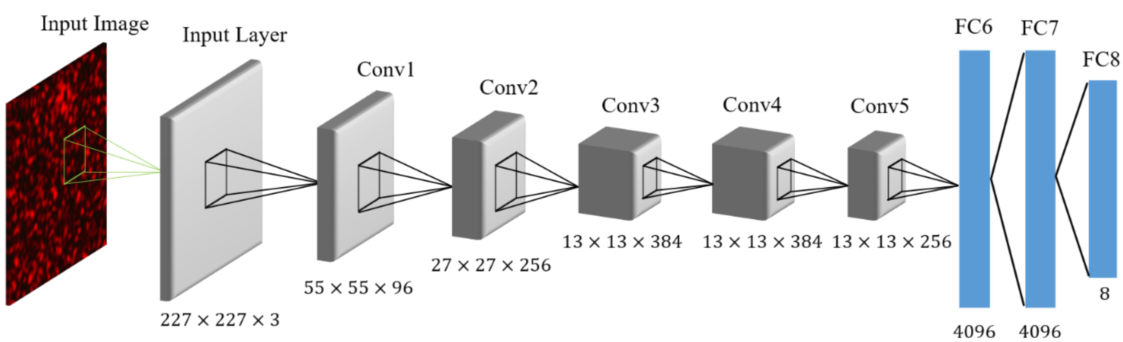

Figure 4. Layer by layer visualization of modified Alexnet architecture.

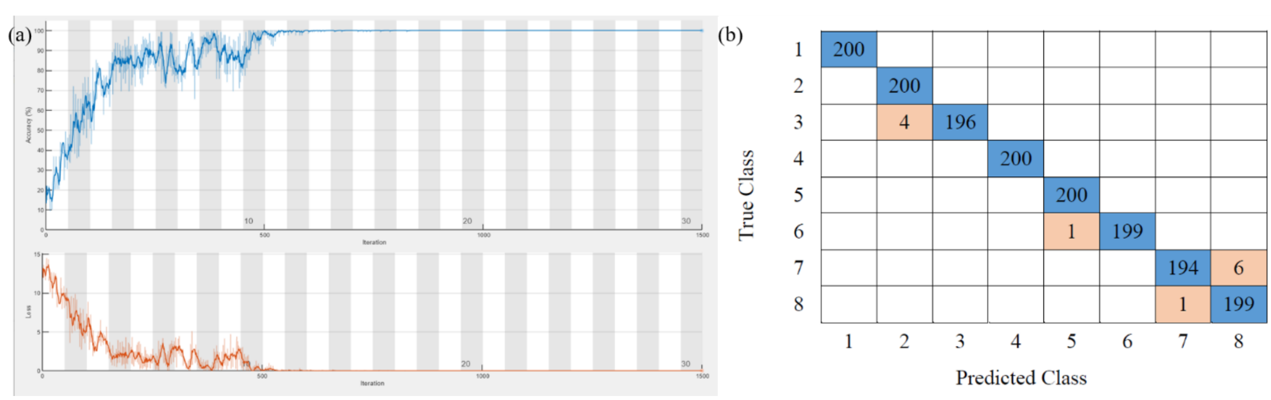

Figure 5. (a) Training and loss plots with number of iteration during the training. (b) Confusion matrix indicating the intermodal cross-talk between the receives OAM modes

6. CONCLUSIONS

We have successfully demonstrated a proof of concept of deep learning model for demultiplexing OAM modes using simulated speckle images of the received field. Compared to the previous state of art, this method has an advantage that we don't need to capture the entire field of the received beam. The model is robust to noise as it is trained for images having random noises. For robust training the number of hyperparameters can be increased but at the same time we have to compromise with accuracy. The confusion matrix indicate that there is more confusion at the higher order modes and it can be eliminated by optimizing the network or skipping some few modes. Our results shows that this model has potential to deploy in free space optical communication systems for demultiplexing.

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