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# Deep Learning Assisted Classification of Noisy Laguerre Gaussian Modes

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**Abstract:** A deep learning assisted scheme for classification of noisy LG modes is proposed. This model is noise and alignment independent and will increase the accuracy and fidelity of OAM mode detection systems. 

## 1. Introduction

Laguerre Gaussian ($\boldsymbol{LG_{pl}}$) beams are the set of propagation beams carrying characteristic Orbital Angular momentum (OAM) and phase singularity. Due to orthogonality property of $LG$ modes, they are used for information encoding. Traditional methods for mode detection and de-multiplexing are very complex and cumbersome [1, 2]. A machine learning approach is proposed and demonstrated to reduce the complexity of the system for OAM mode sorting [3-6]. But these methods are noise limited and also alignment of components is very important as it directly affects the detection accuracy. After propagation these modes get distorted and the accuracy of detecting these modes goes down as the cross-talks among the modes increases and thus reducing the fidelity of the system.

## 2. Concept and Methodology

In practice, generating ideal LG modes (without distortion) is very difficult and requires a very high quality components and lab environment. In case of optical communication, these modes get distorted and become crappy because of the atmospheric turbulences. So for robust training one has to feed distorted images for training but still the trained model will not classify modes with high accuracy and fidelity. We propose new scheme which will solve this problem and does not require any simulated or artificial environment for generating distorted modes. We have generated noisy LG modes of different orders using SLM and these modes are then passed through a random phase mask of known inhomogeneity to generate a scattered field. The intensity images of scattered field are then captured using CCD and fed to a deep neural network for training and testing.

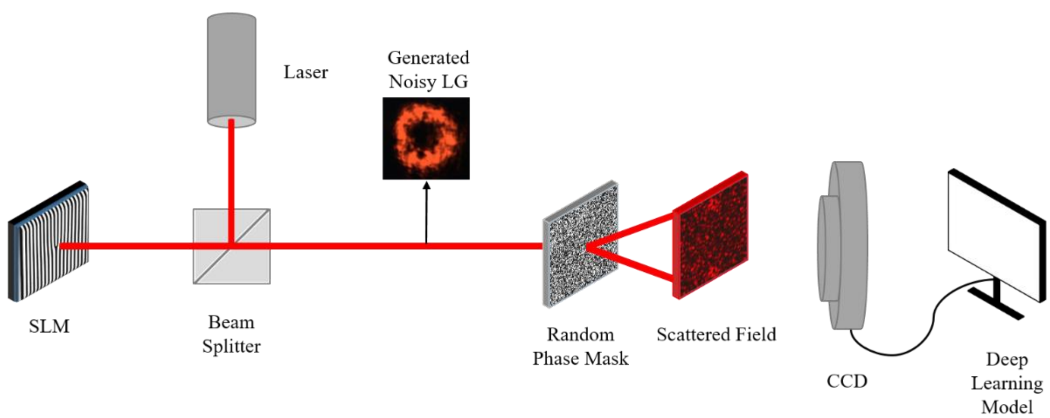


Fig. 1. Experimental arrangement for demultiplexing noisy LG modes using deep learning model.

## 3. Deep Learning based model for LG modes classification

The deep neural network is well known for self-learning from the input data without being explicitly programmed. We use such a pre-trained network, "Alexnet", for developing our model. The network is well known for its accuracy and moderate computing load. As Alexnet is already trained for more than a million images for 1000 classes, it has learned a lot of features. Such networks can be used for classification purposes by changing only the last few layers. The use of such networks reduces the training time and gives the right direction for optimization for the model build from the scratch. The input layer of the network accepts the image of size $227 \times 227 \times 3$, hence we have to preprocess all the images into this format before feeding them to the network. The output layer consists of 1000 classes but we will train this network only for eight OAM modes, therefore, we will modify this layer to give only 8 outputs. This network self-learned itself from the images fed to it. We have trained our network over 2000 simulated and 300 experimentally generated (Figure 1) images of each class with the "Stochastic Gradient Descent with Momentum" (SGDM) algorithm and constant learning rate of 0.0001. The network is tested for various set of images (which were not included during training) and model classified modes with an overall accuracy of 96%. The ratio of experimental images to simulated images can be varied and optimized for getting robust and accurate model.

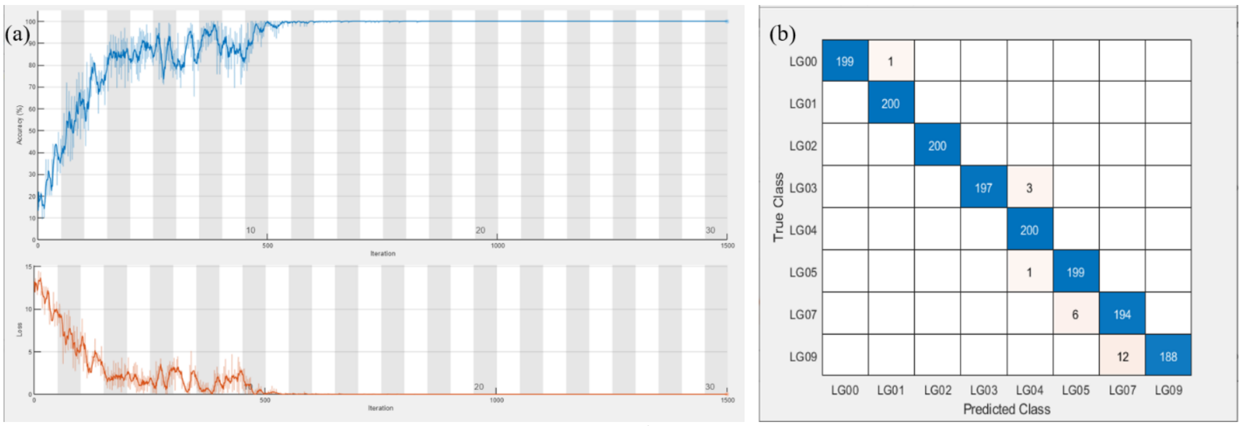


Fig. 2. (a) Accuracy and loss plots per iteration during the training (b) Confusion Matrix indicating the crosstalk between modes. The diagonal represents the number of correct predications whereas off diagonals represent misclassification indicating model's confusion in identification of modes

## 4. Summary and Conclusion

Based on Alexnet network we propose a deep learning model for the classification of noisy LG modes which helps us to build a robust noise and alignment independent OAM mode classifier. For robustness model is trained for different beam sizes and inhomogeneity of random phase mask. As the number of hyperparameters are increased the accuracy goes down. So we have to make a tradeoff between robustness and accuracy. Since we are training the model with the images having random noise, our model is capable of identifying the core pattern of the LG modes by nullifying the noise effects. Another advantage of our model is that the information about the LG field is present all over the image. Thus any portion of the image containing sufficient speckles is enough for identification of mode. This will reduce need for precise alignment and increases the accuracy and fidelity of the system. There is more confusion (Figure 2b) at higher order modes but it can be eliminated by optimizing beam size and other parameters. More experimental results and optimized model will be presented in the conference. We believe this model has the potential to deploy in optical communication systems based on OAM demultiplexing for increasing the fidelity.

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