Convolutional Neural Network Assisted Identification of Gaussian Beams and Vortex Beams

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Abstract

A convolutional neural network (CNN) was created to identify gaussian beams and vortex beams with a topological charge from 1-3. A three-layer CNN was used which had feature extraction and the ability to use a large dataset of colour coded images, of the gaussian and vortex beams as well as the turbulence that was created for each type of beam, to train on. Once the supervised training was completed, the CNN model was able to generalize the data efficiently as well as detect and identify/classify unseen images of beams. The results for the simulation resulted in an average accuracy of over 97% under the influence of weak and strong turbulences.

Introduction

A convolutional neural network is a Deep Learning algorithm that can take an image and assign importance to various aspects of it. It can also distinguish between objects and images based on their features and biases. The CNN is a network of neurons that are connected to the visual field through a restricted region known as the Receptive Field. This region overlaps with the rest of the visual area. CNN's can be used for image classifications with multiple classes. In this case the images are of beams of gaussian (GB) and vortex beams (VL1, VL2, VL3) with a topological charge (l) from 1 – 3. This CNN has 3 layers of which have filters of an increasing order. The atmospheric turbulence created was added to the ideal dataset which therefore created a dataset that was efficiently balanced with noise

Theory

Laguerre Gaussian beams:

The Laguerre gaussian beam is a light beam where the electric field profile is in a plane that is perpendicular to the beam axis which can be portrayed with a Gaussian function and possibly with an added parabolic phase profile. It is also one of the solutions to the Helmholtz equation. The mathematical expression for the amplitude of electric field with polarization in the x direction and the propagation in the positive z direction can be expressed as:

$$E(r,z) = E_o \hat{x} \frac{w_o}{w(z)} exp\left(\frac{-r^2}{w(z)^2}\right) exp\left(-i\left(kz + k\frac{r^2}{2R(z)} - \psi(z)\right)\right) \quad (1)$$

Where E_o is E (0,0) which is the electric field amplitude and phase at the origin where r=0 and z=0, with r being the radial distance from the centre of the beam and z being the axial distance from the beam's waist. The radius where the field amplitudes fall 1/e of their axial values where the plane z is along the beam and w_o = w (0) which is the beams waist. The radius of curvature of the beams wavefronts at z is denoted as R(z) and the Gouy phase ψ(z) at z is an extra phase term beyond that assignable to the phase velocity of light. The imaginary unit is denoted by i.

Vortex beams:

The vortex beam which in other words, an optical vortex is a type of phase singularity that has a spiral wave front around a point where the phase is undefined. In order to model the formation of VB, a conventional Laguerre-Gaussian beam is utilized, and its light eld distribution may be generalized as:

$$\begin{aligned} LG_p^l(r,\varphi,z) = {} & A_{lg}\left[\frac{w_o}{w(z)}\right]\left[\frac{\sqrt{2}r}{w(z)}\right]^{|l|} L_p^{|l|}\left[\frac{2r^2}{w^2(z)}\right] \\ & .exp\left[\frac{-r^2}{w^2(z)}\right] exp\left[-i\frac{k_o r^2 z}{2\left(z^2+z_r^2\right)}\right] \\ & .exp\left[i(2p+|l|+1)\tan^{-1}\left(\frac{z}{z_r}\right)\right] \\ & .exp(-il\varphi)\, exp(-ikz) \end{aligned} \quad (2)$$

A_{lg} in the above equation is the amplitude of the vortex beams.

In the cylindrical coordinate system, r and φ represent the radius and azimuth angle. The beam propagation direction is represented by z. It is also seen that w_o is beam waist size and $w(z) = w_o\left(1+\frac{z^2}{z_o^2}\right)^{\frac{1}{2}}$ is the beam waist size at z. $L_p^{|l|}$ denotes the related Laguerre polynomial, and $z_r = \frac{1}{2kw_o^2}$ denotes the Rayleigh distance. p and l are the radial and angular topological charge values, respectively, and $k = \frac{2\pi}{\lambda}$ is the beam's wavenumber.

Atmospheric turbulence:

The atmospheric turbulence is denoted by C_n^2 which is also known as the atmospheric structure constant, and this indicates the turbulence intensity.

Experimental

The ideal beam images were downloaded and then the turbulences for each type of beams were created using a python program that was iterated many times using a 'for' loop. The turbulence value C_n^2 was varied from (1e-12 to 1e-15) to create some noisy data in the form of images. Thereafter, this dataset of turbulences was added to the respective type of beams.

The convolutional neural was created using various libraries such as TensorFlow, keras, NumPy, matplotlib and others. The training set and validation set/test set ratio was varied to find the best accuracy. In this case the ratio was 80:20. The library keras, that was imported from TensorFlow, created training set and validation/test set.

It is also important to note that the keras function is set by default to shuffle the data when creating the training and validation/test set.

In figure 1 shows a visualisation of a sample of the first nine images from the training set.

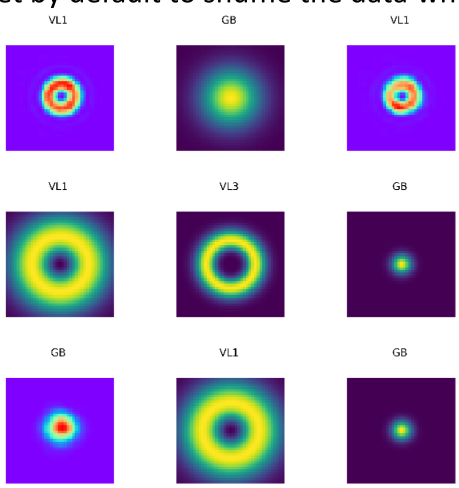

Figure 1: shuffled images in training set

A configuration was done for the dataset to increase the performance of the model and the dataset was normalised and the standardized values were in [0,1]

After the model was trained, the validation/test set accuracy was decreasing, and the loss was increasing. This was a clear indication of overfitting. This overfitting was solved by using data augmentation and using the dropout technique where a number of units of the output layer is dropped out during the training process.

The model was then compiled and trained. The results thereafter were much better. The test set accuracy was increasing, and the loss was decreasing.

The model was then ready to predict on new and unseen data. So, an image of a random gaussian beam was chosen on the internet and used to verify the prediction accuracy of the model.

Results

When the model first ran it gave estimation of the model accuracy and loss. In figure 2 below:

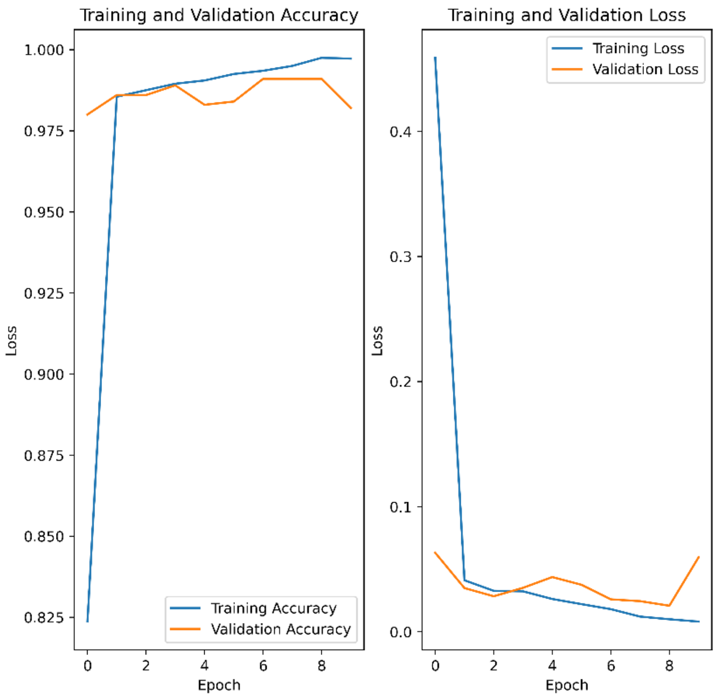

Figure 2: graphical visualisation of the relationships between training and validation accuracy and Loss respectively

In graphs above we can see the validation accuracy decreases and the loss increasing, this means that there is some overfitting occurring and the model is memorizing data.

The problem was solved by using data augmentation and dropping out 20% of the output layer units near the end of the convolutional neural network.

When the model was compiled and trained again the result were the following in figure 3 below:

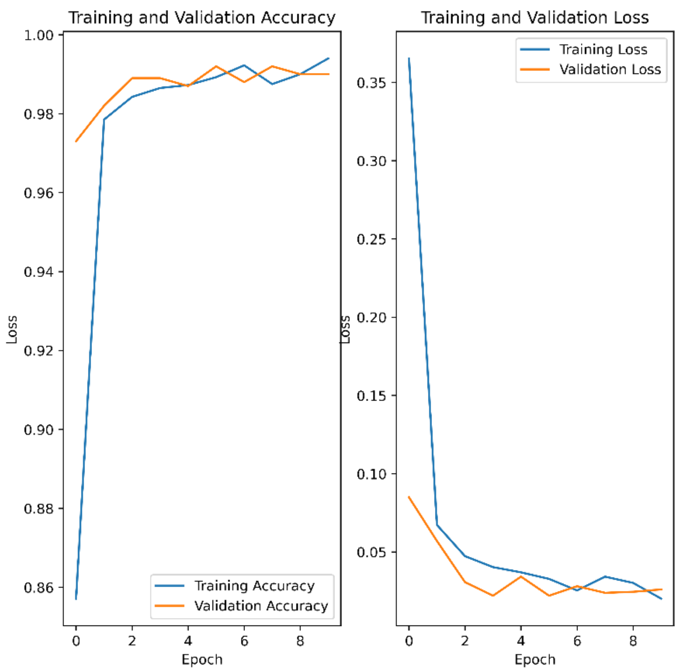

Figure 3: graphical visualisation of the relationships between training and validation accuracy and Loss respectively, after data augmentation and dropout

In graphs above it can be seen that validation accuracy is increasing and the loss is increasing, this is an indication that the model in not memorizing data but learning efficiently with an average accuracy of 97.46%. The model was then tested on unseen data.

The prediction accuracy for an unseen image of a gaussian beam was predicted with 99.57% confidence.

Discussions

The concept of data augmentation is to generate new training data from your current examples by supplementing them with random changes that produce believable-looking visuals. This allows the model to be exposed to more parts of the data and generalize more effectively.

Conclusions

The overall model accuracy was above 97.46%. This model could be seen as efficient as the validation accuracy was increasing and the loss was decreasing, this is two indications that the model was learning instead of memorizing data. The generalisation of data

The prediction accuracy of unseen data was quite efficient as the image was classified as a gaussian beam with 99.57% accuracy.

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