Phase Recovery for Holography using Deep Learning

Sahil Vora[1]

[1]*B.Tech, Department of ICT, Manipal Institute of Technology, Manipal*

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Abstract - *Computer-generated holography (CGH) is the strategy for carefully creating holographic interference designs. A hologram is a true account of an interference design that utilizes diffraction to repeat a 3D light field, bringing about a picture that has the depth, parallax, and different properties of the original scene. A holographic picture can be produced for example by carefully registering a holographic interference example and printing it onto a cover or film for ensuing brightening by a reasonable intelligible light source. However, CGH is an iterative technique to register this interference which is time and asset demanding. This paper proposes a technique utilizing deep learning networks that uses a non-iterative calculation which is proficient when contrasted with CGH and galvanizes the plan to utilize this technique to consolidate computer vision and the field of optics.*

Key Words: CGH, holograms, SLM, GS method, ResNets

1. INTRODUCTION

Holography is a technique that enables a light field (which is generally the result of a light source scattered off objects) to be recorded and later reconstructed when the original light field is no longer present, due to the absence of the original objects. Holograms are either generated digitally using CGH or using laser light which is very pure in its colour and composition. The latter method can be generated in a laboratory but is costly as well as difficult to comprehend. On another hand, CGH depends on Spatial light modulators (SLM), and probably the greatest test here is the inadequate command over light wave for example SLM regulates just the amplitude or the phase of the light wave and along these lines, iterative strategies like the Gerchberg-Saxton(GS) technique are utilized for estimation [1]. Be that as it may, they have a few issues with picture quality and spatial resolution. Since this computation involved is too much in this process due to the iterative approach along with the other forthcomings, this paper proposes a method using Deep Learning (deep neural network) to overcome these shortcomings with the help of a non-iterative method for the inverse propagation from intensity to phase.

This paper builds over the work done in the earlier papers over a non-iterative approach and combines several methods to reconstruct and optimize the algorithm to give better and dominant results over the iterative methods such as the GS method.

2. LITERATURE REVIEW

Ryoichi et al. (2018) in their paper discusses a deep learning method to produce light interference using a non-iterative approach and demonstrates this method for phase-only CGH. This paper was used as the base for the study and work done and complete breakdown is demonstrated and reconstructed with optimized results and a lighter algorithm to generate near accurate results [2].

Yair et al. (2018) developed a model using neural networks to recover the phase and reconstruct holograms and solve the problem of twin-image and self-interference-related spatial artifacts [3].

Ayan et al. (2017) demonstrate for the first time that deep neural networks can be trained to solve end-to-end inverse problems in computer propagation and recover phase objects based on diffraction patterns [4].

Ricardo et al. (2013) where a practical approach to use the GS algorithm is presented to determine the phase from an image and form the basis of the CGH which is an iterative method [5].

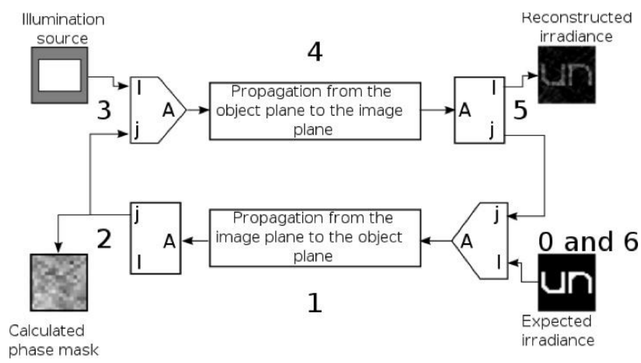

Fig -1: Block Diagram of GS algorithm

3. IMPLEMENTATION

The entire implementation is done using architecture and neural networks with no physical apparatus used. The approach was divided into steps of creating the data-set, training the neural network, validating that neural network, testing it for phase-only holograms and accurately retrieve the phase from an image and then reconstruct the image back from phase-only holograms.

This network promises great results and can be extended for multi-spot simulation.

3.1. Creating the Dataset

To generate the dataset for training our neural network random phase input patterns and computationally propagate to generate patch of intensity patterns using the forward propagation using the following equation

$y = \mathcal{F}[x],$ ... (1)

$\quad = |\mathcal{P}_z[exp(ix)]|^2$ ... (2)

Here $x \in \mathbb{R}^{N^2 \times 1}$ is a phase pattern displayed on SLM, $y \in \mathbb{R}^{N^2 \times 1}$ is the intensity pattern that appear on the image sensor located at distance z from the SLM, and $\mathcal{P}_z[\cdot]$ is the famous Huygens-Fresnel propagation at distance z [6].

$$U(P_0) = \frac{1}{j\lambda} \iint_{\Sigma} U(P_1) \frac{\exp(jkr_{01})}{r_{01}} \cos\theta \, ds \quad .... (3)$$

It expresses the observed field $U(P_0)$ as a superposition of diverging spherical waves $\exp(jkr_{01})/r_{01}$ originating from secondary sources located at each and every point P_1 within the aperture Σ. Here random N^2 matrix has been used to generate our training data. The values used are as followed

- $U(P_1)$ is the random N^2 matrix fed to the equation and the values used are between 0 to 2π.
- N = 64, 32 and 16.
- λ = 632.8nm which is equivalent to the wavelength of the laser 1103P.
- z = 13cm
- It has a phase that leads the phase of the incident wave by 90°, as indicated by the factor 1/j.
- To simulate the source light pattern the pixel width (p) of SLM chosen was 36 µm with pixel count as 768 x 1024.
- The image senor had pixel width as 4.65 µm with pixel count as 768 x 1024.
- Number of pairs generated = 1000, 10000,100000 and 1000000
- Time taken to generate the 100 pairs is 3 min on MATLAB with no GPU. With GPU and parallel computing the time reduced to 1 min for 100 pairs.

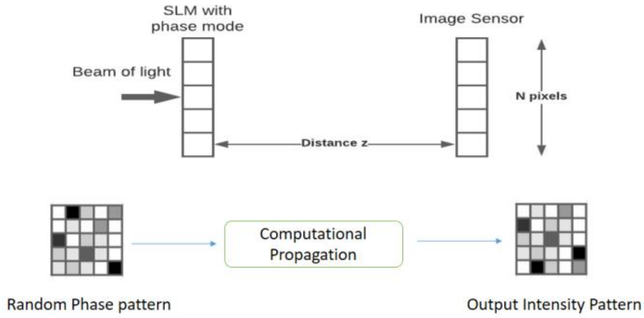

Fig -2: Forward Propagation to create Dataset

3.2. Back Propagation

Since there is no direct formula to go from an intensity pattern to a phase pattern the idea of deep-learning was incorporated here to do the reverse mapping. The inverse process equation is as follows:

$\hat{x} = \mathcal{F}^{-1}[\hat{y}]$ ... (4)

The output of this equation gives us the phase pattern after it is fed to the network where $\hat{x} \in \mathbb{R}^{N^2 \times 1}$ displayed on the SLM to reproduce a target intensity pattern $\hat{y} \in \mathbb{R}^{N^2 \times 1}$ on the image sensor.

3.3. Neural Network Architecture

The network is composed of multiscale residual skip networks (ResNets) [7]. Use of deep convolution ResNet is done because it enables optimization of deep layers by preventing stagnation with skip layers. It has been used for phase retrieval and has shown promising results. With network depth expanding, accuracy gets immersed (which may be obvious) and afterward debases quickly. Suddenly, such debasement isn't brought about by overfitting, and adding more layers to a reasonably profound model prompts higher preparing mistakes. Skip Connections forestalls such degradation.

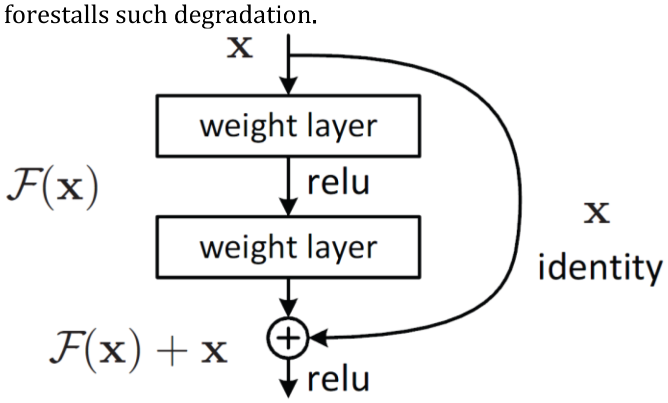

Fig -3: Residual Skip Network (ResNet)

The network built is in the form of an auto-encoder model with various smaller unit working up to get the phase of the images.

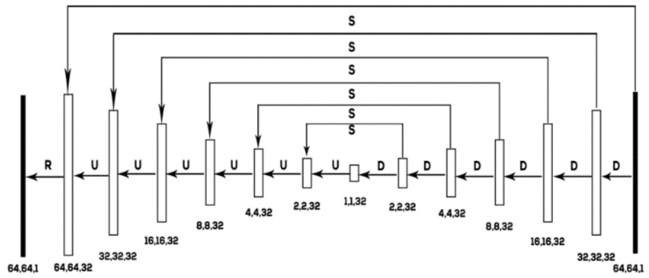

Fig -4: Deep Learning architecture

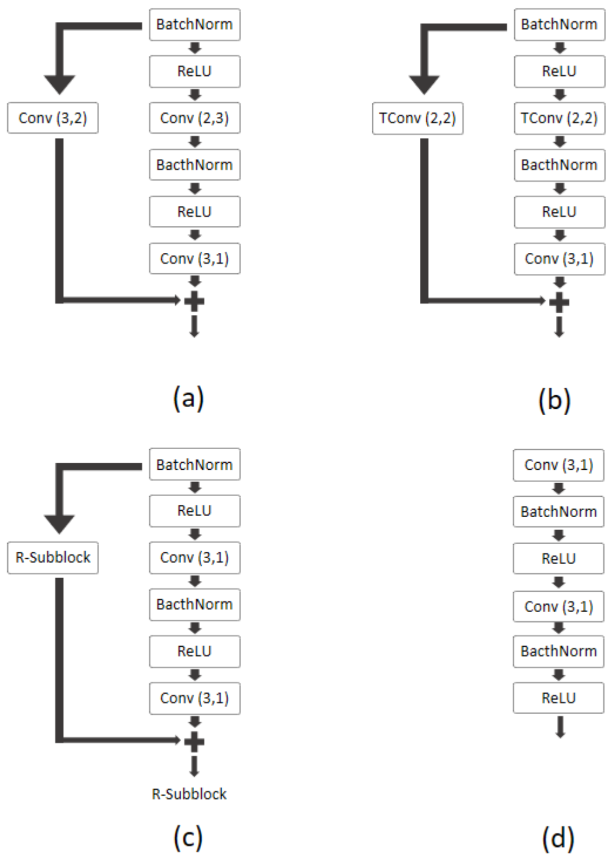

Fig -5: Network of (a) D-block (b) U-block (c) R-block (d) S-block

The smaller network are the down sampling unit, up sampling unit, residual convolutions and skip networks. These units comprises of batch normalization (BatchNorm), Rectified Linear Unit (ReLU), 2-D convolution and transposed convolution layers: Conv (s, l) & TConv(s, l) respectively where s is filter size and l is the number of strides. Here is a summary for training data

Table -1: Parameters used to train the network

Pixel Count for holograms and target output (N^2)	64 x 64
Number of filters at convolution pattern (K)	32
Training data set pairs	100,000
Initial learning rate	0.001
Mini batch size	50
Optimizer	Adam

4. RESULTS

After training the networks while splitting the data into the training and test data in the ratio of 7:3, holograms were retrieved and were then computationally propagated to reconstruct the target pattern. We determine the accuracy with root-mean squared error after running the test for 5, 15 and 100 epochs.

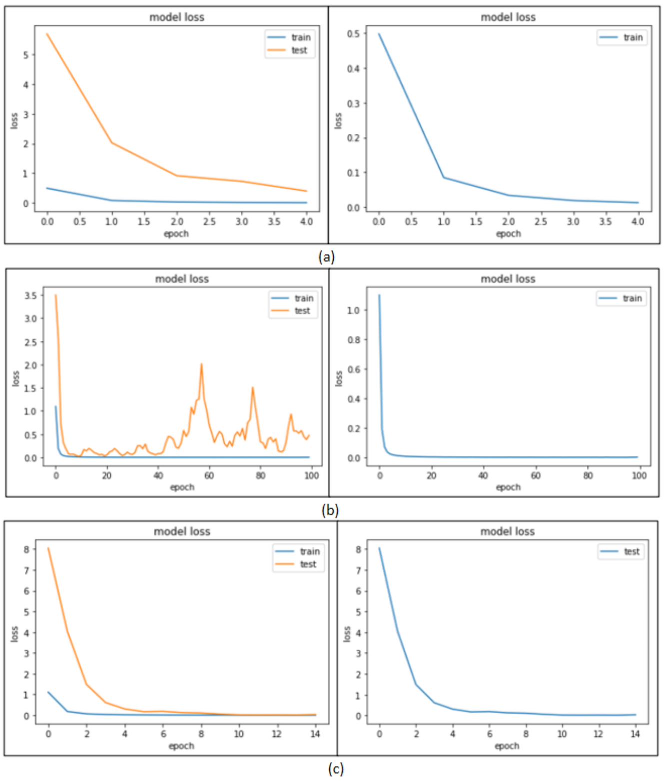

Chart -1: RMSE loss for training and test data after (a) 5 (b) 100 and (c) 15 epochs

This trained network was first used to predict a single spot resolution and was then used to generate results for digital image. The results were then accumulated and were compared to that of GS method.

Table -2: Comparison between deep learning and GS based CGH for 10,000 pairs for N=64

	Deep Learning	GS Method
RMSE	0.16	0.17
Time for reconstruction	26ms	94ms

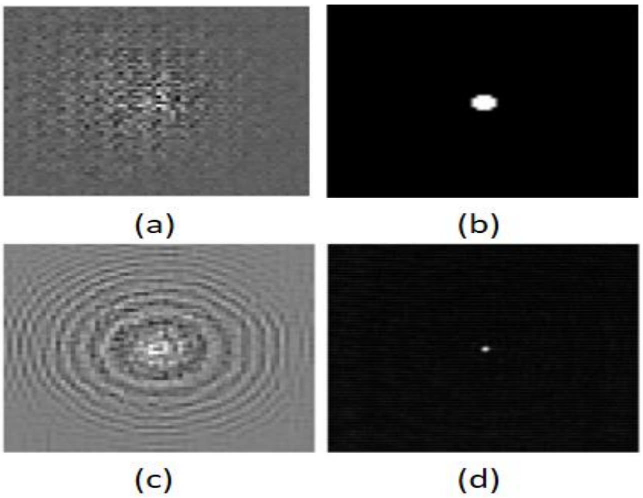

Fig -5: Results obtained for single-point resolution (a) Hologram (b) Reconstructed target for 1000 pairs and (c) Hologram (d) Reconstructed

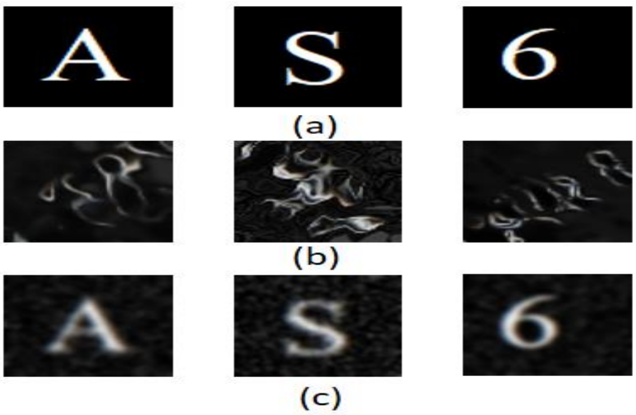

Fig -5: Results obtained for digital images with (a) Target pattern (b) Holograms generated with deep learning (c) Reconstructed image after forward propagation

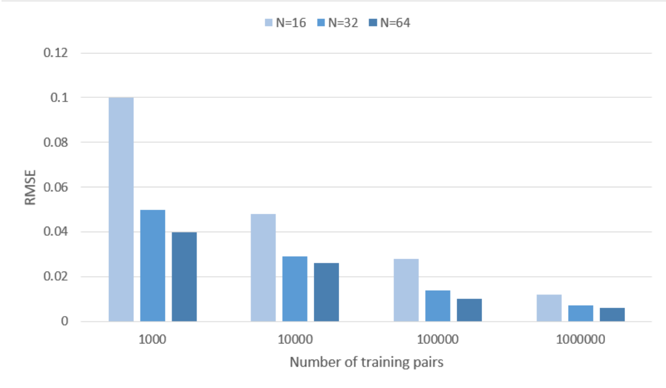

Chart -2: RMSE loss for various set of training pairs and varying size of input matrix.

4. CONCLUSION

Different models and result depicted and proves that deep learning results in better and reasonable image quality of the reproduced intensity pattern and a shorter computational time for the proposed method compared with the conventional one. While this paper works over phase-only holograms it is also possible to use this for phase and amplitude retrieval which could further solve the problem of twin-image resolution, 3-D mapping, phase recovery while its propaganda could be used in field of medical, military, augmented as well as virtual reality.

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