Enhance the Image in Digital Holography by Using an Artificial Neural Network and an Iterative Algorithm

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Abstract

The abundance of information provided by the optical field's amplitude and phase have been found to aid deep learning algorithms substantially. Image reconstruction, zero-order suppression, and hologram fabrication are all possible applications for these approaches. Methods to improve digital and computer-generated holism are examined in this work. From a single intensity-only picture, a deep learning model may be used to generate diffractive optical components. The produced diffractive optical elements have been proved to be of acceptable quality by numerical assessment of the model's performance. Coherent imaging systems may now be used in a wide range of biological and technical research and associated applications thanks to these recent advancements.

Keywords: *Deep Learning; Digital Holography; Computer-Generated Holography; Neural Networks; Object Recognition.*

I. INTRODUCTION

It has provided new avenues for current research in digital image processing to investigate how to reduce picture noise for image improvement. Various types of imaging, such as ultrasound, optical coherence tomography, and digital holography, have all been studied in this way.

Most holographic pictures suffer from Gaussian, Poisson, Erlang (gamma), salt and pepper uniform, intensity, and/or speckle noises, which is why most applications in the literature are designed to enhance the image quality of digital holographic images. This calculation was made in 1971, by Gerchberg and Saxton, to produce noiseless photographs. Rong et al. later proposed noise reduction techniques using multiple polarisation holograms and a low-pass and median filter to recreate three-dimensional (3D) pictures. For the reconstruction of 3D pictures with good image quality, Nakamura et al. suggested an iterative technique based on a phase retrieval procedure. Additionally, image improvement techniques such as noise filtering (2D FIR filter) for ultrasound pictures, artificial neural network (ANN) image processing for high-resolution satellite images, and demonization utilising a feedforward artificial neural network have also been used.

The application of ANNs for picture enhancement in digital holography has already been addressed. In the process of using ANNs to train holographic pictures, however, a variety of issues such as excessive pixel counts and a dearth of available system memory arise. Image segmentation in ANNs is a solution to these issues. This method may also be used to reduce background noise. Pixel-based, point-based, edge-based, region-based, and threshold-based segmentation are only a few of the many forms of segmentation that have been created so far. A strong segmentation approach known as the threshold method may be utilised for photos with luminous objects on a dark backdrop. The histogram technique is used to find the optimal threshold values. Using this information, the histogram is used to choose the most often occurring pixel value, i.e., the one with the greatest frequency of appearance.

It is vital to use picture segmentation to remove noise, yet certain digital image processing software don't work well with it. As a result, we have concentrated our efforts on implementing this procedure in the ANN and iterative method initially suggested by Nakamura et al. Nakamura's technique is the name given to this strategy (NA). They are also compared in terms of how well the images are enhanced.

Image reconstruction and computational imaging

Digital holography's image reconstruction is an ongoing issue since obtaining a high-quality picture from a recorded hologram requires extra processing. Complex and time-consuming zero diffraction order suppression techniques exist. Iterative procedures that need a lot of time and resources may be reduced to one operation by using deep learning techniques for picture reconstruction. Holographic microscopy, for example, makes use of a deep neural network for image reconstruction and phase recovery. A trained model was used for non-iterative picture reconstruction, suppression of twin images, and phase recovery. The model's images were proven to be equivalent to those produced with a single back-propagated hologram using a multi-height reconstruction approach.

Diffractive optical element generation

One of the most difficult challenges in the realm of optical data processing is the creation of DOEs (diffractive optical elements). Focusing elements, 3D sceneries, pattern recognition and etc. can all be achieved using DOE. An iterative procedure like Fien-up or Gerchberg–Saxton is the most common way to generate DOEs. Deep learning algorithms, on the other hand, allow for a single operation to do several tasks, reducing both the time and complexity of the process. Deep learning models were utilised to create computer holograms. A random intensity-only picture was used as a training dataset for the model. From any picture, the model could produce a phase-only DOE. The Gerchberg–Saxton method was able to match the performance of the trained network in terms of computation time and efficiency.

II. SEGMENTATION PROCESS WITH THE NA METHOD

Additionally, image segmentation is a key part of ANNs and noise reduction applications of digital image processing. As a result, the NA approach may be used to accomplish the segmentation procedure. Reconstructed picture pixels are scaled to 0.35, the same ratio used by the MLP network, to accurately compare the NA approach to the MLP network. Figure 1 shows the plotted histogram for the segmentation threshold value.

While it is hoped that the segmentation procedure would significantly reduce picture noise, image enhancement using the NA technique will fall short of expectations.

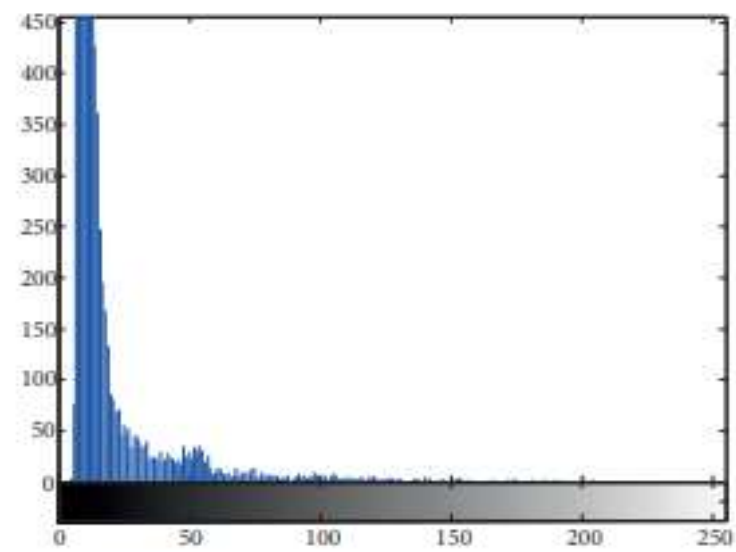


Figure 1. Error histograms obtained by using segmentation with the NA method.

III. RESULTS AND DISCUSSION

In this part, we compare the image enhancement of the reconstructed 3D pictures in digital holography to see how the segmentation process affects the MLP network and the NA approach. When comparing processes, the MLP network with segmentation was the first way employed. The next methodology implemented was the NA method, again with segmentation. The mean squared error (MSE) is used to determine the number of hidden layer neurons after the MLP network has been trained. Using only 12 neurons in the hidden layer resulted in a faulty picture, thus MSE values were used to determine the number of hidden layer neurons. As you can see in the table, the MSE values for training the MLP network depend on the amount of hidden neurons you use.

Table 1 Training MSE values of the MLP network according to different numbers of hidden neurons

Number of hidden neuron layers	MSE values of MLP
4	5.12006e-04
6	4.13796e-04
8	4.14498e-04
10	4.14496e-04
12	4.09697e-04
14	1.27063e-03
16	2.93290e-03
18	2.12113e-03

Figures 2a and 2c illustrate the reconstructed 3D pictures generated by applying the MLP network with segmentation for noise reduction on images of stars and dice, respectively (Figures 2a–2d). Figures 2b and 2d demonstrate their 3D views for intensity distributions. Figures 3a–3d show the 3D perspectives for intensity distributions of the reconstructed 3D pictures generated using the NA technique and segmentation for star and dice images. It is possible to reduce noise in the reconstructed picture by utilising the NA network with segmentation, although this does not completely remove it. The MLP network with segmentation seems to be able to improve the reconstructed pictures in Figure 2.

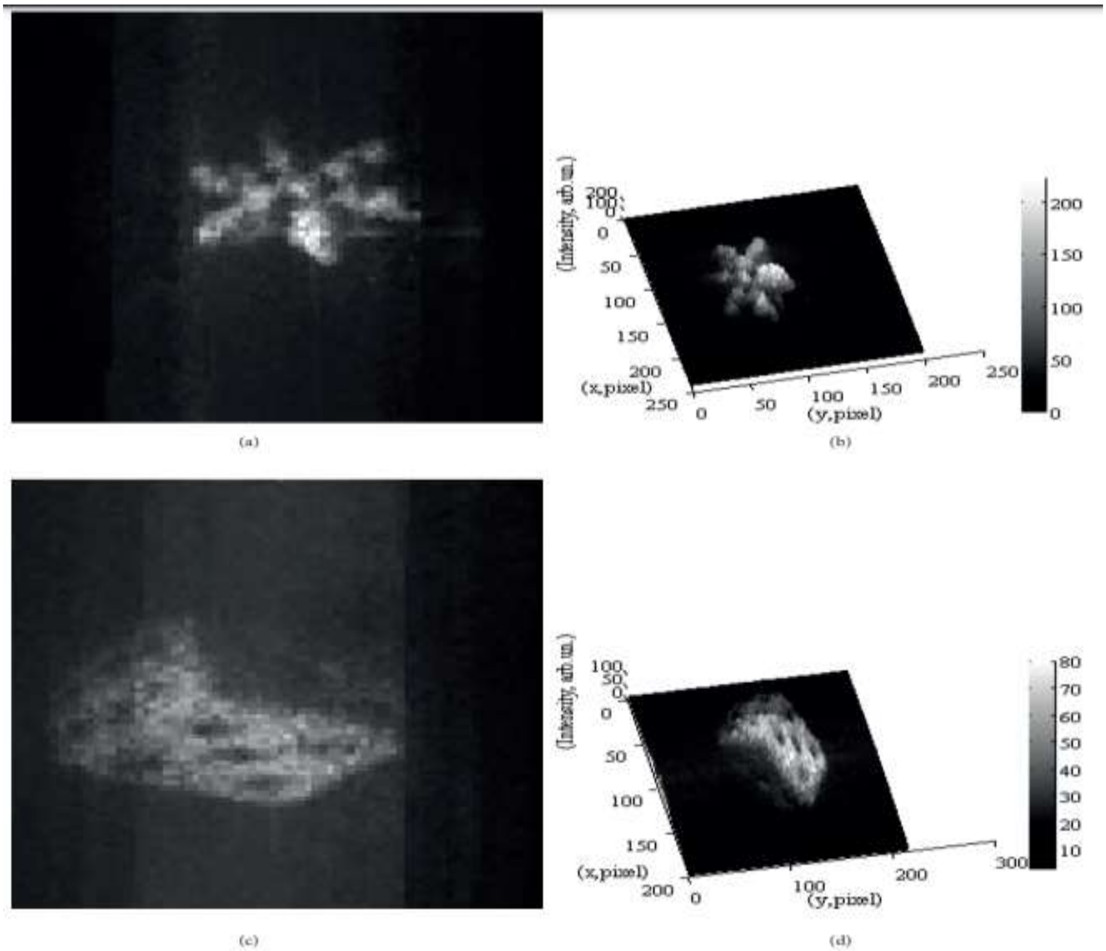
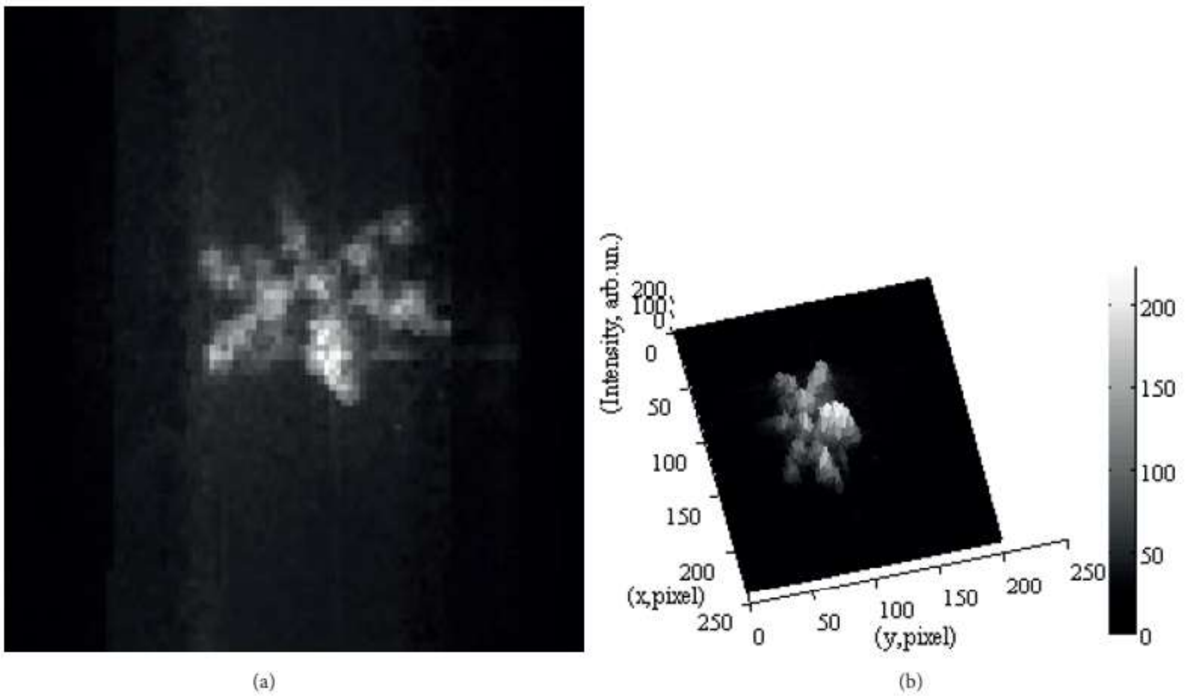
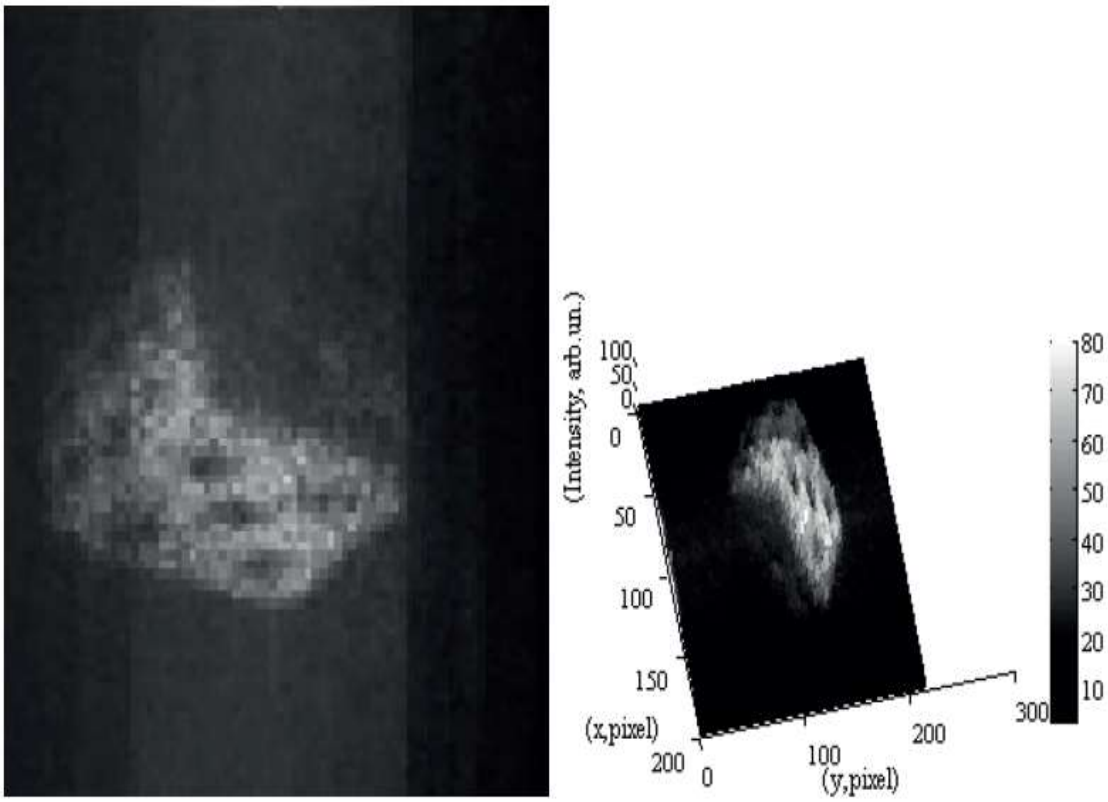


Figure 2. 3D reconstructed images obtained with the MLP network and their 3D perspectives for intensity distribution: a) 3D reconstructed star image, b) 3D perspective for intensity distribution of Figure 2a, c) 3D reconstructed dice image, d) 3D perspective for intensity distribution of Figure 2c





(c) (d)

Figure 2. 3D reconstructed images obtained with the MLP network and their 3D perspectives for intensity distribution: a) 3D reconstructed star image, b) 3D perspective for intensity distribution of Figure 2a, c) 3D reconstructed dice image, d) 3D perspective for intensity distribution of Figure 2c.

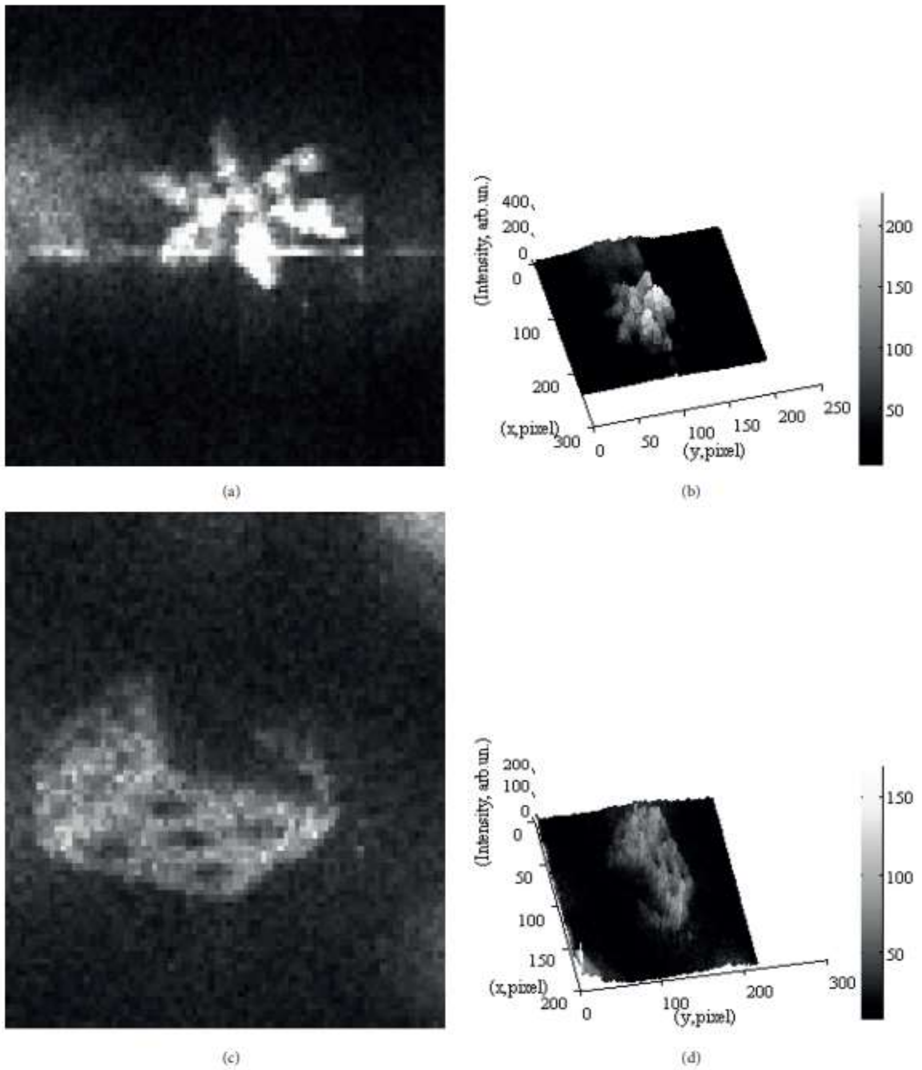


Figure 3: 3D reconstructed images obtained with the NA method and their 3D perspectives for intensity distribution: a) 3D reconstructed star image, b) 3D perspective for intensity distribution of Figure 3a, c) 3D reconstructed dice image, d) 3D perspective for intensity distribution of Figure 3c

Furthermore, the numerical calculations for removing noise from the reconstructed 3D pictures, which were done using MATLAB, are also included in this paper. As a result, the reconstructed pictures produced with and without segmentation are used to compute the relative errors for both approaches. It is revealed that 89% and 41% of the MLP network's pictures have relative errors of stars and dice, respectively. Due to the segmentation process's ability to reduce noise, the reconstructed pictures of the MLP network and the MLP network with segmentation have very different similarity ratios. A number of things are taken into consideration while calculating these inaccuracies. The percentages are 52% and 22%, respectively. These results are lower than those received via the MLP network (89 percent and 41 percent).

IV. CONCLUSION

This procedure has already been utilised in recent research, but no effort has yet been made to reduce noise in digital hologram reconstructions by using the segmentation process. For the first time, the application of the segmentation process to the MLP network and the NA approach is suggested here to improve the reconstructed 3D picture in digital holography. This idea aims to solve an issue that has arisen in image processing on a computer when there is a shortage of memory and huge pixel counts. As a result, the 3D views for intensity distributions are used to compare the picture quality of the MLP network and the NA technique with segmentation. Figures 1 and 2 show the findings from the MLP network, whereas Figures 3b and 3d show the results from the NA approach with segmentation. Figures show that the MLP network with segmentation may provide a result with low noise quite well. Relative errors are estimated for both approaches to corroborate the

3D perspective findings for the intensity distribution of star and dice reconstructed pictures. Error rates for the MLP and NA networks are respectively 89% and 41%, with a difference of 22% between them. Segmentation offers a better outcome for noise reduction when used with the MLP network than than the NA technique. According to our results, utilising the MLP network with segmentation produces a better picture with less noise than using the NA technique without segmentation.

5. REFERENCES

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