The following publication L. Zhou, Y. Xiao and W. Chen, "Learning Based Holographic Reconstruction through a Diffuser," 2019 PhotonIcs & Electromagnetics Research Symposium - Spring (PIERS-Spring), Rome, Italy, 2019, pp. 105-109 is available at https://doi.org/10.1109/PIERS-Spring46901.2019.9017656.

Learning Based Holographic Reconstruction through a Diffuser

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Abstract—Object recovery from speckle patterns has been extensively studied, and holographic reconstruction technique is verified to be highly effective for recovering objects. However, for the holograms recorded through scattering media, conventional holographic techniques cannot retrieve useful information from the holograms. In this paper, we present an approach based on convolution neural network (CNN) for holographic reconstruction through a diffuser. The object is placed behind a diffuser, and the corresponding hologram is recorded by a CCD camera. With pairs of holograms and their original objects sent to the designed learning structure, a CNN model is trained to perform unknown-object retrieval from the holograms. This learning-based approach can make predictions of the unknown test objects in real time. It provides a feasible structure to conduct object recovery from the holograms recorded through a diffuser.

1. INTRODUCTION

Imaging through scattering media is one of the hottest topics in recent years [1-7]. Over the years, much research work has been implemented to deal with inverse problems in imaging, e.g., transmission matrix (TM) and theoretical algorithms [4-8]. However, these methods fail to further recover the object from inhomogeneous media. Hence, it is necessary to explore an effective method to resolve the problem. Recently, machine learning methods have been developed rapidly, and have a great potential to resolve the ill-posed problems in optical fields [9]. Here, we present learning methods to reconstruct the objects recorded through a diffuser. With pairs of holograms and original objects sent into the designed neural network, a learning model is trained to predict the unknown test objects from the recorded holograms. This learning method for object reconstruction through a diffuser is verified to be a substitute of conventional holographic methods.

2. DEMONSTRATION and DISCUSSIONS

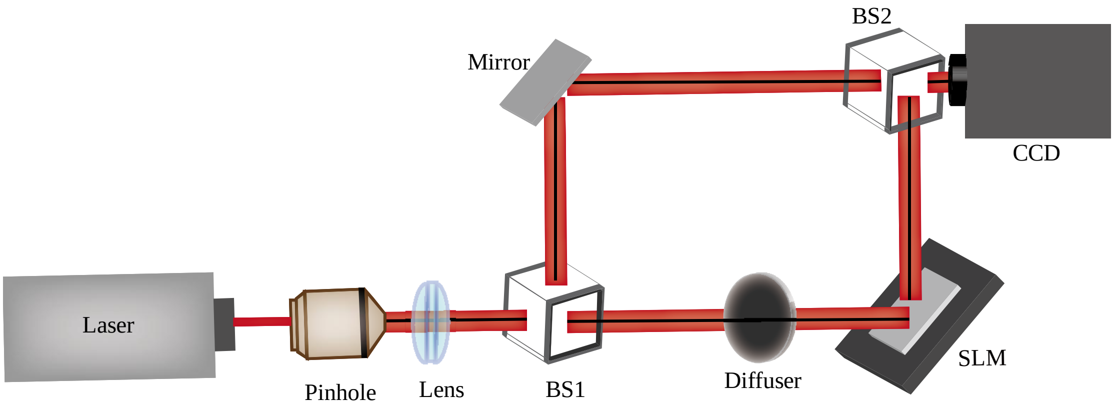

Figure 1. Schematic setup. SLM: Spatial light modulator; BS: Beam splitter cube.

Experimental setup for the presented method is shown in Fig.1. A He-Ne laser beam (Newport, R-30993, 633 nm) is collimated, expanded, and then divided by a beam splitter into two beams. One of the beams (called as object beam) passes through a diffuser, and then illuminates onto a spatial light modulator (SLM, Holoeye, LC-R 720, reflective). The SLM is used to work as an amplitude object. Another beam is called as reference beam. The two beams interfere with each other, and then the holograms are recorded by a CCD camera (Thorlabs, DCC3240M). It is found that conventional holographic algorithms cannot recover the objects from these holograms. Hence, more effective methods should be explored to resolve the problem. Here, a learning method is presented to retrieve the objects from the recorded holograms.
Both simulation and experimental results are presented to show the feasibility of learning methods for holographic reconstruction in scattering media. In holographic reconstruction simulation, original object is scattered by adding speckles. Here, a learning method is studied to directly reconstruct the

objects from the holograms as shown in Fig. 2. The learning model is divided into two parts, including training phase and testing phase. In the training phase, the inputs sent to the learning structure are the holograms recorded by the CCD camera. Then, the input convolves with 20 kernels to form the first convolution layer. To further reduce parameters of the network, processing of pooling is implemented to downsize the first convolution layer. After that, the first pooling layer convolves with 20 kernels again, and then the second convolution layer is downsized by the second pooling layer. The activation functions used in two convolution layers are sigmoid functions. Here, a fully-connected layer is used to reshape dimension of the second pooling layer to be equal to that of the ground truth. With 20000 pairs of handwritten digits from the MNIST database [10] and corresponding holograms sent to the CNN structure, the learning model is trained to predict unknown objects from the holograms obtained in the same condition. The cost function used to evaluate the difference between the output and the ground truth is mean squared error (MSE) given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2, \tag{1}$$

where n denotes the whole pixel number of the ground truth, Y_i and $\hat{Y}_i$ respectively represent pixel value of the ground truth and the output. The optimization function adopted to update the parameters (weights and bias) for the learning model is stochastic gradient descent (SGD) [11]. It is used to minimize the whole loss function $J(w,b)$ which is the sum of all the values of MSE in the training phase. The updating rule of SGD is defined as

$$w = w - v, \tag{2}$$

$$v = mv + \alpha\nabla J(\mathrm{w,b}), \tag{3}$$

$$b = b - v, \tag{4}$$

$$v = mv + \alpha\nabla J(\mathrm{w},b), \tag{5}$$

where the weights (w) and bias (b) are related to momentum m (-9.5×10^{-5}) and learning rate α (10^{-6}) and $\nabla J(\mathrm{w},b)$ is the gradient at w and b. The total training time is about 3 hours. Simulation results in the testing phase are shown in Fig. 3. It is obvious that the test objects are successfully reconstructed by using the trained learning model.

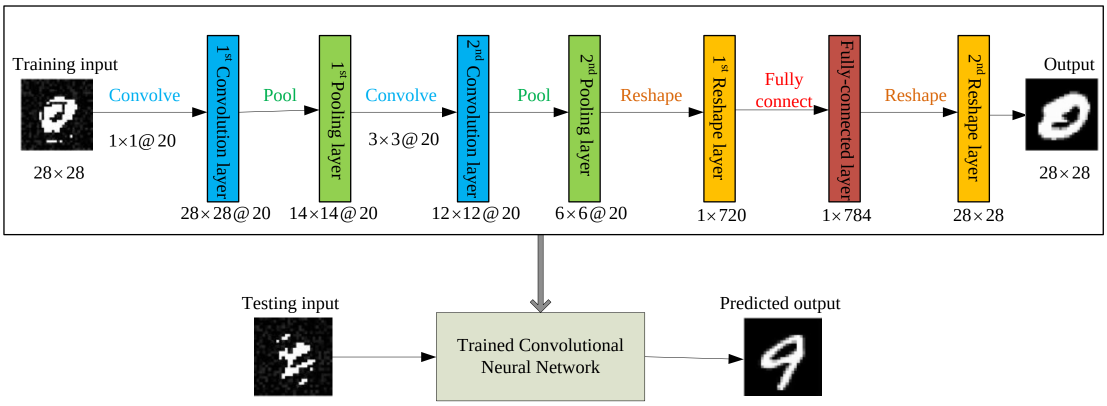

Figure 2. Schematic of the CNN architecture for simulation.

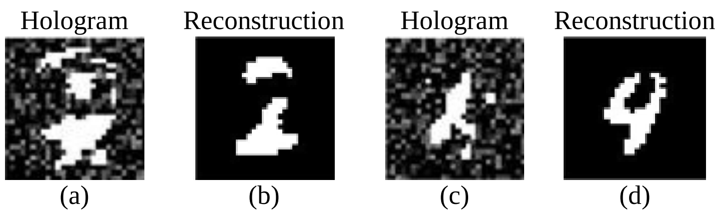

Figure 3. Simulation results in the testing phase: (a) and (c) recorded holograms, (b) and (d) their corresponding reconstructions.

Experimental demonstration of the learning method for holographic reconstruction is also carried out. The learning structure is shown in Fig. 4. The designed CNN architecture is comprised by 2 convolutional layers and 2 pooling layers, and then they are fully connected to a desired output.

Activation functions used in the convolution layers are sigmoid functions. Input data fed to the learning model is the recorded hologram, and output data is original object sent to the SLM. To lower down computational load of the model, size of the holograms is reduced to 100 pixels. It is verified that the cropped images contain sufficient information for the training phase. With 2000 pairs of holograms and their corresponding ground truths fed to the designed learning model, the model is trained to learn the mapping between the input and the output. Finally, the learning model can be applied to make predictions of the test objects from the recorded holograms in real time.

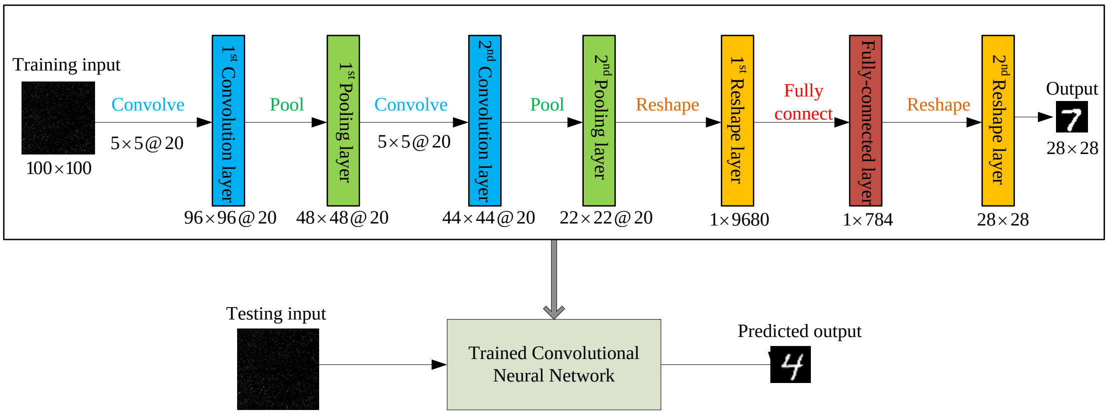

Figure 4. Schematic of the CNN architecture for experiments.

In the training phase, two databases (MNIST database and Fashion-MNIST database) [10,12] are used to train the designed learning model as shown in Fig. 5. 2000 recorded holograms are sent to the model as input, and their corresponding ground truths are sent to the model as output. Total time for training of each database is about 2 hours.

(a) Training of MNIST database

(b) Training of Fashion database

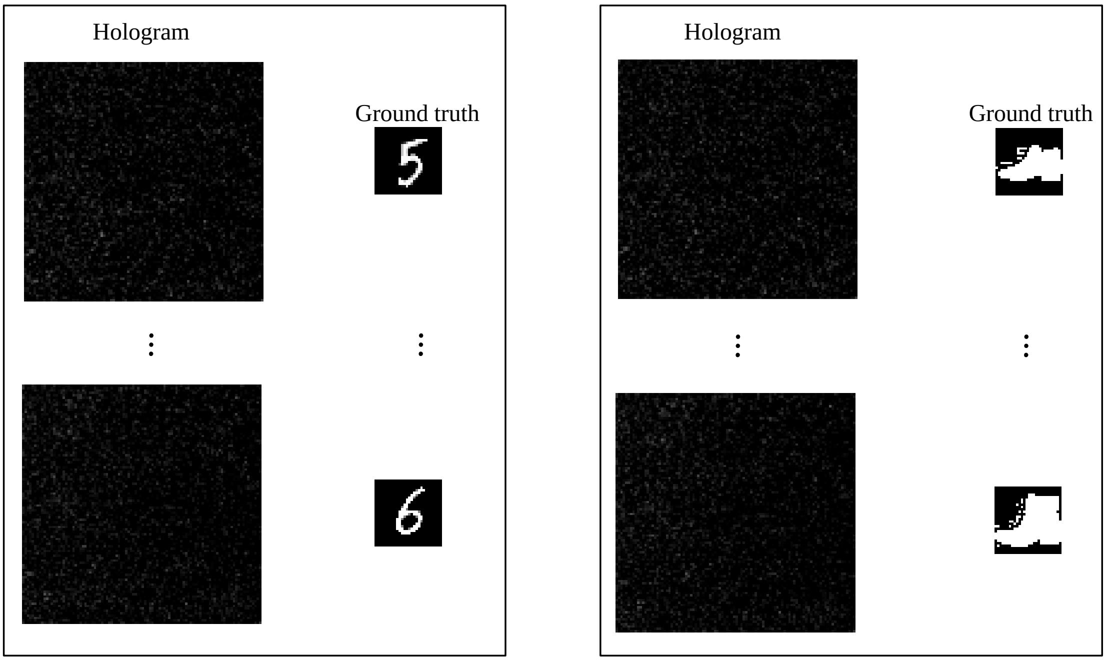

Figure 5. Two databases used in the training phase. (a) Training of MNIST database. (b) Training of Fashion-MNIST database.

After the training process, the trained learning model is used to retrieve unknown objects from the correspondingly recorded holograms in order to verify the effectiveness of the method. Figure 6 shows the experimental results in the testing phase. Recovered objects are shown in Figs. 6(b) and 6(d), and their PSNR (Peak Signal to Noise Ratio) values are $21.31dB$ and $18.64\ dB$, respectively. Hence, our learning model can be used to retrieve object from the recorded hologram in scattering media.

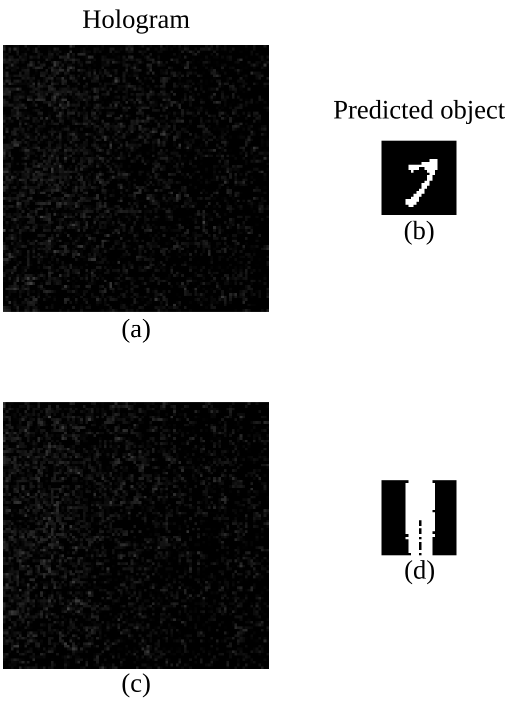

Figure 6. The testing phase: recovery of unknown objects from the holograms using the trained learning model. (a) and (c) The recorded holograms, (b) and (d) the recovered objects.

3. CONCLUSIONS

A CNN model for object reconstruction is presented to resolve the problems existing in conventional holographic methods in scattering media. Once the learning model is trained, it is feasible to make predictions of the test objects in real time. It provides a way for imaging through scattering media, and is expected to play an important role for imaging.

ACKNOWLEDGEMENTS

This work was supported by the National Natural Science Foundation of China (NSFC) (61605165) and Hong Kong Research Grants Council (25201416).

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