Optics Communications 413 (2018) 147–151

Contents lists available at ScienceDirect

Optics Communications

journal homepage: www.elsevier.com/locate/optcom

Computational ghost imaging using deep learning

Tomoyoshi Shimobaba [a,*], Yutaka Endo [b], Takashi Nishitsuji [c], Takayuki Takahashi [a], Yuki Nagahama [a], Satoki Hasegawa [a], Marie Sano [a], Ryuji Hirayama [a], Takashi Kakue [a], Atsushi Shiraki [a], Tomoyoshi Ito [a]

[a] Chiba University, Graduate School of Engineering, 1-33 Yayoi-cho, Inage-ku, Chiba, 263-8522, Japan
[b] Kanazawa University, Institute of Science and Engineering, Kakuma-machi, Kanazawa, Ishikawa 920-1192, Japan
[c] Mitsubishi Electric Corporation, Information Technology R&D Center, 5-1-1 Ofuna, Kamakura, Kanagawa, 247-8501, Japan

ARTICLE INFO

Keywords:
Computational ghost imaging
Ghost imaging
Deep learning

ABSTRACT

Computational ghost imaging (CGI) is a single-pixel imaging technique that exploits the correlation between known random patterns and the measured intensity of light transmitted (or reflected) by an object. Although CGI can obtain two- or three-dimensional images with a single or a few bucket detectors, the quality of the reconstructed images is reduced by noise due to the reconstruction of images from random patterns. In this study, we improve the quality of CGI images using deep learning. A deep neural network is used to automatically learn the features of noise-contaminated CGI images. After training, the network is able to predict low-noise images from new noise-contaminated CGI images.

1. Introduction

Computational ghost imaging (CGI) [1] has garnered attention in recent years as a promising single-pixel imaging method. In CGI, we project several known random patterns onto the object to be imaged and then use a lens to collect the light transmitted an object or reflected by an object. The light intensities are measured by a bucket detector, such as a photodiode. An image of the object is then created by calculating the correlations between the known random patterns and the measured light intensities. CGI can image objects even in noisy environments.

Originally, CGI only measured the light intensity of objects, but methods have also been devised for measuring its phase [2,3]. The acquisition time for CGI schemes is long as they require a large number of illuminating random patterns to objects. Recently, the situation has been improved by using high-speed random pattern illumination [4,5]. In addition, three-dimensional [6] and multi-spectrum CGI [7] have been developed.

Since random patterns are used to create the object images, the reconstructed images are contaminated by noise. To improve the quality of CGI images, improved correlation calculation methods have been devised, such as differential [8] and normalized CGI [9]. Iterative optimization schemes based on the Gerchberg–Saxton algorithm [10] as well as compressed sensing [7,11] have also been applied to CGI.

In this study, we propose an approach to improve CGI image quality by using deep learning [12] and confirm our technique's effectiveness through simulations. Deep neural networks (DNNs) can learn features for the noisy images reconstructed by CGI schemes automatically. We used a dataset of 15,000 images and their CGI reconstructions to train a network. After training, the network could predict lower-noise images from new noisy CGI images that were not included in the training set. In Section 2, we describe our DNN-based CGI scheme. Section 3 presents the simulation results and demonstrates the effectiveness of the proposed method. Finally, Section 4 presents the conclusions of this study.

2. Proposed method

In this section, we first outline the CGI scheme used and then we describe the architecture of the DNN.

2.1. Computational ghost imaging

We use a differential CGI [8] scheme because its image quality is superior to that of traditional CGI [1]. The optical setup required for differential CGI is shown in Fig. 1.

* Corresponding author.
E-mail address: shimobaba@faculty.chiba-u.jp (T. Shimobaba).

https://doi.org/10.1016/j.optcom.2017.12.041
Received 20 October 2017; Received in revised form 13 December 2017; Accepted 15 December 2017
0030-4018/

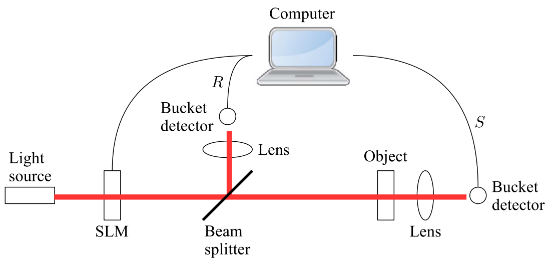

Fig. 1. Optical setup for differential CGI.

In this scheme, a sequence of random patterns is shown on a spatial light modulator (SLM). We denote the ith random pattern as $I_i(x, y)$. The light transmitted by the SLM is divided into two beams by a beam splitter. One beam then irradiated the object to be imaged, and the light transmitted by the object is collected by a lens, and its intensity S_i is measured by a bucket detector for each $I_i(x, y)$. The other beam is immediately focused by a lens, and its intensity R_i is measured by another bucket detector for each $I_i(x, y)$. The final image $O(x, y)$ that is reconstructed by differential CGI is then calculated as follows:

$$O(x, y) = \langle O_i(x, y)\rangle_N, \tag{1}$$

where $\langle a_i\rangle_N = \frac{1}{N}\sum_i^N a_i$ denotes the ensemble average over all N random patterns. The $O_i(x, y)$ are calculated as follows:

$$O_i(x, y) = \left(\frac{S_i}{R_i} - \frac{\langle S_i\rangle_N}{\langle R_i\rangle_N}\right)\left(I_i(x, y) - \langle I_i(x, y)\rangle_N\right). \tag{2}$$

As can be seen from Eq. (2), the reconstructed image is expressed as a superposition of the random patterns; thus, the resulting image is noisy. Fig. 2 shows a series of example images that are reconstructed by differential CGI. The images are arranged from left to right in such a manner that the original image is followed by images that are reconstructed using $N = 1,000$, 2,000, 5,000, and 10,000 patterns. As the number of random pattern N increases, the image quality gradually improves. However, it increases the processing and measurement time of differential CGI.

2.2. Improving image quality using a deep neural network

In this study, we use a DNN to improve the quality of CGI images. Fig. 3 shows the proposed network structure which is called U-Net [13]. This network was originally used for image segmentation, but it can also be used for image restoration [14].

The network consists of the following two paths: a constructing path and expansive path. These paths include convolution, max-pooling, and up-sampling layers denoted as "Conv", "MaxPooling" and "UpSampling", respectively. The convolution layers generate feature maps for

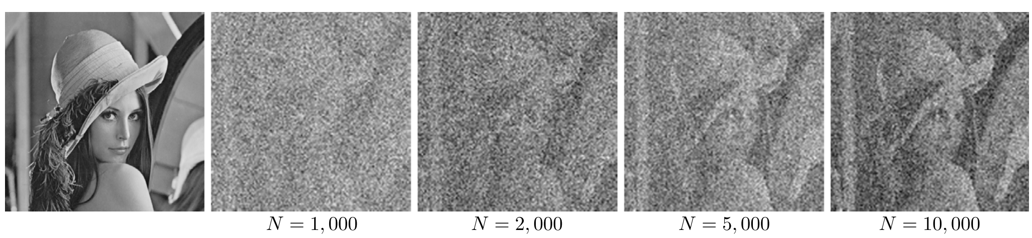

Fig. 2. Example images reconstructed by differential CGI. From left to right, these are the original image that is followed by images reconstructed using $N = 1,000$, 2,000, 5,000, and 10,000 patterns.

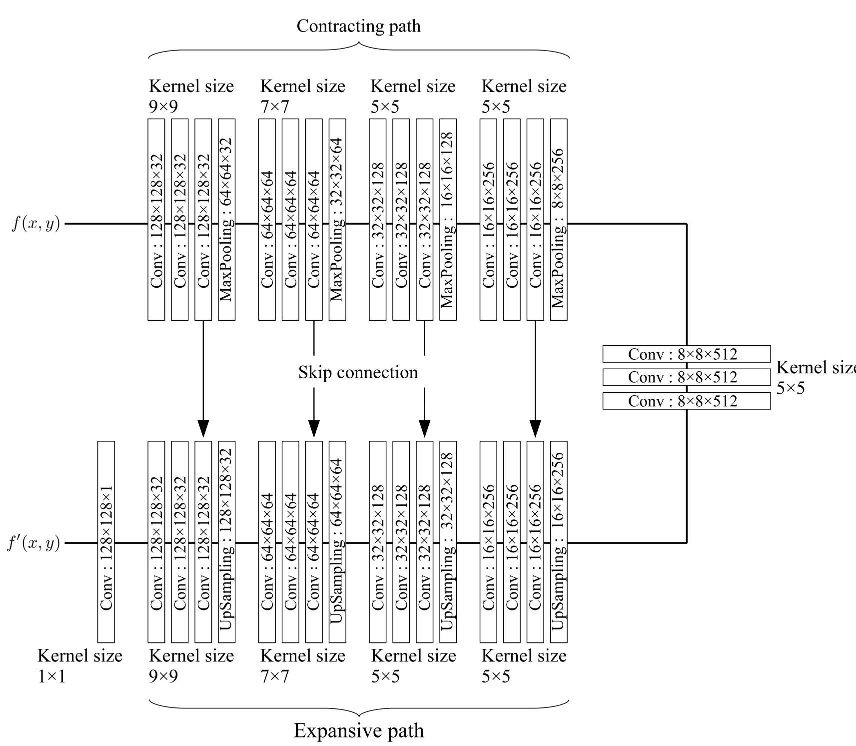

Fig. 3. Our network structure [13]. This network was originally used for image segmentation, but, it can be also used for image restoration [14].