Image Quality Enhancement of Ghost Imaging by Using Gradient Descent

Ikuo Hoshi[1], Tomoyoshi Shimobaba[1], Takashi Kakue[1], Tomoyoshi Ito[1]

E-mail: aeka2345@chiba-u.jp

[1]Guraduate School of Engineering, Chiba University

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ABSTRACT

Ghost imaging reconstructs images only using a single element detector. It has a various advantage. However, one of the challenges is low image quality in undersampling. In this study, we improve the image quality of reconstructed images by using gradient descent.

1 INTRODUCTION

Conventional imaging methods record an image with pixel-array composed of many light detectors such as CCD (Charge-Coupled Device). In contrast, ghost imaging [1,2] is a technique which performs imaging only using a single-element photodetector. From the feature, ghost imaging has various advantages that are capable of imaging in low light environments and in broad wavelength, which is difficult for CCD and CMOS cameras.

As shown in Fig. 1, illumination patterns with a random binary distribution $I_i(x, y)$ are first projected on a target object. The scattered light (or transmitted light) from the target object $T(x, y)$ is collected by a lens as light intensity S_i and recorded it by a single element photodetector. Measured data is obtained by sequentially illuminating the patterns. Finally, we obtain the target object's reconstructed image by performing a correlation calculation between the recorded measured data and the known illumination patterns.

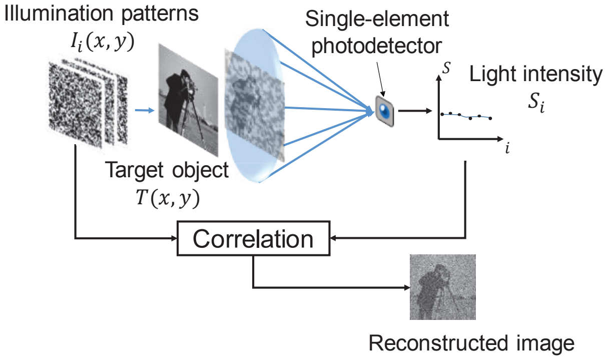

Fig. 1 Schematic of ghost imaging

One of the challenges in ghost imaging is that reconstructed image quality decreases due to a sufficient number of the measurement not allowed by requiring measurement time to illuminate many patterns. Various methods have been proposed to solve the challenge. One of these methods is to improve the image quality by using basis patterns instead of random patterns. The Hadamard basis [3] is well known as a basis pattern. Ghost imaging using basis patterns certainly improves the image quality even if in undersampling. However, it is hard to improve the resolution of the reconstructed image while maintaining undersampling with that reconstruction methods. The resolution depends on the number of illuminating patterns. Therefore, in undersampling, ghost imaging requires patterns that can both improve resolution and image quality.

This study improves the resolution and image quality in undersampling by optimizing illumination patterns using gradient descent. Besides, we evaluated the resolution and image quality of the proposed method compared to conventional random patterns and basis patterns.

2 PROPOSED METHOD

The proposed pattern optimization is shown in Fig. 2. The measurement system of the proposed method is the same as the conventional method shown in Fig. 1. In the optimization, we prepare the image dataset, mnist and simulate the measurement system to obtain light intensities of each image in the dataset. Subsequently, we perform the image reconstruction

To optimize the patterns, we define a loss function E that is the error between reconstructed image and target object. That is, the loss function minimizes the error by updating the illumination patterns.

We use the gradient descent. The gradient of the illuminated patterns for the loss function is calculated and the patterns are updated by using the gradient obtained. The update calculation is shown with the learning rate η as follow,

$$I_i(x, y)_{new} = I_i(x, y) - \eta \frac{\partial E}{\partial I_i(x, y)} \quad . \qquad (1)$$

This procedure is repeated while changing the target object (images in the dataset) to obtain optimized patterns.

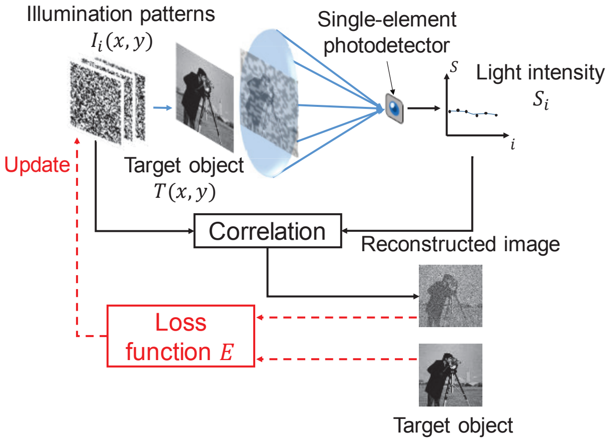

Fig. 2 Procedure of the update of patterns

In this study, we adopted DGI (Differential Ghost Imaging) [4] as the correlation calculation. The DGI is shown as follow,

$$O(x,y)=\langle S_i I_i(x,y)\rangle-\frac{\langle S_i\rangle}{\langle R_i\rangle}\langle R_i I_i(x,y)\rangle, \quad (2)$$

$O(x,y)$ represents a reconstructed image. The subscript i represents the index of patterns. $\langle\ \rangle$ represents the ensemble average. S_i and R_i represent a light intensity illuminated $i$the pattern onto a target object and total light intensity of the pattern. Each equation is as follow,

$$S_i=\iint T(x,y)\,I_i(x,y)\,dxdy\ , \quad (3)$$

$$R_i=\iint I_i(x,y)\,dxdy\ . \quad (4)$$

We adopted mean squared error as the loss function E shown as follow,

$$E=\sum_y^Y\sum_x^X\left(O(x,y)-T(x,y)\right)^2\ , \quad (5)$$

where X and Y indicate the number of pixels in the reconstructed image $O(x,y)$ and the target object $T(x,y)$.

3 SIMULATION AND RESULT

In this section, we evaluated the proposed method by numerical simulation. In this study, we used to calculate gradients of illuminating patterns by the solver of the gradient descent of Eq.(1) implemented in Keras, which is often used in deep learning. The number of illuminating patterns was set to 512 in all simulations. For the basis patterns, we used the origami patterns [5] that were devised from the Hadamard basis. We show the comparison results between each reconstructed image in Fig. 3. The size of the reconstruction images is 64×64 pixels. In addition, we offer quantitative evaluations in Table 1. The PSNRs and SSIMs were used for the evaluation.

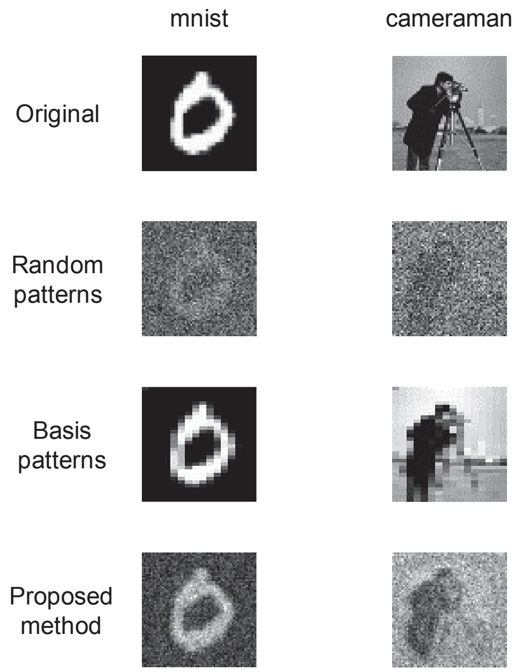

Fig. 3 Comparison of the reconstructed images

Table 1 Quantitative evaluation

		MNIST	Cameraman
Random	PSNR[dB]	8.04	12.64
	SSIM	0.07	0.14
Basis	PSNR[dB]	19.30	14.33
	SSIM	0.83	0.64
Proposed	PSNR[dB]	11.24	13.76
	SSIM	0.25	0.23

Next, Fig. 4 shows reconstructed images when changing the resolution of the patterns. The number of pixels is 32×32 and 64×64.

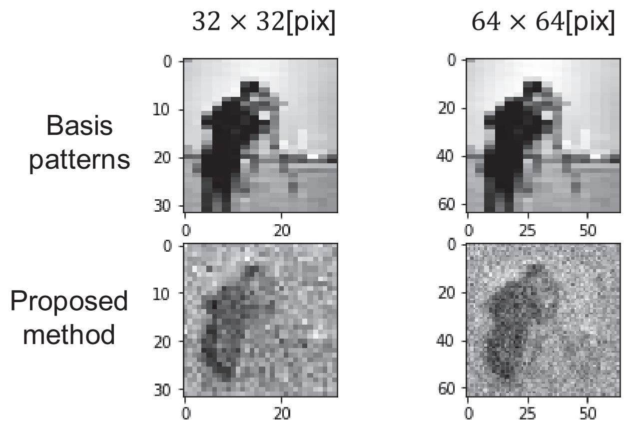

Fig. 4 Comparison of reconstructed images when changing the resolution of the patterns.

4 DISCUSSION

4.1 Image Quality

From the comparison between the random patterns and optimized patterns (proposed method), we confirmed that image quality improved in qualitative and quantitative evaluations. From the comparison between the basis patterns and optimized patterns, the image quality with the basis patterns was better than that with the optimized patterns. It seems to be caused by the optimized patterns that cannot remove the noise enough. However, thanks to the proposed method mimic deep learning, it can incorporate a variety of deep learning techniques, which could improve image quality.

4.2 Resolution

The resolution of the reconstructed images in the basis patterns of 32×32 and 64×64 pixels is almost the same. In contrast, we confirm that the resolution of the proposed method increases. It is the effectiveness of the proposed method.

5 CONCLUSIONS

We proposed optimized patterns for improving the image quality of ghost imaging reconstruction without sacrificing resolution than conventional random pattern illumination. As a result, we succeeded in improving the image quality without the drawbacks of low resolution in the basis patterns. In the future, we will enhance further image quality and larger resolution by incorporating deep learning techniques.

Acknowledgments

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