An Effective Computational Ghost Imaging Based on Noise Estimation and Elimination

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ABSTRACT To improve the quality of ghost image, we propose an efficient computational ghost imaging method in this article. The primary idea is to estimate the noise value of the ghost image by analyzing and eliminating the source of the noise. The innovativeness of this work lies in analyzing a new means of noise by dissecting the qualitative relationship between transmittance in different objects and speckle patterns. While using a scale factor to describe the change of transmittance at different points of the object. The simulation and experimental results prove the effectiveness and feasibility of the proposed method through two parallel experiments. Compared to other methods, the peak signal-to-noise ratio and contrasts both have significantly increased.

INDEX TERMS Computational ghost imaging, speckle pattern, source of the noise, peak signal-to-noise ratio, contrast.

I. INTRODUCTION

Since the pioneering work by Pittman et al. [1], ghost imaging (GI) has attracted significant attention as a novel imaging technique. With GI, two spatially separated but correlated beams of light [2]–[5] can reconstruct the image of an object. One is the reference beam that does not interact with the object but a pixelated detector records it. The other is the object beam that goes through or illuminates the object of interest, and is collected by a bucket detector. It was initially believed that the two beams are a stream of entangled photon pairs [6]–[8], but later it was discovered that such astringent demands could be lifted [9]–[11]. Since then the classical thermal or pseudo-thermal light has also been used for achieving ghost imaging as long as the two beams are correlated. With the advancement of digital projection technology, computation has become an effective method of image reconstruction. This enables GI to be implemented by a digital projection of images and mathematical computations, referred to as computational ghost imaging (CGI) [12]–[15].

An interesting implementation of CGI involves employing a set of speckle patterns generated by a laser striking and a spatial light modulator (SLM). A digital computer controls the whole process. As the speckle patterns are pre-designed, there is no need to record them. Hence, the imaging system can be simplified by removing the pixelated detector on the reference arm [16]–[18]. In addition, a digital projector can be also be utilized to create the speckle patterns, so the system can further be simplified by the removal of the laser and the SLM [19]. However, the resolution of GI is limited by the intensity fluctuations of the light field. This lowers the quality of GI than the quantum GI. Therefore, improvement of the quality of CGI has been a challenge that has attracted significant attention [20]–[26].

Many approaches have been proposed to solve this quality improvement problem. Ferri et al. [26] presented a technology for improving the signal-to-noise ratio (SNR) of GI, namely, differential ghost imaging (DGI). In this method, any unbalance (beam splitters and detectors) between the reference beam and object beam are considered as factors. These unbalances have been described with a noise term. The quality of the ghost image has improved after subtracting the noise term. Because the noise coefficient is constant for each pixel point, the enhance-effect of the DGI is relatively limited. Obviously, it is not reasonable as the severity of the noise is closely related to the transmittance of the illuminated object itself. Iterative computation is used in GI [27]–[29] to further reduce the noise term. Yao et al. [27] presented
a method to de-noise GI by iteration process. The blurring influence of the speckle areas in the beam was reduced in the iteration by setting a threshold. To facilitate the selection of threshold, Zhou et al. [28] proposed an adaptive threshold method to achieve GI. In this method, the peak signal-to-noise ratio (PSNR) has been improved obviously, but the complexity of the computation has also been greatly increased. Meanwhile, more researchers gradually realized that the non-orthogonality of the random speckle field was the main factor for causing noise. Shibuya et al. [30] compared the reconstructed images between ghost imaging and Hadamard transform imaging. Wang and Zhao [31] presented a method to deal with the contradiction between the reconstruction time and the image quality. Hadamard pattern pairs have been used to illuminate an object and generate pairs of detection results, in this method. The corresponding differential detection result is used further. Sun et al. [32] proposed a compressive single-pixel imaging by Hadamard pattern, which can utilize the sparsity in general scenes while avoiding the need for a time-consuming computational overhead. Yu et al. [33] proposed a single-pixel compressive imaging method based on “cake-cutting” Hadamard basis ordering, which is capable of precisely reconstructing images of large resolution from super sub-Nyquist measurements. However, Hadamard pattern can cause distortion or double shadow of ghost image under non-full sampling condition, seriously affecting the quality of imaging. To avoid this, we proposed a new orthogonal speckle field to improve the quality of the ghost image [34]. In our method, two orthogonality sinusoidal pattern pairs have to illuminate the object simultaneously. Then a bucket detector has collected the light intensity of passing through an object. The numerical simulation and experimental results show that the imaging quality has remarkably improved.

From here, we see that the orthogonality speckle field is better than a random speckle field for avoiding the noise of ghost image. However, the problem of noise has not been entirely inhibited because the noise term includes two parts: one is introduced by the speckle field; the reconstruction algorithm causes the other. Therefore, the speckle field and noise are some kinds of paradoxes that cannot fundamentally improve the quality of the GI using the orthogonality speckle field. The most important thing is to find a way to analyze and eliminate noise.

In order to analyze and eliminate the noise in the GI, we propose a new reconstruction algorithm that is based on the principle of second-order correlation calculation, and we regard the auto-correlation of speckle patterns as a basic noise term. Then the noise term can be eliminated by a different method. This method can reconstruct the object with the variable scale factor and is suitable for both single-beams and double-beams. This factor can describe the change of transmittance at different points of the object. Simulations have demonstrated that the proposed method has high resolution with peak signal-to-noise ratio and contrast.

II. NOISE SOURCE ANALYSIS IN CGI

In this section, an experimental setup with a digital light projector (DLP) as an example has been taken [16]. Figure 1 shows a DLP that is driven by a computer and produces a series of speckle patterns, denoted by $I_a(x, y; n)$. Here, $n(n = 1, 2, 3 \cdots)$ is the discrete-time index. Note that all speckle patterns are independently generated, that is, $I_a(x, y; n)$ is independent of $I_a(x, y; m)$ where $m \neq n$. These speckle patterns pass through the object of interest and then a bucket detector collects them. The image of the object can be considered as the fraction of the incident light that is transmitted through the object, referred to as the transmittance $T(x, y)$. Hence, the purpose of CGI is to determine $T(x, y)$.

Without loss of generality, let us consider that a speckle pattern passes through the object, denoted by $I_b(x, y; t)T(x, y)$. Then the intensity of light collected by the bucket detector is

$$I_b(n) = \sum_{x,y} I_a(x, y; n)T(x, y)$$  

(1)

Therefore, the bucket detector wraps the spatial information $T(x, y)$. In order to reconstruct $T(x, y)$, the following is calculated [33], [34]:

$$\hat{T}(x, y) = \langle I_b(n) \cdot I_a(x, y; n) \rangle - \langle I_b(n) \rangle \cdot \langle I_a(x, y; n) \rangle$$

$$= \sum_{u,v} I_a(u, v; n)T(u, v) \cdot I_a(x, y; n) - \sum_{u,v} I_a(u, v; n)T(u, v) \cdot \langle I_a(x, y; n) \rangle$$  

(2)

where $\langle \cdot \rangle$ denotes the correlation operation, and it can be implemented by an average over time. The first term is the correlation between the output of the bucket detector and the recorded pattern $I_a(x, y; n)$, and the second term is the product of the averages $I_b(t)$ and $I_a(x, y; n)$.

However, the poor quality of ghost imaging is an objective fact by Equation (2). To demonstrate this, we carried out a set of experiments on three objects depicted in Figure 2. Here, twenty-thousand $128 \times 128$ random speckle patterns are generated independently to illuminate onto the object, each of which is collected by a bucket detector.

It is obvious from Figure 2 that the ghost images still contain a significant level of noise. To eliminate the noise term of ghost image, we take a specific object with $T(x, y) = D$ for any $(x, y)$ and $D$ is a constant

![FIGURE 1. Schematic diagram of the experimental setup of CGI.](image-url)
between 0 and 1. Figure 3 demonstrates the results of experiments on five special objects, whose transmittances are 1.0, 0.8, 0.6, 0.4, and 0.2. Here, the intensity of a pixel \((x, y)\) obeys the random Gaussian distribution. To visually highlight the difference of the five objects, the color scheme of the image is taken as copper in the figure.

In the ideal case, the object \(D = 1\) can be considered as a full-transmitted object, and the ghost image can do auto-correlation processing for speckle patterns. Hence, the auto-correlation of speckle patterns is also the main cause of noise when reconstructing the object by Equation (2).

For the object with \(T (x, y) = D\) for any \((x, y)\), Equation (2) can be predigested as following:

\[
\hat{T}(x, y) = \left\{ \sum_{u,v} I_0(u, v; n) T(u, v) \cdot I_0(x, y; n) \right\} - \left\{ \sum_{u,v} I_0(u, v; n) T(u, v) \cdot \langle I_0(x, y; n) \rangle \right\} = D \times N^* \quad (3)
\]

where \(N^*\) is the auto-correlation function of speckle patterns.

The proportional relationship between reconstructing term \(\hat{T}(x, y)\) and auto-correlation term \(N^*\) is represented by Equation (3). To demonstrate its universality, we added three more experiments with random speckle patterns under other distribution types, such as Uniform, Exponential, and Poisson. The histogram of ghost images is shown in Figure 4.

From the perspective of shaping in Figure 4, the histograms of the CGI with different transmissions approximately satisfy the Gaussian distribution. That is consistent with the randomness of the random speckle patterns. The distribution of the histogram moves to the left along the horizontal axis as the transmittance decreases, and that is similar to the conclusion of Equation (3). In addition, we repeated the experiment with other kinds of speckle patterns, such as Hadamard and orthogonal sinusoidal, and they also yielded the proportional relationship between the reconstructed and auto-correlation terms.

Above all, it is reasonable to consider \(D\) as a scale factor. The attenuation degree of speckle patterns gradually increases when \(D\) decreases, so that the proportion of noise decreases in \(N^*\). Hence, the reconstructed term \(\hat{T}(x, y)\) is actually equivalent to the noise term for objects with the same transmittance, and is the result of speckle patterns.

For facilitating description, let we consider \(N^*\) as a basic noise and move it to the origin; then the noise term is represented as follows:

\[
\text{Noise} = \begin{cases} D \times (N^* - m) & T \neq 1 \\ N^* & T = 1 \end{cases} \quad (4)
\]

where \(m\) is the midpoint of the histogram horizontal axis of \(N^*\) and \(D\) is a scale factor depending on the transmittance function. Evidently, the contraction degree of the object has increased as the transmittance decreased.

### III. THE VARIABLE SCALE COMPUTATIONAL GHOST IMAGING (VSCGI)

In order to reduce the influence of noise, we attempt to eliminate the magnitude of Equation (4). A simple method is to subtract the same amount of noise from the resulting ghost image in Equation (2). With this, we are able to obtain the improved ghost image:

\[
\hat{T}_1(x, y) = \begin{cases} \hat{T}(x, y) - D \times (N^* - m) & T \neq 1 \\ \hat{T}(x, y) - N^* & T = 1 \end{cases} \quad (5)
\]

Therefore, we can make the following changes to the schematic diagram of CGI as shown in Figure 5.

Obviously, the key problem in Equation (5) is how to determine the specific expression \(D\). However, for the object with \(T(x, y) \neq 1\), the values of the object before and after illuminating are \(\{I_0(x, y)\}\) and \(\{I_b\}\) respectively, so the maximum value of \(D_{\text{max}}\) is

\[
D_{\text{max}} = \langle I_b \rangle / \langle \sum I_0(x, y) \rangle \quad (6)
\]

That is to say, the value of \(D\) ranges from zero to \(D_{\text{max}}\), especially, when \(\{I_b\} = \{\sum I_0(x, y)\}, D_{\text{max}} = 1\).

To further determine the expression \(D\), we carried out another experiment with two objects. Here, the average transmittance of the two objects is the same: the transmittance of background and target images are 0.3/0.7 and 0.1/0.9, respectively. Then 20,000 speckle patterns with \(128 \times 128\) pixels are independently generated to illuminate onto the object. The ghost images and histograms obtained by CGI as shown in Figure 6, and the PSNR are 5.8121 and 4.1949, respectively.
For further analysis, we repeated the above experiment 50 times. The PSNR curves are shown in Figure 7. Here, PSNR1 is the PSNR of ‘+’, in which the transmittance of background and target are 0.3 and 0.7. PSNR2 is the PSNR of ‘−’, in which the transmittance of background and target are 0.1 and 0.9.

From Figure 7, the PSNR of low contrast is better than the high contrast because, for an object with a non-zero binary image, the transmittance of backgrounds and targets can be considered as two targets. Since the histograms of ghost images with different transmissions approximately obey Gaussian distribution, it can, therefore, be regarded as a superposition of the Gaussian distribution of different mean values. Therefore, the two histograms of the background and target under low contrast are much more concentrated than those under high contrast that can be very intuitively represented through Figure 8.

Therefore, the reconstructed object is of CGI, whose background and target with low contrast are much closer to the object, and the PSNR is larger. That is because the mean values of background and target under low contrast are closer than those under high contrast.
For enhancing the resolution of ghost image, two facts need to be considered in CGI. One is the transmittance of the illuminated object, while the other one is the contrast between the background and the target. It is known that the process of object detection and image reconstruction are completely separate in CGI. In order to obtain the transmittance of the unknown object, and the specific expression of object in advance, we utilize the result of CGI to separate in CGI. In order to obtain the transmittance of the background and the target. It is known that the process

\[ \hat{T}(x, y) = \frac{\hat{T}(x, y) - \min(\hat{T}(x, y))}{\max(\hat{T}(x, y)) - \min(\hat{T}(x, y))} \]

By combining Equations (5) and (7), we are able to reconstruct the unknown object. To make the reconstructed object smoother, we define the image reconstruction as follows,

\[ \hat{I}_1(x, y) = \begin{cases} 0 & \hat{I}_1(x, y) < 0 \\ t & \hat{I}_1(x, y) > t \end{cases} \]

Now, we find out that Equation (5) is very similar to the reconstruction Equation of DGI [26].

\[ \hat{T}_1(x, y) = \hat{T}(x, y) - \frac{\langle b \rangle}{\langle a(x, y) \rangle} \times N^* \]

By contrast, there are two important differences: one is that \( D \) is a scale factor as the transmittance varies in this article, while \( D \) is a constant in DGI; the other one is that the reconstruction image has been smoothing to reduce image sharpness by Equation (8).

Although CGI is the improved method of the GI that only has a signal path, the proposed method can still be available for GI because \( N^* \) and \( D \) can be obtained by a pixelated detector in the reference beam and computational derivation, respectively. Therefore, this method has wide applicability in double-beam and single-beam ghost imaging.

To compare the quality of ghost images quantitatively, PSNR and contrast \((\text{Con})\) are used as objective evaluation indices, defined as:

\[ \text{PSNR} = 10 \cdot \log_{10} \left( \frac{(2^n - 1)^2}{\text{MSE}} \right) \]

where \( \text{MSE} = \frac{1}{M} \sum_{x,y} (\hat{T}(x, y) - T(x, y))^2 \) is the mean square error \((\text{MSE})\), \( T(x, y) \) and \( \hat{T}(x, y) \) are the transmittance of the true and reconstructed object, respectively. \( M \) is the number of pixels of the ghost image, \( n \) is the number of bits and is usually about 8.

\[ \text{Con} = \frac{\hat{I}_{1,\text{Obj}} - \hat{I}_{1,\text{Back}}}{\hat{I}_{1,\text{Obj}} + \hat{I}_{1,\text{Back}}} \]

\( \hat{I}_{1,\text{Obj}} \) and \( \hat{I}_{1,\text{Back}} \) are the intensity values of the transmittance zone and the impermeability zone.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we carried out some examples and numerical simulations to show the validity and reasonability of the proposed method. Besides, in the following examples, a digital light projector has generated the \( 128 \times 128 \) pixels speckle pattern to illuminate onto the object.

a. In the first experiment, three objects have been illuminated with random uniform speckle patterns \((\text{total} \ (20,000 \ \text{patterns}))\), and then detected by the bucket detector. The ghost images have been compared with CGI and DGI, and are shown in Figure 9.

![FIGURE 9. Comparison of example results.](image-url)
By comparing the results of Table 1, we can know that the PSNR and Con are better degrees of improvement for the VSCGI than CGI and DGI, and this is the consistent with the imaging theory. For the three objects, the PSNR/Con of VSCGI are improved 38.01%/255.75%, 31.05%/226.73%, and 36.17%/324.05% than that of CGI, and improved 29.75%/202.77%, 22.33%/167.13%, and 25.97%/210.11 percentage than that of DGI. Therefore, the minimum improvement of PSNR and Con is 22.33% and 167.13%, respectively.

In order to highlight the advantages of the proposed method, we repeated the experiment 20 times, and the PSNR and Con curves of different methods are shown in Figure 10. The PSNR3/Con3 curves of VSCGI are much bigger than PSNR2/Con2 of DGI and PSNR1/Con1 of CGI in any case. The results of these experiments show that the combination of the auto-correlation of speckle patterns and $D$ is indeed an effective means to analyze and estimate the noise term in GI. This method can dramatically improve the quality of GI with a single reconstruction. It is worthwhile to note that this method can also be applied in iterative denoising of GI.

Three objects have been illuminated with orthogonality speckle fields, such as Hadamard speckle field (totals 14,000 patterns) and orthogonality sinusoidal speckle field (totals 10,000 patterns) in the second experiment. The ghost images are shown in Figure 11, and the PSNR and Con are shown in Table 2. Here, PSNR1/Con1 is the PSNR/Con of CGI, PSNR2/Con2 is the PSNR/Con of DGI, and PSNR3/Con3 is the PSNR/Con of VSCGI.

From Figure 11, it is obvious to see that PSNR3/Con3 of VSCGI in this article is clearly higher than PSNR/Con of CGI and DGI.

As a result of Figure 11 and Table 2, the proposed method can almost reconstruct the object completely in non-full sampling conditions. In Hadamard speckle field conditions, the PSNR/Con of VSCGI is improved by 15.64%/79.79%, 16.86%/64.55%, and 92.21%/22.82% than that of CGI, and improved by 15.64%/79.79%, 16.86%/64.55%, and 92.21%/22.82% than that of DGI.
We propose a novel computational ghost imaging by eliminating noise. It considers the auto-correlation of speckle patterns as the basic noise and combines the reconstruct result and the orthogonality speckle field except for the random speckle field. Therefore, the VSGI has good generalization, and can be extended to apply in the positive and negative GI.

V. CONCLUSION

We propose a novel computational ghost imaging by eliminating noise. It considers the auto-correlation of speckle patterns as the basic noise and combines the reconstruct result and the orthogonality speckle field except for the random speckle field. Therefore, the VSGI has good generalization, and can be extended to apply in the positive and negative GI.

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84.51%/26.51% over DGI. In orthogonality sinusoidal speckle field conditions, the PSNR/Con of VSGI is improved by 17.19%/77.18%, 37.37%/93.26%, and 143.85%/50.30% over that of CGI, and improved by 15.07%/72.27%, 34.94%/88.14%, and 128.27%/83.08% over that of DGI.

From the above experiment, the VSGI is also suitable for the orthogonality speckle field except for the random speckle field. Therefore, the VSGI has good generalization, and can be extended to apply in the positive and negative GI.

TABLE 2. PSNR and CR comparison of result examples.

| Pattern      | PSNR1 | Con1 | PSNR2 | Con2 | PSNR3 | Con3 |
|--------------|-------|------|-------|------|-------|------|
| school badge | Hadamard | 13.0681 | 0.3810 | 13.0681 | 0.3810 | 15.1333 | 0.6850 |
| Sinusoidal   | 14.2787 | 0.4281 | 14.5416 | 0.4403 | 16.7333 | 0.7585 |
| Floral motifs | Hadamard | 14.6560 | 0.4818 | 14.6560 | 0.4818 | 17.1269 | 0.7928 |
| Sinusoidal   | 13.3305 | 0.4228 | 13.5700 | 0.4343 | 18.3120 | 0.8171 |
| +            | Hadamard | 16.6460 | 0.7304 | 17.3406 | 0.7577 | 31.9945 | 0.9586 |
| Sinusoidal   | 9.9039 | 0.6652 | 10.5797 | 0.5461 | 24.1505 | 0.9998 |
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