Ghost imaging enhancement for detections of the low-transmittance objects

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Abstract
The underwater environment is extremely complex and variable, which makes it difficult for underwater robots detecting or recognizing surroundings using images acquired with cameras. Ghost imaging as a new imaging technique has attracted much attention due to its special physical properties and potential for imaging of objects in optically harsh or noisy environments. In this work, we experimentally study three categories of image reconstruction methods of ghost imaging for objects of different transmittance. For high-transmittance objects, the differential ghost imaging is more efficient than traditional ghost imaging. However, for low-transmittance objects, the reconstructed images using traditional ghost imaging and differential ghost imaging algorithms are both exceedingly blurred and cannot be improved by increasing the number of measurements. A compressive sensing method named augmented Lagrangian and alternating direction algorithm (TVAL3) is proposed to reduce the background noise imposed by the low-transmittance. Experimental results show that compressive ghost imaging can dramatically subtract the background noise and enhance the contrast of the image. The relationship between the quality of the reconstructed image and the complexity of object itself is also discussed.

Keywords
Underwater, ghost imaging, low-transmittance, compressive sensing, TVAL3

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Introduction
Ghost imaging (GI), which is also named correlated imaging, can nonlocally imaging an unknown object never interact with it. Initially, GI is realized by entangled photon pairs¹ and subsequently performed with a pseudo-thermal light source.² The concept of the GI has been developed from “quantum” to “classical.” Since then, GI has attracted much attentions, and its corresponding real-world applications have been continually explored, such as laser radars,³ security optical encryption,⁴ and X-ray tomography.⁵ The actual hot topic directions in the field of GI, such as multiwavelength GI,⁶ compressive sensing GI,⁷ and three-dimensional GI,⁸ have been developed and applied to improve the performance of GI.

Due to the remarkable characteristics of GI, especially its ability to recover images using a non-spatial-resolving detector toward the object, the GI technique offers great potentialities with respect to conventional imaging techniques in harsh optical environments¹¹–¹³ or in week illumination.¹⁴,¹⁵ The influence of environmental noises in the transmission channel on GI has been investigated in

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previous studies,16 and it has proved that GI systems using spatial correlations between separated two way optical fields are more robust against the noise disturbances compared with conventional optical imaging. Similarly, considering the situation where the objects with the poor surface characteristics, such as roughness, the target detailed information may be overwhelmed. Recently, researchers have explored the effects of the roughness on the GI, and experimental results demonstrated that the signal-to-noise ratio (SNR) of GI decreases along with the increase of surface roughness.17,18 As everyone knows, when the difference of the reflectivity or transmittance between objects and background is not apparent, it is difficult for conventional imaging to distinguish them, especially underwater. When the light transferring in the water, the energy will be attenuated or absorbed due to underwater dissolved organic matter and suspended particles, but some proposed method can produce reliable and promising results.19–21 The result of GI under the underwater conditions for different turbidities has confirmed that GI can be a better alternative for underwater optical imaging.22,23 The energy attenuation of light propagation through seawater means the low transmittance. It is still unclear whether GI also suffer performance degradation from the reduced transmittance and whether the results can be improved using compressive sensing. So we use the low-transmittance objects to simulate the attenuation behavior of light underwater environment.

To illustrate the influence of the object’s transmittance (T) on GI, we make an investigation on the GI for objects of different transmittance using three image reconstruction algorithms, including traditional ghost imaging (TGI) algorithm, differential ghost imaging (DGI) algorithm, and the augmented Lagrangian and alternating direction algorithms (TVAL3). The different transmittance of the objects represents different in underwater transmission environment, which can also be used to analyze underwater potential applications. Firstly, we analyze the quality of the TGI and DGI for a transmittance of \( T = 100\% \) and found that DGI algorithm can acquire an image with higher quality. Then, we reduce the transmittance of the objects. The results show that both for traditional DGI and TGI methods, the lower the transmittance, the more blurred the reconstructed image will be. And the results cannot be optimized even if the number of the measurements is increased. Finally, using the compressible GI, we found that it can obtain a perfect imaging for a low-transmittance objects with fewer measurement.

**Experiment**

The experimental setup is sketched in Figure 1. The laser with \( \lambda = 450 \text{ nm} \) passes through a rotating ground glass to produce a pseudo-thermal source, whose size is modulated by a diaphragm D. And then the pseudo-thermal source is further divided into two beams by a nonpolarizing beam splitter, the test beam, and the reference beam. The test beam illuminates the object and after which the light is collected by a lens L3 onto a bucket detector without any spatial resolution. The light intensity detected by the bucket detector is represented as \( S \). In the reference arm, the beam propagates directly into the CCD camera with a spatial resolution of \( 5.5 \text{ mm} \times 5.5 \text{ mm} \) (VC-2MC-M 340), and the intensity distribution at the position \((x, y)\) of the detection plane is recorded as \( I(x, y) \). When the propagation distances are set as \( Z_1 = Z_2 \), the GI of the object are retrieved.

To investigate how ghost images are affected by the transmittance of the object, we performed experiments for six cases: two transmittance objects with a size of \( 100 \times 100 \), a letter “C” and a Chinese character “海,” and three types of transmittance \( T = 100\% \), 60\%, and 40\%, as shown in illustrations of Figure 1.

**Image reconstruction algorithms**

According to the theory of quantum correlation, the TGI \( O(x, y) \) can be retrieved from the correlation function of the
intensity fluctuations between the collected total intensity $S$ and the speckle field intensity distribution $I(x, y)$

$$O_i(x, y) = \frac{1}{C_0 h S} (S - \langle S \rangle) (I(x, y) - \langle I(x, y) \rangle)$$

where $i$ is the $i$th iteration and $\langle \cdot \rangle$ denotes the ensemble average. But for the DGI, which can be used to eliminate extra source of noise, it has been revised as

$$O_i(x, y) = \frac{1}{C_0 h S} (S - \langle S \rangle) (R(x, y) - \langle R(x, y) \rangle)$$

where $R = \int I(x, y) dxdy$ denotes the total intensity over all pixels of CCD camera in the reference arm.

Compressive sensing can improve image quality greatly with far fewer measurements than the traditional Nyquist–Shannon criteria. The problem of solving signal reconstruction with TVAL3 can be described as

$$\min_x \sum_i ||D_i x||, \quad s.t. \quad Ax = b$$

where $D_i x$ is the discrete gradient of the restructured image $x$ at pixel $i$, $A$ is the measurement matrix, and $b$ is the observation of the image $x$ via some linear measurements. The image $x$ is reconstructed by solving the following equation

$$\min_x \sum_i ||D_i x|| + \mu \|Ax - b\|^2$$

The parameter $\mu$ be called primary penalty parameter plays the most important role on the effectiveness of the TVAL3 method, which is related to the noise level in the observation $b$ and the sparsity level of the recovered images $x$. Therefore, further optimization of the $\mu$ need be done in a subsequent step.

**Results and discussions**

Firstly, we experimentally study the object with high-transmittance $T = 100\%$ based on the TGI and DGI algorithms. The reconstructed images for the letter “C” and Chinese character “海” with different number of measurements are demonstrated in Figure 2(a) and (b), respectively. From (a) to (f), the images in the first and second rows are reconstructed by TGI and DGI, respectively. TGI: traditional ghost imaging; DGI: differential ghost imaging.
DGI algorithm can acquire a clearer target image compared with TGI under the same experimental conditions. And the background of TGI reconstruction is always slightly stronger than that of DGI reconstruction under the same sampling number. Along with the growth of the number of measurements, the clarity of imaging results with DGI can be further improved but without significant improvement for TGI. The reason is that the detection intensity is corrupted by the noise from experiment, such as laser intensity fluctuation. The image quality improvement in the DGI and TGI was evaluated using the peak signal-to-noise ratio (PSNR) and visibility. The visibility and PSNR of the letter “C” and Chinese character “海” with increasing number of measurements are shown in Figure 3. It is clearly that utilizing the DGI algorithm could provide the significantly higher visibility and PSNR than that of using TGI algorithm. The results indicate that for high-transmittance objects, the DGI method can reduce the interference of background and enhance the image contrast.

Secondly, let us consider the influence of the low-transmittance objects on the GI. The results shown in Figure 2(c) to (f) present the TGI and DGI images at low-transmittance $T = 60\%$ and $40\%$. Low-transmittance levels bring a strong background and drastically reduce the quality of imaging results. This is because the intensity collected by bucket detector has been decreased heavily due to some impacts such as absorption, scattering, and consumption under the low-transmittance condition. Furthermore, the negative impact cannot be optimized obviously by growing the number of measurements.

Figure 4 compares the visibility and PSNR of reconstructed images with different transmittance. We can see that the background noise of the reconstructed images is getting worse and worse with the decrease of the transmittance. So, the quality of the DGI is valid for objects with high-transmittance but not for the low-transmittance ones.

The relative SNR of DGI in equation (1) to TGI in equation (2) is given by

$$\frac{(\text{SNR})_{\text{DGI}}}{(\text{SNR})_{\text{TGI}}} = 1 + \frac{1}{\sigma_{\text{rel}}^2}$$

where $\sigma_{\text{rel}}^2 = \overline{\delta T^2}/\langle T \rangle^2$, $\overline{\delta T^2} = \overline{T^2} - \langle T \rangle^2$, and $T$ is the average transmission function of the object. Equation (4) can also be used to analyze the effect of transmission to the GI. As can be seen from the equation, for high-transmittance objects ($\overline{T^2} \ll \langle T \rangle^2$, $\sigma_{\text{rel}}^2 \ll 1$), the DGI algorithm is more efficient than TGI. Conversely, for the object with low-transmittance ($\langle T \rangle^2 \ll \overline{T^2} \ll 1$, $\sigma_{\text{rel}}^2 \rightarrow \infty$), DGI and TGI algorithms reconstruct similar SNR. Our experimental results are consistent with the theoretical results. The results prove that the image quality of the reconstruction cannot be further improved significantly by traditional second-order correlation algorithms (DGI and TGI) when $T$ is small. Therefore, it is necessary to propose an effective method to reduce the effect of low-transmittance to improve the imaging quality in applications.

Thirdly, to obtain high-quality GI results in the case of low transmittance, we try to use the compressive sensing called TVAL3 algorithm. TVAL3 has an obvious advantage for preserving the edges or boundaries more accurately and is utilized to give a sharper recovered image, which displays a better recovered information of the object for GI with less time consumption. According to the model described by equation (3), the optimized process by TVAL3 with the variable parameter $\mu$ is illustrated in Figure 5, and one can see that when the parameter $\mu$ is set as 2$^{10}$, the optimal results for the

![Figure 3](image-url)
PSNR and visibility can be obtained. More details of the elaborate description of TVAL3 including theoretical and parameters will be fully stated in Li’s paper.\textsuperscript{27}

We further discuss the effectiveness of the TVAL3, when the algorithm is performed on the low-transmittance \textquotedbl{}C\textquotedbl{} and \textquotedbl{}\textit{海}\textquotedbl{}. The images reconstructed by TVAL3 for transmittance \(T = 60\%\) and \(40\%\) are shown in Figure 6(a) and (b), respectively. When \(T = 60\%\), we observe that GI with clearer edges and lower noise can be retrieved. Besides the simple letter \textquotedbl{}C\textquotedbl{}, even for the complex character \textquotedbl{}\textit{海}\textquotedbl{}, the relatively clear images are obtained only by increasing the number of measurements. To quantitatively compare the imaging quality, the PSNR and visibility of both DGI and TVAL3 with different measurements and different transmittance are calculated, as shown in Figure 7.

The experimental results show that when \(T = 60\%\), with the increase of measurements, the PSNR and visibility reconstructed an enhancement trend using TVAL3 and the similar DGI method. For DGI, when \(T = 60\%\), the visibility is less than 0.5 and the PSNR is lower than 10. However, the results using TVAL3 algorithm demonstrate that the visibility and PSNR have been raised to above 0.8 and 20, respectively. The reconstructed quality of the transmittance \(T = 60\%\) using TVAL3 is almost the same as DGI under the transmittance \(T = 100\%\).

Similarly, when \(T = 40\%\), the quality of reconstruction of the \textquotedbl{}C\textquotedbl{} is always enhanced by the TVAL3 algorithm, as displayed in Figure 6(b), 7(a), and 7(b). However, for complex objects with more details, the negative impact of low-transmittance cannot be ignored, which may bring a strong background and reduce the quality of imaging results. Figure 6(b) presents imperfect results of the \textquotedbl{}\textit{海}\textquotedbl{} reconstructed by TVAL3, although background noise has been subtracted, the clarity of the images is not as significant as that of the simple object (the letter \textquotedbl{}C\textquotedbl{}). Therefore, as shown in Figures 7(c) to (d), the corresponding visibility and PNR of the imaging (\textquotedbl{}\textit{海}\textquotedbl{}) obtained by the TVAL3 is away below the results when \(T = 60\%\). That is to say that if the complexity of objects reaches a certain extent, the influence of low-transmittance for GI should be emphasized.

To summarize, the experimental results demonstrated that, in certain circumstances, the blurring influence imposed by the low-transmittance can be reduced using the compressive GI.

**Conclusion**

In conclusion, we have experimentally investigated the image quality of different GI algorithms. The imaging
quality calculated by traditional DGI and TGI methods is significantly dependent on the transmittance characters of objects. The experimental results also verify that for the simple object, the GI contrast using TVAL3 algorithm can be dramatically improved even with the low-transmittance compared with TGI and DGI algorithms. But, there are some limitations for complex objects. Even so, these results confirm the possibility that compressive GI has a great application potential not only in noisy channels but also in low-transmittance objects. Experimental results may be

**Figure 6.** Experimental reconstruction images by TVAL3 for (a) the letter “C” and (b) the Chinese character “海” with transmittance $T = 40\%$ and 60\%. TVAL3: augmented Lagrangian and alternating direction algorithm.

**Figure 7.** The visibility and PSNR of reconstruction results by TVAL3 and DGI with different number of measurements, where the transmittance of object is $T = 100\%, 60\%,$ and $40\%$, respectively. (a) and (b) are the visibility and PSNR of the letter “C,” respectively; (c) and (d) are the visibility and PSNR of the Chinese character “海,” respectively. PSNR: peak signal-to-noise ratio; TVAL3: augmented Lagrangian and alternating direction algorithm; DGI: differential ghost imaging.
analogous to underwater low-transmittance environment. To obtain better and more underwater imaging or detection information in a low-transmission underwater environment, our next goal is to combine optical and acoustic methods and introduce artificial intelligence algorithms to deal with subsequent image reconstruction.

**Authors’ note**

Weikai He and Yongjian Gu contributed equally to this work and should be considered as the co-corresponding authors.

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