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High-quality compressive ghost imaging

Heyan Huang [a,c,1], Cheng Zhou [b,c,1], Tian Tian [a,c], Dongqi Liu [a,c], Lijun Song [b,c,*]

[a] School of Science, Changchun University, Changchun 130022, China
[b] School of Information Engineering, Jilin Engineering Normal University, Changchun 130052, China
[c] Key Laboratory of Materials Design and Quantum Simulation at universities of Jilin Province, Changchun University, Changchun 130022, China

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ABSTRACT

We propose a high-quality compressive ghost imaging method based on projected Landweber regularization and guided filter, which effectively reduce the undersampling noise and improve the resolution. In our scheme, the original object is reconstructed by decomposing of regularization and denoising steps instead of solving a minimization problem in compressive reconstruction process. The simulation and experimental results show that our method can obtain high ghost imaging quality in terms of PSNR and visual observation.

1. Introduction

Ghost imaging (GI) is a very important imaging technique based on the correlation of the light field fluctuations, and it reconstructs the object by means of intensity correlation of two light beams, i.e., the object beam and the reference beam. The object beam contains information of the object, and its total intensity is collected by a bucket detector. The reference beam is detected by a detector with spatial resolution directly. Recently, many researchers begin to pay close attention to the practical application of GI [1–3], and try to improve the quality of imaging in term of resolution and peak signal noise ratio (PSNR). In order to improve the quality of ghost imaging, many methods have been proposed, including higher-order GI [4], iterative GI [5](IGI), normalized GI [6], compressive GI [7–10] and so on. Compared with the traditional GI, these imaging technologies could obtain better image quality but low PSNR due to the undersampling noise [11]. This kind of noise is produced under finite sampling, which decreases the PSNR of ghost imaging and masks the true information of the object.

In the recent few years, compressive ghost imaging (CGI) has attracted more and more attention because of its high reconstruction quality [12–14]. It restores the image based on compressive sensing (CS), which has also been successfully applied in other fields [15,16]. CS could reconstruct an image almost perfectly with only a few samples by finding its sparsest representation [17–20]. The CGI [7] enables GI from sub-Nyquist samples through exploiting the redundancy in the structure of natural images and largely reduces the acquisition time and requisite samples [8–10].

It is well known that the CS problem is an ill-posed problem [17,18,21,22]. Thus, to obtain the reasonable image estimation, the method of exploiting the geometrical structure of sparse/compressible signals needs to be utilized. In this paper, we propose a high-quality compressive ghost imaging method with decomposing regularization and denoising steps in reconstruction framework instead of the conventional compressive method of solving a minimization problem. In practice, the undersampling noise always exists and cannot be neglected due to the finite sampling number. In order to reduce the effect of undersampling noise and improve the PSNR of reconstructed image, we first utilize the projected Landweber regularization to solve the ill-posed problem, and obtain initial reconstruction image, then, we apply the edge-preserving filter to eliminate the undersampling noise.

2. The scheme of high-quality compressive ghost imaging

Our scheme schematic diagram is presented in Fig. 1. The goal of our scheme is to remove the undersampling noise effectually and improve PSNR in ghost imaging system (GIS). In order to obtain better reconstructed results, the regularization and denoising steps are alternately carried out in our scheme. The IGI [5] also applies the iterative operation on the reconstructed image by adding more measurement pairs. It obtains the recovered image by iteratively calculating the high-order error term. Different from the IGI, our proposed method is a compressive ghost imaging technique and the reconstructed image is obtained by solving linear equations. We first obtain the random speckle matrix and

* Corresponding author at: School of Information Engineering, Jilin Engineering Normal University, Changchun 130052, China.
E-mail address: songlj@jlenu.edu.cn (L. Song).

1 Heyan Huang and Cheng Zhou contributed equally to this work.

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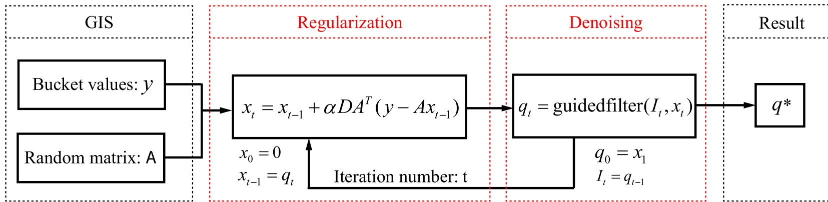

Fig. 1. Schematic diagram of our scheme.

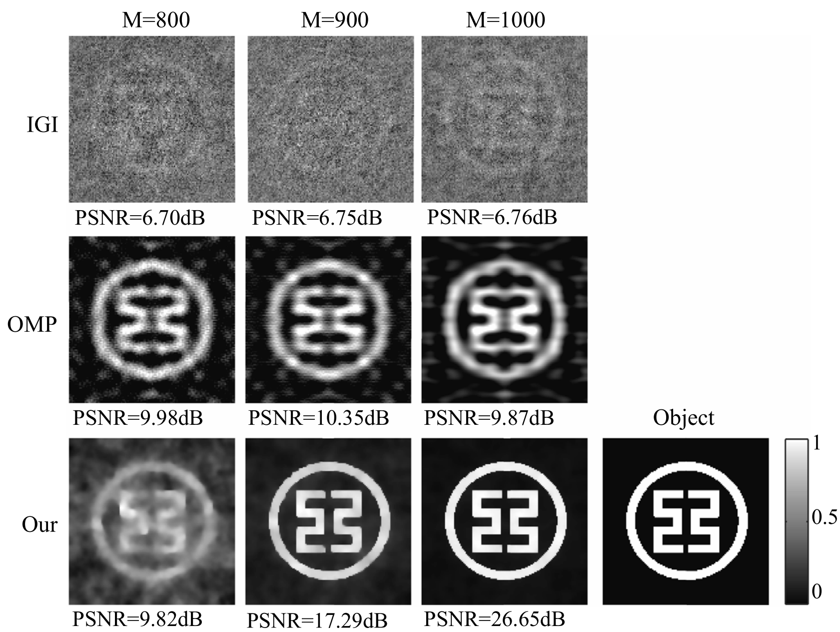

Fig. 2. Simulation results of "gong" with IGI, OMP and our methods with M samples.

bucket values from GIS, then the projected Landweber regularization is utilized to obtain initial reconstructed image, finally, the guided filter is performed to eliminate the undersampling noise in the regularization result. Our scheme procedures in detail in the following subsections.

The speckle field of the mth sample is recorded as $I_m(i,j)$. The indices $i = 1,\dots,r$ and $j = 1,\dots,c$ represent the horizontal and vertical pixel coordinates, and $m = 1,\dots,M$ is the sampling frame index and M is the total sampling number. Then, each of the speckle intensity $I_m(i,j)$ is reshaped as a row vector Ψ_m of size $1 \times N$, where $N = r \times c$. After M samples, we can get a $M \times N$ samples array recorded as A, and it can be written as the following matrix

$$A = \begin{bmatrix} \Psi_1 \\ \Psi_2 \\ \vdots \\ \Psi_M \end{bmatrix} := \begin{bmatrix} I_1(1,1) & I_1(1,2) & \cdots & I_1(r,c) \\ I_2(1,1) & I_2(1,2) & \cdots & I_2(r,c) \\ \vdots & \vdots & \ddots & \vdots \\ I_M(1,1) & I_M(1,2) & \cdots & I_M(r,c) \end{bmatrix}, \tag{1}$$

Meanwhile, the object beam illuminates the object with transmission coefficient $T(i,j)$, and the speckle field transmitted by the object is measured by the bucket detector. The mth sample result in bucket detector is

$$B_m = \sum_{i=1}^{r} \sum_{j=1}^{c} I_m(i,j) T(i,j), \tag{2}$$

Likewise, the M results from the bucket detector can be arranged as a $M \times 1$ column vector y, i.e., $y = \left[B_1, B_2, \dots, B_M\right]^T$. Then, if we denote the unknown object image as an N dimensional column vector $x(N \times 1)$, we will have the framework:

$$y = Ax, \tag{3}$$

Thus, we can reconstruct the image by solving a set of M linear equations (Eq. (3)) [7].

The CS predicts that the sparse signals can be reconstructed from a small number of linear measurements using convex optimization. Algebraically, for reconstructing a sparse signal $x \in R^{N\times 1}$ from the Eq. (3), the CS method needs solving a convex optimization program, searching for the image with a surprising small number of samples. Afterwards, the classical signal reconstruction methods such as Orthogonal Matching Pursuit (OMP) [21], Total Variation (TV) [14], Basis Pursuit De-Noising (BPDN) [23] can be adopted to reconstruct x from A and y. If x is not sparse, the CS relies on the empirical observation that many types of signals can be represented by $K \ll N$ significant coefficients over an basis. The conventional CS reconstruction approaches formulated this problem as one cost functional, and the objective function usually can be written as

$$\min \|\Phi x\|_1 + \frac{\lambda}{2}\|Ax - y\|_2^2, \tag{4}$$

where λ is a nonnegative parameter, $\|v\|_2$ denotes the l_2-norm of v, and $\|v\|_1 = \Sigma_i v_i$ is the l_1-norm of v. The sparse transform Φ is usually exploited a set of fixed bases (e.g. discrete cosine transform and wavelet) for the entirety of an image.

2.1. Regularization

It is generally known that the problem Eq. (3) is ill-posed due to the singularity of A, and some special regularization methods are exploited to solve it. The projected Landweber method [24] has good property for solving Eq. (3) in the iterative methods, and we use it to approximate the solution of Eq. (3). The basic idea is as follows [25]: let x_0 be an