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Исследование ключевых технологий оптического кодирования на основе адаптивной компрессивной призрачной съемки крупноразмерных объектов

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Вычислительная призрачная съемка представляет собою хороший способ оптического кодирования, однако она не вполне применима для получения изображений крупноразмерных объектов или тогда, когда длительность съемки велика. Предложен новый способ оптического кодирования, основанный на сочетании метода адаптивной разреженной поблочной выборки с вычислительной призрачной съемкой. В этой модели крупноразмерный объект разбивается на несколько блоков, затем каждый блок интерпретируется как отдельное изображение, которое обрабатывается методом вычислительной призрачной съемки с собственным параметром выборки, соответствующим зрительной системе человека. В процессе восстановления изображения используется алгоритм разреженной выборки. По сравнению с обычной вычислительной призрачной съемкой качество восстановленных изображений оказывается выше, так что этим методом оказывается возможным получение высококачественных крупноразмерных изображений, а количество передаваемой информации сокращается, что контрастирует с ситуацией при поблочной вычислительной призрачной съемке; последнее позволяет использовать менее объемистые хранилища данных или менее скоростные линии передачи. Эта техника может быть непосредственно использована для получения и передачи изображений и хранения данных, давая преимущества в качестве восстанавливаемой информации, скорости передачи и обеспечении высокой безопасности.

Ключевые слова: *вычислительная призрачная съемка, поблочная вычислительная призрачная съемка, алгоритм разреженной выборки*

Study on the key technology of optical encryption based on adaptive compressive ghost imaging for large-sized object

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Computational ghost imaging is a good optical encryption method, but it can hardly imaging for large-sized object or the time is long. To solve the problem, we propose a novel optical encryption method based on block adaptive compressive sensing with computational ghost imaging. In this model, we divide the large-sized image into several blocks, then every block is considered as a single image to finish ghost imaging, every block has its own sampling ratio according to human visual system. In the recovery process, we use compressive sensing algorithm to reconstruct the image. Compared with computational ghost imaging, the quality of recovery image is better, so large-sized image can also be recovered with high quality with this method, and the number of transmitted information is reduced in contrast with block computational ghost imaging so that it can use fewer spaces, high-efficiency data storage or transmission. This technique can be immediately applied to imaging applications and data storage with the advantages of high quality of reconstructed information and high security, fast transmission.

Keywords: *computational ghost imaging, block computational ghost imaging, compressive sensing algorithm.*

OCIS codes: *110.1085, 110.1758, 110.3010, 060.4785*

1. INTRODUCTION

Over the years extensive studies have been carried out to apply coherent optics methods in real-time communications and image transmission. The recent progress in data-processing networks and communication systems has considerably increased the capacity of information exchange [1–2]. Ghost imaging (GI) is a technique that allows for constructing the image of an object without actually seeing this object [3–6]. Ghost images are obtained by correlating the output of a single-pixel (bucket) photodetector which collects light that has been transmitted through or reflected from an object with the output from a high spatial-resolution scanning photodetector or photodetector array whose illumination has not interacted with that object. The term “ghost image” is apt because neither detector′s output alone can yield an image: the bucket detector has no spatial resolution, while the high spatial-resolution detector has not viewed the object. The computational ghost imaging, in which the pseudothermal source is replaced with a deterministic illuminator that permits a ghost image to be formed using a computed reference field, i.e., with only a bucket detector.

In reference [4], Pittman et al. demonstrated that GI is enabled by specially quantum effects and found that GI could be performed with the pseudothermal light. In reference [5], Shapiro proposed to implement GI using a phase spatial light modulator (SLM) illuminated by a spatially coherent laser beam. In reference [6], Bromberg et al. presented a GI scheme with a single detector, where the rotating diffuser is replaced by a computer controlled SLM. Later, several studies combined compressive sampling (CS) with GI in order to recover higher quality images [7]. While CS also has some shortcomings in that it takes much more time than the calculation of the second-order correlation, and the time consumed increases exponentially with the size of the image to be recovered, or may even fail to work under specific circumstances. Subsequently, several studies demonstrated the encryption of compressive ghost imaging [8–11], but the problem that large-sized image can hardly imaging or the quality is terrible hasn't been solved. Due to the restriction of hardware to GI, the size of image in GI is usually 64×64. Fortunately, these shortcomings can be overcame by a method named compressive adaptive computational ghost imaging (CGI) reported by Aßmann and Bayer [12], and the size of image is 256×256. Other study also present a method named adaptive compressive ghost imaging (ACGI), and the size of image is also 256×256 [13]. However, this method directly uses the patterns that form the sparse basis to replace classical random patterns, and lose a lot of information of the edge easily. So we propose a method named block adaptive compressive sensing computational ghost imaging (BACS-CGI) to solve the problem.

In the method, the large-sized images are divided into several blocks firstly, then every block is considered as an object to finish computational GI, the sampling ratios are depended on the entropy, so it can achieve adaptive sampling and reduce the number of measurements, what′s more, it can also improve the quality of reconstructed image compared with computational GI. This method has three main advantages: first, we can retrieve large-sized gray-scaled images without stringent hardware restrictions, which is difficult for computational GI to solve; second, the number of measurements can be significantly fewer than any other CGI methods and it can reduce the amount of information transmitted then it reduce data storage space; third, by combing the advantages of CS, the weak signals or images in the noisy environments can also be recovered with high quality.

The rest of this article is organized as follows. In Section 2, the ACGI model and the encryption and decryption process are introduced in detail. In Section 3, numerical simulation results and analysis are given. Finally, the conclusion is given in Section 4.

2. OPTICAL ENCRYPTION OF LARGE-SIZED GRAY-SCALED IMAGE BASED ON ADAPTIVE COMPRESSIVE GHOST IMAGING

2.1. The optical information encryption based on the algorithm of computational ghost imaging

The system of computational GI is just as Fig. 1 shows, we suppose that the secret key $\{I_r\}$, consisting of a vector of N components, produced by Alice and shared with Bob. Alice encrypts the image using the system of computational GI. The key part is a SLM, which introduces a set of random phase distributions to generate computer-controlled speckle patterns at the object plane. After passing through the object, the light is collected by a bucket detector (BD). This operation is repeated N times for N different phase profiles $\varphi_i(x, y)$ each of them corresponding to one secret key $\{I_r\}$, generating the intensity values detected by the BD, $\{B_r\}$. These values are shared with the Bob by a public channel, who shall decrypt the image using a proper combination of the phase profiles $\varphi_i(x, y)$ with coefficients $\{B_r\}$ [6–9]. The measurement result $\{B_r\}$ in the BD is a total intensity transmitted through the original image $T(x, y)$, the formula is as follows:

$$B_r = T(x, y)\int dxdyI_r(x, y), \tag{1}$$

where $\{I_r(x, y)\}$ is the intensity distribution of the speckle field, $T(x, y)$ is the original image. $\{I_r(x, y)\}$ can be computed according to Fresnel propagation function, and it is easily obtained by Bob for he holds

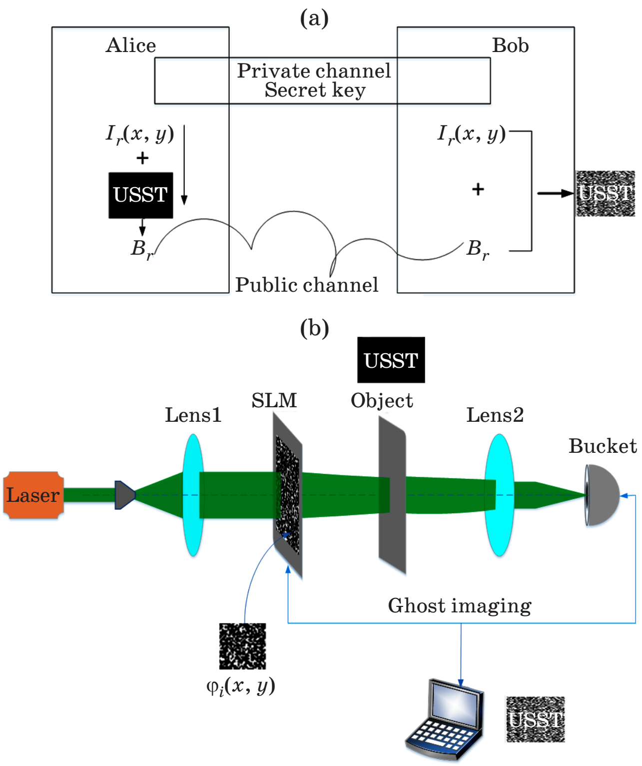

Fig. 1. Scheme of the encryption method based on computational ghost imaging: (a) the encryption/decryption procedure and (b) experimental setup for computational ghost imaging.

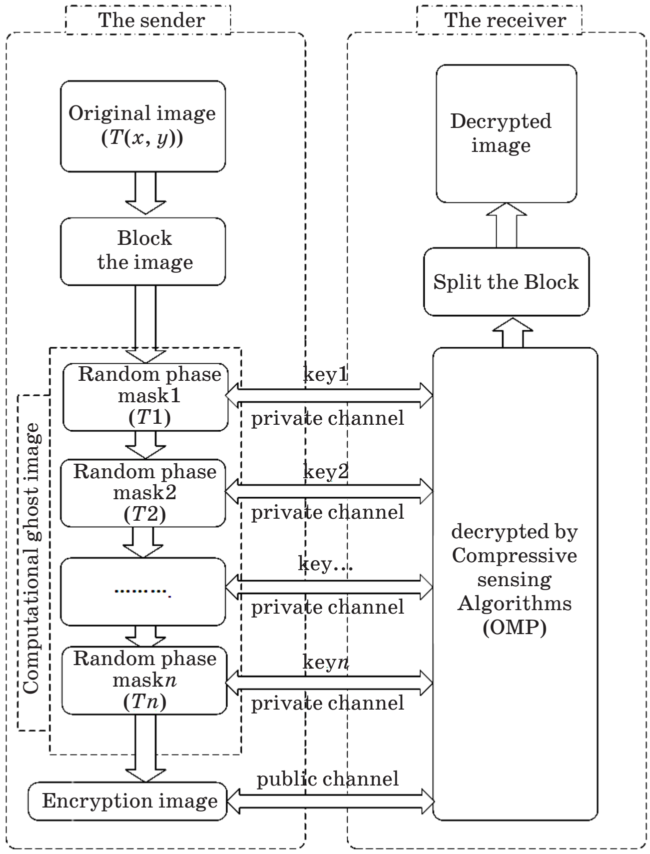

Fig. 2. The scheme proposed in this paper is based on block adaptive compressive sensing with computational ghost imaging (BACS-CGI).

the random phase screens, we can calculate through the formula as follows:

$$I_r(x, y)=\left|E_{\text{in}}(x, y)\exp\left[j\varphi_i(x, y)\right]\otimes h_z(x, y)\right|, \quad (2)$$

where $E_{\text{in}}(x, y)$ is the complex field of the coherent light beam is, $h_z(x, y)$ is the Fresnel propagation kernel at a distance z, and $\otimes$ denotes the 2D convolution operation. The key point to note in the use of GI for optical decryption is that the intensity patterns $\{I_r(x, y)\}$ can be easily computed by Bob according to Eq. (2), provided that the set of phase profiles is known.

For the large-sized gray-scaled image, computational GI is difficult to finish the reconstructed process and the quality of reconstructed image is terrible.

2.2. Optical imaging encryption by block adaptive compressive sensing based on computational ghost imaging

Compressive sensing is regarded as a huge breakthrough in signal acquisition [14–17]. But when it applies to computational GI, it takes much more time than the calculation of the second-order correlation and the quality of recovery image is terrible. Fortunately, we present a method called BACS-CGI to solve this problem. The process is just as Fig. 2 shows.

Firstly, we divide a large-sized image into several blocks, then we decide the sampling ratio on the basis of image block's entropy characteristics. According to the characteristics of the visual system, the eye of the image data in the low-frequency component which low entropy represents has greater sensitivity, the quality of the reconstructed image with the low-frequency component is directly related to the size of the error. The low frequency part of the image weight larger than the high frequency portion in the process of reconstruction so that the low-frequency part of the image data with higher accuracy reconstruction, while the high frequency portion is small due to the weight, the reconstruction error is relatively large. However the quality of image is depended on the low-frequency component-based, so the overall image quality is better constructed. This method ensures accuracy in the low-frequency component of the reconstruction with the cost of the reconstruction precision to the high-frequency component. In this paper, we adopt the idea to consider saving storage space and adaptability to different sizes of image blocks, at the same time we introduce the image frequency weighting function for position changes. The process of adaptive sampling is just as Fig. 3 shows.

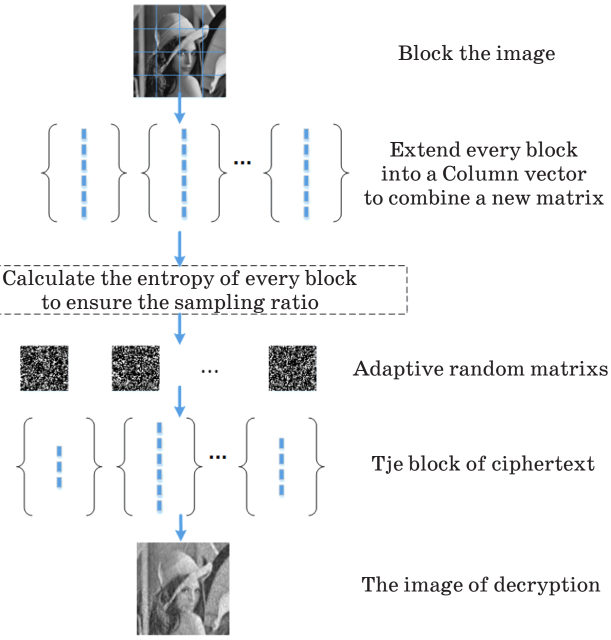

Fig. 3. The process of adaptive sampling.

We define a matrix that the size of matrix is the same as the size of the image $n\times n$, the weighting function is as follows:

$$w(i,j)=1+\frac{1}{1+(i+j)/p}, \tag{3}$$

where the range of i and j are from one to $n-1$, p is a constant number. We know the function is monotonically decreasing as the row and column increase, so the value of high-frequency is smaller than the low-frequency. We use $w(i, j)$ to weigh the intensity distribution of the speckle field $\{I_r(x, y)\}$, so the Eq. 2 and Eq. 3 can describe just as follows:

$$I'_r(x,y)= \\ =\left|E_{\text{in}}(x,y)\exp\left[j\varphi_i(x,y)\right]\otimes h_z(x,y)\right|w(i,j), \tag{4}$$

$$B'_r=T(x,y)\int dxdyI'_r(x,y). \tag{5}$$

We can adaptively select fine determine the minimum number of observations of the reconstructed image block so that we can reduce the total observation number through judging the image block entropy complexity. In this paper, we choose the Image block's variance σ^2 to determine the size of entropy. Firstly, we set a threshold value δ that it can acquire through the experiment, if $\sigma^2 > \delta$, the image block is sensitive block for human, if not, it is insensitive block. So every block has its own sampling ratio so that it achieves adaptive sampling. Then we considered every block as a single object to finish computational GI.

In the recovery process, we replace correlation algorithm with compressive sensing, in this process, we supposed that one size of the two-dimensional intensity distribution and one maximum pixel of the two-dimensional object is setup to n. Further analysis shows that Eq. (5) can be rewritten in a matrix form for N measurement results.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{bmatrix}=\begin{bmatrix} I_{11}^1 & \dots & I_{1n}^1 & \dots & I_{nn}^1 \\ I_{11}^2 & \dots & I_{1n}^2 & \dots & I_{nn}^2 \\ \vdots & \dots & \vdots & \dots & \vdots \\ I_{11}^N & \dots & I_{1n}^N & \dots & I_{nn}^N \end{bmatrix}\begin{bmatrix} T_{11} \\ \vdots \\ T_{1n} \\ \vdots \\ T_{nn} \end{bmatrix}, \tag{6}$$

where $[T_{11}\cdots T_{1n} \cdot\cdot T_{nn}]$ is the one-dimensional reformation of the two-dimensional object information and $[I_{11}^i \cdots I_{1n}^i \cdots I_{nn}^i]$ is the reformed one-dimensional vector (one row, $n\times n$ column) of the two-dimensional light intensity distribution $\{I'(x, y)\}$, I_{nn}^i is the intensity at position $x = n$, $y = n$ for i measurement. We use CS algorithm to recovery image, which needs solving the convex optimization problem just to find an image T_{CS} that minimizes the l_1 – norms in the sparsity basis.

$$T_{CS}=T',\ \operatorname{argmin}\left\|\Psi\left\{T'(x,y)\right\}\right\|_{l_1}. \tag{7}$$

Subject to

$$B_r=\int dxdyI'_r(x,y)T'(x,y),\ \forall i=1,\ \dots,\ N. \tag{8}$$

The method of BACS-CGI can retrieve the large-sized gray-scaled image, it solves the problem of time-consuming and low-quality image which is difficult for compressive sensing and computational GI. The experimental results are shown in Section 3.

3. EXPERIMENTAL RESULTS AND ANALYSES

In this paper, we use adaptive block CS algorithm and computational GI algorithm to obtain real image and use the numerical simulation method to obtain SLM modulation signals. The simulation is conducted with the software of MATLAB, the steps are as follows. The designed object $T(x, y)$ with a sparse space is placed on the object plane of the imaging system and the image is gray-scale. The size of the object is 256×256. Each pixel of the object is modulated by the simulation signals. The speckle pattern is calculated with Eq. (4), where $E_{in}(x, y)$ is a general Gaussian beam. Each random phase screen $\{I_r(x, y)\}$ is uniform distributions over $[0, 2\pi]$ with size of 256×256. The distance between the SLM and the object image is set to $d = 350$ mm. In this paper we choose DCT as the sparsity basis. We recovery the image through the algorithm of Total variation [18–19]. We will verify the feasibility, security, and the quantity of transmission information of the optical encryption method based on BACS-CGI.

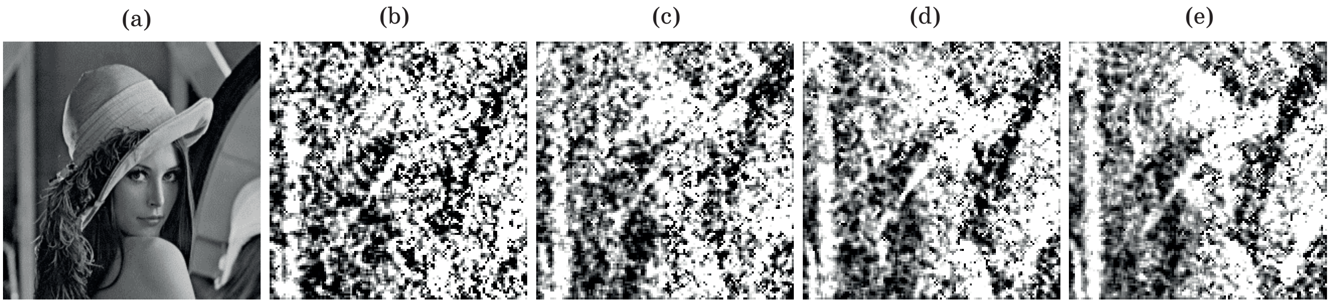

Fig. 4. The reconstructed image via BCS-CGI. The original image (a), the reconstructed images (b, c, d, e) with 24, 48, 72, 96% realizations respectively.

Fig. 5. The reconstructed image via BACS-CGI. The original image (a), the reconstructed images (b, c, d, e) with 24, 48, 72 and 96% realizations respectively.

3.1. Research on the feasibility of the method

In this section, we discuss the feasibility of the approach and demonstrate whether the receiver can recovery the information which the sender transmits to him with the secret key. We compare the algorithm of BACS-CGI with the algorithm of block computational ghost imaging (BCGI). In the algorithm of BCGI, the object is divided into four blocks, and then the blocks apply the encryption algorithm of CGI. The experiment object is "Lena"(256×256), gray-scale character images, the object is divided into four blocks, the simulation results are shown in Fig. 4 and Fig. 5, the peak signal-to-noise ratio (PSNR) is shown in Fig. 6, and the result is not under eavesdropping,

Subjectively speaking, our method shows greater feasibility of reconstructing image through Fig. 4 and 5 compared with BCGI. We use the PSNR to evaluate its quality in objective, the result is shown in Fig. 6. According to the result of subjective and objective, we can sum up that (1) the quality becomes worse as the realizations decrease, (2) the PSNR of our method is higher than BCGI because of adaptive sampling based on human visual system information. So our method is superior to BCGI.

3.2. Research on the sampling ratio of the method

We adopt the idea that the sampling ratio depends on human visual system that the entropy of image represents, so we achieve adaptive sampling to image. We assume the number of pixels of image is n^2, the sampling of sensitive blocks are $0.4n^2$, the sampling of insensitive blocks are $0.1n^2$, in the method of BCGI, the sampling is $0.4n^2$, the reconstructed images are as it is shown in Fig. 7, we use PSNR to evaluate the quality. The quantity of sampling of BACS-CGI is 18739, while the sampling of BCGI is 26214, and the PSNR is 25.6147 and 5.8912 dB respectively.

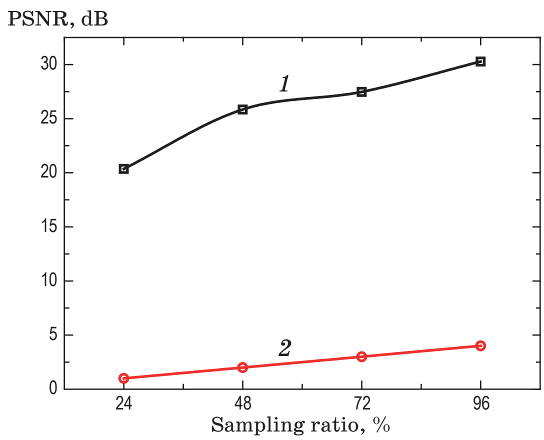

Fig. 6. The PSNR of methods with different realizations (*1* — BACS-CGI, *2* – BCGI).

In this section, we compared the method of BACS-CGI with the method of BCGI by using the number of sampling and PSNR. The result is shown in Fig. 7. The method is not only reduced the measurements, but acquire the high-quality image compared with

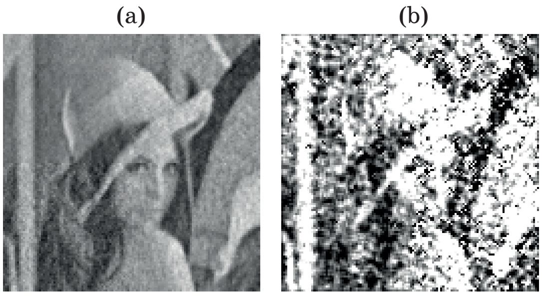

Fig. 7. The reconstructed image with above methods (a — BACS-CGI, b – BCGI).

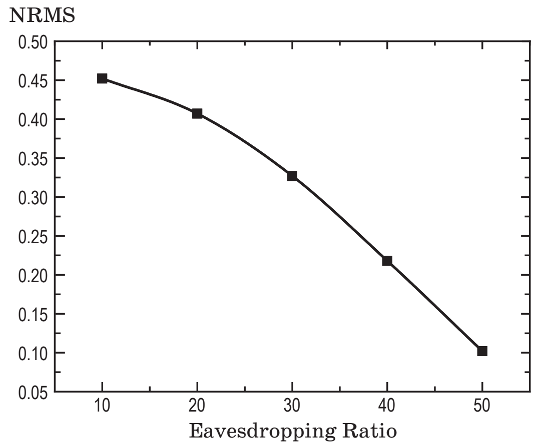

Fig. 9. The relationship between the NRMS and the eavesdropping ratio for BACS-CGI.

conventional method. Simultaneously the method can also reduce the storage and improve the speed of information transmission.

3.3. Research on the security

To evaluate the security of the encrypted image based on our method, we experimentally investigated the retrieved image under different percentages of eavesdropping ratio when an unauthorized attacker ascertains some of the secret key components as it is shown in Fig. 8. We calculated the normalized root mean square (NRMS) for different percentages of eavesdropping. The normalized root mean square gives the size of error for an unauthorized user who has ascertained some of the components of the secret key through eavesdropping [14 the NRMS 15]

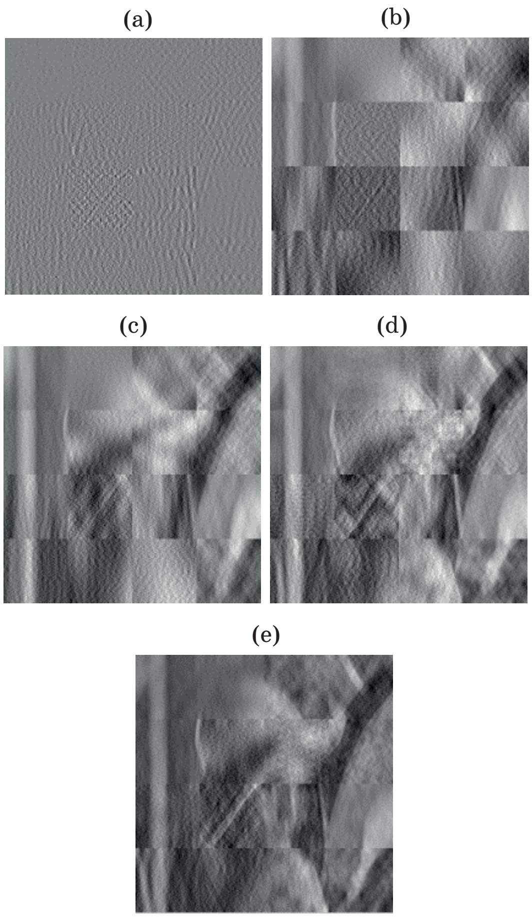

Fig. 8. Decrypt BACS-CGI for 10 (a), 20 (b), 30 (c), 40 (d) and 50% (e) of eavesdropping ratio on the secret key.

$$\mathrm{NRMS}=\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|I_d(x,y)-I_o(x,y)\right|^2}{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|I_o(x,y)\right|^2}, \qquad (9)$$

where I_d and I_o refer to the intensities of the decrypted and original image respectively. The greater NRMS implies the higher security of the encryption system, and NRMS = 0 denotes the perfect decryption.

The result is shown in Fig. 9. The result suggests cryptanalysts recovery the image only when they eavesdrop about 50% secret key just as Fig. 8 shows. So the security is high.

4. SUMMARY

In this method, we use the technique of BACS-CGI to improve the quality of recovery image. In this model, we divide the large-sized image into several blocks, then every block is considered as a single image to finish GI, every block has its own sampling ratio according to human visual system. In the recovery process, we use compressive sensing algorithm to reconstruct the image. We recovery the ciphertext by the algorithm of CS. The strengths of the proposed approach are the three aspects: first, we can retrieve large-sized gray-scaled images without stringent hardware restrictions, which is difficult for CS algorithms and computational GI to solve; second, the number of measurements can be significantly fewer than any other CGI methods; third, by combing the advantages of CS, the weak signals or images in the noisy environments can also be recovered with high quality. We apply computational GI with the large-sized gray-scaled object successfully.

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