Computational imaging technology for high-sensitivity space-image acquisition

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Acquiring deep-space images with high spatial resolution and sensitivity is important for space-debris surveillance and early warning. We propose a novel computational imaging (CI) method for high-sensitivity image acquisition in this letter. The proposed approach introduces CI into image formation. The proposed capturing process conducts minor modifications for cameras to encode more desirable information during capture, which is practical for hardware implementation. The latent image is reconstructed by formulating a recovery problem into an optimization problem, which is solved with iteratively reweighted least square technique. The experimental results clearly show the effectiveness of the proposed method.

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With the increasing interest in the exploration and utilization of outer space, low-cost monitoring of small and dim space debris is crucial. Obtaining high-sensitivity and high-resolution images is also important. Although conventional approaches can pursuit this goal by increasing the optical aperture, enlarging the photosensitive cell size, or extending the exposure time, they are inherently limited by some physical features of hardware. Therefore, conventional approaches are not always applicable. Cameras combined with digital image processing have been modified for image acquisition. The wavefront coding technique[1], which involves the use of a cubic-phase modulating element in conjunction with the digital image processing method, has been proposed to extend the depth of the field of a digital imaging system. In Ref. [2], a light-field camera that uses a micro lens array to capture 4D light-field information about a scene is developed. This camera can be used for producing images focused at different depths. To acquire a clear image under occlusion, a synthetic aperture imaging approach was presented in Ref. [3]. The desired image was reconstructed by a slightly different perspective image sequence, which was obtained by arranging the camera array. A single-pixel camera was developed in Ref. [4], which employed a digital micro mirror array to optically calculate the linear projections of a scene onto pseudorandom binary patterns. By changing it, a series of compressive sensing (CS) measurements was acquired, which could be used for recovering the latent image. A coded aperture approach proposed in Ref. [5] can recover the depth information and all-in-focus image from single photographs. Increasing imaging approaches have recently been presented, e.g., Refs. [6,7], by modifying the capturing process to obtain more desirable information during capture, such as depth information. A comprehensive survey on this topic was provided by Ref. [8].

In this letter, we present a computational imaging (CI) method for high-sensitivity and high-spatial resolution deep-space image acquisition. This method can be applied to small and dim target detection. In addition, the proposed approach is better for debris orbit determination.

We explain the details of CI, discuss its framework and mathematical model, and introduce the approach for reconstructing natural images.

The recently developed data measurement theory called CS in Ref. [9] has a profound effect on signal acquisition and processing. This theory states that as parse signal can be recovered perfectly from few measurements with the measuring vectors incoherent to the sparse representation basis. Motivated by the CS theory, we propose a CI approach and the corresponding reconstruction scheme, as shown in Fig. 1. Distributed random-coded measurements can be obtained sequentially using a single camera with changing random convolution kernels for deep-space data capturing. CI can be realized by inserting a changeable-coded mask within the aperture of the lens. The mask can be implemented with a photo mask sheet[10] or liquid crystal array[11]; we use the former.

The random convolution CS measurement model is

$$\mathrm{O}_i = D\left(K_i \otimes L\right) + n_i, \tag{1}$$

where L denotes the latent high-sensitivity image as $L \in \mathrm{R}^n$, $D \in \mathrm{R}^{m\times n} (m < n)$ denotes the down-sampling operator, n_i denotes the noise term, $\{K_i\}_{i=1}^{I}$ is a set of coded kernels, $\otimes$ is the convolution operator, and $\{O_i\}_{i=1}^{I} \in \mathrm{R}^m$ denotes the multiple observed images.

By designing a measurement matrix, the reconstruction of a latent high-sensitivity image can be transformed to a joint optimization problem, and its mathematical model is

$$L = \underset{L}{\operatorname{argmin}} \Big\{ \sum_{i=1}^{I} ||D(K_i \otimes L) - O_i||_2^2 + \eta \sum_{j=1}^{J} ||G_j \otimes L||^{\alpha} \Big\}. \tag{2}$$

In model (2), we assume that the noise level for each observation is the same following the Gaussian distribution, without loss of generality. The terms of the optimization model are as follows:

(i) The first term is the model fitting constraint, i.e., the reconstructed image should be consistent with the observations with respect to their corresponding degradation model, as shown in Eq. (1).

(ii) The second term is a general sparse prior for natural images using the sparse exponent of the responses of derivative filters to stabilize the solution[12], where $\alpha \in [0.5 \sim 0.8]$ is the hyper-Laplacian parameter, η denotes the regularity weight, and $G_j (j \in 1, 2, \cdots, J)$ denotes the derivative filters.

In high-sensitivity image acquisition, the mathematical model (2) plays an important role for latent image estimation. The conventional image capturing process directly obtains the observed image with down-sampling operator D. The conventional method conducts minor modification to encode more desirable information during capture and uses compressed measurements for recovering natural image. These features contribute to the whole imaging process to obtain larger size image without the down-sampling effect. We refer to the proposed imaging approach as CI.

The mathematical model (2) involves non-convex regularization terms that are difficult to directly minimize. In our scheme, we use the prior of the obtained images and an alternating minimization scheme introduced by recent sparse optimization and image reconstruction studies[13], which reduces the original optimization problem into a sequence of standard least squares problems. Following this scheme, each of the sequence least squares problem is reweighted by the previous step. Then, using a prior derived from the observation image, we can obtain an excellent latent image using a relatively small number of labeled gradients. The overall procedure is described in Algorithm 1.

In model (2), K_i can be used as the natural item obtained by a changeable-coded mask[10]. Thus, we first calculate the weighted matrix as

$$\omega_p^j = ||(G_j \otimes L)_p||^{\alpha-2}, \tag{3}$$

where $(G_j \otimes L)_p$ denotes the value of the gradient map of the latent image L at the position p.

By introducing the weighted matrix ω^j, we can rewrite model (2) as

$$L = \arg\min_L \left\{ \sum_{i=1}^{I} ||D(K_i \otimes L) - O_i||_2^2 + \eta \sum_{j=1}^{J} \left||\omega^j \circ (G_j \otimes L)\right| |_2^2 \right\}. \tag{4}$$

This model can be solved efficiently via the conjugate gradient descent algorithm. In practice, $\circ$ denotes the dot product operator. We use the derivative filter $\{G_1 = [1, -1], G_2 = [1, -1]^{\mathrm{T}}, G_3 = [1, -2, 1], G_4 = [1, -2, 1]^{\mathrm{T}}, G_5 = [1, -1; -1, 1]\}$ and set α= 0.5 as well as the number of iterations (N) to 20.

Several experiments are conducted to validate the effectiveness of the proposed method. We compare our method with a conventional imaging technique, i.e., imaging without mask, from several aspects, including spatial resolution, contrast between the target and the background, and target positioning precision.

In the first experiment, we provide two illustrative examples to evaluate the effectiveness of the proposed

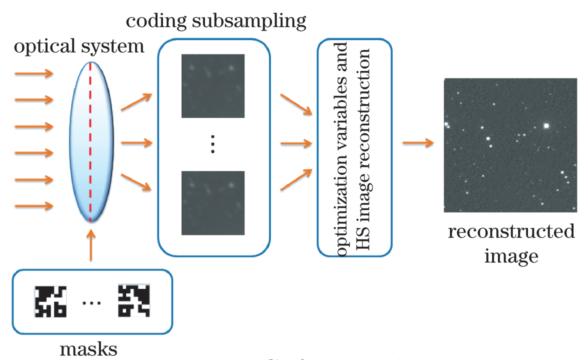
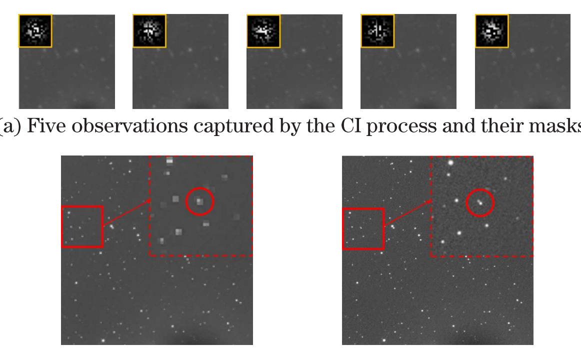


Fig. 1. CI framework.

Algorithm 1: Latent image estimation using iteratively reweighted least squares
Input: Observation image$\{O_i\}_{i=1}^I$, kernel $\{K_i\}_{i=1}^I$, regularity weight η,and hyper-Laplacian parameter α
Initialization: Inner iteration number R and latent imageL_0
For: $r = 1, 2, \cdots, R$
For: $j = 1, 2, \cdots, J$
For: $p = 1, 2, \cdots, P$(T is the number of pixels in the latent image L)
Calculate the weight matrix $\omega_p^j = ||(G_j \otimes L)_p||^{\alpha-2}$
End
End
via $L = \arg\min_L \left\{ \sum_{i=1}^{I} ||D(K_i \otimes L) - O_i| |_2^2 + \eta \sum_{j=1}^{J} \left||\omega^j \circ (G_j \otimes L)\right| |_2^2 \right\}$ Calculate the latent image L_r
End
Output: Estimate the latent image L_R

CI technique. Figures 2 and 3 show the procedure by separately simulating imaging with deep-space and calibration-plate images. The five observations shown in Figs. 2(a) and 3(a) were captured via the proposed CI process. They are used as the input of mathematical model (2). The latent image was reconstructed using iteratively reweighted least squares method, as shown in Fig. 2(c). The image captured by the conventional technique is shown in Fig. 2(b). Two very close pairs of point targets became one diffuse spot in the image obtained by the conventional imaging technique (as shown in Fig. 2(b)). They can be divided into two dispersion spots using the proposed technique (as shown in Fig. 2(c)). Thus, the subsequent processing is facilitated, i.e., the target detection. Figure 3 presents another illustration indicating that the proposed method can recover an image that contains more detailed information. In conclusion, the proposed technique can improve the spatial resolution of cameras at low cost.

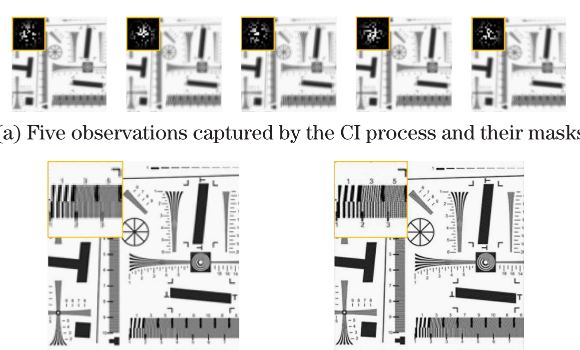
For the second experiment, we illustrate that the proposed method can increase the contrast gray level of the target and background. In Fig. 4, we calculate the contrast value R of the target to its background using $R = T/B$, where T denotes the mean gray level of the target, and B is the mean gray level of the background. In Fig. 4, the solid line shows the value from the image captured by the proposed method, and the broken line shows the value from the conventional imaging technique. Some weak point targets are almost submerged in the background in the conventional observation image, but they are enhanced in the reconstructed image. Thus, the proposed approach is better for dim target detection.



(a) Five observations captured by the CI process and their masks.

(b) Conventional observation. (c) Proposed method.

Fig. 2. Experimental results of deep-sky image.



(a) Five observations captured by the CI process and their masks.

(b) Conventional observation. (c) Proposed method.

Fig. 3. Experimental results of plate-image calibration.

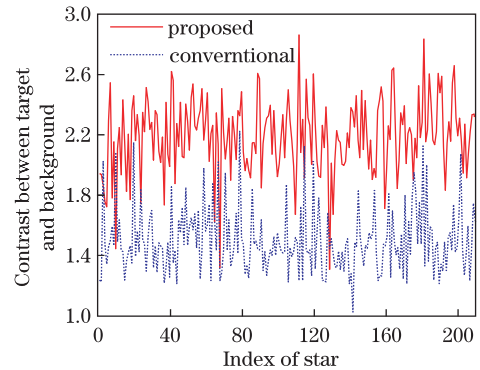


Fig. 4. Contrast of the gray level between target and background.

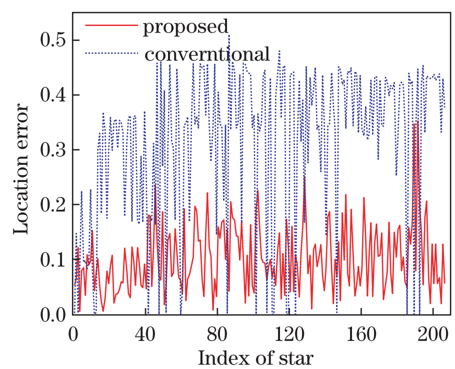


Fig. 5. Curves of the positioning error between the conventional and proposed methods.

Table 1. Positioning Error Comparison

Method	Conventional	Proposed
Mean	0.3171	0.1026
Std	0.1403	0.0601

In the last experiment, we demonstrate that the proposed method can improve the precision for target positioning. In Fig. 5, the broken line is the locating error calculated by the centroid locating method[14] using the conventional image, and the solid line is the locating error calculated by the same method using the reconstructed image. Given that the proposed method can improve the spatial resolution of cameras, the pixel is subdivided, which facilitates the geometric center, instead of the gray balance point, more accurately. Thus, the proposed method is better for high-precision locating with lower system error. The qualitative comparison of the proposed method with the conventional method is presented in Table 1. The proposed method has higher stable positioning accuracy than the conventional method, which verifies the effectiveness of the proposed method.

The proposed CI approach has several advantages over conventional imaging technologies. This approach can easily acquire higher sensitivity and higher spatial resolution image by placing a changeable-coded mask in front of the lens, which is difficult for traditional imaging systems because of their limitations on miniaturization and lowmass. The proposed approach also reduces the size of multiple measurements by coded measurements.

Furthermore, it is more competitive in terms of the application in debris surveillance, as follows.

This method is better suited for dim target detection. The ability of the point target detection algorithm determines the performance of the surveillance system. Thus, the detection of dim targets and close pair of targets is crucial. During detection, regardless of the detection rate of the algorithm, the final result depends on the quality of the observation image, i.e., the dim-point target image submerged in noise, or two very close point targets become a diffuse spot in the image. The proposed imaging method can produce enhanced image quality at a low cost.

The proposed method also facilitates the precision of orbit determination. The accuracy of orbit determination depends on the precision of centroid location in the observation image. The location error is mainly introduced by system and random errors[13]. The system error is generally caused by the geometric center, instead of the gray balance point, thus improving the consistency of the sample point. The light intensity of the sensing area can be used to reduce the system error. The proposed method can subdivide the size of the sample point to be more conducive to error correction and improve the precision of the target location.

In conclusion, a CI approach for high-sensitivity image acquisition is proposed in this letter. The experimental results show that the proposed imaging method can effectively enhance the target signal-to-noise ratio and the spatial resolution of the dim-point debris image. Thus, it is more desirable in small and dim target detection, close pair of target detection, and high-precision orbit determination. Furthermore, the proposed imaging approach can generate high-sensitivity images for improved target surveillance and early warning, with low-performance sensor.

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References

1. E. R. Dowski and W. T. Cathey, Appl. Opt. **34,** 1859 (1995).
2. R. Ng, M. Levoy, M. Br'edif, G. Duval, M. Horowitz, and P. Hanrahan, "Light FieldPhotography with a Hand-Held Plenoptic Camera," Stanford University Computer Science Tech ReportCSTR 2005-02 (2005).
3. M. Levoy, B. Chen, V. Vaish, M. Horowitz, I. McDowall, and M. Bolas, ACM Siggragh **23,** 825 (2004).
4. M. F. Duarte, M. A. Davenport, D. Takhar, J. N. Laska, T. Sun, K. F. Kelly, and R. G. Baraniuk, IEEE Signal Processing Mag. **25,** 83 (2008).
5. A. Levin, R. Fergus, F. Durand, and B. Freeman, ACM Siggragh **26,** 70 (2007).
6. S. M. Kim, W. Baughman, D. S.Wilbert, L. Butler, M. Bolus, S. Balci, and P. Kung, Chin. Opt. Lett. **9,** 110009 (2011).
7. H. Zhao and Y. Li, Chin. Opt. Lett. **10,** 031101 (2012).
8. G. Wetzstein, I. Ihrke, D. Lanman, and W. Heidrich, ACM Siggragh **31,** 11 (2012).
9. D. Donoho, IEEE Trans. Information Theory **52,** 1289 (2006).
10. C. Zhou, S. Lin, and S. Nayar, Int. J. Comput. Vis. **93,** 53 (2011).
11. C. Liang, T. Lin, B. Wong, C. Liu, and H. Chen, ACM Siggragh **27,** 1 (2008).
12. D. Krishnan and R. Fergus, Adv. Neur. Info. Proc. Sys. **22,** 1033 (2009).
13. A. Levin and Y. Weiss, IEEE Trans. PAMI **29,** 1647 (2007).
14. J. Sun, J. Zhou, Z. Zhang, and Y. Zhang, Opt. Precision Engineering **19,** 3041 (2011).