TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.6, June 2014, pp. 4794 ~ 4801
DOI: 10.11591/telkomnika.v12i6.5524

An Efficient Imaging Strategy for Single Pixel Camera in Earth Observation

Chuanrong Li[1], Qi Wang[2], Changyong Cao[3], Lingling Ma*[4]
[1,2,4]Key Laboratory of Quantitative Remote Sensing Information Technology, Academy of Opto-Electronics, Chinese Academy of Sciences, Beijing, 100094, China
[2]University of Chinese Academy of Sciences, Beijing, 100049, China
*Corresponding author, e-mail: crli@aoe.ac.cn[1], wangqi_aoe@foxmail.com[2], changyong.cao@noaa.gov[3], llma@aoe.ac.cn[4]

Abstract

Single pixel camera is a new imaging device that develops from the "ghost" imaging and compressive sensing theory. For high resolution imaging with large amount of data, the process of measurement and reconstruction is time-consuming, which limits its application to remote sensing area. Based on the analysis of the configuration of the single pixel camera, an efficient imaging strategy through combining different numbers of DMD mirrors and local imaging was proposed which is able to image the interested target in high resolution with low time cost. Simulation experiment was carried out for two different types of targets, i.e., three-line target image and the scene consisting of a ship in the ocean. Three types of images, in low, middle and high resolution, are reconstructed respectively by the control of DMD working area and the strategy to combining DMD mirrors. The reconstructed images reached the application requirements at very low measurement and reconstruction time cost. The effectiveness and practicality of this strategy could be applied to other compressive sensing imaging devices.

Keywords: *single pixel camera, digital micro mirror device (DMD), earth observation, compressive sensing, image resolution*

1. Introduction

Single pixel imaging is a new type of imaging technique that draws more and more attention in recent years. It develops from the "ghost" imaging or so-called intensity correlation imaging theory [1] and compressive sensing theory. The first single pixel camera was realized based on digital micro mirror device (DMD) via Marco F. Duarte et al. in 2006 [2]. Unlike imaging by CCD array in conventional imaging system, the new imaging system employes only single-pixel detector to collect multiple measurements. It does not acquire the object's image through one exposure, but calculates the image from the multiple observation measurements collected by the single-pixel detector and the measurement mode realized (recorded) by DMD. The calculation algorithm used is the mathematical method named compressive sensing [3]. Since there is only one sensor in the imaging system, the architecture of the imaging system can be much simpler than conventional cameras. The single-pixel detector can be much more efficient, less expensive while keeping higher sensitivity, and especially suitable for the case of infrared imaging [4].

Earth observation is an important application area of the single pixel camera and it usually related to large amount of data volume. The data amount from the single-pixel detector is small and thus easy to deliver and record, however, the record process of the whole measurement mode needs large amount of disk size, and the image reconstruction process also needs amount of memory size. For example, to image a scene of 1024×1024 pixels with 0.3 sampling rate, and use 1 byte short integer data type to store, there needs 307GB memory to store the measurement matrix. If further reduce the sampling rate, the image resolution would be very low.

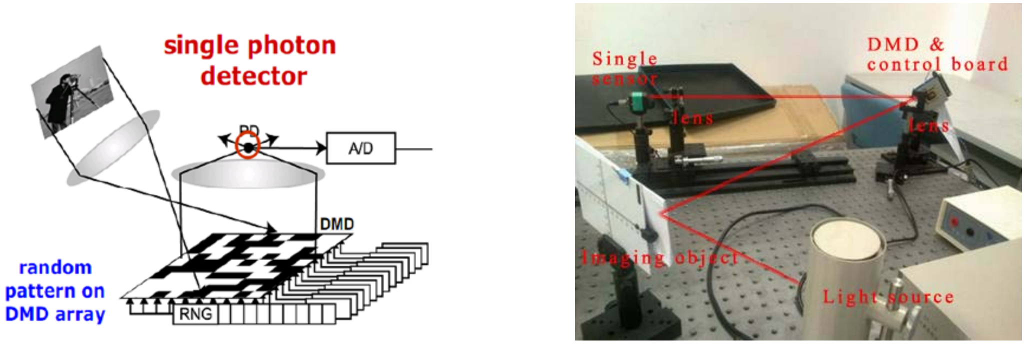
Nevertheless, not all targets in the earth observation scene need to bereconstructed with high resolution. For example, over ocean, only high resolution of the ships in the image scene are needed, and low resolution image of the sea surface is sufficient.In this paper, a new imaging strategy of the single pixel camera suitable for remote sensing imaging is proposed. In

Received December 30, 2013; Revised March 12, 2014; Accepted March 27, 2014

Section 2, the configuration of the single pixel camera and compressive sensing theory is introduced. In Section 3, the DMD block method to adjust imaging resolution is presented and the simulation on three-line target is executed to verify the idea. In Section 4, the strategy to efficiently image the interested target in high resolution is proposed and the simulation experiment to prove the new strategy is executed, and the result is shown and analyzed. In Section 5, the content of this paper is concluded.

2. Introduction of Single Pixel Camera and Compressive Sensing

Figure 1 shows the configuration of the single pixel camera. The main components of the device are an imaging lens, DMD and its control board and the single sensor.



(a) (b)

Figure 1. (a) The schematic of single pixel camera (picture from http://dsp.rice.edu/cscamera)
(b) The experimental apparatus of single pixel camera

The pivotal device in the system to realize random measurement is the DMD, which is a planar array of millions of micro mirrors in the size of micrometers. Each mirror can be controlled to rotate to two directions, called “on” and “off”, so that the light goes into the DMD can be reflected to two different directions. The object is imaged on the DMD first and then DMD reflect different parts of the object to different directions. An imaging lens is placed on the “on” direction to focus on the detector. One type of DMD configuration is related to one measurement value. If changing the pattern on the DMD, more measurement values could be acquired. The pattern for one measurement is called a frame, and the numbers of frames needed to fully reconstruct the image is decided by the dimension of the image scene and the sparsity of the object.

The equation for DMD is expressed by:

$$y_t = \sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij}\Phi_{ijt}. \tag{1}$$

Where m, n is the size of DMD array, x_{ij} is the object’s reflection intensity on position (i, j), and Φ_{ijt} is the status of the mirror on corresponding position, either 0 or 1. y_t is the measurement of t-th time. For M times measurements, t=1,2,…,M.

Compressive sensing theory can be adopted to solve Equation (1). The theory proves that sparse signals can be well reconstructed from incoherent measurements at the sampling rate beyond Nyquist limit. Assuming $x^{N\times 1}$ is the one dimension expansion of x_{ij} and in Equation (1), where $N=mn$. $\Phi^{M\times N}(M<N)$ is the measurement matrix that each row vector is the one dimension expansion of the pattern at one frame. $y^{M\times 1}$ is the measurements of M times. The ratio M/N is called the sampling rate. To solve the underdetermined equation, x should be sufficiently sparse and the sparsest vector among the solution set of the equation is the correct one. The linear equation can be transformed into such optimization problem:

$$\hat{x} = \arg\min \|x\|_0 \quad s.t.\ \Phi x = y. \tag{2}$$

The L0-norm in Equation (2) indicates the number of nonzero elements. While many signals like earth observation objects are non-sparse, a set of basis $\Psi^{N\times K}$ should be found to make the signal's representation under such basis is sparse. The Equation (2) is written as:

$$\hat{s} = \arg\min \|s\|_0 \quad s.t.\ \Phi\Psi s = y. \tag{3}$$

$$x = \Psi s \tag{4}$$

The compressive sensing reconstruction algorithms to solve Equation (3) include various types of L1-norm convex optimization, greedy search algorithms, Bayesian estimation algorithms and so on [5-7]. And the sparse basis Ψ can be DCT basis, wavelet basis or various types of redundant dictionary [8].

3. Effect of the Number of DMD Mirrors to Image Reconstruction

The number of DMD mirrors is equal to the number of reconstructed image's pixels, and it actually represents the image resolution. The larger number of DMD mirrors correspondes to higher resolution reconstructed image, however, there are larger number of unknowns in the equation and hence it costs much more time and memory to reconstruct image. In order to enhance computational efficiency, one compromise is to combine some mirrors into a large block, where the mirrors in the same block perform the same statues, e.g., "on" or "off". Figure 2 shows an example to combine 3×3 mirrors.

(a) (b)

Figure 2. (a) A random pattern of a 6×6 DMD area, the gray grid represents 0 and the white grid represents 1 (b) Combining 3×3 mirrors into a large pixel, mirrors in a large pixel are on the same status

Assuming the DMD block size is $p\times q$, the new image pixel size is $u\times v$, $u=m/p$ and $v=n/p$. Equation (1) can be rewritten as:

$$y_t = \sum_{k=1}^{u}\sum_{l=1}^{v}\left(\sum_{i=(k-1)p+1}^{kp}\ \sum_{j=(l-1)q+1}^{lq} x_{ij}\Phi_{ijt}\right) = \sum_{k=1}^{u}\sum_{l=1}^{v}\left(pq\tilde{x}_{kl}\Phi_{klt}\right). \tag{5}$$

Where $\tilde{x}_{kl}$ is the mean value of each $p\times q$ area and in the area the mirrors are on the same status so the measurement element of the area can be written as Φ_{klt}. Rewrite Equation (5) as:

$$y'_t = \sum_{k=1}^{u}\sum_{l=1}^{v}\left(\tilde{x}_{kl}\Phi_{klt}\right). \tag{6}$$

$$y'_t = \frac{y_t}{pq}. \tag{7}$$

Equation (6) has the same form as (1), and $\tilde{x}_{kl}$ can be solved from it.

In order to demostrate the effect of the number of DMD mirrors to image reconstruction, the three-line bar pattern is employed as the test target. The three-line bar pattern target is widely used to estimate the spatial resolution of optical images. In the simulation experiments, the size of the image consisting of three-line target is 128×128 pixels, as shown as in Figure 3. There are horizontal and vertical stripes of 8, 4, 2, 1 pixels wide. Set the DMD block size to 8, 4, 2, 1 respectively and then reconstruct the image. The other important parameters in the simulation experiment are: 0-1 Bernoulli random matrix as DMD pattern, DCT matrix as sparse representation, SL0 algorithm as spare reconstrction algorithm [9]. The sampling rate is 0.6. The reconstruction images are shown in Figure 4. And the reconstruction time for each image is shown as in Table 1.

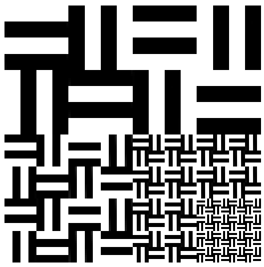
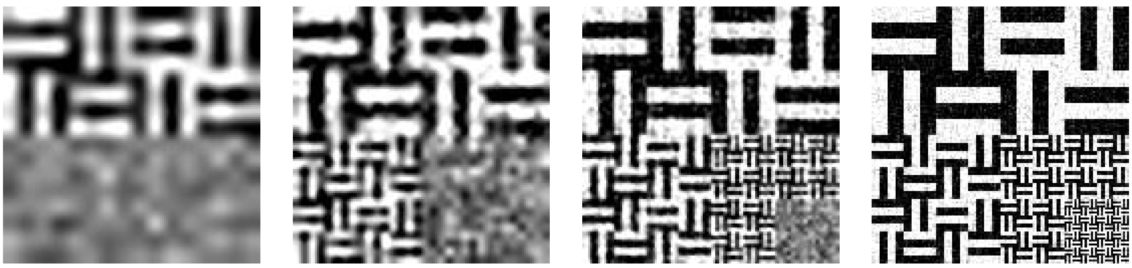


Figure 3. The Three-line Bar Pattern Target



(a) (b) (c) (d)

Figure 4. Reconstructed Images under the Block Size of 8, 4, 2, 1 Respectively

Table 1. The Reconstruction Time of the Three-line Target

Block size	8	4	2	1
Time (s)	0.99	1.76	50.2	4795

Figure 4 shows that the resolution of the reconstructed image is x pixels for the DMD block size x(x=8,4,2,1), which verifies the above presented theory. Combined with Table 1, it can be conclued that the reconstruction time increases dramaticly while the resolution becomes higher. Therefore, it must compromise the image resolution and reconstruction time in the EO application of single pixel camera.

4. Efficient Imaging Strategy for Imaging the Target of Interest

In some earth observation application, the valuable information exists only in small part of the scene. It is more efficient to image just that part of the scene. While changing the optical parameter such as the caliber and focal length of the imaging lens is more complicated and unstable than controlling the DMD mirrors, so the local imaging strategy based on the operation of DMD is a better choice. In Equation (1), the size of the DMD is $m \times n$ and the local imaging area is $[m_1, m_2] \times [n_1, n_2]$, the method is to show the random pattern of just this area and always close the other, that would be 0 in other parts. And Equation (1) can be rewriiten as:

$$y_t = \sum_{i=m_1}^{m_2} \sum_{j=n_1}^{n_2} x_{ij} \Phi_{ijt}. \quad (8)$$

By solving the Equation (8) the size of reconstructed image is $(m_2\text{-}m_1+1) \times (n_2\text{-}n_1+1)$, which is part of the whole sence.

The challenge of the local imaging mode is how to find the interested imaging area and locate in the whole DMD plane without knowing the prior information of the earth observation scene. In this paper, an efficient imaging strategy employing the combining the DMD block and local imaging are proposed. The combination of the DMD block has the advantage for fast reconstructing taget image, though the resolution of the image is low but is helpful for finding the imaging area of interest.

The flow chart of efficient imaging strategy is show in Figure 5.

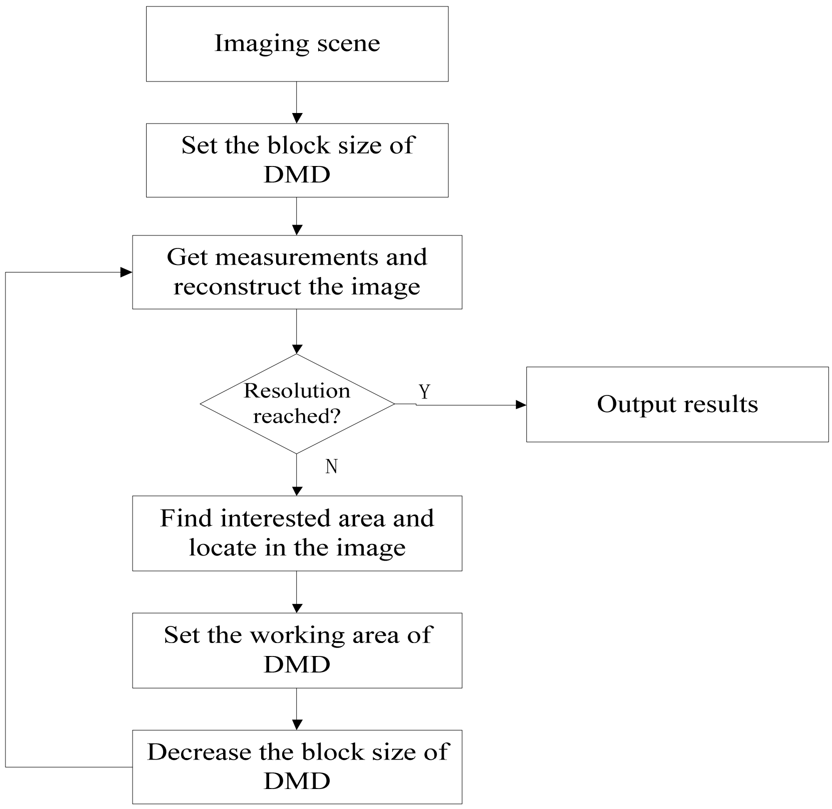


Figure 5. The Flow Chart of Efficient Imaging Strategy

A simulation scene, which consists of a ship in the ocean, is employed as the experiment scene. The image size is 2048×2048 pixels, which equals to the total number of DMD mirrors. As only a small area near the ship or just the flag of the ship is of interest, it's better to reconstruct the image of just that area. The location of target is unknown, and low resolution image of the whole scene to help find such information. The steps to efficiently reconstruct the target of interest are as follows:

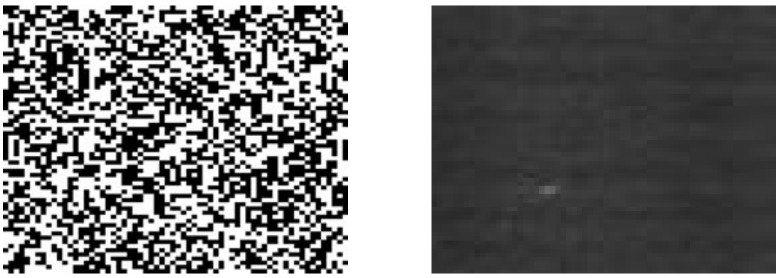
Figure 6. The Simulation Scene of a Ship in the Ocean

Step 1: Set the DMD block size of 32 to combine the mirrors and use all the mirrors of DMD to image the whole scene in low resolution. There are 64×64 pixels in the reconstructed image. The sampling rate is 0.3.

Step 2: Locate the target in the low resolution image and calculate the corresponding cordinate in the DMD plane, and just use 256×256 mirrors around the target spot to image, the unused mirrors are always off. Set the DMD block size 4 to image the ship in middle resolution. There are also 64×64 pixels in the reconstructed image. The sampling rate is 0.6.

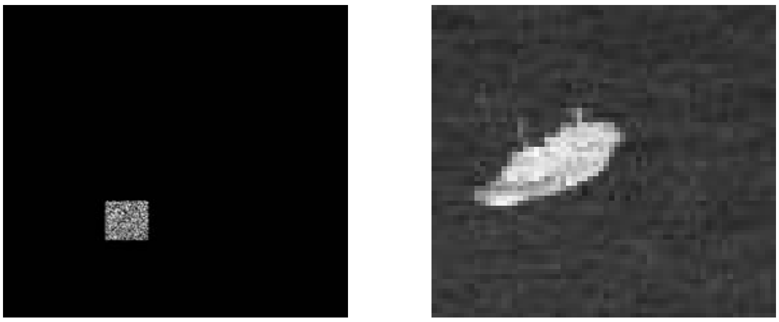
Step 3: Locate the intested part of the ship in the middle resolution image and calculate the corresponding cordinate in the DMD plane, use 64×64 mirrors around the target spot to image, set the DMD block size 1 to image the ship in high resolution. There are also 64×64 pixels in the reconstructed image. The sampling rate is 0.6. The other important parameters is the same as in 3.1.

One of the frames of the DMD and the reconstructed image in Step 1 to 3 are shown respectively as Figure 7, Figure 8 and Figure 9.



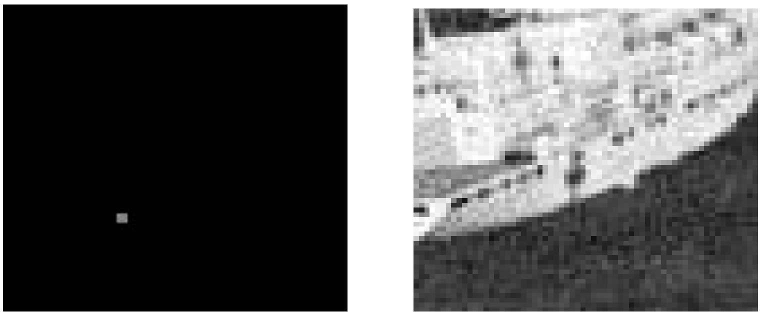
(a) (b)

Figure 7. (a) One of the frames of the DMD pattern in Step 1; (b) The reconstructed low resolution image of 64×64 pixels



(a) (b)

Figure 8. (a) One of the frames of the DMD pattern in Step 2; (b) The reconstructed middle resolution image of 64×64 pixels



(a) (b)

Figure 9. (a) One of the frames of the DMD pattern in Step 3; (b) The reconstructed high resolution image of 64×64 pixels

It can be seen that in the reconstructed low resolution image, only a bright spot on the bottom left can be recognized; in the reconstructed middle resolution image, the shape of the ship can be clearly recognized. The resolution of the image in Step 2 is 8 times higher than that in Step 1. In the reconstructed high resolution image, the detailed information, like the symbol of the ship, can be recognized. As there is no mirror combination in Step 3, the image resolution achieved the highest in this simulation experiment, which is 4 times higher than that in Step 2.

The reconstructed low resolution images can be enlarged to the original size of the imaging scene and the interested area in low resolution image can be replaced by that of the high resolution image, the result is shown in Figure 10.

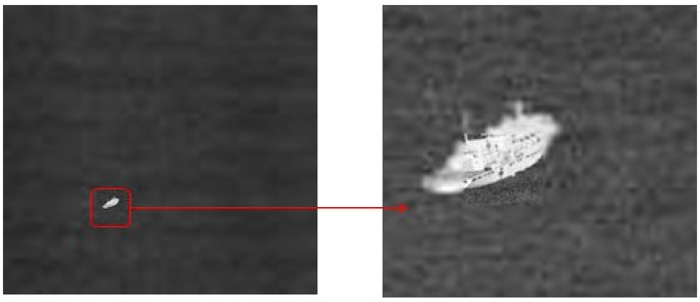


Figure 10. The Integration of Three Reconstructed Images

From the integrated image in Figure 10, not only the position of the object is clearly shown, but also the detailed information of the ship can be recognized.

The total number of frames of the DMD in 3 steps is 64×64×0.3+64×64×0.6+64×64×0.6 =6144, and the memory cost is 19.2MB. If directly reconstruct the whole scene in high resolution, 2048×2048×0.6=2516583 frames of DMD and 9.38TB memeroy must be needed. If the flipping rate of DMD is 1000 times per second, the measurement strategy in this paper need about 6 seconds for observation, while 42 minutes observation time is needed without adopting such strategy. As to the reconstruction time, the total time consumed in 3 steps is 42.8 seconds on an Intel i5-2430M CPU @ 2.40GHz laptop computer with 10GB memory in MATLAB environment. The test of imaging the whole scence whithout adopting th is strategy is not done since there is no enough memory to store such huge data amount of the measurement matrix.

5. Conclusion

In this paper, to meet the application demand of earth obsercation imaging, an efficient strategy of combining different numbers of mirrors in DMD to adjust image resolution and using specific area in DMD to reconstruct the area of interest is presented for single pixel camera. The simulation experiment is carried out to verify the theory by imaging the three-line target and for the application mode to image a ship in the large area of oecan in which three steps to image the scene from low to high resolution are executed. The result shows that the detailed information of the interested object is recognized while consuming much less measurement and calculation time than traditional imaging method, and it validates the effectiveness and practicality of the proposed strategy. Future work will focus on the auotomatic algorithm for target regoconition and location in various earth observation application mode.

Acknowledgements

This work was financially supported by the CAS/SAFEA International Partnership Program for Creative Research Teams and the National High Technology Research and Development Program (No. 2013AA121304).

References

[1] Pittman TB, et al. Optical imaging by means of two-photon quantum entanglement. *Physical Review A*. 1995; 52(5): R3429-R3432.
[2] Duarte MF, Davenport MA, Takbar D, etc. Single-pixel imaging via compressive sampling: Building simpler, smaller, and less-expensive digital cameras. *IEEE Signal Processing Magazine*. 2008; 25(2): 83-91.
[3] Candes EJ, Romberg J, Tao T. Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information. *IEEE Transactions on Information Theory*. 2006; 52(2): 489-509.
[4] Russell, Thomas A, et al. *Compressive hyperspectral sensor for LWIR gas detection*. Proc. of SPIE Vol. 2012; 8365.
[5] Efron B, Hastie T, Johnstone I, etc. least angle regression. *Annal of Statistics*. 2004; 32(2): 407-499.
[6] Needell D, Vershynin, R. Signal recovery from incomplete and inaccurate measurements via regularized orthogonal matching pursuit. *IEEE Journal on Selected Topics in Signal Processing*. 2010; 4(2): 310-316.
[7] Babacan SD, Molina R, Katsaggelos AK. Bayesian compressive sensing using laplace priors. *IEEE Transactions on Image Processing*. 2010; 19(1): 53-63.
[8] Aharon M, Elad M, Bruckstein A. K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation. *IEEE Transactions on Signal Processing*. 2006; 54 11): 4311-4322.
[9] Mohimani GH, Babaie-Zadeh M, Jutten C. *Fast sparse representation based on smoothed L0 norm*. Proceedings of the 7th international conference on Independent component analysis and signal separation, London, UK. 2007; 389-396.