Optics Communications 410 (2018) 35–39

Contents lists available at ScienceDirect

Optics Communications

journal homepage: www.elsevier.com/locate/optcom

Image reconstruction of dynamic infrared single-pixel imaging system

Qi Tong, Yilin Jiang, Haiyan Wang, Limin Guo *

College of Information and Communication Engineering, Harbin Engineering University, Harbin 150001, China

ARTICLE INFO

Keywords:
Single-pixel
Infrared image
Dynamic compressive imaging
System movement

ABSTRACT

Single-pixel imaging technique has recently received much attention. Most of the current single-pixel imaging is aimed at relatively static targets or the imaging system is fixed, which is limited by the number of measurements received through the single detector. In this paper, we proposed a novel dynamic compressive imaging method to solve the imaging problem, where exists imaging system motion behavior, for the infrared (IR) rosette scanning system. The relationship between adjacent target images and scene is analyzed under different system movement scenarios. These relationships are used to build dynamic compressive imaging models. Simulation results demonstrate that the proposed method can improve the reconstruction quality of IR image and enhance the contrast between the target and the background in the presence of system movement.

1. Introduction

Compressive imaging is a growing technique in many fields recently, which benefits from the emergence of compressed sensing (CS) theory [1,2]. CS theory has been widely applied to optical imaging applications such as single-pixel imaging [3–6], lensless imaging [7], radar imaging [8] and terahertz imaging [9]. Compressive imaging technique not only reduces the number of sampling points but restores sufficient quality images. A reconstructed image with better resolution and higher peak signal-to-noise ratio (PSNR) can be captured with fewer samples through the compressive imaging technique. These advantages also led to the rapid development of compressive imaging. The usual way to improve the spatial resolution is to increase the number of detectors. This approach takes more sampling costs and puts a higher demand on the detector size. Compressive imaging technique can solve these problems in a better way. CS theory makes that the spatial resolution of reconstructed image is no longer limited by the pitch of the pixels in the detector array.

Single-pixel camera is a classic compressive imaging application example, which is a new camera architecture based on CS framework and digital micromirror device (DMD) [3]. CS theory enables that an image can be reconstructed with fewer measurements than the number of original image pixels. IR rosette scanning system is a sub-imaging system composed of the single detector and optical scanning device [10]. It is used to complete the detection, identification and tracking of the target for IR imaging guidance. This system scans the scene with a rosette pattern and provides the target location information to servo system. In the traditional imaging mode, the spatial resolution and signal-to-noise ratio of reconstructed image is low due to its incomplete sampling characteristics. Based on its optical scanning system, the scanning device of the IR rosette scanning system can be seen as a compressive imaging platform, the compression process is achieved by the scanning operation [11], which is different from the DMD and mask methods.

Most of the current compressive imaging platform are fixed, especially single-pixel imaging. Single-pixel imaging system can only capture one measurement at a time. Each measurement may come from a different scene in this case, which is detrimental to the image recovery when the system is in motion. In the IR rosette scanning system, the number of measurements required is greatly reduced by the compressive imaging technique. When the system is moving, the scanning target image of each frame is different. The movement of the system in a frame time is negligible, i.e., the target scene can be considered to be relatively stationary in the scanning period of one frame. The proposed dynamic compressive imaging approach for ground targets is built on this basis. In this paper, we focus on the image reconstruction of ground targets and propose a dynamic compressive imaging model based on the IR rosette scanning system. The rest of this paper is organized as follows. IR rosette scanning system is introduced in Section 2. The dynamic compressive imaging model is presented and image reconstruction scheme is analyzed in Section 3. Simulation results and discussions are given in Section 4. Finally the paper is concluded in Section 5.

* Corresponding author.
E-mail address: guolimin@hrbeu.edu.cn (L. Guo).

https://doi.org/10.1016/j.optcom.2017.09.069
Received 16 June 2017; Received in revised form 18 September 2017; Accepted 21 September 2017
0030-4018/

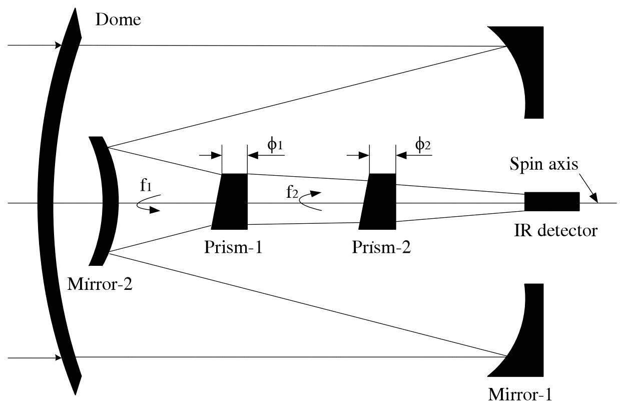

Fig. 1. Schematic of the IR rosette scanning system.

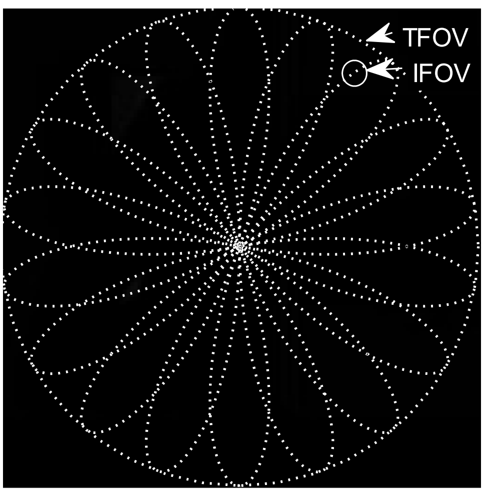

Fig. 2. Rosette scanning pattern.

2. IR rosette scanning system

IR rosette scanning system scans the total field of view (TFOV) through a smaller instantaneous field of view (IFOV) along a rosette pattern and provides an image with positioning information about the target. Fig. 1 shows the schematic of the IR rosette scanning system.

The rosette pattern is realized by two counter-rotating optical elements with frequencies f_1 and f_2 respectively. It can be seen from Fig. 2 that the number of scan lines through the target is not evenly distributed, which creates a certain blind spot in the corners.

3. Dynamic compressive imaging model

3.1. Static compressive imaging

In the IR rosette scanning system, when the target is relatively stationary with the imaging system, the imaging model is described as

$$y = \Phi x = \Phi \Psi s, \tag{1}$$

where x is the original signal, which can be sparsely represented on sparsity basis Ψ as $x = \Psi s$. Φ is an $M \times N$ measurement matrix and y is the measurement vector.

Eq. (1) shows that CS is a dimensionality reduction process from length N to M. The coefficient vector $\hat{s}$ can be solved by the l_0-minimization problem [12]

$$\hat{s} = \arg\min \|s\|_{l_0} \quad s.t. \quad y = \Phi \Psi s, \tag{2}$$

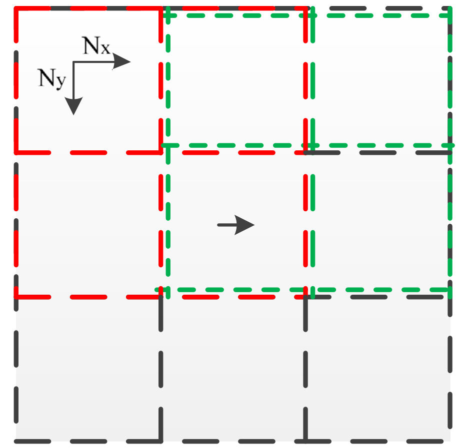

Fig. 3. The black dotted area is the entire scene X. The red area is the target image X_1. The green area is the target image X_2.

where $\|\cdot\|_{l_0}$ denotes the l_0 norm function. The original signal can be recovered by basis pursuit and matching pursuit approach [13–15].

3.2. Dynamic compressive imaging

In the dynamic compressive imaging system, there is a shift between adjacent two frames based on the movement of the imaging system. In order to reconstruct the original scene, it is necessary to find the relationship between the target image of each frame and the scene to be recovered. Three movement scenarios are discussed in this section.

Firstly assume that the system moves a pixel position in the horizontal direction, $N_x = 1$, $N_y = 0$. During the first frame scan period, the target image X_1 is the compressed sampling object. The target image X_2 is the compressed sample of the next frame. It can be seen that both X_1 and X_2 are related to the entire scene. The entire scene X can be reconstructed by finding the relationship between the two target images and the entire scene. Fig. 3 shows the measurement process when the system has a pixel shift in the horizontal direction.

The relationship between the target images and the scene can be expressed as: $X_1 = T_1 X T_1^T$, $X_2 = T_1 X T_2^T$, $X \in R^{(N+1)\times(N+1)}$,

$$T_1 = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & 0 \end{bmatrix}_{N\times(N+1)},$$

$$T_2 = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & 1 \end{bmatrix}_{N\times(N+1)},$$

where T_1, T_2 is the transformation matrix. The relationship of the vertical movement can be derived from the horizontal direction.

Consider the second case that the system moves a pixel position in the vertical and horizontal directions, respectively, $N_x = 1$, $N_y = 1$. Fig. 4 shows the moving scene.

In this scenario, the relationship between the three is $X_1 = T_1 X T_1^T$, $X_2 = T_2 X T_2^T$,

$$T_1 = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & 0 \end{bmatrix}_{N\times(N+1)},$$