Compressive Imaging of Moving Targets Based on Line-Scan Measurements (Postprint)

Authors: Wang Pan, Yao Xuri, Liu Xuefeng, Yu Wenkai, Qiu Peng Zhai Guangjie

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Abstract

Moving target imaging plays a significant role in practical applications, and obtaining high-quality images of moving targets represents a hot research topic in this field. This paper employs a line-scan sampling approach, constructs a motion measurement matrix, and establishes a moving object imaging model based on compressed sensing theory. Through simulations and experiments, the feasibility of this model for recovering moving object image information is verified. Experimental results demonstrate that the proposed method can achieve high-quality moving object imaging. By introducing image quality evaluation metrics, the relationship between imaging quality and object velocity is analyzed. Furthermore, this method is compared with conventional compressed sensing algorithms, with results proving that it produces higher imaging quality at the same velocity. Consequently, this imaging method holds promising application prospects in areas such as UAV ground observation and production line video monitoring.

Full Text

Preamble

Moving Target Compressive Imaging Based on Row-Scanning Measurement

Wang Pan-Pan[1)2)], Yao Xu-Ri[1)], Liu Xue-Feng[1)], Yu Wen-Kai[3)], Qiu Peng[1)2)], Zhai Guang-Jie[1)]*

[1)] Key Laboratory of Electronics and Information Technology for Space Systems, Center for Space Science and Applied Research, Chinese Academy of Sciences, Beijing 100190, China
[2)] University of Chinese Academy of Sciences, Beijing 100190, China
[3)] School of Physics, Beijing Institute of Technology, Beijing 100081, China

Abstract

Moving target imaging plays a crucial role in practical applications, and obtaining high-quality images of moving targets represents a key research challenge in this field. This paper proposes a novel compressive sensing-based imaging model for moving objects that employs a row-scanning sampling approach and constructs a dedicated motion measurement matrix. Through both simulations and experiments, we demonstrate the feasibility of this model for reconstructing moving object image information. Experimental results confirm that the proposed method can achieve high-quality imaging of moving objects. By introducing image quality evaluation metrics, we analyze the relationship between imaging quality and target velocity. Comparative studies with conventional compressive sensing algorithms further demonstrate that our method yields superior imaging quality under identical motion conditions. Consequently, this imaging approach shows promising application prospects in fields such as UAV-based ground observation and production line video monitoring.

Keywords: compressive sensing; moving target imaging; row scanning; measurement matrix

1 Introduction

Compressive Sensing (CS) theory, proposed by Candès, Donoho, Tao, and others, represents a revolutionary signal reconstruction framework [1,2]. The theory establishes that if a signal is compressible or sparse in some transform domain, it can be projected from a high-dimensional space to a low-dimensional one through a random observation matrix, and the original signal can be reconstructed from a small number of projections by solving an optimization problem. By breaking the limitations of the Nyquist sampling theorem, this signal recovery theory has become a hot research topic in recent years [3,4]. The single-pixel camera model developed by Rice University stands as a typical application of CS theory, enabling imaging using only a single point detector [5-7]. Researchers have also applied CS to quantum imaging, remote sensing imaging, medical imaging, and other fields [8-14]. Like other imaging modalities, achieving high-quality imaging constitutes one of the primary objectives of CS algorithms. However, existing CS imaging research has primarily focused on stationary targets.

In practical imaging scenarios, most targets are in motion, making high-quality imaging of moving targets critically important. For instance, in UAV-based ground observation and production line video monitoring, relative motion between the imaging system and the target leads to quality degradation and motion blur [15,16]. In recent years, several CS-based models for moving object imaging have been proposed, including motion ghost imaging deblurring using speckle size and velocity retrieval by Han Shensheng et al. [17,18], optical remote sensing motion-compensated compressive imaging by Liu Jiying et al. from the National University of Defense Technology [19,20], and complementary sampling-based moving target compressive imaging proposed by our research group [21]. Traditional CS imaging algorithms generally employ region-scanning imaging. However, when the pixel size of the image to be reconstructed is large, the measurement matrix becomes correspondingly large, consuming substantial system memory for storage.

This paper proposes a row-scanning sampling approach [23,24] that constructs a motion measurement matrix to establish a novel compressive sensing-based imaging model for moving objects. Row-scanning sampling not only significantly reduces the storage requirements for the measurement matrix but also improves measurement sampling time. Building upon numerical simulations, we have constructed a proof-of-principle experimental setup incorporating a Digital Micromirror Device (DMD) [25-27] to validate that this model can reconstruct high-quality images of moving objects.

2.1 Compressive Sensing Theory

Compressive Sensing (CS) theory, introduced in 2006, has been effectively applied in numerous optical fields as an information processing technique. The theory states that for sparse or compressible signals, a small number of non-adaptive linear measurements can capture sufficient information for signal reconstruction, thereby breaking the traditional Nyquist sampling theorem. By leveraging the prior knowledge of signal sparsity and optimization algorithms, an n-dimensional signal can be recovered from m measurements (where m < n), enabling sub-Nyquist reconstruction of object information.

In the CS mathematical model, a one-dimensional signal can be sparsely represented in a sparse basis Ψ as:

$$x = \Psi x'$$

where x' is sparse. The measurement process can be expressed as:

$$y = Ax + e$$

where y is an m-dimensional vector, A is an m×n measurement matrix (with m potentially less than n), and e represents noise. When matrix A satisfies the Restricted Isometry Property (RIP) condition [6-8], the signal x can be recovered through the following optimization objective function:

$$\min_{x'} \frac{1}{2}\|y - A\Psi x'\|_2^2 + \tau\|x'\|_1$$

where τ is a constant factor and $\|\cdot\|_1$ represents the ℓ_1 norm. Sparse representation of the object signal constitutes a crucial prerequisite and key factor for effective sub-Nyquist recovery in compressive sensing. Additionally, the design and construction of the sampling matrix and the reconstruction algorithm represent core elements of CS [1-4]. Compressive sensing theory has been successfully applied in optical fields due to its unique advantages [8-14].

2.2 Moving Target Compressive Imaging Based on Improved Row-Scanning Measurement Matrices

The algorithm described above has been widely used for compressive sensing imaging of static objects. However, imaging moving objects requires redefinition. This paper establishes a CS-based imaging model for moving objects using row-scanning. The model introduces a parameter v (pixels/sampling) to represent the velocity of the moving object [17,18] and assumes that the object moves in a straight line direction, with the row-scanning direction perpendicular to the object motion direction, as illustrated in [Figure 1: see original paper]. This scanning configuration aligns with practical applications such as airborne scanning and production line video monitoring.

Because the object moves continuously and the detector cannot guarantee complete acquisition of all information from the moving object, we apply image integration theory [28]. Assuming the object moves a distance dl during time dt, as shown in Figure 1 [Figure 1: see original paper], the velocity can be expressed as:

$$v = \frac{dl}{dt}$$

Let the number of pixels per image row be n, and the number of pixels within length dl be ds, then:

$$ds = \frac{n}{dl} \cdot dl = \frac{n}{dl} \cdot vdt$$

Substituting formula (4) into the above equation yields:

$$ds = \frac{n}{dl} \cdot vdt$$

Integrating both sides of this equation with respect to s gives the continuous function of linear object motion, as shown in formula (7):

$$s(t) = s_0 + \int_0^t vdt$$

where s_0 represents the initial position.

We define the object to be imaged as an $n \times n$ image x. Due to the row-scanning strategy, only one row' s worth of pixel content participates in imaging at any given time. Through multiple row-scanning processes, a complete $n \times n$ image is eventually assembled. Because the object moves continuously, the actual content participating in each row-scan imaging consists of more than one row; multiple rows of pixel content are mixed to reconstruct a single row of the final image. Direct solution using conventional CS imaging would result in severe image degradation.

Therefore, to reconstruct high-quality moving object images through CS algorithms, we must identify the correlation between rows of pixels during the imaging process—this is one reason our model adopts row-scanning sampling. In actual sampling, each modulation process in row-scanning involves pixel content from two rows of the object, which we term the "current row" u_x and the "next row" d_x. Moreover, before the current row u_x completely moves out of the detector' s scanning region, the amount of pixel content contained in u_x and d_x continuously changes. Let S represent the pixel information collected by the detector during each row-scan sampling. Substituting into formula (7), S can be expressed as:

$$S = \left[u_s - \int_{t_0}^{t} v dt\right] + \left[\int_{t_0}^{t} v dt\right]$$

where u_s and d_s represent the complete pixel information of the current row u_x and next row d_x, respectively. The first term on the right side of formula (8) represents the pixel information of the current row u_x collected by the detector during continuous object motion, obtained by subtracting the moving-out pixel information (the integral part) from the current row' s complete information u_s. The second term represents the collected pixel information of the next row d_x entering the detector' s sensing range, where the integral part denotes the incoming pixel information. Mapping formula (8) to the CS imaging algorithm yields:

$$y = A\left[(1-p) \cdot u_x + p \cdot d_x\right] + e$$

where p and q represent the weights of pixel content from the current row u_x and next row d_x collected during each row-scan sampling, derived from the integral calculations in formula (9). For uniform motion in this paper, v_0 is constant. Based on the integral relationship in formula (9), we can easily derive:

$$p = \frac{1}{n} \int_{0}^{\Delta t} v_0 dt = \frac{v_0 \Delta t}{n}$$

$$q = 1 - p$$

where p and q denote the weights of pixel content from the current row u_x and next row d_x in each sampling, respectively. When the current row u_x completely moves out of the detector' s scanning region, one row-scan is completed, reconstructing one row of image information. Notably, this reconstructed row is a concatenation of X_1 and X_2 with dimensions $1 \times 2n$, which is converted to $2 \times n$ dimensions when presenting the final imaging result, directly reconstructing the first two rows of image information. During the next row-scan, the original image' s third row becomes the new "current row," and this process continues for $n/2$ interlaced scans to reconstruct the complete image. When sampling reaches the last row, content outside the field of view can also participate in calculations but is discarded when presenting the final result.

The above row-scanning process can be expressed in matrix form as:

$$y = [AP, AQ] \begin{bmatrix} u_x \\ d_x \end{bmatrix} + e = Bx + e$$

According to CS theory, we refer to the matrix $[AP, AQ]$ in formula (11) as the improved motion measurement matrix, denoted as B:

$$B = [AP, AQ] = [P, Q] \otimes A$$

where $\otimes$ denotes the Kronecker product.

From formula (13), we observe that for uniform motion, the object velocity is determined by the matrix values. For non-uniform motion, the P and Q matrices can be adjusted accordingly if the velocity is known at each moment. The elements p_m and q_m correspond to the weights of pixel content from u_x and d_x during the m-th sampling of each row-scan. Before the current row u_x completely exits the detector' s scanning region, the weights of u_x and d_x continuously change—the pixel content of u_x participating in imaging continuously decreases, reducing its weight, while the weight of d_x continuously increases.

In formula (14), A is the measurement matrix from conventional CS algorithms with dimensions $m \times n$, while B is the improved motion measurement matrix in our model with dimensions $m \times 2n$. As long as B satisfies the relevant constraints, the image of the moving target at different velocities can be reconstructed according to CS reconstruction algorithms. y represents the measurement values from each row-scan. x denotes a $2n \times 1$ column vector composed of u_x and d_x, representing the reconstructed image information from experiments. e represents added noise, here taken as Gaussian noise with a standard deviation of 5% of the observation value' s standard deviation, as expressed in formula (17):

$$e \sim \mathcal{N}(0, (0.05 \cdot \mathrm{Std}(y))^2)$$

This improved CS algorithm fully leverages the advantages of row-scanning sampling in handling inter-row pixel correlations, effectively solving the moving object imaging problem.

3 Experiments and Data Analysis

To validate the proposed moving object imaging model based on improved row-scanning measurement matrices, we constructed an experimental setup for CS-based moving object imaging using a Digital Micromirror Device (DMD) [25-27], as shown in Figure 2 [Figure 2: see original paper]. A halogen lamp serves as the light source, which passes through an attenuator and filter before being focused by a condenser lens onto a specific pixel region of the DMD. The DMD used in the experiments features a micromirror array of 1024×768 pixels, with each micromirror measuring 13.68 m × 13.68 m. Each micromirror can be individually controlled to rotate to +12° or -12°, states denoted as 1 and 0, corresponding to "on" and "off" positions. In the "on" state, the DMD reflects light into the subsequent light collection system, while in the "off" state, the reflected light is not collected.

To simplify analysis, the object to be imaged is a binary virtual object [29,30], specifically an uppercase letter "A" with a pixel size of 32×32, as shown in Figure 3(a). Each row-scan covers a 1×32 pixel region. We employ a "pixel expansion" method that maps the 1×32 pixel region of the object to a 24×768 pixel region on the DMD at a 24:1 ratio, with all areas outside this region set to the "off" state. The object motion velocity is set to 1/24 pixels/sampling (meaning the object moves a distance of one pixel width during the 24 samples of each row-scan) [17,18]. When mapped to the expanded DMD, this corresponds to moving a distance of one DMD micromirror width per sampling period. Under these conditions:

$$p = \frac{1}{24}\int_0^{24} \frac{1}{24} dt = \frac{1}{24}$$

The improved motion measurement matrix in formula (14) can then be expressed as formula (19):

$$B = \begin{bmatrix} A & 0 \\ 0 & A \end{bmatrix} \begin{bmatrix} P \\ Q \end{bmatrix}$$

A fundamental principle for selecting the measurement matrix A is that it must satisfy the RIP criterion. Based on previous research [34-36], pseudo-random matrices with Bernoulli distribution of -1/1 values satisfy the RIP criterion and are widely used due to their ease of implementation, which perfectly matches the control requirements of DMDs. Furthermore, random binary matrix elements require only one bit for representation, effectively saving storage space and computation time. Therefore, we design matrix A as a 24×32 pseudo-random matrix with -1/1 values.

We then modulate the pixel content of each row of the object to be imaged using A to obtain measurement values y. The 24 matrices are sequentially loaded onto the DMD to perform compressive sensing measurement and reconstruction for each 1×32 pixel row of the object. Each row-scan involves 24 measurements, and with 32 total rows, we perform 16 interlaced scans. From the improved measurement matrix in formula (19), the sampling rate for each row-scan is $24/64 = 0.375$. The reflected light from the DMD is collected by collection lens L4, and the total light intensity is detected by a photoelectric bucket detector, as shown in Figure 2 [Figure 2: see original paper].

Finally, the measurement values y and improved motion measurement matrix B are input into reconstruction software, and the TVAL3 algorithm [31,32] is used to solve for the moving image information. By concatenating the reconstructed pixel information from each row, we obtain the complete reconstructed image, as shown in Figure 3(c) [Figure 3: see original paper]. Additionally, we compare the capability of conventional CS algorithms and our improved CS algorithm for reconstructing moving object images at different velocities. Experiments demonstrate that the improved CS algorithm exhibits superior moving object reconstruction capability across all tested velocities, as illustrated in Figure 3 [Figure 3: see original paper].

Figure 2. Experimental setup diagram

Figure 3. Experimental reconstruction results: (a) Original image, 32×32 pixels; (b) Conventional CS algorithm at 1/24 pixels/sampling (sampling rate 0.3750); (c) Improved algorithm at 1/24 pixels/sampling (sampling rate 0.3750); (d) Conventional CS algorithm at 1/12 pixels/sampling (sampling rate 0.0833); (e) Improved algorithm at 1/12 pixels/sampling (sampling rate 0.0833).

Experiments confirm that the improved measurement matrix CS imaging method based on row-scanning can achieve high-quality moving object images within a certain velocity range. We further validate the effectiveness of the improved algorithm through simulation experiments. In these simulations, we select a 120×120 region from the classic Lena grayscale test image as the imaging target and define a set of uniform motion velocities for comparison between conventional and improved CS algorithms. The reconstructed moving object images are shown in Figure 4 [Figure 4: see original paper], demonstrating that our proposed improved algorithm yields significant improvements for moving target imaging.

Figure 4. Simulation reconstruction results: (a) Original image, 64×64; (b1) Improved CS algorithm at 0.01163 pixels/sampling; (b2) Conventional CS algorithm at 0.01163 pixels/sampling; (c1) Improved CS algorithm at 0.01724 pixels/sampling; (c2) Conventional algorithm at 0.01724 pixels/sampling; (d1) Improved CS algorithm at 0.02632 pixels/sampling; (d2) Conventional algorithm at 0.02632 pixels/sampling.

4 Performance Comparison

To effectively evaluate reconstruction quality, we introduce the Mean Square Error (MSE) metric, defined in formula (20). This full-reference image quality assessment metric is based on pixel-wise error sensitivity, treating pixel errors as defects in image quality. Smaller MSE values indicate better reconstructed image quality [33]:

$$\mathrm{MSE} = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}(x_{jk} - x'_{jk})^2$$

where x represents the original image signal, x' represents the reconstructed image signal, and the image size is $M \times N$, with j and k denoting row and column indices, respectively. The analysis results are presented in Figure 5 [Figure 5: see original paper], which shows MSE curves as a function of velocity for both conventional CS and our improved motion measurement matrix algorithms. As velocity increases, reconstruction quality degrades for both methods, but the MSE values for our improved algorithm remain consistently lower than those of conventional CS. This demonstrates the significant effectiveness of our improved algorithm in enhancing moving object CS imaging quality.

Furthermore, Figure 5 reveals that when velocity increases beyond a certain threshold, image reconstruction quality deteriorates more rapidly. This occurs because higher velocities result in fewer pixels from each row being sampled during each scan, leading to increasingly severe image degradation. The figure also shows that when motion velocity is below a certain value, MSE changes slowly with velocity because the slow motion provides sufficient row-scan sampling for CS reconstruction requirements. Similarly, when velocity exceeds a certain value, the MSE curve changes slowly because the sampling per row-scan becomes extremely limited, and the reconstructed image approaches a random pattern, making further velocity increases have minimal impact on MSE. Thus, as velocity increases, sampling necessarily decreases, the sampling rate drops, and reconstruction quality gradually deteriorates.

Figure 5. MSE variation curve with velocity

5 Non-Uniform Motion Imaging

The preceding discussion assumes uniform linear motion. This section extends the proposed model to non-uniform linear motion imaging and presents simulation results. From formula (8), non-uniform motion can be addressed by replacing the constant v_0 with a time-varying variable v_t, as shown in formula (21):

$$S = u_s - \int_0^t v_t dt + \int_0^t v_t dt$$

Following the same computational process as for uniform linear motion, we find that for non-uniform linear motion, the matrices P and Q in formula (13) can be adjusted according to the known velocity at each moment to obtain matrices describing the weight relationship between current and next row pixel content. We present computational procedures and simulation results for uniformly accelerated linear motion with known acceleration. Let the acceleration be a (in pixels/sampling^2) and the initial velocity be 0. The instantaneous velocity at any time can be expressed as formula (22):

$$v_t = a \cdot t$$

where t should be understood as the sampling index. Substituting formula (22) into formula (21) and solving the integral yields:

$$S_{ud} = u_s - \frac{1}{2}at^2 + \frac{1}{2}a(t+1)^2$$

As before, u_s and d_s represent the complete pixel information of the current and next rows, respectively. The corresponding CS imaging representation becomes:

$$y = A(P_t \cdot u_x + Q_t \cdot d_x) + e$$

This shows that the computational process for non-uniform motion is fundamentally similar to that for uniform motion. With known acceleration, the velocity at any moment can be determined, and the weights of current and next row pixels can be adjusted accordingly by scaling the elements of matrices P_t and Q_t. We present simulation results for uniformly accelerated linear motion under various acceleration values.

Figure 6. Simulation reconstruction results for uniformly accelerated linear motion: (a) Original image, 160×160; (b) a = 0.027027; (c) a = 0.030303; (d) a = 0.034483; (e) a = 0.076923.

6 Conclusion and Outlook

This paper establishes a compressive sensing-based imaging model for moving objects using a row-scanning sampling approach and a constructed motion measurement matrix. We built a DMD-based proof-of-principle experimental system that validates the model' s superior reconstruction capability for moving object imaging compared to conventional CS algorithms. Our results also reveal that reconstruction quality degrades significantly when velocity exceeds a certain threshold. Currently, the model effectively handles horizontal and vertical motion for both uniform and uniformly accelerated cases. For objects moving along diagonal directions, the model requires appropriate modifications. We will address these limitations in future work. Given the advantages of the proposed row-scanning improved measurement matrix compressive sensing moving imaging algorithm, we believe it will find broad applications in practical imaging fields.

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Note: Figure translations are in progress. See original paper for figures.