High-Resolution Imaging Via Moving Random Exposure and Its Simulation

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Abstract—In this correspondence, we introduce a new imaging method to obtain high-resolution (HR) images. The image acquisition is performed in two stages, compressive measurement and optimization reconstruction. In order to reconstruct HR images by a small number of sensors, compressive measurements are made. Specifically, compressive measurements are made by a low-resolution (LR) camera with randomly fluttering shutter, which can be viewed as a moving random exposure pattern. In the optimization reconstruction stage, the HR image is computed by different models according to the prior knowledge of scenes. The proposed imaging method offers a new way of acquiring HR images of essentially static scenes when the camera resolution is limited by severe constraints such as cost, battery capacity, memory space, transmission bandwidth, etc. and when the prior knowledge of scenes is available. The simulation results demonstrate the effectiveness of the proposed imaging method.

Index Terms—Compressive measurement, high-resolution (HR) imaging, image reconstruction, moving random exposure.

I. INTRODUCTION

High-resolution (HR) images are highly desired in many applications, such as remote sensing monitoring, military reconnaissance, transport and security monitoring, medical diagnosis and pattern recognition. In the traditional imaging method, the image resolution is enhanced by increasing the number of sensors in the camera. However, due to some constraints, such as size, weight, battery capacity, memory space, transmission bandwidth, it is difficult to increase the number of sensors. To address this difficulty, some methods have been proposed to improve the image resolution without increasing the number of sensors. Examples include signal processing method [1]–[3], one-pixel camera [4], compressive coded-aperture imaging [5], [6], task-specific compressive imaging [7], and CMOS compressive imaging [8]. Although these methods can be used to enhance the image resolution, they may bring some problems, such as imprecise results from the lack of enough scene information [1]–[3] and complicated imaging mechanism [4]. These factors limit the use of the previously shown methods.

In this correspondence, we propose a new HR imaging method without increasing the number of sensors. It is performed in two stages: compressive measurement and optimization reconstruction. Compressive measurement can be accomplished by only employing a moving low-resolution (LR) camera with randomly fluttering shutter. This pattern is viewed as a moving random exposure. In this way, the scene can be randomly and compressively measured into a small number of sensor data, which guarantees the acquirement of enough scene information to reconstruct HR images. In optimization reconstruction stage, we model the problem of HR image reconstruction as that of finding the optimal solution to an inverse problem, and this inverse problem can be solved when the prior knowledge of scenes is known. In the simulations, according to three different types of prior knowledge of images, the corresponding models are chosen to reconstruct HR images. The results demonstrate the effectiveness of the proposed imaging method. We believe the proposed imaging method can provide a new way of acquiring HR images of static scenes in the applications limited by severe constraints.

This correspondence is organized as follows. Section II introduces the proposed two-stage HR imaging method. Section III presents the compressive measurement by the moving random exposure pattern, and addresses the application scope of the proposed HR imaging method. Section IV gives the simulation results, and Section V draws the conclusion.

II. HR IMAGING METHOD

A. Traditional Imaging Method

In the traditional imaging method, an image is acquired directly from the scene in the spatial domain. Fig. 1(a) shows the process of imaging method, where $X$ is the scene, $Y$ represents the output of the camera sensors, and $I$ is the image of the scene $X$. There exists one-to-one relationship between $Y$ and $I$. The resolution of the image is equal to the number of sensors in the camera. For example, if we use a camera with $256 \times 256$ sensors to sense a scene, we can only get an image with the resolution $256 \times 256$. Therefore, the number of sensors in the camera must be increased to obtain an HR image.

B. Proposed Imaging Method

Unlike the traditional method, the proposed imaging method treats the whole imaging process as two stages, compressive measurement
and optimization reconstruction, as shown in Fig. 1(b). The measurement data are obtained with a small number of sensors by measuring a scene instead of direct spatial sampling. Then an HR image is achieved from those measurements by optimization reconstruction.

In Fig. 1(b), $X$ is the scene which can be expressed as a discrete form $(x_1, x_2, \ldots, x_N)^T$ with $N$ pixels, $Y$ represents those data compressively measured with $M$ elements, and $\tilde{X}$, with $N$ pixels, denotes the recovered image by optimization reconstruction. Here each point in $Y$ is the linear combination of the components of $X$, and the operation is performed by a special optical control. The number of the elements of $\tilde{X}$ is much larger than that of $Y$, that is $M \ll N$, indicating the reconstruction of an HR image. In our method, we do not directly sample each pixel of the scene $X$ like the traditional imaging method, but compress the weighted sum of information of each pixel in $X$ into each sensor in $Y$. More specifically, the output $Y$ of the sensors is a linear combination of the scene $X$, or

$$Y = \Phi X$$

(1)

where $\Phi$ is a measurement matrix with the size of $M \times N$ ($M \ll N$). This imaging procedure is further illustrated in Fig. 2. The remainder of this section is devoted to image reconstruction while the detailed design of the special optical control shown in Fig. 1(b) is deferred to Section III.

In the reconstruction stage, we use optimization reconstruction to obtain the HR image from measurement data. More precisely, we need solve (1) to extract the scene information $X$ from the measurements $Y$ to reconstruct the HR image $\tilde{X}$. It is clear that this problem is ill-posed due to $M < N$ and $X$ cannot be achieved by directly solving the inverse of $\Phi$. One way to recover the image is to compute

$$\tilde{X} = \arg \min g(X) \quad \text{s.t.} \quad Y = \Phi X$$

(2)

where $g(X)$ is an objective function which incorporates the known prior knowledge of scenes.

It should be claimed that the proposed method focuses on the HR imaging of static scenes. For the moving object in the static scene, the proposed imaging method can be applied to the case where the speed of the moving object is low enough. Concretely, if the image shift of the object with moving distance $D$ (see Fig. 3) is not beyond one pixel in the camera during the whole exposure time, the proposed method can also work well.

For the dynamic scenes of which the image characteristics change, the proposed method is not suitable because the reconstruction model has to be chosen dynamically according to the prior knowledge when photographing a dynamic scene. This will require the long response time. In addition, this will also lead to the high computational complexity.

C. Three Reconstruction Models

Based upon the previously shown analysis, we need to construct a model like (2) to reconstruct the image. However, since the underlying image can have various characteristics, we present three typical reconstruction models in the following, which correspond to three different characteristics of images.

1) TV Minimization Model: Total variation (TV) has been proven to be an effective means in dealing with the piecewise smooth images [9]. The HR image $\tilde{X}$ can be defined as the solution of

$$\tilde{X} = \arg \min TV(X) \quad \text{s.t.} \quad Y = \Phi X$$

(3)

where

$$TV(X) = \sum_{1 \leq i \leq M-1, 1 \leq j \leq N-1} |d(i, j)|$$

$$d(i, j) = \sqrt{|X(i+1, j) - X(i, j)|^2 + |X(i, j+1) - X(i, j)|^2}$$

and $X(i, j)$ is the pixel value at point $(i, j)$.

2) Compressive Sensing (CS) Model: If an image $X$ is exactly or approximately $S$-sparse in a certain basis $\Psi$, CS theory [10]–[12] provides a satisfactory way to deal with this case [13]. CS theory makes it possible to reconstruct an HR image from far fewer measurements with high probability if the basis $\Psi$ is incoherent with the measurement matrix $\Phi$. The recovery $\tilde{X}$ can be achieved by solving the following $l_1$-norm optimization:

$$\tilde{X} = \arg \min \|\Psi^T X\|_1 \quad \text{s.t.} \quad Y = \Phi X$$

(4)

which is called as CS model.

3) MARX Model: It can be found that the images with line and subtle details have obvious varying local structure. A model-guided adaptive recovery of compressive sensing (MARX) model [14] is suitable to identify and explore these structures. Here, the image $\tilde{X}$ is recovered by solving the following optimization problem:

$$\tilde{X} = \arg \min_{X} \sum_{i,j} \left| X(i,j) - \sum_{(u,v) \in D} a_{i,j}(u,v) X(i-u, j-v) \right|$$

(5)

s.t. $Y = \Phi X$
where $D$ is the support set, and $a_{i,j}(u, v), (u, v) \in D$ are auto-regressive parameters of MARX, and $X(i, j)$ is the value at point $(i, j)$.

Since the three models describe three typical characteristics of images, they would be effective in image reconstruction. Further, we notice that all of the three models rely on a random compressive measurement matrix $\Phi$, as mentioned in [9], [13], [14]. Therefore, the next key issue is how to perform the compressive measurement with a desired $\Phi$, which will be discussed in the next section.

### III. MOVING RANDOM EXPOSURE

In order to perform the compressive measurement, we propose a moving random exposure pattern. By moving an LR camera with a randomly fluctuating shutter, a measurement matrix $\Phi$ is obtained. With this process, a scene is measured randomly and compressively. This pattern skillfully compresses the HR image information into the data obtained by a small number of sensors. And an HR image is then obtained from the data by solving the optimization problem.

#### A. Moving Random Exposure Pattern

The proposed moving random exposure is based upon the pattern in [15] where the random exposure is used for the application of image deblurring. Fig. 4(b) shows the random exposure pattern. For a comparison, the traditional exposure pattern is shown in Fig. 4(a). Different from the traditional exposure pattern where the shutter is always open during the exposure time $T$, the shutter of random exposure pattern is open or closed (denoted by 1 or 0) randomly in each time slice. Here, we denote the number of time slices in the exposure time $T$ as $K$. The random on/off slice pattern can be described by a binary uniform random sequence $R = (r_1, r_2, \ldots, r_J, \ldots, r_K)$ where $r_j = 1$ or 0. Such a random sequence will contribute to construct a random measurement matrix.

The proposed moving random exposure pattern is performed by moving a camera with random exposure. During the exposure time $T$, each sensor of the camera continually accumulates the light intensity of different location in the scene, and finally the moving camera grabs a blurred image. In Fig. 5 we take one sensor in the camera as an example, and give the light intensity accumulation process of this sensor. In each time slice, each sensor of the moving camera is ready to sense the different part of the scene. When the shutter is open in this time slice, the sensor accumulates the light intensity of one part in the scene. While the shutter is closed, the sensor does not accumulate the light intensity of one part in the scene. After the whole exposure time $T$, each moving sensor senses every part of the scene and accumulates the light intensity of these parts according to the state of shutter. Finally the total amount of light intensity accumulated by each sensor is the weighted sum of the light intensity of every part in the scene, where the weights $r_i(i = 1, \ldots, K)$ being 0 or 1 are decided by the shutter state.

As a result, the weighted sum of the light intensity of every part in the scene, which reflects the scene information, is compressed into each sensor by moving random exposure. This process can be just considered as compressive measurement, and a random compressive measurement matrix can be obtained by analyzing the moving random exposure pattern.

#### B. Measurement Matrix

For the sake of easy analysis, we only consider 1-D scene. Here, the scene is expressed by $X = (x_1, x_2, \ldots, x_N)^T$, where $N$ is the number of pixels. $Y$ is the measurements of $X$, which is denoted by $(y_1, y_2, \ldots, y_M)^T$ with $M$ being the number of sensors. Let $d = N/M$, signifying the ratio of resolution. And the camera moves with a speed of $s$ pixels/slice along a route parallel with the scene. Without loss of generality, we consider $d$ as an integer and the moving speed to be $s = d$. The binary uniform random sequence controlling the random on/off of the shutter is denoted by the vector $R = (r_1, r_2, \ldots, r_J, \ldots, r_K)$ where $r_j = 1$ or 0.

In the proposed imaging method, we use the LR moving camera to obtain the HR image. Each sensor in the camera can simultaneously sense several pixels in the HR scene at one time slice. Before the measurement matrix is deduced, let us introduce the exposure vector, denoted by $a^t_i$, which is defined to record the exposure state of all pixels in the HR scene sensed by the $i$th sensor at the $j$th time slice. Here, we take the third sensor at the fifth time slice as an example shown in Fig. 6 to illustrate the notion of exposure vector $a^t_3$. In Fig. 6 we assume that the scene $X$ is composed of 24 pixels, denoted by $(x_1, x_2, \ldots, x_{24})^T$. We use a vector with the length of 24 to record the exposure state of all pixels in the scene. If the third sensor can sense the pixels $(x_9, x_{10}, x_{11}, x_{12})$ of the scene at the fifth time slice, then the exposure vector $a^t_3$ is expressed as $(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$. 

![Fig. 4. Two exposure patterns. (a) Traditional exposure. (b) Random exposure.](image)

![Fig. 5. Light intensity accumulation process of one sensor.](image)
Due to the whole imaging process, in the measurements the gray color (marked with white color) is not accumulated by the third sensor. With the movement of the camera, the total amount of light intensity accumulated by the third sensor is

\[ y_i = \sum_{j=1}^{K} r_j a_j^i X. \]  

Fig. 7 shows an example of the light intensity accumulation process of the third sensor (marked with red color) with \( N = 24, M = 6, i = 3, K = 6, s = d = 4 \). In Fig. 7, the index of sensors in the moving camera is 1–6 from right to left. In the third time slice, the third sensor begins to sense the scene \( X \). Here \( r_3 = 1 \), the third sensor can accumulate the light intensity of the part (marked with white color) in the scene \( X \). In the fourth time slice, the third sensor moves to the next position. Due to \( r_4 = 0 \), the light intensity of this part (marked with gray color) is not accumulated by the third sensor. With the movement of the camera, the third sensor continually accumulates or ignores the light intensity of every part of the scene according to the binary random sequence \( R \).

Similar to the third sensor, each sensor in the camera perform the same moving random exposure process. The total amount \( y_i \) is given in (7). By using \( a_j^i \), we denote the exposure matrix of the \( j \)th sensor as

\[ A_i = \begin{pmatrix} a_1^i \\ a_2^i \\ \vdots \\ a_N^i \end{pmatrix}. \]  

With the exposure matrix \( A_i \) and \( R \), the \( i \)th measurement of \( Y \) can be expressed as \( y_i = R A_i X \), where \( i = 1, 2, \ldots, M \). Then the LR image \( Y \) can be written as

\[ Y = \begin{pmatrix} R A_1 \\ R A_2 \\ \vdots \\ R A_M \end{pmatrix} X = \Phi X \]  

where \( a_j^i \) is a matrix with the size of \( 1 \times N \), \( A_i \) is a matrix with the size of \( K \times N \), and \( R A_i \) is a matrix with the size of \( 1 \times N \). From the previously shown analysis, we can deduce the measurement matrix

\[ \Phi = \begin{pmatrix} R A_1 \\ R A_2 \\ \vdots \\ R A_M \end{pmatrix} \]  

with the size of \( M \times N \).

To illustrate the structure of the measurement matrix, we give an example of \( \Phi \) as depicted in Fig. 8, with \( N = 1024 \) pixels, \( M = 128 \) pixels, and \( K = 128 \) slices.

C. Architecture of the Proposed Pattern

In the proposed moving random exposure pattern, camera motion control and random exposure control are two crucial issues. To better understand this pattern, we give its block diagram as shown in Fig. 9, where the controllable camera motion and shutter random exposure are equipped into a low-density CCD camera. In this architecture, the electric controller and driver, and the mechanical controller work together to control the camera motion, and simultaneously the pseudo-random number pulse generator sends the random pulses to control the electric shutter of the camera, accomplishing the proposed moving random exposure.

D. Application Scope of HR Imaging via the Proposed Pattern

Consider the traditional approach by increasing the number of sensors in general consumer cameras. Since the general high-density CCD device develops as fast as the integrated circuit of which the integration doubles in every 18 months, it is relatively easy to achieve high-density
TABLE I

<table>
<thead>
<tr>
<th>Image characteristic</th>
<th>Model</th>
<th>TV Direction</th>
<th>CS(DCT) Direction</th>
<th>MARX Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>vertical</td>
<td>horizontal</td>
<td>vertical</td>
</tr>
<tr>
<td>Piecewise smooth images</td>
<td>Lotus</td>
<td>33.371</td>
<td>33.328</td>
<td>33.133</td>
</tr>
<tr>
<td></td>
<td>Woman</td>
<td>23.323</td>
<td>23.655</td>
<td>23.658</td>
</tr>
<tr>
<td></td>
<td>SAR</td>
<td>18.146</td>
<td>18.118</td>
<td>18.201</td>
</tr>
</tbody>
</table>

CCD sensors. If the proposed moving random exposure pattern, with motion control and random exposure control, is taken into account, the size and weight of the camera will be increased, leading to inconvenient usage. And also these additional electro-mechanical devices will decrease the system reliability. Further, since the time-consuming optimization reconstruction is involved, the HR images cannot be achieved immediately. As a result, in contrast with the traditional approach, the proposed moving random exposure method is not suitable for the application of general consumer cameras.

In the aerospace remote sensing, due to its special application environment, the strict manufacturing process and technique are required. Thus, the aerospace-grade CCD costs several hundred times higher than the general CCD with the same density. And the corresponding additional image signal acquisition/processing cost also rise. Further, as the CCD density increases, the amount of light available will decrease. This will produce shot noise that degrades the image quality severely [16]. While in the proposed moving random exposure pattern, HR images can be achieved without increasing the density of camera sensor. Due to the fact that in remote sensing imaging process, the camera moves along with the aircraft and its speed can be measured by the specialized equipment, the proposed pattern can be accomplished by adding no motion control, but only random exposure control. Further, since the involved random exposure devices are electric chips with small size and low power consumption, they are easy to integrate. Therefore, these added electric devices will cause little impact or burden on other system components.

From the previously shown analysis, we conclude that the proposed approach is suitable for the aerospace remote sensing fields where it is very expensive or difficult to increase the camera CCD density.

As for other applications where the camera resolution is also limited by severe constraints, the proposed moving random exposure pattern may still be applied, such as infrared imaging and multispectral/hyperspectral imaging. The concrete issue is a topic needed to be studied further.

IV. SIMULATION RESULTS

In this section, we give some simulation results to demonstrate the effectiveness of the proposed imaging method.

In the compressive measurement stage, the moving random exposure pattern is adopted. In the experiments, the resolution of the camera is $128 \times 128$, and the resolution of the image to be reconstructed is $512 \times 512$. We move the LR camera vertically and horizontally with a speed of 8 pixel/slice. In order to make our simulation closer to the real case, we consider some real effects in terms of three aspects given in the following, point spread function (PSF), positioning error and light intensity accumulation error.

1) PSF: The PSF is commonly used to reflect the effects of the properties of detector (saturation, nonlinearity, etc) and the light characteristics (diffraction effects, etc). Here, we use a general PSF with the form of Gaussian function to build the exposure vector. The PSF has the following form:

$$f(x) = \alpha e^{-\frac{x^2}{\sigma^2}}$$ (10)
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where \( \alpha \) is the magnitude factor and \( \beta \) is the shape factor. And the exposure vector becomes

\[
a^t_j(n) = \alpha e^{-\beta(\gamma(i,j))^2}, \quad n = 1, \ldots, N
\]  

(11)

where

\[
\gamma(i, j) = \begin{cases} 
(j - i + 1/2)d, & j \geq i \\
(M + j - i + 1/2)d, & j < i
\end{cases}
\]

is the position factor.

2) **Positioning Error:** The positioning error is the difference between the actual and expected positions of the camera. Since it is difficult to keep the camera moving uniformly, the positioning error cannot be avoided. In the simulation, to characterize the effect of the positioning error on the imaging quality, we introduce 8% positioning error as an example into the position factor \( \gamma \) in (11), obtaining the noisy parameter \( \gamma_{\text{noisy}} = d(1 + 0.08\eta) \), where \( d = N/M \) and \( \eta \) is a random number following distribution \( N(0, 1) \).

3) **Light Intensity Accumulation Error:** In order to take the effect of light intensity accumulation error on the imaging quality into account in the simulation, we add 8% random noise into the magnitude factor \( \alpha \) in (11), obtaining the noisy parameter \( \alpha_{\text{noisy}} = \alpha(1 + 0.08\eta) \).

Now we can deduce the noisy measurement matrix by the exposure vector with the noisy parameters \( \gamma_{\text{noisy}} \) and \( \alpha_{\text{noisy}} \). In the simulation, we measure the scene by the noisy measurement matrix, and reconstruct the image with the ideal measurement matrix without noise.

In the reconstruction stage, we use the three reconstruction models, TV, CS, and MARX models described in Section II, to reconstruct the HR images. Notice that these models, respectively, correspond to images with three different characteristics, that is, piecewise smooth images, sparse images, and images with line and subtle details. In this work, for CS model DCT base is chosen as a sparse base to recover the HR image since most of smooth images are sparse in DCT domain. To solve the optimization problem of CS model in (4), many algorithms are available. Here we choose the basis pursuit (BP) [10] algorithm as the recovery algorithm to reconstruct the HR image due to its effectiveness. For MARX model, TV minimization is used to generate the initial value for iteration.

4) **Example1: Piecewise Smooth Image:** The piecewise smooth Lotus image is used as an input image (512 \times 512) shown in Fig. 10(a), which is grabbed by an HR camera. Fig. 10(b) shows the LR image obtained by the proposed method when camera moving vertically. Fig. 10(c)–10(e) show the HR reconstruction results using TV, CS, and MARX models. These reconstruction results indicate that our imaging method can reconstruct the HR image from the LR blurred image. It can also be seen from the third line of Table I that the peak-signal-to-noise ratio (PSNR) of the HR image reconstructed by TV model is higher than that of the other two models no matter whether the camera moving vertically or horizontally.

Example2: Sparse Image in DCT Domain: A Tower image shown in Fig. 11(a) is used as a test image. This image contains plenty of line and subtle details. In the simulation, to characterize the effect of the positioning error on the imaging quality, we introduce 8% positioning error as an example into the position factor \( \gamma \) in (11), obtaining the noisy parameter \( \gamma_{\text{noisy}} = d(1 + 0.08\eta) \), where \( d = N/M \), and \( \eta \) is a random number following distribution \( N(0, 1) \).

These reconstruction results indicate that our imaging method can reconstruct the HR image from the LR blurred image. It can also be seen from the third line of Table I that the peak-signal-to-noise ratio (PSNR) of the HR image reconstructed by TV model is higher than that of the other two models no matter whether the camera moving vertically or horizontally.

Example3: Image With Line and Subtle Details: The electron micrograph of the head of a honey bee is used as a test image, shown in Fig. 12(a). This image contains plenty of line and subtle details.
the proposed method can also work well.

small positioning error and light intensity accumulation error exist, than 8%. These results demonstrate that, for the case in which the recovery quality degrades rapidly when the two errors are both larger
denotes low-quality recovery. From Fig. 13, it can be seen that the PSNR of the reconstructed HR images (scaled between 30.4 dB and
accumulation error. The color of each cell in the figure reflects the
eroof the figure. From the comparison results of PSNR of three examples listed in
Table I, we can see that: TV model is more suitable for piecewise smooth images, CS model has better reconstruction performance for
sparse images, and MARX model can get much higher quality in the
reconstruction of images with line and subtle details. This just verifies
that, the proposed imaging method can use the suitable model to recon-
struct the high-quality HR image according to the prior knowledge of
scenes.

Further, we analyze the effect of change in the positioning error
and the light intensity accumulation error on the reconstruction quality. Here, we take the Lotus image [see Fig. 10(a)] as an exam-
ple. The experiment results of this image is given in Fig. 13. For more
experiment results, please refer to http://see.xidian.edu.cn/fac-
ulty/gmshi/web/index.htm. In Fig. 13, the x-axis corresponds to the
positioning error, and the y-axis corresponds to the light intensity
accumulation error. The color of each cell in the figure reflects the
PSNR of the reconstructed HR images (scaled between 30.4 dB and
33.6 dB). White cell denotes high-quality recovery, and black cell
denotes low-quality recovery. From Fig. 13, it can be seen that the
recovery quality degrades rapidly when the two errors are both larger
than 8%. These results demonstrate that, for the case in which the
small positioning error and light intensity accumulation error exist,
the proposed method can also work well.

V. CONCLUSION

The authors present a new HR imaging method via moving random
exposure. The moving random exposure pattern is preformed by a
moving LR camera with a fluttering shutter. This imaging method
provides a new way for HR imaging in the applications with severe
constraints. The simulation results have demonstrated that the pro-
posed imaging method can achieve good performance.