Fast Tracking of Moving Objects Using Single-Pixel Imaging

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Abstract

Successive images of a scene are captured and then further processed to achieve the moving object tracking. However, due to modulation rate limitations of the spatial light modulator in single-pixel imaging (SPI) system, the imaging frame rate cannot meet the high-resolution and real-time requirements for object tracking. In this paper, we demonstrate a fast object tracking technique based on SPI with an ultra-low sampling rate that is independent of imaging. We construct modulation information that satisfies the projection conditions and can transform 2D images into 1D projection curves. The 1D projection curves, which provide the location information of the moving object, can be obtained with high resolution in real-time, and then the tracking of the moving object is realized. A background subtraction technique for tracking moving objects that removes static components from a scene is also proposed. The proposed technique is verified by computational simulations and laboratory experiments. In the laboratory experiments, we demonstrate that the proposed method can be used to track moving objects with less than 0.2% of the measurements established by the Nyquist criterion, and it presents a resolution of 256$×$256 pixels at ~177 fps. The reported technique accelerates the tracking speed of SPI and provides an efficient strategy for remote sensing and biomedical applications.

Full Text

Preamble

Fast Tracking of Moving Objects Using Single-Pixel Imaging

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Abstract: Conventional moving object tracking relies on capturing successive images of a scene for subsequent processing. However, due to the modulation rate limitations of spatial light modulators in single-pixel imaging (SPI) systems, the imaging frame rate cannot simultaneously satisfy the high-resolution and real-time demands required for effective object tracking. In this paper, we demonstrate a fast object tracking technique based on SPI that operates with an ultra-low sampling rate independent of imaging reconstruction. We construct modulation patterns that satisfy specific projection conditions, enabling the transformation of 2D images into 1D projection curves. These projection curves, which contain the location information of moving objects, can be obtained with high resolution in real time, thereby enabling object tracking. Additionally, we propose a background subtraction technique that removes static components from the scene for tracking moving objects. The proposed technique is validated through computational simulations and laboratory experiments. Our experimental results demonstrate tracking of moving objects using less than 0.2% of the measurements required by the Nyquist criterion, achieving a resolution of 256$×$256 pixels at approximately 177 fps. This technique significantly accelerates tracking speed in SPI and provides an efficient strategy for remote sensing and biomedical applications.

Keywords: Computational imaging; Image reconstruction techniques; Target tracking.

Introduction

Image data represents one of the most critical sources of information for human production and life, with image detection techniques being the predominant approach for acquiring such data. Single-pixel imaging (SPI) [1-33], also known as ghost imaging or computational imaging, is an emerging imaging technique that employs a non-spatially-resolved single-pixel detector to reconstruct object images. Based on different modulation modes, SPI can be categorized into forward modulation [1-16] and backward modulation [17,18] schemes. In forward modulation, structured illumination patterns generated by a spatial light modulator (SLM) or light source array illuminate the object, and the reflected or transmitted light is collected by a single-pixel detector. In backward modulation, the object' s image is sampled by an SLM, and the sampled information is detected by a single-pixel detector. While backward-modulation SPI can operate under both natural background light and active illumination conditions, forward-modulation SPI requires active illumination.

The object image is recovered by correlating the detected intensities with the modulation information from the SLM or light source array. Since SPI uses a detector without spatial resolution to obtain spatially resolved information, it requires a large number of distinct modulation patterns from the SLM or light source array over time, thereby sacrificing temporal resolution in exchange for spatial resolution. Nevertheless, SPI offers significant advantages, including high signal-to-noise ratio imaging under low-light conditions [16] and wide spectral imaging capabilities [17], which have attracted considerable attention in recent years.

Numerous researchers have investigated imaging of moving objects using SPI [19-23]. Beyond imaging alone, tracking the position of moving objects is paramount for applications in remote sensing and biomedicine [34]. Conventional moving object tracking is accomplished using RADAR and LADAR technologies, which rely on directional probe beams that can be scanned spatially or angularly. Methods employing SPI for object tracking have also garnered research interest. Traditional tracking approaches must first obtain time-series images, which are then processed by subsequent algorithms to track the object [21-23].

In [21], Omar et al. proposed an object tracking method using only 2.44% of the measurements required by the Nyquist criterion, achieving 64$×64*pixelresolutionwithentangledphotons.However*, *eachscenereconstructionrequired*13.3*minutesduetolo*
timetrackingcapability.Amethodforcompressivemovingtargettrackingwiththermallightbasedoncomplement
timetrackingexperiments.In[23], *theauthorsacquired*32×$32 pixel real-time video for three-dimensional object tracking at 14 frames per second (fps) using SPI. The performance of traditional tracking algorithms based on successive image capture is closely tied to imaging speed, suggesting that increasing SPI imaging speed for dynamic scenes could improve tracking efficiency.

Recently, deep learning with convolutional auto-encoder networks has been applied to achieve real-time 128$×128*pixelvideoat*30*fps*[10].*Theauthorsin*[11]*demonstratedexperimentalsingle−*
*pixeldetectionwithreal−timereconstructionperformedinparallelwithmeasurementat*11*Hzframerateforhig*
*basedhigh−speedilluminationmoduleachievedanimpressiveframerateof*1000*fpswith*32×32*pixelresolution*[1
modulationmethodoperatesonlyunderactiveilluminationconditions, *anditsimagingresolutionislimitedbythe*
levelresolution(*similartothatofSLMssuchasdigitalmicro−mirrordevices*(*DMDs*)*with*2560×1600*pixelresol*
pixel resolution.

In SPI, DMD systems are widely used as SLMs due to their high reflectivity, high light throughput, high frame rates, and high spatial resolution [35]. Based on the principle of optical reversibility, DMD-based SPI works effectively under both active and passive illumination conditions, making DMD-based SPI research highly significant. However, due to DMD modulation rate limitations, the imaging frame rates of existing technologies cannot meet the high-resolution, high-real-time requirements of object tracking. Nevertheless, to track a moving object, one does not necessarily need to "see" it [34]!

Capturing successive images for further processing is not essential for object tracking. Therefore, we propose a novel, effective method based on DMD-SPI that can track moving objects with high pixel resolution and an ultra-low sampling rate, independent of successive image capture. In our real-time tracking experiments, we achieve 256$×$256 pixel resolution at approximately 177 fps using less than 0.2% of the measurements required by the Nyquist criterion. The remainder of this paper is organized as follows: Section 2 introduces the theoretical principles and methodology, Section 3 presents simulations and experiments evaluating the proposed method, and Section 4 summarizes the conclusions of this work.

2. Principles and Methods

According to the SPI principle, modulation pattern S_n is used to modulate the light at the n-th time step, and a clear pattern image correlated with S_n is presented for the scene containing moving objects. The reflected light from the scene is detected by a single-pixel detector, and the detection intensity I_n can be expressed as

$$I_n = \sum_{x,y} f_t(x, y) \cdot S_n(x, y)$$

where x and y are spatial coordinates, f_t represents the scene information including moving objects at time t, and $\sum_{x,y}$ denotes summation along the x and y directions. The scene image can be recovered by correlating the detected intensity values with the modulation information. However, due to DMD modulation rate limitations, the imaging frame rate of SPI remains insufficient for high-resolution imaging of fast-moving objects. In other words, the imaging frame rate cannot meet the high-resolution, real-time requirements of object tracking, making object tracking a challenging problem for SPI using traditional successive-image-based methods.

Nevertheless, to track a moving object, we need only obtain its positional information in real time. In conventional strategies, positional information is extracted from captured successive images, which are merely a means to this end rather than a necessary component of tracking itself [34]. Constrained by SPI imaging frame rate, a novel technique distinct from traditional imaging strategies is required to recover object positional information. Here, we propose a new method to obtain object positional information from 1D projection curves, which enable us to locate objects based on edges in the projection curves [9]. The projection curve of an $N \times M$-pixel image $f_t(x, y)$ onto the x-axis is expressed as $f_{t,y}(x)$, while the projection onto the y-axis is $f_{t,x}(y)$. These projection curves can be expressed as

$$f_{t,x}(y) = \sum_x f_t(x, y), \quad f_{t,y}(x) = \sum_y f_t(x, y)$$

where $\sum_x$ and $\sum_y$ represent integration along the x and y directions, respectively.

Applying the same operation to the modulation information S_n, the equations transform to

$$I_n = \sum_y f_{t,x}(y) \cdot S_{x,n}(y) = \sum_x f_{t,y}(x) \cdot S_{y,n}(x)$$

where $S_{x,n}(y)$ and $S_{y,n}(x)$ represent the projection curves of $S_n(x, y)$ onto the x- and y-axes, respectively. Figure 1 [Figure 1: see original paper] illustrates the process of obtaining projection curves, with panels A and B showing the projection curves of the scene and modulation information, respectively.

The parameters are adjusted to satisfy the projection conditions. The above formulas demonstrate that the interaction intensities between the illumination pattern and scene coincide with those between the projection curves of the scene and modulation information. We design a specific form of modulation information S_n to satisfy these equations. Here, projection modulation information S_x and S_y with mutually orthogonal properties are constructed from a Hadamard matrix. In Fig. 2 [Figure 2: see original paper], we use a 3rd-order Hadamard matrix as an example. Each row $(S_{x,1}, S_{x,2}, \dots, S_{x,8})$ of the Hadamard matrix constitutes S_x, and each column $(S_{y,1}, S_{y,2}, \dots, S_{y,8})$ constitutes S_y. When constructing modulation information $S_x(x, y)$, each row in the matrix equals a row of data from S_x, yielding 8 modulation information matrices $[S_{x,1}(x, y), S_{x,2}(x, y), \dots, S_{x,8}(x, y)]$. For example, each row of matrix $S_{x,4}(x, y)$ equals the row $S_{x,4}$. Similarly, when constructing $S_y(x, y)$, each column in the matrix equals a column of data from S_y, yielding 8 modulation information matrices $[S_{y,1}(x, y), S_{y,2}(x, y), \dots, S_{y,8}(x, y)]$. For instance, each column of matrix $S_{y,4}(x, y)$ equals the column $S_{y,4}$. The object is illuminated with modulated patterns $S_x(x, y)$ and $S_y(x, y)$, and the corresponding detected intensities I_{nx} and I_{ny} are obtained. Figure 2 demonstrates that these modulation information matrices satisfy the conditions in Eqs. (6) and (7).

Since the modulation information applied by the DMD is known beforehand, the projection curves of the illumination pattern in both directions are also known. According to the SPI principle, the detected intensities combined with S_x and S_y are used to recover the projection curves $f_{t,x}(y)$ and $f_{t,y}(x)$ of the objects, expressed as

$$f_{t,x}(y) = \sum_n I_{ny} \cdot S_{y,n}(x), \quad f_{t,y}(x) = \sum_n I_{nx} \cdot S_{x,n}(y)$$

The above analysis assumes a uniform background. In many practical situations, objects move in complex backgrounds, requiring a background subtraction method [21] to remove background interference and obtain accurate motion trajectories. In such cases, the background is first illuminated with modulation patterns $S_x(x, y)$ and $S_y(x, y)$, and the corresponding background reflected intensities I_{nxb} and I_{nyb} are acquired. When a moving object enters the scene, the corresponding detection intensities I_{nx} and I_{ny} are received. The formulas for obtaining the projection curves of the moving object at time t in a complex background are

$$f_{t,x}(y) = \sum_n (I_{ny} - I_{nyb}) \cdot S_{y,n}(x), \quad f_{t,y}(x) = \sum_n (I_{nx} - I_{nxb}) \cdot S_{x,n}(y)$$

When the object' s projection curves $f_{t,x}(y)$ and $f_{t,y}(x)$ are recovered, a discontinuity occurs at positions corresponding to object edges because the grayscale distribution differs between object and background. We employ a first-derivative edge detection algorithm [36] to identify object edges, as the magnitude of the first derivative can detect edge presence at image points. By acquiring time-series positional information of the moving object, tracking can be achieved. Let the object region be $t(x, y)$ at time t. Then

$$t(x, y) = \begin{cases} 1 & \text{if } x_1 \leq x \leq x_2 \text{ and } y_1 \leq y \leq y_2 \\ 0 & \text{otherwise} \end{cases}$$

where x_1 and x_2 represent the edges of the object region along the x-axis, and y_1 and y_2 represent the edges along the y-axis. Using positional information obtained at different times, continuous tracking of moving objects can be achieved. Our method converts recovered information from 2D image data to 1D projection data, greatly reducing the amount of information to be restored and improving real-time tracking performance. The following section presents experimental validation of the proposed method.

3.1 Computational Simulations

We employed computational simulations to study the proposed method. The test images are shown in Fig. 3 [Figure 3: see original paper], where panel A shows the object to be tracked, panel B shows a complex background scene, and panel C shows the object in the complex scene. All images are 256\$×\$256 pixels. An 8th-order Hadamard matrix was generated, and the modulated projection patterns S_x and S_y in the x and y directions were obtained according to the rules described above. Russian Dolls ordering [18] was applied to the modulated projection patterns to compress the tracking data. The compression sampling rate is defined as

$$\text{Sampling Rate} = \frac{K}{M^2}$$

where K is the number of modulated patterns and M^2 is the number of pixels in the image.

The first experiment localized the object in a uniform black background as shown in Fig. 3A. The object' s projection curves under different numbers of modulated patterns are displayed in Fig. 4 [Figure 4: see original paper], demonstrating that recovered projection curves become more accurate as the number of samples increases. We quantified the accuracy using the percentage root mean square error (RMSE), expressed as

$$\mathrm{RMSE} = \frac{\|f_{x,k} - f_x\|_2}{\|f_x\|_2} \times 100\%, \quad \mathrm{RMSE} = \frac{\|f_{y,k} - f_y\|_2}{\|f_y\|_2} \times 100\%$$

where $R(f_{x,k})$ and $R(f_{y,k})$ represent the RMSEs of the recovered projection curves; $f_{x,k}$ and $f_{y,k}$ are the recovered projection curves in the y and x directions when the sample number is k; and f_x and f_y are the true projection curves in the y and x directions, respectively. The results in Fig. 5 [Figure 5: see original paper] indicate that recovered curves approach true projection curves as sample number increases. When the number of samples exceeds 32, the RMSE falls below 10%.

For moving object tracking, the region information $t(x, y)$ must be obtained. Edge detection is applied to the projection curves to acquire parameters x_1, x_2, y_1, and y_2. The bright points in Fig. 6 [Figure 6: see original paper] show these parameters under different sampling numbers. While errors exist in the obtained position parameters when sample numbers are small, the parameters stabilize as sample number increases. When projection numbers in both x and y directions exceed 128, the acquired positional parameters remain unchanged, indicating that beyond a certain sampling threshold, positional parameters and tracking accuracy become stable.

The second experiment localized the object in the complex scene shown in Fig. 3C. First, the complex scene was illuminated and reflected intensities I_{nxb} and I_{nyb} were obtained. Then the scene containing the object was illuminated and reflected intensities I_{nx} and I_{ny} were received. Using Eqs. (10) and (11) to restore the object' s projection curves with different sample numbers yielded the results shown in Fig. 7 [Figure 7: see original paper], demonstrating that the background subtraction technique effectively removes static components and accurately obtains object positional parameters.

Because Russian Dolls ordering sorts the patterns, the resolution of recovered information gradually increases with sample number, as evident in Figs. 4 and 7. With few samples, the restored projection curve resolution is low, but resolution improves and approaches true values as sample number increases. Since most spatial information energy in projection curves can be recovered using top-ranked patterns [18], we can acquire sufficient energy components to reconstruct high-quality projection curves. Fewer patterns enable higher frame rates, and when positioning resolution requirements are modest, this method effectively increases fps.

The static object simulation results demonstrate that the proposed method effectively achieves object localization. Due to the binary modulation employed, high-speed DMD binary modulation can be utilized for real-time tracking of moving objects at high resolution. Laboratory experiments investigating real-time moving object tracking are presented next.

3.2 Laboratory Experiments

The proposed technique was validated using the experimental system illustrated in Fig. 8 [Figure 8: see original paper]. A 10 W white LED serves as the illumination source. A DMD system (Texas Instruments Discovery V7100 with 1024$\times$768*micro − mirrors)generatestheprojectionpatterns.Asingle − pixeldetector(SD,ThorlabsPMT−PMM02)anddataacquisitionsystem(Pico6407with200MS/ssamplingrate pixeldetector.TheexperimentcontrolanddataprocessingcomputerisaNationalInstrumentsPXIsystemwitha* pixels.

The object is a white button approximately 3 cm in diameter, suspended by a black string and moved by pulling the string. The experimental setup is shown in Fig. 8.

Hadamard patterns are constructed with values of either +1 or -1. Since DMD illumination patterns are binary, positive and negative reflection values cannot be directly implemented. To address this, we use complementary matrix pairs related by subtraction, as detailed in [33]. This approach effectively removes background light influence. Balancing real-time performance and tracking accuracy, we employ Russian Dolls ordering [18] to select 128 patterns (64 positive and 64 negative) for illumination, achieving a sampling rate of approximately 0.195%. The numbers of modulation patterns $S_x(x, y)$ and $S_y(x, y)$ are each 64. The DMD projection frequency is set to 22.7 kHz, yielding an object position acquisition frequency of approximately 177 fps.

Uniform Background Tracking. First, the white button moved randomly in a uniform black background. The object was located approximately 1.6 m from the imaging system, with the DMD illuminating an area of about 13.5$\times$13.5 cm at the object plane. We performed 600 consecutive projection and acquisition cycles, achieving real-time object position acquisition. Figure 9 [Figure 9: see original paper] shows the results, with panel A displaying x-direction projection distributions at different times and panel B showing y-direction distributions. The ordinate represents the time axis, with each row showing the projection curve at a specific time. During the experiment, the object moved out of the field of view (FOV) for a period, accurately recorded and marked with red squares in Fig. 9. During this interval, the projection distribution lacks clear edges compared to when the object is within the FOV, and the algorithm automatically sets the object position to 0. In another instance, only a small portion of the object remained in the FOV, marked with green squares in Fig. 9. When position information $t(x, y)$ is obtained at different times, it is displayed with white squares in time series. Center coordinates of these regions are calculated and plotted versus time (Fig. 10 [Figure 10: see original paper]). A video of this real-time tracking process was created (see Visualization 1), played at 30 fps for 20 seconds. In Figs. 9 and 10, parameter t_m denotes one measurement duration, approximately 5.6 milliseconds.

Complex Background Tracking. Second, the object was tracked in the complex scene shown in Fig. 11 [Figure 11: see original paper], containing two stationary objects and one moving object. The moving white button from the first experiment was used, while the two stationary objects (monkey and mouse) served as the complex background. The moving object was located approximately 1.9 m from the imaging system, with the DMD illuminating a 15$×$15 cm area. We first illuminated the complex background and recorded the reflected intensities, then saved these probe values. When the moving object entered the scene and performed random motion, we received the new reflected intensities. The background subtraction technique was used to recover the real-time projection curves of the moving object. The resulting projection curves in both directions at different times are shown in Fig. 12 [Figure 12: see original paper], demonstrating that the object region can be identified and marked in white. Similarly, 600 experimental cycles were performed and compiled into a video (see Visualization 2), played at 30 fps for 20 seconds. After acquiring area information $t(x, y)$, the region' s center coordinates were calculated (Fig. 13 [Figure 13: see original paper]).

The experimental results demonstrate that with an extremely low sampling rate of approximately 0.20%, real-time tracking of moving objects at 256$\times 256 pixel resolution and 177 fps is achievable using our proposed method. Tracking accuracy is affected by m$ pixel resolution using the complementary modulation acquisition scheme for DMD-SPI [8]. As DMD technology advances, modulation frequencies will increase, further accelerating the proposed technique' s tracking speed. At reduced resolution, frequencies can reach thousands of fps, substantially improving tracking efficiency for applications such as remote sensing and intelligent transportation.

4. Discussion and Conclusions

Investigating moving object tracking capability via SPI is valuable research. In this paper, we proposed a fast object tracking technique based on SPI with an ultra-low sampling rate independent of imaging reconstruction. We constructed modulation patterns satisfying projection conditions, enabling SPI to obtain moving object projection curves in real time and achieve high-resolution real-time tracking. This method requires extremely few samples and can overcome background interference through background subtraction. Both computational simulations and laboratory experiments validate the proposed method' s effectiveness.

Currently, our method has three limitations. First, it can track only a single moving object. Since the method uses only two projection direction curves, multiple moving objects produce entangled solutions. Second, in complex backgrounds, measurement errors occur when the tracked object and background objects have identical reflectivity, causing overlap. Third, the Russian Dolls ordering used in our method reduces resolution and introduces measurement error. Future work will combine pattern recognition and deep learning algorithms to address these limitations.

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