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Stray Light Elimination Method Based on Recursion Multi-Scale Gray-Scale Morphology for Wide-Field Surveillance

ZEMING XU[1,2], DAN LIU[1,2], CHANGXIANG YAN[1,3], AND CHUNHUI HU[1]
[1]Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun 130033, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China
[3]Center of Materials Science and Optoelectronics Engineering, University of Chinese Academy of Science, Beijing 100049, China

Corresponding author: Changxiang Yan (yancxciomp@163.com)

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ABSTRACT The wide-field surveillance camera plays a critical role in space debris detection and the visible light situational awareness required for early warning. However, stray light in such a system has always been a serious problem. Current methods cannot effectively eliminate the interference of stray light, which directly lead to the inability to accurately segment the target and background, which greatly reduce the accuracy of target recognition. To solve this problem, we proposed an accurate stray light elimination method based on recursion multi-scale gray-scale morphology (RMGM). First, we defined two structural operators with different domains. These two structural operators can make full use of the difference information between the target region and the surrounding background region, which is the basic premise to ensure high-precision correction. Then we used the two structural operators with different domains to perform morphological processing on the surveillance image to eliminate stray light. Finally, in order to ensure that targets with different sizes in the surveillance image are not lost, we adopt a recursion multi-scale method. We increase the size of structural operator and perform the morphological operation again on the estimated and eliminated stray light non-uniform background in order to retrieve the lost larger size target. In addition, we add an automatic decision mechanism on the recursion multi-scale method by using corresponding threshold judgment. Further experimental results on real captured image datasets show that compared with other methods, the proposed RMGM method can simultaneously have high-precision stray light elimination effect, high-precision target retention rate, and faster computation time.

INDEX TERMS Stray light, 3D ray tracing, gray-scale morphology, recursive multi-scale, wide-field surveillance.

I. INTRODUCTION

With the development of science and technology, the exploration of space is becoming more and more frequent, and the number of spacecraft in orbit is increasing rapidly [1], [2]. Wide-field surveillance camera is of great significance for perceiving space situation, avoiding space collision and maintaining space environment security [3], given the Fengyun Satellite [4], and the Space-Based Space Surveillance Project [5], [6]. However, as the field of view of the wide-field surveillance camera increases, the stray light entering the system will also increase further [7], [8]. This will have a fatal impact on the wide-field surveillance camera. A large amount of stray light will make the background of the surveillance image show very serious non-uniform noise. On the one hand, this non-uniform noise not only reduces the signal-to-noise ratio and image quality of the surveillance image [9], but also makes it impossible to detect dim targets at the edges [10], [11]. On the other hand, this non-uniform noise seriously affects applications that depend on the accuracy and intensity of the scene, such as star image stitching, registration, multi-frame imaging, optical flow estimation, and dim and small target extraction and tracking [12], [13]. For these applications, eliminating non-uniform noise is an important prerequisite for achieving high-quality results. In addition, as a critical and basic step in the design of

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a wide-field surveillance camera, the precise segmentation of target and background will influence the accuracy and efficiency of the subsequent steps. The target and background will not be segmented accurately without removing the interference, which affects target recognition accuracy. In short, the existence of stray light non-uniform background noise seriously affects the accuracy of target recognition. At the same time, there are many targets in the surveillance image with different sizes, how to accurately eliminate stray light while ensuring that targets with different sizes are not lost has not been effectively resolved. Therefore, researches on the elimination method of stray light for the surveillance image are urgent.

Generally speaking, a well-designed lens baffle that considers the working orbit and exact space task can help the wide-field surveillance camera overcome most stray light problems [14]. However, due to the existence of strong stray light sources (sun, moon, etc.) and the absorptivity of the baffle and vane is always between 95% and 97% [15], the strong stray light after weakening will still be received by the detector. In order to obtain a clean, clear surveillance image, we need to eliminate this non-uniform noise in the surveillance image. At present, the research on eliminating non-uniform noise mainly focuses on the following two aspects: (1) a method based on model parameters; (2) a method based on image scene. For method based on model parameters, the deep learning-based method developed in recent years have shown excellent performance in all aspects, it has achieved excellent results in many eliminating non-uniform noise problems [16], [17]. However, this method mainly focuses on super-resolution [18] and deblurring [19]. Since the surveillance image contains a large number of stars, space targets and complex and varied stray light sources. On the one hand, we are unable to obtain a large number of complete surveillance image data sets, and we cannot obtain surveillance image without stray light non-uniform background noise, which also makes it impossible for us to train data to establish and optimize model. That is, the incompleteness of image data brings difficulties to the parameter estimation based on the model method. On the other hand, it is difficult for deep learning-based method to distinguish the dim target from the cluttered background in surveillance image with low signal-to-noise ratio [20]. Therefore, this method is temporarily unable to eliminate the non-uniform background noise in the surveillance image, and there is no relevant deep learning-based method to solve the problem of this paper at this stage. In addition, this method has poor real-time performance in the preprocessing stage (non-uniform background elimination) of the surveillance image [21]. For some other model parameter methods such as calibration-based method [22]–[24]. Similarly, due to insufficient data sets and huge differences of non-uniform background in different frames, fixed model parameters will cause huge damage to useful information such as targets when eliminating the stray light non-uniform background. Therefore, these methods based on model parameters are not suitable for eliminating this non-uniform noise caused by stray light in the surveillance image.

For method based on image scene, the characteristic of this method is that it does not depend on the model parameters, but only considers the image itself, which can deal with the problem of non-uniform noise elimination in a variety of unknown situations. There are mainly frequency-domain and spatial-domain approaches. For frequency-domain methods, such as curvelet-based method and wavelet-based method [25]–[27]. These methods are too complicated and will take a lot of computation time. In addition, they cannot accurately distinguish the target from the noise in the case of low signal-to-noise ratio [28]. Therefore, they are not suitable for eliminating this non-uniform noise in the surveillance image. For spatial-domain methods, such as average filtering and gradient based thresholding [29], morphology operation [30], [31], mean iterative filtering [32], and new star target segmentation (NSTS) method [33] etc. Although these methods can better eliminate the non-uniform background noise caused by stray light in the surveillance image. However, these methods cannot have both high-precision stray light non-uniform background elimination accuracy, high-precision target retention rate, and faster computation time.

In order to have a deeper understanding of the causes and effects of non-uniform background of surveillance image caused by stray light, we used stray light analysis method to analyze this process in detail. And we use the 3D ray tracing method to verify the analysis results. Then, to overcome the defects of existing methods, we proposed an accurate stray light elimination method named recursion multi-scale gray-scale morphology (RMGM) in this study. The block diagram of the proposed RMGM method is shown in Fig. 1, the method is roughly divided into three processes: (1) Construction of structural operators; (2) Morphological operation estimation and removal of non-uniform background based on constructed structural operators; (3) Perform threshold judgment to determine whether to retrieve the lost target or stop the recursive operation. In the first process, we defined two structural operators with different domains. These two structural operators can make full use of the difference information between the target region and the surrounding background region, which is the basic premise to ensure high-precision elimination effect. In the second process, we used these two structural operators with different domains to perform morphological processing on the surveillance image. Due to the different domains, we will preserve the target region pixels very well and only use surrounding background region pixels to participate in morphological operation. In the third process, in order to ensure that targets with different sizes in the surveillance image are not lost, we adopt a recursion multi-scale method. We increase the size of structural operator and perform the morphological operation again on the estimated and eliminated stray light non-uniform background in order to retrieve the lost larger size target. This is also the reason why the proposed RMGM method has a

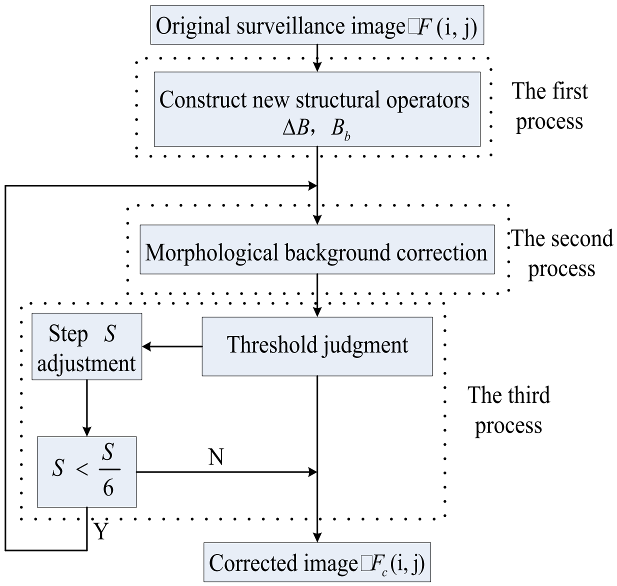

FIGURE 1. Block diagram of the proposed RMGM method.

high-precision target retention rate. In addition, we set up a corresponding threshold judgment mechanism to improve accuracy and reduce computation time. This can not only automatically change and determine the size of structural operator, but also ensure that no target is mistaken for stray light and eliminated when eliminating the stray light non-uniform background. The further experimental results for real captured image datasets, demonstrate the accuracy and effectiveness in eliminating stray light.

II. THE EFFECT OF STRAY LIGHT ON THE SURVEILLANCE IMAGE

The presence of stray light will increase the gray value of the surveillance image and bring very serious non-uniform background noise. Based on this, in this section, in order to better understand the impact of stray light on the surveillance image, we will use the energy transfer equation to analyze the effect of stray light on the surveillance image in detail.

According to the theory of radiation energy conduction, light energy travels between two media surfaces is:

$$d\Phi_c = \frac{L_s \cdot dA_s \cdot \cos\theta_s \cdot dA_c \cdot \cos\theta_c}{R_{sc}^2} \tag{1}$$

where $d\Phi_c$ is the flux on receiving surface, L_s is the radiance of source plane, A_s and A_c are the area of both source plane and receiving surface, θ_s and θ_c are the angles that the line of sight from the source plane to the receiving surface makes with their respective normals, R_{sc} is the length from center of source plane to that of receiving surface. Eq.(1) can be rewritten as three factors that help simplify distribution function of stray light:

$$d\Phi_c = \left(\frac{L_s}{E_s}\right)(E_s \cdot dA_s)\left(\frac{\cos\theta_s \cdot \cos\theta_c \cdot dA_c}{R_{sc}^2}\right) \tag{2}$$

$$d\Phi_c = \mathrm{BRDF} \cdot d\Phi_s \cdot d\Omega_{sc} \tag{3}$$

where E_s is the incident irradiance on the source plane, $d\Phi_s$ is output flux on the source plane, BRDF represents the scattering characteristics of the material surface, the BRDF defines the ratio of the scattering radiance to the incident irradiance for rough surface, therefore a function of the surface characteristics only, $d\Omega_{sc}$ is the projected solid angle (PSA) from the source plane to the receiving surface. According to Eq. (2) and (3), we can roughly understand that the distribution of stray light presents a gradual form without sudden change.

In order to verify our point of view and intuitively understand the impact of stray light on the surveillance image, we use a 3D ray tracing method to simulate the stray light, and the simulation results are shown in Fig. 2(a) and Fig. 2(b).

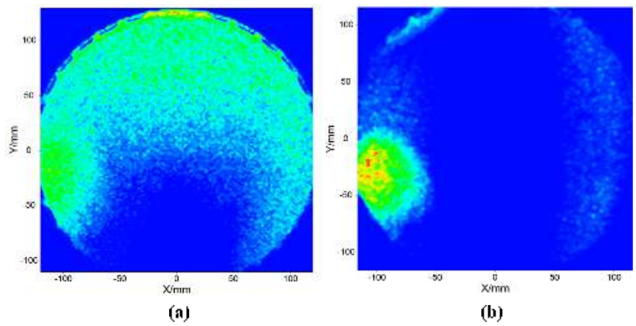

FIGURE 2. Three-dimensional ray tracing diagram of stray light background.

From Fig. 2 we can see that the non-uniform background noise caused by stray light has the characteristic of slowly changing. This kind of stray light non-uniform background noise can be roughly divided into two basic situations: global and local. For the global stray light non-uniform background, the gray scale of the entire surveillance image will increase greatly, as shown in Fig. 2(a). For the local stray light non-uniform background, it will make the surveillance image present a locally brighter area, and its brightness will gradually diffuse to the surrounding area and decrease, as shown in Fig. 2(b). We can think of these as two basic forms of stray light non-uniform background. The impact of any other stray light on the surveillance image can be simply regarded as a combination of these two situations.

From the above analysis, we can also know that the model parameter is unable to eliminate the stray light non-uniform background in the surveillance image. Due to the complexity of stray light background, we cannot accurately know the distribution or combination of stray light background in advance, we can only roughly know the existence form and influence of stray light. When the parameters cannot be matched with the image, the target with low signal-to-noise ratio will be severely damaged. However, through the analysis of stray light, we know that the stray light non-uniform background noise has a slowly changing characteristic, which is why we can use morphology-based method to eliminate the stray light non-uniform background.

III. STRAY LIGHT ELIMINATE METHOD

In this section, we will introduce in detail how our proposed RMGM method eliminates stray light in surveillance image, so as to ensure the effective recognition of subsequent space targets and stars.

A. DEFINITION OF STRUCTURAL OPERATOR

As we all know, although the background of surveillance image is affected by stray light, the gray value of target region is always higher than the gray value of the background region around the target. This difference information is the fundamental reason why we can eliminate stray light. In order to make better use of this difference information, we first define two structural operators with different domains as shown in Fig. 3(a) and Fig. 3(b) to eliminate stray light and keep target.

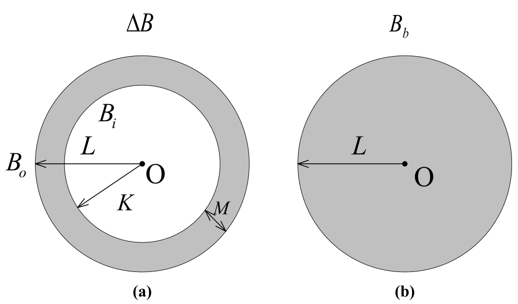

FIGURE 3. Used structural operators in the proposed RMGM method.

Where B_i and B_o are respectively defined as the inner structural operator and the outer structural operator of the structural operator ΔB, $\Delta B = B_o - B_i$, K represents the size of B_i, L represents the size of B_o and B_b respectively, $L > K$, $M = L - K$.

B. STRAY LIGHT ELIMINATION BASED ON GRAY-SCALE MORPHOLOGY

First, in order to make full use of the gray difference information between the target region and the surrounding background region, we use structural operator ΔB to perform dilation operation on the surveillance image to obtain the image F_1, as shown in Eq. (4).

$$F_1 = F \oplus \Delta B = \max\{F(i-m, j-n) + \Delta B(m,n)\} \\ |(m,n) \in D_{\Delta B}\} \quad (4)$$

where $D_{\Delta B}$ represents the domain of ΔB. According to the definition of dilation operation [34], star or space target with a size smaller than K will be replaced by the pixel values of the surrounding background region ($M = L - K$). At this time, not only the star and space target region are retained, but the number of pixels involved in the operation of star and space target region is reduced in the subsequent operations, which will greatly improve the accuracy of stray light elimination.

Then we use structural operator B_b to perform erosion operation on the image F_1, as shown in Eq. (5).

$$F_2 = F_1 \Theta B_b = \min\{F_1(i+m, j+n) - B_b(m,n)\} \\ \big|(m,n) \in D_{B_b}\} \quad (5)$$

where D_{B_b} represents the domain of B_b. Erosion operation on the image F_1 will adjust the overall bright region of the image, and it will reduce the gray value of star and space target replaced by surrounding background region to ensure that the eliminated stray light will not weaken the brightness of star and space target too much.

When the surveillance image performs the dilation operation of Eq. (4), if there is no target in the operation region, the relationship between this region before and after processing is uncertain. In addition, in order to better smooth the image and improve the accuracy of stray light elimination, we take the minimum value of the processed image F_2 and the original image F as shown in Eq. (6).

$$F_3 = \min(F, F_2) \quad (6)$$

where F_3 is the stray light background non-uniform background image that needs to be eliminated.

C. RECURSION MULTI-SCALE ADJUSTMENT

According to Eq. (4), we can know that star and space target with a size smaller than K will not participate in subsequent calculations and will be well retained in the image that eliminates stray light. However, star and space target with a size greater than K will not be replaced by the pixels of the surrounding background region after the operation of Eq. (4), so they will continue to participate in subsequent calculations and be mistaken for stray light and eliminated. Therefore, in order to ensure that large size stars and space targets will not be lost, we adopt a recursion multi-scale method, that is, increase the size of these two structural operators (ΔB and B_b), and repeat the operation in Section III(B) for the eliminated stray light image F_3 to retrieve the stars and space targets that were mistakenly eliminated as stray light.

In addition, in order to automatically adjust the step size of structural operator in the recursion multi-scale operation and the recursion number required for the recursion multi-scale operation, we introduce the image mean as the automatic adjustment factor. The definition is as follows:

$$F_n = F - F_{ns} \quad (7)$$

where F_n is the surveillance image after n recursive multi-scale processing, F is the original surveillance image affected by stray light, F_{ns} is the stray light background after n recursive multi-scale processing that needs to be eliminated. If the image F_n undergoes n times recursive multi-scale operation, if there is no target loss and no residual stray light, the mean change of the image will be very small. The detailed steps of the method are as follows:

Step 1: We keep M unchanged and set it as small as possible, so that when two targets are relatively close, no target pixel will fall into M, which will affect each other due to the introduction of target pixels during the expansion operation, otherwise the dilation operation will cause mutual influence due to the introduction of target pixel. Then we increase the size of L and K with the same step size S.

Step 2: If $M_n - M_{n-1} < th_0$, where M_n and M_{n-1} are the mean of image F_n and image F_{n-1} respectively, and th_0 is the set judgment threshold. We believe that there is no target loss or residual stray light and terminate the recursive multi-scale operation, and F_{n-1} is taken as the final surveillance image without stray light non-uniform background.

For th_0, we can calculate it by Eq. (8).

$$th_0 = \frac{S_{n-1} \cdot S_{n-1} \cdot T_{n-1}}{I} \tag{8}$$

where S_{n-1} is the size of the structural operator used in the $n-1$ time recursion, T_{n-1} is the adaptive threshold of the surveillance image that eliminates the stray light background after the $n-1$ time recursion, and we use the adaptive threshold method proposed by Xi *et al.* [32] to calculate the threshold T_{n-1}, I is the imaging pixels of the surveillance image.

Step 3: If $M_n - M_{n-1} > th_1$, where th_1 is the set judgment threshold. We think that there is stray light that is mistaken for the target and remains in the image F_n. That means that the step size S of structural operator increase is too large. For this reason, we change the step size S to $\frac{S}{2}$, and recalculate F_n with the step size $\frac{S}{2}$.

For th_1, we can calculate it by Eq. (9).

$$th_1 = \frac{S_n \cdot S_n \cdot E_{n-1}}{I} \tag{9}$$

where E_{n-1} is the adaptive threshold of the stray light non-uniform background estimated and eliminated after $n-1$ time recursion.

Step 4: If the step size S becomes $\frac{S}{6}$, there is still $M_n - M_{n-1} > th_1$. In order to ensure a faster computation time, in many experiments and taking into account the size of target in the surveillance image, if the step size is reduced from S to $\frac{S}{6}$, there is still $M_n - M_{n-1} > th_1$, which we think that all the lost targets have been retrieved from the eliminated non-uniform background. Therefore, we think that F_{n-1} is the final surveillance image that includes all targets and no stray light remains.

Based on the aforementioned proposed RMGM method, we can not only eliminate stray light non-uniform background noise accurately, but also ensure that targets with different sizes will not be lost.

IV. EXPERIMENTS AND DISCUSSIONS

In this section, we compared the proposed RMGM method with three other methods, including the classic method and the excellent method in recent years, which are suitable for eliminating the stray light non-uniform background noise in surveillance image. The compared methods are Top-Hat transformation (THT) method [31], mean iterative filtering (MIF) method [32], NSTS method [33]. These methods are used to perform stray light elimination experiments in the same real captured image datasets (600 images).

A. ACCURACY OF STRAY LIGHT BACKGROUND ELIMINATION

The real surveillance image was taken by the telescope with a $10° \times 10°$ field of view. The telescope equipped with a CMOS sensor with 2s exposure time, and have 10K × 10K imaging pixels, and 12 bits of grayscale. In order to be displayed more clearly, we only cut 1024*1024 pixels for display. Some results of stray light non-uniform background elimination are shown in Fig. 4. In Fig. 4, (a)-(c) are the surveillance images affected by different stray light, and $(a_n) - (c_n)$ are the surveillance images after using different methods to eliminate stray light.

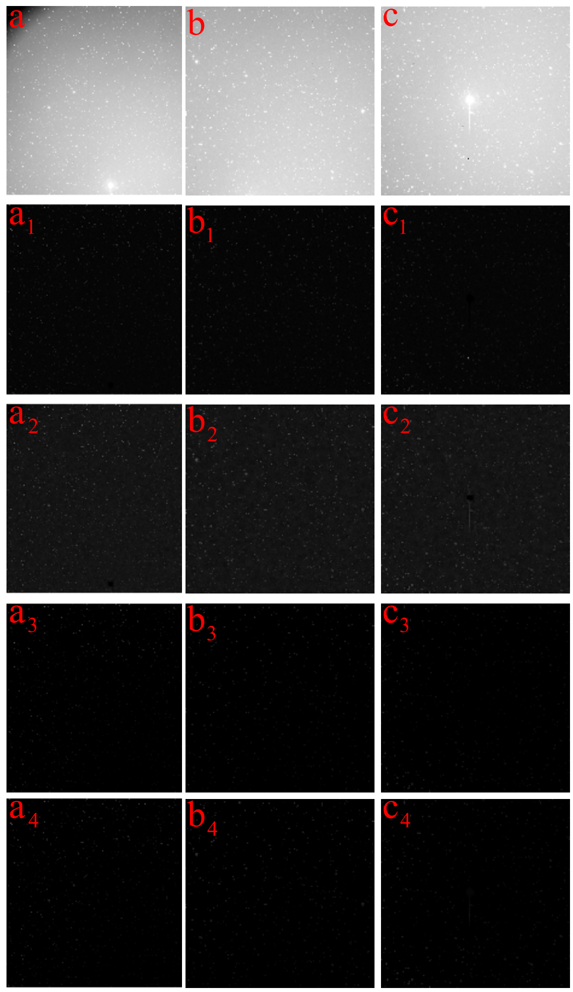

FIGURE 4. Stray light elimination result of four different methods. (a)-(c) Original surveillance images, (a_1)-(c_1) Stray light elimination result of the MIF method, (a_2)-(c_2) Stray light elimination result of the THT method, (a_3)-(c_3) Stray light elimination result of the NSTS method, (a_4)-(c_4) Stray light elimination result of the proposed RMGM method.

In order to further quantitatively analyze the accuracy of different methods in eliminating stray light background, we adopt a method based on the mean and variance of residual image. In the residual image, considering that the mean of noise is zero, if the residual mean and residual standard deviation in the surveillance image after eliminating stray light are closer to zero, it means that the accuracy of method is higher, and there is no residual slowly changing stray light background in the surveillance image after eliminating stray light. Since there are a large number of targets in the surveillance image, we need to eliminate the targets when calculating the mean and variance of the residual image, otherwise the targets will seriously affect the statistical distribution of the residual image. Therefore, an excluded domain method based on adaptive threshold is introduced to eliminate target interference. First, we use the adaptive threshold method proposed by Xi *et al.* [32] to calculate the threshold T. Then, we use the threshold T to establish the excluded domain E_d.

$$E_d(i,j) = \begin{cases} 1, & F_c(i,j) < T \\ 0, & F_c(i,j) > T \end{cases} \tag{10}$$

where $F_c(i,j)$ represents the surveillance image after eliminating stray light. Finally, we can get the residual image R that eliminates the influence of target.

$$R(i,j) = F_c(i,j)\, E_d(i,j) \tag{11}$$

The results of the residual image mean and variance of different methods are shown in Table 1.

TABLE 1. The results of the residual image mean and variance.

	Fig. 4(a)		Fig. 4(b)		Fig. 4(c)	
Background Residual	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Original image	25.99	54.27	16.44	50.54	106.02	100.22
MIF method	4.83	4.09	6.19	5.09	6.84	6.06
THT method	19.41	44.03	6.55	30.92	70.64	88.69
NSTS method	0.60	0.57	0.65	0.59	0.99	0.90
the proposed RMGM method	0.05	0.04	0.05	0.03	0.10	0.08

For all methods suitable for eliminating stray light non-uniform background in surveillance image. The THT method has the worst effect, that is, it will still leave a large amount of non-uniform background noise in the processed surveillance image when eliminating the stray light background. Since the domain of structural operator of the THT method includes all pixels in the region (including target and background), the pixels in the target region will also participate in the calculation, which greatly interferes with the accuracy of the non-uniform noise calculation. In addition, the fixed structural operator cannot be applied to different situations, and the accuracy of eliminating non-uniform background noise under complex situations is greatly reduced. For MIF method (five iterations), although multiple iterations can improve the accuracy of stray light background elimination, and have better results in variety of complex environments. However, the same as the THT method, the MIF method still makes all the pixels in the surveillance image participate in the calculation, which makes it difficult for this method to further improve the accuracy on this basis. For NSTS method and the proposed RMGM method, since they use two structural operators with different domains, this will greatly reduce the number of target region pixels involved in operations. This will greatly improve the accuracy of eliminating stray light background. However, because the NSTS method uses fixed-size structural operator, some region of the surrounding background of some smaller-sized targets are mistakenly regarded as target and remain. This greatly reduces the accuracy of stray light non-uniform background elimination. For the proposed RMGM method, we use a recursive multi-scale method, the size of structural operator gradually changes with the size of target. Compared with the NSTS method, this will make the surrounding background region of targets of different sizes be better eliminated, thereby greatly improving the accuracy stray light non-uniform background elimination. We can see that compared with other methods, the proposed RMGM method has much higher accuracy in eliminating stray light than other methods.

B. TARGET RETENTION ACCURACY ANALYSIS

As mentioned above, the purpose of eliminating the non-uniform noise caused by stray light is to fundamentally improve the accuracy of target recognition. Then when eliminating the non-uniform background, on the one hand, the accuracy of non-uniform noise elimination must be considered, on the other hand, the retention accuracy of the target is also extremely important, which directly affects the accuracy of target recognition. We can intuitively see the target retention accuracy of different methods from the eliminated non-uniform background in Fig. 5. In Fig. 5, (a)-(c) are the surveillance images affected by different stray light, and $(a_n) - (c_n)$ are the stray light non-uniform background estimated and eliminated by the four methods.

TABLE 2. The results of the target detection.

Method	Fig. 5(a)	Fig. 5(b)	Fig. 5(c)
MIF method	89%	90%	88%
THT method	82%	85%	80%
NSTS method	92%	93%	91%
the proposed RMGM method	99%	99%	98%

It can be seen intuitively from Fig. 5 that the proposed RMGM method has higher target retention accuracy. In order to further quantify the target retention accuracy of different methods, we use the target detection method proposed by Liu *et al.* [10] to detect the target. The results of the target detection are shown in Table 2.

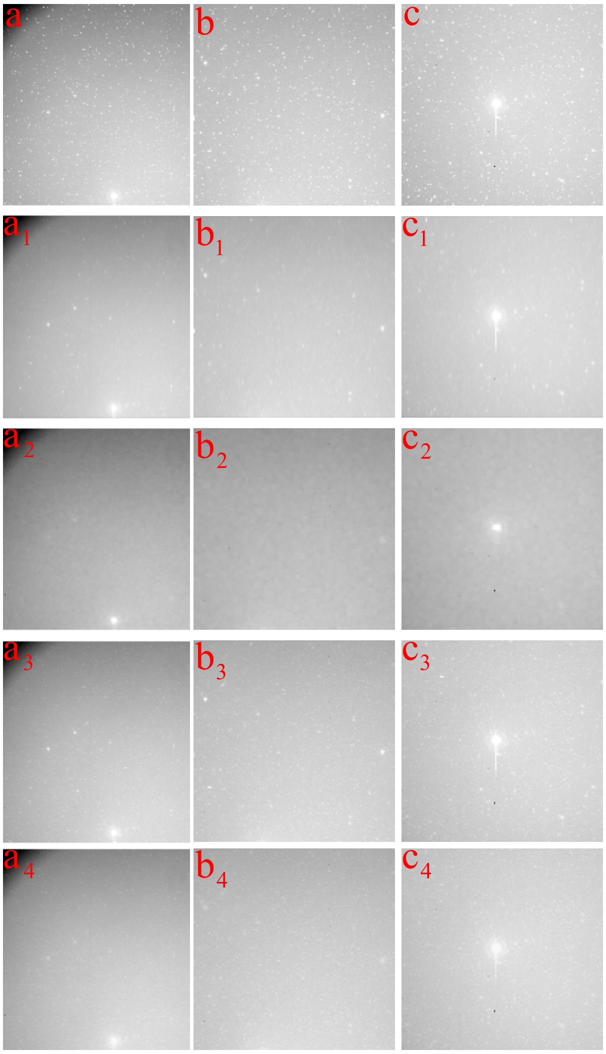

FIGURE 5. Stray light non-uniform background obtained by four different methods. (a)-(c) Original surveillance images, (a_1)-(c_1) Stray light non-uniform background obtained by MIF method, (a_2)-(c_2) Stray light non-uniform background obtained by THT method, (a_3)-(c_3) Stray light non-uniform background obtained by NSTS method, (a_4)-(c_4) Stray light non-uniform background obtained by the proposed RMGM method.

For MIF method (five iterations), although multiple iterations can improve the accuracy of stray light background elimination. However, due to the process of multiple iterations, the gray value of each target in the surveillance image will also be greatly reduced to a certain extent, especially for the target with low signal-to-noise ratio, this may lead to direct loss of target with low signal-to-noise ratio. In addition, some brighter targets will be mistaken for non-uniform noise and eliminated. For THT method. As mentioned in Section IV(A), due to the low accuracy of the THT method in eliminating stray light non-uniform noise, this also means that there are still serious non-uniform noises in the processed surveillance image, which also makes the target recognition accuracy greatly reduce. In other words, the target retention accuracy of THT method is not high. For NSTS method, although this method has high accuracy in eliminating stray light non-uniform background, it is too sensitive to the structural operator, the fixed-size structural operator cannot cover all-size targets, resulting in some larger-size targets being mistaken for stray light non-uniform background and lost. For the proposed RMGM method, since we add a multi-scale operation, this method can continuously retrieve the lost target in the eliminated stray light non-uniform background. This also greatly improves the accuracy of target detection.

C. COMPUTATION OF COMPUTATION TIME

In order to compare the computation time of different methods, all methods implemented in MATLAB R2016a, and the PC specifications include an i5- 3210M CPU (2.50 GHz) with 8 GB of main memory. Image size is 10K $\times$ 10K pixels. The computation time of different methods is shown in Table 3.

TABLE 3. The computation time results of different methods.

Method	Computation Time (s)
MIF method	25.12
THT method	0.50
NSTS method	0.32
the proposed RMGM method	0.75

For MIF method (five iterations), due to the process of multiple iterations, this will take a lot of computation time, but the huge time overhead is unacceptable. For the other three methods, they have a faster computation time and can meet the requirement of the wide-field surveillance camera. Although the computation time of the proposed RMGM method is increased due to the multi-scale process, the corresponding stray light non-uniform background elimination accuracy and target retention accuracy have been greatly improved, which is exactly what the target recognition needs.

V. CONCLUSION

In order to solve the problem that the current methods cannot effectively eliminate the non-uniform noise caused by stray light in the surveillance image, we proposed an accurate stray light elimination method based on recursion multi-scale gray-scale morphology (RMGM).

In this paper, in order to have a deeper understanding of the causes and effects of non-uniform background of surveillance image caused by stray light, we used stray light analysis method to analyze this process in detail. And we use the 3D ray tracing method to verify the analysis results. Then, we used two structural operators with different domains to perform morphological processing on the surveillance image, which can accurately eliminate stray light while retaining the target. In addition, in order to ensure that targets with different sizes in the surveillance image are not lost, we adopt a recursion multi-scale method. We increase the size of structural operator and perform the morphological operation again on the estimated and eliminated stray light non-uniform background in order to retrieve the lost larger-size target. And we add an automatic decision mechanism on the recursion multi-scale method by using corresponding threshold judgment to determine the time of recursion. Compared with other methods, further real captured image experiments verify the superiority of our proposed RMGM method. The proposed RMGM method can simultaneously have high-precision stray light elimination effect, high-precision target retention rate, and faster computation time.

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ZEMING XU was born in Heihe, Heilongjiang, China, in 1993. He received the B.S. degree in physics from Shandong University, Jinan, China, in 2016. He is currently pursuing the Ph.D. degree with the Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun, China.

His research interests include stray light suppression, weak target detection, and image processing.

DAN LIU received the B.S. degree in engineering from Jilin University, Changchun, China, in 2016. She is currently pursuing the Ph.D. degree with the Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun.

Her research interests include image processing, faint target detection, and computer vision.

CHANGXIANG YAN was born in Honghu, Hubei, China, in 1973. He received the M.S. degree in engineering from Zhejiang University, Zhejiang, China, in 1998, and the Ph.D. degree from the Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun, China, in 2001.

Since 2010, he has been the Director of the Space Optics Laboratory, Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences. His research interests include opto-mechatronics technology for space optical remote sensing instruments, multispectral and hyperspectral spatial remote sensing imaging, polarization detection, and space surveillance.

CHUNHUI HU was born in Xinyang, Henan, China, in 1986. He received the B.S. degree in optical information science and technology from Northwestern Polytechnical University, China, in 2008, and the Ph.D. degree in optical engineering from the Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun, China, in 2013.

He is currently an Assistant Research with the Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences. His current research interest includes the installation and inspection of optical systems.