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Moving Target Shadow Detection and Global Background Reconstruction for VideoSAR Based on Single-Frame Imagery

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ABSTRACT The indication of moving targets with low velocities, which is an extremely serious problem for traditional ground moving targets indication (GMTI), can be achieved relatively easily by shadow detection in VideoSAR imagery. Numerous image and video processing technologies have been applied to shadow detection in VideoSAR to improve the performance for GMTI. Among these processing technologies, background modeling is the key technology, which has received lots of research based on multi-frame imagery but little on single-frame imagery. This paper introduces the formation of the moving target shadows and adds the concepts of occlusion, umbra, and penumbra to prior work. In addition to this, the paper proposed a local feature analysis method based on single-frame imagery, which can accurately detect moving target shadows. Based on the result of this method, the background model can be reconstructed using single-frame imagery, which avoids the "ghost" phenomenon in moving target detection algorithms based on multi-frame imagery. Finally, we replace the initial frame in the visual background extractor (ViBe) algorithm by the reconstructed background model we get, and the result shows that the ghosts are removed effectively.

INDEX TERMS VideoSAR, moving target shadow detection, local feature analysis, global background reconstruction.

I. INTRODUCTION

The detection and analysis of moving targets have always been research hotspots in the field of ground moving targets indication system based on the synthetic aperture radar (SAR-GMTI). Nevertheless, the robustness and the location accuracy of conventional detection techniques, especially for slow target detection, are still unsatisfactory because the frequency spectrum of the moving target with low velocity cannot be distinguished from that of the stationary background [1]–[4].

VideoSAR technique can offer collection and processing of phase history data, allowing observation during inclement weather or atmospheric conditions by forming high-frame-rate VideoSAR sequence images [5]. In VideoSAR, unlike the energy of moving targets, the shadows will be casted in the actual position of moving targets without smear and displacement, which is effective for the detection of moving targets. Hence, many scholars have focused their attention on the detection of shadow information in VideoSAR. Ann Marie Raynal, Douglas L. Bickel and Armin W. Doerry of Sandia National Laboratories explained in detail the formation and characteristics of shadows in VideoSAR imagery [6]. A. Doerry *et al.* studied the impact of ground mover motion and windowing on stationary and moving shadows [7]. In [8], Zhang *et al.* proposed a novel approach for shadow enhancement in high-resolution SAR imagery. Huanjian Xu and others used the enhanced shadow information as authentication to aid the moving target detection in multichannel SAR-GMTI system [9]–[11], which proved the significance of the shadow information in moving target detection.

Algorithms for detecting shadows in VideoSAR are also proposed. A common and simple practice is to extract moving target shadows by morphological operations [12]. However, this method cannot eliminate the false alarm of stationary target shadows, and requires precise path information as a prerequisite. To solve the problem, the algorithms based on multiple frames in VideoSAR are proposed [13], [14]. The algorithm builds a background model using sequence images in VideoSAR and extracting moving target shadows

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by subtracting background model from an original image. Although the multi-frame-based algorithms are effective, the background modeling can only be achieved with accurate registration, fixed scene, and a certain number of sequence images. These requirements limit application of the algorithms in velocity independent continuous tracking radar (VICTR) mode of VideoSAR, which gets a changing scene. In this case, the focus of the research is on the single-frame-based method, which is free from accurate registration and the limitation of changing scenes. The method can provide a timely and fit background model for sudden changes in scenes during video processing. The codebook [15] algorithm, ViBe [16] and other video moving target detection algorithms proposed recently take advantage of this method and initial their background model by single frame image. Then, they use the detection results of other frames to improve their background models continually. However, without prior knowledge, the moving targets in the initial frame will be regard as the background and the ghosts will be left for several frames [17], [18].

Based on the work presented in [6], this paper clarifies the concepts of penumbra and umbra, and distinguishes the difference between occlusions and shadows. A method based on local feature analysis is also proposed to detect moving target shadows in single-frame VideoSAR image. In addition, the local features can be used to generate a simulated local background to fill the shadow region and the global background model can be reconstructed. We use the background model to replace the initial frame in ViBe algorithm and remove the ghosts effectively.

This paper is organized as follows: Section II introduces the characteristics of moving target shadows in SAR imagery. Section III describes the principle of the moving target shadow detection method proposed. Section IV describes the reconstruction of the global background model and the ViBe algorithm. Section V shows the results of the moving target shadow detection method using real VideoSAR data. In addition, the background reconstruction and the results of the improved ViBe algorithm are also shown in this section.

II. MOVING TARGET SHADOW CHARACTERISTICS IN VIDEOSAR IMAGERY

To design a better algorithm, it is necessary to understand the formation and composition of the moving target shadows in SAR imagery. In fact, an entire moving target shadow is composed by two parts: shadow and occlusion. And a shadow is also composed by two parts, umbra and penumbra.

A. UMBRA AND PENUMBRA

Shadows in SAR are created when incident radar electromagnetic waves are blocked by a target from the ground plane immediately behind the target, which is similar to the shadows in optical imaging. Using two concepts of astronomy as analogy, A shadow consists of umbra and penumbra.

Umbra is the area where radar energy cannot reach during a synthetic aperture. This part is generally the center of the shadow and its backscatter intensity should theoretically be equal to 0. The area which is illuminated by radar energy in a part of a synthetic aperture constitutes the penumbra. Penumbra generally appears on the edge of a shadow and is more blurred than umbra, which is one of the main reasons for the blurring of shadows in SAR imagery. Figure 1 shows the formation of the umbra and penumbra.

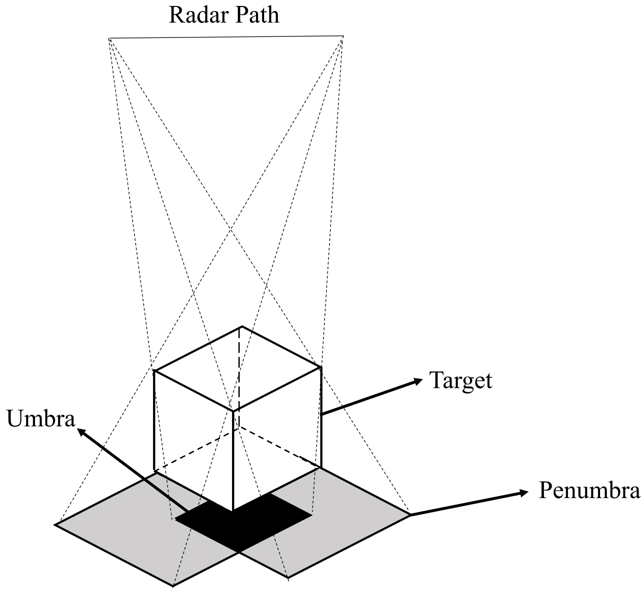


FIGURE 1. Formation of umbra and penumbra.

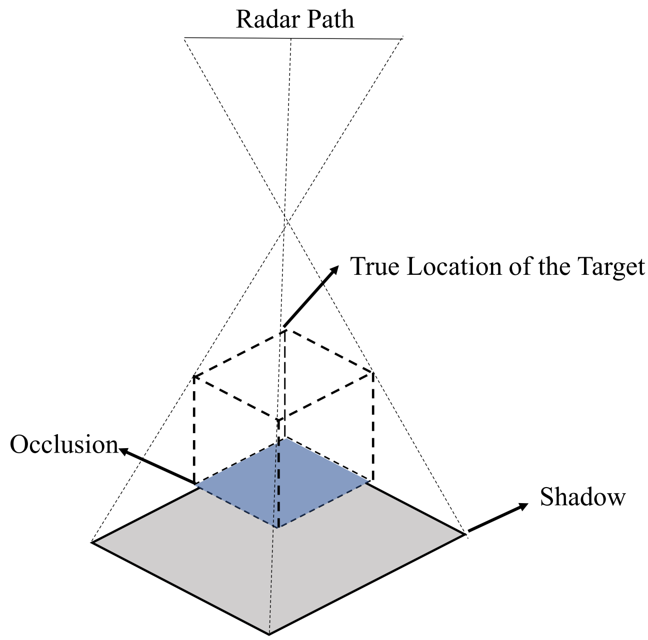


FIGURE 2. Schematic diagram of occlusion.

B. OCCLUSION

Occlusion refers to the completely missing of the background information due to the obscuration of the foreground object. Fig. 2 shows the formation of occlusion. When the target is displaced from the true location, the occluded part of the

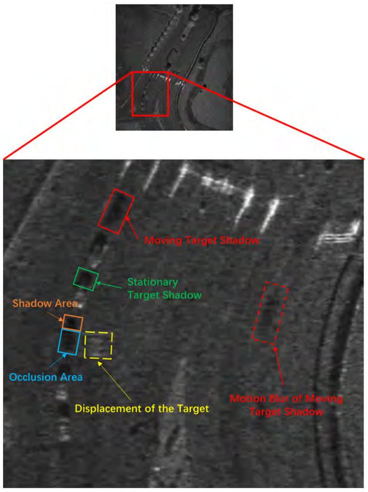


FIGURE 3. Two types of shadows in single-frame VideoSAR image.

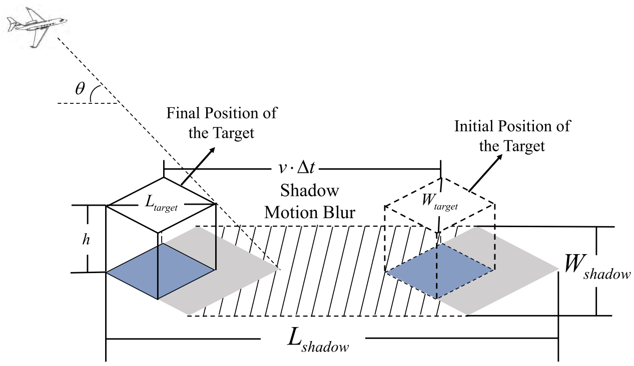


FIGURE 4. Motion blur of shadows caused by the motion of targets during a synthetic aperture.

background has been lost and leaves a dark region in SAR image. The dark region left at the true location of the moving target is the result of the occlusion.

In SAR imagery, the shadow compositions of stationary targets and moving targets are different. Two types of shadows in a real SAR radar image are shown in Fig. 3. The shadow of a stationary target is similar to that of optical imaging. Besides the true shadow, a moving target shadow is also composed of occlusion region caused by the displacement of the moving target in SAR imagery.

C. MOTION BLUR OF MOVING TARGET SHADOWS

The shadow of a moving target may get blurred due to the fast movement of the target during the synthetic aperture. Motion blur will cause the stretching of the shadow along the motion direction and reduce the quality of the shadow. The formation of the motion blur is shown in Fig. 4.

Adding the occlusion to the research of [6], the dimension of the shadow is

$$\boldsymbol{L}_{shadow} = \boldsymbol{h} \tan\theta + \boldsymbol{L}_{target} + \boldsymbol{v} \cdot \boldsymbol{\Delta t} \tag{1}$$

$$\boldsymbol{W}_{shadow} \approx \boldsymbol{W}_{target} \tag{2}$$

where L_{shadow} denotes the length of the shadow along the direction of motion and L_{target} is that of the target. W_{shadow} denotes the width of the shadow vertical to the motion direction, and W_{target} is that of the target. The height of the target h and the target velocity v are the main cause of the differences between the various shadows. θ is the depression angle of the radar. Δt is the time of the target motion in the synthetic aperture. As the target speed up, the signal to clutter ratio (SCR) of shadows will increase (reduce the contrast between shadows and background, in other words), which can be verified in Fig. 3.

In addition to the blur caused by the target motion, the platform vibration, wind field, and turbulence can also affect the quality of the shadows. Related research can be seen in [19], [20].

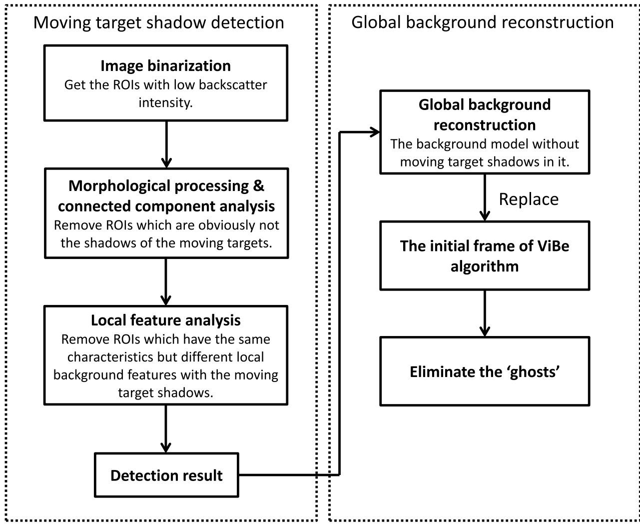


FIGURE 5. The flowchart of the moving target shadow detection method and global background reconstruction.

III. MOVING TARGET SHADOW DETECTION BASED ON LOCAL FEATURE ANALYSIS IN SINGLE-FRAME IMAGERY

The method we proposed can extract moving target shadows effectively in single-frame VideoSAR imagery by taking the features of the local area of the shadow into account. The flowchart of the method is presented in Fig. 5. The image binarization is a convenient way to obtain the regions of interest (ROI). So, the well-developed OTSU algorithm [21]–[23] is an effective way to binarize the image. Morphological processing and connected component analysis will eliminate ROIs which are obviously impossible. Then, we use local background features to exclude ROIs which are similar to moving target shadows (like stationary target shadows and some dark regions in background). So far, the moving target shadow detection has been completed.

A. BINARIZATION OF VIDEOSAR IMAGE

The OTSU is an efficient algorithm for image binarization. The basic principle of it is to divide all the resolution cells into two types (target cells and background cells) using threshold which maximize the variance between two types of cells.

The variance is defined as (3).

$$\sigma^2(K) = \max\left(\frac{[u_r\omega(k) - u(k)]^2}{\omega(k)[1-\omega(k)]}\right) \tag{3}$$

where K denotes the threshold and u_r denotes the average intensity of entire image. $u(k)$ and $\omega(k)$ are the average intensity and the probability of occurrence of target cells, respectively.

The performance of the OTSU algorithm depends on the SCR of the shadows. As mentioned in Section II, targets with high-speed will cast shadows with low contrast (SCR near 0) because of the motion blur of shadows. The performance of OTSU in different SCR cases is shown in Section V.

B. MORPHOLOGICAL PROCESSING AND CONNECTED COMPONENT ANALYSIS

Among ROIs obtained in step A, there are lots of them are obviously not the shadows of moving targets such as speckle noise, road edges and the dark region near the edge of the image. Morphological processing and connected component analysis can remove these regions easily.

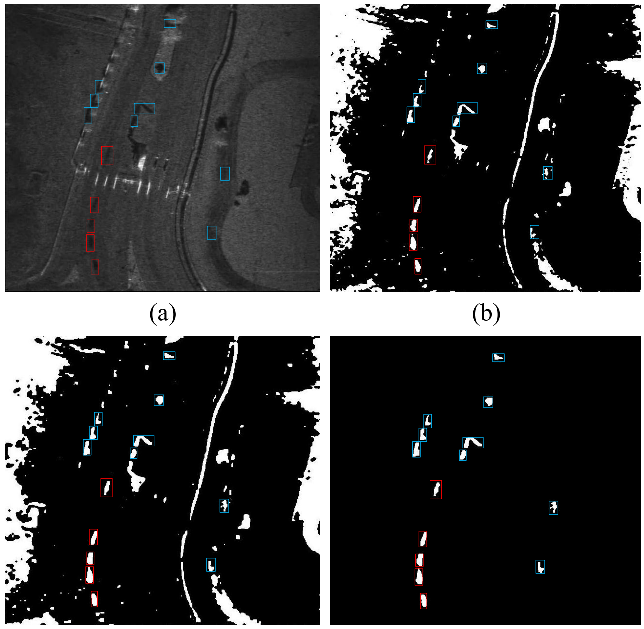
First, image dilation and erosion are used to fill the voids and slits in ROIs to avoid unnecessary false alarms. Then, we use the features of ROIs (such as the areas and aspect ratios of ROIs) to exclude the ROIs which are obviously not the shadow regions of moving targets.

The thresholds of areas and aspect ratios can be determined by the sizes of targets, the velocities of targets and the depression angle of radar platform as explained in Section II, or be manually set based on prior knowledge. In fact, VideoSAR is composed of a high-frame-rate SAR image sequence, which means the time interval between frames is short (about 30 frames per second). In this case, the velocities of targets have little effect on the sizes of the shadows, which greatly reduces the uncertainty of the sizes of shadows and makes setting the thresholds easier. The processing result is shown in Fig. 6.

C. LOCAL FEATURE ANALYSIS

After step B, most of the wrong ROIs have been ruled out, but there are still some false alarms which are similar to the moving target shadows, like stationary target shadows and some dark regions of background. It is critical to find a feature to eliminate them. Though observation, we choose a simple and feasible feature, the local SCR, as the feature to distinguish moving target shadows from false alarms. It is easy to find that the stationary target shadows are always immediately behind their casters with strong backscatter intensity, but the moving target shadows are not because of the Doppler displacement and smear of their casters. And shadows of stationary targets will have lower backscatter intensity without motion blur (mentioned in Section II). These will make the local images of stationary target shadows get lower SCR (higher contrasts), if we regard the shadows as signals. As for the dark regions of the background, they always occur in homogeneous areas, which means the signal (dark regions) and the local background have similar backscatter intensities but not on the same side of the OTSU threshold. So, the local SCR of them are high (near 0, like the two false alarms on the right side of Fig. 6(d)). Therefore, setting thresholds for the SCR of the local area can effectively eliminate the false alarms. In fact, the local SCR are always negative because the backscatter intensity of shadow is always lower than that of local background.

We choose a window model shown in Fig. 7. The size of local background window is approximately twice that of the bounding box, which contains a certain area of background and avoids being so large to introduce other disturbances.



(a) (b) (c) (d)

FIGURE 6. The effect of the morphological processing and connected component analysis. (a) is an original single-frame VideoSAR image. (b) is the OTSU result of (a) and (c) is the result after the dilation and erosion. (d) is connected component analysis. The moving target shadows are in the red boxes and the false alarms are in the blue boxes.

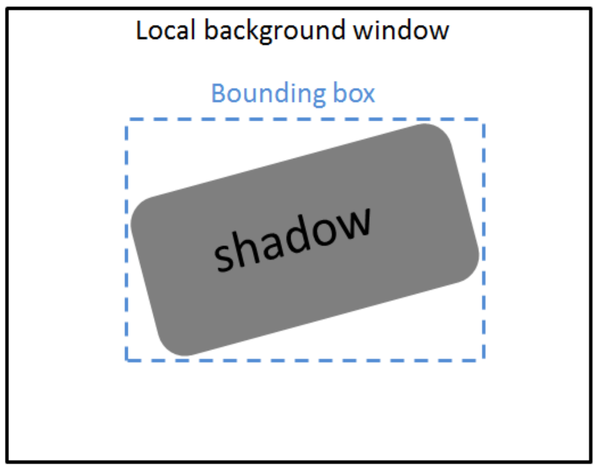


FIGURE 7. The structure schematic of local background window model.

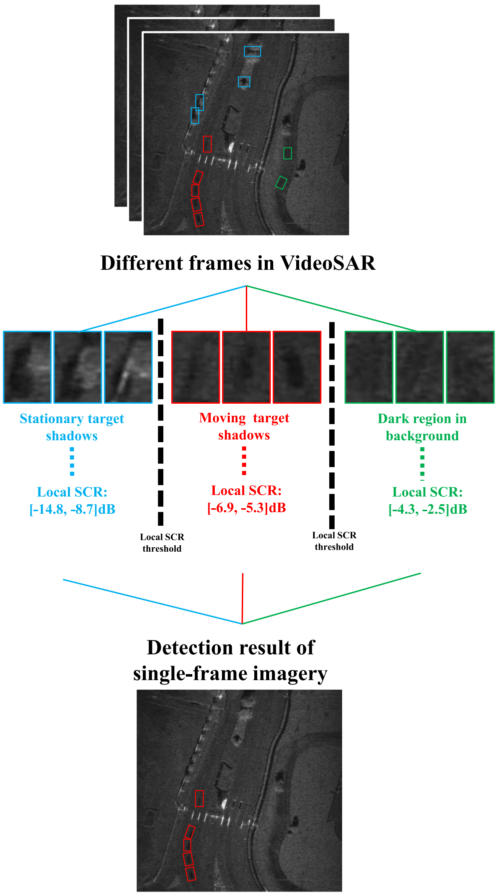


FIGURE 8. The setting of local contrast thresholds and the detection result of step C.

The ROIs obtained in step B are taken as the targets and the other resolution cells in local background window as the background. The moving target shadows are obtained after removing the ROIs whose local SCR are not in the interval we set. Figure 8 shows the setting of local SCR thresholds and the result of step C. The range of local SCR of ROIs in different frames is just to illustrate the validity of the thresholds. When thresholds have been set, it is not necessary to use other frames as auxiliaries.

In fact, in addition to SCR, some local background statistical features will be used in background reconstruction in Section IV.

IV. GLOBAL BACKGROUND RECONSTRUCTION

Background modeling is a very critical step in motion detection. Moving target detection in video can be easily achieved based on the background model. Classical methods based on single distribution (methods assume that the backscatter intensity of the resolution cell is consistent with single distribution or single value) and multiple frames like median filter method and single Gaussian model are not suitable for VideoSAR. Unlike the normal video sequences with relatively fixed background, VideoSAR is implemented by circle SAR which changes its view angle all the time. Thus,

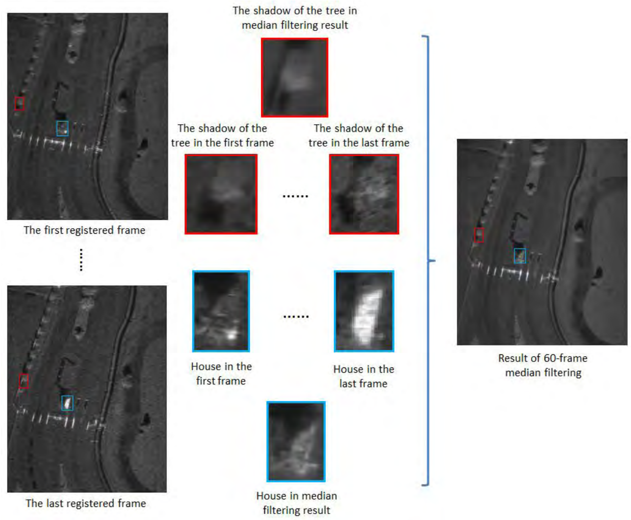


FIGURE 9. The problems of single-distribution background modeling based on multiple frames in VideoSAR.

accurate registration of frames is a big challenge. Even if the registration is precise, the scenes of images will get changed (like artificial targets with significant directional difference and the directions in which stationary target shadows are casted) because of the view angle changes over time. There are not enough frames in the same view angle to make these algorithms get accurate background models. These situations are shown in Fig. 9 and the experiment results are shown in Section V, Fig. 14.

The algorithms based on multi-distribution, like Gaussian mixture model (GMM), codebook and visual background extractor (ViBe), have made great achievements in background subtraction. They can adapt to a slight jitter in the background to some extent. The Vibe algorithm has better performance than other algorithms [16]. The algorithm assumes that the backscatter intensity of the resolution cells has the same distribution (or distributions) as those of the eight-neighbor cells around them. ViBe uses the first frame (or key frame whose background is different from the backgrounds of previous frames) to initialize the background model and update the background model by the detection results of the next frames. The flowchart of the ViBe algorithm is shown in Fig. 10. The biggest advantage of the ViBe is that it can initial the background model by a single frame and is robust to background changes. However, without prior knowledge, the moving targets in the initial frame (or key frame) will be regard as background and the ghosts will be left for several frames [16], [17].

With the prior knowledge that the only foregrounds in VideoSAR are the shadows of moving targets, the single-frame background modeling method based on shadow detection is proposed. Based on the result in Section III, we fill the moving target shadows using reconstructed background based on statistical characteristics of local background. The resolution cells of local background (cells except that of the shadow in the local background widow) are used to get

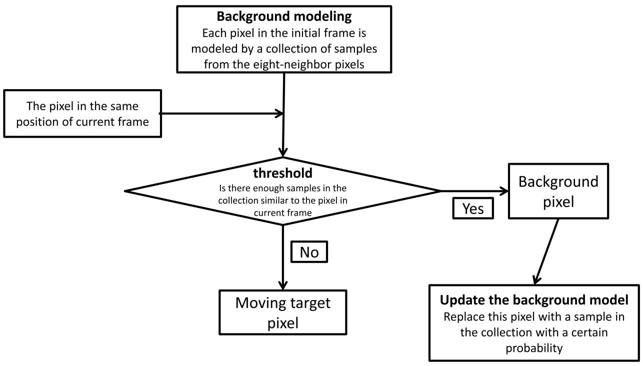


FIGURE 10. **The flowchart of the ViBe algorithm.**

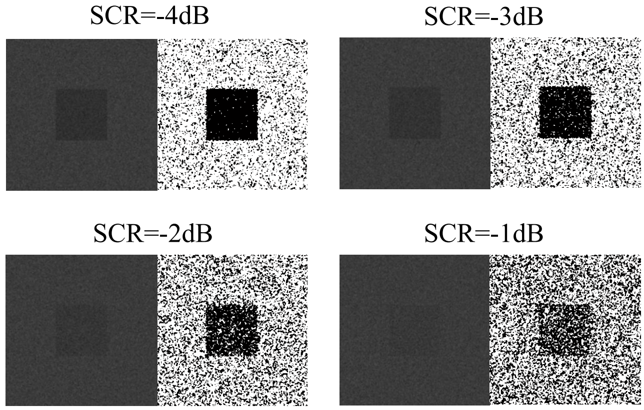


FIGURE 11. **The results of the OTSU algorithm in different SCR cases.**

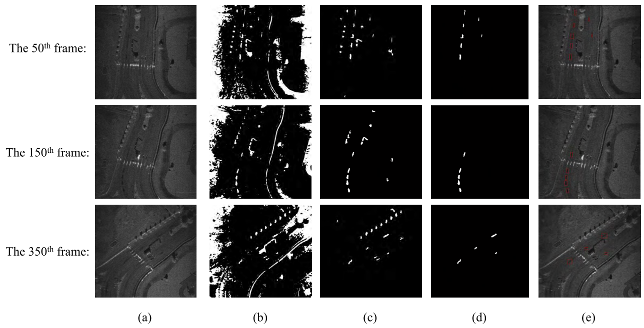


FIGURE 12. **The results of moving target shadow detection in different frames. (a) is an original single-frame VideoSAR image. (b) is the OTSU result of (a) and (c) is the result after the Morphological processing and connected component analysis. (d) and (e) are the final results of moving target shadow detection.**

the distributions of backscatter intensity. Assuming that the local background is homogeneous, the reconstruction of the local background can be obtained by (4) and (5)

$$f(x, y) = s(x, y)n(x, y) \tag{4}$$

$$Log(f(x, y)) = Log(s(x, y)) + Log(n(x, y)) \tag{5}$$

where (x, y) denote the coordinate of azimuth and range. $f(x, y)$ denotes the observed intensity of the backscatter. $s(x, y)$ denotes the real intensity of the backscatter. $n(x, y)$ is the noise and $Log(n(x, y))$ fits the Gaussian distribution [24], [25]. We use the mean of the $Log(f(x, y))$ of the local background cells as the estimate of $Log(s(x, y))$ and use the distribution of them to estimate the distribution of $Log(n(x, y))$. Then, bring them into (5) to get the reconstructed backgrounds. The global background reconstruction will be done after filling the shadows with the reconstructed background.

Although the background modeling method we proposed is accurate, the robustness of it is low when the background model is directly used to frames nearby because of the phenomena shown in Fig. 9. At the same time, modeling the background and detecting the moving target shadows of each frame are inefficient. Therefore, we use the background model we get to replace the initial frame (or key frame) in ViBe, which ensures that there is no moving target gets misjudged as background. Therefore, this method can eliminate ghosts effectively.

V. RESULTS AND ANALYSIS

The experiment uses the high-resolution VideoSAR footage of a gate at Kirtland Air Force Base published by the Sandia National Laboratory for moving target shadow detection. Detailed information about the data can be obtained at www.sandia.gov/radar/video.

A. MOVING TARGET SHADOW DETECTION

In fact, there are many factors that affect performance of the image binarization. But in the end, all of them are ultimately reflected in the SCR of shadows. We simulated the performance of the OTSU algorithm in different SCR cases and obtained the result shown in Fig. 11. When the SCR of shadow is close to 0 (the backscatter intensity of the background is too low or the velocities of targets are too high), it is impossible to detect shadow by image processing. Taking account of the speckle noise, the detection of moving target shadows can be well achieved when SCR of the shadow is less than -3dB.

In fact, most of the articles use the shadow detection algorithms based on multi-frame or multi-channel processing [9]–[11], [13], [14]. A few articles use only morphological processing or CA-CFAR algorithms for moving target shadow detection in simple background without interference such as stationary target shadows, which get results similar to the step B in section III (or results similar to Fig. 12(c)). Therefore, only the results of the proposed algorithm are shown here. We choose a few representative frames in VideoSAR for testing the moving target shadow detection method proposed. The results are shown in Fig. 12.

B. GLOBAL BACKGROUND RECONSTRUCTION

The background was reconstructed using the method proposed in section 3 and compared to median filter method (the background models in other methods like GMM and Vibe cannot be shown in the form of pictures). The method of median filter method will change the detail features of the dark regions in the edge of the VideoSAR image which causes

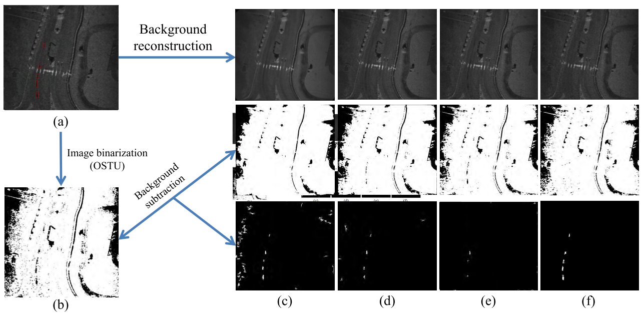


FIGURE 13. The results of background reconstruction and background subtraction. (a) and (b) Original image and the binarization of it. (c), (d), and (e) Results of median filter with 60 frames, 30 frames and 10 frames, respectively. (f) Result of the method proposed in this paper.

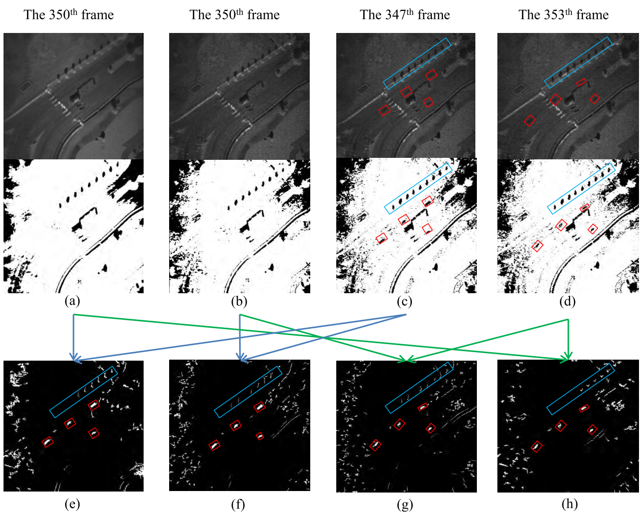


FIGURE 14. The results of the background modeling when it is used to other frames. (a) and (b) Background reconstruction of median filter and method proposed this paper of the 350th frame, respectively. (c) Original image of 347th frame and (d) is the original image of 353th frame. (c) and (d) Registered with the 350th frame. (e), (f), (g) and (h) Results of the background subtraction. The moving target shadows are in the red boxes and the shadows of the trees are in the blue box.

the false alarms in the edge of the image (like Fig. 13(c)). This phenomenon gradually diminishes as the number of frames used for median filter method. However, the slow targets will remain in the background when the number of the frames is insufficient (like Fig. 13(d) & (e)). The method we proposed gets the accurate background model of the current frame with the minimal alteration to the frame.

Figure 14 shows the low robustness of the background model when it is used directly to other frames. The dark regions in the edge of different frames are difficult to completely eliminate. Furthermore, the shadows of the stationary targets also get changed as the angle of view changes, which is shown in blue boxes of Fig. 14. These phenomena make the robustness of the methods based on single distribution (or single value, include our method) get low.

We use the method we proposed to improve the ViBe method and compare it with the ViBe. The results are shown in Fig. 15. Because there are moving target shadows in the initial frame, ghosts will appear at the same position of

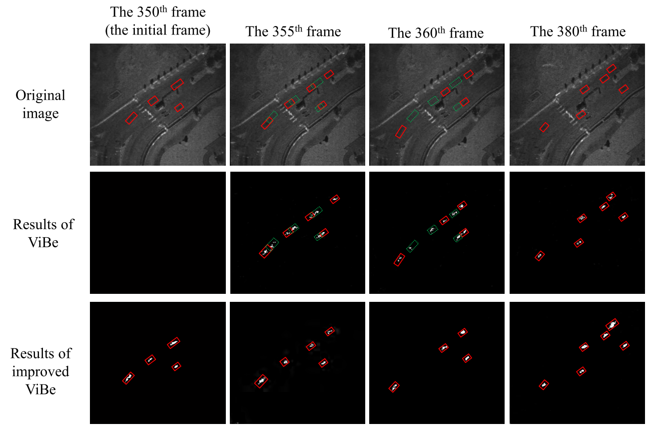


FIGURE 15. The results of the ViBe and the improved ViBe using our reconstructed background. The moving target shadows are in the red boxes and the ghosts are in the green dotted boxes.

the moving target shadows in the initial frame during next few frames. However, as the background model continually gets improved, the ghosts will gradually disappear. However, when using the reconstructed background without moving target shadows we get, the ghosts are removed effectively.

VI. CONCLUSION

Slow target detection is a complex issue in SAR-GMTI. Many related researches have focused on shadow detection to solve the problem because its operation in the image domain is effective and lots of algorithms to use for reference. First of all, we detail the formation principles and components of shadows in SAR image. Drawing on the idea of algorithms in image processing, we propose a moving target shadow detection method based on local feature analysis and a method to reconstruct the global background. Using the reconstructed background to replace the initial frame in ViBe algorithm can effectively eliminate the ghost phenomenon.

In the current situation where most moving target shadow detection algorithms are based on multiple frames, the main problem solved in this paper is how to detect moving target shadows based on single-frame SAR imagery, which is lack of information and previous studies.

Still, our algorithm has something to improve, like how to set the local background window automatically to contains more local background and less interference; how to set local SCR thresholds appropriately to get the least false alarm and how to detect moving targets with large differences in size and shape at one time.

As the core of the algorithm, we also tested many local features as the basis for the judgement, such as the proportion of the resolution cells with high RCS in the local background window. We even try to build a mixed Gaussian model for the RCS of all the resolution cells in the local background window to check how well they match. But the results show that the complex local features can eliminate the false alarm to a certain extent, but it will increase the computational complexity and reduce the robustness of the algorithm. Nevertheless, we still believe that there are local features to make the algorithms more efficient and accurate, and we are working on it.

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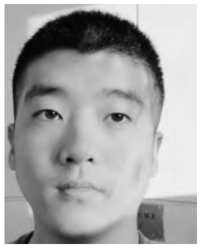

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