ISSN 2616-5775 Vol. 5, Issue 11: 73-78, DOI: 10.25236/AJCIS.2022.051111

Research on moving object shadow removal algorithm based on video surveillance

Wang Wenzhi*,Wang Zhibo

Guizhou Police College, Guiyang, China
Email: 913847985@qq.com
**Corresponding author*

Abstract: *In order to solve the problem of accurate shadow location for moving objects, a shadow removal algorithm based on cross correlation and local maximum information entropy is proposed. Firstly, the background is established by using the mixed Gaussian model to obtain the moving object; Then, the dark part of the moving object is detected by cross correlation; Finally, the local maximum information entropy is used to analyze the texture characteristics of the dark part, and then realization the shadow remove of the moving object. The experimental results show that the algorithm is robust to some extent.*

Keywords: *Moving object detection, Cross correlation, Maximum information entropy, Shadow Removal, Textural features*

1. Introduction

In recent years, moving object detection under video surveillance has become a hot research topic for many scholars in the field of computer vision. The shadow of moving object is an important factor that affects the accuracy of object detection. Therefore, shadow detection and removal is a very important work before moving object extraction.

There are two methods for shadow detection and removal: shadow model based method and shadow attribute based method. The method based on shadow model is usually used to detect special scenes, which has great limitations; the attribute based method uses the brightness and texture characteristics of the shadow region to detect shadows. Qiu [1] proposed a method to detect moving shadows using illumination invariance and local texture features of regional color； Gao [2] realized shadow detection and removal of indoor scenes by using local ternary mode texture features and combining Markov random field; Yan [3] established the background based on the mixed Gaussian model, and introduced shadow features into the traditional mixed Gaussian model by using histogram statistics. On the basis of the model, he proposed a foreground shadow elimination algorithm, matching foreground pixels with the shadow model, to realize the determination and elimination of shadows; Lu [4] describes based on the features of gray image and global texture to detect and remove shadows; Liang [5] assumes that the shadow does not change the correlation of the image in the grayscale video sequence image, and uses the normalized cross-correlation to judge the shadow points.

Although these methods can detect better shadow areas, the computational complexity is large and requires large storage space, which is not conducive to the application of real-time monitoring systems. Therefore, this paper proposes a shadow remove algorithm based on the cross correlation and local maximum information entropy. firstly, the background is established by using the mixed Gaussian model to obtain the moving object; then, the dark part of the moving object is detected by cross correlation; finally, using the local maximum information entropy to analyze the texture characteristics of the darker part to remove the shadow outside the object, and then realization the shadow remove of the moving object.

2. Mixed Gaussian model

Background modeling using mixed Gaussian model, the mixed Gaussian model of pixel values at a point i in the image at time t is defined $I_{(i,t)}$ as follows:

ISSN 2616-5775 Vol. 5, Issue 11: 73-78, DOI: 10.25236/AJCIS.2022.051111

$$G(I_{(i,t)})=\sum_{k=1}^{K}\omega_{(i,t,k)}N_k(I_{(i,t)},u_{(i,t,k)},\delta_{(i,t,k)}) \tag{1}$$

In formula (1), $I_{(i,t)}$ is the pixel value at time t of point i; $\omega_{(i,t,k)}$ is the weight of the k-th Gaussian distribution at time t of position i, and has $\sum_{k=1}^{K}\omega_{(i,t,k)}=1$; $u_{(i,t,k)}$ is the mean of the k-th Gaussian distribution; $\delta_{(i,t,k)}$ is the variance of the k-th Gaussian distribution; The number of Gauss K is generally (3-5), In this paper K=4.

2.1. Background update

The first frame image is used as the background. Since the background point is represented by only one pixel value at this time, and each point in the image is described by k Gaussian functions, the pixel value of the i-th position in the image is used as the mean value of the first Gaussian function of the point, and the variance is assigned a larger value ($\delta^2=36$). The weight of the first Gaussian function $\omega_{(i,1,1)}=1$, the mean value, variance and weight of other $2\sim K$ Gaussian functions are assigned to 0, With the passage of time t, if the pixel at point i of the image at time t matches with the k-th Gaussian of the background point, Then formula (2) is satisfied:

$$|I_{(i,t)}-u_{(i,t-1,k)}|<2.5\delta_{(i,t-1,k)} \tag{2}$$

It is believed that the matching background parameters need to be updated in real time to obtain better background images because they match the background points. The other unmatched Gaussian functions do not need to update their parameters. The update methods are divided into three forms:

The first form: when k<K in the (2) formula, increase the Gaussian distribution, and assign the initial value to the k+1 Gaussian function, then assign the pixel value at the i-th position of the current image to the k+1 Gaussian as its mean value, and the variance is assigned a larger value ($\delta^2=36$), and assign an arbitrarily smaller value to the weight value, which is normalized by the weight value. The normalization formula is as follows:

$$\omega_{(i,t,k)}=\frac{\omega_{(i,t,k)}}{\sum_{k=1}^{K}\omega_{(i,t,k)}} \tag{3}$$

The second form: when the Gaussian distribution reaches K=4, when the pixel value of t at a certain time at i does not match the K Gauss, the Gaussian function with the lowest weight value should be updated, and the K Gaussian distributions should also be retained. The average value of the updated Gaussian function is the pixel value of the pixel i, the variance is 36, and its weight value is an arbitrary decimal. The updated formula is as follows:

$$\begin{cases} m_{(k1)}=\min(\frac{\omega_{(i,t,1)}}{\delta_{(i,t,1)}},\cdots,\frac{\omega_{(i,t,K)}}{\delta_{(i,t,K)}}),(1\le k1\le K) \\ u_{(i,t,k)=I_{(i,t)}},\delta_{(i,t,k)}=6,\omega_{(i,t,k)}=\varepsilon,(k=k1) \\ \omega_{(i,t,k)}=\frac{\omega_{(i,t,k)}}{\sum_{k=1}^{K}\omega_{(i,t,k)}},(1\le k\le K) \end{cases} \tag{4}$$

In formula (4), $m_{(k1)}$ is the Gaussian function with the minimum weight at point i,

ISSN 2616-5775 Vol. 5, Issue 11: 73-78, DOI: 10.25236/AJCIS.2022.051111

The third form: when the Gaussian distribution reaches K=4, when the pixel value of t at a certain time at i matched any one of the K Gaussian distribution, the parameters of the matched Gaussian distribution function are updated as follows:

$$\begin{cases} u_{(i,t,k)} = (1-\alpha)u_{(i,t-1,k)} + \alpha I_{(i,t)} \\ \delta_{(i,t,k)} = (1-\beta)\delta_{(i,t-1,k)} + \beta(I_{(i,t)} - u_{(i,t-1,k)})^2 \\ \beta = \dfrac{\alpha}{\omega_{(i,t-1,k)}}, \omega'_{(i,t,k)} = (1-r)\omega_{(i,t-1,k)} + \lambda r \\ \omega_{(i,t,k)} = \dfrac{\omega'_{(i,t,k)}}{\sum_{k=1}^{K}\omega'_{(i,t,k)}} \end{cases} \tag{5}$$

In formula (5), α, β, r, they are updated coefficients, the matched distribution function $\lambda=1$, and the unmatched distribution $\lambda=0$.

2.2. Background estimation

For the background image created by the mixed Gaussian model, the Gaussian distribution is sorted $\frac{\omega_{(i,t,k)}}{\delta_{(i,t,k)}}$ from large to small, and then the first B Gaussian component is selected as the background model. The selection formula of background model B is as follows:

$$B_{(i,t)} = \arg\min_{b}(\sum_{k=1}^{b}\omega_{(i,t,k)} > T) \tag{6}$$

In formula (6), $B_{(i,t)}$ is the number of background models at image point i, and the threshold T is the weight of the Gaussian function selected as the background. The threshold is determined according to the application scenario and experiments, generally (0.8-0.85) In this paper T=0.83.

3. Shadow detection and removal

3.1. Shadow detection

Using the background difference method to obtain the moving object may have the influence of shadow, which changes the shape of the object, and cannot get the real object. Therefore, the normalized cross correlation method mentioned in [5] is used for processing. A template with the size of [N * N] is used at object point i to calculate the correlation of its neighborhood with point i as the center. The formula is as follows:

$$NCC(i,t) = \frac{ER(i,t)}{E_B(i,t)E_I(i,t)} \tag{9}$$

In formula (9), $ER(i,t) = \sum_{n=-N}^{N} B(i+n,t)I(i+n,t)$, $E_B(i,t) = \sqrt{\sum_{n=-N}^{N} B(i+n,t)^2}$,

$E_I(i,t) = \sqrt{\sum_{n=-N}^{N} I(i+n,t)^2}$,if point i is a shadow point, the correlation of the point should be a relatively large value, and the energy $E_B(i,t)$ of the background image of the corresponding neighborhood of the point is greater than the energy $E_I(i,t)$ judged as the shadow point, that is, if the

ISSN 2616-5775 Vol. 5, Issue 11: 73-78, DOI: 10.25236/AJCIS.2022.051111

following formula is met, the point i is judged as the shadow point:

$$\begin{cases} NCC(i,t) \geq Lncc \\ E_I(i,t) \leq E_B(i,t) \end{cases} \tag{10}$$

In formula (10), $Lncc$ is a fixed threshold, which is an empirical value obtained through experiments. If the value is smaller, the real target point may be incorrectly classified as a shadow pixel. In addition, if the value is larger, the real shadow pixel point may not be detected, so this value must be set according to the scene.

3.2. Shadow removal

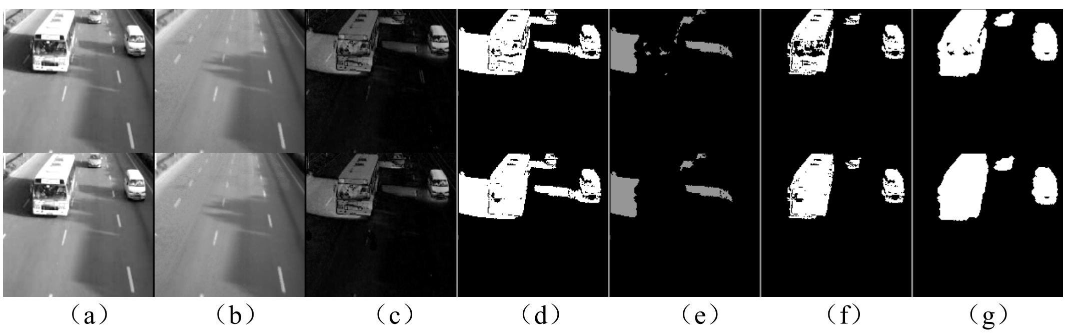
The formation of the object shadow is due to the fact that the object blocks the passage of the sun light. When the light source is taken as the starting point, the object is taken as the end point, and the shadow area is generated on the other side of the object. When we conduct experiments on the gray image, because the shadow points are relatively dark, the shadow points initially detected by correlation include the shadow points on the object, Even darker points on the target (such as the glass on the car) rather than real shadow points; If we only use the correlation of pixel points to segment shadows, the real object points will be used as shadows for segmentation, which is easy to change the shape and size of the object, and is not conducive to moving object tracking. Therefore, we further subdivide the shadows detected by correlation. Since the texture information characteristics of the background before and after shadow coverage remain unchanged, when the shadow is covered on the object, the texture information on the object is different from the texture information on the real background, and the maximum entropy pair, as an effective texture operator, has strong classification ability and high computing efficiency. Therefore, we apply the maximum information entropy to carve shadows in one step. In this paper, we detect the correlation detected shadow points, consider a correlation neighborhood, and take this point i as the center, and the local size is [M * M] rectangular area, Calculate the local texture features of the shadow candidate point and the corresponding background point. The local maximum entropy is expressed as follows:

$$W_{(i)} = -\sum_{g_1=1}^{M}\sum_{g_2=1}^{M} p(g_1, g_2)\log p(g_{1,}g_2) \tag{11}$$

In formula (11), $p(g_1, g_2)$ is the probability of its local neighborhood, $g_{1,}g_2$ is the local location. Due to the existence of noise, the object obtained after shadow removal often has many empty small regions and small gaps. Therefore, this paper uses morphological method to fill the small gaps in the image, so as to obtain a complete moving object.

4. Experimental results and analysis

In order to verify the effectiveness of the algorithm in this paper for shadow removal, the test experiment video used is three videos containing shadows. The platform used is: Intel (R) Core (TM) i7-3770 CPU @ 3.403.40, an ordinary PC with memory of 4, the operating system is Windiws7, and MATLAB 7.1 programming is used for experiments to detect and remove shadows from vehicle videos with shadows. The algorithm in the literature [2,3, 4] is selected to compare with the algorithm proposed in this paper, Some of the experimental results are as follows:

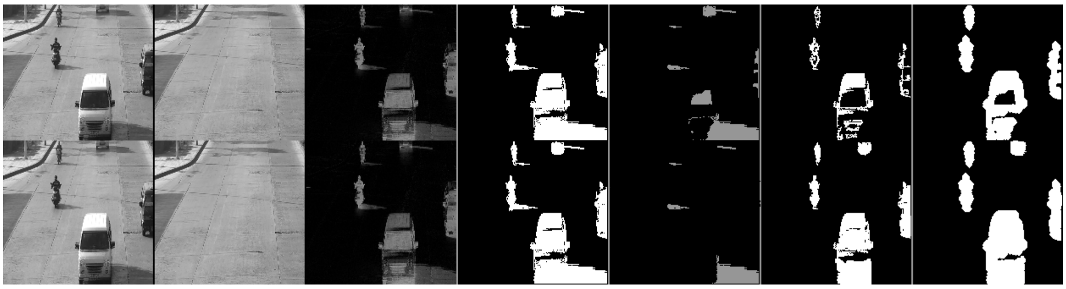


（a） （b） （c） （d） （e） （f） （g）

Figure 1 Shadow Removal Process of Moving Objects

ISSN 2616-5775 Vol. 5, Issue 11: 73-78, DOI: 10.25236/AJCIS.2022.051111

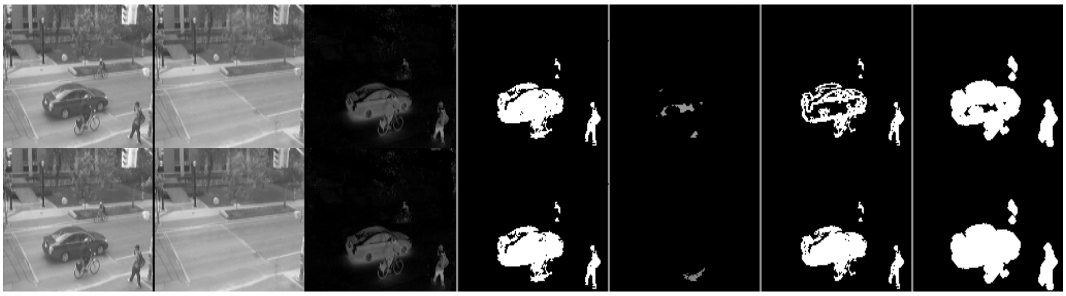
Figure 1. (a) List is the current frame image, (b) List is the background image, (c) List is background difference image, (d) List is the binary image, (e) List is the shadow detection image. In this list, the algorithm in literature [2] can not distinguish the detected self shadows, while the algorithm in this paper also distinguishes the texture of shadow areas, so as to better distinguish self shadows and non self shadows. It can be seen from list (f) that the two algorithms can separate multiple connected car. However, when the car shadow area is relatively large, the car own shadow is segmented in the literature [2] algorithm. Then the moving object image with shadow removed obtained in list (g) through morphological processing will, to some extent, appear hollow, while the algorithm in this paper can better handle the car shadow segmentation effect.



（a） （b） （c） （d） （e） （f） （g）

Figure 2 Shadow Removal Process of Moving Objects

Figure 2. (a) List is the current detection frame image of the two algorithms, (b) List is the background frame image, (c) List is the background difference image, (d) List is the binary image, (e) is only the shadow part image, (f) List is the moving target image with the shadow removed, and (g) is the image after morphological processing on the (f) list. From the shadow images in list (e), it is found that the algorithm in this paper can detect and remove shadows better. For example, most of the windows are black because they are pasted with a layer of black tape on the windows to prevent direct sunlight from entering the car. Therefore, the shadows collected in literature [3] include windows and other parts, which can change the shape of moving object invisibly. When the detected car window is large, it also causes cavities in the object.



（a） （b） （c） （d） （e） （f） （g）

Figure 3 Shadow Removal Process of Moving Objects

Figure 3, (a) List is the detection image frame, (b) List is the background frame, (c) List is the difference image, (d) List is the binary image, (e) List is the shadow part image, (f) is the moving object image, and (g) List is the image after morphological processing. Observing the video frame image, it can be found that the current detection frame image contains four moving objects. It is found from list (e) and list (f) that the algorithm in document [4] cannot detect and segment all the shadows formed by cycling, but also remove the glass and some parts of the car as shadows, resulting in the loss of important information such as the car detected in the first line of list (f). This algorithm can effectively improve this problem.

It can be seen from the experimental results that the algorithm proposed in this paper is effective, but in the experimental process, it will lead to the hollow phenomenon of the detected moving object, because the color of the object itself is equal to or similar to the background, so we should focus on solving this problem in the future.

5. Conclusions

In this paper, firstly, the background image is extracted by the mixed Gaussian model, and then the moving object is obtained by combining the background difference method; Using the local maximum information entropy to analyze the texture characteristics of the darker part, the shadow outside the object is removed, and then realization the shadow remove of the moving object. From the simulation results, we can know that this method can accurately detect the moving object, which lays a good foundation for the following research on object tracking.

Acknowledgements

The work was supported by Guizhou provincial Science and Technology Talent Development foundation (QJHKY [2022]336). We thank the anonymous reviewers for their detailed comments, which helped improve the presentation of the paper.

References

[1] Qiu,L.Y ., Chen,W.L., Li,F.M., [J].(2022) A fast moving target detection algorithm based on LBP texture features in complex background . Journal of Infrared and Millimeter Waves, 3,639-651.
[2] Gao, Fan, [D] (2021) Moving object detection based on texture feature and consistency analysis. Lanzhou University,
[3] Yang,Shuguo, He,W.J., Liu,Y.L., [J](2019) A hybrid moving object detection algorithm based on morphological Gaussian model and eight neighborhood frame difference method . Computer and Modernization, 7, 32-36.
[4] Lu, X. H., Liu, M.Y., Long, Q.J., [J]. (2019) Moving target feature detection algorithm based on gray histogram. Computer and Modernization, 6, 71-75.
[5] Liang, L., Liu, H., Liang, Q, J., (2019) [J]. Shadow removal algorithm combining cross-correlation and gradient features in gray-scale sequence images. Journal of Nanjing Normal University (Engineering Technology Edition), 2, 59-67.