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Object Detection and Shadow Detection Algorithm for Computer Vision

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Computer vision is an interdisciplinary research area, enabling computers to get advanced understanding from digital images or videos. From an engineering perspective, it tries to automatically replicate human vision tasks. Computer vision includes the understanding of acquisition, processing, and digital image analysis, as well as the extraction of high dimensional data from the real world, such as the form of decision making. Computer vision is an interdisciplinary field, which involves how to make computer acquire high-level knowledge from digital images or videos. From an engineering perspective, it aims to automate the tasks that the human vision system can do. In the field of intelligent video surveillance, the current foreground detection technology usually has one main drawback: Shadows are usually a part of the foreground. Therefore, how to get clear and accurate representations in the presence of shadows has become an important aspect of computer vision study. This paper includes an overview of shadow detection methods and explores the hybrid Gauss model based on foreground detection.

1. FOREWORD

1.1 Background and Significance

Motion analysis based on vision is a very active field of scientific research. In recent years, it has attracted the attention of many universities and research institutions. In the field of vision research, the main direction of scholars is to make machines more intelligent, so that computers can simulate the functions of human eyes and help human society. With the rapid development of computer vision technology, Internet technology, artificial intelligence and communication network, people pay more and more attention to their own security. Video surveillance has become more and more common in daily life. For example, the British government has installed more than 2 million 400 thousand surveillance cameras (14 cameras per person) [1]. With a large number of cameras, the huge monitoring network environment enables us to get a lot of monitoring data in an instant. Therefore, how to extract abundant and useful information from these massive data has become a core issue, and one of the problems that must be solved in intelligent video surveillance technology. The existence of intelligent video surveillance technology is to let the computer simulate the thinking of the human brain, by letting the camera imitate the eyes to observe the world, let the computer intelligently analyze the video sequence from the camera, and then monitor the content of the scene. This needs an understanding of the abnormal behavior through intelligent execution and automatic alarm [2]

Motion analysis based on vision includes target detection, object classification, object tracking and understanding of target behavior in video images, [3]. Human behavior recognition belongs to the advanced processing part of human gait and behavior recognition. It involves extracting unique visual features from video sequences and expressing them in concise computer understanding mode. Finally, we use some patterns to explain the information to achieve recognition. Understanding human behavior [4] through the study of human behavior and gait patterns will bring new interactive ways of characterizing people's lives, and it is also one of the hot issues in future scientific research.

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1.2 Foreign Research Status

Rita Cucchiara [5] proposed a moving object detection algorithm based on statistics and knowledge and implemented an intelligent video monitoring system called Sakbot. This video system can detect moving objects in image sequences. A variety of novel background modeling techniques can establish a background reference with high efficiency, and then obtain the prospects through background checking techniques, and classify the foreground to get MVO, MVOSH, GHOST, GSH, and use different background updates for different foreground area types. Strategies to efficiently detect targets [6], based on previous work, proposed the quantitative (detection rate and discrimination rate) and the qualitative (single-case and target independence) for the evaluation of existing motion shadow detection algorithms, and flexibility for shadow scenarios. In order to examine the differences between different detection algorithms, he organized the shadow detection algorithm into two layers.The first level of classification considers whether uncertainty is introduced and used in the decision-making process.The second level of classification is based on whether or not the model and parameters are selected.

1.3 State of the Art in Research in China

Xu Dong [7] proposed a novel motion projection shadow detection algorithm to solve the problem that some cast shadows are category errors in the core of the foreground. Since common projection shadow detection methods are mainly based on results of change detection, static edge detection, occlusion change, and penumbra detection, there are some problems in these methods that cannot be overcome. For example, some regions of a moving target, such as a face can be easily classified as shaded because these consistent colors have the same properties as shadows. He uses a series of techniques in the algorithm, such as initial change masking, canny edge detection, shadow area detection through mufti-frame integration, edge matching and conditional expansion, and post-processing operations to skillfully perform shadow detection tasks.Ruiqi Guo [8] proposed a novel algorithm for shadow detection and cancellation on still images. He used feature-based training classifiers such as color and texture chi-square distances, RGB average gray ratios, and chroma-calibrated normalized distances. The same and different illumination pairs in the same material region are used to classify these paired relationships. Shadows are detected by the plotting method. Combined with the illumination model (direct light and ambient light), the shading coefficients and k values are statistically calculated to obtain no shadows. Illustration.

1.4 Analysis of the Current Situation

Although the projected shadow detection technology has made great progress in the field of video surveillance and even computer vision, there are still many deficiencies in specific areas: (1) **Background modeling** in the field of computer vision, to detect our sense of interesting sports goals must be marked in the visual area of interest, that is, target detection. In the process of target detection, the background difference technique is often used, and the detection of moving targets in the case of complex scenes is employed, ie, cloudy days, leaf shaking, camera motion, light changes, background external movements of the interested targets, and other external conditions Next, how to quickly establish a stable and dynamic background still has certain difficulties. (2) **Foreground segmentation** The foreground target areas acquired by the background difference technique mostly contain motion shadows, because the shadows produced by these target motions share the same motion pattern as the foreground targets, and the difference technique cannot correctly classify the foreground and shadows. The wrong shadow classification will lead to errors in the subsequent target tracking, the estimation of the quantity, and the accuracy of the gesture-based behavior recognition. (3) **Robustness issues** In practical work scenarios, it is necessary to carry out a large amount of work to extend the theoretical research techniques obtained from laboratory research to complex practical applications. This requires a strong adaptability of the system. It usually requires the system to be able to work automatically and continuously. This demand for practical applications requires that the video surveillance system is insensitive to factors such as noise, changes in lighting, and weather conditions. The detection effect of the shadow area is easily affected by the illumination and the difference result, so these problems must be solved in practical applications. (4) **Feature Extraction** The feature commonly used in the shadow detection technology at the feature extraction stage includes the chromatic feature, physical feature, geometric feature, and brightness feature. However, due to the different environments applicable to each feature, the best one for the specific application must be found. Features still have great difficulty. (5) **Performance Evaluation** The robustness and accuracy of shadow detection are important indicators. Whether these systems can be robustly affected by noise, whether they have target independence, scene independence, and balanced computing load, can help detect indirect shadows and penumbra. These complicated and varied problems make the video monitoring technology more cumbersome and flexible, so the evaluation indicators for finding more effective shadow detections are constantly being determined

2. OVERVIEW OF SHADOW DETECTION METHODS

2.1 Definition of Shadow

Shadow is a common natural phenomenon in daily life. The existence of shadows in video images will be harmful to the problems of computer vision, such as object recognition, object tracking and behavior understanding. Therefore, the study of shadow detection and suppression in video images is widely studied. Shading in still images has always been a difficult problem. The goal of shadow removal is to restore

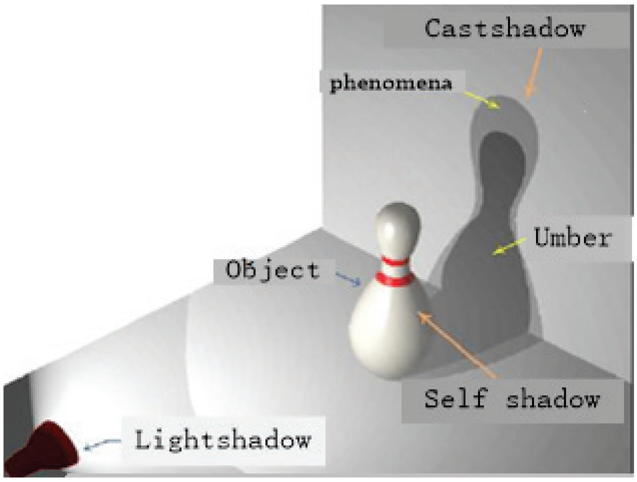

Figure 1 To cast shadows.

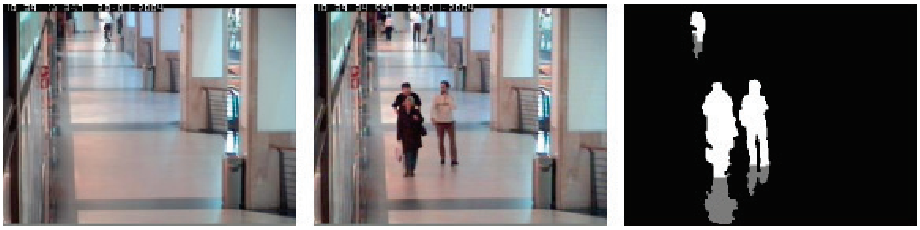

Figure 2 Static and Dynamic Shadows.

the brightness and color of the pixels of the shadow region in the pixel region to the same effect as the illumination of the non-shaded region, so as to provide visual consistency on the entire image. For shadow detection in surveillance applications, it is relatively simple to use some algorithm to detect cast shadows, then remove the shadowed parts and get more accurate motion targets. Based on the analysis of the causes of shadows, their chromatic features, geometric features, and texture features, this paper studies the detection of shadows produced by moving objects in video [9]. The background model is dynamically created using some frames of the video sequence. Then the background difference technique is used to obtain the binary image and obtain the foreground extraction, and then the shadow is rendered through a unique feature. The detection and determination then suppress the detected shadows and then one obtains a clean motion target.

2.2 Type of Shadow

Usually the researchers divide the shadows in the image into two main types: self-shadowing and cast shadows. Self-shadowing occurs on the surface of the part that is not directly illuminated by direct light. Cast shadows are natural phenomena that are caused by objects blocking the light source. Cast shadows can further subdivided into the umbra and penumbra. The phenomenon formed by the area where the direct light is completely blocked is called the umbra, and the partially blocked area is called the penumbra. These definitions can be seen in Figure 1.

Shadows in video images can usually be divided into two types: static shadows and dynamic shadows. The formation of static shadows is usually due to the creation of stationary objects, such as buildings in a video image, pillars, parked vehicles, and the like. The moving object detection algorithm does not crash due to static shadows because the static shadows are modeled as part of the background model during the background modeling phase. On the contrary, the dynamic shadow, which is the problem that this paper tries to solve, will affect the accuracy of the moving target detection algorithm. The cast shadow may be directly connected to the moving object, namely MVO shadow in the shadow detection algorithm proposed by Rita Cucchiara [10], or is not connected, ie "ghost". In Figure 2, the static shadow formed by the pillars in the first image is the result of the background subtraction. That is, the third image is not shown, and the shadow cast by the human body in motion is performed after the detection algorithm is executed. The sports body is then detected together. From the experimental results, it can be seen that the presence of the cast shadow causes the changed shape of the target to occur, which can negatively affect the subsequent target tracking and target classification. Therefore we want to eliminate these cast shadows by some kind of shadow suppression algorithm.

2.3 Shadow Detection Method

The shadow area and the foreground area have different visual perception characteristics in the video frame image. The target of interest extracted by the traditional target detection algorithm often contains shadows generated by the target. The basic approach of common shadow detection is to model the background of the video frame sequence and use the detected binary mask image. Using information corresponding to the foreground region and the background reference corresponding to the binary mask, feature extraction

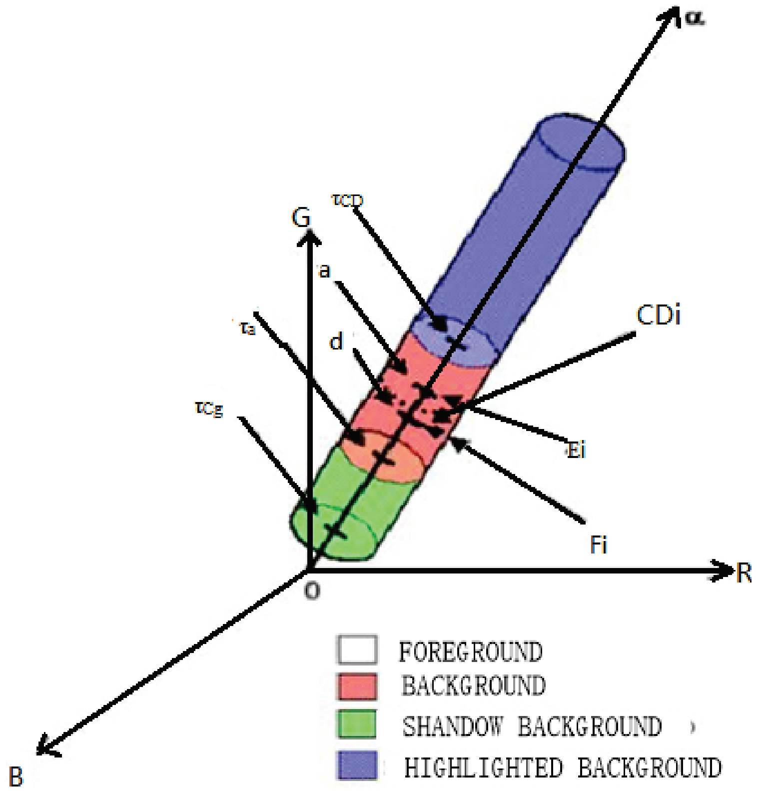

Figure 3 Color Model in RGB Color Space.

is performed to determine the shadow. The existence of the shadow region has the following properties:

(1) Since the direction of the light source is blocked, the brightness of the area covered by the shadow is lower than the brightness of the entire image, and the reduction of the brightness has a certain range due to the existence of ambient light. This can usually be used as the initial step to detect candidate shadow areas.

(2) Although the brightness of the shaded area decreases, the chromatic is a shade metric that is independent of the brightness and the area covered by the shaded area maintains the chromatic of the corresponding background.

(3) The area covered by the shadow maintains the texture characteristics of the original area. In addition, researchers also have a physics-based approach that considers two sources (white light and ambient light) to better predict changes in the shadow region. The core of this approach is a linear decay model that attempts to model or learn shadow pixels. The specific appearance method is often referred to as a physical method.

2.4 Shadow Detection Algorithm Based on Color Space Conversion

Porterhouse [11] is based on a novel computational color model for shadow detection. The algorithm is based on pixel modeling and background differentiation. The first N frames are used to calculate the mean and variance of each color channel for each pixel. Ei $= \mu_R$(i), μ_G(i)μ_B(i)) is the mean vector and the corresponding S_i is the variance vector. Next calculate the luminance-distorted dominance distortion of the difference between the expected color of one pixel and the value in the current image, and normalize the illuminance distortion a_i and dominance distortion CDi with respect to the ems value, and then perform the pixel classification. The classification: where $\tau_{CD,}\tau_{a1,}\tau_{a2}$ is a threshold used to determine the similarity between the luminance and dominanceof the background image and the current video frame, and they are obtained by the difference between the obtained luminance difference and the chromatic difference. The value is determined based on the defined detection rate r afterstatistics are made using the histogram. From the Figure 3 below, we can see the different regions corresponding to the different parameters of the above formula. The image shows that the region detected as the foreground in the RGB color space is white, the background is red, the shadow is green, and the highlight is blue.

2.5 Shadow Detection Algorithm Based on the Color Feature Invariant

The color feature invariant is a function that describes the color configuration information of each image point irrespective of the influence of occlusion, shadow, and strong light. These functions are shown to remain invariant with respect to changes in imaging conditions, such as: the direction of the viewing angle, the direction of the target surface, and lighting. We assume that F_L is the above-mentioned color feature invariant. F_S is the value under the light, but the shadow overwrites the value of this pixel:

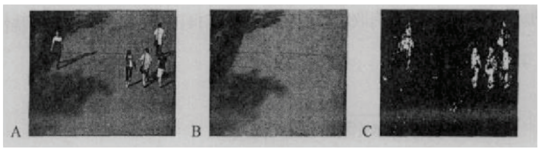

Figure 4 Color-dependent invariant c1c2c3 shadow suppression results.

$$F_L = F_S$$

Examples of color feature invariant are normalized rob, c1c2c3, and $l_1l_2l_3$. Elena Salvador [12][38] uses c1c2c3 for shadow removal. The c1c2c3 color feature invariant is defined as follows:

$$c1(x, y) = \arctan \frac{R(x, y)}{\max(G(x, y), B(x, y))}$$
$$c2(x, y) = \arctan \frac{G(x, y)}{\max(R(x, y), B(x, y))}$$
$$c3(x, y) = \arctan \frac{B(x, y)}{\max(R(x, y), G(x, y))}$$

Where R, G, B represent the red, green and blue color components of a pixel in the image. The normalized rgb color space defined by formula (2.6) is a kind of color feature invariant, and the literature [40] defines another color feature invariant $l_1l_2l_3$:

$$l_1 = \frac{|R-G|}{|R-G|+|R-B|+|G-B|}$$
$$l_2 = \frac{|R-B|}{|R-G|+|R-B|+|G-B|}$$
$$l_3 = \frac{|G-B|}{|R-G|+|R-B|+|G-B|}$$

We can use spectral and geometric properties to automatically identify shadows in video sequences. During the operation of the algorithm, a low-to-high three-level analysis mechanism is used. The hierarchical control structure uses a hypothesis and testing approach for shadow detection. The existence of a shadow is assumed according to some initial features. Then one uses additional theory to verify the presence or absence of the shaded region. Finally one uses the information integration phase to determine or reject the initial hypothesis. We can use the target detection algorithm to detect the foreground region and establish a reference background image, which can be an image in a video sequence frame or an image that is reconstructed by a certain background modeling algorithm. The analysis is only performed by the motion detector. The areas of change are identified in the image, and the determined areas correspond to the moving objects and their shadows. A pixel value of a pixel in the current video image corresponds to a pixel value in the RGB color space. A triplet represents the pixel value of the corresponding pixel in the corresponding background image obtained by a certain method, if the following three are satisfied for the formula, the point is initially considered as a candidate shadow point.

$$R(x_b, y_b) > R(x, y)$$
$$G(x_b, y_b) > G(x, y)$$
$$B(x_b, y_b) > B(x, y)$$

In Figure 4, The first panel is the original video, which is a pedestrian video under strong sunlight, the second is the reference background extracted by the background modeling method, and the third panel is the unfiltered wave after the shadow suppression with color feature variants. As a result, from the following three figures, we can see that when strong shadow removal is performed using color feature variants, the moving objects are partially removed while eliminating strong motion shadows.

2.6 Summary

This section mainly reviews the current shadow detection methods and the feature extraction methods used. It first introduces the types of shadows in video images. Depending on whether the shadow is moving, it is divided into moving shadows and still shadows [16]. Shadows are classified as ghosts and moving targets based on whether or not the cast shadow is connected to the target. It mainly describes the features used in shadow detection. These features have chromatic features, texture features, geometric features. Shadow detection methods based on geometric features have strict assumptions and cannot be generalized to a variety of environments but can be used when the interested target is easy to model and the shadows have different directions Very straightforward choice. Chroma-based methods can be quickly implemented and run, but they are susceptible to noise and are less than ideal in low-saturation scenarios. Although the texture-based shadow detection method has very unique properties, the process of requiring texture association is particularly resource-consuming. Finally, the classification of shadow detection methods under different standards is given, and the commonly used evaluation criteria and reference video sequences of shadow detection algorithms are given.

3. MOTION TARGET DETECTION ALGORITHM

Rial Amato [12] summarized the existing classical moving object detection methods, which can be divided into three types: optical flow method, inter-frame difference method, and background subtraction method. Although many algorithms for moving target detection have been proposed in the literature, the problem of determining moving targets in complex environments is far from being solved by scholars.

3.1 Optical Flow Method

Figure 5 gives a brief description of the basic principles of the optical flow method. The graph shows the optical flow vector

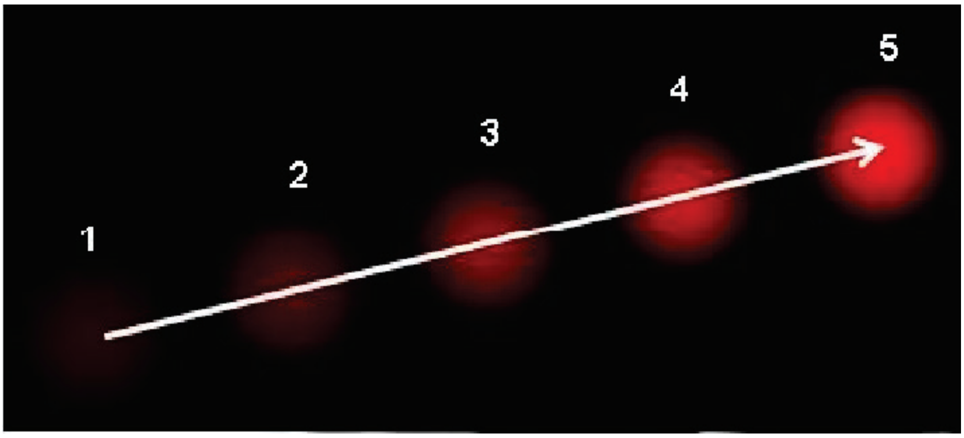

Figure 5 Briefly illustrates the basic principle.

of the moving object in video sequence. The bubbles represent the number of frames in the video, the arrow indicates the target vector. The syntax error of Microsoft must be changed to optical flow vector image. That is to say, optical flow is the relative motion of image pixels or regions from one frame to the next. This is a typical "constant luminance" hypothesis. The basic computation of optical flow can help us detect and track our targets.

3.2 Inter-frame Difference Method

A frame difference method is used to determine the existence of moving objects by calculating the difference between two adjacent images. Time difference technology usually uses pixel by pixel difference between two adjacent frames in video images to extract moving objects. The calculation is simple and easy to be realized. This method has strong adaptability to dynamic scene change. However, when the moving target stops in the viewing area, the difference between adjacent frames cannot detect the changed area, resulting in the loss of the target. Inter frame difference method also has its own shortcomings, especially if the object of interest has a unified texture or slow motion, this method does not always complete the motion target extraction of the related pixels and usually there is an empty phenomenon [15]. Therefore, the frame difference method needs special processing, when the mobile object stops in a certain part of the viewing area.

Target detection can usually be accomplished by creating the representation of scenes, called the background reference model, and obtaining the difference between each current frame and the model. Any significant change of the background model represents the existence of the mobile target, and marks the pixels that constitute the changing area for further processing. The connection area analysis (CCA) method is usually used to mark pixel regions corresponding to moving objects. This process is called the background subtraction algorithm.

Evaluation of Differences: The advantage of optical flow method is to support camera motion, rich information collection, large computation of defects and sensitivity to noise. The advantage of the frame difference method is that the algorithm is simple and easy to understand, and the computation is small. It is not affected by the environmental changes. The drawback is that the accuracy is low and the camera motion is not supported. The advantage of background subtraction is that it has a small amount of computation. It can accurately detect the shortcomings of the moving target. It is insensitive to the change of light and does not support camera motion.

3.3 Mixed Gaussian Model

The hybrid Gauss model is a classical background modeling algorithm for moving target detection under relatively stable background conditions. It is developed from the single Gauss model, which is robust to multi-modal backgrounds, such as leaf jitters, water ripple and so on. Before introducing the mixture of Gauss models, we first introduce a Gauss model.

3.3.1 Single Gauss Model

The color value of each pixel in the image is considered as a random process, and the probability of the occurrence of the pixel value of the point follows the Gauss distribution. The basic principle of the algorithm is to establish the Gauss model of each pixel location, and the model preserves the mean and variance of pixels. For example, the variance is the average of the standard deviation. The parameters of the model parameters can be expressed as functions of three variables, because the input of the video sequence and the parameters of the model are changed at different times. The basic process of motion detection based on single Gauss model includes two steps: initialization model, update parameter and detection. (1) Model initialization

The initialization of the model is to initialize the corresponding Gauss model parameters at each pixel location. Initialization is done using the following formula:

$$\begin{cases} u(x, y, 0) = I(x, y, 0) \\ \sigma^2(x, y, 0) = std\_init^2 \\ \sigma(x, y, 0) = std\_init \end{cases} \tag{1}$$

The first pixel value of the video image sequence in this location is set to itself if you can set it. (2) Update parameters and detect

Every time you read new pictures, determine whether the corresponding pixels in the new picture are in the range described by the Gauss model. If so, the point will be identified as the background, otherwise the point will be identified as the foreground. Assuming that the foreground detection result has the location representation of the whichever pixel value, the formula is as follows:

$$output(x,y,t)=\begin{cases}0, & |I(x,y,t)-u(x,y,t-1)| \\ & <\lambda\times\sigma(x,y,t-1) \\ 1, & otherwise\end{cases} \tag{2}$$

Among them, λ is a constant that you set yourself, if you can$\lambda = 2.5$. The meaning of the above formula is: If the pixel value of the corresponding position in the new image is less than the standard deviation of the pixel value in the corresponding model λ Times, this point is the background, otherwise it is the foreground.

The model is updated using the following formula:

$$\begin{cases}u(x,y,t)=(1-\alpha)\times u(x,y,t-1)+\alpha\times u(x,y,t) \\ \sigma^2(x,y,t)=(1-\alpha)\times\sigma^2(x,y,t-1)+\alpha \\ \qquad\qquad\times \mathrm{I}(x,y,t)-u(x,y,t)^2 \\ \sigma(x,y,t)=\sqrt{\sigma^2(x,y,t)}\end{cases} \tag{3}$$

Where parameters α which expresses the update rate is also a constant set by oneself. The existence of this constant can make the model have certain robustness when the background is slowly changing, such as the slow and brightening or darkening of the light.

3.4 Gaussian Mixture Model

The Gaussian Mixture model is a generalization of the single Gauss model. The single Gauss model can only describe the single mode of the background. When the background appears to be a multi-modal form, such as leaf jitters, it is easy to detect errors. The basic idea of Gaussian mixture model is to use multiple Gauss models as a pixel location model, making the model strong in multi-modal background. Taking a leaf background as an example, when leaves leave a certain location, the location of pixel information is represented by Gauss model. When the leaves swing to this position, another Gauss model is used to represent the pixel information at that location. In this way, no matter what the Gauss model is, the pixels in the new image will be regarded as the background. Further the leaf is also considered as a mobile target, which increases the robustness of the model.

The basic steps of the Gaussian Mixture model algorithm are as follows:

(1) Definition of Pixel Model

Each pixel is described by several single models.: $P(p) = \{w_i(x,y,t), u_i(x,y,t), \sigma_i(x,y,t)^2\}$, $i = 1,2,\ldots\ldots,K$. The value of K is generally between 3 and 5, indicating the number of single models included in the Gaussian mixture model.$w_i(x,y,t)$ Represents the weight of each model and satisfies:

$$\sum_{i=1}^{K} w_i(x,y,t)=1 \tag{4}$$

Three parameters (weight, mean, variance) determine a single model.

(2) Update parameters and perform foreground detection

Step 1:

If the picture in the newly read video image sequence is (x,y) The pixel value at$i = 1,2,\ldots\ldots,K$ Satisfy $|I(x,y,t)-u_i(x,y,t)| \leqslant \lambda\cdot\sigma_i(x,y,t)$

Then, the new pixel matches the single model [13]. If there is a single model that matches the new pixel, the point is determined as the background and Step 2 is entered; there is no model that matches the new pixel, the point is judged to be the foreground, and Step 3 is entered.

Step 2:

Fixed the weight of a single model that matches the new Pixel. Weight gain is $dw = \alpha\cdot(1-w_i(x,y,t-1))$ The new weights are expressed as follows:

$$\begin{aligned}w_i(x,y,t)&=w_i(x,y,t-1)+dw \\ &=w_i(x,y,t-1)+\alpha\cdot(1-w_i(x,y,t-1))\end{aligned} \tag{5}$$

Fixed the average and variance of a single model that matches the new Pixel. See equation (3) for the same Gaussian model.

Complete Step2 and go directly to Step4.

Step 3:

If the new pixel does not match any single model, then:

(If the number of current single models has reached the maximum number allowed, remove the least important single model in the current multi-purpose set. For the calculation of importance, see step 3).

(Add a new single model. The weight of the new model is a small value [14] (0.001 in the experiment). The mean value is the new pixel value and the variance is the given larger value (20 in the experiment).

Step 4:

Weight normalization

$$w_i(x,y,t)=\frac{w_i(x,y,t)}{\sum_{j=1}^{K} w_i(x,y,t)}, (i=1,2,\ldots,K) \tag{6}$$

(4) Sorting and Deletion of Multiple Single Gaussian Models

The model of each pixel in theGaussian Mixture background model is composed of several single Gaussian models. In order to improve the efficiency of the algorithm, we must sort the single Gaussian models according to their importance and delete the non-background models in time.

We assume that the background model has the following characteristics: (The weight is significant: the frequency of occurrence of the background is high; (small variance: the pixel value does not change much. According to this, we have

$$sort\_key=\frac{w_i(x,y,t)}{\sigma_i(x,y,t)} \tag{7}$$

which is the basis for the importance of ranking

The sorting and deleting processes are as follows:

(1) Calculating the importance of each model.

(2) A single model is ranked according to the importance of the importance of the first row. If the weights of the first N single models are satisfied $\sum_{i=1}^{N} w_i(x, y, t) > T$ Only use these N single models as the background model, delete other models, generally $T = 0.7$.

Although the Gaussian mixture model has good results, it also has the disadvantages of large computational complexity and consistent update rate α. The establishment of the Gaussian Mixture model cannot eliminate the shadow and other defects caused by the moving target, and the emphasis can be placed on these later.

4. CONCLUSIONS

Because of the complexity of video scenes and the diversification of intelligent surveillance tasks, shadow detection has become a challenging research topic. A motion shadow detection algorithm is proposed, but moving shadows are detected in complex video environments. This problem solution is not comprehensive enough. The application of motion shadow detection in intelligent video surveillance and the lack of shadow detection methods are studied in the future. (1) the current shadow detection algorithm is based on chromatic features, texture features, geometric features and physical features but they are limited. The performance of shadow detection is determined by whether we can make full use of the characteristic attributes of the shadow. In order to find more unique shadow features, it will become the future direction. (2) because of the complexity of video scenes and the diversity of monitoring tasks, the use of single type features has not played a good role. How can we combine multiple features to adapt to the complex changes of video scenes? Therefore, mufti feature fusion is still a key problem in shadow detection algorithms. (3) in supervised learning algorithm,a small number of training samples can be used to get better detection results. However, off-line detection algorithms are still not well adapted to scene change and complex task needs. In future shadow detection algorithm, in the absence of training samples, how can one learn the characteristics of the shadow and this makes effective classification still an important scientific problem. (4) in most of the existing shadow detection algorithms, most of the parameters depend on parameter selection and artificial experience, but this will surely bring problems. How to identify the adaptive threshold has become a trend in future research.

REFERENCES

1. Khare M, Srivastava R K, Khare A. Moving shadow detection and removal – a wavelet transform based approach[J]. Computer Vision Iet, 2014, 8(6):701–717.
2. Gao J, Dai J, Zhang P. Region-Based Moving Shadow Detection Using Watershed Algorithm[C]// International Symposium on Computer, Consumer and Control. IEEE, 2016:846–849.
3. T. Jose J, K. Govindan V. Efficient Algorithm for Varying Area based Shadow Detection in Video Sequences[J]. International Journal of Computer Applications, 2014, 72(16):20–26.
4. Shi W, Li J. Shadow detection in color aerial images based on HSI space and color attenuation relationship[J]. Eurasip Journal on Advances in Signal Processing, 2012, 2012(1):141.
5. Li Q, Bernal E A, Shreve M, et al. Scene-independent feature- and classifier-based vehicle headlight and shadow removal in video sequences[C]// IEEE Winter Applications of Computer Vision Workshops. IEEE, 2016:1–8.
6. Amato A, Huerta I, Mozerov M G, et al. Moving Cast Shadows Detection Methods for Video Surveillance Applications[M]// Wide Area Surveillance. Springer Berlin Heidelberg, 2014:23–47.
7. Qi P, Zhong S D, Tu L F. Cast shadow detection for moving objects based on binocular stereo vision[J]. Journal of Central South University, 2014, 21(2):651–658.
8. Wang B, Zhu W, Zhao Y, et al. Moving Cast Shadow Detection Using Joint Color and Texture Features with Neighboring Information[M]// Image and Video Technology – PSIVT 2015 Workshops. Springer International Publishing, 2015:15–25.
9. Xu H, Yang Z, Tian M, et al. An Extended Moving Target Detection Approach for High-Resolution Multichannel SAR-GMTI Systems Based on Enhanced Shadow-Aided Decision[J]. IEEE Transactions on Geoscience & Remote Sensing, 2018, (99):1–15.
10. Tang F, Zhang J X, Cai T, et al. A Calculating Method for Adaptive Human Shadows Moving Target Detection Algorithm[J]. Applied Mechanics & Materials, 2014, 667:255–259.
11. Álvarez S, Llorca D F, Sotelo M A, et al. Monocular target detection on transport infrastructures with dynamic and variable environments[C]// International IEEE Conference on Intelligent Transportation Systems. IEEE, 2012:61–66.