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A Robust Algorithm for Shadow Removal of Foreground Detection In Video Surveillance

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Abstract—We proposed an accurate algorithm to prevent moving shadows from being misclassified as part of moving objects in video target segmentation in this paper. Firstly, moving objects were achieved through background subtraction using adaptive Gaussian mixture models. Then, moving shadows were eliminated by a shadow detection algorithm. Finally, we performed a morphological reconstruction algorithm to recover the foreground distorted after shadow removal process. The experimental results proved its validity and accuracy in various fixed outdoor video scenes.

Keywords-Gaussian mixture models; shadow removal; HSV color space; morphological reconstruction; video segmentation

I. INTRODUCTION

Detecting moving objects in video sequences is very important in visual surveillance. When the video images are captured with a fixed camera, background subtraction is a commonly used technique to segment moving objects. The foreground objects are identified if they differ significantly from the background [1]. However, the detecting results of moving objects are usually under the influence of cast-shadows. The existence of cast-shadows would change the shape and size of the moving objects. Because the shadows usually move along the moving objects so that they may cause false classification, which can cause various unwanted behavior such as object shape distortion and object merging. For these reasons, it is critical to detect and segment cast-shadows in order to describe moving object correctly in visual surveillance and monitoring systems.

Shadows can be divided into self-shadows and cast-shadows[2], and we only concern moving cast-shadows. According to recent literatures introduced, moving shadow detection can be categorized into two methods based on models and properties respectively. The model method supposes that the shapes of the objects and the property of the light are known first, so it is unpractical to compute the shadows' shape and location [3,4]. The method based on properties uses some representative characters to identify shadows such as color, texture and gradient. According to the color property, Elgamma distinguishes the background and foreground in RGB color space [5,6]. In [7,8], Salvador supposed that the color was invariable. All of these methods are based on this hypothesis that: the cast-shadow cannot change the color information on the covered background. According to the texture property, Chien supposed that the shadow gradient changed slowly, and they could be removed by gradient filter. However, this method only suits to simple background [9]. In [10], Javad extracted some deep color background as candidate shadows, but if the self-shadows are too large, they would be removed with the results misidentified.

In this paper, we proposed a shadow removal method based on color and gradient information, aiming to solve the problem that the moving objects detection are usually under the influence of cast-shadows. Additionally, in order to get an integral foreground segmentation image, a morphology reconstruction algorithm is employed to recover the foreground distorted by shadow removal.

II. GMM EXTRACTING THE FOREGROUND

In visual surveillance systems, moving objects extraction is the first step in video processing. We present a robust and automatic segmentation approach based on the background subtraction. Time-adaptive mixtures of Gaussians background models (GMM) can solve the problems caused by complex background such as listed as follows:

- The gradual changing background: like the gradual illumination;
- The non-static background: like the swing leaves in wind and the changing television displays;
- The sudden change of the background: such as the objects are added or removed from the scene suddenly.

Consequently, GMM has been a popular choice for modeling complex and time varying background recently.

A. Background Modeling

In [11,12], each pixel is modeled as a pixel process; each process consists of a mixture of K adaptive Gaussian distributions. The probability that a pixel of a particular distribution will occur at time t is determined by:

$$p(x_t) = \sum_{i=1}^{K} \omega_{i,t} \eta_i (I_t, \mu_{i,t}, \sigma_{i,t}) \qquad (1)$$

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Where K is the number of Gaussian distributions, $\omega_{i,t}$ is the weight estimate of the ith Gaussian in the mixture at time, $\mu_{i,t}$ and $\sigma_{i,t}$ are the mean value and covariance matrix of the ith Gaussian at time t, and η_i is the Gaussian probability density function. The distributions are ordered based on least variance and maximum weight.

B. Background Model Matching and Updating

Every new pixel X_t is checked with each of K current Gaussian distributions. A fast match is found if the pixel grey value is within 2.5 times standard deviation of a distribution. Then, the parameters $\mu_{j,t}$ and $\sigma^2_{j,t}$ for the matching distribution are updated as:

$$\begin{cases} \mu_{j,t} = (1-\alpha)\cdot\mu_{j,t-1} + \alpha\cdot I_t \\ \sigma^2_{j,t} = (1-\alpha)\cdot\sigma^2_{j,t-1} + \alpha\cdot(\mu_{j,t} - I_t)^2 \end{cases} \qquad (2)$$

Where α is the Gaussian adaptation learning rate. If the current pixel value matches none of the distributions, the least probable distribution is updated with the current pixel values, a high variance and low prior weight. The prior weights of the K distributions are updated at time t according to:

$$\omega_{n,t} = (1-\alpha)\cdot\omega_{n,t-1} + \alpha\cdot M_{n,t} \qquad n\in[1,K] \qquad (3)$$

Where α is the learning rate and $M_{n,t}$ is 1 for the model which matched the pixel and 0 for the remaining models.

The Gaussians are ordered based on the descending ratio of ω/σ. This increases as the Gaussian's weight increases and its variance decreases. The first B distributions accounting for a proportion T of the observed data are defined as background. We set $T = 0.8$ here as in:

$$B = \arg\min\left(\sum_{k=1}^{b}\omega_k > T\right) \qquad (4)$$

For the non-background pixel, we calculate the difference between this pixel in current image and in background model. Only the pixel with the difference over the threshold 10 is labeled as foreground pixel.

III. Shadow Detection

When the foreground objects are extracted by GMM algorithm above, they usually include moving objects, cast-shadows and speckle noises. So the shadow removal method should be employed. Due to the reason that the shadow removal method based on model is only applied to some special scenes with large and complex computations, we chose the shadow removal method base on properties of color information and gradient information.

A. Shadow Detection in HSV space

In [13,14], HSV color space matches people's visual feeling better than RGB color space and other color spaces, additionally the luminance and chrominance variety can be detected more effectively in HSV color space, especially in the outdoor scenes. For these reasons, HSV color space is chosen to distinguish luminance (V) from chrominance (H and S). It is based on the simple idea that, shadows change the brightness of the background, but do not really affect the chrominance and saturation in HSV color space. The pixels are confirmed as shadows when the result of both the two conditions corroborates. A given pixel can be removed as shadow according to:

$$SP_m(x,y) = \begin{cases} 1, \quad if \quad T_{V1} < \dfrac{I_m^V(x,y)}{B_m^V(x,y)} < T_{V2} \quad and \\ \qquad \left|I_m^h(x,y) - B_m^h(x,y)\right| < T_h \quad and \\ \qquad \left|I_m^V(x,y) - B_m^V(x,y)\right| < T_S \\ 0, \quad else \end{cases} \qquad (5)$$

Where I_m and B_m are the current and background images respectively. T_{V1}, T_{V2}, T_h and T_S are all parameters to be chosen according to experiments and experience. T_h and T_S are the differences between cast-shadow and background on chrominance and saturation respectively. T_{V1} and T_{V2} are parameters about the threshold of luminance. T_{V2} can prevent some background speckle noises from misclassifying as shadows, and T_{V1} includes some practical shadow characters such as the intensity of the sunlight. The more intensive the sunlight is, the small value T_{V1} is. Generally, T_{V1} and T_{V2} are met : $0 < T_{V1} < T_{V2} < 1$.

B. Shadow Detection in Gradient

The moving object could be removed as shadows if we only use the property based on color, if the gradient can be accepted, the foreground can be detected more effectively. In a video surveillance system, vehicles and people always have abundant texture information. Similar to the color-based shadow removal method, a texture distortion measure can detect possible foreground shadow pixels.

The gradient of pixel S is a two-dimensional vector, and can be expressed as: $V_t(s) = (V_x, V_y)$, where its first partial derivatives are defined as： $V_x = \nabla_x I(s,t)$ and

$V_y = \nabla_y I(s,t)$, in which V_x and V_y can be got by Sober operators as (6)and (7):

$$V_x = \nabla_x I(s,t) = I(i+1, j+1) + 2 * I(i, j+1) + I(i-1, j+1) - I(i+1, j-1) - 2 * I(i, j-1) - I(i-1, j-1) \quad (6)$$

$$V_y = \nabla_y I(s,t) = I(i+1, j+1) + 2 * I(i, j+1) + I(i-1, j+1) - I(i+1, j-1) - 2 * I(i, j-1) - I(i-1, j-1) \quad (7)$$

The position meaning of each gradient operator is shown as table1.

TABLE I. THE NINE POSITION OF ABOVE OPERATOR

(i-1,j-1)	(i-1,j)	(i-1,j+1)
(i,j-1)	(i,j)	(i,j+1)
(i+1,j-1)	(i+1,j)	(i+1,j+1)

The above operators consider the horizontal and vertical edge, which is simple but can well present gradient feature. Our approach is to get the gradient image of moving foreground and the relevant background. Gradient information of moving foreground includes gradient of moving objects and moving shadows, while Gradient information of relevant background includes gradient of background only. According to the above analysis, the difference of the two gradient images will reserve more gradient information at the moving vehicles areas and remove most of the shadow gradient at shadow region.

IV. FOREGROUND RECONSTRUCTION

A. *Result of Color and Gradient Shadow Removal*

According to the above algorithms, shadow removal process is a significant step for the foreground segmentation. The pixels are classified as shadows only if they satisfied with both the color information and the gradient information. The two algorithms are in a relation of intersection.

However, the cast-shadow removal is a destructive process. The pixels will be wrongly identified if the foreground objects having similar colors to the shadowed background regions. Similarly, the foreground regions having similar textures to the corresponding background may also be misclassified. Due to these reasons, original object shapes are likely distorted. Morphological theory can be employed to reconstruct the foreground distorted after color and gradient shadow removal.

B. *Foreground Reconstruction*

Mathematical morphology reconstruction uses the "marker" image to rebuild the foreground in a "mask" image.

In Fig.1,Fig.2and Fig.3, The "marker" images (c1,c2,c3) are binary images where a pixel is set at "1" when it corresponds to a foreground, not cast shadow pixel. On the other hand, the "mask" images (b1,b2,b3) are also binary images where a "1" pixel can correspond to a foreground pixel, or cast shadow pixel, or speckle noise.

It is highly desirable that the "marker" image $\tilde{M}$, contains only real foreground object pixels, not any shadow pixels, because those regions cannot be reconstructed. Therefore, the use of very appropriate thresholds is necessary in the foregoing color-based removal process to assure that all the shadow pixels are removed. As a result, only the regions not affected by noise which are clearly free of shadows are subject to the shape reconstruction process shown in (8)：

$$R = M_s \cap (\tilde{M} \oplus SE) \qquad (8)$$

Where M_s is the mask image, $\tilde{M}$ is the marker image and SE is the structuring element whose size usually depends on the size of the objects of interest, although a 3×3 square element proved to work well in all our tests.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Several outdoor scenarios have been tested using the proposed method. The video was sampled at a resolution of 320×240 and a rate of 25 frames per second. The experiment results are shown below, Figure1 shows the results of Frame 350th and 820th in scene1, and Figure2 shows the results of Frame 275th and 375th in scene2. Figure3 shows the results of Frame 550th and 1850th in scene3.

In Fig.1,Fig.2 and Fig.3, images (a1,a2,a3) are the original images; Images (b1,b2,b3) are the "mask" images from foreground detection after using GMM; and it is obvious that the foreground inludes the moving object, cast shadow and speckle noise; Images (c1,c2,c3) are the "masker" images after shadows removal based on color and gradient information; and we can see clearly that some foreground pixels are regarded as shadows and removed, consequently. The shapes of moving objects here have been distorted. Images (d1,d2,d3) are the final reconstructed objects shapes. It is clearly that the shape between the foreground and the original objects are similar after morphology reconstruction.

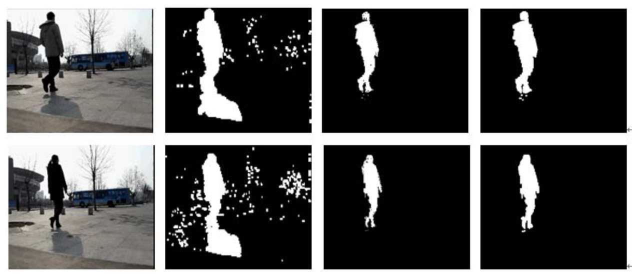

Figure 1. Experimental results in scene1. (a1) the original images; (b1) the "mask" image of foreground segmented by GMM; (c1) the "masker" image after shadow removingl based on color and gradient information; and (d1) the final reconstructed foreground.

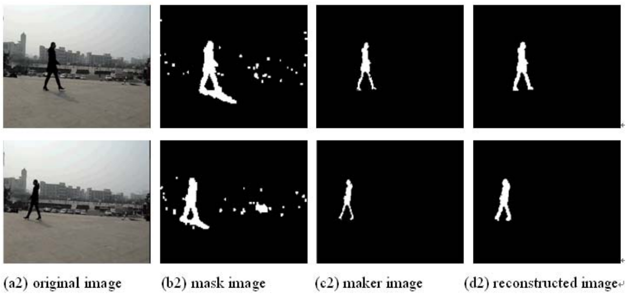

Figure 2. Experimental results in scene2. (a2) the original images; (b2) the "mask" images after GMM; (c2) the "masker" images after shadow removal; and (d2) the final reconstructed foreground.

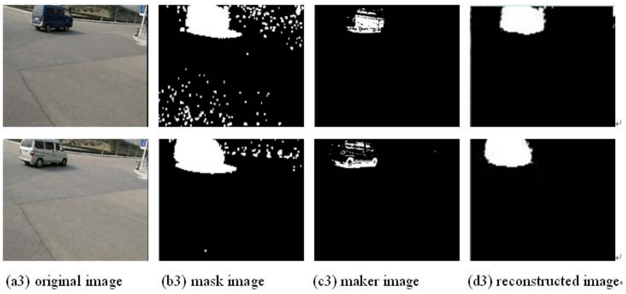

Figure 3. Experimental results in scene3. (a3) the original images; (b3) the "mask" images after GMM; (c3) the "masker" images after shadow removal; and (d3) the final reconstructed foreground.

Obviously, the luminance of light and shadow in scene1 is more intensive than that in scene2, and the algorithm we proposed above can remove shadows efficiently, no matter in strong light or weak light. Meanwhile, the shape of moving objects and shadows in scenc2 are much smaller than that in scene1, the algorithm can also extract the moving objects exactly. In scene3, we can see that the first vehicle's color has much difference with the shadow's color, so most part of the vehicle are reserved after shadow removal , while the second vehicle's color is similar to the shadow's, so most part of the vehicle is eliminated after shadow removal. But after morphology reconstruction, both of the two vehicles can be reconstructed integrated. Consequently, the experiments prove that our algorithm is simple and robust to fixed outdoor scenes.

VI. CONCLUDES

In this paper, we have proposed an accurate algorithm, which can get integral foreground results in many outdoor scenes. The experiments prove that our method is simple and effective. We needn't to care about the orientation of the sunlight, or modeling the objects either. Our method is robust to the gradual variation of the sunlight. However, there are still some disadvantages, and it can not resolve the problem well such as the sudden change of the illumination, and the more complex background. So how to improve the method of shadow elimination is an interesting future direction that we will try to research. Moreover, our future work will also focus on the subject about tracking and behavior identification of the moving objects.

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REFERENCES

[1] Lvanov, A. Bobick, J, Liu. "Fast Lighting Independent Background Subtraction". Int. J. Comp. Vis., 37(2), pp.199-207, June 2000.

[2] Mohamed Dahmane,Jean Meunier. Real-time moving object detection and shadow removing in video surveillance[J]. 3rd International Conference: IEEE of Sciences of Electronic, Technologies of Information and Telecommunications March 27-31,2005.

[3] Thirion J B. Realistic 3D Simulation of Shapes and Shadows for Image Processing[J]. Graphical Models and Image Processing, 1992 , 54(1) : 82.

[4] Koller D, Danilidis K, Nagel H. Model-based Object Tracking In Monocular Image Sequences of Road Traffic Scenes[J], Computer Vision, 1993, 10(3):257-281.

[5] Stauder J, Mech R, Ostermann. Detection of moving cast shadows for object segmentation [J]. IEEE Transactions on Multimedia, 1999,1(1):65-76.

[6] Wang Y, Loe K F, Wu J K. A dynamic conditional random field model for foreground and shadow segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence,2007,28(2): 279-289

[7] Mikic I, Cosman P C, Kogut G T, Trivedi M,M. Moving shadow and object detection in traffic scenes//proceedings of the IEEE International Conference on Pattern Recognition. Los Alanitos, California,2000:321-324.

[8] Cucchiara R, Grana C, Piccardi M. Detecting moving objects, ghosts and shadow in video streams. IEEE Transaction on Pattern Analysis and Machine Intelligence,2003,25(10):1337-1342.

[9] Stauffer, C., Grimson, W.: Adaptive Background Mixture Models for Real-Time Tracking. Proc. IEEE Conf. on Computer Vision and Pattern Recognition, (1999) 246-252.

[10] Javed O, Shah M1 Tracking and object classification for automated surveillance[C] //Proceedings of the 7th European Conference on Computer Vision , Copenhagen , 2002 : 28-31

[11] Huang Mao chi, Yen Shwuhuey. A Real-time and color-based computer vision for traffic monitoring system [J] . IEEE International Conference on Multimedia and ICME, 2004,(3) : 2119-2122.

[12] Zhu Minghan, Luo Da-yong. Moving objects detection algorithm based on two consecutive frames subtraction and background subtraction [J]. Computer Measurement & Control, 2005,13（3）:215-217.

[13] R.Cucchiara, C. Grana, M. Piccardi, A. Prati, and S.Sirotti, "Improving shadow suppression in moving object detection weth HSV color information," in Proceedings of IEEE Int'l Conference on Intelligent Transportation Systems, Aug. 2001,pp.334-339.

[14] Liu Hong, Jintao Li, Qian Yueliang, et al1 Motion and gray based automatic road segment method MGARS in urban traffic surveillance[M] //Lecture Notes in Computer Science1 Heidel2 berg: Springer-Verlag, 2006 , 4153 : 85-94.