Shadow Suppression Based on Adaptive Gaussian Mixture Model

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***Abstract*—According to the HSV color space characteristics , changes the modeling space in the process of Gaussian mixture model, based on the setting of each component, deals with shadow casted by using the Gaussian mixture model algorithm detecting the moving objects. Morphological operators are used to compensate edge detail information and to remove the noise. Finally, using the similarity of gray density, texture value and the gradient value, a good result can be obtained. The experimental result showed that this method can effectively solve the shadow and have good real-time performance and robustness.**

Keywords-HSV color space; Gaussian mixture model; morphological; shadow; image gradient

I. INTRODUCTION

Moving object detection is an important research direction of computer vision, but also is the prerequisite for behavior identifying and analysis. [1][2]Nowadays, there are mainly three ways of moving object detection: optical flow, temporal differencing and background subtraction.

In the case of camera movement, you can use the optical flow method and the adjacent frame difference method. These two methods of dynamic scenes have strong adaptability. [3]Optical flow method is based on the displacement vector of optical flow field, is widely used for target detection in the camera movement, but the calculation is complex, anti-noise performance, rarely used in the monitoring system in real-time and accuracy requirements. Adjacent frame difference method is the threshold, according to the difference of two adjacent pixels in a continuous image sequence to extract moving target in the image. Smaller adjacent frame difference of light, strong ability to adapt, but cannot extract the characteristics of the moving target pixels within the moving target is prone to producing cavities, the test results prone to ghosting.

Background subtraction method is used in the camera stationary and able to extract more completely target prospects. Background subtraction method can do differential treatment with the current image and background image, set the threshold to the difference image and binaryzation to extract moving target. The background image will change as the illumination variation and slowly changes of scene, so the key to the use of background subtraction is to establish the background model and update background in real time to adapt to changes in the background. [4] While in natural scenes, background modeling of dynamic change would result in challenging difficulties. The choice of adaptive Gaussian mixture background modeling, has the analytical form and higher operational efficiency, and is able to describe the cyclical movement in the scene, the background modeling method is superior to other forms of the most successful background modeling one of the methods.[5] But in the actual detection process, the shadow is often detected as moving objects by mistake, so that follow-up experiment is not accurate enough. So this algorithm is improved to inhibit the shadow generated.

This paper is supported by the National Natural Science Foundation (No. 61040047 & No.60903064), Natural Science Foundation of Shandong Province (ZR2011FQ003) and the Open Foundation of the State Key Laboratory of Virtual Reality Technology and Systems (BUAA-VR-11KF).

II. SYSTEM FRAMEWORK

In this paper, the adaptive Gaussian mixture model shadow suppression algorithm flowchart is shown in Fig. 1. The first video image is converted from the RGB color space to the HSV color space , then remove the shadow by the characteristics of the shadow in the HSV color space and extract foreground image by the Gaussian mixture model. At last, the morphological method is used to remove the noises in the foreground image.

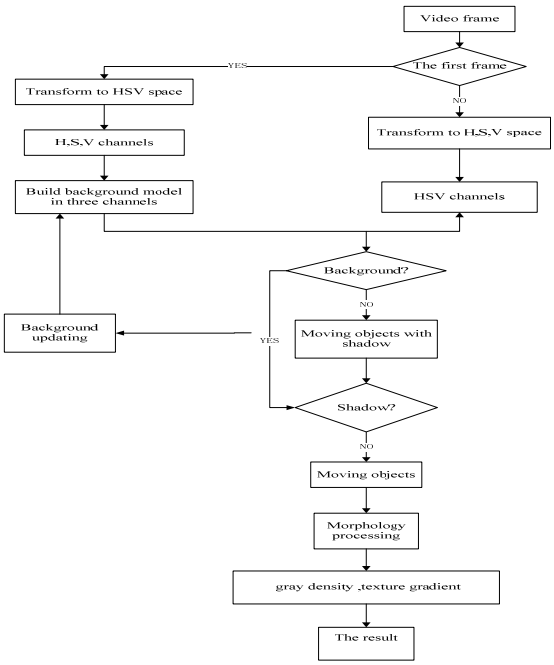

Figure1. Algorithm flow chart

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III. ALGORITHM ANALYSIS AND IMPROVEMENT

A. *Adaptive Gaussian mixture model*

Stauffer proposed adaptive Gaussian mixture model for each pixel defined K (the general values of 3 to 5) states that each state with a Gaussian function and said that the sum of the weight of each Gaussian model is one. [6]The model in which greater weight and smaller variance of all models is classified as background model. Generally, we assumed that each pixel of R, G, B 3 color channels is mutually independent, that is, one-dimensional Gaussian mixture model is established for each color channel. First, each pixel is given the initial parameters ω_0、μ_0、σ_0 to initialize each Gaussian distribution and the three parameters are denoted respectively, the Gaussian distribution of initial weight, the mean and variance; As the scene changes, each pixel of the Gaussian mixture model needs to be real-timely learning and updated. First of all first, K Gaussian mixture models are arrayed in descending order in accordance with $\omega^i_{i,t}/\sigma^i_{i,t}$ and satisfies if

$$|I_t - \mu_{i,t-1}| \le D\sigma_{i,t-1} \tag{1}$$

Where $\mu_{i,t-1}$ is the mean value, D is the defined parameters, the general value of about 2.5, $\sigma_{i,t-1}$ for the standard deviation. And we can show that I_t can match the Gaussian function, then the parameters of the distribution are updated by the following formula:

$$\omega_{i,t} = (1-\alpha)\cdot\omega_{i,t\text{-}1} + \alpha \tag{2}$$

$$\mu_t = (1-\rho)\cdot\mu_{i,t\text{-}1} + \rho\cdot I_t \tag{3}$$

$$\sigma^2_{i,t} = (1-\rho)\cdot\sigma^2_{i,t\text{-}1} + \rho\cdot(\mu_{i,t} - I_t)^2 \tag{4}$$

Where α is the learning rate, and 0 ≤ α ≤ 1, ρ is the parameter of learning rate, and generally take $\rho = \alpha / \omega_{i,t\text{-}1}$

If there is no any Gaussian distribution can match I_t, weights of the smallest Gaussian distribution in the models will be updated by the new Gaussian distribution, new distribution of the mean is I_t and initialize a bigger standard deviation σ_0 and a smaller weights ω_0. The rest of the Gaussian distribution is to maintain the same mean and variance, but their right to the value of attenuation, such as:

$$\omega_{i,t} = (1-\alpha)\cdot\omega_{i,t\text{-}1} \tag{5}$$

After the update is completed, the weight of each Gaussian component is normalized. And each Gaussian distribution is arranged in descending order according to $\omega^i_{i,t}/\sigma^i_{i,t}$. The number states of Gaussian mixture of K, if the previous M of Gaussian distributions meet that $\sum_{k=1}^{M}\omega_{k,t} \ge \pi$, the M distributions will be considered to be the background distribution. According to the formula (1), if the absolute value of the difference in I_t and each background distribution of the mean are D times than the distribution criteria of the difference, I_t is judged to be moving foreground, otherwise background.

B. *Shadow suppression*

In the image, the shadow is created by the light that blocking objects. These shadows will impact on the analysis of the moving object. In this paper, the video images are converted into HSV space and processed. HSV color space is a more intuitive model. A three-dimensional representation of the model shown in Fig. 2 is evolved from the RGB cube, corresponding to the conical subset of the cylindrical coordinate system.

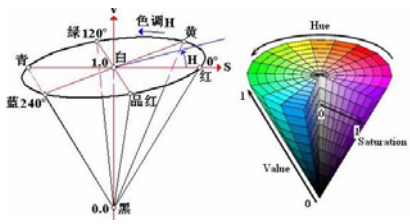


Figure2. HSV color space

HSV color space is very sensitive to the brightness levels of the image, and it well describes the feature information of the shadow. [7]The effect of shadow detection is better than in the RGB color space based on this, but usually the images are in RGB color space. Therefore we make the video images convert into the HSV color space, the algorithm is as follows:

$$H_1 = ar\cos\left\{\frac{[(R-G)+(R-B)]/2}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\right\}$$

$$H = H_1 \quad if \quad B > G$$

$$H = 360^\circ - H_1 \quad if \quad B > G$$

$$S = \frac{Max(R,G,B) - Min(R,G,B)}{Max(R,G,B)}$$

$$V = \frac{Max(R,G,B)}{255} \tag{6}$$

Shadow detection method currently used is based on the HSV color space. [8] These methods are more accurately than in the RGB color space. According to the following judgment formula to determine whether the pixel value may be shadows:

$$sp(x,y)=\begin{cases}1, a_s \le \dfrac{I_v(x,y)}{B_v(x,y)} \le \beta_s \\ \Lambda(I_s(x,y)-B_s(x,y)) \le \tau_s \\ \Lambda\left|I_H(x,y)-B_H(x,y)\right| \le \tau_R \\ 0, else\end{cases} \tag{7}$$

Where I (x, y) represents the current image, B (x, y) represents the current background image, τ S, τ R respectively are the threshold value of the color and the chrome. Because the shadow points of V (brightness) value is usually less than the corresponding points in the V value of the non-shaded, so the value of β_s is less than 1。 Considering of the current intensity of light, usually the stronger the light is, the higher height of the sun is (such as noon), the value of a_s is made smaller. Shadow usually has a relatively low value for S, and the difference of the shadow with the background model is negative for S; H is considered simply to get a better treatment effect. The selection of S can be determined by experiment.

The video image obtained will create Gaussian mixture models for each pixel point in H, S, and V channel. Then those models are matched and updated. The moving objects detected will be out of shadow.

C. Morphological optimization

Foreground mentioned at this time, include noise point. Point for moving target internal noise, the noise is removed by the morphology of the first closed open computing. Fill a moving target point within the fragmentation region, such operations to remove the internal isolated noise point, smoothing the boundary of the target. During the processing of removing shadow, the threshold chosen results in inconsistent image and cavities, as shown in Fig .3. So it's necessary to process further.

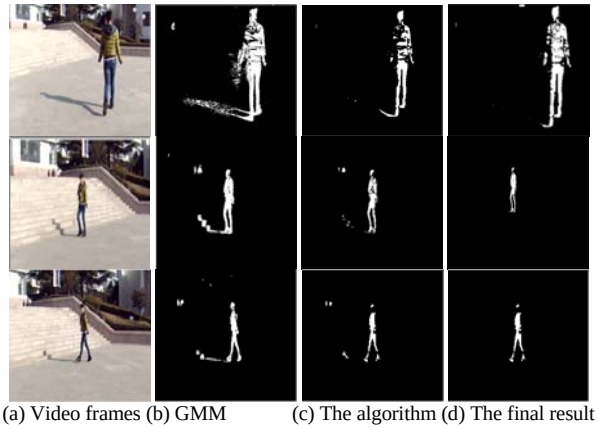
Figure3.The result after morphology

By using the properties of shadows, the texture of shadows is sparser. [9] So we can expand the image based on gray-value and gradient. First, we scan every point in the foreground obtained .If the differences of gray scale, texture and gradient in the adjacent two points are all below the corresponding threshold values, this point will belong to the foreground image. Then we can make this point be in the foreground image. Through this method, we can expand the image and obtain the objects without shadow, as shown in Fig 4.

Figure4 Object without shadow

IV. EXPERIMENT RESULTS AND ANALYSES

In this paper, the traffic surveillance science's moving object segmentation is as an experiment example, in the experiment, DahengVT142 video capture card is used for video image capture, and captured video image's pixel size is 240*320, then use the Visual Studio 2008 and opencv2.1 in the Intel(R) Pentium(R) D 2.83GHz CPU and 3.5G memory on EVOC IPC to program and experiment, the relevant results are as follows in Fig 5.



(a) Video frames (b) GMM (c) The algorithm (d) The final result

Figure5.The result of the comparison

Fig 5 shows that the proposed algorithm compared with tradition GMM algorithm. The leftmost column is the original image of real-time video frames. The second column shows the result processed by the GMM algorithm. The rightmost column shows the final result using the method of this paper.

According to the above results, it comes to a conclusion that the new algorithm is very effective. Compared with the traditional algorithm, the algorithm that this paper puts forward can accurately and robustly segment the video object and is better to remove the object shadow. Through the subsequent processing of the morphology we can avoid producing the blocks of noise and cavities.

V. CONCLUDES

This paper proposes shadow suppression based on adaptive Gaussian mixture model. The algorithm is adaptive to scene changing, illumination variation and so on in real time. The experimental result indicates that the algorithm of removing shadow is fast and exact, improves the accuracy of the moving object detection. And the algorithm can segment the

foreground objects under complex environment correctly and efficiently. Make preparation for the subsequent projects.

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