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Adaptive Gaussian MixtureBackground and Shadow Model

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Abstract—Inmany video surveillance systems, we usuallycreatethe background imagesand compare the input images with the background images, then capture the foreground objects. The main considerable topic for this study is a dynamic environment.The environment with the same location may show the different luminance and different background for the color display, however, the light towards environment will also change over time.To buildthe background of a dynamic scene,weemploy Adaptive Gaussian Mixture to achieve the requirements of robustness and security.We usually adapts (Adaptive Gaussian Mixture Model), for multiple Gaussian functions to describe the various background values which occur repeatedly so that we can adapt to the changes of the light by the adjustment of function parameter values. However, the conventional background modelsdid not regard the shadow as a part of backgrounds, so that the shadow was often captured as a foreground object, which caused an error on applications. The main purpose of this study is to build an adaptablemodel which combines background with shadow. So in a dynamic environment, we can capture the images without shadows from the foreground objects by using this model. Finally, experimental results reveal the effectiveness of the proposed method.

Index Terms— dynamic environment; adaptable Gaussian Mixture Model; foreground detection; shadow detection.

1 Introduction

Video surveillance systems has two main drawbacks: firstly they are not adaptable to different operative scenarios (they only work for a well known structured model). Secondly they need a human assistance to identify and label a specific event [1] Mixture-of-Gaussians (MoG) background model is widely used in such application to segment moving foreground for its effectiveness in dealing with gradual lighting changes and repetitive motion of leaves[2].human lives, such as: the people in order to protect their own property, so that each building is almost installed anti-theft system; An usually applicable assumption is that the images of the scene without the intruding objects exhibit some regular behavior that can be well described by a statistical model [3].Modern automobilesand the increasing demand in the automotive at the same time, for a small area in china, the parking has become very important, so parking in the car park management gradually being taken seriously, so more and more research and development is considering parking control system to achieve management of parking spaces; still more in many of the counting system, but for the building within the statistical number of pedestrian counting system and to master the usage of road traffic counting system. Another similar work was done in [4].These systems mentioned above are making life more Convenient, more secure, and therefore enhance the effectiveness of the monitoring system is very important.Wherein the visual monitoring system, to achieve a more efficient and accurate monitoring purposes, we usually adapt a very important pre-processing step, that is, (foreground detection). In recent years, the establishment of the background model generally considered a dynamic environment and change of lighting conditions.Dynamic environment refer to the same location may be more different brightness and color to show the background, such as shaking the water, swaying leaves; light refers to a scene change, a change in light irradiation angle or shelter because of the strength of the resulting degree. The above two conditions may bring instability makes the prospect of background material constructed to detect the problem of inaccurate, and therefore must have background construct more adaptability and can tolerate a variety of background values. In this study, we consider two points: first, how to establish a suitable background model in a dynamic environment, this part contains adapt to changing light and create a dynamic background; second, according to the results of shadow detection in detection out of the shadow pixel shading added Gaussian distribution in the background model. Hope to establish the most suitable background model based on the prevailing circumstances, so that when we use the background subtraction when removing the prospect can take out no more shadows prospect.

The rest of this paper is organized as follows. Section 2 reviews the related works. Section 3 introduces the proposed method and flow chart in detail. Section 4

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presents the experimental results. Concluding remarks are given in Section 5.

2. Related Works

Adaptable shaded background modelsinclude two important tasks: first, the dynamic background model, second, shadow detection. The following two paragraphs of this work were done to explore the related work.

2.1Background Modeling

We can establish background model in many different ways, divided into four methods: average method (Selective update using temporal averaging) timeline, (statistical model), and the (edge model) and (block-based model) to the basis of the block. The method can be divided into a statistical model (parametric model) and non-parametric models.

Average method is to use a (long-term time average method); Dagless et al. [5]point by the use of each location over a period of time more and get the pixel values of the average background model. Statistical model method is the use of an image sequence frequency statistics of pixel values appear to establish a background model, according to describe the value of the function at different frequencies can be divided into parametric and non-parametric modelmethod. Parametric model method the image information will be collected from; in particular statistical model to approximate the position of each point appears color distribution. Such as: Wren et al [6]using a single Gaussian model to represent the intensity distribution of the pixels in the background image, and using the updated parameter value way for Gaussian model to adapt to changes in light. Gaussian mixture model (Gaussian Mixture Model) [7] proposed the use of a combination of multiple Gaussian background models to represent a dynamic environment, the establishment of such methods can be used to represent multiple Gaussian distribution Show a variety of backgrounds. Edge model is based on an edge feature of the image to create the background model, for example: Jabri et al [8] proposed to strengthen the stability of the plus edge information after the color of the background model build the background model. With block-based model is based on the block to represent a little more change in the background, for example: the whole slice of smooth white wall or a table in the background environment. Cuevas et al. [9, 10, and 11] use a nonparametric modeling and a particle filter tracking for moving object detection. Hsu et al. [12]proposed using a binary polynomial represented disadvantage block, this method is that, if the image processing is not a simple background, in a block of an image started is not very accurate, so this method can only be applied in the context of relatively monotonous environment, the background model cannot accurately model complex for outdoor scenes.

2.2 Shadow Detection

Shadow detection methods divided into property-based and model-based categories, property-based approach utilizing characteristic values, such as: geometry, (brightness) or color, as a judge of the shadow basis; Model-based methods require geometric properties of scenery, lighting and other foreground objects or prior knowledge, the use of model based solution on a priori knowledge of the brightness of the shadows, to determine the scope of the shadow. Property-based method most commonly used to reduce the brightness of the shadow projection surface, but maintains the same color nature; Salvador et al. [13].Cucchiara et al. [14]proposed to convert the color space to HSV color space to perform shadow detection.

3. Proposed Method

3.1 System process

Figure 1 shows a flow chart of the operation of the system, which consists of two main parts: the background and shadow training update and the prospect of capture (foreground extraction). First of all, the first of some images do general Gaussian background model and updated Gaussian mixture model for judgment belongs to the background of the Gaussian distribution, then the video input pixel judgment is in line with the background pixels or, according to the classification results can be taken prospect image. Remove the foreground image to be used to train the shadow of the Gaussian distribution, so the prospects for the implementation of the shadow detection removed the judgment of the shadow pixel point pixel values are used to add or update the shadow of a Gaussian distribution. After a period of training, you can get a more stable Gaussian mixture model combined with the background and shadow, then as long as the input image pixel values to determine whether the background or shadow of a Gaussian distribution, if they meet one of them, then regarded as the background. So you can directly remove shadow image prospects.

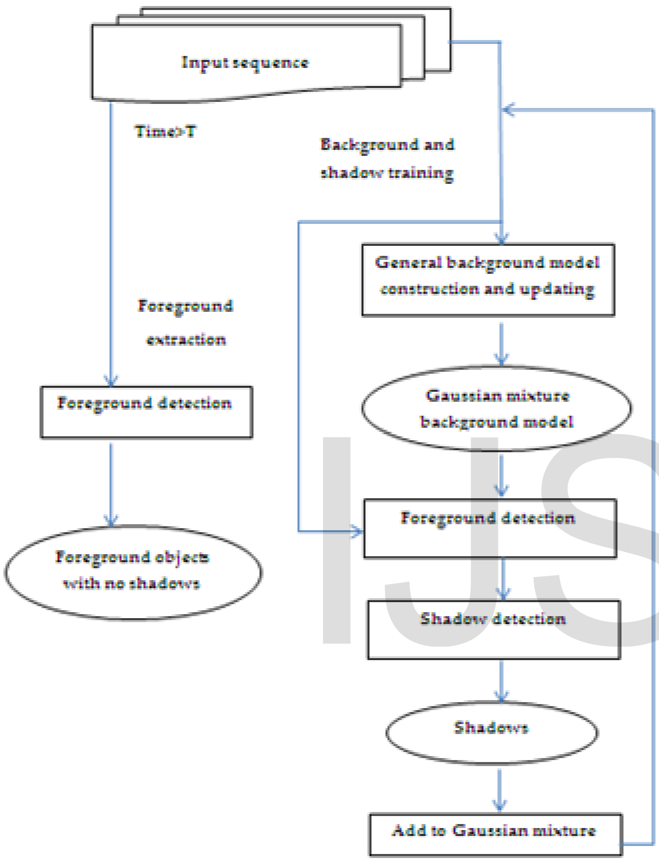

Fig 1 system flow

3.2 System operation

3.2.1 Training and updating background

Generally refers to a pixel value background image in the sequence more frequently appeared in a short time, the background pixel value because many different causes changes, in the results presented assuming a normal distribution, a Gaussian distribution can be used to describe the background pixel value color distribution. In time, because the relationship between the light brightness of the pixel value changes sharply, it can be used to adjust the Gaussian model parameter values, to adapt to the distribution of background values.However, in many cases, the color distribution of the points in the same location on the RGB space is no change in the same region close to, but a variety of backgrounds to show the value, so the use of a plurality of Gaussian distribution 2-3 describe the color distribution of the different regions. Background construction Gaussian mixture model is based on pixels individually, first enter a video, in pixels, individual training period at each pixel location will create individual Gaussian mixture model, and mixing each point model may be a single or a combination of a plurality of Gaussian distribution. Gaussian function expressed using three parameters, namely, represents the average (mean) the position of the Gaussian distribution, showing data distribution standard deviation (standard deviation) also indicate the importance of the right to a Gaussian distribution of the weight value (weight), for the three parameters, use the current input image pixel values to adjust the aim is to adjust the background pixels by budding model to approximate the real background distribution. Construct a background image shown in Figure 2-a. After a period of training, you can start at the same time continue to update the background model image capture prospects, but this time the prospects may have shadows, not the foreground image that we want, so the initial image detected by the prospect of continuing to do the shadows detection.

3.2.2 Training and update shadow

After the completion of the construction background, foreground image for preliminary detection do shadow detection, currently only considering projected shadow on the background, called cast shadow. First the difference between the shadow and the background, only based on the assumption that the difference in brightness projection, removing the foreground image pixel brightness values which are brighter than the background brightness of the pixels. Then determine the shadow pixels and background pixels R, G, B three channel recession rate, we really tested as sampling pixels relative to the background of the dark shadow of recession rate is not proportional decline. Because the shadow caused by the light source is obscured because the objects produced, less sun shaded area only

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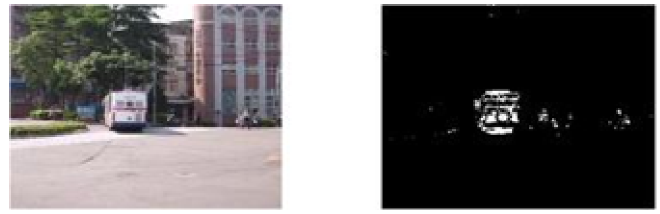
source of energy around the skylight give. The relationship between the daylight atmospheres due to reflected light, so that the sky looks blue, and the shadow on the R and G channel will drop more than B channel. After capturing the shadow may be based on the assumption that block, the shadow blocks may be obtained, in accordance with the reflectivity of the block is subdivided into sub-blocks of the same reflectivity, and finally, these cell blocks and database comparison, the shadow cell block left to get shadow pixels, the shadow detection image shown in Figure 2-a. Using this pixel information, add or update a Gaussian mixture model in the shadow of the Gaussian distribution.

(a) (b)

Fig2 (a) original image (b) background images

This study is considering to original images, capturing the unshaded prospects. After completing the shadow detection work, the information can be incorporated into the shadows Gaussian mixture model, so we build the background model contains a Gaussian distribution can describe the background and description of the shadow of a Gaussian distribution. Prospects within the subsequent detection, to determine whether the new pixels into the background or shadow falls on the Gaussian distribution, will fall within these two Gaussian distributions are considered to be background pixels, can be directly removed without foreground image of the shadow, the prospect capture images in Figure3Describing the capture prospects.



(a) (b)

Figure 3 (a) original image (b) prospects of detection

4. Establishment of adaptive Gaussian mixture model

Usually refers to the background image in the sequence appear more often, considering the same location point, it refers to the pixel values occur more frequently. In short, the background pixel values for various reasons (such as: air refraction), and a slight change in the results assuming normal distribution changes, we can use the Gaussian model to describe the background value. In time, because the relationship between the light (such as: position of the sun changes), the luminance pixel value changes sharply, it can be used to adjust the Gaussian model parameter values, to adapt to the distribution of background values. But in many cases, the same point where the distribution of color on the RGB color space is not near the same area change, but there is a variety of backgrounds to show the value (for example: Flashing lake, flickering computer screen, shaking the leaves, follow Figure4), a single Gaussian distribution cannot meet the above-described case, therefore, extending the single Gaussian probability density function, using a plurality of Gaussian distribution is necessary.

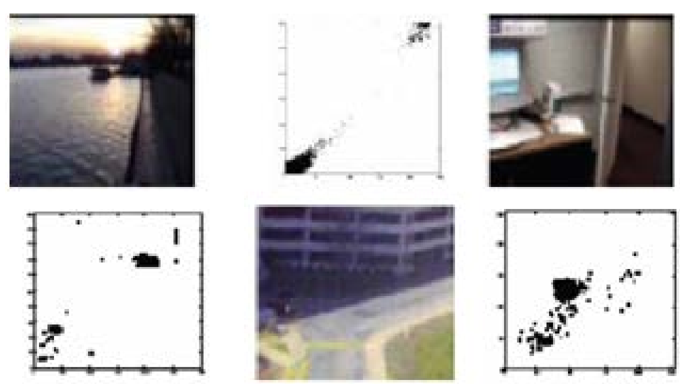


Figure 4 colors in the real environment R, G band profile from [4]

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Taking these two questions, the current research on the visual monitoring system, commonly used Gaussian mixture model (Gaussian Mixture Model, referred to as GMM) to create a model of the background image. Gaussian mixture model is the use of multiple Gaussian distribution, linear combination, as shown in Figure 5, 6 is formed by a combination of three Gaussian distribution. Assuming a position at time 1 ~ t observed pixel values $X = \{X_1, ..., X_t\}$, $P(X_t)$ represents the probability of X_t appears t, if the use of Gaussian mixture model to represent, then3-2

$$P(X_t) = \sum_{i=1}^{k} w_{i,t} * \eta(X_t, \mu_{i,t}, C_{i,t}) \qquad 3\text{–}1$$

Where K represents the number of Gaussian distribution, $\omega_{i,t}$Shows a Gaussian distribution at time t i the weight value,$\mu_{i,t}$,$C_{i,t}$ Respectively represent the i-th Gaussian at time t and the average covariance matrix, ηRepresents a Gaussian probability density function value, expressed as:

$$\eta(X_t, \mu_t, C_t) = \frac{1}{(2\pi)^{\frac{n}{2}} |C_t|^{\frac{1}{2}}} exp^{\frac{1}{2}(x_t-\mu_t)^T C_t^{-1}(x_t-\mu_t)} \qquad 3\text{-}2$$

Wherein, n is the dimension of the feature vector, here we consider the three dimensions of a pixel RGB values, i.e., $n = 3$. In order to reduce the computational complexity, assuming each dimension are statistically independent of each other, so C is a diagonal covariance matrix (diagonal covariance matrix), 3-3 formula:

$$C_{k,t} = \sigma^2_{k,t} I \qquad 3\text{-}3$$

As represented by Formula 3-1.

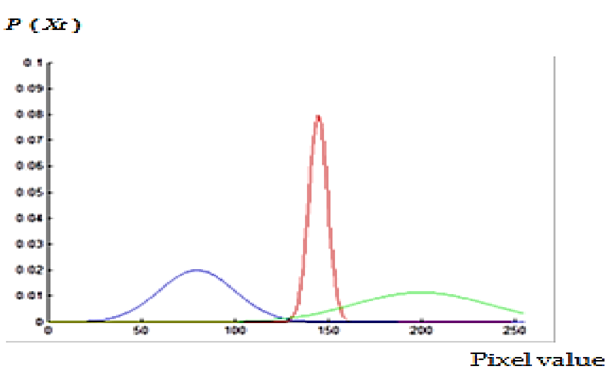

Figure 3-2 Gaussian distribution of a pixel established

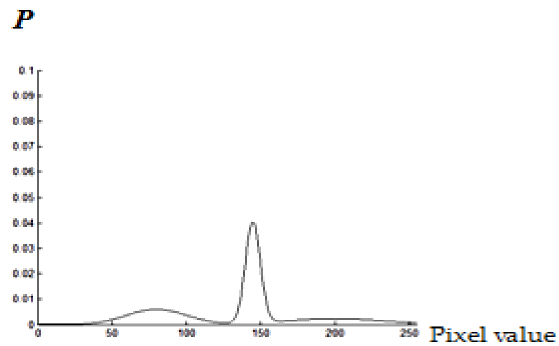

Figure 6 Gaussian mixture model probability distributions

5. Experimental Results

Development Platform for this project is opencv 3.2 C ++ , the operating system is Windows 7, the hardware test equipment system is Intel core i5 @ 3.20GHz, resolution of 320 × 240 images.

The results of the general intersection image, this scene contains shaking the leaves, the situation shown in red frame, in figure 7-8 there is shown in the shaded foreground objects. As can be seen from the results in the emergence of a variety of backgrounds to show when it is able to establish a stable background model; for shadow detection also has a good effect.

Figure 7-8 sunny shadow intersection of detection and capture prospects

Table -1Parameters for Gaussian mixture model established in the experiment is used as below:

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Parameters	Value	Parameters	Value
Standard deviation σ	50	*N*	2.5
Weight ω	0.001	α	0.05
Number of Gaussian K	5	ξ	0.00001
Number of Shadow Gaussian	1	*T*	0.78

6. Conclusionand Future Work

Background model developed in this study is to establish a method of providing good prospects for follow-up imaging application that allows applications to enhance the effect. In future work, there is hope for improvement three parts, the first to detect the shadow of some of the processing time is very long, about an image takes one minute, so I hope can improve the speed of detection of the shadows, second, because the shadows there are self-shadow and cast shadow, the shadow of the current detector detects only cast shadow, hope for the future can detect self-shadow, shadow joining classification, third, to increase the number of samples in the context of library materials, outdoor water can be increased , dirt, etc., indoor flooring material can be trained tiles, wood, etc., to improve the detection results.

References:

[1] Subra Mukherjee, Karen Das,"an adaptive gmm approach to background subtraction for application in real time surveillance", International Journal of Research in Engineering and Technology, Jan 2013.

[2] Hao Zhou Xuejie Zhang Yun Gao Pengfei Yu, "Video Background Subtraction Using Improved Adaptive-K Gaussian Mixture Model"- 2010 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE).

[3] Z. Zivkovic, "Improved adaptive Gaussian mixture model for background subtraction," International Conference on Pattern Recognition, vol. 2, pp. 28-31, 2004.

[4] E.L. Dagless,A.T. Ali, J.B. Cruz, "Visual road traffic monitoring and data collection ," Proc. IEEE Vehicle Navigation and Information Systems Conf.,pp. 146-149, 1993.

[5] C.R. Wren, A. Azarbayejani, T. Darrell and A.P. Pentland, "Pfinder: real-time tracking of the human body," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.19, pp. 780-785, 1997.

[6] Li Yao* and Miaogen Ling," An Improved Mixture-of-Gaussians Background Model with Frame Difference and Blob Tracking in Video Stream", ScientificWorldJournal. 2014.

[7] C. Stauffer, W. Grimson, "Adaptive background mixture models for real-timetracking," IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol.2, pp. 246-252, 1999.

[8] S. Jabri, Z. Duric, H. Wechsler and A. Rosenfeld, "Detection and location of people in video images using adaptive fusion of color and edge information," International Conference on Pattern Recognition, vol.4, pp. 627-630, 2000.

[9] Cuevas C, Mohedano R, Jaureguizar F, García N. High-quality real-time moving object detection by non-parametric segmentation. Electronics Letters. 2010; 46(13):910–911.

[10] Cuevas C, García N. Moving object detection for real-time high-quality lightweight applications on smart cameras. Proceedings of the IEEE International Conference on Consumer Electronics (ICCE '11); January 2011; pp. 479–480.

[11] Cuevas C, García N. Efficient moving object detection for lightweight applications on smart cameras.IEEE Transactions on Circuits and Systems for Video Technology. 2013; 23(1):1–14.

[12] Y. Hsu, H. H. Nagel and G. Rekers, "New likelihood test methods for change detection in image sequences," Computer Vision Image Process, vol.26, pp,73-106, 1984.

[13] E. Salvador, A. Cavallaro and T. Ebrahimi, "Cast shadow segmentation using invariant color features," Computer Vision and Image Understanding, pp. 238-259, 2004.

[14] R. Cucchiara, C. Grana, M. Piccardi, A. Prati and S. Sirotti, "Improving shadow suppression in moving object detection with HSV color information,"Proc. IEEE Intelligent Transportation Systems Conf., pp. 334-339, 2001.