Implementation Based on Dual Background & Modelling for detection of moving shadows

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***Abstract*—Moving object images in video sequence are obtained by subtracting the background images with the current frame images, background extraction is an important process. Firstly, in this paper, the background and moving objects are extracted by using the improved Gaussian mixture background modeling. Then, the previous moving object and moving object of frame difference are effectively integrated into a moving foreground object we are interested in. Finally, we extract the background region under the moving foreground object. Due to the influence of illumination, the foreground objects contain moving shadows, which affect the performance of moving object detection. This paper proposes a simple and effective method which uses the difference of texture feature and color information in gray foreground image and gray background image to remove the shadow of the foreground object, and then detect the real foreground object.**

Keywords—Gaussian mixture background models; color information; texture feature; shadow detection

I. Introduction

State-of-the-art video monitoring techniques are becoming more relevant in real life given rising living standards, growing awareness of personal possession security, and progress in machine vision. Detection of moving targets is particularly important because people are typically interested in identifying or tracking such targets. Shadows exist as long as light sources are present for indoor or outdoor video monitoring. Locating the shadow can improve accuracy of moving target detection and behavior analysis. By monitoring the environment in real time, an intelligent video monitoring system can collect various information, such as the number of visitors, queues, and behavior analysis. This type of data forms the foundation for making the correct monitoring management decisions in real time. Existing methods for detecting moving targets typically utilize background modeling or inter-frame difference, where the detected moving region contains the real target and its shadow. Shadow detection has been the subject of extensive research in recent years. Shadow detection methods can be classified into two categories: shape-based shadow detection and frequency spectrum-based shadow detection.

The shape-based method detects the shadow by using a prior geometrical message on the target, the scenario, and the position of the light source. An obvious limitation is the requirement for a prior geometrical message. Compared with the shape-based scheme, the frequency spectrum-based method is more practical and popular since the message on the frequency spectrum between the target and shadowed region usually depends solely on illumination, and is nearly independent of light source position and object shape. This paper proposes a method for detecting a target using dual background models. A novel algorithm is developed that detects moving shadows using the color information (*YUV* space) and texture information.

II. Target Detection Using Dual Models

Target detection refers to effective target segmentation by extracting the target from the video sequence. Target detection is critical for post analysis such as target classification, target tracking, and understanding behavior. Target tracking is also the foundation for video monitoring and video conference. In real-world scenarios, the background is not completely static due to the influence of illumination and weather. As a result, foreground and background movement may occur meanwhile in the video, making target detection challenging. Target detection is a complex task that attracts much attention from the computer vision and image processing community.

A. Background Subtraction

As a prevalent moving target detection method, the background subtraction algorithm [1][2][3] utilizes historical image data to model the background in complex scenarios. The algorithm performs a difference operation on the current image frame and the background model to determine if it is the background or foreground by using the similarity criterion. Background modeling is the key aspect of the background subtraction method; it should accurately fit the model distribution of the background and dynamically adapt to changes of the complex scenario inreal time. Furthermore, the algorithm is expected to effectively distinguish between background and foreground. It can be difficult to achieve both abilities and researchers usually try to find a balance for optimal detection results. Various methods have been proposed to model the background: the Gaussian model by Wren, the Gaussian mixture model by Zivkovic., the kernel estimation method by Elgammal, and the eigen method by Shlens. These modeling methods can achieve a detailed shape of the target, but by describing static and dynamic backgrounds using gray-scale level statistical information, one cannot depict irregular movement of the background accurately.

B. Frame Difference Method

As a simple and practical moving target detection method, the frame difference method [4] [5] [6] [7] performs a difference operation on two similar frames. A proper threshold is selected to extract the region of the moving target. This method is simple, computationally efficient, and operates in real time. However, the algorithm's detection performance is moderate because it cannot adapt well to complex dynamic scenarios. In addition, the choice of threshold is critical to detection of the moving target. In 1998, Lipton proposed the frame difference method [8] and effectively applied it to detection of moving targets. Afterwards, many researchers studied and improved the inter-frame difference method. A variant is the multi-frame difference algorithm, which makes this difference-type scheme more adaptive to complex dynamic scenarios while maintaining real-time performance.

C. Foreground Extraction Using Dual Modeling

Considering that the inter-frame difference scheme has low computational load and provides real-time performance, the moving foreground is first pre-extracted from the pre-processed video. But the inter-frame difference scheme cannot adapt to complex dynamic scenarios, such as thieves wandering or river surface ripples. Hence, the pre-extracted moving foreground contains some non-moving targets. Gaussian mixture background modeling is performed again on the pre-extracted moving foreground. The inter-frame difference method is unable to handle the cases of thieves wandering or river surface ripples; however, both can be addressed effectively by using the Gaussian mixture background model, as the extracted moving foreground is quite complete. Since the Gaussian mixture background model may be affected by illumination, there are still some shadows in the moving foreground extracted in this way. The process of extracting the foreground using dual models is shown in Figure 1.

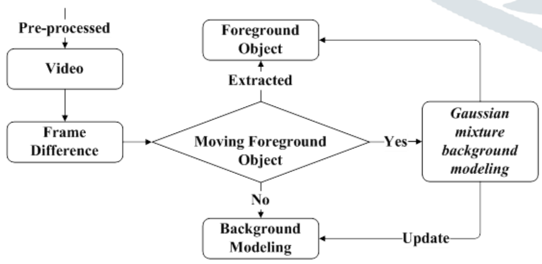

Fig. 1. Process of extracting the foreground using dual models

III. SHADOW DETECTION

Many algorithms have been proposed for shadow detection, including the model-based method [9] and the property-based method. The model-based approach constructs shadow models using prior knowledge of scenarios, moving targets, and illuminations. The constructed models are then used to accurately compute shadow shape and location. In many cases, prior knowledge is not available; therefore, the algorithm is only feasible for specific applications. The property-based method detects shadows by utilizing their brightness, color, texture, gradient, and edge. Experimental results show that, compared with background pixels, the pixels in projected shadows have lower brightness and saturation, but Chrominance is almost unchanged [10]. Hence, shadow detection based on color variation characteristics [11] is primarily achieved by converting the space which represents colors of pixel points. The objective is to detect shadows by transforming RGB images into HSV images, YUV images and normalized RGB images. Texture information-based shadow removal is highly dependent on the difference in brightness between pixels in the projected shadows and those in the background. Brightness varies substantially, while texture is largely unchanged. However, shadow detection algorithms based on texture characteristics [12] tend to identify target regions where brightness is lower than that of background pixels, but where Chrominance is similar to background pixels. Hence, the LBP operator-based texture algorithm usually fails for regions with slight texture variations, such as the gray levels in neighboring sky and grass pixels. Based on the strengths and weaknesses of both algorithms, this paper proposes a novel shadow detection algorithm as described in Figure 2.

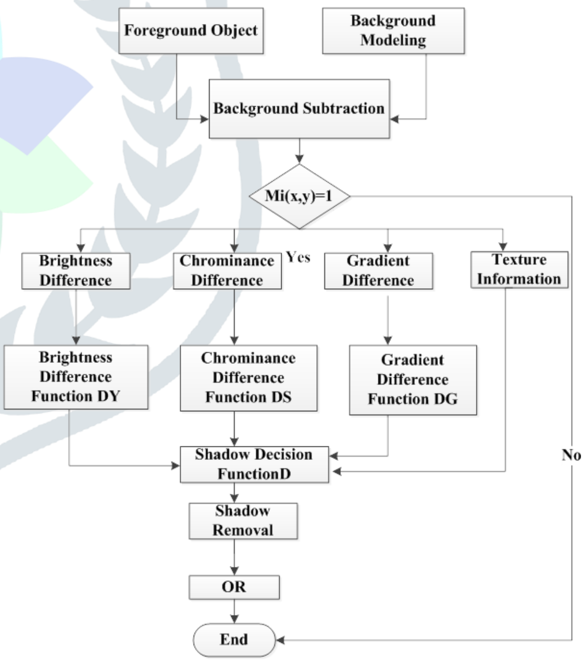

Fig. 2. Shadow detection algorithm process

D. YUV Color Space

Analyzing images based on RGB channels is a complex process. In order to more effectively analyze shadows during video detection of moving targets, the color space is transformed from RGB to YUV .

In the YUV color space, Y denotes brightness and U and V denote components of R_Y and B_Y, respectively. They are also called Chrominance, which represents color saturation. The strength of the YUV space is that brightness information Y and Chrominance information UV are mutually independent. U and V adequately represent the color. Image information obtained from the video sequence is usually in the RGB color model. It can be converted to YUV color space by using the following traditional method:

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{pmatrix} \begin{pmatrix} r \\ g \\ b \end{pmatrix} + \begin{pmatrix} 16 \\ 128 \\ 128 \end{pmatrix} \tag{1}$$

Taking into account the environmental factor of illumination and camera flutter, the brightness and Chrominance of pixels in some regions may vary significantly. Therefore, the RGB values of each pixel are replaced with the mean of the 3×3 neighborhoods centered on this pixel:

$$r = \sum_{i=1}^{9} R/9, g = \sum_{i=1}^{9} G/9, b = \sum_{i=1}^{9} B/9 \tag{2}$$

(1) For RGB values of the current image and background image obtained through dual background modeling, use Equation (2) to obtain RGB values of the current image and background image via mean processing. Then, compute YUV values of the current image and background image using Equation (1).

(2) Define three matching functions based on the pixel properties of brightness, Chrominance, and gradient density: brightness difference function DY , Chrominance difference function DS , and gradient density difference function DG . Finally, combine these three independent functions to form a shadow decision function D .

a) Brightness difference function DY . When $M_i(x, y) = 1$, for position (x, y) in the frame i input image and in the frame i background image, subtract the pixel brightness to obtain the brightness difference of this pixel point $DY(x, y)$. Define a threshold to obtain the brightness difference function DY and determine whether this pixel is in the projected shadow.

b) Chrominance difference function DS . When $M_i(x, y) = 1$, for position (x, y) in the frame i input image and in the frame i background image, subtract the pixel Chrominance components UV and compute the absolute value of their difference to obtain the Chrominance difference of this pixel point $DS(x, y)$. Based on this second feature of the projected shadow, obtain the Chrominance difference function DS using two thresholds: ds_1 and ds_2 . Determine whether the pixel is in the projected shadow.

c) Gradient density difference function DG . When $M_i(x, y) = 1$, for position (x, y) in the frame i input image and in the frame i background image, subtract the gradient density of these two positions to obtain the gradient density difference of this pixel point $DG(x, y)$. Based on this third feature of the projected shadow, obtain the gradient density difference function DG using two thresholds: dg_1 and dg_2 . Determine whether the pixel is in the projected shadow.

d) Shadow decision function D . Considering mutually independent computations of DY , DS, DG , these three function variables are combined to determine the shadow decision function D :

$$D_i(x, y) = DY_i(x, y) \times DS_i(x, y) \times DG_i(x, y) \times \beta \tag{3}$$

where β is a correction factor ranging from 0 to 1. Based on experimental results, β is set to 0.45.

E. Algorithm for Eliminating Local Texture Shadows

LBP is an efficient local texture descriptor due to its extraordinary gray-level and rotation invariance and low computational complexity. The principle is based on selecting a center pixel point and comparing the gray level to that of its neighbors within a radius R . The center is used as the threshold to obtain a binary system representation of gray level variation within a radius R . This binary system represents gray level variation and its LBP value is computed. A high radius means greater accuracy in representing local gray level variation, but requires more computational load. Here $(P, R) = (8,1)$, the accuracy and real-time performance meets the overall system requirements. This paper improves the original LBP operator in the following way:

$$u(g_i - g_o) = \begin{cases} 1 & |g_i - g_o| \geq 10 \\ 0 & |g_i - g_o| < 10 \end{cases} \tag{4}$$

$$LBP_{P,R}(x_o, y_o) = \sum_{i=0}^{P-1} S(g_i - g_o)2^i \tag{5}$$

The details of the algorithm for eliminating local texture shadows are as follows. When $M_i(x, y) = 1$ for position (x, y) in the frame i input image and in the frame i background image, subtract the LBP value of these two positions using Equation (4) and Equation (5). Compare their absolute values and define thresholds to determine whether the foreground pixel is in the projected shadow.

F. OR Operation

The image normalization-based method for eliminating shadows using the YUV color space is dependent on threshold and is prone to detect a moving target whose brightness is similar to the background but higher than the shadow, thus eliminating it as the shadow. But the LBP based on local texture elimination algorithm can maintain bright regions where the foreground target is located. The reason for this is that the bright region varies more than dark regions of the foreground target and its texture is more apparent. Hence, these two methods complement one another. The OR operation-based shadow region can be represented as:

$$Sh = \begin{cases} 0 & Sh_{color}(x, y) = 0 \quad and \quad Sh_{LBP}(x, y) = 0 \\ 1 & others \end{cases} \quad (6)$$

where 0 denotes shadow and 1 denotes foreground target.

IV. Experimental Results

In order to evaluate the proposed algorithm, experiments were conducted on the captured video image sequence using the *VS* platform. The experiments assess scenarios where the correction factor β is added and not added, and scenarios where local texture information is added and not added.

With the correction factor β not added, the moving target detection algorithm is used to obtain the background model and the foreground target as shown in Figure 3(b) and Figure 3(c), respectively. The white object in the foreground target image is the foreground object, that is $M_i(x, y) = 1$. Brightness, Chrominance, and gradient density difference of pixels in the original video image and background model regions are computed in *YUV* space with $M_i(x, y) = 1$.

This yields the shadow decision function used to detect the shadow of the moving target and eliminate the shadow. Elimination of brightness difference, Chrominance difference, and gradient density difference are shown in Figure 3(d), Figure 3(e) and Figure 3(f), respectively. Results of experiments without adding the correction factor β are shown in Figure 3(g).

The same experimental steps are followed after adding the correction factor β and the results are shown in Figure 3(h).

With local texture information introduced, the moving target detection algorithm is again used to obtain the foreground target and the background model. The white object in the foreground target image is the foreground object, that is $M_i(x, y) = 1$. The *LBP* values of the original video image and background model regions are computed in gray space with $M_i(x, y) = 1$ .This yields detection of the moving target and elimination of the shadow. Experimental results are shown in Figure 3(i) and the final foreground target is shown in Figure 3(j).

V CONCLUSION

This paper proposed a novel algorithm that achieves target detection by using dual background models. A method for detecting moving shadows based on color (*YUV* space) and texture information was proposed. A correction factor β, was introduced to help compensate the algorithm. Experimental results show that the proposed algorithms have the ability to effectively detect and eliminate moving target shadows. The proposed algorithm's real-time performance, adaptability, and robustness were verified

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