Shadow removal in Moving object detection using integrated approach

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***Abstract*—Cast shadows of moving objects often cause problems in many vision applications. In this paper, we present an integrated approach to detect shadows. We first use the Gaussian Mixture Model to abstract the background and the foreground. Then we use physical model and HSV color space to detect the shadows in the foreground. Experimental results show that our integrated approach is rapid and accurate.**

***Index Terms*—GMM, shadow removal, HSV, real-time**

I. Introduction

Moving objects detection from videos is used for various vision applications such as video surveillance, object location, classification and tracking. However, moving shadows produced by the moving objects cause serious problems such as merging of objects, false location, shape distortion and object losses. For these reasons, it is critical to detect cast shadows. Many algorithms have been proposed to detect shadows. [1] uses RGB color space model and they assume that the color of shadow pixels of the background are similar to the color of the corresponding pixels of the background. [2] analyzes pixels in the HSV color space because they find HSV color space separates chromaticity and luminosity which proves easier than the RGB space for shadow detection. [3] uses physical model and detects shadows in several steps. [4], [5] and [6]also use the physical model. [7] uses an improved physical model, Bi-Illuminant Dichromatic Reflection Model(BIDR) [8]. Some algorithms use other information to improve the efficiency of removing shadows. [9] uses the object texture and [10] takes into account of the ratio edge. Classical algorithms of removing shadows are compared and evaluated in [11]. There are many difficulties and restrictions in removing shadows because sometimes the colors of shadows are similar to the moving objects. In addition, in different environments, the parameters of the algorithms should be changed greatly. We should also take into account of the computing time because most of the applications are used in real-time conditions. All the algorithms above including ours are not always proper for all the environments. A good algorithm should detect most of the shadows and provide a relatively accurate and rapid result. We propose an integrated approach to solve the problem which can be used for real-time applications. In this paper, we first describe the shadows by the model proposed in [8]. We also appraise some algorithms according to the model. Then we detect the foreground with GMM [12]. After the foreground is abstracted, we detect the moving shadows using our integrated approach. At last the results of the experiments will be showed. Fig.1 shows a schematic diagram for our general approach.

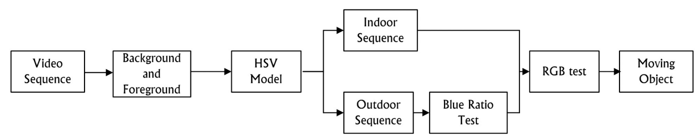

Fig. 1. the schematic diagram for our approach

II. Physical Model of the Shadows

Shafer [13]analyze the reflection of light from inhomogeneous materials(Fig.2) and proposes the classical physical model and he assumes amibent illumination is constant for each material. Using this model, the illumination I of each pixel can be approximated as

$$I = m_l(l,e,s)C_l(\lambda) + m_b(l,e,s)C_b(\lambda) + C_a \qquad (1)$$

where m_l,m_b are the geometric terms, the parameters l,e,s define the angel among the light, the material and the camera. C_l and C_b are relative SPDs due to surface and body reflections.

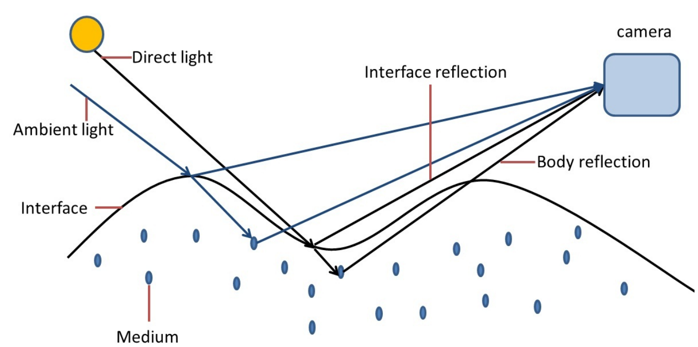

Fig. 2. Reflection of Light from an Inhomogeneous Material.

Maxwell et al. [8]extend the classical physical model [13]. In their model,the reflection of the ambient light is the same as the direct light. Therefore, they proposed the BIDR model, which contains four terms: two types of reflection for the direct light sources and ambient illumination. The details of the model are showed in the paper [8]. If the surface reflection is neglected, a sensor such as a camera show each pixel in a video can expressed as following:

$$g_i = \alpha F_i m_b c_b^i l_d^i + F_i c_b^i M_a b^i, i \in R, G, B \tag{2}$$

Where g_i indicates the color of each pixel, The right side of the equation represents the direct illumination and the ambient illumination respectively. F means the color sensitivity of the camera. Usually, the range of F is $(0.9, 1]$. For different pixels the values of F are different. The range of the α is $(0, 1]$ when the pixel is a shadow pixel $\alpha < 1$, otherwise $\alpha = 1$. A pixel RGB values in different conditions are showed in Fig.3.

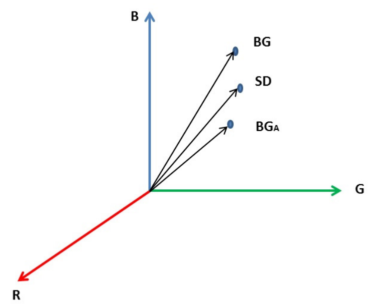

Fig. 3. The contribution of all direct light source and ambient illuminance. The shadow values SD are expected to be observed between background value and ambient term BG_A.

[7]and [4] assume that all potential shadow points will fall into the grey region (Fig.4). However, according to(2), the values of F are different among the pixels. In addition, according to [3], in outdoor scenes although all RGB values are lower in the shadow region, the amount of the reduction is not proportional. Therefore, the model will miss some shadow pixels or falsely group some foreground pixels into shadows.

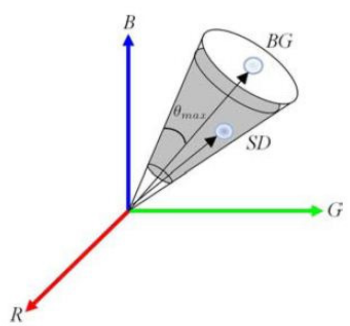

Fig. 4. Some algorithms assume that a point falls into the grey area will be considered as potential shadow point

III. Detecting Shadows with integrated approach

Our approach relies on the GMM model, BIDR model and HSV model. Since the lights of outdoor scenes are more blue than indoor scenes and we add a blue ratio test as [3] to detect the outdoor shadows. The shadows are detected as follows.

A. *Background modeling using GMM*

C.Stauffer [12] assumes that the probable background colors are the ones which stay longer and more static. C.Stauffer models each background pixel by a mixture of K Gaussian distributions(K is from 3 to 5). Different Gaussians represent different colors. the weight parameters of the model represnet the time proportions that the colors stay in the scene. The probability that a pixel has a value of X_N at time N can be written as

$$p(X_N) = \sum_{i=1}^{k} w_i \eta(X_N; \theta_i) \tag{3}$$

where w_k is the weight parameter of the k th Gaussian component. $\eta(X_N; \theta_i)$ is the Normal distribution of k th Gaussion distribution. To allow the model to adapt to changes in real-time, an update scheme of $w_i$and η was applied. Every new pixel value is checked against existing Guassian distributions and the model will be updated. The details of the update are inStauffer1999. Since the model uses more than one Gaussian distribution, the GMM is robust and accurate when there are shaking objects in the background. After modeling the background we can also get the foreground set FG which includes the moving objects and moving shadows and we define a foreground mask FM for the detected foreground.

B. *Detecting Shadows in HSV color space*

Cucchiara [2]uses HSV color space because this color space is more accurate to distinguish shadows than the RGB color space. As [2], we analyze the three kinds of points belonging to moving objects,shadows and background seperately and defines $I_v^k(x, y)$ as the intensity value for the component V of the HSV pixel at coordinates(x,y) in the frame k. We also defines a shadow mask SP_k for each pixel in FG with three conditions as follows:

$$SP_k(x,y) = \begin{cases} 1 & \alpha \le \frac{I_K^V(x,y)}{B_K^V(x,y)} \le \beta \\ & \wedge (I_K^S - B_K^S(x,y)) \le \tau_S \\ & \wedge |I_K^H - B_K^H(x,y)| \le \tau_H \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The first condition works on the luminance. α and β take into account how strong the light source is and in different scenes the two prarametes should be changed. On components S and H we assume that the chrominance of shadowed and non-shadowed points do not vary too much.

C. *Initial shadow test*

If we only use the HSV color space model, some pixels belonging to the moving objects will be falsely detected as shadows. In step2 and step3, we use the RGB color model to avoid false detection. According to (2) , when a point is shadowed, $\alpha < 1$ and the RGB values of the pixels in shadow regions are lower than the background. The relationship between a shadow pixel and its corresponding background which is not shadowed is

$$I_K^i(x,y) < B_K^i(x,y), i \in R, G, B \tag{5}$$

D. Blue Ratio test

According to [3], in outdoor scenes, shadow pixels which have a low saturate(<0.3) falling on neutral surfaces, such as asphalt roads, tend to be more blue because shadow regions are illuminated by the sky and sky is assumed to be blue. So we can get if a pixel belongs to the shadow region, then

$$if I_K^S(x,y) < 0.3 \quad \begin{array}{l} \frac{I_K^B(x,y)}{B_K^B(x,y)} > \frac{I_K^R(x,y)}{B_K^R(x,y)}, \\ \frac{I_K^B(x,y)}{B_K^B(x,y)} > \frac{I_K^G(x,y)}{B_K^G(x,y)} \end{array} \tag{6}$$

To sum up, we modify the conditions of detecting shadows in HSV model and we get the new conditions. When we detect the shadows in indoor scenes with HSV color model, $SP_K(x,y) = 1$ should be in the conditions as follows:

$$\begin{array}{l} I_K^i(x,y) < B_K^i(x,y), i \in R, G, B \\ \alpha \leq \frac{I_K^V(x,y)}{B_K^V(x,y)} \leq \beta \\ (I_K^S - B_K^S(x,y)) \leq \tau_S \\ |I_K^H - B_K^H(x,y)| \leq \tau_H \end{array} \tag{7}$$

Similarly, in outdoor scenes, the conditions $SP_k(x,y) = 1$ are

$$\begin{array}{l} I_K^i(x,y) < B_K^i(x,y), i \in R, G, B \\ \alpha \leq \frac{I_K^V(x,y)}{B_K^V(x,y)} \leq \beta \\ (I_K^S - B_K^S(x,y)) \leq \tau_S \\ |I_K^H - B_K^H(x,y)| \leq \tau_H \\ \\ \text{if} I_K^S(x,y) < 0.3 \\ \frac{I_K^B(x,y)}{B_K^B(x,y)} > \frac{I_K^R(x,y)}{B_K^R(x,y)}, \\ \frac{I_K^B(x,y)}{B_K^B(x,y)} > \frac{I_K^G(x,y)}{B_K^G(x,y)} \end{array} \tag{8}$$

After detecting the foreground, we detect and eliminate the shadows by using the modified conditions and get the much more accurate moving objects. For each pixel $FM_k(x,y)$in the foreground mask FM,

$$FM_k(x,y) = 0 \text{ ,if } SP_k = 1 \tag{9}$$

IV. Experiment Results

This section presents the results of our integrated approach. The approach gives satisfactory results in shadows suppression and performs well on various videos. The results of the indoor and outdoor scenes are showed. The first video size is 320*240,10fps and the second is 768*576, 25fps. We use OpenCV and run our program with the Intel Core2 CPU, 1.86GHz. The calculating time for each frame of the two videos are about 30ms and 100ms respectively. In these two videos, we use 3 Gaussian models to get the foreground masks. The parameters of the HSV model conditions for the two videos are the same:$\alpha = 0.6$,$\beta = 1$, $\tau_S = 20$, $\tau_H = 20$. However, in most times different scenes should set different parameters in order to get good results. We show the original frames, the foreground masks using GMM model and the foreground masks using integrated approach. Results show that our method is accurate and can be used in the real-time applications.

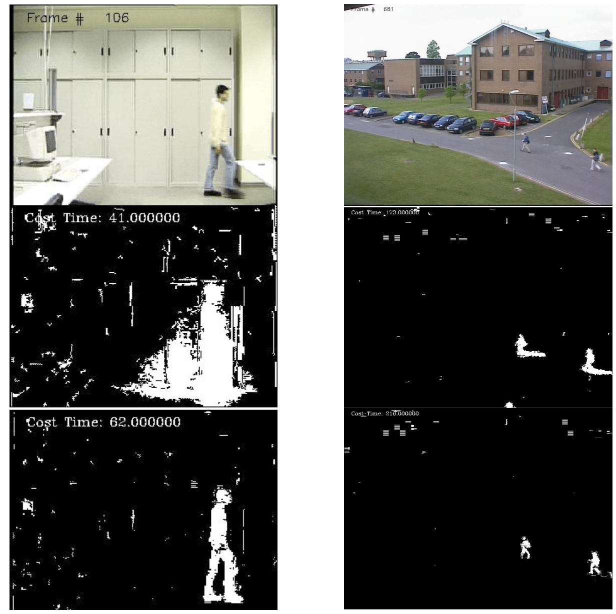

Fig. 5. the results above from top to down are the original frames of the indoor and outdoor videos, foreground masks using GMM model and foreground masks using integrated approach

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