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Moving Cast Shadow Detection

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1. Introduction

Moving shadow detection is an important topic in computer vision applications, including video conference, vehicle tracking, and three-dimensional (3-D) object identification, and has been actively investigated in recent years. Because, in real world scenes, moving cast shadows may be detected as foreground object and plague the moving objects segmentation. For example, in traffic surveillance situation, shadows cast by moving vehicles may be segmented as part of vehicles, which not only interfere with the size and shape information but also generate occlusions (as Fig. 1 illustrates). At the same time, moving cast shadow detection can provide reference information to the understanding of the illumination in the scenes. Therefore, an effective shadow detection algorithm can greatly benefit the practical image analysis system.



Fig. 1. Examples of moving cast shadows.

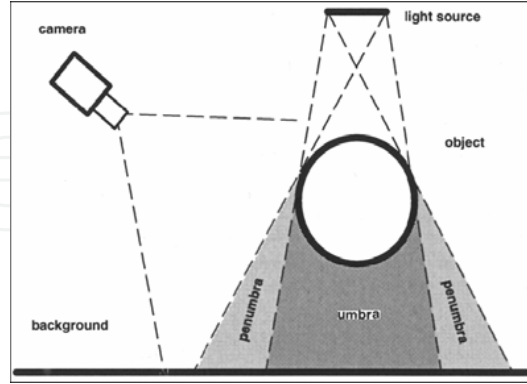


Fig. 2. Illumination model of moving cast shadows: the umbra, penumbra, and geometric relationship.

Essentially, shadow is formed by the change of illumination conditions and shadow detection comes down to a problem of finding the illumination invariant features. From the viewpoint of geometric relationship, shadow can be divided into umbra and penumbra (Stander et al., 1999). The umbra corresponds to the background area where the direct light is almost totally blocked by the foreground object, whereas in the penumbra area, the light is partially blocked (as Fig. 2 illustrates). From the viewpoint of motion property, shadow can be divided into static shadow and dynamic shadow. Static shadow is cast by static object while dynamic shadow is cast by moving object. In video surveillance application, static shadows have little effect on the moving objects segmentation. Therefore, we concentrate on the detection of dynamic/moving cast shadows in the image sequence captured by static camera in this chapter.

2. Illumination property of cast shadow

For an image acquired by camera, the intensity of pixel $f(x,y)$ can be given as:

$$f(x,y) = i(x,y) \times r(x,y) \quad (1)$$

where $i(x,y)$ represents the illumination component and $r(x,y)$ represents the reflectance component of object surface. $i(x,y)$ is computed as the amount of light power per receiving object surface area and can further be expressed as follows (Stander et al., 1999).

$$i(x,y) = \begin{cases} c_a + c_p \cdot \cos(j) & \text{illuminated area} \\ c_a + t(x,y) \cdot c_p \cdot \cos(j) & \text{penumbra area} \\ c_a & \text{umbra area} \end{cases} \quad (2)$$

where

- c_p intensity of the light source;
- φ angle enclosed by light source direction and surface normal;
- c_a intensity of ambient light;
- t transition inside the penumbra which depends on the light source and scene geometry, and $0 \leq t(x,y) \leq 1$.

Many works have been put forward in the literature for moving shadow detection. From

the viewpoint of the information and model utilized, these methods can be classified into three categories: color model, textural model, and geometric model. Additionally, statistical model is used to tackle the problem. Most of the state-of-the-art are based on the reference image and we consider it has been acquired beforehand. Let the reference image and shaded image be B and F , respectively. In the following part of this chapter, we introduce each categories of methods for moving cast shadow detection.

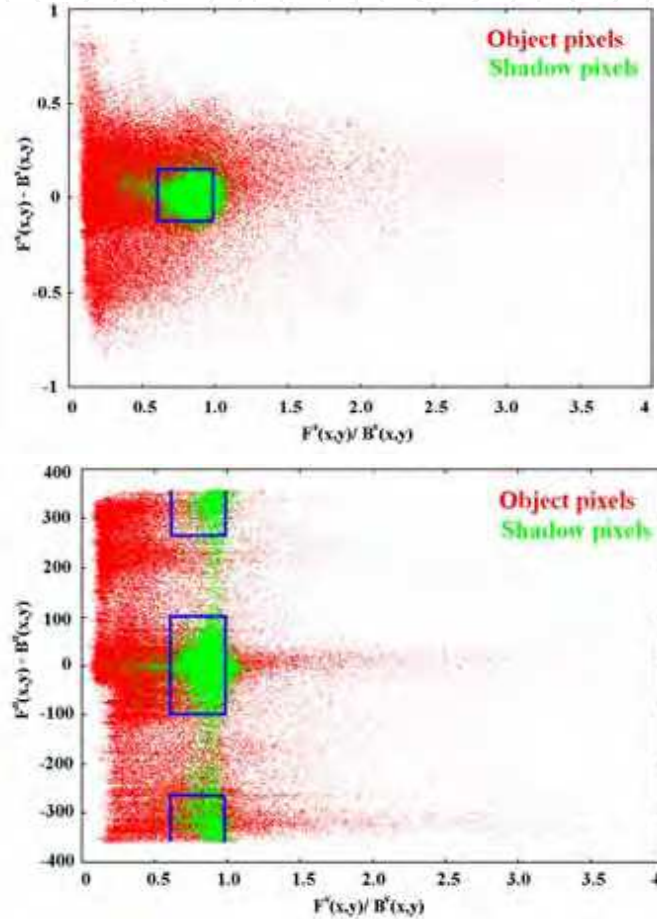


Fig. 3. The distribution of the background difference and background ratio in HSV color space: shadow pixels and foreground pixels.

3. Colour/Spectrum-based shadow detection

The color/spectrum model attempts to describe the color change of shaded pixel and find the color feature that is illumination invariant. Cucchiara *et al.* (Cucchiara et al., 2001; Cucchiara et al., 2003) investigated the Hue-Saturation-Value (HSV) color property of cast

shadows, and it is found that shadows change the hue component slightly and decrease the saturation component significantly. The distribution of $F^V(x, y)/B^V(x, y)$, $F^S(x, y)-B^S(x, y)$, and $|F^H(x, y)-B^H(x, y)|$ are given in Fig. 3 for shadows pixels and foreground pixels, respectively. It can be found that shadow pixels cluster in a small region and have distinct distribution compared with foreground pixels. The shadows are then discriminated from foreground objects by using empirical thresholds on HSV color space as follows.

$$(\alpha \leq \frac{F^V(x, y)}{B^V(x, y)} \leq \beta) \text{AND} ((F^S(x, y) - B^S(x, y)) \leq \tau_s) \text{AND} (|F^H(x, y) - B^H(x, y)| \leq \tau_H) \quad (3)$$

By using above method, the shadow pixels can be discriminated from foreground pixels effectively. This method has been included in the Sakbot system (Statistical and Knowledge-Based Object Tracker).

Salvador *et al.* (Salvador et al. 2004) proposed a normalized RGB color space, $C_1C_2C_3$, to segment the shadows in still images and video sequences. The $C_1C_2C_3$ is defined as follows.

$$\begin{aligned} C_1(x, y) &= \arctan \frac{R(x, y)}{\max(G(x, y), B(x, y))}; \\ C_2(x, y) &= \arctan \frac{G(x, y)}{\max(R(x, y), B(x, y))}; \\ C_3(x, y) &= \arctan \frac{B(x, y)}{\max(R(x, y), G(x, y))}; \end{aligned} \quad (4)$$

After integrating the intensity of neighbouring region, the shadow is detected as the pixels change greatly in $C_1C_2C_3$ colour space. Considering the shadow decrease the intensity of RGB component in a same scale, it can be found that $C_1C_2C_3$ is illumination invariant.

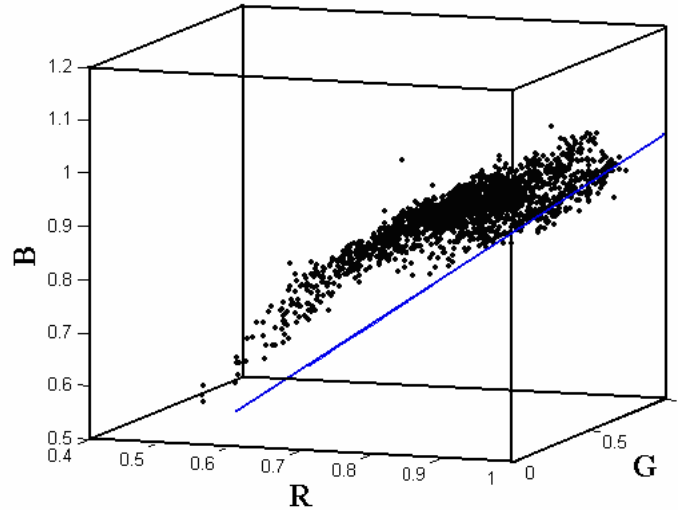


Fig. 4. A scatter plot in the color ratios space of a shaded pixels set. The line corresponds to the equal ratio in RGB components.

Siala *et al.* (Siala et al., 2004) consider the pixel's intensity change equally in RGB colour components and a diagonal model is proposed to describe the color distortion of shadow in RGB space. The color distortion is defined as $(d_R=F_R/B_R, d_G=F_G/B_G, d_B=F_B/B_B)$, and the color distortion of shaded pixel is distributed near the line $d_R=d_G=d_B$ (as show in Fig. 4), which does not hold for foreground objects. Therefore, the shadow pixels are discriminated from foreground objects according to the distance between pixel's color distortion and the line $d_R=d_G=d_B$.

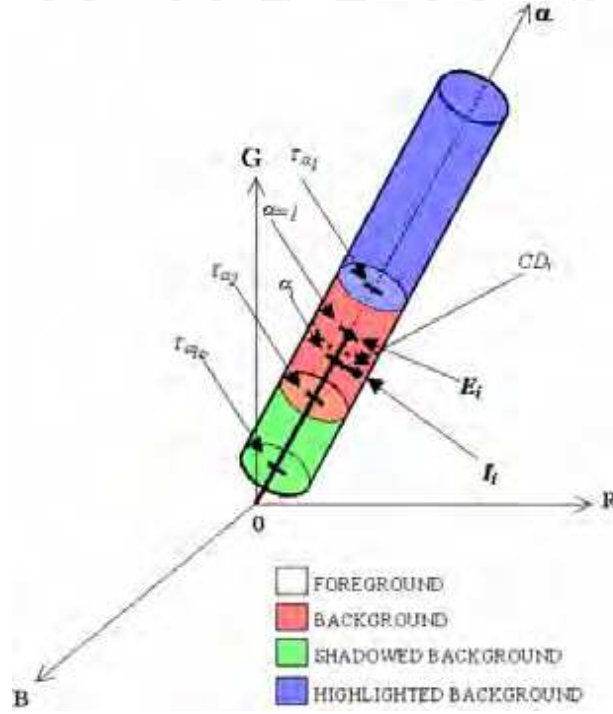


Fig. 5. Pixels classification using the normalized color distortion and normalized brightness distortion: original background, shaded background, highlight background, and moving foreground objects.

Horprasert *et al.* (Horprasert et al., 1999) proposed a computational color model which separates brightness from the chromaticity component using brightness distortions (BD) and chromaticity distortions (CD), which are defined as follows.

$$BD(x, y) = \frac{\frac{F_R(x, y) \cdot \mu_R(x, y)}{\sigma_R^2(x, y)} + \frac{F_G(x, y) \cdot \mu_G(x, y)}{\sigma_G^2(x, y)} + \frac{F_B(x, y) \cdot \mu_B(x, y)}{\sigma_B^2(x, y)}}{\left[\frac{\mu_R(x, y)}{\sigma_R(x, y)} \right]^2 + \left[\frac{\mu_G(x, y)}{\sigma_G(x, y)} \right]^2 + \left[\frac{\mu_B(x, y)}{\sigma_B(x, y)} \right]^2}; \quad (5)$$

$$CD(x, y) = \sqrt{\left(\frac{F_R(x, y) - BD \cdot \mu_R(x, y)}{\sigma_R(x, y)} \right)^2 + \left(\frac{F_G(x, y) - BD \cdot \mu_G(x, y)}{\sigma_G(x, y)} \right)^2 + \left(\frac{F_B(x, y) - BD \cdot \mu_B(x, y)}{\sigma_B(x, y)} \right)^2};$$

In which (μ_R, μ_G, μ_B) and $(\sigma_R, \sigma_G, \sigma_B)$ are the arithmetic means and variance of the pixel's red, green, and blue values computed over N background frames. By imposing thresholds on the normalized color distortion (NCD) and normalized brightness distortion (NBD), the pixels are classified into original background, shaded background, highlight background, and moving foreground objects as follows.

$$\begin{cases} \text{Foreground : } \text{NCD} > \tau_{CD} \text{ OR } \text{NBD} < \tau_{alo}, \text{ else} \\ \text{Background : } \text{NBD} < \tau_{a1} \text{ AND } \text{NBD} < \tau_{a2}, \text{ else} \\ \text{Shadow : } \text{NBD} < 0, \text{ else} \\ \text{Highlight : otherwise} \end{cases} \quad (6)$$

The strategy used in Eq. (6) is depicted in Fig. 5.

Nadimi, S. & Bhanu, B (Nadimi, S. & Bhanu, B., 2004) employed a physical approach for moving shadow detection in outdoor scenes. A dichromatic reflection model and a spatio-temporal albedo normalization test are used for learning the background color and separating shadow from foreground in outdoor image sequences. According to the dichromatic reflection model, pixel value $F(x,y)$ in the outdoor scene can be represented as follows.

$$F(x,y) = \int_{\Delta\lambda_1} K_{(x,y),1} L_{(x,y),1}(\lambda) f(l,e,s) d\lambda + \int_{\Delta\lambda_2} K_{(x,y),2} L_{(x,y),1}(\lambda) d\lambda; \quad (7)$$

in which the first and second items correspond to the intensiy caused by the sun and sky; $K_{(x,y),1}$ and $K_{(x,y),2}$ are the coefficient of reflectances due to sun and sky; $L_{(x,y),1}$ and $L_{(x,y),2}$ are intensity of the illumination sources of sun and sky; $f(l,e,s)$ is geometric term; l is the incident angle of illumination; e is the angle for viewing direction; s is the angle for specular reflection. The spatio-temporal albedo H between pixel $F(x,y)$ and its neighboring pixel (take $F(x+1,y)$ as example) is defined as follows.

$$\begin{aligned} H(F(x,y), F(x+1,y)) &= \frac{R_1 - R_2}{R_1 + R_2}; \\ R_1 &= \frac{F_{t+1}(x,y) - F_t(x,y)}{F_{t+1}(x,y) + F_t(x,y)}; R_2 = \frac{F_{t+1}(x+1,y) - F_t(x+1,y)}{F_{t+1}(x+1,y) + F_t(x+1,y)}; \end{aligned} \quad (8)$$

Pixel $F(x,y)$ and $F(x+1,y)$ is assumed to have the same reflectance if the following condition is satisfied:

$$C[F(x,y), F(x+1,y)] = \begin{cases} 1 & \text{if } |H(F(x,y), F(x+1,y))| < T \\ 0 & \text{Otherwise} \end{cases}; \quad (9)$$

Cavallaro *et al.* (Cavallaro et al., 2005) detected shadow by exploiting color information in a selective way. In each image the relevant areas to analyze are identified and the color components that carry most of discriminating information are selected for shadow detection.

Color model has shown its powerfulness in shadow detection. Nevertheless, the foreground objects may have similar color with the moving shadows, and it becomes not reliable to detect moving shadows by using only the color information of the isolated points.

4. Texture-based shadow detection

The principle behind the textural model is that the texture of foreground objects is different with that of the background, while the texture of shaded area remains the same as that of the background.

In (Xu et al., 2005), several techniques have been developed to detect moving cast shadows in a normal indoor environment. These techniques include the generation of initial change detection masks and canny edge maps, the detection of shadow region by multi-frame integration, edge matching, conditional dilation, and post-processing (as Fig.6 illustrates).

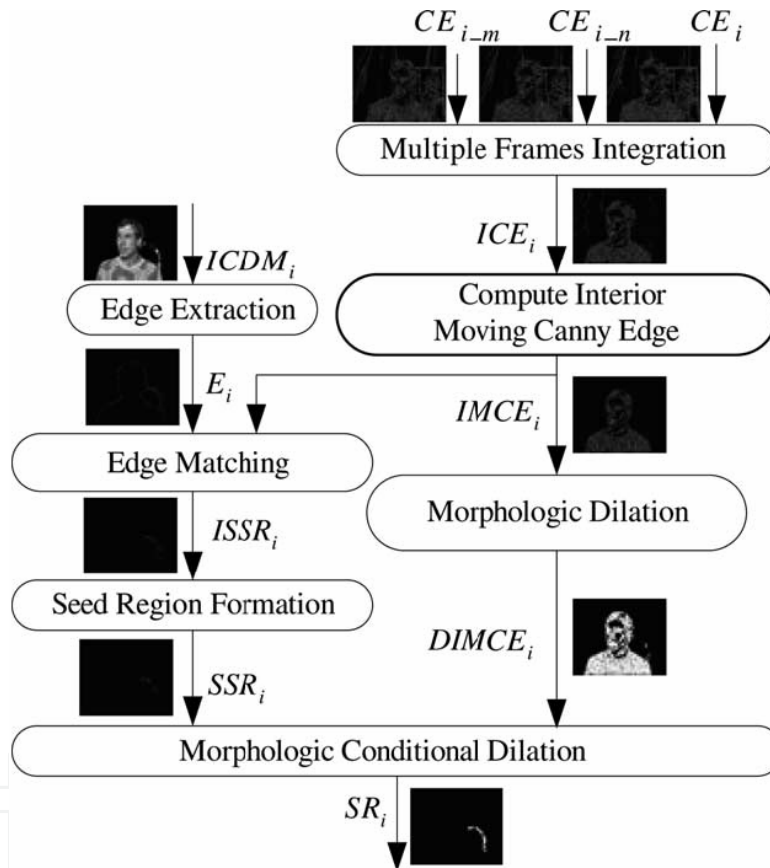


Fig. 6. Moving cast shadow detection by using the edge information.

McKenna *et al.* (McKenna et al., 2000) assumed cast shadow results in significant change in intensity without much change in chromaticity. Each pixel's chromaticity is modeled using its means and variances, and each background pixel's first-order gradient is modeled by using gradient means and magnitude variances. The moving shadows are then classified as background if the chromaticity or gradient information supports their classification. Leone *et al.* (Leone et al., 2006) represented textural information in terms of redundant systems of

functions, and the shadows are discriminated from foreground objects based on a pursuit scheme by using an over-complete dictionary. Matching Pursuit algorithm (MP) is used to represent texture as linear combination of elements of a big set of functions, and MP selects the best little set of atoms of 2D Gabor dictionary for features selection. Zhang *et al.* (Zhang *et al.*, 2006) used the normalized coefficients of the orthogonal transformation for moving cast shadow detection. Five kind of orthogonal transforms (DCT, DFT, Haar Transform, SVD, and Hadamard Transform) are analyzed, and their normalized coefficients are proved to be illumination invariant in a small image block. The cast shadows are then detected by using a simple threshold on the normalized coefficients (as Fig.7 illustrates).

Zhang *et al.* (Zhang *et al.*, 2006) use the ratio edge for shadow detection, which are defined as follows.

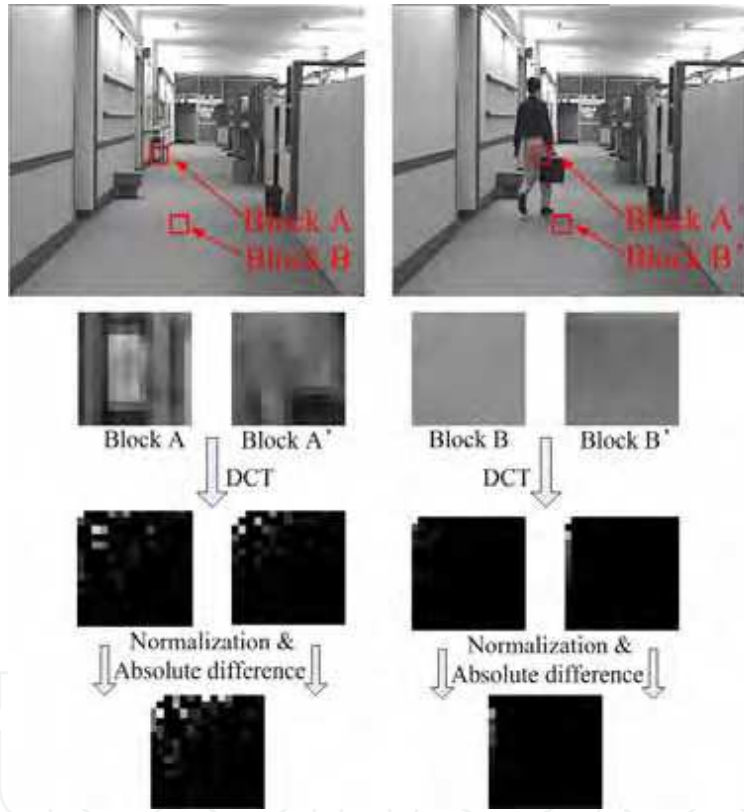


Fig. 7. Moving cast shadow detection based on the normalized coefficients of orthogonal transformation.

$$\Theta(x,y)=\{F(x+i,y+j) \mid 0 < i^2+j^2 \leq r^2\} \quad (10)$$

$$R(x,y) = \sum_{(i,j): F(i,j) \in \Theta(x,y)} \frac{F(x,y)}{F(i,j)}; \quad (11)$$

According to the illumination model in Eq. (2), the ratio edge is proved to be illumination

invariant. The shadow are then detected by imposing a threshold on the ratio edge difference $R_D(x,y)$ defined as follows.

$$R_D(x,y) = \sum_{\substack{(i,j): \\ B(i,j) \in \Theta_B(x,y) \\ F(i,j) \in \Theta_S(x,y)}} \left(\frac{B(x,y)}{B(i,j)} - \frac{F(x,y)}{F(i,j)} \right)^2; \quad (12)$$



Fig. 8. The textural property of ratio edge.

in which $\Theta_B(x,y)$ and $\Theta_S(x,y)$ are the neighboring region of $B(x,y)$ and $F(x,y)$, respectively. The ratio edge of Eq. (12) is given in Fig.8, it can be seen that ratio edge can represent the quantity of the texture in the neighboring region.

Fung *et al.* (Fung et al., 2002) analyzed the characteristics of cast shadows in the luminance, chrominance, gradient density, and geometry domains, and a combined probability map is obtained which is called as shadow confidence score (SCS), as shown in Fig. 9.

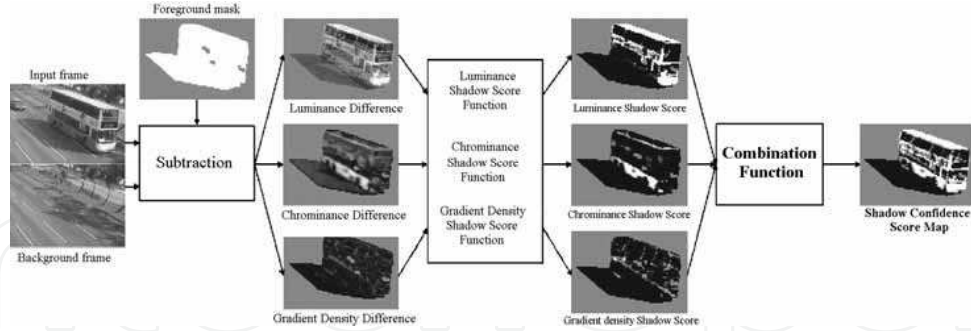


Fig. 9. Moving cast shadow detection based on shadow confidence score.

From the edge map of the input image, each edge pixel is examined to determine whether it belongs to the vehicle region based on its neighboring SCSs. The cast shadows are identified as those regions with high SCSs, which are outside the convex hull of the selected vehicle's edge pixels.

Textural model may be the most promising technique for shadow detection, whereas the state-of-the-art of textural model are intricate in implementation. Moreover, in the

homogeneous regions of the images, the textural information of the scenes may be very faint and cannot be captured by traditional methods.

5. Geometry-based shadow detection

Geometric model makes use of the camera location, the ground surface, and the object geometry, etc., to detect the moving cast shadows.

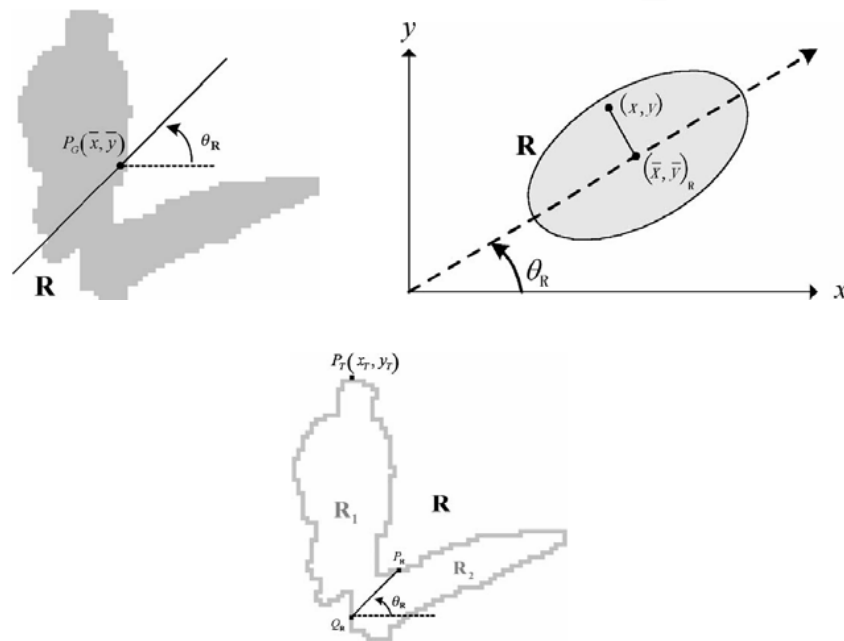


Fig. 10. The Gaussian geometric shadow model used for the detection of pedestrian's shadow.

In (Hsieh et al., 2003), Gaussian shadow model was proposed to detect the shadows of pedestrian. The model is parameterized with several features including the orientation, mean intensity, and center position of a shadow region (as Fig.10 illustrates), with the orientation and centroid position being estimated from the properties of object moments.

Hsieh *et al.* (Hsieh et al., 2004; Hsieh et al., 2006) proposed a histogram-based method to detect different lane dividing lines from traffic video sequence. According to these lines, a line-based shadow modeling process is applied to eliminate the shadows of vehicles. Two kinds of lines are used, including the ones parallel and vertical to lane directions, which can be used to eliminate shadows in the different positions of vehicles. Yoneyama *et al.* (Yoneyama et al., 2003; Yoneyama et al., 2005) proposed joint 2D vehicle/shadow models to suppress the moving shadows of vehicles. The proposed 2D vehicle/shadow models are classified into six types (as Fig.11 illustrates) and the parameters of these models can be estimated by fitting the segmented vehicles with these models.

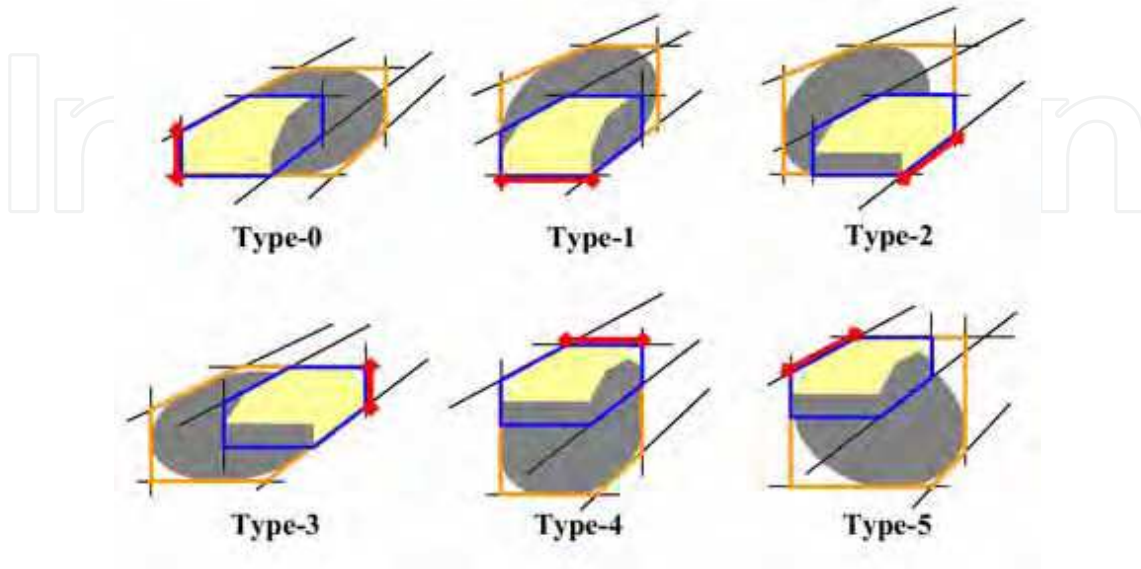


Fig. 11. Six vehicle model types with the corresponding cast shadow.

All these methods of geometric model strongly depend on the geometric relationships of the objects in the scenes, and when these geometric relationships change, these methods become ineffective.

6. Statistical inference for shadow model

Another useful tool for shadow detection is statistical model, which can further improve the performance of different shadow model. Most of these methods are based on the noise shadow model:

$$F(x, y) = \Phi(x, y) \cdot B(x, y) + \varepsilon(x, y); \varepsilon(x, y) \sim N(0, \sigma^2);$$

$$\Phi(x, y) = \frac{c_a + t(x, y) \cdot c_p \cdot \cos(j)}{c_a + c_p \cdot \cos(j)}; 0 \leq \Phi(x, y) \leq 1; \quad (13)$$

in which $t(x, y)$, c_p , and c_a are ones defined in Eq. (2).

Toth *et al.* (Toth et al., 2004) use the quantity given in Eq. (14) for shadow detection, which is normally distributed with variance $(1+1/\Phi^2) \sigma^2$.

$$\tilde{B}(x, y) - \frac{1}{\Phi(x, y)} \cdot F(x, y) = \varepsilon(x, y) - \frac{1}{\Phi(x, y)} \cdot \varepsilon(x, y);$$

$$\tilde{B}(x, y) = B(x, y) + \varepsilon(x, y); \quad (14)$$

Each moving pixel is then classified into foreground object or shadow by performing a significance test. Wang *et al.* (Wang et al., 2003) modeled the background, shadow, and edge information as Gaussian distributions which are updated adaptively. A Bayesian framework

is then utilized to describe the relationships among the segmentation label, background intensity, and edge information. Markov random field (MRF) is used to improve the spatial connectivity of the segmented regions. Nicolas *et al.* (Martel-Brisson, N. & Zaccarin, A., 2005) introduce Gaussian mixture model (GMM) for the detection of moving cast shadows. The proposed algorithm consists of identification the distributions that could represent shadows, modification the learning rates of the distributions to allow them to converge within the GMM, and build of a GMM for moving shadows by using identified distributions. Mikic *et al.* (Mikic et al., 2000) model the shadow pixel as a Gaussian distribution with $(\mu_{S,R}, \mu_{S,G}, \mu_{S,B}, \sigma_{S,R}, \sigma_{S,G}, \sigma_{S,B})$ being the mean and variance, while the illuminated pixel is also model as a Gaussian distribution with $(\mu_{L,R}, \mu_{L,G}, \mu_{L,B}, \sigma_{L,R}, \sigma_{L,G}, \sigma_{L,B})$ being the mean and variance. Let $D = \text{diag}(d_R, d_G, d_B)$ being the camera response for the same point when it is shadowed. Therefore, we have the following relationships.

$$\begin{aligned}\mu_{S,R} &= d_R \mu_{L,R}, \mu_{S,G} = d_G \mu_{L,G}, \mu_{S,B} = d_B \mu_{L,B}; \\ \sigma_{S,R} &= d_R \sigma_{L,R}, \sigma_{S,G} = d_G \sigma_{L,G}, \sigma_{S,B} = d_B \sigma_{L,B};\end{aligned}\quad (15)$$

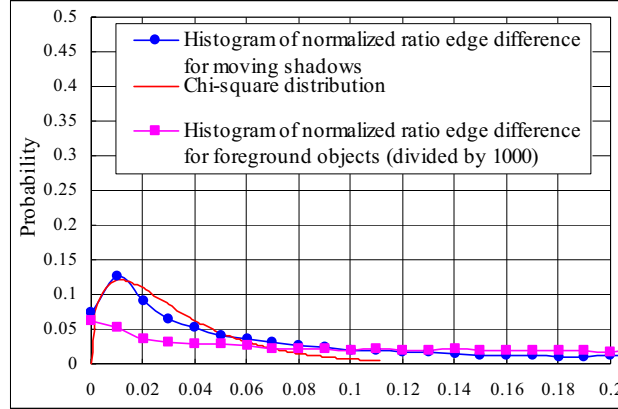


Fig. 12. Histogram of the normalized ratio edge difference for moving cast shadows and foreground, and comparison with Chi-square distribution.

The distribution of foreground objects is assumed to be uniform distribution. A maximum posteriori probability (MAP) is then used to classify the pixel into background(C_1), shadow(C_2), and foreground(C_3) according to its color vector v :

$$p(C_i | v) = \frac{p(v | C_i) \cdot p(C_i)}{\sum_{j=1,2,3} p(v | C_j) \cdot p(C_j)}; \quad (16)$$

In (Zhang et al., 2006), the distribution of the normalized background difference of ratio edge in shaded background area is also analyzed and is approximated to be a chi-square distribution. Therefore, a significance test can be used for automatic shadow detection. The distribution of $R_D(x,y)$ in Eq.(12) is depicted for moving shadows and foreground objects in Fig. 12. It can be found that ratio edge difference of moving shadows has much different distribution compared with that of foreground objects. The distribution of $R_D(x,y)$ of moving

shadows is also compared with Chi-square distribution in Fig. 12 and we can see that a good fitting can be reached.

7. Conclusion

In this chapter, we have provided a brief overview of the works about moving cast shadow detection. The state-of-the-art methods have been categorized into color model, textural model, and geometric model according to the information and model utilized, which have been discussed systematically. Furthermore, all kinds of statistical models have been employed to tackle the problem, which are also analyzed in detail. From the results, we can see that different methods are fit for different situations and it is very hard to get a method in common use. Therefore, the future work may be the fusion of different information by statistical models to realize robust shadow detection.

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Vision Systems: Segmentation and Pattern Recognition

Edited by Goro Obinata and Ashish Dutta

ISBN 978-3-902613-05-9

Hard cover, 536 pages

Publisher I-Tech Education and Publishing

Published online 01, June, 2007

Published in print edition June, 2007

Research in computer vision has exponentially increased in the last two decades due to the availability of cheap cameras and fast processors. This increase has also been accompanied by a blurring of the boundaries between the different applications of vision, making it truly interdisciplinary. In this book we have attempted to put together state-of-the-art research and developments in segmentation and pattern recognition. The first nine chapters on segmentation deal with advanced algorithms and models, and various applications of segmentation in robot path planning, human face tracking, etc. The later chapters are devoted to pattern recognition and covers diverse topics ranging from biological image analysis, remote sensing, text recognition, advanced filter design for data analysis, etc.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Wei Zhang, Q.M. Jonathan Wu and Xiangzhong Fang (2007). Moving Cast Shadow Detection, Vision Systems: Segmentation and Pattern Recognition, Goro Obinata and Ashish Dutta (Ed.), ISBN: 978-3-902613-05-9, InTech, Available from:

http://www.intechopen.com/books/vision_systems_segmentation_and_pattern_recognition/moving_cast_shadow_detection

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