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A Survey of Moving Cast Shadow Detection Methods

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Abstract— This paper presents a survey of recent techniques for moving cast shadow detection. Cast shadows need careful consideration in the development of robust dynamic scene analysis systems. Cast shadow detection is critical for accurate object detection in video streams and their misclassification can cause errors in segmentation and tracking. The survey covers methods in a feature-based taxonomy comprised of 3 categories: chromacity, geometry and texture that are analysed either in a chronological manner or parallel manner. A number of moving cast shadow detection methods have been developed which has its own advantages and disadvantages.

Index Terms— cast shadows, feature-based, light source, literature review, segmentation, shadow removal, tracking.

1 Introduction

Many computer vision applications dealing with video require detecting and tracking moving objects and often required to differentiate between objects and their shadows. Consequently, shadow detection is useful in many applications including scene interpretation, image segmentation, object recognition and tracking. Shadows are major issue for object recognition in video sequences- as a shadow has similar dynamics to the object it is cast by. Further, shadow points are easily misclassified as foreground since they typically differ significantly from the background. For these reasons, in object recognition, shadow identification is critical for both image sequences (video) and still images. Automated video surveillance systems require mechanisms for tracking objects in the field of view. In object tracking, cast shadows can be classified as objects due to their visual characteristics. Hence the misclassification of shadows may result in object merging and shape alteration, which may cause significant confusion to the tracking system.

A survey on moving cast shadow detection conducted by Prati & etal.,(2003), classified algorithms using two layer taxonomy- that is deterministic and statistical approaches, based on whether the decision process introduces and exploits uncertainty. From each class, the authors selected one algorithm to do a comparative evaluation. The main conclusion was that only the simplest methods were suitable for generalisation, but in almost every particular scenario the results could be significantly improved by adding assumptions. As a consequence, there was no single robust shadow detection technique and it was better for each particular application to develop its own technique according to the nature of the scene. Since the review by Prati & et al., many new methods have been proposed.The proposed survey categorize the cast shadow detection.

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Alternative ways of classifying cast shadow detection algorithms exists and this paper proposes the combination of feature-based methods either in a chronological or parallel manner. There is a large volume of literature on shadow detection and it is not practical to detail the precise contribution of each publication; the survey conducted in this paper is therefore based on a selection of recent key papers representative of the distinct features to shadow detection that have been proposed. For clarity of presentation, the paper is organised as follows: Section 2 describes the features of the moving cast shadows, Section 3 describes few methods for chronological processing of the features, and Section 4 describes few methods for parallel processing of the features. Finally, advantages and disadvantages of the methods are discussed and the paper is concluded.

2 Features Describing Moving Cast Shadows

At a broader sense, features are classified as spectral, spatial and temporal [7]. The choice of features has a greater impact on shadow detection results compared to the choice of algorithms. Furthermore, the spectral features are divided into intensity, chromacity and physical properties. The spatial features are classified into geometry and textures.

2.1 Intensity

The simplest assumption that can be used to detect cast shadows is that regions under shadow become darker as they are blocked from the illumination source. Furthermore, since there is also ambient illumination, there is a limit on how much darker they can become. These assumptions can be used to predict the range of intensity reduction of a region under shadow, which is often used as a first-stage to reject non-shadow regions. However, there are no methods which rely primarily on intensity information for discriminating between shadows and objects.

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2.2 Chromacity

Most shadow detection methods based on spectral features use colour information. They use the assumption that regions under shadow become darker but retain their chromacity. Chromacity is a measure of colour that is independent of intensity. For instance, after a green pixel is covered by shadow it becomes dark-green, which is darker than green but has the same chromacity. This colour transition model where the intensity is reduced but the chromacity remains the same is referred to as colour constancy or linear attenuation. Methods that use this model for detecting shadows often use a colour space with better separation between chromacity and intensity than the RGB colour space.

2.3 Physical properties

The linear attenuation model assumes that the illumination source produces pure white light, which is often not the case. In outdoor environments, the two major illumination sources are the sun (white light) and the light reflected from the sky (blue light). Normally, the white light from the sun dominates any other light source. When the sun's light is blocked, the effect of sky illumination increases, shifting the chromacity of the region under shadow towards the blue component.

2.4 Geometry

In theory, the orientation, size and even shape of the shadows can be predicted with proper knowledge of the illumination source, object shape and the ground plane. Some methods use this information to split shadows from objects. The main advantage of geometry features is that they work directly in the input frame; therefore they do not rely on an accurate estimation of the background reference.

2.5 Textures

Some methods exploit the fact that regions under shadow retain most of their texture. Texture-based shadow detection methods typically follow two steps: i) selection of candidate shadow pixels or regions, and ii) classification of the candidate pixels or regions as either foreground or shadow based on texture correlation. Selection of shadow candidate is done with a weak shadow detector, usually based on spectral features. Then each shadow candidate pixel is classified as either object or shadow by correlating the texture in the frame with the texture in the background reference. If the candidate's texture is similar in both the frame and the background, it is classified as a shadow.

2.6 Temporal Features

Finally, since moving cast shadows share the same movement pattern as the objects that produce them, the same temporal consistency filters that have been applied to the objects can be applied to the shadows. This filtering usually enhances the detection results by keeping only the pixels that are consistent time. However, as with the intensity features, there are no methods which rely primarily on temporal features for shadow detection.

3. METHODS ANALYSING THE FEATURES IN CHRONOLOGICAL ORDER

3.1 Chromacity based methods

Choi and et al.,[2] proposed an adaptive shadow estimator to detect and eliminate the shadow of moving object while adapting to variation of illumination and the environment in an automatic manner. It discriminates between the shadow and the moving object by cascading three estimators which use the properties of chromacity, brightness and local intensity ratio.

First, a background is made in real time using the input images. This method assumes that the background does not change and Gaussian mixture model (GMM) is used to estimate it. The set of moving pixels is obtained by subtracting the estimated background image from the current image and this differential image includes the moving object pixels as well as the shadow pixels. The 1st candidate set of shadow pixels, the 2nd set of shadow pixels and the final candidate set of shadow pixels are defined as the set of pixels which are determined to be the shadow pixels by the chromacity difference estimator, brightness difference estimator and local relation estimator, in that order. The mean and standard deviation of chromacity difference and the brightness difference estimators are calculated using maximum likelihood estimation (MLE) as follows:

$$m_{CD}^{K} = \frac{1}{N_M} \sum_{p(x,y)\in M} CD^{K}(x,y), \qquad m_{BD}^{K} = \frac{1}{N_M} \sum_{p(x,y)\in M} BD^{K}(x,y),$$

$$(\sigma_{CD}^{K})^2 = \frac{1}{N_M} \sum_{p(x,y)\in M} (CD^{K}(x,y) - m_{CD}^{K})^2 \quad (\sigma_{BD}^{K})^2 = \frac{1}{N_M} \sum_{p(x,y)\in M} (BD^{K}(x,y) - m_{BD}^{K})^2 \tag{1}$$

Finally, in spatial adjustment step, the method compensates for accumulated errors in the cascading process.

Amato and et al., suggested a method by assuming that in luminance ratio space, a lower gradient constancy is present in all shadowed regions due to a local color constancy effect caused by reflectance suppression. To detect the moving cast shadows, all pixels in the frame image must be previously segmented into background and motion regions and this algorithm works only on the motion areas. To obtain a binary mask of motion regions, a standard background subtraction algorithm is used. To detect regions with local color constancy, first the luminance ratio for a single pixel is calculated as:

$$D(x) = \frac{L^{bg}(x) + v}{L^{im}(x) + v} \tag{2}$$

where $L^{im}(x)$ denote the pixels belonging to cast shadows in the current frame and $L^{bg}(x)$ those that do not and v is a quantization constant, which is chosen to unity for the standard

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eight bit input signal. When the background image is divided by the current image, the luminance ratio image D is segmented into two types of regions: foreground images where $2^{-8} \le D(x) \le 1$ and shadow like regions where $1 \le D(x) \le 2^8$.

3.2 Chromaciy & Texture-based method

Sanin and etal.,[7] proposed a method that uses chromacity and gradient information to achieve high shadow detection rate and shadow discrimination rate at the same time. The method has five steps: (i) Pre-selection of shadow pixels based on chromacity invariance: A pixel p is considered to be part of a shadow if:

$$\alpha \le \left(F_p^{\,v} - B_p^{\,v}\right) \le \beta$$
$$\left(F_p^{\,s} - B_p^{\,s}\right) \le \tau_s \;\&\; \left|F_p^{\,H} - F_p^{\,H}\right| \le \tau_H \qquad (3)$$

In the above equation, $F_p^{\,C}$ and $B_p^{\,C}$ represent the component values, C, of HSV for the pixel position p in the (F) and in the background reference (B) image, respectively, $\alpha, \beta, \tau_s, \tau_H$ represents the thresholds that are optimised empirically.

(ii) Grouping of shadow pixels based into candidate shadow pixels: Connected components are extracted from the resulting mask, with each component corresponding to a candidate shadow region.

(iii) Selection of pixels with significant gradient magnitude in each region: For each connected component, the gradient magnitude $\left|\Delta_p\right|$ and gradient direction θ_p at each pixel p=(x,y) are calculated using:

$$\left|\Delta_p\right| = \sqrt{\Delta x^2 + \Delta y^2}$$
$$\theta_p = \arctan 2\left(\frac{\Delta_y}{\Delta_x}\right) \qquad (4)$$

(iv) Calculation of the gradient direction distance between the given frame and the background reference image for each selected pixel: For each pixel p=(x,y) that was selected due to significant magnitude , the difference in gradient direction between frame F and background B is calculated:

$$\Delta\theta p = \arccos\left[\frac{\Delta_x^F \Delta_x^B + \Delta_y^F \Delta_y^B}{\left\{\left(\Delta_x^{F^2} + \Delta_y^{F^2}\right)\left(\Delta_x^{B^2} + \Delta_x^{B^2}\right)\right\}^{\frac{1}{2}}}\right] \qquad (5)$$

Since the gradient direction is a circular variable, the difference has to be calculated as angular distance.

(v) The gradient direction correlation between the frame and the background is estimated using:

$$c = \left\{\sum_{p=1}^{n} H\left(\tau_\alpha - \Delta\theta_p\right)\right\} / n \qquad (6)$$

where n is the number of pixels selected in the candidate shadow region and H(.) is the unit step function which, in this case evaluates to 1 if the angular difference is less than or equal to the threshold τ_α, and 0 otherwise. In essence, c is the fraction of pixels in the region whose gradient direction is similar in both the frame and the background. If c is greater than the threshold τ_α, the candidate region is considered a shadow region and it is removed from the foreground mask.

3.3 Chromacity & Geometric –based method

Zhu and etal.,[9] presented a shadow removal method with background difference method based on shadow position and edge attributes. First, a novel background subtraction method is used to obtain the moving objects and its edges. Second, the shadow suppression is done using HSV color space first and then the direction of shadow is determined by shadow edges and positions combining with the horizontal and vertical projections of the edge image, respectively, the position of the shadow is located accurately through proportion model, the shadow can be removed finally.

The HSV color space can reflect the intensity and color information better than a RGB color space, and it has better color perception consistency in HSV color space. In shadow detection , relative to the pixels of background region, V component becomes smaller with big change, which helps to distinguish shadows from foreground regions. S component has little value and its difference with the background will be negative. H component varies hardly. However, shadow suppression in HSV color space is not reliable when the background brightness is low or the background has similar chrominance with foreground. To overcome the shortcomings, this method uses the shadow position and shadow edge attributes after HSV suppression.

In order to locate shadow position, each frame of the edge video sequence PVOPalpha$_n$(j,i) is projected to horizontal and vertical directions respectively as shown in the below equation:

if (pVOPalpha$_n$(j,i) == 255)
Horizontal$_n$[i]=Horizontal$_n$[i]+1; (7)
Vertical$_n$[j]=Vertical$_n$[j]+1;

After accurately locating the shadow position, count the pixel values of each line and column in horizontal and vertical directions of shadow region. In the shadow region, comparing the pixel values of each row or each column, once the number is smaller than the threshold obtained by experiments, the row or column is removed by setting the value as zero in the edge image, that the shadows will be eliminated from. That is the key to keep moving objects extracted completely.

4. Methods Analysing the Features in a Parallel Mode

4.1 Chromacity-based method

Sun and etal.,[10] proposed a novel moving cast shadows de-

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tection approach using combined color models. In the first step, the ratio of hue over intensity is employed to determine whether the pixel is a shadow pixel or not. Because the intensity of shadow region is lower than that of object region, the HSI color model can reflect this problem better than other models, such as RGB, YUV. Here, the ratio of the hue over the intensity is applied. The following equation is aimed to transform RGB into HIS color model.

$$\begin{bmatrix} 1 \\ V1 \\ V2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\frac{\sqrt{6}}{6} & -\frac{\sqrt{6}}{6} & \frac{\sqrt{6}}{3} \\ \frac{1}{\sqrt{6}} & -\frac{2}{\sqrt{6}} & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (8)$$

$$S = \sqrt{V_1^{\,2} + V_2^{\,2}}$$

$$H = \tan^{-1}\left(\frac{V_1}{V_2}\right), if V_1 \neq 1$$

$$H = undefined, otherwise$$

In the HSI color model , H and I components denote the hue and intensity components respectively. In the second step, three Gaussian models in color model c1c2c3 are established to detect shadows. The c1c2c3 invariant color features can be adaptive to variable illumination conditions. A spectral property of shadows can be derived by considering photometric color invariants. Photometric color invariants are functions which describe the color configuration of each point discounted by shadows and highlights. These functions are demonstrated to be invariant to changes in viewing direction and illumination condition. One of the typical photometric color invariants is color model c1c2c3 and c1c2c3 is defined as follows.

$$c1 = \arctan\left[\frac{R}{\max(G,B)}\right] \quad (9)$$

$$c2 = \arctan\left[\frac{G}{\max(R,B)}\right]$$

$$c3 = \arctan\left[\frac{B}{\max(R,G)}\right]$$

Where R, G, B is the corresponding value of red, green and blue component of a pixel.

The block diagram of this shadow detection procedure is illustrated in Figure 4.1. Finally, two shadow images are got from the two color models and a rough shadow image by synthesizing the above two images using logical operation. Post Processing is used to correct failed shadowevaluation e and object detection in order to improve the accuracy of shadow detection.

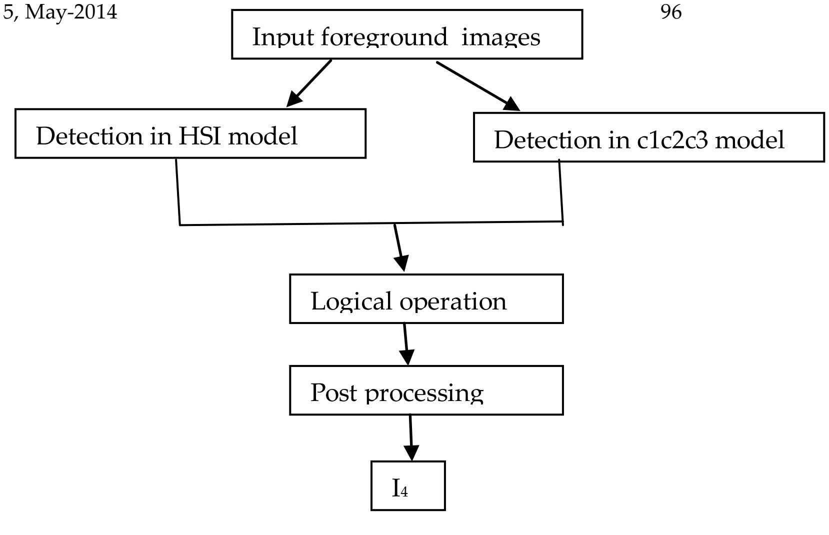

Figure 4.1 Block Diagram of shadow detection using combined color model method

4.2 Texture- based method

Meher and Murty[5] proposed an efficient method for the discrimination of moving object and moving shadow regions in a video sequence, with no human intervention. The workflow of the method is shown in Figure 4.3. At first, the moving regions are segmented using mean-shift (MS) algorithm. The segmentation operation effectively separates the homogeneous regions from the rest. The searching of shadow regions from these segmented regions is then made from 8 different directions of the frame as shown in Figure 4.2. In this process, all homogeneous regions at the border are first obtained. The nearby regions are merged with the previous detected regions based on the homogeneity difference estimated through variance of two regions. To reduce the computational burden, statistical analysis is done, where the whole regions are analysed using PCA with two principal axes which reduces the search space 1:4.

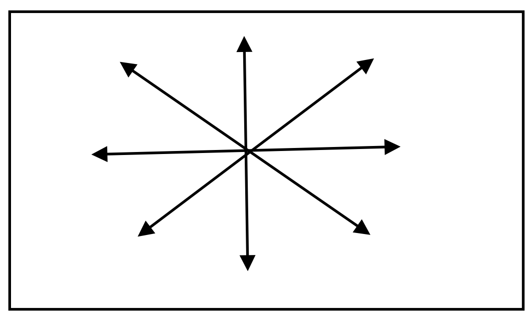

Figure 4.2: Eight directions of shadow search for a particular frame.

4.3 Multiple Features: Color & Texture

Qin and etal.,[6] proposed a novel algorithm for detection of moving cast shadows, based on local texture descriptor called Scale Invariant Local Ternary Pattern (SILTP). An assumption is made that the texture properties of cast shadows bears similar patterns to those of the background beneath them. The likelihood of cast shadows is derived using information in both color and texture. A flow diagram of this algorithm is illustrated in Figure 4.2. For each pixel p, a background model is learned by the nonparametric KDE method in the RGB

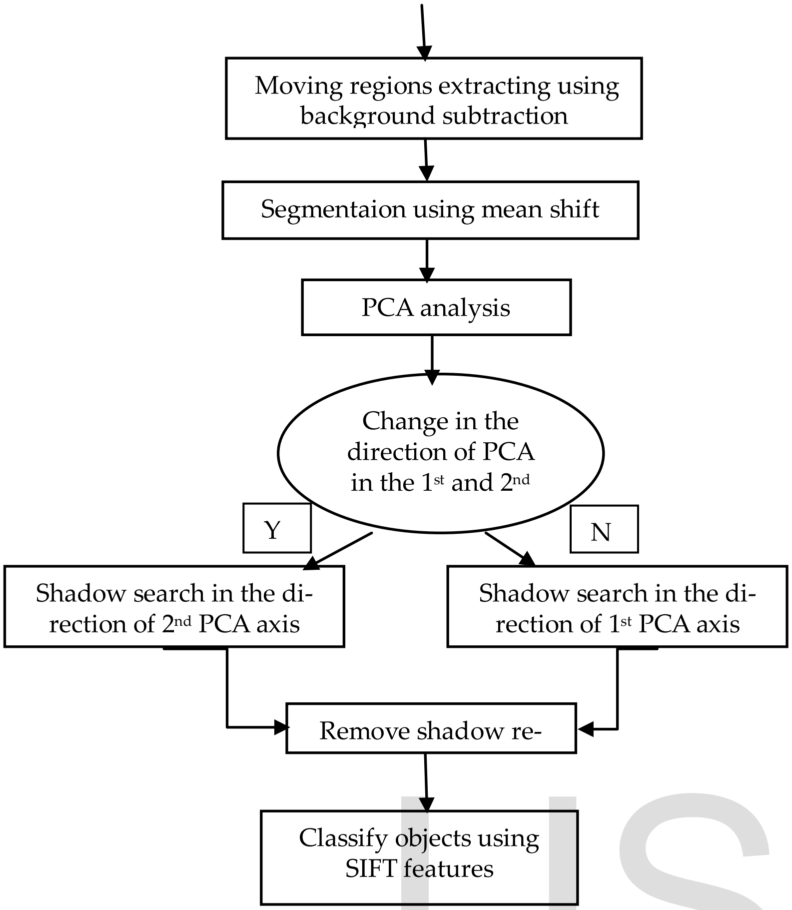

Figure 4.3: Schematic flow diagram of the PCA based method of shadow removal and object classification

space, from which the foreground probability can be estimated. After that, potential moving objects are segmented, and within it evaluation of the likelihood probability of cast shadows over both the color and texture domain as follows

$$P(MP \mid S, p) = \sum_{i=1,2} P(MP \mid D_i, S, p) P(D_i \mid S, p) \qquad (10)$$

where MP denotes potential moving pixels, S denotes shadow, D1 and D2 represent the texture and color domains respectively.

The shadow model in texture space is created using the SILTP encoded for any pixel location (x_c,y_c) as

$$SILTP^{\tau}_{N,R}(x_c, y_c) = \oplus_{K=0}^{N-1} S_{\tau}(I_c, I_k) \qquad (11)$$

where I_c is the gray intensity value of the center pixel, I_k(k=0,1,…N-1) are that of its N neighbourhood pixels equally spaced on a circle of radius R[1], symbol is defined as concatenation operator of binary strings, and S_τ denotes a piecewise function defined as

$$S_\tau(I_c, I_k) = \begin{cases} 01, if I_k > (1+\tau) I_c, \\ 10, if I_k < (1-\tau) I_c, \\ 00, otherwise \end{cases} \qquad (12)$$

Gaussian mixture model (GMM) is applied with two states to learn a universal likelihood distribution of such distance as the shadow model in texture space. SILTP can represent shadows similar with the corresponding backgrounds, thus

Table 1 Comparison of various feature based methods

Method	Pros	Cons
Chromacity based methods	Easy to implement. Computationally inexpensive.	Sensitive to noise and Fail whe ow regions are darker and objects have similar color info with background.
Geometry based methods	Efficient than chrominance invariant method. Works well when the color of background is similar to texture color of moving objects.	Need prior knowledge abou ground,illumination sources, conditions etc.,
Texture based methods	Independent of color information and against illumination changes.	Fail when moving objects and regions possess similar textu mation with corresponding ground information.

discriminating them from moving objects. Yet it also shows that with SILTP some flat surfaces of moving objects are also similar with the flat background regions. However, in this case the surface colors of the two are different. Therefore a color shadow model is also learned for a complement with textures. A GMM with 5 components is adopted to learn the parameter distribution as a color shadow model. The likelihood of cast shadows is derived using information in both color and texture. An online learning scheme is employed to update the shadow model adaptively. Finally, the posterior probability of cast shadow region is formulated by further incorporating prior contextual contraints using a Markov Random Field(MRF) model. The optimal solution is given using graph cuts.

5. COMPARISON

The comparison of the individual feature-based methods is given in the Table 1. The methods discussed above use either single or multiple features to detect the moving cast shadows either in a chronological order or parallel manner. The single

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feature methods lead to misclassification for moving cast shadows. Hence multiple feature fusion is becoming an active research area and exhibits a significant trade-off between the features. The methods described in Section3 are using multiple features and the flow of extracting them is in a sequential manner. The methods described in Section4 are using multiple measures of single feature or simply multiple features to extract the shadow information in a parallel manner. When compared with the methods working in a serial fashion, simultaneously feature extraction exhibits excellent performance.

6 Conclusion

In this paper, a survey of various moving cast shadow detection methods based on the features analysed either in a chronological order or parallel manner is presented. The features are categorised as chromaciy, texture and geometry and the methods discussed use either one of the features or various measures of a single feature or multiple features to detect the moving cast shadows effectively to perform the object detection or analysis in various dynamic scene analysis, video surveillance applications. The features used for detecting moving cast shadows and the way of analysing them, they decide on the effectiveness of the algorithm design. When compared to chronological order, the survey shows parallelism shows better performance.

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