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Moving-object Detection Based on Shadow Removal and Prospect Reconstruction

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Abstract. In the process of moving target detection, moving objects and their shadows are often extracted both. It leads to the failure of moving target positioning, segmentation, tracking and classification in the moving-object detection. Thus the shadow removal is an important task in the intelligent monitoring system. In the process of shadow removal, using color features to detect shadow is easy to cause that some parts of the prospect with the same color as the shadow may be mistakenly removed, so that have an impact on the connection and integrity of the prospect. In this paper, in order to obtain a complete prospect as well as remove shadow, we propose a moving target detection algorithm based on shadow removal and prospect reconstruction. Our algorithm can effectively restore the prospect which is mistakenly removed as shadow, and the experimental results confirm our algorithm.

1. Introduction

Video surveillance system is an important part of security system. Because of the advantage of intuitive, accurate and rich content, video surveillance is widely used in many occasions. In the video sequence analysis, moving-object detection plays an important role that its result can be used to describe the features of the two-dimensional moving objects. However, in many practical scenarios, we often extract the moving objects with the shadows caused by blocking the light, shown in Fig. 1. It may lead to the failure of positioning, segmentation, tracking and classification of moving target in the moving-object detection. Thus the shadow removal is not only a primary step in the process of the moving-object detection, but also a hot issue and an active field in the research of intelligent monitoring system.

There are two important features which bring the shadow removal extremely difficulties as follows:

(1) The shaded region is so different from the background region. It may be mistakenly segmented into prospect region.

(2) The shaded region has the same motion properties as the moving objects. Shadows could connect the moving objects tightly.

(a) Initial video frames.

(b) Binary frames corresponding to (a).

Fig. 1. Moving objects extraction.

In order to remove shadows, there are many methods for shadow detection with a majority of them based on following two categories: Model-based and feature-based method. Model-based method uses prior information (e.g., scenes, moving objects and illumination conditions, etc) to establish shadow models. According to the input video, Akio et al. [1] propose a two-dimensional vehicle / shadow joint model to estimate its parameter and category, through which extract the shadow from the vehicle. However, this kind of method needs so much prior information, such as three-dimensional constitution of the scene and model description of the prospect objects, that can only apply to special scenes. Also, its complex computation is not suitable for real-time applications. Feature-based method identifies the moving objects and their shadows via analyzing features (e.g., color, gradient, texture, etc) of the video sequences. Ref. [2] is such a typical algorithm that uses the luminance variation and chrominance offset of pixels in normalized RGB space to distinguish shadows from moving objects. In YUV space, Cucchiara et al. [3] use the property of shadow linearly reduces the value of the pixels of the covered background to identify the shadow. In HSV space, Nicolas et al. [4] present a method based on the variation of luminance, chrominance, saturation to establish the shadow model. Color-based method is always sensitive to the luminance variance of the scenario. If the partial pixels of the moving objects have the same color feature as the shadow, these pixels may be mistaken for shadows to be removed. In Ref. [5], assuming that the shadow gradient changes slowly, gradient filtering is used to remove the shadow of the input image. This method is efficient to indoor scenarios with simple background and weak shadow, but not to the shadow edge removal. Hoang et al. [6] introduces a texture-based object extraction, on the basis of shadow does not change the texture of background. Though it can remove the shadow, it has a large amount of computation and it is difficult to set the threshold.

2. Shadow removal based on normalized *RGB*

Based on little change in pixel value when shadow appears, Wang [2] introduces a hybrid color space to suppress the shadow. It suppresses the shadow in different color spaces when pixel X has different luminance:

$$x = \begin{cases} (r, g, I)\, if \quad I \geq Itd \\ (R, G, I)\, if \quad I < Itd \end{cases}, \tag{1}$$

where r and g is the normalized component R and G in RGB color space, and I represents the luminance:

$$\begin{cases} r = R/\left(R+G+B\right) \\ g = G/\left(R+G+B\right). \\ I = \left(R+G+B\right)/3 \end{cases} \tag{2}$$

Eq. 1 shows that it suppresses the shadow in (r, g, I) space when luminance of the scenario is higher than threshold Itd and in space (R, G, I) when the luminance is lower. Since in the low light condition, the values of r and g of the background pixels have no regular variance before and after being covered by shadow. It may cause false detection. Therefore, it is necessary to combine the two color spaces to suppress the shadow.

Ref. [2] assumes that in (r, g, I) space, the value of background pixel is (r_b, g_b, I_b) and the current pixel value is (r_t, g_t, I_t) which represents the shadow, then,

$$\begin{cases} \beta \le I_t / I_b \le 1 \\ r_b = r_t \\ g_b = g_t \end{cases} . \tag{3}$$

3. Moving-object detection based on shadow removal and prospect reconstruction

The shadow removal method introduced above is real-time and has little computation. However, the image FM_{sn} in the Fig. 2 (c), representing the result of operating shadow removal algorithm on the original prospect image FM, shows that some prospect part with the same color as shadow is mistakenly removed. It may affect the connection and integrity of the prospect objects. In this paper, we propose a moving-object detection algorithm based on shadow removal and prospect reconstruction to obtain an integrate prospect. The reconstruction algorithm combines the binary image of integrated prospect with set operation. The experimental results prove that our algorithm can efficiently repair the prospect which is misinterpreted as shadow to be removed.

(a) 100,198,394 frames of the initial video.

(b) Moving objects extraction.

(c) Color-based shadow removal and denoising.

(d) Repaired image using mophological dilate operation.

Fig. 2. Shadow removal based on RGB color space.

Generally, operating morphological dilate on the image FM_{sn} can connect small faults and holes. However, the attempt to use dilate operation alone to get the fully connected region may lead to over-expansion. The obtained target is quite larger than the real size. It will mislead the target feature computation in the next step, such as centroid, area, and contour, etc. Thus, we just take a small-scale dilation to get the image FM_{sne} , seen in Fig. 2 (d).

We define $FM_{sne}^{comp\_k}$ as the k th connected component of the dilated image FM_{sne} , where $k = 1, 2, \cdots$ represents the number of connected components. The bounding rectangle of each connected component is presented as:

$$\mathrm{Re}c^{comp\_k}\left(W_1^k, W_2^k, L_1^k, L_2^k\right), \quad k = 1, 2, \cdots \quad , \tag{4}$$

where $W_1^k = \min\limits_{\substack{x \\ P\in FM_{sne}^{comp\_k}}} \left\{P(x,y)\right\}$, $W_2^k = \max\limits_{\substack{x \\ P\in FM_{sne}^{comp\_k}}} \left\{P(x,y)\right\}$, $L_1^k = \min\limits_{\substack{y \\ P\in FM_{sne}^{comp\_k}}} \left\{P(x,y)\right\}$, $L_2^k = \max\limits_{\substack{y \\ P\in FM_{sne}^{comp\_k}}} \left\{P(x,y)\right\}$.

We choose any two from the connected component set $FM_{sne}^{comp\_k}$, denoted by $FM_{sne}^{comp\_i}$, $FM_{sne}^{comp\_j}$, to find out that whether both of them belong to the same connected component or not. If they belong to the same connected component, in order to avoid mistaking the shadow in the original binary image as the same connected component, we calculate the distance between their bounding rectangles. When the distance is within a certain threshold, we merge the two connected component into one.

$$\begin{aligned} & if \quad D\_Rec < Th \\ & \mathrm{Re}c^{comp\_i}\left(W_1^i, W_2^i, L_1^i, L_2^i\right) = \left\{\mathrm{Re}c^{comp\_i}\left(W_1^i, W_2^i, L_1^i, L_2^i\right), \quad \mathrm{Re}c^{comp\_j}\left(W_1^j, W_2^j, L_1^j, L_2^j\right)\right\} \end{aligned} \quad , \tag{5}$$

where $\mathrm{Re}c^{comp\_i}\left(W_1^i, W_2^i, L_1^i, L_2^i\right)$ and $\mathrm{Re}c^{comp\_j}\left(W_1^j, W_2^j, L_1^j, L_2^j\right)$ are bounding rectangles of the two connected components. The midpoints of the each side of the two bounding rectangles can be denoted by $\left(R^{comp\_i}(x_1, y_1), R^{comp\_i}(x_2, y_2), R^{comp\_i}(x_3, y_3), R^{comp\_i}(x_4, y_4)\right)$ and $\left(R^{comp\_j}(x_1, y_1), R^{comp\_j}(x_2, y_2), R^{comp\_j}(x_3, y_3), R^{comp\_j}(x_4, y_4)\right)$. Calculate the Euclidean distance between every two midpoints, we can obtain sixteen distances:

$$d_t = \sqrt{\left(x_{t1} - x_{t2}\right)^2 + \left(y_{t1} - y_{t2}\right)^2} . \tag{6}$$

From the sixteen distances, we choose the smallest one as the distance between two bounding rectangles D_Rec :

$$D\_Rec = \min_t\left(d_t\right). \tag{7}$$

After obtaining the expanded bounding rectangle, we search for the corresponding prospect pixels in original binary image to get the auxiliary reconstruction image FM_h. Finally, we make union operation on FM_{sne} and FM_h to obtain the reconstruction image FM_R :

$$FM_R = FM_{sne} \cup FM_h . \tag{8}$$

4. Experimental Results

The detailed algorithm steps are given as follows:

(1) Binarize the moving target image to get the original moving prospect image FM .

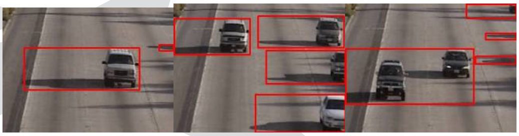
(2) Remove the shadow based on normalized *RGB* algorithm to get the shadow removal image FM_s.

(3) Combine the projection filter and median filter to remove noise from FM_s, and get the denoised image FM_{sn}.

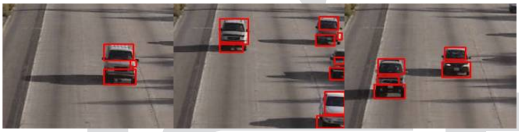
(4) Use morphological dilation to repair and connect the small faults several times, and get repaired image $FM_{sne} = \left(\left(\cdots\left(FM_{sn} \oplus N\right) \oplus N\right) \oplus \cdots\right) \oplus N$, where N is $3*3$ dilated structure operator.

(5) Use the prospect reconstruction method proposed above to get the integral image FM_R.

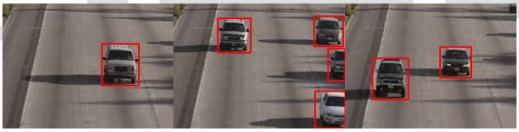
In this paper, campus scene and standard test video are selected to verify the validity of our algorithm. Fig. 3 and Fig. 4 give the experimental results based on our proposed method on the sequence of Standard Test Video – Highway I_Raw and pedestrians in a campus scene at night respectively. We can conclude from Fig. 3 (a) that moving objects and their shadows are all detected without shadow removal which severely affects positioning the moving objects. Fig. 3 (b) is the result of color-based shadow removal [2]. Even though it removes the shadow successfully, the integrity and connectivity are both not achieved. The result of our proposed algorithm is shown in Fig. 3 (c) which gets precise real moving objects and their bounding rectangles. This experimental result demonstrates that our proposed method not only successfully removes the shadow, but also reconstructs the prospect which mistakenly removed as shadow. But from Fig. 4 (c), there is still some other object remains. Since the original moving-object detection is not precise enough.



(a) Moving objects detection without shadow removal.



(b) Moving objects detection with color-based shadow removal [2].



(c) Moving objects detection based on our proposed algorithm.

Fig. 3. Moving objects detection based on shadow removal and prospect reconstruction.

(a) Moving objects detection without shadow removal.

(b) Moving objects detection with color-based shadow removal [2].

(c) Moving objects detection based on our proposed algorithm.

Fig. 4. Moving objects detection based on shadow removal and prospect reconstruction.

5. Conclusions

In this paper, we introduce a shadow removal method based on normalized RGB . We also propose a moving-object detection algorithm based on shadow removal and prospect reconstruction which combines binary image of integrated prospect with set operation to recovery the real prospect. From the comparison experiments, we can conclude that our algorithm reconstruct the prospect very efficient and robust and improve the accuracy of the moving-object detection, which makes a solid foundation on the subsequent work.

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