Research Journal of Applied Sciences, Engineering and Technology 6(24): 4642-4645, 2013
ISSN: 2040-7459; e-ISSN: 2040-7467
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Submitted: February 27, 2013 Accepted: April 02, 2013 Published: December 25, 2013

Moving Target Detection and Tracking

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Abstract: This study proposes a background update algorithm based on the correlation coefficient, overcome the shortcomings of fuzzy image of the average background updating. Then, it uses subtraction background method to detect moving targets and record the moving target region and use projection histogram to resize the center of the target and calculate the confidence coefficient of the current frame and the subsequent frame to research the center of the target in the subsequent frames. Then, the moving target could be tracked in the subsequent frames. The experimental results show that the algorithm can accurately detect and automatically track moving targets.

Keywords: Background update, projection histogram, track

INTRODUCTION

The problem of tracking non-rigid targets and recognizing them in video sequences is of increasing importance to many applications. Examples include a motion detector in video surveillance systems, action analysis for animation medical imaging and Human Computer Interaction (HCI). Tracking a deformable target in consecutive frames is of particular concern in video surveillance systems. There have been various researches for video-based target extraction and tracking. One of the simplest methods is to track regions of difference between a pair of consecutive frames (Haritaoglu *et al*., 2000) and its performance can be improved by using adaptive background generation and subtraction. Although the simple difference-based tracking method is efficient in tracking an target under noise-free circumstances, it often fails under noisy, complicated background. The tracking performance is further degraded if a camera moves either intentionally or unintentionally. For tracking targets in the presence of shadows, noise and occlusion, a non-linear target feature voting scheme has been proposed in Amer (2003). As an alternative method to frame difference based tracking, a blob or region tracking, can be used to locate the centroid of an target. Based on the assumption of stationary background, Wren *et al*. (1997) proposed a real-time blob tracking algorithm. Another blob tracking methods that use targets histogram and mean shift approach have been proposed in Comaniciu *et al*. (2003).

This study proposes a background update algorithm based on the correlation coefficient, overcome the shortcomings of fuzzy image of the average background updating. Then, it uses background subtraction method to detect moving targets and record the moving target region and adopts projection histogram method to track moving targets.

METHODOLOGY

Background method: We randomly save the current scene in which no targets are moving as the background. But the scene will be change according to time, light and weather condition and so on. It is necessary to update background in real time. Therefore, the paper proposes a method to update background. The main steps are shown in the following:

- Saving the current scene image and divided into the scene image matrixes of size 16*16
- Calculating the scene image matrixes' variance
- Dividing the background image into the matrixes of size 16*16, and calculating their variance
- Calculating covariance and correlation coefficient ρ between the scene image matrix of size 16*16 and its corresponding background matrix
- Comparing ρ and threshold, if ρ is bigger than threshold, using the scene image in place of its corresponding background image, otherwise, saving the original background image

Correlation coefficient:

$$\rho = \frac{\operatorname{cov}(B, I)}{\sqrt{D_B + D_I}} \tag{1}$$

where,

B, I : The ground image and the scene image of size M*N, their two-dimensional matrixes are expressed as f (x, y), g (x, y), (1≤x≤M, 0≤y≤N)

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cov (B, I) : Two-dimensional matrixes' covariance
D_B, D_I : Variance of B and I

Cov (B, I), D_B, D_I are described as:

$$\mathrm{cov}(B,I)=\frac{1}{M*N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(f(i,j)-\bar{B})(g(i,j)-\bar{I}) \tag{2}$$

$$D_B=\frac{1}{M*N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(f(i,j)-\bar{B})^2 \tag{3}$$

$$D_I=\frac{1}{M*N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(g(i,j)-\bar{I})^2 \tag{4}$$

where, $\bar{B}$, $\bar{I}$ stand for B and I's mean ρ∈ [-1, 1]. If ρ' s absolute value is more close to 1, the scene image is more same as the ground image. It's necessary to use the scene image in place of its corresponding background image. Otherwise, saving the original background image. Background updating model is shown in the following:

$$B_{t+1}\{i,j\}=\begin{cases} I_t\{i,j\}_{16*16},\rho_{i,j}>=k \\ B_t\{i,j\}_{16*16},\rho_{i,j}<k \end{cases} \tag{5}$$

where,
k : Threshold and generally is the value from 0.7 to 1
$I_t\ \{i,j\}_{16*16}$: The scene image of size 16*16 in row i and column j
$B_t\ \{i,j\}_{16*16}$: The background image of size 16*16 in row i and column j

Moving target detection method: The background image can be updated in real time, so we could use subtraction background method to detect moving target. Subtraction background method is shown in the following:

$$f(x)=\begin{cases} 255,|I_t(x)-B_t(x)|\geq T \\ 0,|I_t(x)-B_t(x)|\prec T \end{cases} \tag{6}$$

where,
I_t (x) : The scene image
B_t (x) : The background image in t time

The result of differential between I_t (x) and B_t (x) is shown in (6) after binarization processing. Where T is threshold and generally is the value from 5 to 15. x stands for the pixel position of the image.

Target tracking: We can record the moving target region in the method above and could lock the moving target in the window of size W×H. Then we use projection histograms as in Wang *et al*. (2006) to shift the middle bins of the histogram to the geometric center of the target. Specifically, the normalized horizontal (i.e., $\bar{H}_x$ (m) and vertical (i.e., $\bar{H}_y$ (n)) shape projection histograms are defined as follows:

$$\begin{aligned} &\bar{H}_x(m)=\{(x_i,y)\,|\,(x_i,y)\in R\}, \\ &\bar{H}_y(n)=\{(x,y_i)\,|\,(x,y_i)\in R\}, \\ &m=x_i-x+M/2, \\ &n=y_i-y+N/2. \end{aligned} \tag{7}$$

where,
(x, y) : The geometric center of the target (i.e., the center of the best-fitting ellipse)
m & n : Indices
M & N : The number of bins in the horizontal and vertical projection histograms

In order to reduce the effects of background noise and image outliers, we introduce weights to improve the robustness of the normalized shape projection histograms. This is done by employing an isotropic kernel function k (·) in a similar way as in Comaniciu *et al*. (2005). The role of the kernel function is to assign smaller weights to pixels farther away from the center bin of the project histogram. Then, the weighted target model histograms, denoted as $H^T{}_x$ (m) and $H^T{}_y$ (n), are defined as follows:

$$H_x^T(m)=\frac{\bar{H}_x(m)+k(.)}{\sum_{m=1}^{M}\bar{H}_x(m)+k(.)} \quad H_y^T(n)=\frac{\bar{H}_y(n)+k(.)}{\sum_{n=1}^{N}\bar{H}_y(n)+k(.)} \tag{8}$$

where, k (x_i, y_i) = c- [(x_i, x)^2 + (y_i - y)^2], c = (w/2 + 1)^2 + (h/2 + 1)^2 (i.e., computed from the size w×h of the target).

To find the targets in subsequent frames, we search a window of size W×H in the region of locking the moving target in first scene image. Then, candidate targets are identified in this window. The weighted target candidate projection histograms, denoted as $H^C{}_x$ (m) and $H^C{}_y$ (n), are defined as follows:

$$H_x^C(m)=\frac{\bar{H}_x(m)+g(.)}{\sum_{m=1}^{M}\bar{H}_x(m)+g(.)} \quad H_y^C(n)=\frac{\bar{H}_y(n)+g(.)}{\sum_{n=1}^{N}\bar{H}_y(n)+g(.)} \tag{9}$$

where,

$$g(x_i,y_i)=c-\{[(x_i-x)/h]^2+[(y_i-y)/h]^2\}$$

$$h=W*H\ ,c=(W/2+1)^2+(H/2+1)^2$$

To find the location of a target in subsequent frames, we use a ratio as the confidence coefficient of shape matching and it is defined below:

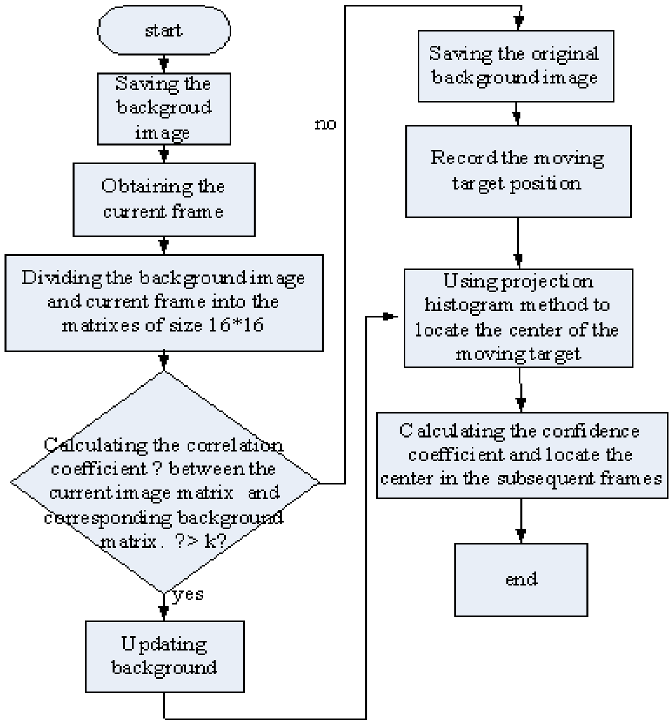


Fig. 1: The specific flow of the experiment

$$\xi_x(l) = \sum_{x_i \in R(l)} \sqrt{\frac{H^T_{x^k(l)}[x_i - x^k(l) + M/2]}{H^C_x[x^k(l) - x + M/2]}}$$

$$\xi_y(l) = \sum_{y_i \in R(l)} \sqrt{\frac{H^T_{y^k(l)}[y_i - y^k(l) + N/2]}{H^C_y[y^k(l) - y + N/2]}} \tag{10}$$

Then, the target center in the window of size W×H will be updated in the following:

$$x^k(l) = x^k(l-1) * \xi_x(l-1) \quad \mathrm{y}^k(l) = \mathrm{y}^k(l-1) * \xi_{\mathrm{y}}(l-1) \tag{11}$$

TEST RESULTS

We randomly save the current scene in which no targets are moving as the background in the experiment. Then, we update the background image and use subtraction background method to detect moving target. And lock the moving target in the window W*H. We use projection histogram to resize the center of the target and calculate the confidence coefficient of the current frame and the subsequent frame to research the center of the target in the subsequent frames. Then, the moving target could be tracked in the subsequent frames. The specific flow is shown in Fig. 1.

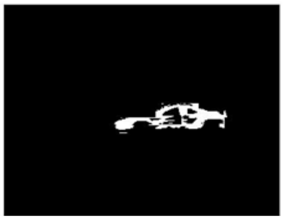
In experiment, the total number of frames is 120 and size of them is 320*240. The background frame is shown in Fig. 2. The current frame is shown in Fig. 3. The result of updating background is shown in Fig. 4 (k is set to 0.7).

Fig. 2: Background frame

Fig. 3: Current frame

Fig. 4: Updating background

After updating background, we can use subtraction background method to detect moving target and record the moving region. The result of recording the moving region is shown in Fig. 5 (a, b) (T is set to 15).



(a)

(b)

Fig. 5: Recording moving region

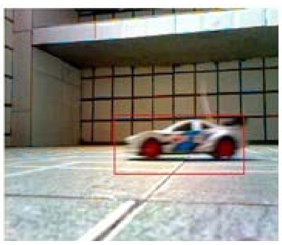
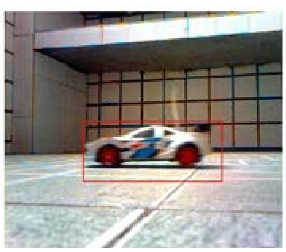


Fig. 6: Locking the moving target



(a)

(b)

Fig. 7: Tracking the moving target

We use projection histogram to resize the center of the target and calculate the confidence coefficient of the current frame and the subsequent frame to research the center of the target in the subsequent frames. Then, the moving target could be tracked in the subsequent frames. The result is shown in Fig. 6 and 7.

Table 1: Comparing between frame-based detection and projection histogram-based detection

	Total number of frames	Accurately track the number of frames	Accuracy rate (%)
Frame-based detection	345	310	89.9
Projection histogram-based detection	345	340	98.6

Table 1 is shown that projection histogram-based detection is more accuracy than Frame-based detection. It can more accurately detect and tracking moving target.

CONCLUSION

We have proposed a background update algorithm based on the correlation coefficient and uses subtraction background method to detect moving targets and record the moving target region and use projection histogram to resize the center of the target and calculate the confidence coefficient of the current frame and the subsequent frame to research the center of the target in the subsequent frames. Then, the moving target could be tracked in the subsequent frames. We use the algorithm in experiment and compared Frame-based detection and projection histogram-based detection. The experimental results show that the algorithm can accurately detect and automatically track moving targets.

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