DETECTION AND TRACKING OF MOVING OBJECTS IN IMAGE SEQUENCES WITH VARYING ILLUMINATION

Min Xu, Ruixin Niu, Pramod K. Varshney

Department of Electrical Engineering & Computer Science
Syracuse University, Syracuse, NY, 13244, USA
varshney@syr.edu

ABSTRACT

Change detection is known to be a significant and difficult research problem in automated surveillance systems. In this paper, we propose a new change detection approach based on the least squares method, which is robust to changes in illumination and shadow conditions. This new approach is employed to design our detection and tracking system that is shown to successfully detect a moving object in a complex outdoor environment.

1. INTRODUCTION

Detection of moving objects plays a very important role in real-time image analysis with many applications such as video surveillance for detection of intruders and traffic flow analysis. Frame differencing is widely used for change detection in dynamic image sequences. One key issue is robustness of the change detection algorithm. Robustness is essential to deal with variations in illumination and background. It is also desirable that the algorithm has real-time capability [1].

The existing change detection approaches can be classified into two categories: pixel-based and region-based methods. The most intuitive technique for change detection is to simply threshold the difference images [2]. Change detection at the pixel level requires less computation since only one pixel is considered at a time. But due to its very nature it is very sensitive to noise and illumination changes. Region based change detection approaches are more robust and are mostly adopted for applications in real environments. Some researchers have used statistical approaches, which use the difference image as the test statistic, e.g. Toth *et al.* [3] and Aach and Kaup[4]. Toth *et al.* assume that the image noise follows the Laplacian distribution. Then hypothesis testing by thresholding the sum of the absolute difference within a sliding window, which follows the χ^2 distribution, is carried out. A likelihood ratio test method is proposed by Aach *et al* [4]. It models the noises under different hypotheses as Gaussian distributions with different parameters. In order to obtain the probability density functions, some parameters like the variance need to be estimated first. But the estimate of variance is not accurate because it contains not only noise but also the texture information. Statistical approach is an effective way for change detection but it is difficult to obtain the distribution of noise in images. Therefore, the detection results are not good in complex environments. Li and Leung [2] present a change detection method using a weighted combination of the intensity difference and a texture difference measure based on the gradient vectors of corresponding variations rather than the raw intensity difference. But it has a relatively large computational requirement. Another change detection method proposed by Durucan and Ebrahimi [5] is based on a linear dependence model. Liu *et al.* [6] compare the Circular shift moments (CSM). But the illumination model they are based on does not include the ambient light. Therefore, it is not robust enough to deal with the illumination problem in the outdoor environment.

In this paper, a novel illumination invariant change detection method is proposed. It is derived from the least squares method in Section 2. In this method no noise distribution is assumed. This computationally efficient detection method is very effective in detecting the edges of the objects in complex environments especially under changing illumination conditions. However, it is less effective in homogenous regions of the moving objects. This method is quite successful in detecting moving objects in our detection and tracking system, because only the texture information of the objects is needed in the recognition process. An effective detection and tracking system includes change detection, object recognition, and object tracking. After change detection, the detected moving objects need be matched between frames of the video sequences. The Co-occurrence matrix-based features such as entropy have been proven to be powerful features to recognize the object. The whole detection and tracking

0-7803-8554-3/04/$20.00 ©2004 IEEE.

system is presented in Section 3. Simulation results are shown in Section 4. Concluding remarks are provided in Section 5.

2. CHANGE DETECTION BASED ON THE LEAST SQUARES METHOD

2.1 Illumination Model

According to the general illumination model, the intensity of a pixel is influenced by three factors, the ambient light, diffuse reflection, and specular reflection. Therefore, it can be represented as [2]

$$I_p = I^{amb} + I^L S_p \tag{1}$$

where I^{amb} and I^L are the intensities of the ambient light and the light source respectively, which may change as the time varies. $S_p = k_{diff} \cos\theta + k_{spec} \cos^n \phi$ is the shading coefficient of the pixel p, which is different for each pixel. k_{diff} and k_{spec} are the reflection coefficients, θ is the angle of incidence between the light-source direction and the normal of the surface, ϕ is the viewing angle relative to the specular reflection direction.

From the illumination model (1), we have for the two images under consideration

$$\begin{cases} I_{1p} = I_1^{amb} + I_1^L S_p \\ I_{2p} = I_2^{amb} + I_2^L S_p \end{cases} \tag{2}$$

Then, it is easy to show that

$$I_{2p} = a_p I_{1p} + b_p \tag{3}$$

where $a_p = \dfrac{I_2^L}{I_1^L}$, $b_p = I_2^{amb} - a_p I_1^{amb}$. This defines the pixel-by-pixel relationship between the two images. This illumination model based relation is used for change detection.

2.2 Least Squares Approach to Change Detection

We assume that a_p and b_p are constant within a small image region due to the smoothness of local illumination. Therefore, for I_{1i} and $I_{2i}, i = 1,2,...N$, within a small window (N is the number of the pixels within this window. In our experiment we have used a 5×5 window consisting of 25 pixels), the relationship $I_{2i} = a_p I_{1i} + b_p$ should hold in the absence of any changes. I_{1i} and I_{2i} can be considered as signal data ; a_p and b_p are unknown parameters.

The least squares error between the actual pixel intensities I_{2i} and the intensity predicted by the model given by (3) for pixel p is

$$J_p = \sum_{i=1}^{N} (I_{2i} - a_p I_{1i} - b_p)^2 . \tag{4}$$

By minimizing J_p, we can obtain the least squares estimates $\hat{a}_p$ and $\hat{b}_p$ [7]. We set the appropriate derivatives equal to zero. That is,

$$\text{That is, } \left.\frac{\partial J_p}{\partial a_p}\right|_{a_p = \hat{a}_p} = 0, \ \left.\frac{\partial J_p}{\partial b_p}\right|_{b_p = \hat{b}_p} = 0 \tag{5}$$

to obtain,

$$\hat{a}_p = \frac{\sum_{i=1}^{N} (I_{2i} - \overline{I_{2i}})(I_{1i} - \overline{I_{1i}})}{\sum_{i=1}^{N} (I_{1i} - \overline{I_{1i}})^2}, \ \hat{b}_p = \overline{I_{2i}} - \hat{a}_p \overline{I_{1i}} \tag{6}$$

where $\overline{I_{1i}} = \frac{1}{N}\sum_{i=1}^{N} I_{1i}$, $\overline{I_{2i}} = \frac{1}{N}\sum_{i=1}^{N} I_{2i}$

Then the minimum least squares (LS) error of pixel p can be computed as

$$J_{\min p} = \sum_{i=1}^{N} (I_{2i} - \hat{a}_p I_{1i} - \hat{b}_p)^2 \tag{7}$$

If the actual data fits the model (3) well, the LS error $J_{\min p}$ should be very small, that is to say, there are no changes except uniform changes between the corresponding pixels of the two images. If the LS error is large, it means that a change has occurred in the second image. Finally, we can make the change decision based on the following threshold test:

$J_{\min p} < T$: No change $Mask(p) = 0$;

$J_{\min p} > T$: There is a change $Mask(p) = 1$.

Mask is the binary image after change detection.

2.3 Thresholding Based on Euler Number

For real time change detection, adaptive threshold selection is quite important. A technique based on Euler numbers has been successfully applied to background subtraction to find the optimal threshold by Rosin [8] and Snidaro *et al.* [9]. In this paper, we use it to find the

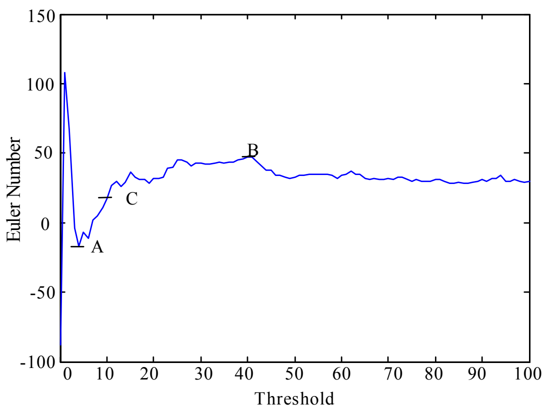

Fig.1. Euler Number against Threshold

optimal threshold for least square errors corresponding to two consecutive frames.

Fig. 1 shows a typical graph of the Euler number against the threshold. At the threshold that has a lower Euler number, like A, some noise still remains in the image even though the whole object can be detected. In the region of a stable Euler number, for any threshold, noise is completely removed. However, only the main edges of the object are visible.

The techniques proposed in [8] and [9] tend to select a threshold that produces stable Euler numbers. During our experiments, the thresholds from [8,9] were always found to be too high. Therefore, we use a threshold C that is the middle point between the minimum point A and the maximum point B in the stable area. Our experiments show that it yields best detection results. Fig. 3 (f), Fig. 3 (g) and Fig. 3 (h) show the detection results with thresholds set at C, A and B.

The method we propose in this paper can successfully detect the moving object in image sequences with low SNR. We can clearly detect the edges of the moving object adaptively. Another advantage is that the shadow is deleted since it is homogeneous.

3. DETECTION AND TRACKING SYSTEM FOR MOVING OBJECTS

The change detection method is employed in the system shown in Fig.2. The goal of the system is not only to detect changes in consecutive frames but also to track the moving object.

First a median filter is used to preprocess the images to remove noise. Then the least squares based change detection approach is used to detect the changed pixels. After the change detection process, we obtain a binary image, where “0” and “1” indicate the unchanged pixel and changed pixel respectively. Then a morphological filter is employed to delete some freckles produced by noise and group changed pixels into objects.

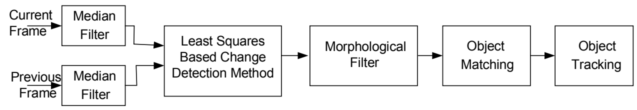

Fig.2. Detection and Tracking System for Moving Objects

After the change detection process, objects need to be matched between the frames. This matching is performed based on co-occurrence matrix-based texture features. We compose the co-occurrence matrix of the detected object first. If we establish the co-occurrence matrix in 8 directions and base it on the binary mask image, which has only 2 shades of gray as used in our experiment, we will obtain an 8×2×2 co-occurrence matrix for frame i. Then we employ the entropy of the co-occurrence matrix of the object to match the currently detected moving objects with those detected in the previous image. The object in frame i can be represented as a vector of length 8, such as $Object_i = (e_{i1}, e_{i2}, \ldots e_{i8})$, where e_{ij} is the entropy of co-occurrence matrix in direction j. Once the object in the new frame is matched with the previous one, the centroid of the points in the object is computed. Finally, a Kalman filter is employed to track the moving object through change detection. The development of tracking algorithms to track moving objects in the scene is beyond the scope of this paper.

4. ILLUSTRATIVE EXAMPLE

The proposed system is tested in a complex outdoor environment by using a video sequence from a road monitor. In this sequence a car is passing through a road and illumination varies noticeably along with lots of noise. The image size is 256×256. Fig.3 (c) shows the difference of Fig.3 (a) and Fig.3 (b), which shows the complexity of the environment.

For comparison, we also employed two other methods to perform change detection for the same video sequence. In Fig.3 (d) and Fig.3 (e), results for the statistical method described in [3] and a linear independence method [5] are presented.

We find that the statistical method cannot handle the illumination changes well as shown in Fig.3 (d). In order to eliminate the influence of illumination, a relatively high threshold has to be used for the Linear Independence method, which results in incomplete contours of the moving object as seen in Fig.3 (e). As shown in Fig.3 (f), the least squares method is able to detect the texture of the object almost completely. However, the interior of the object cannot be detected. But this information is sufficient to be able to match the object between two frames by using the co-occurrence matrix. The Euclidian distances of the entropy of the co-occurrence matrix

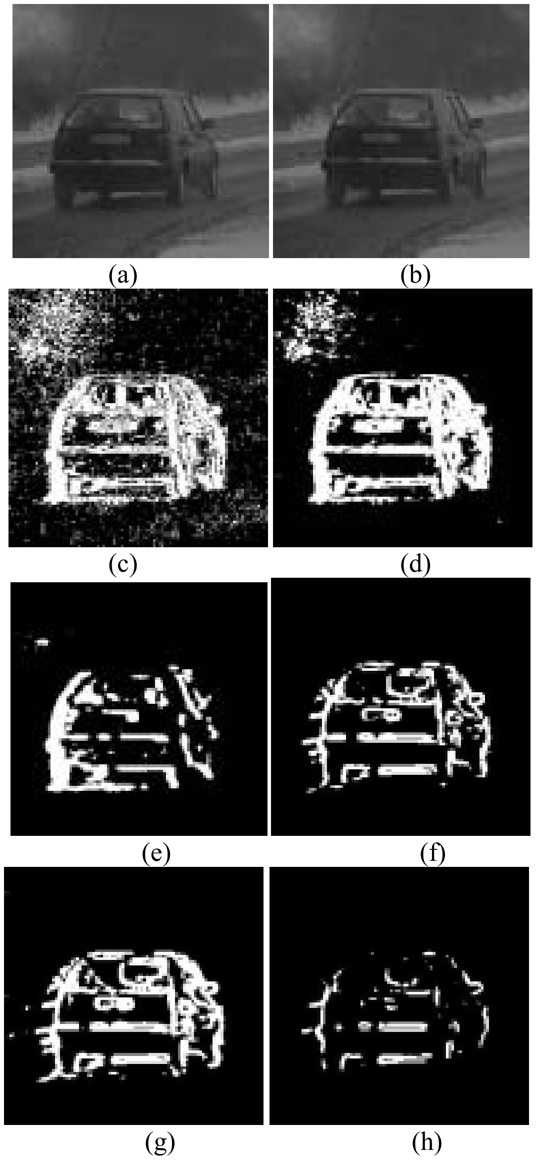

Fig.3. Change Detection Results

(a) Previous Frame, (b) Current Frame, (c) Difference of frames, (d) Statistical method, (e) Linear independence method, (f) Least squares method with threshold C, (g) Least squares method with threshold A, (h) Least squares method with threshold B.

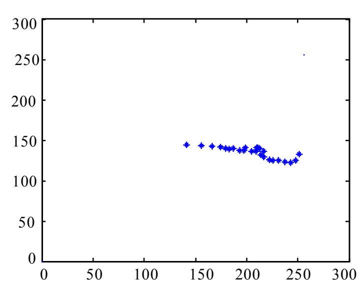

Fig. 4. Trail of the car for consecutive frames

between two frames are less than 3.5%. Thus the information of the co-occurrence matrix of the object can be used to characterize the vehicle. Because the Euclidian distances are shown to be small, the objects between frames are matched.

Fig. 4 shows the trail of the car in the scene as determined by our detection and tracking system, in which 30 frames are processed.

5. SUMMARY AND CONCLUSIONS

A least squares based change detection approach is proposed in this paper. It is tested and proved to be a much better method than other existing methods for detection and tracking in varying illumination conditions. In order to improve its performance in low SNR conditions, a median filter and a morphological filter are used to minimize the influence of the noise, which make the whole system more robust. Although our detection process does not detect the whole object, it provides the edges of the moving object clearly. Our results show that this system can detect and track the moving object robustly and successfully.

6. REFERENCES

[1] E. Durucan and T. Ebrahimi, “Change detection and background extraction by linear algebra”, *Proceedings of IEEE,* vol. 89, pp. 1368-1381, Oct. 2001.

[2] L. Li and K. H. Leung, “Integrating intensity and texture differences for robust change detection”, *IEEE Trans. Image Processing*, vol. 11, pp. 105-112, Feb. 2002.

[3] D. Toth, T. Aach and V. Metzler, “Bayesian spatio-temporal motion detection under varying illumination”, *EUSIPCO 2000*, Tempere, Finland, pp. 2081-2084, 2000.

[4] T. Aach and A. Kaup, “Statistical model-based change detection in moving video”, *Signal Processing*, vol. 31, pp. 165-180, March 1993.

[5] E. Durucan and T. Ebrahimi, “Robust and illumination invariant change detection based on linear dependence for surveillance application” *EUSIPCO 2000*, Tempere, Finland, pp. 1141-1144, Sept. 2000.

[6] S. Liu, C. Fu and S. Chang, “Statistical change detection with moments under time-varying illumination”, *IEEE Trans. Image Processing*, vol. 7, pp. 1258-1268, Sept. 1998.

[7] Steven M. Kay, *Fundamentals of statistical signal processing: estimation theory*, Prentice Hall, March 1993.

[8] Rosin P. “Thresholding for change detection”, *ICCV98 Proceedings*. pp. 274-279, 1998.

[9] L. Snidaro, G. L. Foresti, “Real-time thresholding with Euler numbers”*, Pattern Recognition Letters*, vol. 24, pp. 1533-1544, 2003.