Moving Object Detection Based on Kirsch Operator Combined with Optical Flow

Ping Gao, Xiangju Sun, Wei Wang

School of Information Science and Engineering, Lanzhou University
Lanzhou, China
sunxiangjulz@yahoo.com.cn

***Abstract*—The detection of moving object is important in many tasks, such as video surveillance and moving object tracking. Although there are some methods for the moving object detection, it is still a challenging area. In this paper, a new method which combines the Kirsch operator with the Optical Flow method (KOF) is proposed. On the one hand, the Kirsch operator is used to compute the contour of the objects in the video. On the other hand, the Optical Flow method is adopted to establish the motion vector field for the video sequence. Then the Otsu method is implemented after the Optical Flow method in order to distinguish the moving object and the background clearly. Finally the contour information fuses the information of motion vector field to label the moving objects in the video sequences. The experiment results prove that the proposed method is effective for the moving objects detection.**

***Keywords*— Moving object detection, KOF, Kirsch operator, Optical Flow, Otsu method**

I. Introduction

Moving object detection is the first step in video analysis. It can be used in many regions such as video surveillance, traffic monitoring and people tracking [1-2].

Generally speaking, there are three common motion segmentation techniques, which are frame difference, background subtraction and optical flow method. Frame difference method [3-5] has less computational complexity, and it is easy to implement, but generally does a poor job of extracting the complete shapes of certain types of moving objects [6]. Background subtraction method uses the current frame minus the reference background image. The pixels where the difference is above a threshold are classified as the moving object. The Mixture of Gaussians method is widely used for the background modeling since it was proposed by Friedman and Russell [7]. Stauffer [8] presented an adaptive background mixture model by a mixture of K Gaussian distributions. Optical flow method[9-10] can detect the moving object even when the camera moves, but it needs more time for its computational complexity, and it is very sensitive to the noise. The motion area usually appears quite noisy in real images and optical flow estimation involves only local computation [6]. So the optical flow method can not detect the exact contour of the moving object. From the above it is clear that there are some shortcomings in the traditional moving object detection methods:

- Frame difference can not detect the exact contour of the moving object.
- Optical flow method is sensitive to the noise.

The KOF method which is proposed in this paper can solve the above problems. KOF method uses the Kirsch operator to acquire the boundaries information of the moving objects, meanwhile the optical flow method is used to get the motion vector field of the moving objects. Then both of the information acquired above is fused. At last, the moving objects are labeled with the minimum rectangle outside. The experiment results show that the present method is effective.

The organization of this paper is settled as follows: section II shows the KOF method which includes the edge detection algorithm, the optical flow algorithm, the process of binary, the data fusion and morphologic operation, section III provides the experimental results, section IV presents our conclusions.

II. Proposed Moving Object Method

A. The outline of the method

The process of KOF method is shown in Fig. 1. The proposed method mainly consists of the edge detection, optical flow, data fusion and morphologic operation. Consider the requirements of the simplicity and effectiveness, Kirsch operator [11-12] is used for the edge detection. For the task of the optical flow, the Lucas-Kanade method [13] is adopted, which can quickly provide the dense optical flow vector of the moving object. The binary process adopts the Otsu algorithm [14]. It can decide the threshold which is used to distinguish the background and the moving objects self-adaptively. However, because of the noise, the optical flow method can not detect the accurate boundaries of the moving objects. The edge detection algorithm mentioned just before can solve this problem. Moreover, the edge image acquired by the Kirsch operator can be regarded as space gradient, while the optical flow image is time gradient [15]. Combining the space gradient information with time gradient information can give us the more accurately information of the moving objects, so in the data fusion, the AND operator is used between the edge binary image and the optical flow binary image. In order to get the more exact contour of the moving objects, the morphologic operations such as Close and Hole Filling are implemented. Finally, the moving object is extracted from the image.

B. The edge detection method

The edge image can be regarded as the space gradient.

978-1-4244-5555-3/10/$26.00 ©2010 IEEE

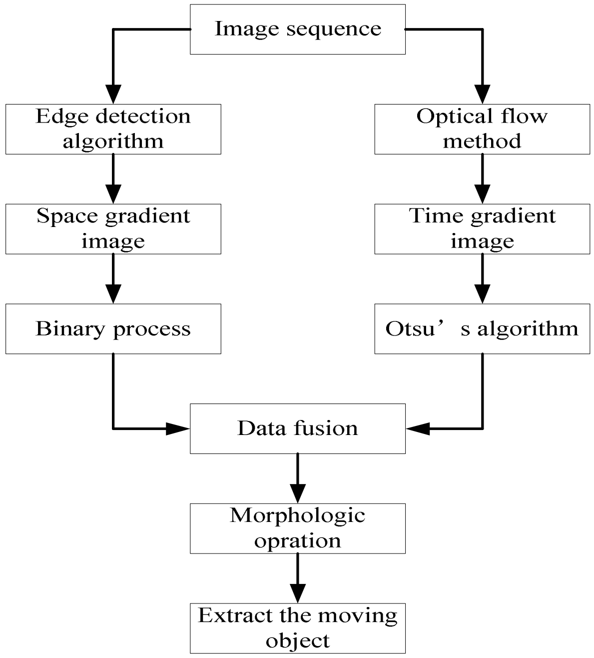


Fig. 1 The flowchart of the algorithm for moving object detection

There are some gradient operators, such as Sobel, Robert, Kirsch etc. As Kirsch operator [16-17] can adjust the threshold automatically according to the character of the image, the Kirsch gradient operator is chosen to extract the contour of the object. The Kirsch operator has eight window templates. Every template makes the greatest response to a particular direction. The eight template operators are shown in Fig. 2. Except the outermost column and the outermost row, every pixel and its 3×3 eight neighborhoods in an image convolved with these eight templates respectively, so every pixel has eight outputs, the maximum output of the eight templates is chosen to be the value in this position. The gray value of a point and its eight neighborhoods in the image are illustrated as in Fig. 3.

$$M0=\begin{bmatrix}5&5&5\\-3&0&-3\\-3&-3&-3\end{bmatrix}\quad M1=\begin{bmatrix}5&5&-3\\5&0&-3\\-3&-3&-3\end{bmatrix}\quad M2=\begin{bmatrix}5&-3&-3\\5&0&-3\\5&-3&-3\end{bmatrix}\quad M3=\begin{bmatrix}-3&-3&-3\\5&0&-3\\5&5&-3\end{bmatrix}$$

$$M4=\begin{bmatrix}-3&-3&-3\\-3&0&-3\\5&5&5\end{bmatrix}\quad M5=\begin{bmatrix}-3&-3&-3\\-3&0&5\\-3&5&5\end{bmatrix}\quad M6=\begin{bmatrix}-3&-3&5\\-3&0&5\\-3&-3&5\end{bmatrix}\quad M7=\begin{bmatrix}-3&5&5\\-3&0&5\\-3&-3&-3\end{bmatrix}$$

Fig. 2 the eight templates of the kirsch operator

$$\begin{bmatrix}P0&P1&P2\\P7&P(i,j)&P3\\P6&P5&P4\end{bmatrix}$$

Fig. 3 the gray value of a point and its eight neighborhoods P

Assume $q_k(k=0,1,\cdots7)$ is the output which is operated by the k_{th} template of the Kirsch operators, q_k can be obtained from the below equation:

$$q_k = M_k * P(k=0,1,...7) \tag{1}$$

where M_k is the k_{th} template operator in the eight Kirsch operators, P are the gray values of a pixel and its 3×3 eight neighborhoods. The edge intensity $S(i,j)$ of $P(i,j)$ is defined as $S(i,j)=\max\{q_k\}(k=0,1,\cdots7)$. Every pixel does the operation above, so the edge intensity image S is accepted. If the gray value difference between the object and the background is small in the image and the detected edge feature is not obvious, the follow-up study can not continue. So the binary process is necessary. When the value of the edge intensity image is above a threshold, it will be classified as the edge of the object. After the above operation, the edge binary image is acquired. Some video sequences including both outdoors and indoors are experimented: the results are shown in Fig. 4. The first column is the outdoor scene and the second column is the indoor scene. It is clear that the Sobel and Robert operators lose part of the contour of the objects, while the Kirsch can detect the boundary of the objects clearly.

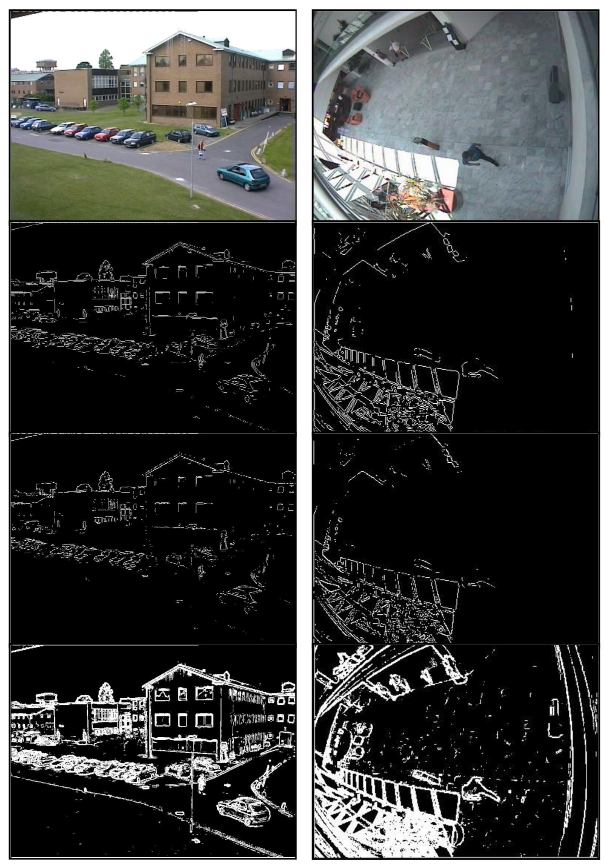


Fig. 4 the results of edge detection operators, the first row are the original images, the second row are the results with the Sobel operator, the third row are the results with the Robert operator, the fourth row are results with the Kirsch operators.

C. The Optical Flow method

There are some methods for computing the optical flow such as differential, matching, energy-based, and phase-based methods. In this paper, the Lucas-Kanade method [9], [13] is used. The optical flow constrained equation is as (2):

$$I(x,t) = I(x - Vt, 0) \tag{2}$$

Where $V = (\mu, \upsilon)^T$. μ is the horizontal component of the optical flow, υ is the vertical component of the optical flow. From a Taylor expansion of (2) or more generally from an assumption that intensity is conserved, $dI(x,t)/dt = 0$, the gradient constraint equation is derived:

$$\nabla I(x,t) \cdot V + I_t(x,t) = 0 \tag{3}$$

Where $I_t(x,t)$ denotes the partial time derivative of $I(x,t)$, $\nabla I(x,t) = (I_x(x,t), I_y(x,t))^T$. Lucas and Kanade assume that the motion vector keeps constant in a small spatial neighborhood, and they use the weighted least-squares to estimate the optical flow. So in the small spatial neighborhood Ω , the error of the optical flow is defined as:

$$\sum_{x \in \Omega} W^2(x)[\nabla I(x,t) \cdot V + I_t(x,t)]^2 \tag{4}$$

Where $W(x)$ denotes a window function that gives more influence to constraints at the center of the neighborhood than those at the periphery. The solution to (4) is given by

$$A^T W^2 A V = A^T W^2 b \tag{5}$$

Where, for n points $x_i \in \Omega$ at a single time t

$$A = [\nabla I(x_1), ..., \nabla I(x_n)]^T$$

$$W = diag[W(x_1), ..., W(x_n)]$$

$$b = -[I_t(x_1), ..., I_t(x_n)]^T$$

The solution to (5) is $V = [A^T W^2 A]^{-1} A^T W^2 b$. Only one component of the optical flow can not reflect the motion information of the objects. So the two factors must be combined together. By experiment, the optical flow image, scilicet time gradient image is defined as: $x = \mu^2 + \upsilon^2$ in this paper. After the optical flow method, in the binary process, the Otsu algorithm [14] is adopted. The Otsu algorithm can select the threshold which is used to distinguish the moving object and the background adaptively. It is a classic non-parametric, unsupervised adaptive threshold selection method.

D. Data fusion and the morphologic operation

After the above operation, the space gradient binary image and the time gradient binary image are acquired. In order to get the exact contour, the AND operator is used between the two binary images in the data fusion. The process can be simplified as an equation as follows:

$$D_{bw}(i,j) = \begin{cases} 1, & S_{bw}(i,j) = 1 \quad and \quad T_{bw}(i,j) = 1 \\ 0, & otherwise \end{cases} \tag{6}$$

Where

D_{bw} denotes the result of the data fusion.

S_{bw} denotes the space gradient binary image.

T_{bw} denotes the time gradient binary image.

(i, j) denotes the coordinate of the pixel in the image.

And then, the morphologic operators such as Close and Hole filling are used to eliminate the discontinuity of object. At last, the area of each connected region is calculated, and the regions that below a threshold are discarded. The remaining areas are considered as the moving objects.

III. Experiment Result

Some video sequences both indoor and outdoor environment are collected for evaluating the performance of the novel method.

A. The experiments on outdoor dataset

Fig. 5 shows a moving object detection results on the outdoor dataset which can be acquired from [18]. Fig. 5 (a) is the original image from an outdoor video sequence, where a person is walking from the left to the right and a car is moving from the right to the left on the road. Fig. 5 (b) is the optical flow motion vector image between Fig. 5 (a) and its next frame in the video sequence, it is clear that lots of noise appear in optical flow motion vector image, the grass waving in the wind is also detected.

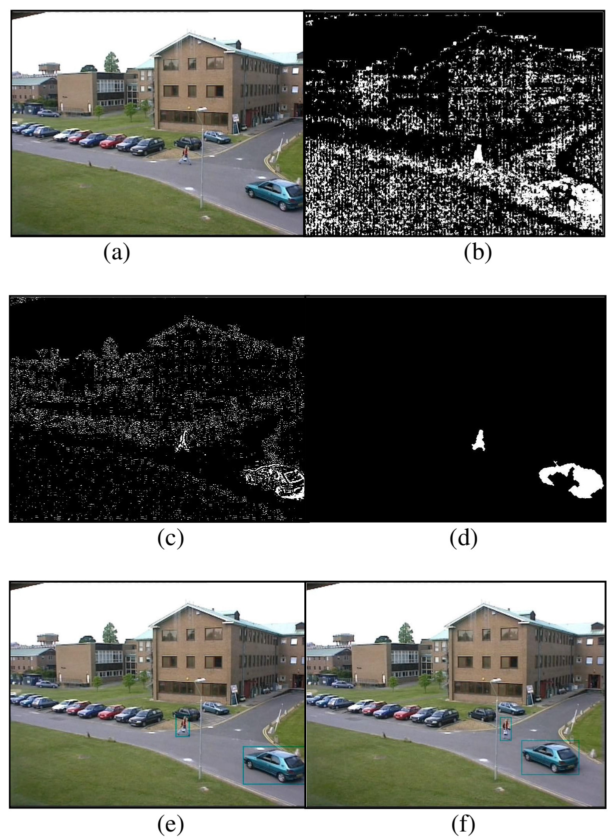


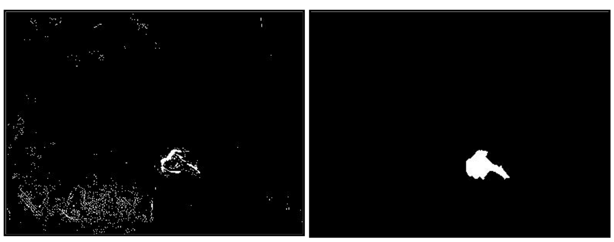
Fig. 5 Moving object analysis on an outdoor environment where a person is walking and a car is moving. (a) The original image, (b) the Optical Flow image, (c) the Frame Difference result, (d) the result with our method, (e) the segment result with the minimum rectangle outside the moving objects, (f) the tracking detection segment result in the sequence.

Fig. 5 (c) is the frame difference result between Fig. 5 (a) and its next frame in the video sequence. As shown in Fig. 5 (c), the contours of the moving objects are vague. Fig. 5 (d) is the result with the proposed method. The KOF method adopts the edge detection operator—Kirsch which has eight window templates and every template makes the greatest response to a particular direction. It can detect the contour of the objects precisely. As shown in Fig. 5 (d), KOF method combines the space gradient information with the time gradient information has good anti-noise performance. The effect of the waving grass is eliminated. Compared to Fig. 5 (b) and Fig. 5 (c), the result in Fig. 5 (d) also has the precise contour. Fig. 5 (e) is the segmented result with the minimum rectangle outside the moving objects. Fig. 5 (f) is the tracking detection segmented result in the sequence. As Fig. 5 (e) (f) shown, the moving objects—a person and a car are detected precisely.

B. The experiments on indoor dataset

Fig. 6 and Fig. 7 show the moving object detection results

(a) (b)



(c) (d)

(e) (f)

Fig. 6 Moving object analysis on an indoor environment with a person walking. (a) The original image, (b) the Optical Flow image, (c) the Frame Difference result, (d) the result with our method, (e) the segment result with the minimum rectangle outside the moving objects, (f) the tracking detection segment result in the sequence.

(a) (b)

(c) (d)

(e) (f)

Fig. 7 Moving object analysis on an indoor environment with two people running. (a) The original image, (b) the Optical Flow image, (c) the Frame Difference result, (d) the result with our method, (e) the segment result with the minimum rectangle outside the moving objects, (f) the tracking detection segment result in the sequence.

of KOF method for the indoor test sequence which can be downloaded from [19]. In one video sequence, a person was walking, while in the other sequence, two running men were include in every image. Compared to the sequence mentioned in experiment A, these two ones are the indoor environment sequences. As Fig. 6 and Fig. 7 show, the KOF method can handle both situations successfully. It can detect the moving objects clearly.

C. Compare with other methods

Meanwhile, the experiment using Lucas-Kanade optical flow and the background subtraction method proposed in [8] had also been performed for the comparison purpose. Part of the “Walk3” sequence, from 220th frame to 320th frame (random choose) which can be downloaded from [19] is used as the test sequence. The performance of these methods is shown in Table I.

The False frames consist of the situations below:

- The KOF method detects the area without moving objects.
- The KOF method can not detect the moving objects.

TABLE I
COMPARISON WITH SOME OTHER METHODS

Methods	**The performance of each method**	
	The recognition rate in this scene	**False frames**
Optical Flow	59%	41
Background Subtraction	85%	15
The proposed method	91%	9

As Table I show, the optical flow method which has the low anti-noise performance has the low recognition rate in this scene, and the background subtraction doesn't have the good performance either. Compared to the above two methods, the KOF method has the high recognition rate for moving objects. In a word, the experimental results prove that the KOF is an effective method for moving object detection in both outdoor and indoor environments.

IV. CONCLUSIONS

In this paper, a novel method which combines the Kirsch operator with the optical flow is proposed for the moving object detection. Consider the edge image as the space gradient while the optical flow image is time gradient. The KOF method contains both the space gradient information and the time gradient information. Otsu algorithm and morphologic operation are also used as the supporting techniques. Contrast with the three traditional moving object detection methods, the KOF method not only can give the exact boundary of the moving objects, but also has the better anti-noise performance. Although the method is a little time-consuming, the fast development of the hardware of the computer can solve this problem. The experiment results prove that the method is effective for the moving object detection.

ACKNOWLEDGMENT

The work is supported by grant of National Nature Science Fund of China (No. 30970876） and Gansu Nature Science Fund of China (No.3ZS0 51-A25-090), corresponding to author: Wei wang, wangw@lzu.edu.cn.

Some of the video sequences data come from the EC Funded CAVIAR project/IST 2001 37540, found at URL: http://homepages.inf.ed.ac.uk/rbf/CAVIAR/.

REFERENCES

[1] C. Stauffer and W. E. L. Grimson, “Learning patterns of activity using real-time tracking,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, No. 8, pp. 747–757, Aug. 2000.

[2] K. Q. Huang, L. S. Wang, T. N. Tan, and S. Maybank, “A real-time object detecting and tracking system for outdoor night surveillance,” *Pattern Recognition,* vol. 41, pp. 432–444, Jan. 2008.

[3] J. R. Bergen, P. J. Burt, R. Hingorani, and S. Peleg, “A three-frame algorithm for estimating two-component image motion”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, No. 9, pp. 886-896, Sep. 1992.

[4] R. J. Radke, S. Andra, O. AI-Kofahi, and B. Roysam, “Image change detection algorithms: a systematic survey”, *IEEE Transactions on Image Processing*, vol. 14, No. 3, pp. 294-307, Mar. 2005.

[5] O. Miller, A. Averbuch, and Y. Keller, “Automatic adaptive segmentation of moving objects based on spatio-temporal information,” in *Proc. VIIth Digital Image Computing: Techniques and Applications*, 2003, pp.1007-1016.

[6] D. X. Zhou, and H. Zhang, “Modified GMM background modeling and optical flow for detection of moving objects,” in *2005 IEEE International Conference on System, Man and Cybernetics,* Oct. 2005, vol. 3, pp. 2224-2229.

[7] N. Friedman, and S. Russell, “Image segmentation in video sequences: a probabilistic approach”, in *Proc. Thirteenth Annual Conference on Uncertainty in Artificial Intelligence*, 1997, pp. 175-181.

[8] C. Stauffer, and W. E. L. Grimson, “Adaptive background mixture models for real-time tracking,” in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1999, Vol. 2, pp. 246- 252.

[9] J. L. Barron, D.J. Fleet, and S. S. Beauchemin, “Performance of optical flow techniques,” *International Journal of Computer Vision*, vol. 12, pp. 43–77, 1994.

[10] B. K. P. Horn, and B. G. Schunck, “Determining optical flow,” *Artificial Intelligence*, vol. 17, pp. 185–203, 1981.

[11] Y. Yu, J. H. Lu, and J. L. Zheng, “Color image edge detection algorithm,” *Journal of Tsinghua University (Science and Technology)* vol. 45, No. 10, pp. 1339-1343, 2005.

[12] J. B. Lu, “An algorithm for edge extraction based on fast kirsch and the probability of being true edges,” *Computer Applications*, vol. 21, pp. 33–35, Feb. 2001.

[13] B. D. Lucas, and T. Kanade, “An iterative image registration technique with an application to stereo vision,” in *Proc. 7th Intl Joint Conf on Artificial Intelligence*, 1981, pp. 674–679.

[14] N. Otsu, “A threshold selection method from gray-level histograms,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, No. 1, pp. 62–66, 1979.

[15] C. H. Zhan, X. H. Duan, S. Y. Xu, Z. Song, and M. Luo, “An improved moving object detection algorithm based on frame difference and edge detection,” in *Fourth International Conference on Image and Graphics*, Aug. 2007, pp. 519-523.

[16] R. A. Kirsch, “Computer determination of the constituent structure of biological images,” *Computers and Biomedical Research*, vol. 4, pp. 315-328, 1971.

[17] X. Q. Xue, H. Y. Wu, and H. S. You, “Application of an improved Ostu method in the Kirsch edge detection,” *Computer & Digital Engineering*, vol. 37, No. 3, pp. 167-171. 2009.

[18] http://ftp.pets.rdg.ac.uk/

[19] http://homepages.inf.ed.ac.uk/rbf/CAVIAR/.