ISSN:0975-9646

B.Naresh Reddy et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 3 (5) , 2012,5259-5264

Detection of moving object using KOF method

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***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. 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 cannot 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 cannot detect the exact contour of the moving object.
- Optical flow method is sensitive to the noise.

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.

Moving object detection is required in many vision applications such as human-computer interfaces, video communication/compression, road traffic control, and security and surveillance systems. Often the goal is to obtain a record of the trajectory of the moving single or multiple objects over time and space, by processing information from distributed sensors. Object detection and tracking in video sequences requires on-line processing of a large amount of data and is time-expensive. Additionally, most of the problems encountered in visual tracking are nonlinear, non- Gaussian, multi-modal or any combination of these. Different techniques are available in the literature for solving tracking tasks in vision and can be divided in general into two groups: i).Classical applications, where targets do not interact much with each other, behave independently such as aircrafts that do not cross their paths. ii).Applications in which targets do not behave independently (ants, bees, robots, people), their identity is not always very well distinguishable. Tracking multiple identical objects has its own challenges when the targets pass close to each other or merge.

Here 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.

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 cannot 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.

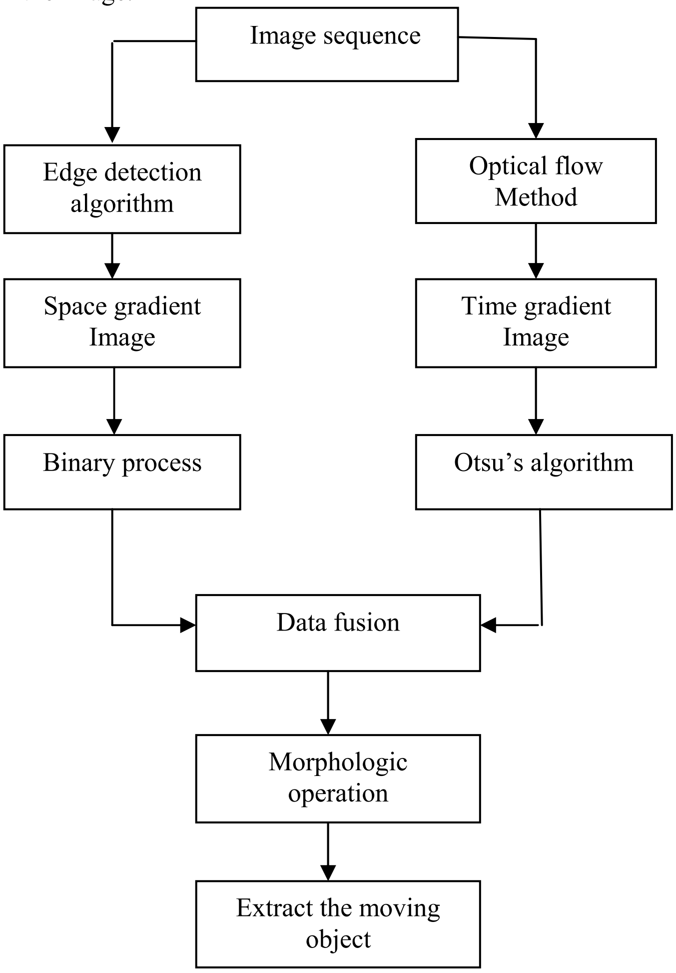


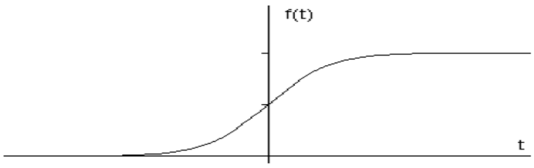
Fig 1: The flow chart of the algorithm for moving object detection

B. ***The edge detection method:***

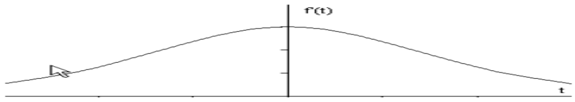
Edge detection refers to the process of identifying and locating sharp discontinuities in an image.The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There are an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. Variables involved in the selection of an edge detection operator include Edge orientation,Noise environment and Edge structure. performance of the various techniques in different conditions. There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories:

1). *Gradient based Edge Detection*: The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.

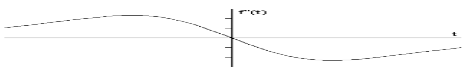
2). Laplacian based Edge Detection: The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location. Suppose we have the following signal, with an edge shown by the jump in intensity below:



If we take the gradient of this signal (which, in one dimension, is just the first derivative with respect to t) we get the following:



Clearly, the derivative shows a maximum located at the center of the edge in the original signal. This method of locating an edge is characteristic of the "gradient filter" family of edge detection filters and includes the Sobel method.when the first derivative is at a maximum, the second derivative is zero. As a result, another alternative to finding the location of an edge is to locate the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal is shown below.



C***). Edge Detection Techniques:***

*3.1). A. Sobel Operator:*The sobel operator [20] consists of a pair of 3×3 convolution kernels as shown in Fig 4.1. One kernel is simply the other rotated by 90°

-1	0	1
-2	0	2
-1	0	1

G_x

-1	-2	-1
0	0	0
1	2	1

G_y

Fig 2: Masks used by Sobel Operator

The gradient magnitude is given by

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (1)$$

Typically, an approximate magnitude is computed using:

$$|G| = |G_x| + |G_y| \quad (2)$$

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$q = arc\tan\left(\frac{G_y}{G_x}\right) \quad (3)$$

3.2). Robert's cross operator: The Roberts Cross operator [20] performs a simple, quick to compute, 2-D spatial gradient measurement on an image. This is very similar to the Sobel operator.

-1	0
0	1

G_x

0	-1
1	0

G_y

Fig 3: Masks used by Robert's Operator

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations. The gradient magnitude is given by

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (4)$$

Typically, an approximate magnitude is computed using

$$|G| = |G_x| + |G_y| \quad (5)$$

This is much faster to compute.

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$q = arc\tan\left(\frac{G_y}{G_x}\right) - \frac{3}{4}\Pi \quad (6)$$

3.3). Prewitt's operator*:* Prewitt operator [20] is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images.

-1	0	+1
-1	0	+1
-1	0	+1

G_x

-1	-1	-1
0	0	0
+1	+1	+1

G_y

Fig 4: Masks for the Prewitt's gradient edge detector

3.4). Laplacian of Gaussian**:** The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image The Laplacian L(x, y) of an image with pixel intensity values I(x, y) is given by

$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (7)$$

Three Commonly used small kernels are shown in Fig 5.

1	1	1
1	-8	1
1	1	1

G_X

-1	2	-1
2	4	2
-1	2	-1

G_Y

Fig 5**:** three commonly used discrete approximations to the Laplacian filter

The 2-D LoG function centered on zero and with Gaussian standard deviation σ has the form

$$\log(x, y) = \frac{-1}{\pi\sigma^4}\left[1 - \left(\frac{x^2 + y^2}{2\sigma^2}\right)\right] e^{\frac{x^2 + y^2}{2\sigma^2}} \quad (8)$$

And is shown in Fig 6.

0	1	0
1	-4	1
0	1	0

Fig 6: Laplacian of Gaussian kernel

3.5). Kirsch operator: As Kirsch operator can adjust the threshold automatically according to the character of the image, the Kirsch gradient [16-17] 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.4.6. 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.8

.

M0		
5	5	5
–3	0	–3
–3	–3	–3

M1		
5	5	–3
5	0	–3
–3	–3	–3

M2		
5	–3	–3
5	0	–3
5	–3	–3

M3		
–3	–3	–3
5	0	–3
5	5	–3

M4		
–3	–3	–3
–3	0	–3
5	5	5

M5		
–3	–3	–3
–3	0	5
–3	5	5

M6		
–3	–3	5
–3	0	5
–3	–3	5

M7		
–3	5	5
–3	0	5
–3	–3	–3

Fig.7: the eight templates of the kirsch operator

P0	P1	P2
P7	P(I,J)	P3
P6	P5	P4

Fig 8: The gray value of a point and its eight neighborhoods

P Assume q_k (k= 0,1,2…7) is the output which is operated by the k_{th} template of the Kirsch operators, q_k can be obtained from the below equation

$$q_k = M_k \times p(1, 2, \ldots 7) \quad (9)$$

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,… 7). 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 cannot 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.

D.The optical flow method:

Optic flow refers to the image motion of the environment projected on the retina during our movement in the world. Differential methods of estimating optical flow [23], based on partial derivatives of the image signal and/or the sought flow field and higher-order partial derivatives, such as: Lucas–Kanade Optical Flow Method, Horn–Schunck method,Buxton–Buxton method,Black–Jepson method

1. Lucas-Kanade method

There are some methods for computing the optical flow such as differential, matching, energy-based, and phase based methods. Here, the Lucas-Kanade method [9], [13] is used. The optical flow constrained equation is as (10).

$$I(x,t)=I(x-Vt,0) \tag{10}$$

Where V $=(\mu\ \mathrm{u})^T$. μ is the horizontal component of the optical flow, u is the vertical component of the optical flow. From a Taylor expansion of (10) or more generally from an assumption that intensity is conserved, dI (x, t) / dt = 0, the gradient constraint equation is derived.

$$\nabla I(x,t).V+I_t(x,t)=0 \tag{11}$$

where $I_t(x,t)$ denotes the partial time derivative of $I(x,t)$,

$$\nabla I(x,t)=(I_x(x,t),I_y(x,t))^T \tag{12}$$

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

$$\sum_{x\in\Omega} W^2(x)[\nabla I(x,t).V+I_t(x,t)]^2 \tag{13}$$

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 (5.9) is given by

$$A^TW^2AV=A^TW^2b \tag{14}$$

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

$$A=[\nabla I(x_1),\ldots..\nabla I(x_n)]^T$$
$$W=diag[W(x_1),\ldots..,W(x_n)]$$
$$b=-[I_t(x_1),\ldots..,I_t(x_n)]^T$$

The solution to (14) is $V=[A^TW^2A]^{-1}A^TW^2b$.

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 = μ^2+v^2 . 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.

E).Otsu's method:

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance, defined as a weighted sum of variances of the two classes

$$\sigma^2_\omega(t)=\omega_1(t)\sigma^2_1(t)+\omega_2(t)\sigma^2_2(t) \tag{15}$$

weights ω_i are the probabilities of the two classes separated by a threshold *t* and σ^2_i variances of these classes. Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance

$$\sigma^2_b(t)=\sigma^2-\sigma^2_\omega(t)=\omega_1(t)\omega_2(t)\left[\mu_1(t)-\mu_2\right]^2 \tag{5.12}$$

which is expressed in terms of class probabilities ω_i and class means μ_i which in turn can be updated iteratively. This idea yields an effective algorithm.

1). Algorithm

1. Compute histogram and probabilities of each intensity level
2. Set up initial $\omega_i(0)$ and $\mu_i(0)$
3. Step through all possible thresholds t = 1 maximum intensity
    1. Update ω_i and μ_i
    2. Compute $\sigma^2_b(t)$
4. Desired threshold corresponds to the maximum $\sigma^2_b(t)$

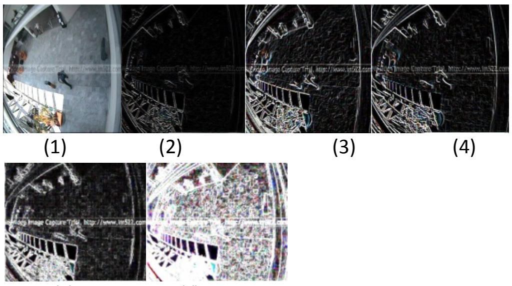
F). Data fusion: After the above operation, the space gradient binary image and the time gradient binary image are acquired. In order to get the exact contour, the AND operator is used between the two binary images in the data fusion. The process can be simplified as an equation as follows

$$D_{bw}(i,j)=\begin{cases}1, & S_{bw}(i,j)=1 \quad and \quad T_{bw}(i,j)=1\\ 0, & otherwise\end{cases} \tag{16}$$

G.Morphologic operation: Morphological Image Processing is an important tool in the Digital Image processing, since that science can rigorously quantify many aspects of the geometrical structure of the way that agrees with the human intuition and perception.

III.RESULTS AND ANALYSIS

Fig 9: Input image sequences



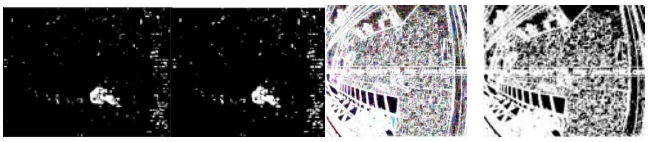
(1) (2) (3) (4)

(5). (6)

Fig 10: Edge detection resultsa).input 2).Robert image3).Sobel image 4).Prewitt image5).Laplacian image6). kirsch image

(1) (2) (3)

Fig 11. Optical flow Results 1 & 2)..input image 3). Optical flow image



(1) (2) (3) (4)

Fig 12. Otsu method Results 1). optical Flow image2). Otsu output 3). kirsch image 4). Otsu output

Fig(13). Data Fusion and morphological operation results1). Data fusion with kirsch image2). KOF output3). The segment

Table 1: Comparison with other methods

Methods	The performance of each method	
	The recognion rate in this scene	False frames
Optical Flow	59%	41
Back ground subtraction	85%	15
The praposed method	91%	9

As Table 1 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

CONCLUSION

A novel method which combines the Kirsch operator with the optical flow is proposed for the moving object detection. 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.

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