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EFFICIENT FOREGROUND EXTRACTION BASED ON OPTICAL FLOW AND SMED FOR ROAD TRAFFIC ANALYSIS

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Abstract**-- Foreground detection is a key procedure in video analysis such as object detection and tracking. Several foreground detection techniques and edge detectors have been developed until now but the problem is, usually it is difficult to obtain an optimal foreground due to weather, light, shadow and clutter interference. Background subtract is a common method in foreground detection. In background subtract noise appears at fixed place, when it is used to deal with long image sequence there may be much accumulate error in the foreground. In OF (Optical Flow) noise appears randomly and this covers long distance over long period of time. Optical flow cannot get rid of the light influences which result in background noises. To overcome this SMED (Separable Morphological Edge Detector) is used. SMED has robustness to light changing and even slight movement in the video sequence. This paper proposes a new foreground detection approach called OF and SMED which is more accurate in foreground detection and elimination of noises is very high. This approach is useful for efficient crowd and traffic monitoring, user friendly, highly automatic intelligent, computationally efficient system.**

Index terms: **Foreground Extraction, Optical flow, SMED, Background subtraction, Surveillance sytems, Traffic Analysis.**

I. INTRODUCTION

A video surveillance system [8] must be capable of continuous operation under various weather and illumination conditions. Moreover, background subtraction is a very important part of surveillance applications for successful segmentation of objects from video sequences, and the accuracy, computational complexity, and memory requirements of the initial background extraction are crucial in any background subtraction method [2]. Foreground detection algorithm should exactly detect moving objects that is the detection result contains no noises possibly. Now the existing foreground detection algorithms can be divided into three categories: frame difference, optical flow and background subtract.

Frame difference [18] calculates pixel gray scale difference between adjacent two frames in a continuous image sequences and determines foreground by setting threshold. Lipton utilized double-frame difference for moving object detection and then classification and tracking. Frame difference method can be used in dynamic environment, but it cannot completely extract all the foreground area, the central part of target will be lost, which results in bad target recognition. In addition, this method is difficult to accurately detect fast moving or slowly moving objects as well as multiple objects.

Optical flow [7] is the velocity field which warps one image into another (usually very similar) image. The research of optical flow utilizes pixel intensity changing and relevance to determine the movement of pixels in image sequence. In fact, it is very difficult to calculate the true velocity field using image sequence and optical flow represents information of moving objects, so the optical flow field can be used to replace velocity field. However, each optical flow cannot get rid of the light influences which result in background noises.

Background subtract [9] is a common method used in foreground detection. It calculates the difference between the current image and background image and detects foreground by setting threshold. There are two methods to obtain background image, one is to appoint an image as background artificially, another method uses model to training background, such as Gaussian background model (GBM). Compared to the former, the latter is more accurate and the result of foreground detection is much better. Background subtract method has robustness to light changing and slight movement, but when using this method to deal with long image sequence there may be much accumulate error in the foreground. Optical flow covers long distance and the noise due to brightness change is less which results in less accumulate error percentage.

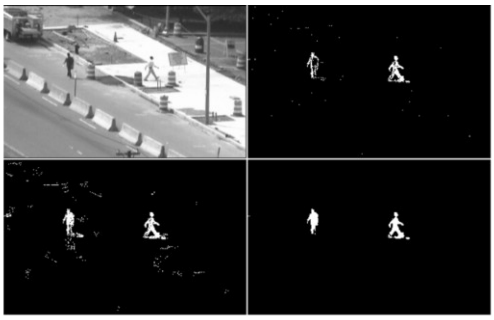

Fig 1: Background subtraction

In digital image processing [10], the edge detection is important technique. Edge detection is the process of finding meaningful transitions in an image. There are various edge detection [3] algorithms are proposed, and that are based on gradient operator or statistical approaches have been developed. Mostly the gradient operators are easily affected by noise, and the filtering operators are used to reduce the noise rate. In edge detection, morphological edge detectors [5] are also available which are effective than the gradient operators. Some kinds of morphological detectors are also available and those are not efficient while comparing to separable morphological edge detector. A mathematical morphology is a kind of morphological tool which is used to deal with various problems in image processing. But the edges at different angles are not covered and thin edges are missed by this mathematical morphological detector. Hence separable morphological edge detector detects thin edges and the edges at different angles with lesser noise [4]. This paper primarily aims at the new technique of video image processing used to solve problems associated with the real-time road traffic control systems. A new foreground detection approach called Optical flow and SMED (OF-SMED) based on optical flow and edge detection methods. The rest of the paper is organized as follows, section II involves literature survey, and section III introduces the proposed approach which is called optical flow and SMED (OF-SMED). In section IV some experimental results and discussions will verify the proposed approach is useful and feasible. Finally, the paper is concluded in section V.

II. LITERATURE SURVEY

Various methods have been proposed to video image processing until now. But these existing methods have some difficulties with congestion, shadows, noise and various lighting conditions. This literature report describes various techniques involved, their constraints like memory, computing tie, complexity. The following are some of the existing methods and their constraints.

Video surveillance method [12] has been proposed, aims at robustness with low volume of false positive and false negative rate simultaneously. But the requirement is to have zero false negative rates and also it should cope with varying illumination condition, occlusion situations and low contrast. Real time video surveillance [17] deals with real time detection of moving objects. This deals with problems like storage space and time consumption to record the video. To avoid the above problems this uses motion detection algorithm but this covers only the video that has important information. In real time visual surveillance W4 [13] method is the low cost PC based real time visual surveillance system. It has been implemented to track people and their parts of the body. It has the problem like sudden illumination changes, shadow and occlusion.W4S is an integrated real time stereo has addressed the limitation that W4 met. It deals with tracking of people in outdoor environment. But this makes tracking is much harder in intensity images. End-to-End method has been proposed which is used for removing moving targets from a stream of real time videos, sorts them according to image based properties. But this involves in forceful tracking of moving targets. Smart video surveillance systems support the human operators with identification of significant events in video. It can do object detection in outdoor and indoor environments under varying illumination conditions. But this is based on the shape of detected objects. Automatic video surveillance using background subtraction has different problems. Pixel based multi colour background model is a successful solution to this problem. However this method suffers from slow learning at the beginning and couldn't differentiate between moving objects and moving shadows. Multimedia surveillance [3] utilizes assorted number of related media streams, each of which has a different assurance level to attain numerous surveillance tasks. It is difficult to insert a new stream in the system with no knowledge of prior history.

Edge detection has been a challenging problem in image processing. Due to lack of edge information the output image is not visually pleasing.edge detection techniques transforms images into edge images benefiting from the changes of grey tones in the images edge are the sign of lack of continuity and ending .as a result of this transformation ,edge image is obtained without encountering any changes in physical qualities of the main image Various types of edge detectors are discussed here, Robert edge detector [12] detects edges which run along vertical axis of 45 and 135 degree. Only drawback is that takes long time to compute. Gaussian edge detector reduces noise by smoothing images and gives better results in noisy environment. The difficulty is that it is very time consuming and very complex for computation. Zero crossing detectors uses second derivative and it includes laplacian operator. It is having fixed characteristics in all directions. But it is sensitive to noise. Canny edge detector approach is that low threshold produce false edges and high threshold miss important edges. The problem is not very susceptible to noise [3].

To overcome all the above problems involved in the existing techniques a new proposed approach is adapted. This is very effective and overcomes all the above mentioned problems like congestion, shadow and lighting transitions, robustness to light changing and even slight movement. This proposed approach will be very effective and best choice for both crowd and traffic monitoring.

III.PROPOSED SYSTEM

a) OPTICAL FLOW

A new foreground detection approach called OF-SMED which makes use of Lucas-Kanade optical flow [1] is proposed. A perfect foreground cannot be obtained by using optical flow alone due to some brightness change. But, optimal foreground can be obtained by OF-SMED effectively.

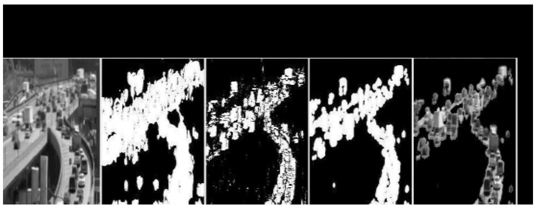

Fig 2: Cars on highway-Optical flow

It is known that there are five kinds of optical flow method and LK optical flow is a kind of gradient-based algorithm [4]. If $I(x; y; t)$ is the intensity of pixel $m(x; y)$ at time t, $vm = [vx; vy]$ is the velocity vector of pixel $m(x; y)$, then after a short time interval Δt, the optical flow constrain equation

$$\nabla I . Vm + \frac{\partial I}{\partial t} = 0 \qquad (1)$$

Where

$\nabla I = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right] T$ is the spatial intensity gradient vector. Because vm is two dimension variable, more constraints are needed to settle this question. LK optical flow method estimates vm by v expressed in (2) on the assumption that vm is a constant in a small spatial neighbourhood Ω.

$\sum_{m} = W^2 (m$ [redacted] $+\frac{\partial I}{\partial t})^2$ (2)

In (2), $W2$ (m) is a window function making the central part of the neighborhood has greater weight than the peripheral part.For the pixels mi (i = 1, 2 ..., n) in Ω, the solution v can be obtained by

$$v = (A^T W^2 A)^{-1} A^T W^2 b \qquad (3)$$

Where

A = (∇I (m1)... ∇I (mn)) T;
W = diag (W (m1)... W (mn))

And

$$b = -\left(\frac{\partial I(m1)}{\partial t}, \ldots, \frac{\partial I(m1)}{\partial t}\right)$$

Because LK method calculates optical flow on every pixel, so by using this method we can detect all the changes between adjacent frames, therefore it's the best choice in detecting crowd movement [11]. However, optical flow methods are very sensitive to brightness change, when using LK method it's difficult to find a proper threshold to segment foreground and background. In fact, no matter how to make a choice, the detection result may either lose some foreground area or contain some background noises. Obviously we cannot obtain an optimal foreground by using LK method alone, so we try to use other method to improve the result, after a lot of experiments we found that by combining LK optical flow and SMED method we could get a perfect result.

GBM [5] is one among kinds of background subtract method. In this method, K Gaussian models are used to approximate pixel values in the image, these models are updated on every frames of the video. If the residual value of pixel value and approximate value is larger than the set threshold, this pixel is regarded as foreground, otherwise it is background. Using K Gaussian mixture models, the gray probability function of pixel X at time t is given as

$$\mathbf{P(X)} = \sum\nolimits_{n=1} \mathbf{w_n} \frac{1}{\sqrt{2\pi\sigma n}} e^{-\frac{(x-\mu n)2}{\delta 2n}} \qquad (4)$$

Where w_n is the weight of number n Gaussian model whose mean and variance are μ_n and δ^2 n .Usually, the value of K is from 3 to 5. In order to represent a complex scene, we need to use larger K. It should be noted that the calculation time will increase with larger K.

By combining LK and GBM we propose a new approach OFBM which is shown in Fig.1.

It can be seen that OFBM method applies LK optical flow and GBM in parallel. On the one hand, we firstly use the two adjacent images $f(x; y; t-1)$ and $f(x; y; t)$ to calculate the LK optical flow field, then median filter and Gaussian filter are used to eliminate high-frequency noises and salt and pepper noises respectively. After that we use a threshold Tlk to segment optical flow field to get LK foreground mask $flk(x; y; t)$, our test results show the range of Tlk is [0.05, 0.20], choosing smaller Tlk will produce larger foreground area including background noises, while choosing bigger threshold may lose some foreground area. In order to detect all the movement area we select the smallest value 0.05, and then we try to eliminate the noises in the foreground mask flk($x; y; t$). On the other hand, GBM method is used to get another foreground mask where the scale filter is employed for segmenting foreground and background. In the scale filter, we set another threshold Tg that means an area of pixel block. For an obtained foreground image, if a pixel block has smaller size than Tg, it will be classified as background; otherwise it is kept as foreground. Hence, we can get a new foreground mask fg($x; y; t$). In our test, the value of Tg should be near 1=400 of the image area. For example, when the size of image is 320×240, the range of Tg is [160, 200]. As like LK method, we select the smallest Tg to obtain the largest foreground mask $fg(x; y; t)$. Finally, these two masks are multiplied and we operate morphological processing [6] to join the adjacent areas and exclude small blocks in the foreground, then an optimal foreground $fore(x; y; t)$ can be obtained as shown in Fig.1. Note that though both $flk(x; y; t)$ and $fg(x; y; t)$ contain noises, the noise in $flk(x; y; t)$ is caused by brightness alteration and randomly appears on the profiles of objects, in $fg(x; y; t)$ the noise occurs on the edge of objects and with time going by, the noise appears at the same place. Because the two noises appear at different place, we can eliminate most background noises by multiplying $flk(x; y; t)$ and $fg(x; y; t)$. The foreground image $for(x; y; t)$ obtained by OFBM is then used in density estimation.

Optical flow [16] and GBM not proves to be very efficient as optimal foreground is not obtained Error percentage also ranks high. Optical flow alone consists of possibly less noises due to filtering and also it is robust to brightness change.

b) SEPERABLE MORPHOLOGICAL EDGE DETECTOR

Edge is a basic feature of image. The image edges include rich information that is very significant for obtaining the image characteristic by object recognition. Edge detection refers to the process of identifying and locating sharp discontinuities in an image. There are various edge detection algorithms [3] are proposed, and that are based on gradient operator or statistical approaches have been developed. Mostly the gradient operators are easily affected by noise, and the filtering operators are used to reduce the noise rate. In edge detection, morphological edge detectors are also available which are effective than the gradient operators. Some kinds of morphological detectors [15] are also available and those are not efficient while comparing to separable morphological edge detector. The effectiveness of many image processing and computer vision tasks depends on the perfection of detecting meaningful edges. Due to lack of object edge information the output image is not visually pleasing.

Various types of edges are:

- Convex roof edge
- Concave roof edge
- Concave ramp edge
- Step edge
- Bar edge

Existing edge detectors are also available but the main disadvantage is that they are sensitive to noise and inaccurate. Some examples are Robel edge detector and Sobel edge detector.

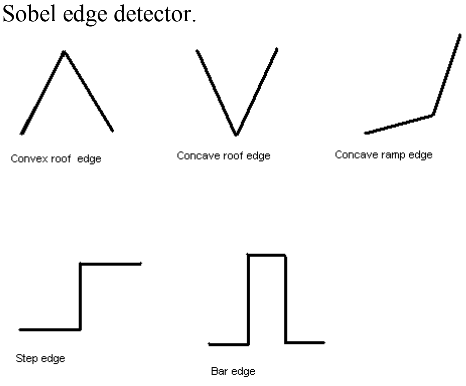

Fig 3: Various types of edges

The Roberts Detection

In Robert cross algorithm [3] the horizontal and vertical edges bring out individually and then they put together for the resulting edge detection.

+1	0
0	-1

G_x G_y

Fig 4: Robert edge detector

The two individual images G_x and G_y are combined using the approximation equation $|G| = |G_x| + |G_y|$ or by using $G = \text{sqrt}(G_x * G_x + G_y * G_y)$ to get the exact magnitude values. As the Roberts Cross kernels are relatively small, they are highly susceptible to noise.

Prewitt detection

The prewitt edge detector is an appropriate way to estimate the magnitude and orientation of an edge. Although differential gradient edge detection needs a rather time consuming calculation to estimate the orientation from the magnitudes in the xandy-directions, the compass edge detection obtains the orientation directly from the kernel with the maximum response. The prewitt operator is limited to 8 possible orientations, however experience shows that most direct orientation estimates are not much more accurate. This gradient based edge detector is estimated in the 3x3neighbourhood for eight directions. All the eight convolution masks are calculated. One convolution mask is then selected, namely that with thelargest module.

-1	+1	+1
-1	-2	+1
-1	+1	+1

0°

+1	+1	+1
-1	-2	+1
-1	-1	+1

45°

Sobel Edge Detection

The Sobel edge detection [3] technique is similar to that of the Roberts Cross algorithm. Despite the design of Sobel and Robert are common, the main difference is the kernels that each uses to obtain the image is different. The sobel kernels are more suitable to detect edges along the horizontal and vertical axis whereas the Roberts's able to detect edges run along the vertical axis of 45° and 135°.

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

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

Fig 5: Sobel Edge Detector

As existing edge detectors have some disadvantages with noise, a new morphological edge-detection operator separable morphological edge detector (SMED) [4] is proposed. This has a lower computational requirement while having comparable performance to other morphological operators. The reasons for adopting SMED operator in our application are as follows.

1) SMED can detect edges at different angles, while other morphological operators are unable to detect all kinds of edges.
2) The strength of the edges detected by SMED is twice than other edge detectors.
3) SMED [15] uses separable median filtering to remove noise. Separable median filtering has shown to have comparable performance to the true median filtering, but requires less computational power. SMED, which uses compatible and easily implementable operators, has a lower computational requirement, compared to the other morphological edge-detection operator .Open–close has better performance than SMED operator does, but it has about eight times more computational power requirement, therefore, it is not suitable for real-time applications. In order to apply edge-based techniques to a window, several steps have been taken to achieve real time and accurate measurement of traffic parameters. These steps are as follows.

1) The length of the windows used for counting vehicles should be wide enough to allow most edges of a car passing along a lane to be detected. In practice it should nearly be equal to the width of the lane.
2) The width of the window should be more than three lines of the image to compensate the effect of noise and to ensure creating edges by passing vehicles.
3) A dynamic threshold selection algorithm is used to compensate edges produced by the road surface or the background.

Optical Flow with SMED

- The output frames of the optical flow and background modeling method is taken as the input to SMED.
- The two consecutive frames are taken and SMED edge detector is applied to the frames.
- So, the edge are sharpen while compare to the former and the median filter is applied again in order to reduce the noise.

(a) (b) (c) (d)

Fig 6 : (a) Original (b) Canny (c) OFBM
(d) OFSMED (Thicker edges)

When using SMED method, the foreground containing much accumulated error due to noise should be eliminated. Optical flow consisting probably less noises can further be removed by applying separable morphological edge detector which makes the approach more effective than already existing approaches. While using the proposed OF-SMED approach, almost all noises are removed, and no foreground is lost, so the final object detection result will be optimal. OFSMED approach is effective.

IV. RESULTS AND DISCUSSION

Foreground detection [1] is the base of motion analysis, such as object tracking, image segmentation, and motion estimation. Proposed approach is carried out on several different videos and a sample of 100 images and result is discussed.

Average error rate is calculated for all methods which show OF-SMED is very effective and has less error rate. Numerical result shows OF-SMED is better the error rate is only 1.74%. It can be seen that when using optical flow method, there are some background noises because each motion area is detected. The algorithm uses a recent technique by applying simple but effective operations. This approach reduces computation time while compared to other using vehicle detection operation. The vehicle detection operation is a less sensitive edge-based technique. The threshold selection is done dynamically to reduce the effects of variations of lighting. The measurement algorithm has been applied to traffic scenes with different lighting conditions [10]. When using SMED method, the foreground contains much accumulates error should be eliminated [14].

As SMED possess median filtering it eliminates all noise present in optical flow. Crowd density estimation is very important in surveillance. Texture analysis and moment analysis are two common ways to estimate crowd density, in texture analysis a set of density features can be extracted from Gray level co-occurrence matrix (GLCM) which is calculated from foreground image. If M is the GLCM of foreground image, we can calculate a new feature F_M *defined* as follows.

$$\mathbf{F_M = -\sum_{i,j} M(i,j)^2 - \sum_{i,j} M(i,j) \ln M(i,j)} \qquad \textbf{- (1)}$$

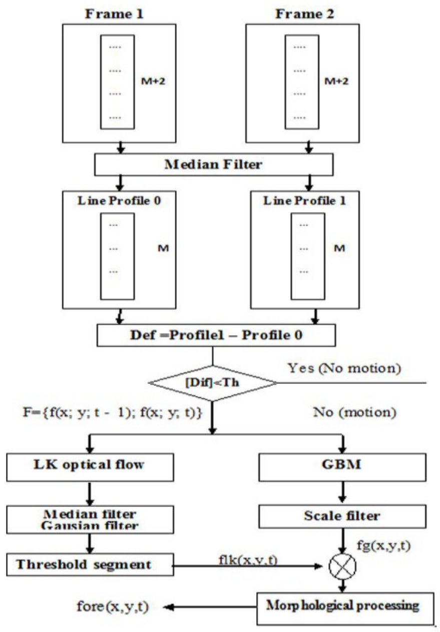

Fig 7: Flowchart of OF-SMED

In moment analysis, because the zeroth order moment represents the total mass of the given image. So we propose another feature F_{00} defined as follows,

$$F00 = -ln\frac{m00}{Af} = \ln A_f - \ln m_{00} \qquad \textbf{- (2)}$$

Where A_f *is* the area of foreground and $m00$ is the zeroth order moment of foreground image. Both FM and $F00$ can be used to estimate crowd density, the larger values of FM and the smaller values of $F00$ mean higher density. In our test, we used FM to estimate the crowds in different scenes and use $F00$ to measure the different crowds in fix scene. We carried out our approach on seven different videos which contain 1200 frames of image, and we randomly picked up 100 images to estimate OF-SMED. First we artificially appointed foreground area on each image which is the real foreground, and then we used the following equations to test the error rate of OFBM

$$\mathbf{r = |A_{real} - A| / A_{real} \times 100\%} \qquad \textbf{- (3)}$$

Where A_{real} is the area of real foreground, A is the area of experimental result foreground, so r is the error rate and R is the average error rate.

$$\mathbf{R = \sum_{i=1}^{100} r_i / 100} \qquad \textbf{- (4)}$$

Where r is the error rate and R is the average error rate. The test result can be seen in Table1

Approach	SMED	OFBM	OF-SMED
Error rate	4.85%	2.01%	1.74%

Table 1: Comparison of average error rate

Approach	SMED	OFBM	OF-SMED
Execution time (20 frames)	4.85%	2.01%	1.74%

Table 2 : Comparison of Execution time (20 frames)

While comparing average error rate of SMED, OFBM, OF-SMED numerical result shows, OF-SMED is better than the other two, the error rate is only 1.74%. Also, the OF-SMED has thicker edges than that of OFBM. The execution time of OF-SMED is better than than the OFBM. Thus OF-SMED is an Optimal approach for both traffic as well as crowd monitoring.

V. CONCLUSION

Optical flow method [7] is used to detect foreground which contains some background noises due to brightness change. The proposed approach OF-SMED combines the foreground together to eliminate noise. In optical flow the noise appears randomly and in SMED [4] method the noise appears at fix place such as the edge of building, so by doing the combination almost all the noises can be eliminated. When using the proposed OFSMED approach, we can see that almost all noises are removed, and no foreground is lost, so the final object detection result is optimal. The processing of OF-SMED is very fast with low computation time and cost effective approach. The low cost vision based system OF-SMED play an important role in monitoring, controlling, and managing the whole traffic system and has the potential to be used for applications such as electronic road pricing, car park management system, detecting stolen vehicles. Thus OF-SMED proves to be an optimal approach for traffic and crowd monitoring with error rate of 1.74% which is a satisfied result. Also, the execution time of OF-SMED is comparatively better than the OFBM.

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