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Robust Pedestrian Detection Framework using Harris Corner Detector and Kalman Filter

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***Abstract*— Detecting and tracking objects are among the most prevalent and challenging tasks that a surveillance system. Under the business intelligence notion, an object is a human, a queue of people, a crowd. In this paper we introduce the reader to main trends and provide taxonomy of popular methods to give an insight to underlying ideas as well as to show their limitations in the hopes of facilitating integration of object detection and tracking for more effective business oriented video analytics.**

Conditioned on these results, we then address object interactions, tracking, and prediction during a second step. The approach is through an experiment evaluated on many long and tough video sequences from busy inner-city locations. Our results show that the projected integration makes it doable to deliver robust tracking performance in scenes of realistic complexness.

Keywords*—— *Multiple Pedestrian Tracking, Harries Detector, Kalman Filtering

I. INTRODUCTION

Detection and tracking moving objects have many applications in the field of machine vision like video compression, monitoring systems, industrial control, and gesture-based computer interaction. Yilmaz et al. evaluated and classified moving object tracking methods [1]. According to their classification, tracking methods are divided into three categories: point-based tracking, kernel-based tracking, and Silhouette tracking. The point-based technique is further divided into two groups: deterministic and statistical. The kernel-based technique is additionally divided into two groups, that are pattern matching and classifier-use. The last one, Silhouette technique, uses the shape of objects and evaluate object contour methods.

According to Yilmaz et al., moving object tracking methods in various areas are faced with issues such as overlapping moving objects, change in brightness, little background motion, lack of motion stability in background and camera moving. to fix any of these problems, we should seek appropriate solutions [1].

According to Wu-Chih Hu et.al Moving object detection is relatively difficult for video captured by a moving camera since camera motion and object motion are mixed. During this technique, the feature points within the frames are found and then classified as belonging to foreground or background features. Next, moving object regions are obtained exploitation Associate in Nursing integration theme supported foreground feature points and foreground regions, which are obtained using an image difference scheme. [2]
Slim et al. [3] projected a method for tracking pedestrians with a mobile camera using a color histogram. The problem of pedestrians overlapping was eliminated with considering bar chart of people's head in the overlapping region. Lee et al. [3] introduced a technique for pursuit a mobile automaton by another mobile robot; in their method, for tracking the target robot by the tracker, they set up a angle of view of mobile tracking camera for tracking desired position and target robot by means of position information and motion information regarding each robots. However, in their method, tracking could face problems like barriers in front of the robot tracker camera, overlapping target robot and its disappearance. Yokoyama [4] used contour-based object technique for tracking and feature a gradient method for detecting and tracking objects supported optical flow and edge. Zhan et al. [5] used background difference method for moving the object supported background update model.

In this paper, a robust and fast yet simple technique for detecting and tracking moving objects is given. This technique is based on following mobility edge through fixed edges. The results show that the proposed technique, any to its efficiency, will overcome challenges such as brightness variations and background changes over time.

II. FEATURE POINT CLASSIFICATION

The proposed method has three main parts, namely the classification of feature points, the moving object detection, and the moving object tracking. An algorithm flowchart is shown in fig.1. To detect pedestrians in the wide area, video sequences Harries corner detection and are used as appearance based methods and Gaussian mixture model (GMM) was used to extract moving pedestrians. Like our approach, we combined the Harris corner detectors at the decision level to give a new detector. These algorithms are discussed in details in the following subsections.

1. GAUSSIAN MIXTURE MODEL

An adaptive online background mixture model that can robustly deal with lighting changes, repetitive motions, clutter, introducing or removing objects from the scene and slowly moving objects[17]. Their motivation was that a unimodal background model couldn't handle image acquisition noise, light change and multiple surfaces for a particular pixel at the same time [18].

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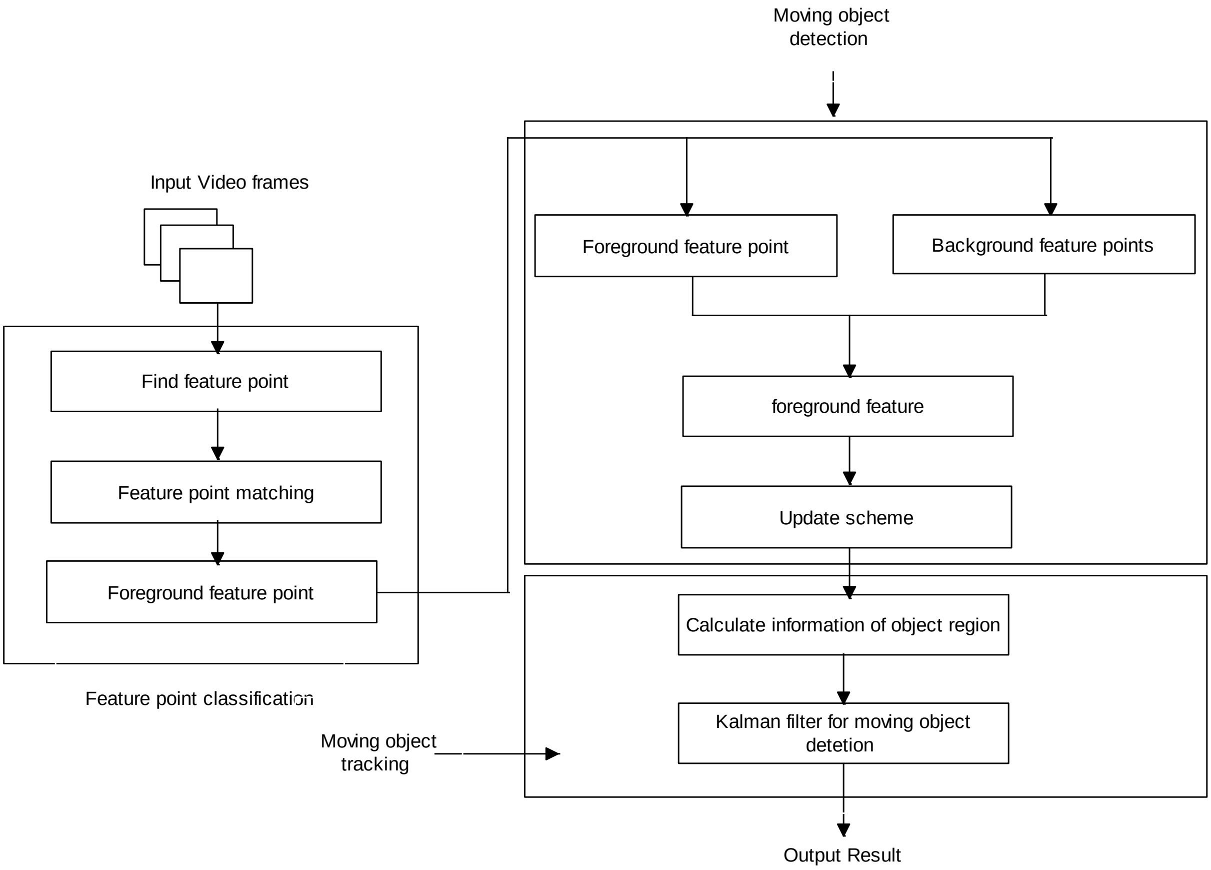

Fig.1 Flowchart of proposed method

Thus, we used a mixture of Gaussian distributions to represent every pixel in the model. Due to its promising features, we implemented and integrated this model in our visual surveillance system. in this method, the values of an single pixel (e. g. Scalars for gray values or vectors for color images) over time is considered as a "pixel process" and the recent history of each pixel, , is modeled by a mixture of K Gaussian distributions. The probability of observing a current pixel value then becomes:

$$P(Xt) = \sum_{i=1}^{k} w_{i,t} * (Xt, \mu i, t, \sum i, t) \tag{1}$$

where wi,t is an estimate of the weight of the ith Gaussian (Gi,t) in the mixture at time t, μ i,t is the mean value of Gi,t and Σi,t is the variance matrix of Gi,t is a Gaussian probability density function. The procedure for detecting foreground pixels is as follows. At the starting of the system, the K Gaussian distributions for a pixel are initialized with predefined mean, high variance and low previous weight. Once a new pixel is observed within the image sequence, to determine its type, its RGB vector is observed against the K Gaussians, until a match is found.

2. HARRIES CORNER DETECTOR

The Harris corner tracker is based on an assumption that corners are associated with maxima of the local autocorrelation function. It is less sensitive to noise within the image than most other algorithms, because the computations are based entirely on first derivatives [14]. The algorithm is popular due to its high reliability in finding junctions and its sensible temporal stability, creating it a lovely corner detector for pursuit [16]. It has to be noted that as a result of these algorithms rely on spatial derivatives, image smoothing is commonly required to enhance their performance. While up the detection dependableness, it's been shown that smoothing could end in poor localization accuracy. Shifting the window in any direction should large change in appearance; Harris corner detector offers a mathematical approach for deciding that case holds: flat, edge or corner; Let gradient vectors as a set of (dx,dy) points with a middle of mass outlined as being at (0,0); work an ellipse to that set of points via scatter matrix. For small shift [u,v] we have a bilinear approximation:

$$E(u,v) \cong [u,v] M \begin{bmatrix} u \\ v \end{bmatrix} \tag{2}$$

(a) (b)

Fig.2. Results obtained using Harries Corner Detector (a) Enter exit frame 133 (b) library1 frame 90

Where M is 2*2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I^2_x & I_x I_y \\ I_x I_y & I^2_y \end{bmatrix} \tag{3}$$

Change of intensity for the shift [u,v]:

$$E(u,v) = \sum_{x,y} w(x,y)[I(x+u, y+v) - I(x,y)]^2 \tag{4}$$

Measure of corner response:

$$R = \det M - k(traceM)^2 \tag{5}$$

$$\det M = \lambda_1 \lambda_2$$

$$traceM = \lambda_1 + \lambda_2$$

(k is empirically determined constant: k-0.04-0.06)

(a) (b)

Fig.3. Results obtained for Oneshop frame 53(a) Background subtraction (b) Person detection

III. MULTIPLE PERSON DETCTION AND TRACKING

The difference between a typical Kalman filter and the enhanced Kalman filter are highlighted by occlusion rate calculation which making the tracking during occlusion is capable and the involvement of occlusion scene determination. [18].

Besides that, object recognition capability is added to the enhanced Kalman filter so that the tracking target can be recognized by others. This feature is running all the time to assure that the targeted object will be acknowledged all the time.

The Kalman filter has two distinctive features. One is that its mathematical model is described regarding state-space concepts. Another is that the solution is computed recursively. Usually, the Kalman filter is described by system state model and measurement model. The state-space model is described as a system state model and analysis model as shown in (6) and (7) respectively.

$$s(t) = O(t-1)s(t-1) + w(t) \tag{6}$$

$$z(t) = H(t)s(t) + v(t) \tag{7}$$

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(a) (b)

Fig. 4. Results obtained for Enterexit frame 100(a) Foreground detection (b) Person detection

(a) (b)

Fig.5. Results obtained for Library 2 frame 320 (a) Foreground detection (b) Person tracking

Where O(t -1) and H(t) are the state transition matrix and measurement matrix . The w(t) and v(t) are white Gaussian noise with zero means.

Kalman filter has two phases: prediction step and correction step. The prediction step is cause for projecting forward the current state, obtaining a prior estimate of the state s (t).The work of the correction step is for the feedback. It incorporates an actual measurement into the previous estimate to obtain an improved posterior estimate s+ (t), which is written as shown in (8).

$$S^{+}(t)=S^{-}(t)+k(t)[z(t)-H(t)S^{-}(t)] \tag{8}$$

The algorithm of the proposed tracking scheme of multiple person detections is given below.

Step 1: find the width and height of every tracked person. If there's no tracked person, then go to Step five.

Step 2: tracked person is searched for among the search region S_R. Four conditions are checked and dealt with.

Search region is defined as:

(9)

Where W, H are the width and height of minimum bounding box of moving person.

(1) If there are multiple monitored people within the search area SR, then go to Step three.

(2) If there's no tracked person within the search space SR, then head to Step four.

(3)If there's just one moving person and it's not half-tracked. Within the search region SR, then find width, and height and so go to Step five.

(4) If there is just one moving person and it's tracked in the search region SR, then there are multiple overlapping objects. Go to Step five.

Step 3: Calculate the gap Di between the tracked person and each moving person. Calculate the difference of the Minimum

Bounding box ri between the tracked object and each moving person, find the smallest Di and ri, and this object isn't tracked, then its location is that the new location of the tracked object, go to Step five.

Step 4: Apply prediction tracking to the moving object using the Kalman filter, find the location and so go to Step five.

Step 5: Predict the location of each moving person using the Kalman filter to find the width, and height of every tracked object. If the retention time of the tracked object is larger than the given threshold TR, the data and Kalman filter of the tracked object are removed. Go to Step one. In the planned algorithm for multiple moving object tracking, the given threshold of the retention time TR = 0:1s is set from experience. If a new moving object is added, it's assigned as a candidate tracked object. If the time of incidence of the candidate tracked object is larger than 0:5s, the Kalman filter is used for the prediction trailing. The proposed algorithm will track overlapping objects and objects whose scale changes (object is moving toward or away from the camera).

IV. EXPERIMENTAL RESULTS

Experiments are done on a computer with an Intel Core i5 2.3 GHz CPU and 4 GB of RAM. The algorithms were implemented in Matlab13.

4.1 Performance evaluation of self made dataset

In order to illustrate the performance of person detection and tracking, the true detection rate TR and the false detection rate FR were adopted as defined in Eqs. (1) And (2), respectively, where N is the total number of moving objects, TP is the total number of true detection objects, and FN is the total number of false detection objects. Ts The results of the performance explain for the self-made dataset are shown in

$$TR = \left(\frac{TP}{N}\right) * 100\% \quad (9)$$

$$TP = \left(\frac{FN}{TP + FN}\right) * 100\% \quad (10)$$

TABLE I.

Sequence	Resolution	Frames
Library 1	1280 x 720	822
Library 2	1280 x 720	880
Library 3	1280 x 720	1475

Fig.7. Description of self made dataset

TABLE II.

Sequence	N	TP	FN	TR%	FR%
Library 1	822	1166	0	90.24	0
Library 2	880	1041	0	86.96	0
Library 3	1475	1359	70	70.41	4.89

Fig.7. Performance evaluation of self made dataset

4.2 Performance evaluation of public dataset

A public dataset that includes three video sequences (Enter exit, one shop, TUD stadtmitte) was used to evaluate the performance of proposed method.

In order to illustrate the performance of public dataset, Precision (P) and Recall (R) were adopted as defined in Eqs. 11–12, respectively, where TP is the total number of true positive pixels, FP is the total number of false positive pixels, and FN is the total number of false negative pixels.

$$P = \frac{TP}{TP + FP} \quad (11)$$

$$R = \frac{TP}{TP + FN} \quad (12)$$

This paper proposed a novel method capable of detecting and tracking people in cluttered real-world scenes with many people and changing backgrounds. Kalman filter improve people-detection by people-tracklet detection in image sequences. Those tracklets are then used to enable people tracking in complex scenes with many people and long-term occlusions. In the future we will extend the proposed approach using a 3D limb model to allow people-detection from arbitrary viewpoints and across multiple cameras.

table 2. Experimental results show that the proposed technique performs better than other method. The proposed method has good performance in terms of true detection rate and false detection rate. So, the proposed technique greatly increases the performance of person tracking.

TABLE III.

Sequence	Enter exit		One shop		TUD stand	
Techniques	R	P	R	P	R	P
ACF[9]	0.58	0.76	0.32	0.48	-	-
DPM[9]	0.74	0.89	0.63	0.90	0.77 [10]	0.97 [10]
HOG/ SVM[9]	0.62	0.77	0.32	0.48	-	-
KSP[7]	-	-	-	-	0.63	0.79
Online CRF[8]	-	-	-	-	0.85	0.86
GMCP[11]	-	-	-	-	0.81	0.95
Proposed Method	0.93	0.84	1	0.52	0.93	0.84

Fig.8 Performance evaluation and comparison of public dataset

V. CONCLUSION

The method of multiple pedestrian detection in video sequences is proposed in this paper. Feature points in each and every frame are detected and then classified as foreground and background features. We have used harries corner detector for

Extracting features from frames. Foreground feature points then used to detect the pedestrian in the frame. These foreground feature points are then updated for every frame. Then foreground is extracted by background subtraction algorithm in combination with harries feature point detector to have better results. Moving pedestrian is obtained from above method is then tracked by Kalman Filter which will track the pedestrian with minimum bounding box.

We have tested our method on various available public datasets. Experimental results show that the proposed method gives better result. Therefore the proposed method is useful for surveillance and other pedestrian related applications.

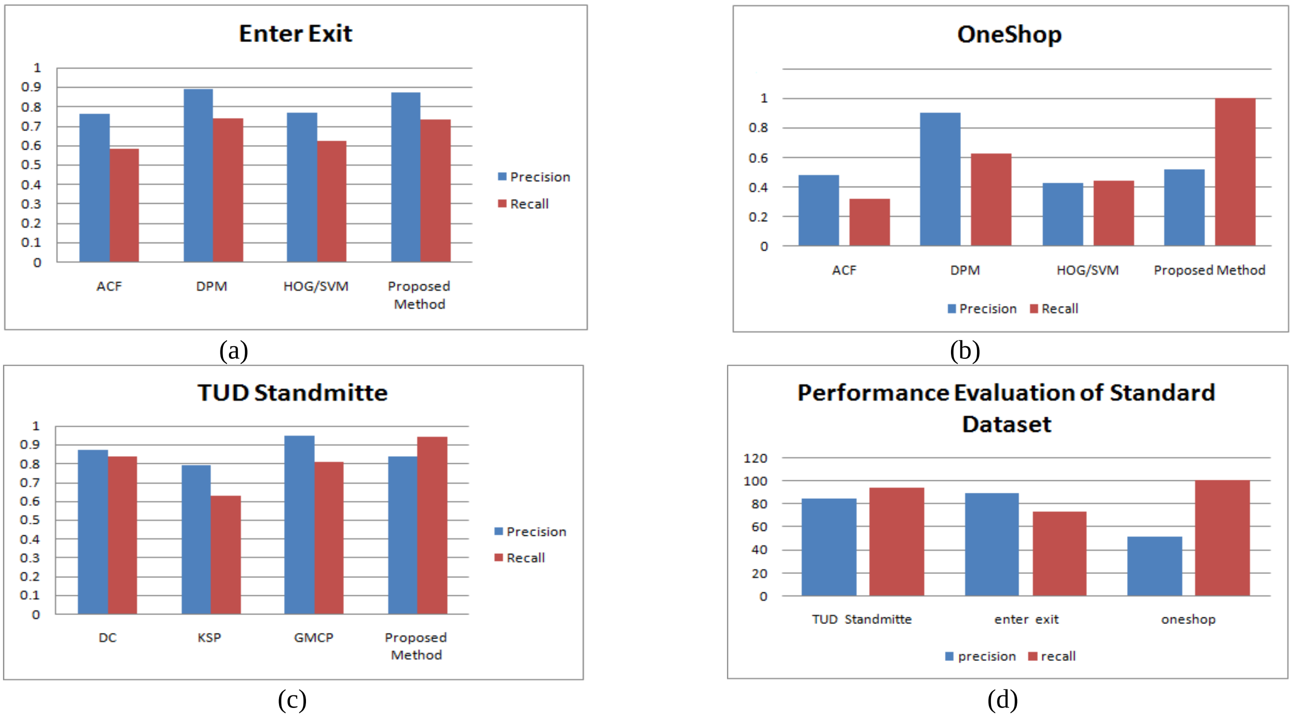

Fig.6. Bar chart (%) of performance evaluation of public dataset (a)Enter Exit, (b) One shop, (c)TUD Stadtmitte, (d)Performance evaluation

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