Detection of Stationary Foreground Objects in Region of Interest from Traffic Video Sequences

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Abstract
Detecting stationary objects such as an Abandoned object or a Parked vehicle is very critical and has extensive series of applications. This paper presents a new method for detecting stationary objects in video sequences of traffic taken from a static camera. It uses Running average to model the background image at every pixel position. The background obtained is then used to detect the stationary foreground object in the video. Stationary foreground object can then be classified as illegally parked vehicle or an abandoned object based on the amount of time it has been stationary. The system has been evaluated using public datasets and has been robust to high noise levels. Potential applications include Urban Traffic Surveillance and Incident detection on roads.

Keywords: *Closed-circuit television (CCTV), Road users, traffic analysis, Urban traffic, Parked vehicle detection, abandoned Object detection, Surveillance, Background subtraction, object tracking, visual surveillance*

1. Introduction

The deployment of CCTV systems for the purpose of Surveillance has led to enormous amount of Video data which in turn has augmented the requirement of Automated Monitoring from Video. Thanks to the rapidly increasing number of surveillance cameras which have lead the way to a strong demand of automated analysis of Video. Need for Automated analysis of Video is strongly felt in private and government sectors with the main aim concentrating on the safety of the public and Infrastructure. Automated analysis has definitely been an initiative against Terrorism and Crime. Automated analysis of Video data will definitely help in preventing damages caused to Public Infrastructure.

This paper describes the overall architecture, flow of the algorithm, and how it detects the Stationary objects and presents the experimental results on i-LIDS datasets. The simplicity and efficiency of the algorithm will lead its applicability in Real-time systems. A system skilled of Automatic accurate Stationary Object Detection will be of great assistance to those people who are employed for monitoring.

2. Organization of the Paper

The paper is organized as follows. Relevant previous work is given in Section 3. In section 4, the proposed method is described.

Fig.1 Scenario indicating lane under analysis. ROI(Marked in Orange) indicates No-Parking Area

Fig.2 A sample original image

Details of Background Modeling, Updation of Background Model, Identification of Stationary object and Region based Tracking are provided in Section 4.1, Section 4.2, Section 4.3 and Section 4.4 respectively. Details of Performance metrics are provided in Section 5. Experimental results are provided in Section 6. The Paper concludes with Section 7.

3. Related Work

Stationary foreground object detection depends greatly on building a dynamic background model. There are many published works on moving object detection including vehicle detection [1]-[5] but there has been less research in stationary foreground detection. Foreground blogs are tracked over time with a variety of methods thus creating Spatiotemporal objects (Target)[6]. Targets may be declared stationary and various events may be detected. Stauffer et al [4] modeled each pixel as K mixtures of Gaussian distributions and compared with the incoming pixels. If a match is found, the parameters of the model are adjusted.

4. Proposed Approach

Our focus here is to detect the Stationary foreground objects in the region of Interest. Localizing the location of interest is not a part of this work. Sample Region of Interest (ROI) and an original frame are shown in figure 1 and figure 2 respectively. The whole algorithm encompasses the following steps: Background Estimation, Background Updation, and Object Tracking. Flowchart of the algorithm is depicted in Figure 3.

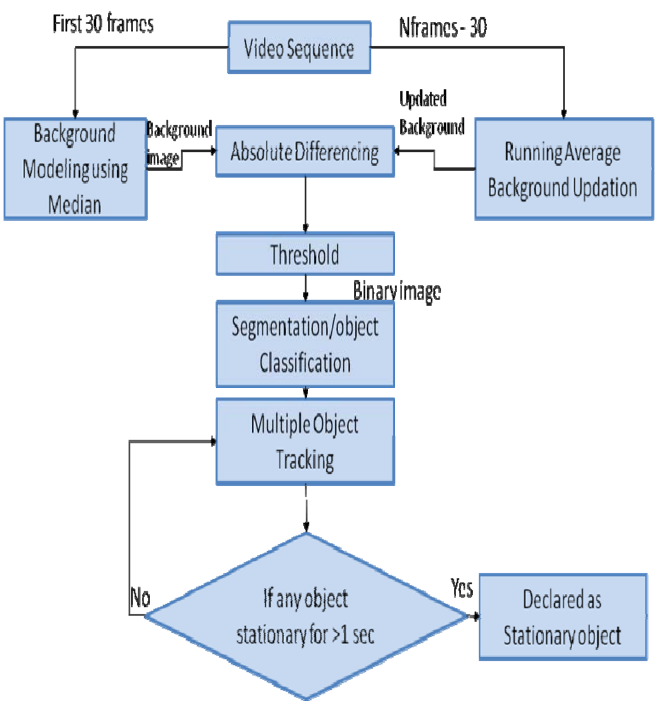


Fig 3 Framework of the proposed system

In this paper we process Gray level Image sequences instead of Color Image Sequences.

4.1 Initial Background Estimation

Detection of moving object is the very first step in information extraction in many computer vision applications. In order to detect moving objects in videos we need to first estimate the background which does not consists of any moving objects.

In the case of our background modeling, background for the initial few frames are obtained using median of the intensities at every coordinate position of the frame.

i-LIDS Parking Vehicle Challenge Dataset:

Level of Difficulty: Day time, Easy ***Level of Difficulty: Day time, Medium***

(a)

(d)

(b)

(e)

(c)

(f)

Fig 4. (a) Result of Background updation using Median (for initial 20 frames) (b) Result of Background modeling using Median (c) Result of Background updation using Running Average after 300th frame (d) Result of Background model using Median (for initial 20 frames) (e) Result of Background updation using Running Average after 150th frame (f) Result of Background updation using Running Average after 330th frame

4.2 Background model update:

Running average is used to update the background obtained in the previous stage.

i-LIDS Parking Vehicle Challenge Dataset

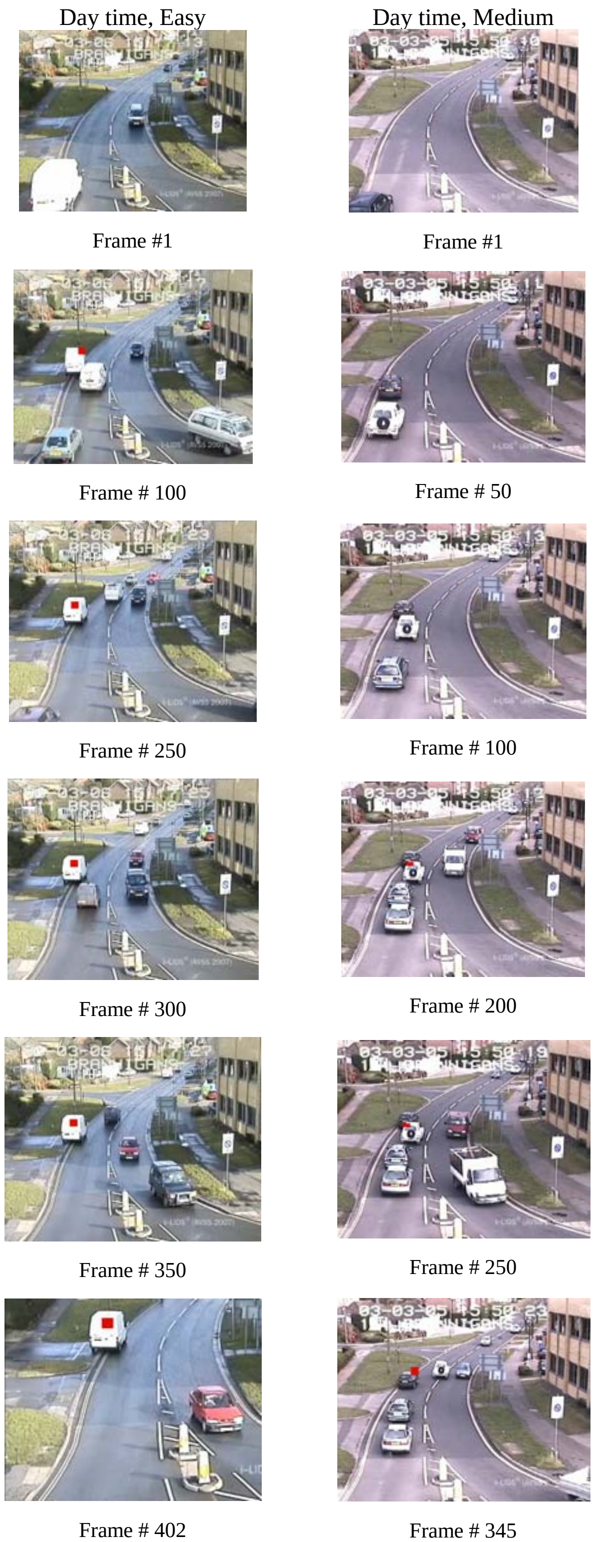


Fig.5 Result of the Proposed approach. Red spot indicates the centroid of the tranquilized object

Background adapts to the illumination variations in the scene. The updating formula is as given in (1):

$$B_{t+1}(x,y) = (1-\alpha)B_t(x,y) + \alpha F_t(x,y) \quad (1)$$

α is the updating rate representing the speed of new changes in the scene. Larger the value of α helps in updating the stationary moving object. B_t represents the background image at time t, F_t corresponds to the current frame at time t. Running average is used to compute the background because it has low computational complexity and space complexity. Figure 4 shows the result of Background Estimation and updation.

4.3 Identification of Stationary object:

Dynamic updation of the background facilitates in obtaining the stationary moving object in the scene. Updated background is now used in finding the moving object which becomes stationary over the time. Here we are finding the illegally parked vehicle in the area marked by a yellow box in figure 1. Absolute Difference between the updated background for every frame and the background for the initial frames is done only in the Region of Interest to reduce computation. Median filter is applied on this thresholded image to eliminate noise.

4.4 Region-based Tracking:

Region based Tracking is done on the stationary foreground blob(assumed as object) identified in the previous step. Multiple blobs are tracked throughout and the stationary blobs are identified. Tracking is done by tracking region-based blob. The object is declared as a parked vehicle or an abandoned baggage or an abandoned object in general if it is stationary for some time. Here for the traffic scenario considered we have considered the time limit to be atleast 1 minute. Result of the proposed approach is shown in figure 5.

5. Performance Metrics

Qualitative Evaluation:

To evaluate the performance of any system, it is essential to define the metrics to be used. These qualitative evaluation metrics are different depending on the final application. For measuring accuracy, we adopted different Frame-based Accuracy Metrics, namely Precision, Recall, F1, Similarity, False Alarm rate and Tracking accuracy for evaluating our work.

5.1 Recall (or) Detection Rate

Recall gives the percentage of the detected True positives as compared to the total number of true positives in the ground truth. Detection rate is calculated as follows:

$$\mathrm{Re}\,call = \frac{TP}{(TP + FN)} \tag{2}$$

A true positive (TP) indicates the total number of frames in which the hypothesis is true and our tests accepts it. A true negative (TN) indicates the total number of frames in which the hypothesis is false and our test rejects it. A false negative (FN) indicates the total number of frames in which the hypothesis is true but our tests rejects it. A false positive (FP) indicates the total number of frames in which the hypothesis is false but our test accepts it. (TP + FN) indicates the total number of items present in the ground truth. Recall acts as a frame based metric.

5.2 Precision

Precision also known as Positive Prediction gives the percentage of detected True positives as compared to the total number of items detected by the method.

$$\mathrm{Pr}\,ecision = \frac{TP}{(TP + FP)} \tag{3}$$

Using the above mentioned metrics, generally a method is considered good if it reaches high Recall values, without sacrificing Precision.

5.3 Figure of Merit or F-Measure

F1 metric also known as Figure of Merit is the weighted harmonic mean of Precision and Recall

$$F1 = \frac{(2 * \mathrm{Re}\,call * \mathrm{Pr}\,ecision)}{(\mathrm{Re}\,call + \mathrm{Pr}\,ecision)} \tag{4}$$

Figure of merit indicates a good accuracy of the architecture used

5.4 False Alarm Rate

False Alarm rate is calculated as follows:

$$FAR = \frac{FP}{(TP + FP)} \tag{5}$$

5.5 Tracking Accuracy

Tracking Accuracy is also calculated for detected objects frame by frame.

6. Experimental results and evaluation:

We tested our system on the parked vehicle scenarios, by looking for a vehicle stopped in an area of interest (No-Parking Zones) for at least 60 seconds. Each frame is processed in its original resolution. Real time processing is possible because we reduced the processing time by focusing on only the Region of Interest (ROI). Results of all video sequences are accurate. Table 1 shows the results. Our system detects two illegally parked vehicles as one vehicle. Reason for that is two vehicles came to No-Parking Zone together. Table 2 shows the valuesRecall, Precision, F1 measure, Similarity.

Summary of Frame-based accuracy values for I-Lid Parked Vehicle detection Challenge Sequences Easy and

Table 1

Video Sequence (Event)	*True positives*	*True negatives*	*False positives*	*False negatives*
Easy	312	83	1	6
Medium	145	45	10	145

Table 2

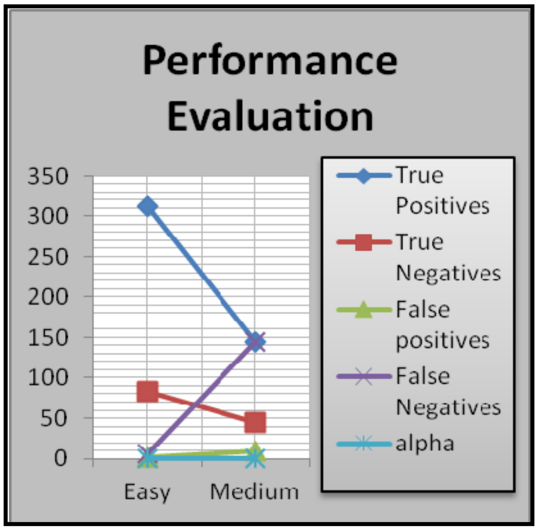
Video Sequence (Event)	*Recall*	*Precision*	*F1*	*Similarity*
Easy	0.981	0.9968	0.988	0.978
Medium	0.5	0.9354	0.651	0.483

Table 3

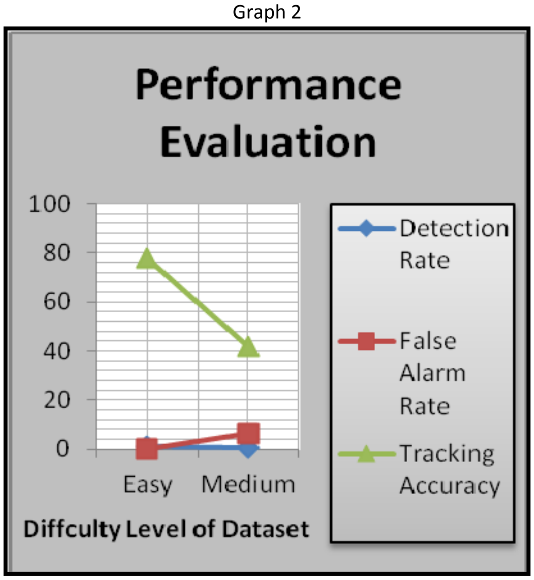
Video Sequence (Event)	*False Alarm Rate*	*Tracking accuracy (%)*
Easy	0.003194888	77.6119403
Medium	6.451612903	42.02898551

Table 1 provides a summary of the metrics obtained from the surveillance videos. Tracking performance shows a good tracking performance for the parked vehicles except for the few false alarms and detections due to the shadow of the vehicle itself, Shadow of nearby vehicles, occlusion of nearby vehicles. Table 2 and Table 3 present a summary of the tracking performance on i-Lids database.

Graph 1



Graph 2



7. Conclusion and Future work

In this paper we presented a method for detecting stationary objects using mid-level motion features. We were able to successfully detect stationary foreground objects by accurately tracking the objects in the Region of interest in the scene of observation. The proposed approach has been thoroughly evaluated using huge datasets. Our method makes few assumptions about the alpha value considered for background modeling and choosing the No-Parking area for reducing computation. Limitation of this approach is that it fails to detect parked vehicles when the vehicles are crowded.

Future work includes improving the background image so that false alarm can be reduced. Other areas where improvement is required are detection of vehicles when there is a busy traffic and when the vehicles crowd. There is a growing possibility for adopting video analysis for Traffic measurement.

Acknowledgments

The authors would like to express their gratitude to the anonymous reviewers for their useful comments and thank all of the participants in the subjective testing for their time and effort.

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