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VEHICLE DETECTION, TRACKING AND COUNTING USING LINEAR QUADRATIC ESTIMATION TECHNIQUE

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***Abstract*— In modern digital world one of the most challenging issue is the detection of moving object in a video frame and further tracking it. Same thing becomes more and more difficult when we replace these moving objects with a moving vehicle on a road. With the increasing number of vehicles the traffic monitoring system has become a very vast field for research. Although there already have been many works done in the field however our paper presents a very simple approach for detecting vehicles in urban traffic scenes by means of background subtraction and Linear Quadratic Estimation (LQE). In our proposed system, a video is taken and then the video is subtracted into masks to detect the vehicles. Binary Morphological operation is used to remove the noise from the video. Simple Linear Quadratic Estimation (LQE) is then used to predict the vehicle path and count all detected vehicles. Our proposed method is less complex and acquires almost 99% result successfully.**

Keywords—Vehicle detection, Vehicle count, Vehicle tracking, Linear Quadratic Estimation (LQE), Background Subtraction.

I. Introduction

Traffic analysis studies are done to determine the traffic flow and the prevailing traffic patterns at the intersections. At the key intersections, video camera is deployed and footage is taken for a specific period of time to study about the traffic at that intersection. From the analyzed video data is generally used detect and count the number of moving vehicles at that place. The main cause of increase in traffic congestion in metro cities is due to increase in the population [13,14,15]. The Traffic jams creates lot of pollution, loss of money and directly affect the human routine lives and some time causes the loss of human lives as well [16,17,18].

In our proposed method at first a video camera is set up on the road. Then the video is taken for real-time analysis. At first the video is differentiated between background and foreground mask. Then the noise form the video is removed using the binary morphological operation. The removal of noise helps in better vehicle detection and tracking.

In computer vision vehicle detection and counting is a challenging problem. The field of vision research[6] has been dominated by machine learning and statistics. Traffic analysis and security are such important practical applications. Using camera in monitoring system is comparatively inexpensive then other methods. Manually counting vehicles is not a good choice. A little interaction or no human connection to the system will give more and more correct result. So, we are proposing this method to detect and count vehicles.

Our rest of the paper has been organized as follows- Literature review is given in section II. Our proposed method is briefly described in section III, Experimental Results Data and Conclusion have been explained in section IV and section V respectively.

II. Related Work

There are many researches already have been done in the field of vehicle detection and counting using Linear Quadratic Estimation (LQE). This section briefly mentions some of the related studies in order to understand the importance and limitation of those researches.

Megha C. Narhe and Dr. M.S. Nagmode in [1] have done a project to Vehicle Count using Video Image Processing. In this research Scale Invariant Feature transform (SIFT) algorithm is used for vehicle counting. The vehicle classification and counting technique used in the paper produces the good result. However, using this technique increases the complexity of the whole process. Moreover as the features are extracted according to the described features, the vehicles which doesn't match with the features are not counted.

In [2] K.B. Neelima and Dr. T. Saravanam have done oobject detection and count using Open Computer Vision. In this paper mainly used openCV to detect and count. But using this process to detect and count vehicles, makes the system slow. Nilesh J. Uke and Ravindra C. Thool in [3] worked in a project named Moving Vehicle Detection for Measuring Traffic Count Using OpenCV to detect and count vehicle. System in this paper is designed and implemented with Visual C++ software with Intel's OpenCV video stream processing system to realize the real-time automatic vehicle detection and vehicle counting. But same as [2] using this process to detect and count vehicles, makes the system slow.

In [4] Hyeok Jang, In-Su Won, and Dong-Seok Jeong have made an Automatic Vehicle Detection and Counting Algorithm. The unique feature of this algorithm is to calculate an approximate value of speed while counting vehicles using GMM background modeling, object histogram and pyramidal Lucas Kanade method. As the process is based on the approximate value of speed to detect and count vehicles on the road, it provides result with huge error. In [5] Mrs. P.M.Daigavane and Dr. P.R.Bajaj proposed an algorithm named Real Time Vehicle Detection and Counting Method for Unsupervised Traffic Video on Highways. The background subtraction and image segmentation based on morphological transformation for tracking and counting vehicles on highways is proposed. This algorithm uses erosion followed by dilation on various frames. But because of ambiguous poses the vehicle counting gives a huge amount of error.

Chen et al., [7], [8] have addressed the issues regarding unsupervised image segmentation and object modelling with multimedia inputs to capture the spatial and temporal behavior of the object for traffic monitoring. But using this process makes the makes the process complicated to understand. In [9] algorithms for vision-based detection and classification of vehicles in monocular image sequences of traffic scenes are recorded by a stationary camera. Processing is done at three levels: raw images, region level, and vehicle level. In this process vehicle detection and counting is done from separate images, which is not efficient to work. Daniel et al., [10] presents the background subtraction and modelling technique that estimates the traffic speed using a sequence of images from an uncalibrated camera. The combination of moving cameras and lack of calibration makes the concept of speed estimation a challenging job. As the camera is not calibrated here, the video taken from the camera is not suitable to analyze to get the data. Because of the camera movement there is a possibility of noise in the video.

Cheng and Kamath [11] compare the performance of a large set of different background models on urban traffic video. They experimented with sequences filmed in weather conditions such as snow and fog, for which a robust background model is required. Because of different weather conditions this process needs a robust background, which makes the process more complicated and heavy to use. Toufiq P. et al., in [12] describes background subtraction as the widely used paradigm for detection of moving objects in videos taken from static camera which has a very wide range of applications. The main idea behind this concept is to automatically generate and maintain a representation of the background, which can be later used to classify any new observation as background or foreground. But using this process without removing noise is not a good process to detect and count vehicles because noise affects the vehicle detection and counting a lot.

Despite the large amount of researches on vehicle detection and tracking, there is lots of scope of further research in this filed. Because of noise, robust background, specific features of vehicles and also the non calibrated camera with complicated methods make it difficult to find the perfect result. We have devised a very simple approach of vehicle detection, tracking and counting using background subtraction in integration with Linear Quadratic Estimation (LQE). The entire method has been implemented in MATLAB.

III. Proposed Work

The actual process start with taking video from a camera installed on road to cover vehicle traffic. There after each frame of the video has been processed to detect, tract and count vehicles. The entire working process of the system is represented in block diagram.

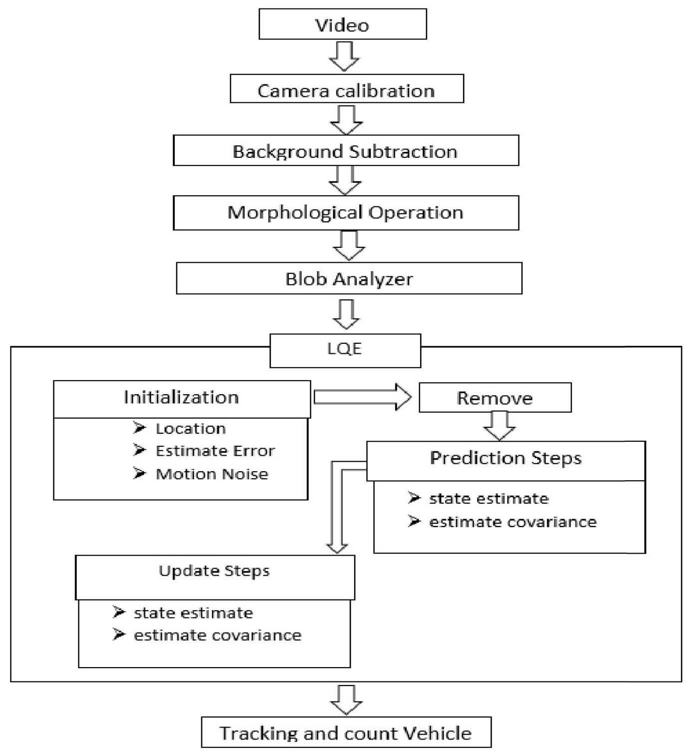

Fig. 1. Block Diagram

A. Camera Calibration

Geometric camera calibration, also referred to as camera re-sectioning, estimates the parameters of a lens and image sensor of an image or video camera. The these parameters are used to correct for lens distortion, reduce noise due to camera movement and captures the proper shape of the object in the image. The camera re-sectioning tasks are very important in applications such as object detection, tracking and measurement the objects size and shape. With the camera movement and lens distortion noise is added to the video, therefore it becomes difficult to detect the accurate moving vehicle in the frames.Hence it is very necessary to calibrate the camera properly to capture the correct picture of traffic. The result of Camera Calibration performed in MATLAB represented in figure 2 and 3.

Fig. 2. Before applying camera calibration

Fig. 3. After applying camera calibration

B. Background Subtraction

After camera calibration, the background subtraction is done to identify and extract any object from the video frame. Before applying the Background subtraction video is converted form RGB frame to gray scale frame. Figure 3 and Figure 4 shows the outcome of the converted frame from RGB to gray scale.

Fig. 4. RGB video

After conversion into the gray scale, the Mask analyzer has been applied on video frame to differentiate foreground mask from the background mask. Initially the background mask is totally black. However, when something was detected moving on the background mask, it is subtracted from it.

C. Morphological Operation

Binary Morphological operation is used to remove the unnecessary noise from the frame and to extract the exact shape of the detected object. This operation enhance the boundary of the detected object after the background subtraction. In figure 5 the noises in the videos are shown as a hole after

Fig. 5. Gray scale video

background subtraction. Those holes has been removed using binary morphological operation. Fig 6. shows the outcome of the Binary morphological operation.

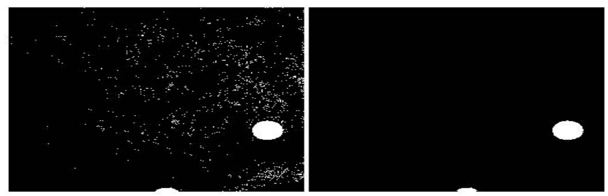

Fig. 6. Morphological operation

D. Vehicle Detection

After the image enhancement, blob analyzer is applied on the moving object. Blob analyzer will help us to correctly detect the moving object as a vehicle or not. During blob analysis, we have specified size of blob for a vehicle. If the size of blob is less than threshold value, the detected object is not considered as a vehicle. Hence the proposed method is very robust in identifying, detecting and tracking of moving vehicles on road only. The system will automatically discard all other object in frame those are not vehicles, due to less than threshold value.

E. Vehicle tracking

LQE technique is used to track the detected vehicle in the considered frame. Linear Quadratic Estimation (LQE) also know as Kalman filtering is an algorithm which produces estimates of unknown variables over time that tend to be more accurate than a single measurement. The algorithm works into two steps. In the prediction step, the LQE produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. The LQE algorithm is recursive process. It runs in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required. The LQE does not make any assumption that the errors are Gaussian. However, the filter yields the exact conditional probability estimate in the special case that all errors are Gaussian-distributed.

On detection of the vehicle, blob ID is created; it is surrounded by a blob and initialized with serial 1. The vehicle surrounded with Blob in its frame of detection acts as an initialization factor for Linear Quadratic Estimation (LQE) Filter. In that frame the estimation error and motion error is also initialized. Then with the help of LQE Filter it predicts its next position of the blob in the next frame. Whenever a new vehicle comes and detected into the frame, a new Bold ID is automatically assigned to the vehicle and linear quadratic estimation (LQE) automatically starts the calculation and tracking of the vehicle in consecutive frames. The LQE algorithm predicted (a priori) new location estimate by

$$X_{k|k-1} = F_k X_{k-1|k-1} + B_k u_k \tag{1}$$

and predicted (a priori) corrected estimate co-variance by

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{2}$$

Here,F_k is the state-transition model and Q_k is the co-variance of the process noise and B_k is the control-input model, for each time-step, k.

When predicted variance is also calculated, it is checked for the next position of the blob and if the predicted position of the blob is same or close to one another. If the initial position and the predicted position are same or close then they are taken as same vehicle. Otherwise, they are identified as different vehicles. The identified vehicles are counted using the blob IDs, which gives the number of vehicles on the road. LQE therefore calculate the updated (a posteriori) state estimate by

$$X_{k|k} = X_{k|k-1} + K_k y_k \tag{3}$$

and updated (a posteriori) estimate co-variance by

$$P_{k|k} = P_{k|k-1} + K_k S_k K_k^T \tag{4}$$

Here.y_k is innovation or measurement pre-fit residual, S_k is Innovation (or pre-fit residual) co-variance and K_k is Optimal LQE gain.

IV. Result Analysis

After the video analysis and background subtraction from the video vehicles and the blobs are shown in the video player and the mask player in the figure 7, figure 8, figure 9 and figure 10. The detected vehicle is surrounded by a blob. The vehicle count in the frame is mentioned on top left corner of the blob. This value is called blob ID and it increases automatically when the new vehicle detected into the frame.

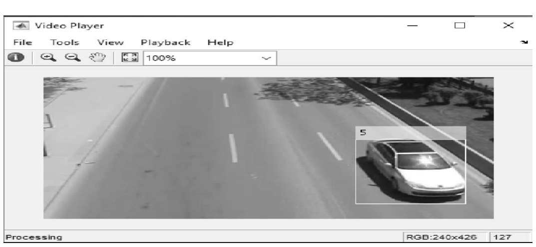

Fig. 7. Detection of single Vehicle in video player

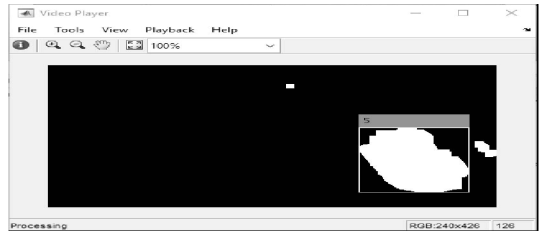

Fig. 8. Detection of single vehicle in mask player

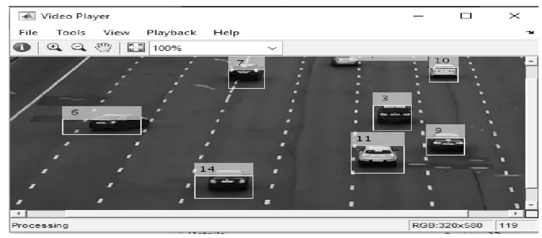

Fig. 9. Detection of multiple vehicle in video player

Input Video	Format	Frame	Actual no. of vehicle	Detected no. of Vehicles	Accuracy
Video1	Gray Scale	2000	47	21	55
Video2	Gray Scale	400	20	07	65
Video3	Gray Scale	300	33	19	42
Video4	Gray Scale	500	17	11	35

TABLE I. Results before Camera Calibration

Input Video	Format	Frame	Actual no. of vehicle	Detected no. of Vehicles	Accuracy
Video1	Gray Scale	2000	47	45	96
Video2	Gray Scale	400	20	20	100
Video3	Gray Scale	300	33	30	91
Video4	Gray Scale	500	17	18	94

TABLE II. Results after Camera Calibration

This experiment was performed on 4 videos with different density of traffic on road. First the videos were used without removing the lens distortion from the frames. The results concept obtained are shown in Table 1. It is clearly evident that, due to edge noise and lens distortion accuracy rate is very low. However same video were used again and lens distortion was removed. The result obtained after applying the camera calibration shown in Table 2 are very accurate and encouraging. Sometimes due to occlusions two objects are merged together and treated as a single entity. Sometimes because of variance the vehicle count can also be increased.

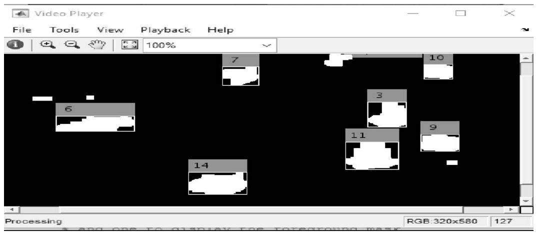

Fig. 10. Detection of multiple vehicle in mask player

V. Conclusion

We have successfully detected and counted the moving vehicles with excellent accuracy rate. The vehicle count has been effectively increased after the camera calibration. Whereas the results was not so encouraging before calibrating the camera. On the other hand, sometimes two or more vehicles moving in the same direction with same velocity is detected as one vehicle due to partial and complete occlusion. To solve this problem, two or more camera can be used from different angle to capture the image of vehicle. Comparison and integration of these pictures from different angle can address problem of occlusion. However, further research work is required to address this. The statistical noise and some inaccuracies related to recursive method are also affects the vehicle detection at some stages. This problem can be reduced by using other Bayesian recursive algorithm like particle filter. This implementation of vehicle detection using particle filter and comparison the results with our present method is our future scope of work.

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