Image Processing Based Vehicle Detection and Tracking Method

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***Abstract* – Vehicle detection and tracking plays an effective and significant role in the area of traffic surveillance system where efficient traffic management and safety is the main concern. In this paper, we discuss and address the issue of detecting vehicle / traffic data from video frames. Although various researches have been done in this area and many methods have been implemented, still this area has room for improvements. With a view to do improvements, it is proposed to develop an unique algorithm for vehicle data recognition and tracking using Gaussian mixture model and blob detection methods. First, we differentiate the foreground from background in frames by learning the background. Here, foreground detector detects the object and a binary computation is done to define rectangular regions around every detected object. To detect the moving object correctly and to remove the noise some morphological operations have been applied. Then the final counting is done by tracking the detected objects and their regions. The results are encouraging and we got more than 91% of average accuracy in detection and tracking using the Gaussian Mixture Model and Blob Detection methods.**

Keywords – Image Processing, Vehicle Detection, Vehicle Tracking, Vehicle Counting.

I. INTRODUCTION

Automatic recognition of vehicle data has been widely used in the vehicle information system and intelligent traffic system. It has acquired more attention of researchers from the last decade with the advancement of digital imaging technology and computational capacity. Automatic vehicle detection systems are keys to road traffic control nowadays; some applications of these systems are traffic response system, traffic signal controller, lane departure warning system, automatic vehicle accident detection and automatic traffic density estimation [1], [8].

An Automatic vehicle counting system makes use of video data acquired from stationary traffic cameras, performing causal mathematical operations over a set of frames obtained from the video to estimate the number of vehicles present in a scene. It is just the ability of automatically extract and recognize the traffic data e.g. total number of vehicles, vehicle number and label from a video. Counting vehicles gives us the information needed to obtain a basic understanding over the flow of traffic in any region under surveillance. So, the first data we have tried to gather is counting of vehicles from available traffic videos from various libraries. In each video frame, Gaussian mixture model differentiates objects in motion from the background by tracking detected objects inside a specific region of the frame, and then counting is carried out.

The goal of this current research is to develop an automatic vehicle counting system, which can process videos recorded from stationary cameras over roads e.g. CCTV cameras installed near traffic intersections / junctions and counting the number of vehicles passing a spot in a particular time for further collection of vehicle / traffic data. A simple approach was carried out to tackle the problem by using Gaussian mixture model based object detection, a non-predictive regional tracking and a counting of tracked objects based on simple rules.

The remaining part of this paper is organized in various sections. Section II describes about the recent related works done in this area. Based on that related works we propose video-based vehicle detection and tracking algorithm for traffic data retrieval. Section III describes the image processing based method of detection and tracking of vehicles. Section IV shows the experimental results done on traffic videos. Finally, conclusions are drawn in section V.

II. RELATED WORK

In the recent years of researches, various approaches have been applied in this particular area of detecting vehicle data but still the gap is there as it needs improvement in detection and tracking for accurate prediction. Mithun *et al.* [6] applied the technique of virtual line based detector which mainly uses multiple time-spatial images (TSIs), each one obtained from a multiple virtual detector (MVDL) line on the frames of a vehicle video. MVDL-based method may be highly effective in intelligent transportation system but accuracy may or may not be satisfactory in complex traffic situations. Lin *et al.* [3] applied the technique of detecting possible vehicles in the specified blind-spot area by integrating the appearance-based features and edge-based features but the results are slightly unsatisfactory due to the complex background. Feed-forward neural network has been used to identify the vehicles by P. Rajesh for solving problems such as classification, clustering, and function approximation but it needs clear video input to stop mis-detection of vehicles [11].

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Huang *et al.* [12] presented a feature-based method of vehicle analysis and counting for bi-directional roads in a real-time traffic surveillance system but it is not clear that how much it is perfect in the scenarios of increased traffic volume. Hashmi *et al.* [2] proposed a different approach based on statistical parameters to determine the traffic situation at heavily crowded junctions in urban areas and this method need optimization in parameters i.e. color, shape, size and classification of vehicles. Nandyall and Patil [13] used automatic vehicle detection and classification based on pair wise geometrical histogram and edge features to represent the model of vehicle type. Then these features are trained with neural network which works fine but counting of vehicles is dependent on threshold value and may not be accurate in heavy traffic. Kota and Rao [14] proposed the frame difference method to detect the moving regions with different time instances to classify and count the vehicles. However, the performance of this system is significantly affected by the selected thresholds. A vision based detection and attribute-based search of vehicles in dense traffic monitoring has been presented by Feris *et al.* [4] using multiple detectors and can be extended to large scale adaptation. Huang and Ma [7] proposed moving object detection algorithm from video for localization of vehicle by differentiating current image and background image and applying connectivity and relabeling technique to count vehicles. Although the approach has filtered background noise from video using opening operation, still it has some noise clustering which cannot be filtered easily.

Zhao and Wang [10] have proposed a new approach to count vehicles in complex traffic scenarios by utilizing the information from semantic regions and counting vehicles on each path separately. The approach has some limitations as a semantic region could be detected if pedestrians frequently walk through a zebra crossing causing difficulty on trajectory clustering. Bouvie *et al.* [9] presented an alternative using particle motion information but interrupted traffic flow and occlusion may downgrade the results. Very small vehicles can be missed, since the number of particles may be insufficient to generate a cluster. Soo Siang Teoh and Thomas Bräunl [5] proposed a mechanism for vehicle tracking and controlling in consecutive video frames based on Kalman filter and a reliability point system. The most probable location of a detected vehicle in the subsequent video frame is predicted by Kalman filter and this data is used by the tracking function to narrow down the search area for re-detecting a vehicle. It also helps to smooth out the irregularities due to the measurement error. To monitor the quality of tracking for the vehicles in the tracking list, this system uses reliability points. Each vehicle is assigned with a reliability point, which can be increased or decreased at every tracking cycle depending on how consistent the vehicle is being re-detected.

III. METHODOLOGY

The proposed automatic vehicle counting system makes use of video data acquired from stationary traffic cameras, performing causal mathematical operations over a set of frames obtained from the video to estimate the number of vehicles present in a scene. In each frame, Gaussian mixture model differentiates the object in motion from the background by tracking detected objects inside a specific region and then counting is carried out.

A. Gaussian Mixture Model

A Gaussian Mixture Model (GMM) is a function to measure parametric probability density represented as a weighted sum of Gaussian component densities. GMMs are extensively used in a various areas of applications. Some of the fields which use GMMs are Machine learning, astronomy, computational biochemistry and many more. In this application, GMM carries out the job of separating the foreground and background from image frames by learning the background of a scene.

Here, the work is aimed to achieve the need of robust vehicle detection and tracking algorithm that can be used in a traffic monitoring system to deal with the current challenges in this area. Firstly, for all pixels in a set of pixels, Gaussian mixture model uses a common observable property change factor between the current image and the reference image i.e. modeled background, to deal with the changes in image frames and automatic gain by the camera. Then, the Mahalanobis distance of the Gaussian is calculated based on the common observable property change factor, current intensity of color and estimation of mean of Gaussian component. The objective specification of the quality of a color regardless of its luminance in the image is obtained by considering color brands using rescaling of color values with the help of pixel standard deviation. A threshold value is calculated to determine the similarities of the objective specification of the quality of a color regardless of its luminance between the background learnt by GMM and the current observed image is a pixel in the foreground obtained by the GMM. The algorithm for threshold selection was based on the work done by Horprasert et al. [15].

B. Blob Detection

In the area of image processing, Blob detection is a technique by which system can trace the movements of objects within frame. A blob is a group of pixels identifies as an object. This detection mechanism finds the blob's position in successive image frames. The blob area must be defined before any detection of blob where Pixels with similar light values or color values are grouped together to find the blob. Every surface has subtle variations in real world scenario, so if only one light or color value is selected, a blob might be only few pixels. When trying to group images into useful components it might be useless as a complete unit.

The system must detect the blobs in the new image and make meaningful connections between the seemingly different blobs present in each frame. It needs to define the relative importance of factors including location, size and color to decide if the blob in the new frame is similar enough to the previous blob to receive the same label. It can be explained like the following steps:

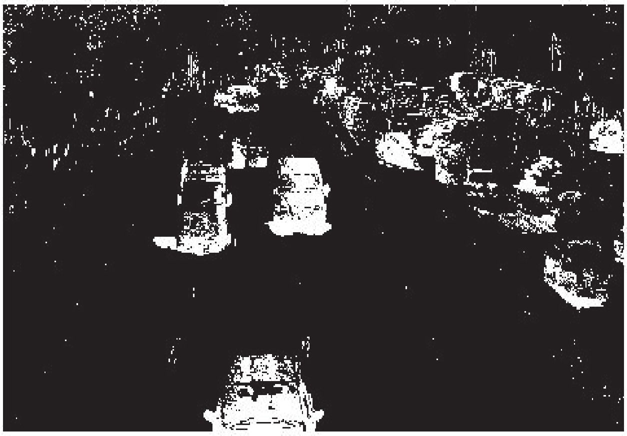
```
search through each pixel in the array:

check if the pixel is a blob color, label it '1'
   otherwise label it 0

go and search the next pixel
   if it is also a blob color
      and if it is adjacent to blob 1
         label it '1'
      else label it '2' (or more)

repeat the loop until all pixels are done
```

In this research blob detection uses contrast in a binary image to compute a detected region, it's centroid, and the area of the blob. The GMM supplies the pixels detected as foreground. These pixels are grouped, in current frame, together by utilizing a contour detection algorithm [16]. The contour detection algorithm groups the individual pixels into disconnected classes, and then finds the contours surrounding each class. Each class is marked as a candidate blob (CB). These CB are then checked by their size and small blobs are removed from the algorithm to reduce false detections. The positions of the CB, in current frame, are compared using the k-Means clustering that finds the centers of clusters and groups the input samples CB around the clusters to identify the vehicles in each region. The moving vehicle is counted when it passes the base line. When the vehicle passes through that area, the frame is recorded. In each region the blob with the same label are analyzed and the vehicle count is incremented.

C. GMMs and Image Noise Filtering

The GMMs were trained for 150 images, with typical frame rate of video being 30fps; the first 5 seconds are lost in training the GMMs. A GMM foreground detector with three Gaussian models and a minimum background ratio of 0.7 produced foreground separation as shown in Fig. 1 (b).

(a)



(b)

(c)

Fig. 1: Steps in vehicle detection and tracking. (a) Frame taken from a traffic video, (b) Binary image computed by GMMs, (c) Filtered binary image obtained by pixel manipulation.

Some pixel manipulation techniques were carried out to de-noise and filter the binary image like eroding blobs and noise pixels by 4 pixels in area, and filling closed contours in the binary image.

D. Blob Analysis

Blob analysis identifies potential objects and puts a box around them. It finds the area of the blob and from the rectangular fit around each blob, the centroid of the object can be extracted for tracking the object. An additional rule that the ratio of area of blob to the area of rectangle around a blob should be greater than 0.4 ensures that unnecessary objects are not detected.

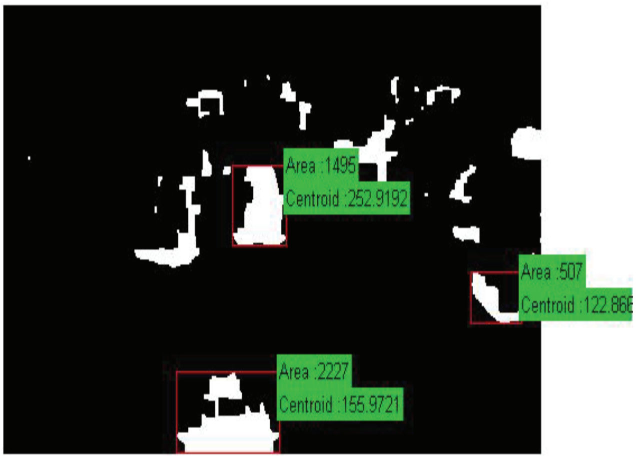
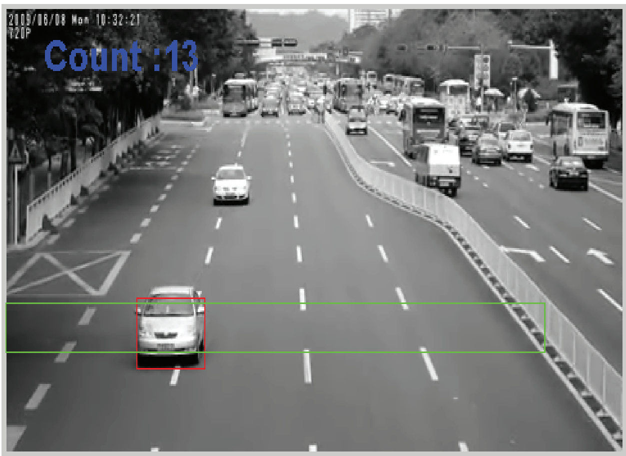


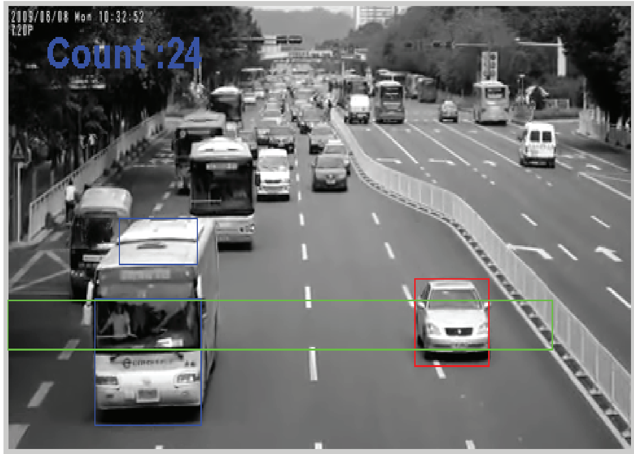
Fig. 2 Features extracted from Blob Analysis

E. Tracking and Counting

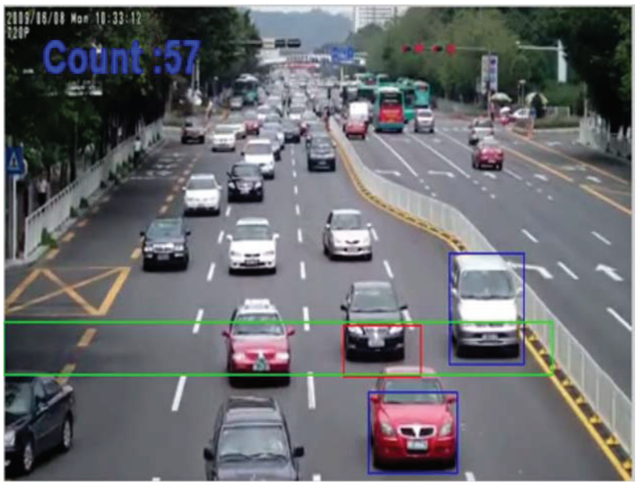
Tracking is carried out only inside a specific region of the frame, called Count Box, to ensure unnecessary redundancy in computation and higher performance. The green box in Figure 3 is the count box region. Tracking is done by searching for centroids in a small rectangular region around centroids detected in the earlier frame, if not found then it is added to a 'tracks' array as a newly found object. Below in Figure 3(a),(b),(c) a low, medium and high traffic situation is shown.



(a)



(b)



(c)

Fig. 3 Vehicle Tracking and counting (a) Tracking and counting vehicles in high and then low traffic, (b) Tracking and counting vehicles in a average Medium traffic, (c) Tracking and counting of vehicles in a mix of low, medium and high traffic scene.

IV. Results

The experimental result consists of comparing the automatic vehicle counting from videos against the manual counting done by the researcher (ground truth). In this table, vehicle video1 denotes the comparatively high and then low traffic flow in Fig 3(a), vehicle video2 denotes an average medium traffic flow in Fig 3(b) and vehicle video3 denotes a mix of low, medium and high traffic flow as shown in Fig 3(c). The evaluation results obtained by proposed algorithm were compared with a similar purpose algorithm proposed by Hashmi et.al [2] and offering a satisfactory success rate for counting the vehicles in a traffic surveillance system. In the proposed method, over all the results are good and can be applied in real time scenario where we get more than 91% of average accurate counting.

Automatic vehicle counting system counts somewhat less than the actual number of vehicle due to congestion and heavy traffic flow situation in one scenario. Statistical computer vision method proposed by Hashmi et al. counts more numbers of vehicles than the actual number of vehicle in video sequences due to the false positive error factor. Table 1 shows the experimental results obtained by the proposed method and the comparison done with the similar purpose method [2].

TABLE I. COUNTED VEHICLES FROM TRAFFIC VIDEOS USING OUR METHOD AND COMPARISON OF OUR METHOD WITH REFERENCE [2]

	Our Proposed Method			Similar Method [2]		
Vehicle Video	Exact No. of Vehicles in Video	No. Of Vehicles Calculated by Sys	Success Rate in Percent	Exact No. of Vehicles in Video	No. Of Vehicles Calculaed by System	Success Rate in Percent
1	17	13	76.47 %	17	21	80.95 %
2	27	24	88.88 %	27	34	79.41 %
3	59	57	96.61 %	59	73	80.82 %
Avg.	103	94	**91.26**	103	128	**80.46**

V. CONCLUSION

A simple and effective system which solves the problem under study has been developed. The detection of vehicles in a mix traffic situation of low, medium and high traffic is precisely as expected and the counting algorithm is accurate. The limitation of the developed method is that for every camera data feed a considerable amount of tuning of the parameters is required to achieve the best performance. Also, it requires somewhat more processing time in highly denced traffic conditions.

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