Vehicle Counting and Classification from a Traffic Scene

Conference Paper · September 2008

Upul Sonnadara
University of Colombo

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M. Pancharatnam, D.U.J. Sonnadara
Department of physics, University of Colombo, Sri Lanka

ABSTRACT

This work was carried out to determine the performance of image processing techniques in classifying and counting moving vehicles in video streams of traffic scenes recorded by stationary cameras. The detection and tracking approach is as follows. The moving vehicles are first extracted from the traffic scene by applying the adoptive background subtraction technique. After the background subtraction, using threshold and median filters, isolated image blobs are identified as individual vehicles. Once the blobs are identified, counting and classification of vehicles in a selected region are carried out.

The preliminary results show that the developed system can efficiently and reliably track vehicles when unobstructed view of the traffic scene can be obtained. For optimal camera calibration, an accuracy better than 80% in counting vehicles was observed. The present system performs better with video data in which the vehicles are moving away from the camera compared to the video data in which the vehicles are moving towards the camera. The results obtained through the developed system show that with further improvements the system can be used in real-time to count and classify vehicles on busy traffic routes.

1. INTRODUCTION

Traffic management has become an important daily routine in cities today with the exponential growth of traffic on roads. Automatic vehicle detection from traffic scenes and extracting essential parameters related to vehicular traffic can help better management of traffic on busy highways and road intersections. Monitoring traffic flow and estimating traffic parameters can be carried out using sensors [1, 2] as well as through image processing techniques.

With the advances in technology, monitoring traffic through image processing techniques yield a wide range of traffic parameters such as flow of traffic, speed of vehicles, number of vehicles, classification of vehicles, density of vehicles etc. Since the vehicles can be tracked over a selected segment of a roadway, rather than at a single point, it is possible to measure the "true" density of vehicles for each lane. Image processing techniques can also be applied to traffic video surveillance to detect the vehicles in motion, number plate identification, recognition of obstacles etc. Traffic monitoring through image processing techniques can lead to better control of the flow of traffic as well as to identification of reckless users and speed violators.

In the past, many research studies have been conducted on automated vehicle detection using image processing techniques. The focus of this project was to test the performance in identifying the moving vehicles from a traffic scene and to count and classify vehicles within a given time period.

The following are the required processing steps:

- Converting a video stream to a sequence of single frames.
- Detecting a stable image from a dynamically changing background image.
- Calibration of the camera.
- Identification of vehicles.
- Tracking moving vehicles in each lane.
- Counting vehicles.
- Classifying vehicles.

The paper starts with a brief overview of related work followed by a description of the approach including segmentation, calibration, tracking, and classification. The paper concludes with results and final conclusions.

2. RELATED WORK

In reference [3], a system for detection and classification of vehicles is described. It uses a self adaptive background subtraction technique to separate vehicles from the background. The resulting connected regions are then tracked over a sequence of images using a spatial matching method. The tracked regions are grouped together to form vehicles. Reference [4] also uses adaptive background detection method to identify vehicles. The vehicles are tracked based on contour extraction. Prewitt filter kernel is used for edge detection. The contour linking method used for connecting separated edge parts of the original object into one closed contour. A contour labelling method is used to mark and calculate vehicles within frames. In reference [5], feature based tracking algorithm has been used. Offline camera calibration has been carried out to detect the parameters such as line correspondences for a projective mapping, detection region and multiple fiducially points for camera stabilization. Here, projective transformation is necessary as the features are tracked in world coordinates to exploit known physical constraints on vehicle motion. The transformation is used to calculate distance based measures such as position, velocity and density. In reference [6], adaptive background learning for vehicle detection and spatio-temporal tracking is described. A framework is proposed to analyze the traffic video sequence using unsupervised vehicle detection and spatio-temporal tracking that includes an image/video segmentation method, a background learning/subtraction method and an object tracking algorithm. In reference [7], a system on vehicle detection under day and night illumination is described. Vehicle detection at day time is done by using consecutive three frame subtraction method by detecting moving points. The moving points are classified and labelled as vehicles. Vehicle detection at night time is done by identifying vehicles in terms of pair of headlights. To detect only the objects related headlights, the system perform detection via morphological analysis, by taking into account aspects like shape, size and minimal distance between vehicles. Finally, the verification is based on the correlation between headlights belonging to the same pair. In reference [8], a system for fast vehicle detection with probabilistic feature grouping and its application to vehicle tracking is described. The images were obtained from three cameras installed on a roof of a 30-story building alongside a freeway in order to avoid overlapping of vehicles. System introduces a new vehicle tracking approach based on a model-based 3-D vehicle detection and description algorithm. The proposed algorithm uses a probabilistic “line” feature grouping method to detect vehicles. The tracking is performed based on the zero-mean cross correlation matching technique. System detects vehicles at the entrance area and track the detected vehicles based on their intensity profiles. In reference [9], a system for vehicle detection and tracking is described. This system is fully based on the Block Matching Algorithm (BMA), which is the motion estimation algorithm employed in the MPEG compression standard. BMA partitions the current frame in small, fixed size blocks and matches them in the previous frame in order to estimate displacement of blocks between two successive frames. The detection and tracking approach is as follows. BMA provides motion vectors, which are then regularised using a Vector Median Filter. After the regularisation step, motion vectors are grouped based on their adjacency and similarity, and a set of vehicles is identified per singular frame. Finally, the tracking algorithm establishes the correspondences between the vehicles detected in each frames of the sequence, allowing the estimation of their trajectories as well as the detection of new entries and exits. The tracking algorithm is strongly based on the BMA. It consider the BMA output as the basic tracking information associated with each block and combine this information with the already available block-level tracking as a grouped output in order to achieve the desired result.

3. METHEDOLOGY

This section presents the essential steps in project implementation, starting from a video clip of a traffic scene and ending in vehicle classification and counting. The work was carried out with freely available video clips of traffic scenes.

3.1 Background Detection

To extract stable background image, adaptive background detection method was used [3]. This method uses mean value of pixels within a range of frames to detect the background. If the variance of a given pixel is below a predefined threshold, then the pixel is considered to be stable. The background image is updated according to the equation given below.

$$B_{t+1} = B_t + S_t \times M_t$$

Here, B_t is old background image, S_t is a mask which varies between 0 and 1 depending on the variance and M_t is mean value of pixels.

Fig 1: Stable background image

Fig 2: Image under investigation

3.2 Camera Calibration

Camera calibration plays an important role in the identification process. Camera calibration is carried out to transform the image coordinates to world coordinates [5]. This is essential for the vehicle classification. It is also important if one wishes to extract the speed of the vehicles. In this work following assumptions were taken.

- Road is straight
- Road is flat
- *X* axis of the road space correspond to the direction perpendicular to the traffic flow and the *Y* axis is parallel to the traffic flow.

The transformation that has been carried out from the image space to world space is the projection transformation. Assume that the width and the length of the selected area in road space (which are known) are *w* and *h* respectively. The equation to find the projective transformation matrix that maps the image space coordinates (*ax,ay; bx,by; cx,cy; dx,dy*) to their corresponding road space coordinates is;

$$\begin{bmatrix} A & B & C \\ D & E & F \\ G & H & I \end{bmatrix} \begin{bmatrix} ax & bx & cx & dx \\ ay & by & cy & dy \\ 1 & 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0 & w & w & 0 \\ 0 & 0 & h & h \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

To optimize the results of projection transformation matrix, least squares optimization method was used. The projection transformation was used as the initial guess and the best projection matrix was found by using the following objective function [5].

$$\sum_{i=1}^{4} \left(\frac{Axi + Byi + C}{Gxi + Hyi + 1} - ui\right)^2 + \left(\frac{Dxi + Eyi + F}{Gxi + Hyi + 1} - Vi\right)^2$$

3.3 Lane Calibration

Since the goal of the project is to identify the vehicles in each lane separately, the lanes must be defined and the centreline of each lane must be identified. User is allowed to select the region of interest by selecting the centre of lanes first and then the starting and ending points on each lane to define the tracking region. The screen space coordinates were first transformed into road space coordinates and then projected onto the lane line.

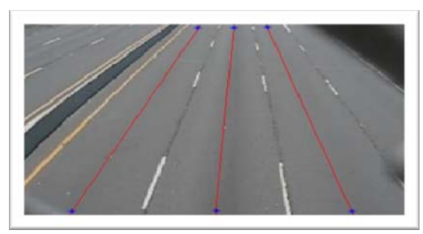


Fig 3: Selected centreline on each lane

Vehicles were tracked alone the centreline on each lane within the user define tracking area.

Fig 4: Current frame and extracted pixels on lane lines

3.3 Vehicle Tracking

Numerous techniques have been developed to track moving objects in tracking regions such as tracking points, tracking centroids, tracking rectangles etc. In this work, the bottom coordinates of the identified objects have been used to track moving vehicles in the selected area.

While reading new frame, beginning of the centreline of interest has been examined and if a positive value (here it is 1) is seen, the algorithm considers it as the bottom coordinate of a vehicle. If a positive value was seen in the previous frame and it has now changed, it suggests that the vehicle is in motion in the selected region of interest. By detecting the column vector having top to bottom positive stream of values the vehicle could be detected. Figure 5 illustrates the stated algorithm.

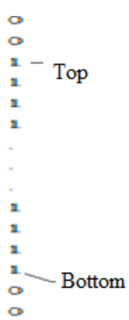


Fig 5: Binary pixel value of column vector of an identified vehicle

By calculating the length of the positive column vector which is the difference between the top and the bottom pixel values of the positive stream of numbers and convert it to the world coordinate space, minimum length of vehicle could be verified. Vehicles that do not satisfy the minimum length requirement were rejected. If a new vehicle is found, it is added to the vehicle array of the lane.

For each vector in the vehicle array, algorithm starts from the last known position of the bottom of the vector and search forward along the centreline to find the next position of the vector in the next frame. If the search ended up in reaching the end of the region, the vehicle is considered to be exited from the region of interest. This process is repeated for all defined centerlines.

3.4 Vehicle Classification

Classification is done by categorizing the vehicles into three classes according to the size of the vehicles, namely, large, medium and small. Since it is easy to find the length of vectors, the length has been taken as the parameter to classify vehicles according to the defined sizes. The following table shows the classification used in this work.

Large	Containers, Lorries, Buses
Medium	Cars, Vans, Pickups
Small	Two wheelers, Three wheelers

Table 1: Classification of vehicles

For each new vehicle that enters into the line on the region of interest, the length of vector has been calculated and subjected to the minimum length requirement. Classification was carried out for those vehicles that pass the length requirement.

4. RESULTS AND DISCUSSION

Since the success of the project depend on providing a proper line of site for the camera view, placing the camera on an overhead bridge directly over the flow of traffic route was necessary to minimize the vehicle occlusion. Due to security situation in the country, tests were carried out (to debug the developed algorithms and to evaluate the performance) with freely available video clips on internet, one with vehicles moving away from the camera view and another with vehicles moving towards the camera view (see Figure 6).

Fig 6: Video clips used to test the developed algorithms

The accuracy of the results depends on the camera calibration which takes place to find the projection matrix between the image coordinate and the world coordinate, lane selection and the tracking region. The system has been tested with several camera calibrations to find the optimum results. Figure 7 illustrates results of two camera calibrations for the video clip 1.

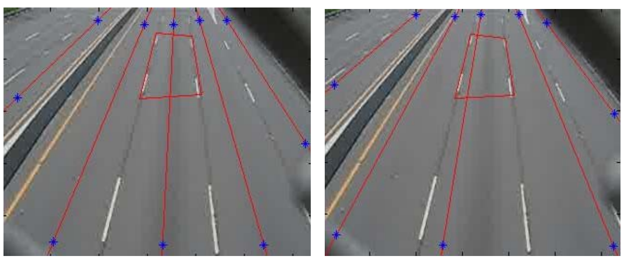


Fig 7: Camera calibrations (1) Optimum calibration (2) Improper lane selection

In order to reach the desired goal, the video clips were subjected to a series of independent tests that were discussed earlier to carry out vehicle identification, tracking, classification and counting.

For the video clip 1, manually counted results and counting results of the developed system (CCT system) for each lane is given in Table 2. Here, in lane 1, vehicles are moving towards the camera and in lane 2, lane 3, lane 4 and lane 5, vehicles are moving away from the camera view.

Calibration	Lane 1	Lane 2	Lane 3	Lane 4	Lane 5
Manual	32	36	38	41	4
CCT System	32	37	42	36	12

Table 2: Comparison between actual counting and CCT system counting

It can be seen that except for lanes 4 and 5, other 3 lanes produce results within 10% of the manual counting. As expected, errors increase when the lanes are skewed in the camera view. The developed system tends to produce errors especially when the vehicles do not travel within the selected lanes and when tall vehicles (such as containers) tend to be in the side lanes often covering two lanes in the camera view.

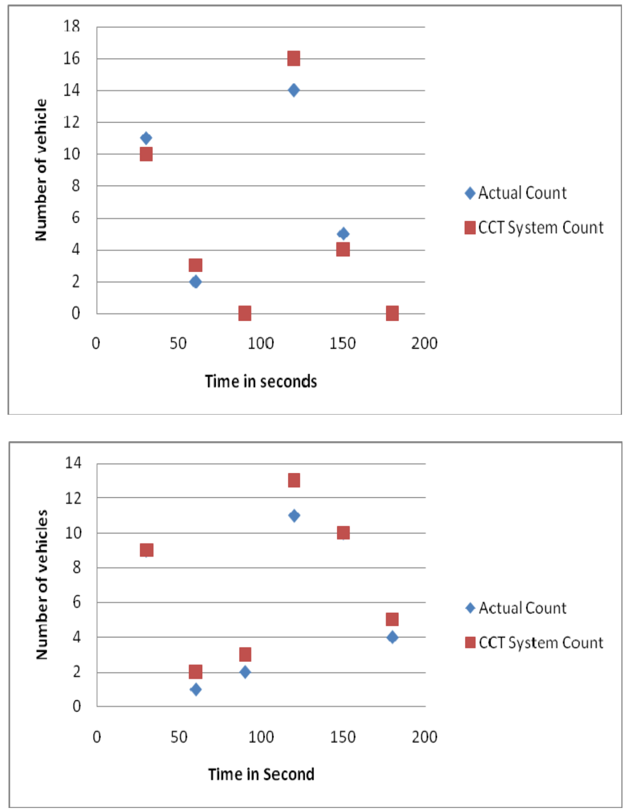


Fig 8: Comparison of counting results for different time intervals for lane 1 and 3

In order to check the performance of the CCT system with the traffic flow rate, data were collected for time intervals of 30 seconds. Figure 8 shows the results obtained for different time intervals for lane 1 and lane 3 for video clip 1.

The classification of identified vehicles was carried out according to the definitions given in Table 1. The main criterion used in the CCT system to classify the vehicles is the length of the vehicles. Figure 9 shows the comparison of vehicle classification between actual classification (visual) and CCT system classification for total (1), large (2), medium (3) and misidentification (4).

5. CONCLUSIONS

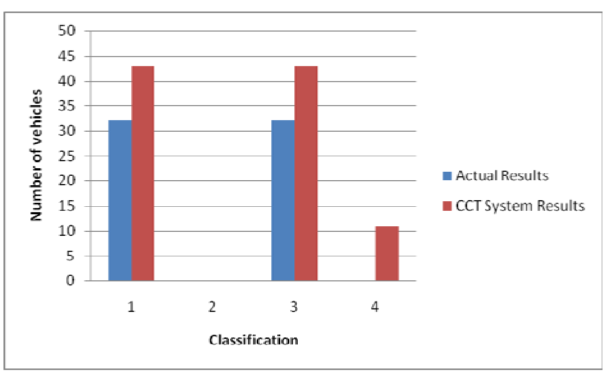
Preliminary results for developing an automated system for counting and classification of vehicles in motion, based on image processing techniques were presented in this paper. The developed system was able to track vehicles and classify them with a reasonable accuracy. The system is capable of handling video clips of traffic scenes with 15 frames per second in real time.

The results strongly depend on the camera calibration used. If the camera calibration is not optimal, it can easily affect the system performance. When the camera calibration is optimal, developed system showed an accuracy of 93% for lane 1, 97% for lane 2 and 90% for lane 3. As expected, lane 5, which is the furthest lane from camera view and often obstructed due to heavy vehicles showed poor performance in counting.

The results obtained through the developed system show that with further improvements it can be used in real-time to count and classify vehicles on busy traffic routes. Especially, if an obstructed view of the traffic movement can be obtained, the system can perform quite accurately.

6. ACKNOWLEDGMENT

Financial assistance given by the National Science Foundation, Sri Lanka for the research grant number RG/07/E/03 is greatly acknowledged.



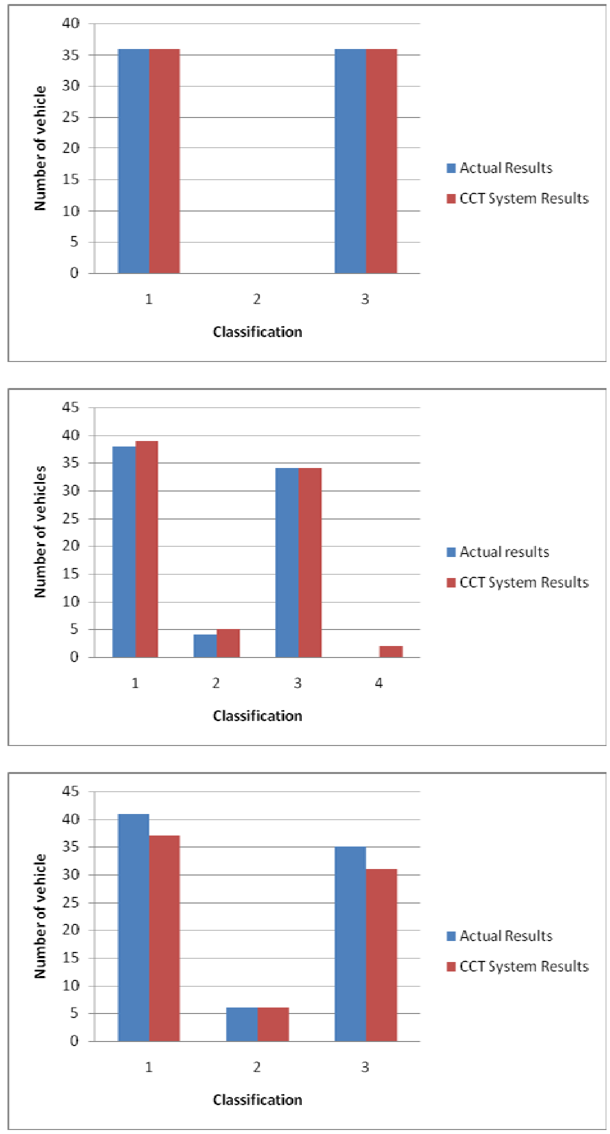


Fig 9: Comparison of classification between actual and CCT system for each lane

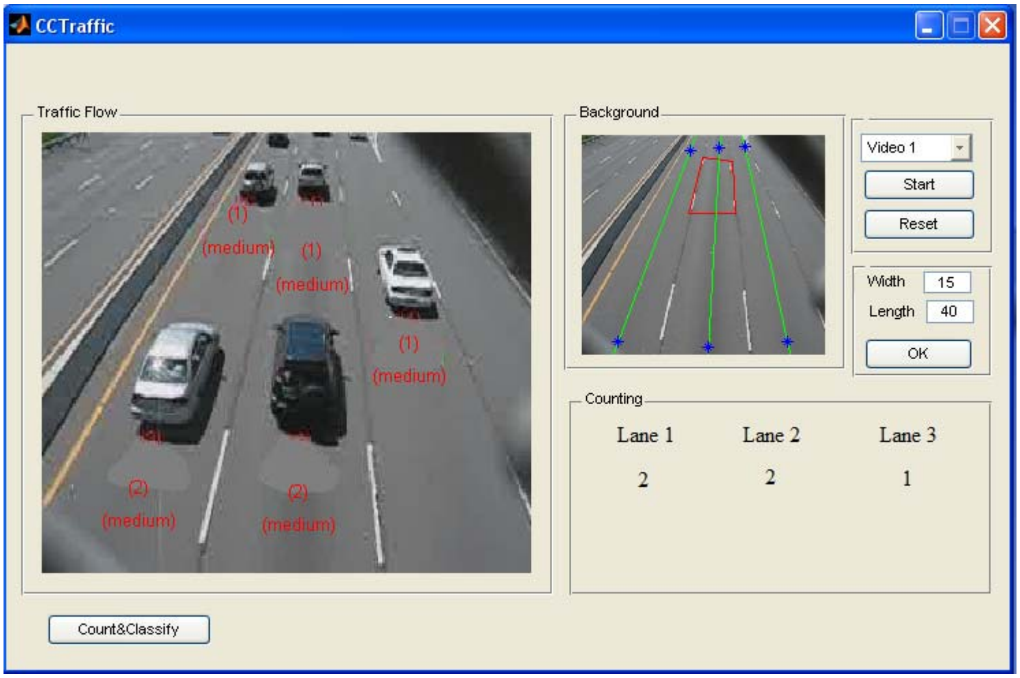


Fig 10: GUI interface of the developed CCT system.

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