Traffic Data Collection under Mixed Traffic Conditions Using Video Image Processing

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Abstract: Traffic data collection under mixed traffic conditions is one of the major problems faced by researchers as well as traffic regulatory authorities. Study and analysis of traffic behavior is critically dependent on the availability of observed traffic data. For mixed traffic observed in developing countries, no suitable tool is available for this purpose. Keeping in view these necessities and problems in data collection, a novel offline image processing-based data collection system, suitable for mixed traffic conditions, is developed. Its underlying ability to detect, track, and classify vehicles makes it useful in collecting traffic data under varying traffic conditions. This system can automatically analyze traffic videos and provide macroscopic traffic characteristics such as classified vehicle flows, average vehicle speeds and average occupancies, and microscopic characteristics such as individual vehicle trajectories, lateral, and longitudinal spacing. It is observed that this new system is working well even under congested mixed traffic conditions.


CE Database subject headings: Traffic analysis; Traffic patterns; Data collection; Heterogeneity; Imaging techniques.

Introduction

Empirical traffic data are the basic input in any traffic management scheme and in building and analyzing traffic flow models. Very limited empirical data are available for this purpose. For collecting data under homogeneous traffic conditions, several types of equipment are available. Among these, induction loops are widely used for both traffic management and traffic flow modeling purposes. Induction loops are useful in collecting microscopic as well as macroscopic traffic data. Generally, induction loops are employed for each lane and may not be useful to collect data under mixed traffic conditions. Recently, some video image processing system (VIPS)-based data collection techniques are being used, which mimic induction loops in data collection.

In developing countries, traffic is composed of different types of vehicles such as cars, buses, trucks, two wheelers (TW’s), three wheelers (also called autos), etc. These two wheelers and three wheelers are small in size; due to the presence of these vehicles, lane discipline of the traffic is disturbed. Induction loops may not be useful to collect data under these conditions. Alternatively, researchers are using either manual data collection techniques or video-filming-based methods. These methods are useful in collecting some macroscopic data such as classified traffic flow and not useful in collecting microscopic data.

Vehicle detection and analysis through image processing, owing to its nonintrusive nature and resourcefulness in computing nontrivial data has been an area of interest in both transportation as well as computer vision communities for the past few years. Wide varieties of algorithms are used in this area and a detailed review is presented in the following section. Images can be collected either by remote sensing or by using video camera. In both ways, traffic behavior can be captured over a certain length of the road, thus, useful in obtaining vehicle trajectory data. A lot of useful information can be extracted from vehicle trajectory data such as driver behavioral aspects. Specifically, collecting the traffic data over a certain road length is useful under mixed traffic conditions compared to the data collected at a section. This is also evident from the past works carried out for mixed traffic conditions (Nagaraj et al. 1990; Singh 1999; Arasan and Koshy 2005). In this study, an offline image processing-based system is developed to obtain data from video film. The robust classification mechanism used enables vehicle classification into four different categories, namely light motor vehicles (LMVs), heavy motor vehicles (HMVs), motorized TWs, and motorized three-wheelers (autos). The system is also capable of computing individual vehicle characteristics such as trajectory, thus, enabling one to compute microscopic and macroscopic traffic characteristics over a certain length of the road.

Literature Review

In this section, a brief review of data collection techniques used under mixed traffic conditions and image processing-based vehicle detection methodologies are presented.

In addition to the manual method, which is normally used to collect data under mixed traffic conditions, different researchers in the past have used different techniques. Chari and Badarinath (1983) used a time-lapse photographic technique to measure the areal density. Areal density is defined as the sum of the total
vehicle area projected on the ground per unit area of road way. A time lapse camera, with a 1 sec interval between successive exposures of the film, was used for data collection. Identified vehicles are traced for a minimum of 5 sec. Using this, space-mean speeds of different vehicle groups are obtained. Gupta and Khanna (1986) have also used time-lapse photography to establish speed-flow relationships for various types of vehicles under mixed traffic conditions. Nagaraj et al. (1990) have carried out an extensive data collection study, using a video recording technique. In their study, which was the first of its kind for mixed traffic, data regarding linear and lateral spacing maintained by different vehicles at different speeds were collected. Kumar (1994) employed a different technique to collect traffic data on national highways in India. In this work, four persons were employed on each end of the road stretch of 1 km length to collect vehicle data such as time of entry, registration number, and type of vehicle, simultaneously. From the collected field data, average flow, average space-mean speed, and density observed over the stretch as well as headway data were obtained. Singh (1999) used a video recording technique to study traffic features under mixed traffic conditions. By calibrating the image size and distance relationship, speeds, headways, and lateral spacing were obtained. Chandra (2004) and Arasan and Koshy (2005) have used a similar technique to obtain the necessary data to study the traffic behavior. The video recording technique has its own advantages and limitations. It is very useful in getting offline classified flow data, which are an important characteristic of mixed traffic. As seen in the literature, some microscopic data can also be collected with further effort. A major limitation of this technique is that it is very time consuming and labor intensive.

Traffic data collection and analysis using image processing and computer vision algorithms has been sought after because of its ease in use and ability to extract microscopic as well as macroscopic data. The following is a broad outline of how an image processing system goes about solving the vehicle detection and classification problem.

Image processing algorithms take a sequence of images containing a traffic scene as an input, generally originating from a camera or from a recorded video in the case of offline processing systems. The algorithm identifies potential portions of the scene that might contain a vehicle. This identification methodology will differ from one approach to another. Once this is done, those portions are segmented out and are subjected to further analysis. In this phase, relevant features are extracted under which the vehicles are classified.

There are quite a few existing systems that perform vehicle detection through image processing. All these algorithms more or less stick to the control flow described above, but differ in the way they do the “detection” and “classification.” Existing detection techniques broadly fall under the following categories:

1. Motion based: moving objects are segmented using frame differencing/background subtraction (Zhao and Nevatia 2001). While frame differencing is straightforward, subtraction of frames with an application of some threshold, in background subtraction, on the other hand, the scene background is learned at the beginning, which may be dynamically updated later. This approach works fairly well in sparse conditions but the performance drops as the density increases since more than one vehicle can be detected as a single vehicle.

2. Patch based: scene is divided into patches and the background at each patch is memorized. The presence of a vehicle is detected by comparing it with the background of the patch. This approach too is vulnerable to dense situations and situations where lane discipline is not there, which is quite prevalent in developing countries.

Thus, after the “detection” phase, every scene will result in the foreground. Portions of this foreground may be compared with predefined patterns to identify the vehicle type. Several researchers used (Chang and Kunhuan 1993; Kanade et al. 1998; Lipton et al. 1998) trained neural networks for this comparison. Zhao and Nevatia (2001) presented an algorithm that detects moving objects using background subtraction, and uses a higher order statistical closeness measure, to detect moving vehicles.

Koller et al. (1994) and Ervin et al. (2000) have used background subtraction to do vehicle detection. In this approach, the background is dynamically estimated from incoming images, and the difference between the current and the background images is thresholded to form “blobs” corresponding to vehicles. This algorithm gives reliable vehicle detection given a favorable illumination condition and a camera angle. However, the performance of the background subtraction algorithms significantly degrades in the presence of heavy shadows. It is difficult to separate a shadow from the vehicle because the shadow moves along with the vehicle. Further, an occlusion or a shadow cast on nearby vehicles makes the separation between vehicles difficult. In addition, the background estimation performance is degraded when the traffic is dense because of the slow movements of the vehicles and a significant part of the background is not observable.

Kim and Malik (2003a, b) and Kim et al. (2005) used an approach based on a 3D vehicle detection and description algorithm. The detection and description algorithm uses line features. They detect vehicles at the entrance area (where the viewing angle is favorable), and track the detected vehicles based on their intensity profiles. Though the system seems to perform well on lane disciplined traffic, its applicability to highly dense traffic without any kind of lane discipline remains a question. Masoud et al. (2001) used a region-based tracking method, which operates in three levels. Features are obtained at the lowest level by a simple recursive filtering technique. In the second level, which deals with blobs, feature images are segmented to obtain blobs, which are subsequently tracked. Finally, tracked blobs are used in the third level where the relation between vehicles and blobs as well as information about vehicles is inferred. Veeraraghavan and Papanikolopoulos (2004) presented a tracking system by making use of multiple cues such as blobs obtained through an adaptive background subtraction method and the color of the tracked vehicles. Both blobs and color are used to obtain a vehicle’s position in each frame. Blobs are tracked from frame to frame using a blob tracking method and the color of vehicles is used for localizing them in subsequent frames using a mean shift tracking procedure. The cues are then fused sequentially using an extended Kalman filter. Further, Veeraraghavan et al. (2005) have developed a tracking-based system for vision-based detection of traffic at intersections. However, their system can handle congested traffic in a limited manner.

Kolling and Nagel (1997) developed a model-based system. They proposed to use image gradients instead of edges for pose estimation. They fitted image gradients to synthetic model gradients, which have been projected on the image. A Kalman filter was used to stabilize the tracking. Optical flow was used to generate object candidates at the initialization stage only. The selection of the model was done manually for each vehicle. Beymer et al. (1997) used corner features. In this approach, individually extracted and tracked corner features are grouped based on the proximity of their positions and the similarity of the motion. This
approach gives good detection even with less favorable illumination conditions. However, it still has the following limitations:

1. The location and the dimension of a detected vehicle may not be accurate because they are estimated from the corner features, which do not cover the whole vehicle (moreover, some of them may belong to the shadow).

2. The position error caused by missing features (tracking failures) may introduce a significant error in the velocity estimation.

3. The feature grouping is based on only the locations and the motions of corner features. Thus, there may be situations such as features of nearby vehicles (of the same speed) are grouped together, or the features of a large vehicle (for example, trailer trucks) are not grouped together.

Apart from the research prototypes, there exist a few commercial systems used in tracking and identifying the vehicle class. Some of them are given in Table 1. All of these are patch-based methods. The motion-based and patch-based systems described above, particularly do not search for vehicles in the entire scene; rather, they limit their search to a predetermined grid on the road. Thus, their performance is dependent on the density and lane discipline of the traffic. So the adaptation of these systems to traffic in developing countries such as India is not feasible.

### Table 1. Commercial Systems for Vehicle Tracking and Identification

<table>
<thead>
<tr>
<th>U.S. patent no.</th>
<th>Company</th>
<th>System</th>
<th>Technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>6760061</td>
<td>Nestor Traffic Systems, Inc.</td>
<td>Traffic sensor</td>
<td>Luminance and edge variation from a reference frame+neural network edge-based classifier</td>
</tr>
<tr>
<td>5402118</td>
<td>Sumitomo Electric</td>
<td>Method and apparatus for measuring traffic flow</td>
<td>Intensity, edge info, Fuzzy set theory and neural network</td>
</tr>
<tr>
<td>5761326</td>
<td>Minnesota Mining and Manufacturing Company</td>
<td>Method and apparatus for machine vision classification and tracking</td>
<td></td>
</tr>
<tr>
<td>5809161</td>
<td>Commonwealth Scientific and Industrial Research Organization, Australia</td>
<td>Vehicle monitoring system</td>
<td>Background subtraction</td>
</tr>
</tbody>
</table>

### Scope of the Present Study

Keeping in mind the problems discussed above, an offline image processing system is developed in this study. Considering the problems with the existing VIPS, a modified methodology is adopted to suit the vehicle tracking under mixed traffic conditions. This methodology is developed such that even under extremely congested urban traffic conditions, vehicle classification and tracking are done successfully. This system is named TRAFFIC Analyzer and Enumerator—TRAZER. The underlying mechanism of TRAZER (described in the following sections) does not assume lane discipline and is not constrained by the traffic density. This method can even handle up to 30% of occlusion. It can detect, track (with tracking ranges of 25–30 m), and classify vehicles even under dense traffic conditions. A full discussion on the data that can be collected using the software is presented in the section, Data Collection Methodology. TRAZER detects vehicles with an average accuracy of 95% and classifies with an average accuracy of 85%. The results have been established after testing 15 videos shot at various parts of Delhi, India with varied angles and under different lighting conditions. Other data collected using TRAZER can be found in Satish Kumar (2007).

### TRAZER: Methodology Adopted

TRAZER uses a cascade of boosted classifiers (Viola and Jones 2001) for the detection of vehicles. Spurious detections are discarded by spatial and temporal filtering. Relevant features are extracted for each vehicle in the learning phase and are used for classifying them into four categories. The following subsections describe various phases of this methodology.

#### Learning

This is an offline phase and the goal of this is to characterize a vehicle category in an effective manner so that it can later be searched efficiently. Vehicle image samples of a particular category are taken and a description of the vehicle class is learned. As described by Freund and Schapire (1995), it is hard to describe a complex object such as a vehicle with one strong classifier. So a boosted cascade of weak classifiers is used in this study. A vehicle is best characterized with edges. Hence, a vehicle is characterized as a boosted cascade of Haar-like features (Viola and Jones 2001). Sample Haar-like features used are shown in Fig. 1. The cascade is trained with classification and regression trees (CARTs) of Haar-like features as the weak classifier since it accounts for variability in the edge representation with change in the model of the car.

Since four different classes of vehicles have to be detected and classified, for each vehicle class, around 400 positives (vehicle images) and around 1,200 negatives (images that do not contain vehicles) are taken as input in training the classifier. At the end of the training, each vehicle class is described as a tree of features. For example a car can be characterized with Haar-like features as shown in Fig. 1. The image shows only two dominant

#### Fig. 1. (a) Sample Haar-like features; (b) dominant features overlaid on a vehicle
features but the complete set contains around 100 such features. The tree of features is referred to as the *Haar classifier*.

**Detection and Classification**

In the postlearning phase, TRAZER takes traffic videos, classifier output from the learning phase, and calibration data (mapping from image coordinates to world coordinates) as input. Every frame of the video is processed using the Haar classifier and the results obtained are pruned and tracked. Relevant features are extracted for each vehicle and classified appropriately.

**Primitive Detection**

A vehicle classifier is a tree of Haar-like features. Evaluation of a classifier on a window of the image determines the presence of a vehicle in that region. Since vehicles can be present in any part of the image with any size, a classifier is evaluated for all subwindows of the image. To account for the variability of the vehicle size, the subwindow size is also varied in an appropriate range. Hence, vehicles should be searched extensively, i.e., at every window for a range of scales. This process is expedited by constructing the integral image (Viola and Jones 2001) without which the searching would have been computationally intensive. With the help of this, any feature at any scale can be computed with a fixed number of pixel operations. At the end of the classifier evaluation, several vehicles are detected at various positions of the image; some will be spurious in nature. All these raw detections are filtered as described in the following section.

**Filtering and Tracking**

Spatial filtering of raw detections, matching against existing vehicles, and updating the vehicle states accordingly, are the important tasks carried out in the filtering. Raw detections are spatially filtered to eliminate multiple detections of the same vehicle. The detections are now temporally filtered to eliminate persistent false detections. Temporal filtering is done by abstracting the detections into two different types, namely, probable vehicles and vehicles. Any new detection is considered as a probable vehicle. If the probable vehicle is temporally stable, i.e., detections occur in the subsequent frames, then it is considered as a vehicle. Each vehicle will carry a unique identity (ID), its location (top-left and bottom-right corners in image coordinates) in the current frame, age (indicates temporal stability), senility (indicates temporal instability), and its trajectory for the past 25 frames. Based on these definitions, the temporal tracking methodology is explained below.

Let $S$ be the set of all vehicles (probable and otherwise). $S$ denotes the state of the tracking system

$$ S = O \cup P $$

(1)

where $O=$set of existing vehicles, i.e., vehicles that are currently being detected; and $P=$set of probable vehicles, i.e., probable vehicles that are currently being detected.

Let the set of spatially filtered detections of this frame be $D$. For each element in $S$ (vehicle/probable vehicle) its position in the next frame is predicted using Kalman prediction (Kalman 1960). Each element in $D$ (new detection) is matched against the predicted states of the vehicles. When a match is found in set $O$, the trajectory of the vehicle is updated. If the match is from set $P$, the probable vehicle’s age is incremented. At this point probable vehicles that have the required amount of age become vehicles. Detections that do not, match with any of the existing vehicles join the probable vehicles set. Senility is increased for the probable vehicles and vehicles that are not updated in the current frame. The state transitions are depicted in Fig. 2. The output of the filtering process when applied to a series of frames in a traffic video is shown in Fig. 3.

**Feature Extraction and Classification**

Visual similarities between heterogeneous vehicle classes make it difficult to classify vehicles based on edge information alone. For example, the frontal portion of light commercial vehicles (LCVs) look similar to LMVs. Hence, even though there is a considerable size difference between both of them, using only edge information classifies both of them into the same class. Thus, it is necessary to extract and use relevant features, which can differentiate vehicle classes. Two wheelers are not considered in this analysis, as their aspect ratio is completely different. i.e., two wheelers are classified only on the basis of Haar feature information.

It is observed that the low classification accuracy is because Haar feature information does not encapsulate vehicle size information. Hence, this information is augmented and a classifier is built for vehicle classification. Each vehicle will have a trajectory associated with it. For each vehicle, the following features are computed:

- Haar feedback: all vehicle classifiers are evaluated on this vehicle and the response is recorded in a vector. Each element in
Table 2. Features Related to Some Vehicle Categories

<table>
<thead>
<tr>
<th>Vehicle ID</th>
<th>Vehicle size</th>
<th>LMV claims</th>
<th>Auto claims</th>
<th>HMV claims</th>
<th>LCV claims</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMV_511</td>
<td>9.27</td>
<td>1.29</td>
<td>0</td>
<td>0</td>
<td>0.14</td>
</tr>
<tr>
<td>Auto_8</td>
<td>7.92</td>
<td>0.47</td>
<td>1.63</td>
<td>0.47</td>
<td>0.23</td>
</tr>
<tr>
<td>LCV_230</td>
<td>11.21</td>
<td>0.19</td>
<td>0</td>
<td>0</td>
<td>0.77</td>
</tr>
<tr>
<td>HMV_444</td>
<td>11.02</td>
<td>0.23</td>
<td>0</td>
<td>0.91</td>
<td>0.57</td>
</tr>
<tr>
<td>LMV_1036</td>
<td>10.87</td>
<td>1.96</td>
<td>0</td>
<td>0</td>
<td>0.22</td>
</tr>
<tr>
<td>LMV_250</td>
<td>10.94</td>
<td>1.94</td>
<td>0</td>
<td>0.9</td>
<td>1.49</td>
</tr>
</tbody>
</table>

Note: LMV=light motor vehicle; Auto=motorized three wheeler; LCV=light commercial vehicle; and HMV=heavy motor vehicle.

Data Collection Methodology

To use the image processing technique, some specifications must be followed while taking the video. As far as possible, a video camera must be placed over the center line of the road section under consideration. It must also be able to cover a considerable amount of road area so that valuable traffic data can be collected. As discussed earlier, object size is one of the important parameters considered in image processing. Keeping this in view, while taking the video, care must be taken to obtain proper object size for small vehicles such as two wheelers.

The video film used in this study was collected near the Indra Prastha (IP) T-junction in East Delhi, New Delhi. This intersection is level separated, and two main approach roads are perpendicular to each other. Traffic on the approach used in the present study is controlled by traffic signals. Different types of vehicles, ranging from two wheelers to trucks are observed in traffic and flows range from moderate to high. A video camera is placed on the fly-over bridge, which is in right angles to the subject approach, exactly on the center line of the road. A 30-min video was collected covering a road stretch of 30 m. The width of the road section is 17 m, and it is constant over the coverage area. Necessary field measurements are carried out to match the image and world coordinates. Data extracted from the film using TRAZER software are discussed in detail in the following section.

Data from TRAZER

The traffic flow pattern is unique near intersections under mixed traffic conditions. In addition to no-lane discipline, “seepage” of small vehicles is a common feature observed near intersections. In these conditions, queue formation is also different from that of the lane disciplined traffic. In the case of the present study area, the road is divided into four lanes. If traffic follows lane discipline, four parallel queue formations may be observed. However, a particular queue pattern is not found in reality. In some cases, four to five two wheelers in addition to cars are standing in the front row of the queue.

A specific advantage of the TRAZER for mixed traffic is its ability to track vehicles, even when there is a lateral movement. It could also track vehicles, even under dense traffic conditions. Trajectories obtained from TRAZER are smoothened using a local regression technique (Cleveland et al. 1988). Velocities and acceleration values are obtained by performing first and second order differentiation on the trajectory equation. Since the trajectories of all vehicles are available, it is possible to measure the lateral and longitudinal spacing maintained by different vehicles with respect to nearest neighbor vehicles.

Since this new methodology is robust in collecting data near intersections where the traffic is denser, it is expected that the
efficiency will be much better near midblock. Near the same intersection when the signal is green, average flows, speeds, and occupancies are collected. Whenever the vehicles are crossing an imaginary line drawn on the road, classified flow, speed, and occupancy data are obtained. Occupancy measured in this study is the time taken by any vehicle to cross the imaginary line.

Analysis and Results

A detailed discussion on the data collected using TRAZER is necessary to know its accuracy and usefulness. Some of the vehicle trajectories obtained over a certain road length are shown in Fig. 4. Trajectories in this figure represent the vehicles approaching the intersection with the median as the origin. Labels attached to each trajectory denote vehicle type and ID. As shown in Fig. 4, except in the case of few trajectories, all the vehicles are tracked continuously over time and space. Since the data are collected under congested conditions, some gaps are observed in trajectories due to an occlusion problem. However, once a vehicle is detected, even though it is not tracked in between for some time, once the vehicle came out of occlusion, it is reidentified. For example, LMV_117 (label for LMV with number 117) and Auto_8 (label for auto with number 8) are not tracked in between for some time, but are tracked again once they come out of occlusion. Vehicle classification data obtained from the TRAZER are presented in Table 4. In Table 4, percentage accuracies achieved in measuring flow values are also shown. In the same table, errors in vehicle classification are also presented.

Additional data have been collected on the Dabri road, in the suburbs of Delhi, India. Video film was collected with the specifications mentioned in the previous sections. Classified vehicle trajectory data have been obtained for all the vehicles observed during this period. Different microscopic and macroscopic variables have been extracted from this trajectory information. The methodology used and data collected can be found in Satish Kumar (2007). A part of the 6 h data collected near this location are presented in Table 5. In this table, classified flow data observed in each 15 min interval are compared with the data obtained from the TRAZER for the corresponding time intervals.

Since trajectory data are available for almost all vehicles passing through, it is possible to extract microscopic and macroscopic traffic variables. From Fig. 4, it can be seen that vehicle trajectories are obtained over a distance of 25 m. Lateral movements of different vehicles near the stop line, captured by TRAZER can also be seen in Fig. 4. Using TRAZER, acceleration/deceleration behavior of vehicles approaching the stop line is also captured. Fluctuations in velocity and acceleration for two cars are shown in Figs. 5 and 6. The acceleration behavior of a vehicle that is approaching the intersection at the end of the green period is shown in Fig. 5. Since the driver has realized that the signal is becoming red, the vehicle coasted to a stop. The acceleration behavior of another car, which is following the above-mentioned car, is shown in Fig. 6. It can be seen in the figure that the acceleration behavior of this vehicle is different since the driver is unaware of the leading vehicle driver’s intention.

Lateral spacing maintained by different vehicles is also obtained from TRAZER. Lateral spacing maintained by the vehicle

| Table 4. Flow Values Obtained from TRAZER and Observed Flow |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Vehicle type    | Observed flow   | From TRAZER     | Classified vehicles | Miss | Junk | Cross classification FP* | % accuracy |
| LMV             | 104             | 98              | 90               | 6    | 0    | Auto  | 0    | 0    | 0    | 0    | 94 |
| HMV             | 7               | 7               | 7                | 0    | 0    | HMV   | 0    | 0    | 0    | 0    | 100 |
| Auto            | 3               | 2               | 2                | 1    | 9    | Auto   | 0    | 0    | 0    | 0    | 67 |
| TW              | 52              | 48              | 48               | 4    | 17   | TW     | 0    | 0    | 0    | 0    | 92 |
| Total           | 88.25           |                 |                  |      |      |        |      |      |      |      |     |

Note: *false positives; TW= motorized two wheeler; LMV= light motor vehicle; Auto= motorized three wheeler; LCV= light commercial vehicle; and HMV= heavy motor vehicle.

| Table 5. Comparison of Observed Flow and Flow Values Obtained from TRAZER |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Time            | Observed flow   | Flow from TRAZER |                 |                 |                 |                 |                 |                 |                 |                 |                 |                 |                 |                 |                 |                 |
|                 | LMV | HMV | Auto | TW | Total | LMV | HMV | Auto | TW | Total | LMV | HMV | Auto | TW | Total | LMV | HMV | Auto | TW | Total |
| 10:15–10:30     | 417  | 8   | 24   | 354 | 803   | 376  | 7   | 24   | 340 | 747   |
| 10:30–10:45     | 417  | 8   | 24   | 344 | 793   | 368  | 7   | 24   | 321 | 720   |
| 10:45–11:00     | 356  | 5   | 28   | 268 | 657   | 320  | 5   | 28   | 250 | 603   |
| 11:00–11:15     | 327  | 9   | 17   | 254 | 607   | 304  | 9   | 17   | 246 | 576   |
| Total           | 1,517 | 30  | 93   | 1,220 | 2,860 | 1,368 | 28  | 93   | 1,157 | 2,646 |

Note: TW= motorized two wheeler; LMV= light motor vehicle; Auto= motorized three wheeler; LCV= light commercial vehicle; and HMV= heavy motor vehicle.
LMV_122 over a certain period is shown in Table 6. As shown in this table, over a certain period, the right side of a neighboring vehicle is TW_373 and for the remaining period it is TW_382. Lateral spacing with TW_373 is varying around 7.3 m and with TW_382 this value is varying around 3.9 m. Similarly, gaps maintained by different vehicles while passing/overtaking different vehicles at different speeds can also be obtained.

Summary, Conclusions, and Future Work

Traffic data collection under mixed traffic conditions is one of the difficult tasks faced by the research community. Several data collection systems that were tried in the past proved to be inefficient for mixed traffic. Image processing-based data collection systems are useful in collecting vehicle trajectory data over a
certain road length. Data collected in this way are more useful in characterizing the mixed traffic than the data collected at a section. Existing image processing techniques are not suitable for mixed and no-lane disciplined traffic. In this study, an offline image processing system named TRAZER is developed to collect data under mixed traffic conditions. TRAZER is capable of tracking vehicles even under highly congested traffic conditions. The specific advantage of this system is that it is able to capture lateral movements, which is a typical feature of no-lane disciplined traffic. It is also able to track small sized vehicles such as two wheelers and three wheelers under dense traffic conditions. From trajectory data, several microscopic and macroscopic traffic features are extracted. Among the microscopic characteristics, lateral spacing maintained by different vehicles over the study area is measured. TRAZER could also capture acceleration/deceleration behavior of vehicles. Among the macroscopic characteristics, classified traffic volume, average occupancy, and average speeds are collected. TRAZER gives high detection accuracies if the video camera is aligned with the central lane of the road and at a certain altitude. The accuracy decreases slightly if the camera deviates from the central lane.

This work can be improved and extended in the following aspects:

1. Enabling more convenient video filming by eliminating the constraints on vantage points.
2. The current system is offline. Making this system online is useful in the following scenarios:
   - In developing an offense detection system; and
   - In area traffic control.
3. Making the system more robust and accurate.
4. Further analysis and modeling of data generated from TRAZER.

Acknowledgments

TRAZER has been developed at Kritikal Solutions Private Limited, India with support from Geetam Tiwari and Dinesh Mohan, TRIPP, IIT Delhi, India. Technical inputs were taken from the Department of Computer Science, IIT Delhi, India.

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