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Dynamic data collection of following and merging behavior in mixed traffic

Anuj Budhkar[a]*, Akhilesh Kumar Maurya[b], Avijit Maji[c]

[a]*Post-doctoral Fellow, Department of Civil Engineering, IIT Bombay, Mumbai, Maharashtra 400076, India.*
[b]*Associate Professor, Department of Civil Engineering, IIT Guwahati, Guwahati, Assam 781039, India.*
[c]*Associate Professor, Department of Civil Engineering, IIT Bombay, Mumbai, Maharashtra 400076, India.*

Abstract

Developing economies have mixed traffic with heterogeneous vehicles and weak lane-discipline. Vehicles thus interact longitudinally as well as laterally. The performance measures related to lateral and longitudinal distances such as headway, centerline separation, speeds need to be accurately calculated for entire vehicle interactions in mid-block sections or during events (merging traffic, lane drop, etc.) for a longer stretch of road. This paper describes a dynamic traffic data-collection technique, which calculates car-following parameters using in-vehicle video-camera footage and its calibration, and accurate speed data obtained by GPS device fitted in a test vehicle. This test vehicle is driven on arterial roads of Mumbai and Guwahati cities in India. Further, it compares data obtained using this method with that obtained using external video recording. The data extraction, processing, accuracy and error are discussed. Further, car-following and merging data are processed using this method and analyzed.
It is observed that headway maintained in mid-block and merging maneuvers increases with speed, and decrease in staggering between the vehicles. There is a significant difference in longitudinal gaps during car-following and merging behaviors.

Keywords: data collection; instrumented vehicle; mixed traffic; camera calibration.

* Corresponding author. Tel.: +91-969-989-3836.
E-mail address: anuj.budhkar@iitb.ac.in

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1. Introduction and objectives

The traffic in developing economies like India is heterogeneous in nature, consisting of a variety of vehicle types. Further, the drivers do not maintain lane discipline due to variation in sizes of these vehicle types. So the vehicles do not travel in demarcated paths or lanes, but are spread over the entire width. This results in large number of interactions- longitudinal as well as lateral- that a driver needs to pay attention while maneuvering his/her vehicle in this traffic. It is important to study the driver behavior while interacting with neighboring vehicles. The behavior can be studied using performance measures such as driver's response to a stimulus in the form of acceleration, braking, steering and gap-maintaining. Acquiring field data for a non-lane-based traffic is a major challenge. Hence limited researches in this field are available compared to lane-based traffic.

Several traffic data collection methods are available commercially and in developmental phase used by researchers worldwide. To study driver behavior, a study of trajectory data of vehicles about the entire interaction maneuver is essential. There are ways developed to extract trajectory data from GPS devices, sensors and external cameras. However, they lack in representing either the entire interaction (in case of static image based methods) or representing accurate trajectories over the entire interaction. Further, identification and classification of vehicles in a heterogeneous traffic mix has been a challenge and methods adopted to do so have partial success. Further, response to different scenarios such as impact of a sudden merging traffic, road width narrowing, effect of road geometry etc. requires separate setups from ideal vantage points in each of these scenarios. Thus, to study impact of each scenario and to trace the entire car-following maneuver, there is a need to develop an image-based setup for data collection from within the following vehicle. This paper has attempted the same.

The objective of this paper is development of an in-vehicle trajectory data collection system which provides the inter-vehicular performance measures such as maintained gaps, speeds and driver reaction. The methodology for this is developed in mixed traffic conditions using camera calibration and in-vehicle GPS data. The mid-block car-following data obtained by this method are also compared with data collected from a fixed location. Further, applicability of the developed methodology to study driver behavior with merging traffic is explored.

The scope of this study is limited to ideal road sections without any vertical curves. Only mid-block and merging traffic streams are explored in urban traffic scenario. Since the main aim of the study is to develop data collection methodology, requisite data collection is conducted for these mid-block streams and applicability in other scenarios is explored. This paper is divided into literature review, data collection methodology and error calculation, followed by sample data analysis and future scope.

2. Literature review

This section highlights previous traffic data collection methodologies, previous works conducted for data collection in mixed traffic, followed by usage of an instrumented vehicle for traffic data collection in the third subsection.

The traffic data collection can be conducted using intrusive and non-intrusive static data collection devices. Quick data collection is possible using pneumatic road tubes (FHWA, 2007) which record the difference in pressure change as traffic passes over them. Similarly, piezoelectric sensors as developed by Li *et al.* (2006) can record presence and weight of vehicles. Magnetic loops arranged in specific formats by Kwong *et al.* (2009) generate a magnetic field on the passing of a vehicle. These are intrusive techniques which are costly and cannot detect the vehicle type. The vehicle types could be classified based on their weights or sizes, but similar sized vehicles (such as compact commercial trucks and sports utility vehicles, three wheelers and mini-cars, etc) cannot be identified with accuracy. The vehicle detection is possible with the help of passive and active infrared sensors as developed by Grabner, *et al.* (2008) or microwave radar sensors developed by Zwahlen *et al.* (2005). Presence, speed and size can be sensed by ultrasonic sensors (Kim, 1998) used over larger research works such as Budhkar and Maurya (2017a) or Venter and Knoetze (2013). The precise identification of a vehicle is possible only by means of its recorded image. Data collection by video-recording is the most popular method used these days. A detailed literature review based on image-sensing of vehicles has been presented by Sun *et al.* (2004).

Trajectory extraction from recorded images of videos remains a challenge. There are some efforts in this regard by Metkari *et al.* (2013), Jin *et al.* (2011) and others. In some works, the road sections were physically marked with strips of known width. However, several researches have been made to calibrate the road section points from their corresponding points visible in the image. Efforts in this regard include those by Fukui (1981), Courtney *et al.* (1984), Bas and Chrisman (1997) and Fung *et al.* (2003). Based on visible trajectory, image detection and camera calibration, vehicle trajectory data extractor software are developed Vehicle trajectory data can be obtained using machine learning techniques by means of image-processing software. One of such software (suitable for developing countries' traffic conditions) is TRAZER or Traffic Analyzer and Enumerator (*website: http://www.kritikalsolutions.com/products-and-ips/video-based-object-detection-analytics-platform/trazer).* If vehicles are accurately classified, their positions can be calculated to a fair level of accuracy by this method. However, in weak lane disciplined conditions, these detection software are not popular since vehicle classification rate is not highly accurate and vehicles need to be reclassified manually. In such cases, there is a need for semi-manual data collection method, which can manually classify and trace vehicle trajectories of neighboring vehicles. Softwares based on this concept were used to obtain vehicle trajectories (Munigety *et al.*, 2013 or Kanagaraj, 2015) or to study inter-vehicular gaps (Budhkar and Maurya, 2015). However, these authors recorded a video of traffic stream from a static camera placed at a high vantage point. The entire vehicular interaction cannot be recorded since cameras can just focus on particular road section in this method which is at the most 100 m in length. Any attempt to capture the entire interaction between vehicles would involve either a compromise on a resolution to mark the trajectory or complicated methods by means of video-stitching by recording from several simultaneous videos not attempted earlier. It is, therefore, necessary to use an instrumented vehicle for capturing video.

The instrumented vehicles equipped with GPS devices are used to extract trajectories of test vehicle such as Bokare (2013), or inter-vehicular gaps such as those by Wong and Qidwai (2004), Venter and Knoetze (2008) or Budhkar and Maurya (2017a). The image information from inside the instrumented vehicle is not yet explored for trajectory data.

From this literature review, it is clear that a methodology is not developed for a dynamic and image-based semi-manual approach of vehicle trajectory tracking of neighboring influencing vehicles. Due to this, entire car-following and overtaking trajectories in mixed traffic are not captured. There is thus a need to develop this technique using a combination of (i) camera-calibration method by Fung *et al.* (2003) and (ii) GPS data of vehicle. Further, since vehicle tracking, identification and classification for an in-vehicle technique (back view) will not be accurate, vehicle trajectories can be manually tracked from the image. The next section describes the stepwise methodology for data collection.

3. Data collection methodology

This section describes the data collection methodology by dynamic video recording, using an instrumented vehicle. It also mentions the calibration process, precautions necessary during data collection and the error and comparison with the earlier literature.

3.1 Instrumented vehicle Setup

The in-vehicle tracking setup used in this experiment consists of (i) Video camera with pre-calibrated readings; and (ii) GPS device. A video camera is placed at the front, focusing the roadway as visible to the driver. It captures continuous video at high quality and known frame rate (25 fps). The error due to edge distortion is eliminated in the laboratory. The image calibration of the video camera is described in the next subsection.

A GPS device is synchronized with this camera and records vehicle position at 20 Hz frequency. The synchronized setup is available commercially by Racelogic company as ‘Video V-box'. The setup photograph is shown in Fig. 1.

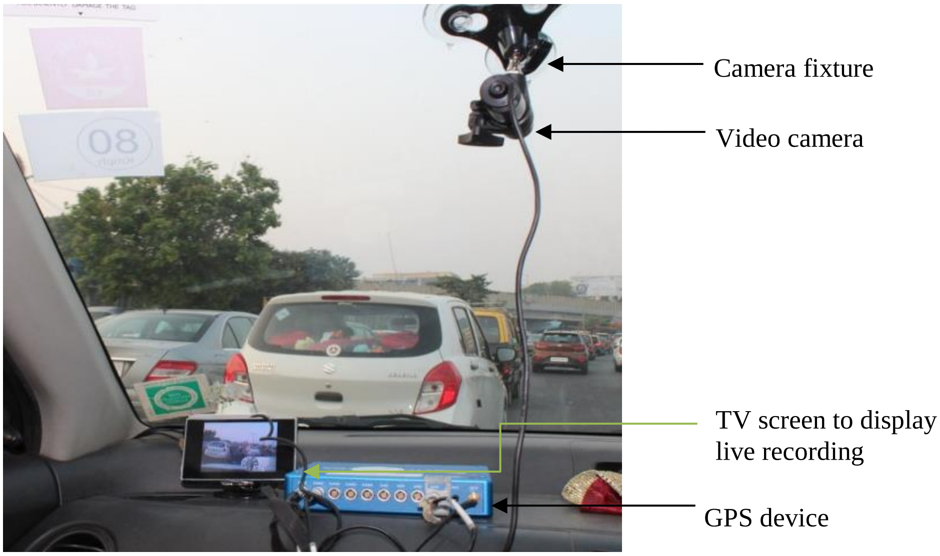

Fig. 1 Video camera and GPS device attached to record leading traffic from inside test vehicle

3.2 Calibration

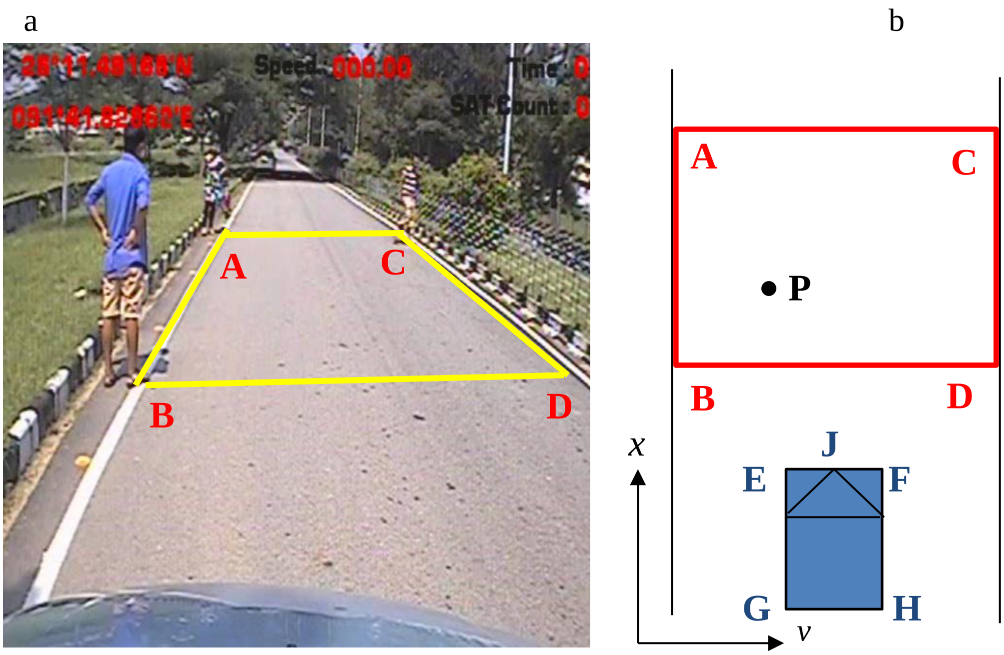

Fig. 2 Camera calibration for dynamic data collection technique (a) in the field (b) representation

Camera calibration of the recorded in-vehicle video is conducted by means of vanishing point technique developed by Fung *et al.* (2003), where image coordinates of four points representing a perfect rectangle in the field need to be captured. Based on calculated camera parameters (pan angle, tilt angle, swing angle, focal length and distance of the plane from the camera lens) and image coordinates of any point lying within the real plane of these four points, the real position of this point can be known by this method. Details of this technique are explained with reference to Fig. 2.

Consider the test vehicle (EFGH) with its front centre (point J) parked parallel to the road edge (AB). Before the actual experiment, four points are marked (as shown in Fig. 2-a) on a flat road, which represents an exact rectangle in the field (ABDC in Fig. 2a and 2b). The points A, B, D and C are named and marked in the image using a mouse click according to nomenclature mentioned in Fung *et al.* (2003). They are marked several times and the average pixel value for each point is used to reduce error due to manual mouse clicking. The lateral and longitudinal distance of one of these points from one corner of the test vehicle also needs to be known (Say, point B from point E). For any point P lying in the plane ABCD (i.e. plane of the road) its camera co-ordinates (x_P, y_P) can be calculated and subtracted from coordinates of point B and E so as to obtain the lateral and longitudinal offset of point P. In other words, lateral offset = $y_P - (y_E - y_B) + (y_J - y_E)$, longitudinal offset= $(x_B - x_P) + (x_E - x_B)$. The distances $(x_E - x_B)$, $(y_E - y_B)$ and $(y_J - y_E)$ are accurately measured in the field.

A video player is developed in MATLAB to play the recorded video, pause and mark image coordinates using a mouse click, at given frame frequency. A snapshot of this player is attached in Fig. 3. To calculate the lateral and longitudinal offsets of any leading vehicle in the vicinity of the test vehicle, image coordinates of its two back corners (bottom side) are marked in the video frame once, using the developed software. Vehicle width, the lateral and longitudinal offset of the back center of leading vehicle are thus calculated and stored in a separate file (Say, file A). For every fixed interval throughout the interaction (say, one second or 25 frames or 10 GPS readings), an observer needs to mark image coordinates of any one corner of the vehicle. The developed video player stores frame number and image coordinates in second file (say, File B). They are converted in real world coordinates using the information from file A. A third file is generated by GPS device (say, file C) which provides position, acceleration and speed information of test vehicle at every 20 Hz frequency level. These three files are combined together to make a master-file consisting information of vehicle types, the width of the interacting vehicle, the speed of test and interacting vehicle, the time-stamp of interaction, the lateral distance between the centerlines (hereafter termed as 'centerline separation or CS), and longitudinal gap (*LG*) between two vehicles. The speed of the interacting vehicle can be calculated using time-stamp and *LG* readings of consecutive data-points and speed of test vehicle at that data-point.

3.3 Precautions during data collection

In this experiment, the basic assumption is that all data points are considered lying on a plane passing through the contact points of four tyres of a test vehicle on the road surface. Following precautions are necessary for this purpose.

- *Camera orientation*- It should not change with the roadway. For this purpose, camera movement can be sealed by means of the fixture to the vehicle, and the vehicle should carry uniform weight throughout the experiment so as not to disturb the vehicle (thus camera) orientation with respect to the road.
- *Coplanarity*- The interacting and test vehicle should rest on the same plane. Data extraction cannot be conducted on a vertical curve since the point (point P referred in earlier subsection) will lie out of plane ABDC used for calibration. Data could be collected on a uniform gradient.
- *Identification of points on the road surface*- Most vehicle types have rear overhangs and estimating the projected point on road surface may become difficult for data extractor. The authors propose two solutions for this approach- (i) mark coordinates of back tyres of vehicles and deduct rear overhang length (obtained from vehicle manufacturer's details) from obtained *LG*; or (ii) For unknown vehicle models, project rear edge (vertical) line and line joining both tyres from each end using a screen marker.

3.4 Error in calculating distance

Since the position of vehicle corner needs to be determined by means of a mouse click, error in calculating distance will depend on how accurately the user clicks on a certain point. An average extractor makes mouse-clicking with an accuracy of 6 pixels (Budhkar and Maurya, 2016). These 6 pixels correspond to different distances in the field, and error in calculating longitudinal gap will increase as field distance from point B (refer Fig. 2) increases. The maximum error (normally distributed, 3σ) increases from 1.2% for a point exactly on point B, to 11.7% for a point 30 m ahead of B for the experiment conducted on Guwahati roads (when point B was 3 m ahead of test vehicle’s front edge). The error will vary depending on camera orientation, zooming and ability of an extractor.

3.5 Validation of obtained data with static video recording and previous literature

Mid-block data obtained using this methodology is compared with (i) static data obtained using external video recording, and (ii) earlier literature. A video camera attached at a high vantage point capture vehicles over a considerable road stretch (upto 50 m). The camera calibration procedure is performed similarly to section 3.2. Inter-vehicular gaps (longitudinal gap or *LG* and centerline separation or *CS*) are extracted for a pair of interacting vehicles, and their speeds are calculated based on their trajectories. The video cameras record the vehicular interactions on the same roads traversed by the test vehicle at similar flow levels. Location of vantage points includes Sarusajai stadium on Guwahati bypass, Guwahati, Ismail Yusuf college on Western express highway Mumbai, and Powai Hiranandani bus-stop on Jogeshwari Vikhroli Link road. The dataset of lateral and longitudinal gaps at different average speeds obtained using both the methods is compared. For this purpose, an obtained dataset of *LG* vs CS and speed using dynamic and static methods is compared at different CS and v levels using t-test. Table 1 provides a detailed comparison of vehicle types cars and two-wheelers which were predominantly observed in the traffic stream.

Table 1. p-values of *t*-test for comparison of longitudinal gaps obtained by static and dynamic levels at various speeds and CS for (i) cars, (ii) Two wheelers and (iii) Three wheelers. NaN indicates no available data for comparison.

CS (m)	A car following another car			A car following three wheeler			A car following Two wheeler	
Speed (km/h)	0-1 m	1-2 m	2-3 m	0-1 m	1-2 m	2-3 m	0-1 m	1-2 m
0-10	0.000	0.004	NaN	NaN	0.855	0.026	NaN	NaN
10-20	0.778	0.173	0.190	0.162	0.890	NaN	0.043	0.373
20-30	0.197	0.225	0.548	0.325	0.009	0.098	0.918	0.023
30-40	0.716	0.519	0.528	0.641	0.881	NaN	0.067	0.161
40-50	0.351	0.188	0.090	NaN	NaN	0.164	0.058	0.781
50-60	0.361	0.181	0.999	NaN	NaN	NaN	0.235	0.108

From Table 1, one can observe that there is a statistical similarity between obtained dataset by static camera placement and dynamic placement (inside the vehicle), for most speed and CS levels for all vehicle types (as indicated by red highlighted cells with p-values less than 0.05). Thus, the methodology is comparable with usual video recording procedure to obtain data.

The results obtained from Fig. 3 are also compared with Gunay (2007) where the authors have compared staggering with time headway and from the plot in Gunay (2007), the results are similar. They are also statistically similar with the mid-block results obtained by video-recording methods in mixed traffic section by Budhkar and Maurya (2017b).

4. Data collection and analysis

This section consists of car-following and merging traffic data collected and analyzed using developed in-vehicle image-based methodology.

4.1 Site details for data collection

Arterial urban roads in Mumbai and Guwahati cities in India are chosen for data extraction of mid-block and merging/overtaking maneuvers. They include Jogeshwari-Vikhroli link road, Western express highway, Babasaheb Ambedkar road in Mumbai; and Guwahati bypass, Assam trunk road, Jalukbari-Changsari road (NH 31), Guwahati-Shillong road in Guwahati. Three instrumented sedan cars are driven on these roads with the setup in peak and lean-peak hours (10 am to 1 pm and 5 pm to 7 pm). Interacting vehicle positions are marked at every second. Each marking provides a data-point. Using the methodology in section 3, the relative position of the test vehicle and neighboring vehicles can be calculated. Based on the (lateral and longitudinal) difference in relative position of interacting vehicles and speed of test vehicle (from GPS device), the speed of interacting vehicles is calculated. Further, vehicle sizes and types are marked manually to accurately calculate inter-vehicular gaps can be calculated. The setup is installed in Sedan cars for all experiments. The data extracted consist of parameters centerline separation (CS), longitudinal gap, speeds of test vehicle (following vehicle or FV) and interacting vehicle – leading vehicle (LV) for car-following and merging vehicle (MV) for vehicles merging in front of test vehicle, and vehicle type of interacting vehicle.

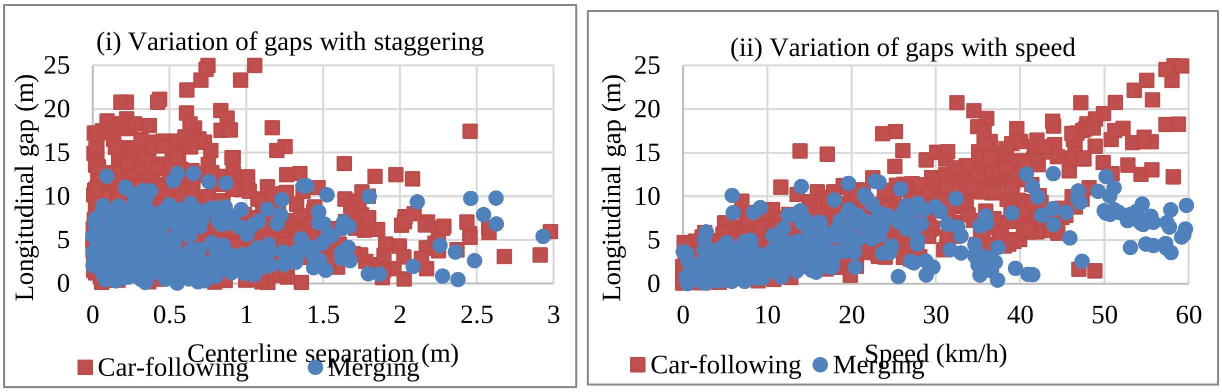

Fig. 3 Extracted gap-maintaining data using dynamic recording and its variation with (i) staggering and (ii) speed.

4.2 Gap-maintaining behavior in car-following and merging

Car-following data extracted in mid-block section are segregated. No conflicting streams are visible while extracting these data, and the relative speed is contained within +/-5 km/h to ensure data obtained while stable car- following. Fig. 3 shows obtained data as variation of longitudinal gaps with (i) centerline separation or staggering and (ii) average speed for car-following and merging. It is observed that there is increase in longitudinal gap with decrease of centerline separation and increase of average speed for both the cases.

A similar data extraction exercise is also conducted for vehicle-merging scenarios for all vehicle types. In this experiment, vehicle merging is defined as obstruction to the path of test vehicle either due to crossing by other vehicles in the same stream or due to merging from conflicting streams moving in the same direction (for example- ramps). The traffic parameters (*LG*, CS and average speed) are extracted from vehicles merging and crossing over in front of test vehicle and are also plotted in Fig. 3. The *LG* during car-following and merging data presented in Fig. 3 are compared at various speed and CS levels using *t*-tests, and the comparison is provided in Table 2.

Table 2. p-value of *t*-test results of the comparison of LG in car-following and merging sections. NaN indicates no data available for comparison.

CS (m)	Car-car interaction			Car-two wheeler interaction	
Speed (km/h)	0-1 m	1-2 m	2-3 m	0-1 m	1-2 m
0-10	0.000	0.113	NaN	0.077	0.024
10-20	0.000	0.622	NaN	0.270	NaN
20-30	0.097	0.019	0.111	0.339	NaN
30-40	0.000	0.000	0.282	0.592	0.225
40-50	0.160	0.225	0.439	0.522	0.386
50-60	0.000	0.000	NaN	NaN	NaN

From Table 2, an inference can be drawn that there is a significant decrease in the longitudinal gap at lower staggering levels when a merging vehicle suddenly maneuvers in between LV and FV (as indicated by red colored cells having p-values less than 0.05). However, the trend is not observed when the interacting vehicle is a two-wheeler.

4.3 Extraction of gap-acceptance data while merging

When a merging vehicle (MV) accepts the gap between LV and FV, the instance of lateral overlapping of MV with FV's edge is marked and parameters (speeds, longitudinal and lateral gaps) are calculated. The exercise is conducted on a limited dataset of 26 different merging vehicles at different scenarios. It is observed that mean accepted gap between LV and FV by FV within 20-30 km/h speed range is 14.5 m (σ 3.3 m), which correspond to average time headway 2.2 s. This accepted gap may change with speed and staggering between LV and FV. For a robust modeling approach, higher sample size is necessary. A future research can be considered to model gap-acceptance, also considering the vehicle type-wise variations with staggering and speeds of LV, MV and FV as independent variables.

5. Conclusion and future scope

This paper describes a dynamic traffic data-collection technique, which consists of an in-vehicle video and speed recording technique by means of camera and GPS device. This calculates car-following and traffic-merging parameters from obtained images by camera calibration of video. Parameters obtained include headway, relative speeds, staggering, and time-gap acceptance. They are extracted manually from video by means of mouse-click of vehicle corners and converting image-coordinates to real-world coordinates by means of vanishing point methodology. Developed methodology is found to have error within limits and extracted data by this method is similar to previous literature. This exercise is conducted for mid-block and merging sections. It is observed that longitudinal gap increases with increase in speed and decrease in centerline separation for both the cases. Longitudinal gap between merging and following vehicle is significantly lesser than that during car-following. An average time-gap of 2.2 seconds is accepted by vehicles in 20-30 km/h speed levels while merging in between two vehicles.

The future scope of this paper is manifold. Some driver behavioral studies where this methodology can be adopted include (i) bidirectional roads, to study overtaking behavior (ii) car-following behavior on curves, (iii) A detailed car-following model can be developed if time-series based dataset of following and reaction to various stimuli of leading vehicle is studied (iv) Further, the traffic merging behaviors can be studied for various cases such as merging on ramps, during reduction in road width (lane-drops), while changing lateral position, etc. for various vehicle types. This methodology can pave way for further research in the field of mixed traffic.

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