Trajectory Data and Flow Characteristics of Mixed Traffic

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Models of driving behavior (e.g., car following and lane changing) describe the longitudinal and lateral movements of vehicles in the traffic stream. Calibration and validation of these models require detailed vehicle trajectory data. Trajectory data about traffic in cities in the developing world are not publicly available. These cities are characterized by a heterogeneous mix of vehicle types and by a lack of lane discipline. This paper reports on an effort to create a data set of vehicle trajectory data in mixed traffic and on the first results of analysis of these data. The data were collected through video photography in an urban midblock road section in Chennai, India. The trajectory data were extracted from the video sequences with specialized software, and the locally weighted regression method was used to process the data to reduce measurement errors and obtain continuous position, speed, and acceleration functions. The collected data were freely available at http://toledo.net.technion.ac.il/downloads. The traffic flow characteristics of these trajectories, such as speed, acceleration and deceleration, and longitudinal spacing, were investigated. The results show statistically significant differences between the various vehicle types in travel speeds, accelerations, distance keeping, and selection of lateral positions on the roadway. The results further indicate that vehicles, particularly motorcycles, move substantially in the lateral direction and that in a substantial fraction of the observations, drivers are not strictly following their leaders. The results suggest directions for development of a driving behavior model for mixed traffic streams.

The study of vehicle-to-vehicle interactions is necessary for an understanding of the traffic flow and safety problem. Driving behavior models describe driver maneuvering in various traffic situations. The core behavioral models, those for car following and acceleration and those for lane changing, have been studied for several decades. Many theories about the functional forms governing these behaviors have been proposed. Comprehensive reviews of these models have been provided, for example, by Brackstone and McDonald (*1*) and Toledo (*2*). However, far less research has focused on the use of observational data to calibrate and validate models of driving behavior. One reason for this gap in the literature is the difficulty in obtaining the required data, which consist of time–space trajectories of the vehicles in a section of road. From these data, time series of the variables that are used in driving models (e.g., positions, speeds, and accelerations of the various vehicles; relative speeds; time and space headways) are extracted. The validity of driving behavior models depends on the availability and quality of these data. FHWA'S next generation simulation (NGSIM) project collected and shared several data sets of vehicle trajectories on expressway and urban arterials in the United States (*3*). These have been used extensively to calibrate and validate driving behavior models (*4–8*).

The literature on modeling mixed traffic in developing countries at the microscopic level is growing steadily. For example, Cho and Wu developed a model for the longitudinal movement of motorcycles based on their desired speed, space headway, and safety margin (*9*). Lan and Chang studied situations in which the driver follows a single leader or multiple leaders, including when the lateral overlap is partial in mixed streams (*10*). Gunay developed a car following model based on safety distances that takes into account the lateral frictions between the subject and other vehicles (*11*). Budhkar and Maurya used a variant of this model in a simulation model for bidirectional traffic (*12*). Jin et al. modeled a staggered car following model that uses the optimal velocity model structure by taking into account the lateral separation between the vehicles (*13*). The longitudinal movement model of Lee et al. introduced more complex behavior patterns, such as squeezing through small lateral gaps, moving abreast of other vehicles in the same lane, oblique following, and swerving (*14*). In the context of lateral movement, Munigety et al. used a discrete choice model for the choice of lateral movement (*15*). The literature proposes a wide and growing range of behaviors that must be captured for the microscopic modeling of mixed traffic streams and has offered a variety of competing behavioral theories proposed for this purpose. However, calibration and validation of driving behavior, in the context of mixed traffic modeling, have mostly been based on macroscopic flow characteristics, such as flows, speeds and densities (*16, 17*). This approach limits the level of detail that can be captured in the developed models. A few studies have used trajectory data, but these are often small samples collected for a specific study. For example, Kanagaraj et al. collected the trajectories of the subject and lead and lag vehicles in a merging situation (*18*). Sangole and Patil selectively collected trajectories for the involved vehicles in group gap acceptance behavior at an uncontrolled intersection (*19*). Vehicle trajectory data related to mixed traffic appear not to be publicly available, possibly because data collection and extraction are difficult and expensive and because of the technical complexities associated with a wide mix of vehicles types of varying physical dimensions and dynamics characteristics (speed and acceleration capabilities) and non-lane-based movements (*20*).

This paper reports on an effort to create a set of vehicle trajectory data in mixed traffic and reports on the first results of analysis of these data. The data were collected with video photography in an

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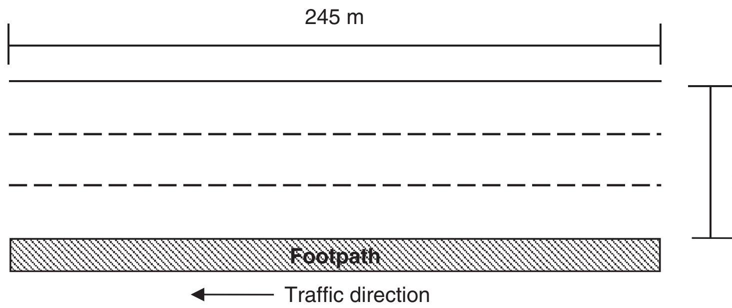

FIGURE 1 Data collection site in Chennai.

urban midblock road section in Chennai, India. The trajectory data were extracted from the video sequences with Trajectory Extractor (*21*) and then were processed with the locally weighted regression method (*22, 23*) to reduce measurement errors and to obtain continuous position functions that may be differentiated once or twice to obtain speed and acceleration functions, respectively. Finally, the traffic flow characteristics of these trajectories were investigated.

DATA COLLECTION

Site

The video data were collected on a six-lane separated urban arterial road at the Maraimalai Adigalar Bridge in Saidapet, Chennai, India. Collection took place on the northbound approach, shown in Figure 1. The section was on a bridge, which ensured that the road geometry was uniform and that there were no nearby intersections, bus stops, parked vehicles, or other side factors that could affect drivers' behavior. Furthermore, there was no interaction between the vehicle traffic and pedestrians, because the pedestrian walkway is segregated by a barrier. The video data were recorded between 10:00 a.m. and 3:30 p.m. on February 13, 2014.

Trajectory Extraction

Over the years, several automated or semiautomated tools for extracting trajectory data from video sequences have been developed, including VEVID (*24*), NGSIM video (*25*), and Trajectory Extractor (*21*). The latter has been used to collect motorcycle and bicycle trajectories in London. TRAZER (*26*) and Traffic Data Extractor (*20*) were developed and used for trajectory extraction in mixed traffic.

In this study, Trajectory Extractor was used to obtain the coordinates, dimensions, and vehicle class of all vehicles that appeared in the video sequences during the 30 min between 2:45 and 3:15 p.m. (*21*). This period represents medium-level traffic flows, which exhibit both vehicle following and lateral shift behaviors. The trajectories were extracted at a time resolution of 0.5 s. The extraction was semiautomated. A Windows-based graphical user interface allowed a human operator to use the mouse to identify the edges of vehicles on the screen. The system converts these points into real-world coordinates and calculates vehicle position, speed, and acceleration. The coordinate conversion relies on four reference points in the video images and their coordinates in the real world.

Figure 2 shows the software's graphical user interface with an image from the road section in the study.

Data Smoothing

Once the position data have been extracted, they must be smoothed to overcome missing observations (e.g., those caused by occlusions), reduce measurement errors, and calculate other variables of interest, such as speeds, accelerations, and intervehicle relations. Several studies have shown that this step is necessary for obtaining unbiased and internally consistent trajectories (*27–29*). Methods for trajectory data processing relied on signal filtering (*30, 31*), smoothing methods (*23, 32*), or moving average techniques (*28, 33*).

The locally weighted regression approach proposed and validated by Toledo et al. was used for data smoothing (*23*). The method uses a set of N (window size) observations before and after the measurement point of interest, t_0. The trajectory function around this point is assumed to be a polynomial function of time:

$$x(t) = f_{t_0}\left(t, \beta_{t_0}\right) + \varepsilon_{t_0,t} = \sum_{m=0}^{M} \beta_{t_0,m}(t)^m + \varepsilon_{t_0,t} \quad (1)$$

where

$\beta_{t_0} = [\beta_{t_0,0} \quad \beta_{t_0,1} \quad \beta_{t_0,2} \ldots \beta_{t_0,M}]$

= vector of $M + 1$ parameters of polynomial function estimated around time t_0,

$f_{t_0}(t, \beta_{t_0})$ = fitted position at time t estimated by local regression function centered at time t_0, and

$\varepsilon_{t_0,t}$ = normally distributed error terms.

FIGURE 2 Trajectory extractor user interface showing road section and reference points.

The parameters of this local function are estimated with N observations in the window around t_0 with a weighted least-squares estimator:

$$\beta_{t_0} = \arg\min_{\beta}\left[X_{t_0} - f_{t_0}(t,\beta)\right]' W_{t_0}\left[X_{t_0} - f_{t_0}(t,\beta)\right] \tag{2}$$

where

X_{t_0} = column vector of N position observations used to estimate a trajectory function centered on t_0,
$f_{t_0}(t, \beta_{t_0})$ = corresponding vector of fitted values, and
W_{t_0} = $[N \times N]$ diagonal matrix with elements corresponding to the weights of the observations.

The observation weights are a tricube function of its distance from the point of interest t_0:

$$w(t_0, t) = \left(1 - \left(\frac{|t - t_0|}{d}\right)^3\right)^3 \tag{3}$$

where $w(t_0, t)$ is the weight assigned to the observation at time t in fitting a curve centered at t_0 and d is the distance from t_0 to the nearest point outside the window of N points to be considered in fitting the curve.

Upper and lower bound constraints on the estimated speeds and accelerations are also added to the optimization problem in Equation 2. Instantaneous speeds and accelerations are calculated as the first and second derivatives with respect to time of the fitted position polynomial function.

The longitudinal and lateral positions were smoothed independently of each other. Following the results in Toledo et al. (*23*) and some experimentation with the current data set, a window size of $N = 7$ and polynomial order $M = 4$ were used in both cases. In the longitudinal direction, the smoothed data have a mean average error (MAE) of 0.544 m and a root mean square error (RMSE) of 0.788 m, compared with the raw data. In the lateral dimension the errors are MAE = 0.062 m and RMSE = 0.082 m.

Punzo et al. defined consistency conditions that must be met for the trajectory data to be useful in studying driving behavior (*29*). The internal consistency condition guarantees agreement between position, speed, and acceleration values. The smoothing method used here defines the position as a continuous function and defines speeds and accelerations as its derivatives. Thus, the internal consistency condition is satisfied by definition. The platoon consistency constraint guarantees that there are no overlaps between the trajectories of vehicles, which imply collisions. Initially, 4,107 position points (3.7%) violated this condition. In these cases, the two overlapping vehicles were moved to eliminate the collisions, and the smoothing process was repeated. In the final data set, 4,199 observations (3.73%) with platoon consistency problems remain. Both these and the corrected observations were flagged in the data set. These observations should be used in macroscopic-level analysis of the data (e.g., vehicle counts and densities) but should be removed or be used with caution in microscopic-level analysis (e.g., headway between leader–follower pairs). The final data set is available at http://toledo.net.technion.ac.il/downloads.

TRAFFIC FLOW CHARACTERISTICS

The collected data set includes 3,005 vehicle trajectories. The positions are observed at a resolution of 0.5 s, for a total of 111,629 observations. Mixed traffic flow has distinct characteristics that distinguish it from homogeneous traffic. The first is a more varied vehicle mix. This is well demonstrated in the collected data: only 26.6% of the vehicles in the traffic flow were passenger cars, 56.4% were motorcycles, 12.2% were autorickshaws, and 4.8% were heavy vehicles, including light and heavy trucks and buses.

Longitudinal Movement

Table 1 presents summary statistics of the traffic flow characteristics in the longitudinal direction. Traffic flows and densities are 1-min averages. The reported speed and acceleration statistics are for instantaneous values. The total traffic flow observed in the study section is 6,010 vehicles per hour (vph). Instantaneous speeds vary from 0 to 15.22 m/s with a mean of 5.88 m/s. The average speeds of the various vehicle types in the stream differ. The mean speed of cars is the highest (6.13 m/s), followed by motorcycles (6.01 m/s). Heavy vehicles (5.64 m/s) and, especially, autorickshaws (5.06 m/s) travel at lower speeds. Analysis of variance (ANOVA) tests were conducted for the average speeds of individual vehicles. These test showed that the differences among the vehicle types are statistically significant [$F(3, 3001) = 114.93$, p-value < .001]. Pairwise comparisons show the mean speeds of autorickshaws and heavy vehicles are each statically significant compared with those of motorcycles and cars. All four differences are significant with p-value ≤ .001. The mean speeds of motorcycles and cars are not statistically significant (p-value = .590). These differences may stem from the higher operating capabilities of cars and the higher maneuverability of motorcycles within the traffic stream, compared with the lower maneuverability of heavy vehicles and poor dynamics characteristics of autorickshaws.

The acceleration rates applied by the various vehicle types also differ for both acceleration and deceleration [$F(3, 3{,}001) = 51.76$, p-value < .001, and $F(3, 3{,}001) = 64.21$, p-value < .001, respectively]. The mean deceleration and acceleration rates of motorcycles (–0.731 m/s^2 and 0.761 m/s^2, respectively) are higher compared with those of other types of vehicles. The post hoc analysis showed that these are statistically different from all other types in both acceleration and deceleration (p-value < .001 in all cases). This difference may be because of the greater maneuverability of motorcycles, which allows their drivers to apply higher acceleration and deceleration rates as they weave through traffic. Other vehicle types are more constrained by the vehicles surrounding them because of size and less maneuvering ability.

Lateral Movement

An important characteristic of mixed traffic is the existence of substantial lateral movement and lack of lane discipline. Table 2 presents summary statistics of lateral movements in the collected data. Speeds as well as accelerations and decelerations in this direction are much lower compared with the longitudinal direction. However, the differences among vehicle types remain similar.

Motorcycles and cars have higher average lateral speeds (0.116 m/s and 0.095 m/s, respectively) compared with autorickshaws and heavy vehicles (0.082 m/s and 0.088 m/s, respectively). ANOVA results show that these differences are statistically significant [$F(3, 3001) = 109.27$, p-value < .001], both overall and in a comparison of pairs of vehicle types (p-value < .001 in all cases). This result may be related to swerving or weaving in traffic by motorcycles as allowed by their size and higher maneuverability compared with those of other vehicle types. Motorcycles also have higher values of mean lateral deceleration

TABLE 1 Longitudinal Traffic Flow Characteristics

Vehicle Type	Mean	SD	Median	Minimum	Maximum
Flow (vph)					
Motorcycle	3,390	643.5	3,300	2,040	4,920
Car	1,600	454.3	1,500	960	2,880
Autorickshaw	732	220.3	720	240	1,080
Heavy vehicles	288	124.5	270	60	540
All types	6,010	1,004.5	5,940	3,960	7,860
Density (vpkpl)					
Motorcycle	67.1	13.2	64.1	40.8	91.9
Car	31.9	11.1	31.4	12.2	59.5
Autorickshaw	18.0	5.2	18.5	4.2	26.5
Heavy vehicles	6.5	2.7	6.8	0.7	11.2
All types	123.5	24.0	120.4	77.7	186.9
Speed (m/s)					
Motorcycle	6.01	1.44	5.94	0.02	15.22
Car	6.13	1.29	6.06	0.37	13.96
Autorickshaw	5.06	1.19	5.03	0	11.51
Heavy vehicles	5.64	1.13	5.67	0	10.40
All types	5.88	1.40	5.82	0	15.22
Acceleration (m/s^2)					
Motorcycle	0.761	0.748	0.519	0	4.734
Car	0.646	0.653	0.431	0	4.436
Autorickshaw	0.692	0.712	0.459	0	4.501
Heavy vehicles	0.672	0.652	0.465	0	3.981
All types	0.717	0.717	0.484	0	4.734
Deceleration (m/s^2)					
Motorcycle	–0.731	0.714	–0.503	–4.659	0
Car	–0.605	0.608	–0.407	–4.371	0
Autorickshaw	–0.654	0.668	–0.426	–4.340	0
Heavy vehicles	–0.630	0.623	–0.420	–4.208	0
All types	–0.681	0.679	–0.460	–4.659	0

NOTE: SD = standard deviation; vpkpl = vehicles per kilometer per hour.

TABLE 2 Lateral Traffic Flow Characteristics

Vehicle Type	Mean	SD	Median	Minimum	Maximum
Speed (m/s)					
Motorcycle	0.116	0.107	0.087	0	1.458
Car	0.095	0.089	0.071	0	1.209
Autorickshaw	0.082	0.075	0.062	0	1.215
Heavy vehicles	0.088	0.079	0.067	0	0.798
All types	0.104	0.098	0.078	0	1.458
Acceleration (m/s^2)					
Motorcycle	0.090	0.075	0.072	0	0.648
Car	0.083	0.069	0.066	0	0.606
Autorickshaw	0.077	0.065	0.061	0	0.639
Heavy vehicles	0.084	0.069	0.067	0	0.548
All types	0.086	0.072	0.068	0	0.648
Deceleration (m/s^2)					
Motorcycle	–0.091	0.078	–0.070	–0.639	0
Car	–0.082	0.072	–0.064	–0.592	0
Autorickshaw	–0.077	0.069	–0.059	–0.652	0
Heavy vehicles	–0.080	0.070	–0.062	–0.561	0
All types	–0.086	0.075	–0.066	–0.652	0

and acceleration (–0.091 m/s^2 and 0.090 m/s^2, respectively). Autorickshaws have the lowest mean values (–0.077 m/s^2 and 0.077 m/s^2, respectively). The inequality of mean lateral deceleration and acceleration values among the vehicle classes is statistically significant [$F(3, 3{,}001) = 90.33$, p-value < .001, and $F(3, 3{,}001) = 65.73$, p-value < .001, respectively]. The post hoc test shows that lateral decelerations and accelerations of motorcycles are different from those of all other vehicle types (p-value < .001 in all cases). The values of cars and autorickshaws are also statistically significant in both decelerations and accelerations (p-value = .006 and p-value < .001, respectively).

Lateral Position

The lack of lane discipline affects driver choice related to the lateral positions of their vehicles. Figure 3 shows the distribution of lateral positions by vehicle type. Driving in India is on the left-hand side. The lateral position 0.0 is on the leftmost (near) side of the roadway and is 11.2 on the rightmost (far) side. The mean lateral positions of motorcycles (4.39 m) and autorickshaws (4.51 m) are to the left of those of heavy vehicles (5.85 m) and cars (7.16 m). The lateral position distributions of motorcycles

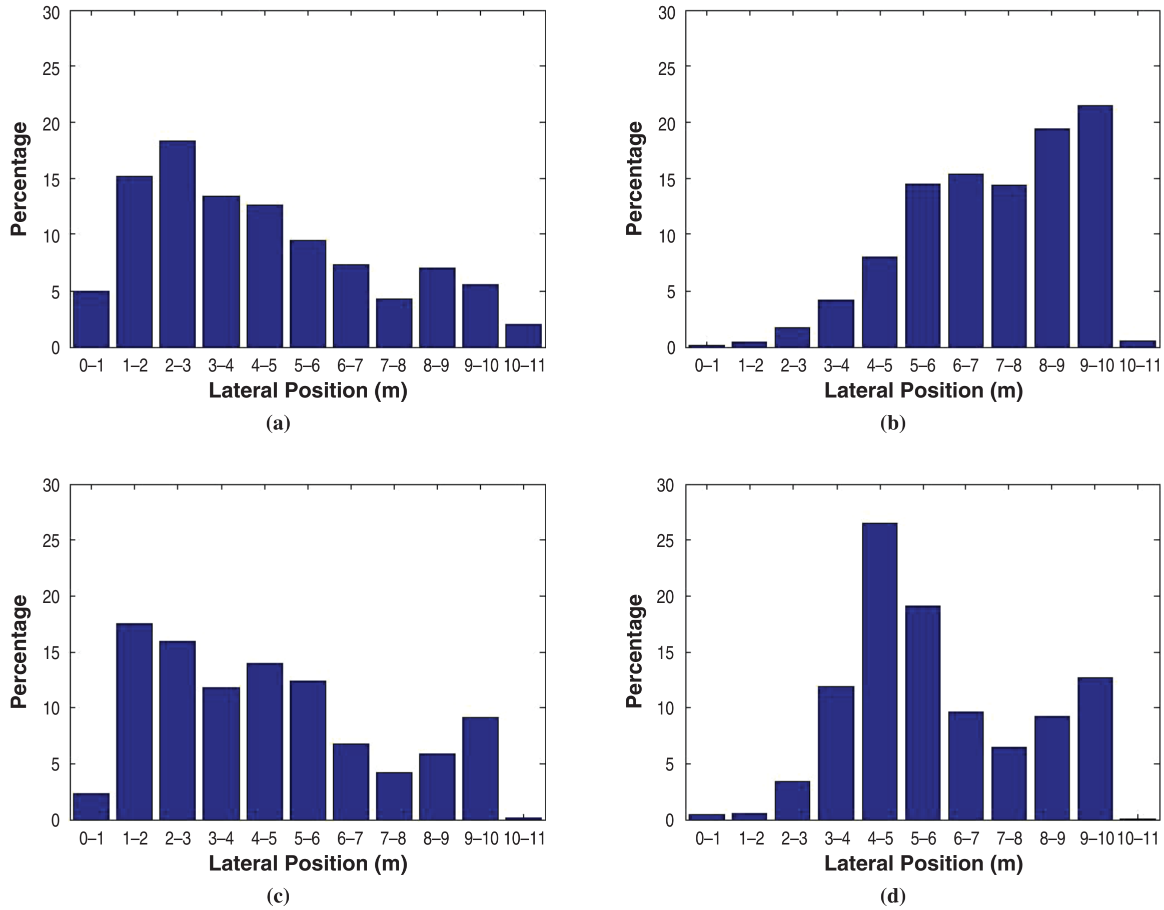

FIGURE 3 Distributions of lateral positions of (*a*) motorcycle, (*b*) car, (*c*) autorickshaw, and (*d*) heavy vehicle.

and autorickshaws are skewed to the near side. Nearly 74% of the motorcycles and 62% of the autorickshaws are observed on the near third of the roadway (0.0 to 3.73 m), and only 18.82% and 19.32% of motorcycles and autorickshaws, respectively, are observed on the far third (7.47 to 11.20 m, respectively). In contrast, the lateral position distribution of cars is skewed to the far side of the roadway. Fifty-six percent of the cars are observed in the far third, and only 6% are observed in the near third. Heavy vehicles tend to be in the middle third of the roadway (3.74 to 7.46 m); 55% of cars are in this part and about 16% and 29% are on the near and far sides, respectively. ANOVA tests on the positions of the various types of vehicles show that they are significantly different [$F(3, 3{,}001) = 241.33$, p-value $< .001$]. All pairwise comparisons are statistically significant (p-value $< .001$ in all cases) except those of motorcycles and autorickshaws. A possible explanation is that drivers of cars tend to prefer the higher speeds and lower friction with other vehicle types and obstructions (e.g., parked vehicles, bicycles, pedestrians) offered by the far side of the roadway. The maneuverability of motorcycles enables them to obtain higher speeds even on the near side. Therefore, motorcycle drivers may prefer to avoid interacting with larger cars and heavy vehicles and so keep to the near side. Autorickshaws stop for passengers on the near side, which may further affect their tendency to stay on this side of the roadway. Most of the heavy vehicles in the section are buses. Bus drivers need to make stops on the near side but also may prefer to avoid interacting with the smaller vehicle types and other obstructions that are more present on the near side.

Lateral Movement Variation

For evaluating the extent of lateral movement that vehicles undertake within the section, the standard deviation of the lateral positions within the section was calculated. Figure 4 presents the distributions of these standard deviations. Overall, autorickshaws make the fewest lateral movements (0.43 m), followed by heavy vehicles (0.49 m) and cars (0.51 m). Motorcycles have a higher value (0.62 m). The differences in these values are statistically significant [$F(3, 3{,}001) = 34.01$, p-value $< .001$]. Again, it is plausible that the smaller size and higher maneuverability of motorcycles allow easier lateral movement compared with the other vehicles. This supposition is supported by less lateral movement by heavy vehicles and autorickshaws, which are characterized by large size (heavy vehicles) and poor maneuverability.

Longitudinal Spacing

Longitudinal spacing is an important explanatory variable in car following models that captures the relationships between vehicles in the stream. In non-lane-based traffic, the definitions of leader and follower are not trivial. For this purpose a leader is the nearest vehicle in front of the subject that laterally overlaps it, and the spacing between the two vehicles is less than 30 m (roughly 2 s). Figures 5 and 6 present the distributions of longitudinal spacing by vehicle type of the leader and the follower, respectively. For

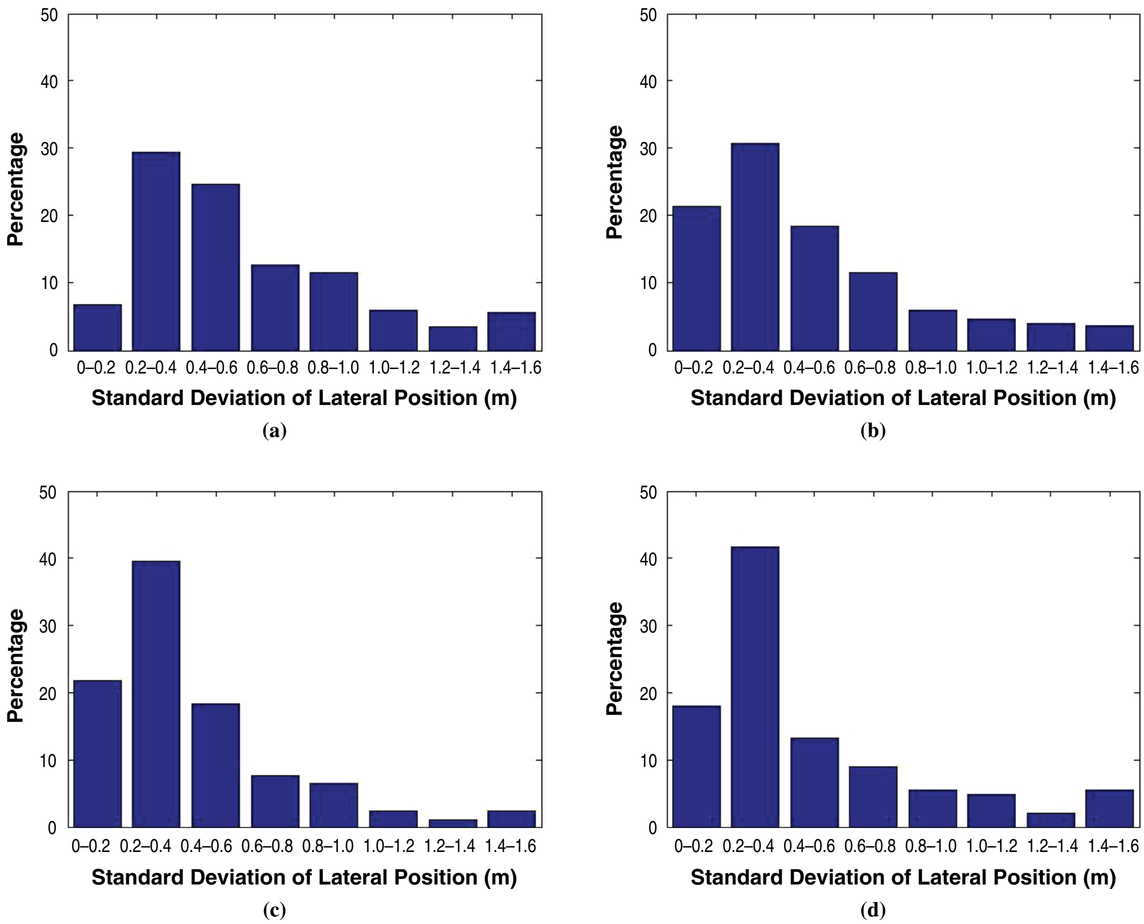

FIGURE 4 Distributions of standard deviations of lateral positions of (*a*) motorcycle, (*b*) car, (*c*) autorickshaw, and (*d*) heavy vehicle.

leader type, vehicles maintain larger spacing with heavy vehicles (16.19 m), followed by autorickshaws (15.12 m), and maintain lower spacing with motorcycles (14.77 m) and cars (14.52 m). ANOVA analysis shows that the effect of the leader type is statistically significant [$F(3, 1{,}503) = 3.77$, p-value = .010]. However, in pairwise comparisons, only the differences between heavy vehicles and motorcycles (p-value = .046) and cars (p-value = .017) are significant. A similar trend is observed for follower type. Heavy vehicles (15.83 m) and autorickshaws (15.64 m) maintain larger spacing compared with motorcycles (14.40 m) and cars (14.63 m). These differences are statistically significant [$F(3, 1{,}504) = 6.43$, p-value < .001].

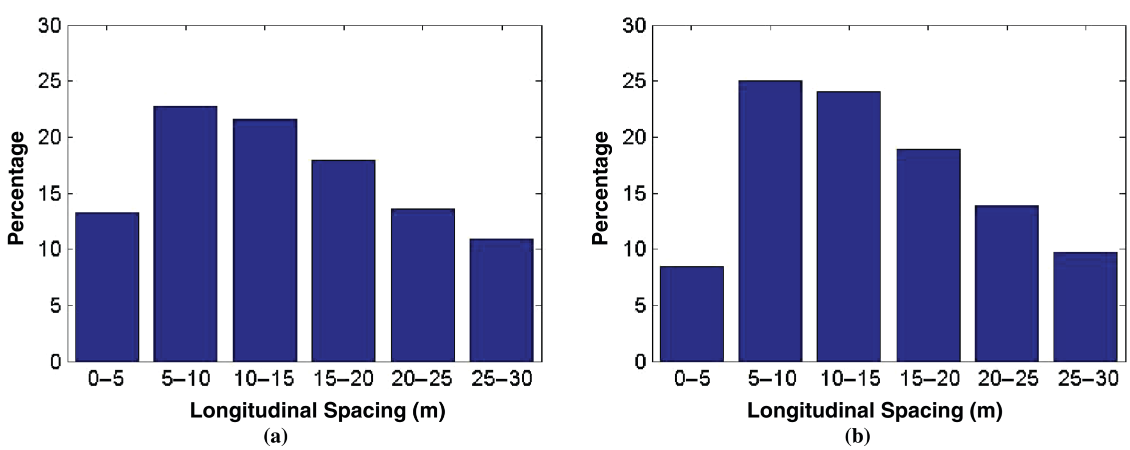

FIGURE 5 Distributions of longitudinal spacing based on leader type: (*a*) motorcycle and (*b*) car.

(continued)

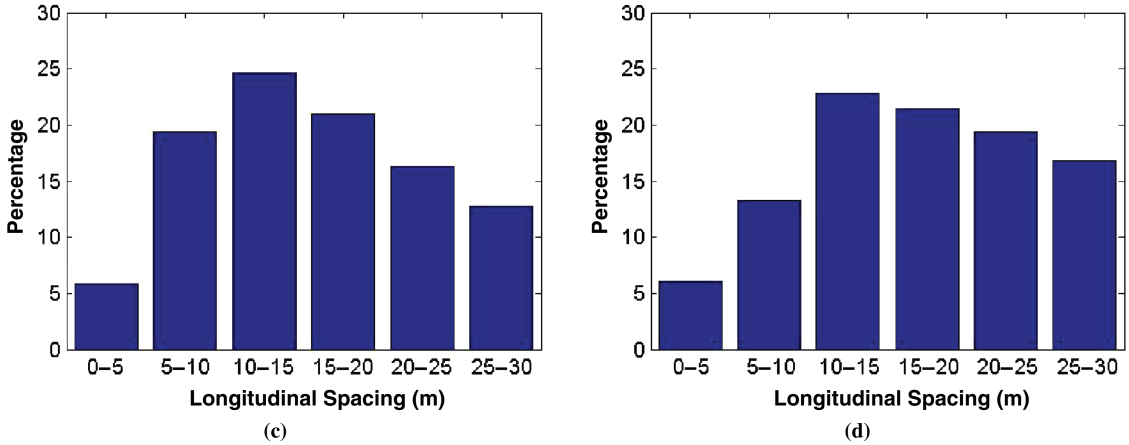

FIGURE 5 *(continued)* Distributions of longitudinal spacing based on leader type: (*c*) autorickshaw and (*d*) heavy vehicle.

Lateral Overlap

In homogeneous traffic, vehicles are predominantly cars that adhere to lane discipline. Most of the time, therefore, a vehicle strictly follows the leader in the same lane. In mixed traffic, the lack of lane discipline and the mix of vehicles of different widths cause different types of relations between vehicles in the stream. For the car following scenario, the extent of lateral overlap between a leader and a follower is the percentage of the follower width that laterally overlaps the leader. The widths of the leader and follower may differ substantially. Therefore, the overlap is defined by the smaller distance between opposite edges of the two vehicles, as

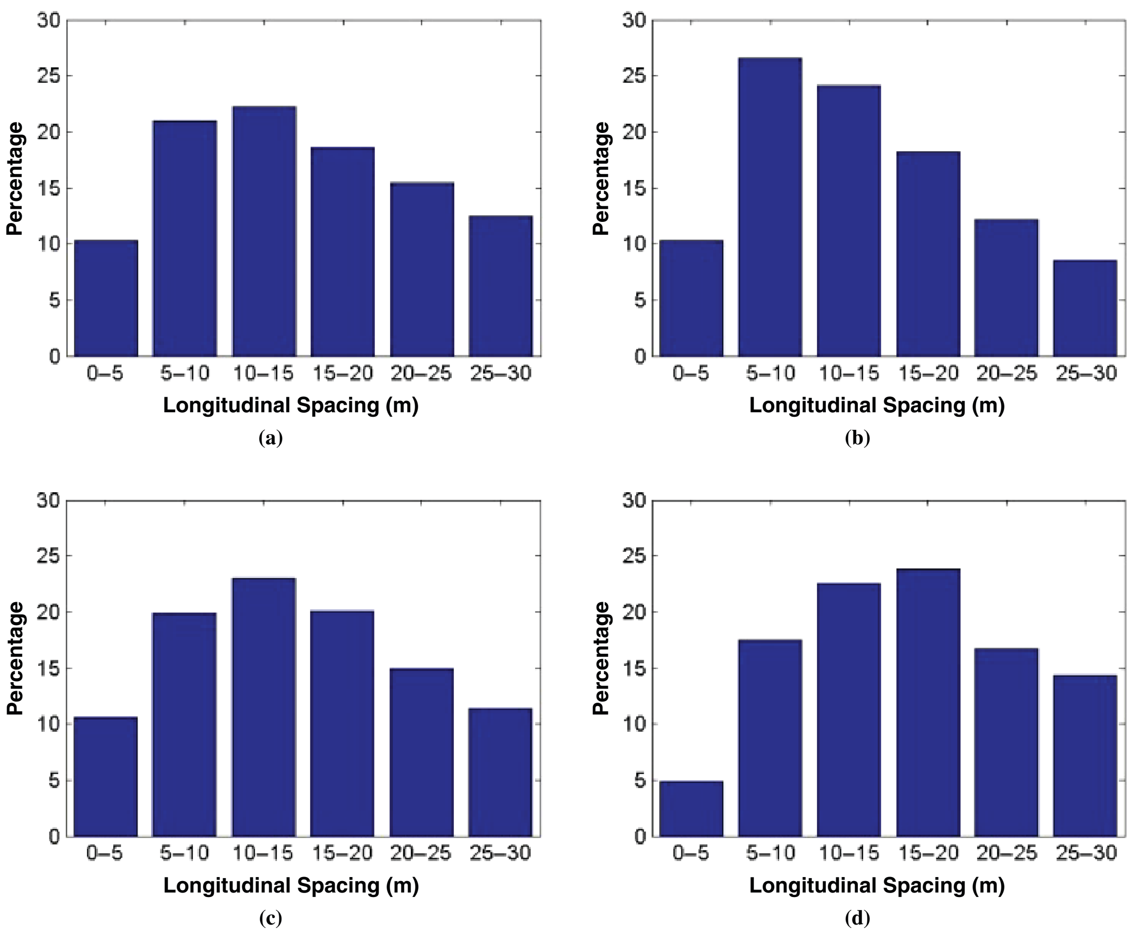

FIGURE 6 Distributions of longitudinal spacing based on follower type: (*a*) motorcycle, (*b*) car, (*c*) autorickshaw, and (*d*) heavy vehicle.

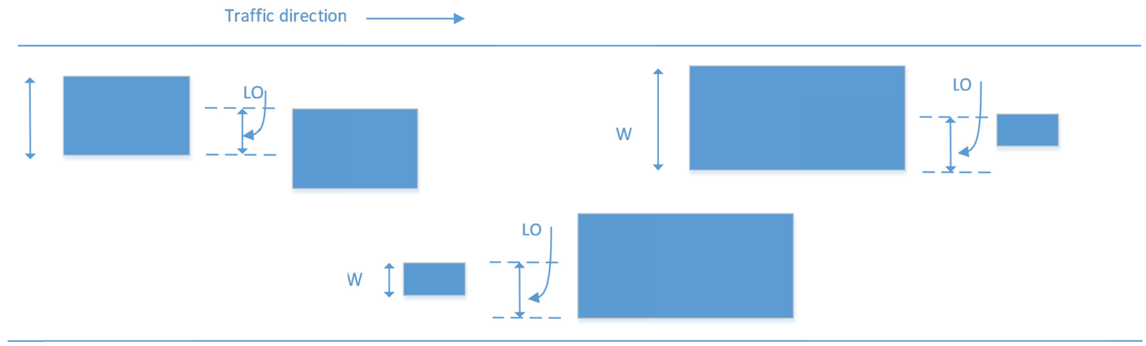

FIGURE 7 Definition of lateral overlap (LO) (W = width).

shown in Figure 7. With this definition, the lateral overlap may exceed 100% if the follower is narrower and entirely overlaps the leader.

The distributions of lateral overlap are shown in Figure 8. The mean value for lateral overlap is higher for motorcycles (61%), followed by cars (51%). Autorickshaws (45%) and heavy vehicles (40%) have lower overlap values. These differences among the vehicle types are statistically significant [$F(3, 1{,}503) = 38.78$, p-value < .001]. All pairwise comparisons, except that of heavy vehicles and autorickshaws (p-value = .804), are statistically significant. Overall, the figure shows a wide range of overlap values. In 45% of the observations the overlap between the leader and the

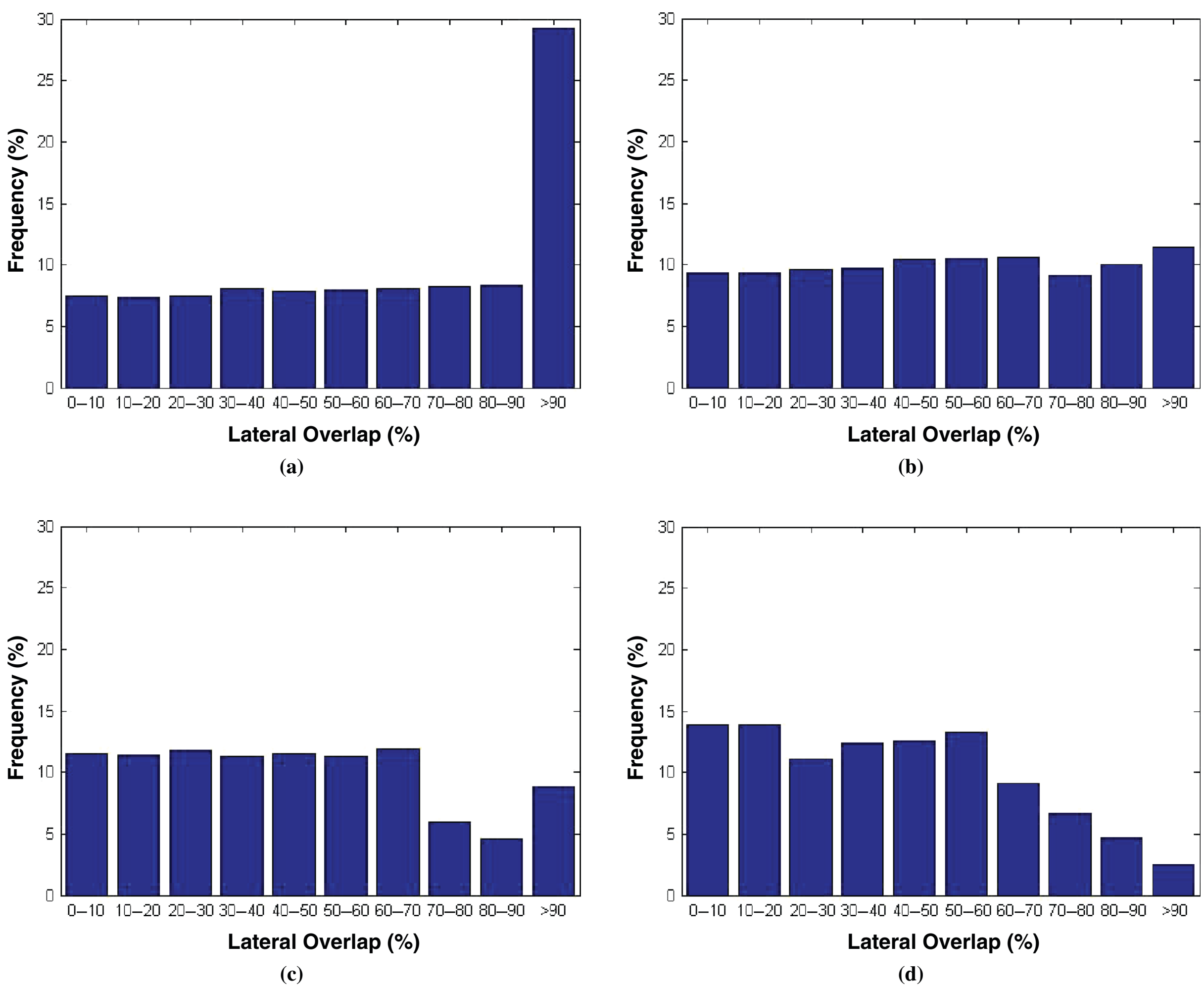

FIGURE 8 Distributions of lateral overlap of (*a*) motorcycle, (*b*) car, (*c*) autorickshaw, and (*d*) heavy vehicle.

follower is less than half the follower width. Thus, it is not evident that car following behavior is applicable to these situations, and there is a need to study other types of following behavior (e.g., staggered following) in mixed traffic streams.

IMPLICATIONS FOR MODELING

The presented results suggest several directions and aspects that need to be taken into account in microscopic modeling of mixed traffic streams. First, the results clearly demonstrate the variability in behavior among various types of vehicles. Most analyzed traffic characteristics differ significantly by vehicle type. These differences are most pronounced in the selection of lateral positions. However, significant differences also exist in all speed and acceleration distributions, in both the longitudinal and lateral dimensions and distance keeping. Among the four vehicle types represented in the data, motorcycles stand out as having distinctive behavior. They tend to travel faster and to be more proactive in changing speeds and moving laterally. In contrast, trucks and autorickshaws tend to be slower and to maneuver less. These differences likely stem from the differences in physical dimensions and dynamic capabilities and maneuverability of the vehicles. In modeling, these differences may be captured by vehicle-type-specific sets of parameters. However, this approach may result in many model parameters that have to be estimated. Therefore, in model development, behaviors and parameters should be selected that will be modeled as type specific and others should be selected that will be modeled generically.

Second, results indicate that in a large fraction of the observations, vehicles are not strictly aligned laterally with the vehicle in front. This effect may be caused by the different dimensions (especially width) of vehicles, maneuverability, and lack of lane discipline, and it affects following behavior. Different following behaviors may be modeled in different situations, as illustrated in Figure 9. Recent research in this direction, focusing on staggered following, assumed that drivers have an incentive to increase their line of sight and thus

(a) (b) (c) (d)

FIGURE 9 Following behaviors in mixed traffic: (*a*) car following, (*b*) staggered following, (*c*) following between two vehicles, and (*d*) passing.

to increase their options to overtake their leader within the stream (*9, 13, 14*).

Finally, the lack of lane discipline and strict following behavior suggests that adjacent vehicles that are not laterally overlapping the subject vehicle may also affect its behavior. Their effects are not captured in current models. The need to account for their effects is underscored by the substantial lateral movement that vehicles—in particular, motorcycles—undertake in the mixed stream.

SUMMARY

This paper focused on the study of the traffic characteristics of mixed traffic. A detailed set of vehicle trajectory data was collected in an urban midblock road section in Chennai. These data were processed and smoothed to reduce the effects of measurement errors and to estimate instantaneous position, speed, and acceleration values. The data are freely available.

The resulting data were studied for aggregate traffic flow characteristics and variables related to the longitudinal and lateral movement of the vehicles. Several insights have been gained from this analysis:

1. A main characteristic of mixed traffic is the presence of significant amounts of vehicles of various types in the stream. There are substantial differences in the flow characteristics between these vehicle types. The results show differences in travel speeds, accelerations, choice of lateral position on the roadway, and almost all other measures that were studied.
2. Car following is a critical component of driving behavior. Analysis of the relationships between leaders and followers showed differences in distance keeping between the various types of vehicles. Furthermore, in almost half the observations, strict following (in which a vehicle follows almost exactly behind another one) was not present.
3. Another characteristic of mixed traffic is weak lane discipline. The study showed that vehicles in the mixed stream—in particular, motorcycles—move substantially in the lateral direction.

Driving behavior models for mixed traffic streams should account for these characteristics. Models must account for the different capabilities and preferences of various vehicle types, for longitudinal movements that are not based on strict car following, and for the effects of vehicles around the subject that do not have a leader–follower relationship with it. The trajectory data collected in this study may be useful for such studies.

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