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Empirical Approach for Identifying Potential Rear-End Collisions Using Trajectory Data

Narayana Raju [a], Shriniwas Arkatkar [b], Said Easa[c], Gaurang Joshi [d]

[a] Postdoc, Delft University of Technology (TU Delft), and PhD from Sardar Vallabhbhai National Institute of Technology, India
E-mail: s.s.n.raju@tudelft.nl

[b] Associate Professor, Sardar Vallabhbhai National Institute of Technology, India
E-mail: sarkatkar@gmail.com

[c] Professor, Ryerson University, Canada
E-mail: seasa@ryerson.ca

[c] Professor, Sardar Vallabhbhai National Institute of Technology, India
E-mail: gjsvnit92@gmail.com

ABSTRACT

This paper proposes a novel approach for examining rear-end collisions between successive vehicles in a traffic stream. In this approach, a new safety measure of the follower driver's attentiveness is proposed, referred to herein as instantaneous heeding time (IHT), reflecting the subject follower's heeding nature concerning its leader. A safety framework that integrates the IHT with the distance gap and the instantaneous follower's speed is presented. The applicability of the framework is demonstrated using an Indian-traffic trajectory database (developed in this study) and the homogeneous traffic database of the next generation simulation (NGSIM) project developed in the United States (U.S.). Five study sections in India and two study sections in the U.S. are analyzed for three traffic-flow levels. For Indian traffic, the results show that motorized two-wheelers (MTW) have degraded road safety due to the unrestrained lateral crisscross movements. Due to the presence of MTW, the Indian-traffic stream operates in a disorderly fashion, thereby increasing the probability of rear-end collisions with other vehicle classes. Further, the importance of implementing cautioning measures for drivers that reduce the probability of collisions is demonstrated. Besides, the NGSIM application results confirmed the proposed framework's applicability to both Indian and homogeneous traffic conditions. In practice, the proposed framework can be used in real-time to monitor the driver's aggressive instincts.

Keywords: Trajectory data, Safety thresholds, Heeding time, Hysteresis, Rear-end collisions.

BACKGROUND

Over the years, with the increase in modernized high-speed vehicles on existing roadway facilities, traffic safety has become a major concern. However, monitoring safe traffic movements in a given traffic stream is a mammoth challenge. Initially, researchers related safety with the stability of the calibrated car-following models over a given road section (Brackstone & McDonald, 1999; Herman, Montroll, Potts, & Rothery, 1959; Wang, Daamen, Hoogendoorn, & van Arem, 2016; Zhang & Jarrett, 1997), but due to data constraints and limitations in the mathematical formulation, those methodologies have not progressed to the desired level of developing safety thresholds, particularly focusing on rear-end collisions. Further, previous studies (Deffenbacher, Deffenbacher, Lynch, & Richards, 2003; Hochnadel & Beymer, 1998; Hoffmann & Mortimer, 1994; Milakis, Van Arem, & Van Wee, 2017; Van Der Horst & Hogema, 1993) relied heavily on experimental setups for understanding the responses of drivers. Then, the responses were correlated with the test conditions and lastly related to safety over a given road section. Based on these experiments, safety measures such as driver reaction time (Balmer, Nagel, & Raney, 2004; Johansson & Rumar, 1971; Triggs & Harris, 1982) was assessed for computing highway geometric elements, such as stopping, passing, and decision sight distance.

Further, with the technological and computer advances, conducting experiments using simulated traffic conditions for assessing drivers' responses became possible. Numerous studies have been conducted for different applications, such as the use of the mobile phone (Byon, Abdulhai, & Shalaby, 2009; WOO & LIN, 2001), driving stress levels (Y. Chen, 2013), gap acceptance (Winter & Spek, 2009), age difference (Lambert, 2013), road geometry (Bella & D'Agostini, 2010), potential impacts(Olia, Abdelgawad, Abdulhai, & Razavi, 2016) and weather conditions (Hofman et al., 2012). While such studies have provided a better understanding of driver behavior, the practical applicability of the approaches was doubtful due to calibration issues related to driving simulators in assessing safety over the road sections considering real field conditions. Besides, for safety assessment, Lee (1976) proposed the time-to-collision (TTC) concept to estimate driver attentiveness and modeled safety thresholds. The basic logic behind TTC is the time available to apply to brake and decelerate to avoid a collision, based on which safety regimes were proposed. With the help of advanced tools, researchers used the TTC concept over varied traffic conditions (Cavallo & Laurent, 1988; R. Chen, Sherony, & Gabler, 2016; Kiefer, Flannagan, & Jerome, 2006; Kiefer, Leblanc, & Flannagan, 2005; Stewart, Cudworth, & Lishman, 1993) and proposed a collision-avoidance system for vehicles. The TTC concept's main limitation is that it provides the same TTC value and, in turn, the same probability of rear-end collisions for situations that exhibit a difference in safety levels. For example, distance gaps of 10 m and 20 m that are associated with relative speeds of 5 m/s and 10 m/s, respectively, would yield the same TTC of 2 s.

On the other hand, driver behavior is significantly different under Indian traffic conditions, particularly due to the predominant proportion of motorized two-wheelers (MTW) and weak lane discipline. To this end, it becomes extremely complex to monitor safety in traffic streams with a higher number of MTW. The present study is an attempt to develop a new measure of safety, delineating a safety framework for traffic conditions under lane-based as well as no lane-based traffic conditions. Based on the literature, it is inferred that driving behavior can be a root source for investigating safety over the road network. This can be attempted particularly with a better understanding of the follower vehicle's attention (or simply follower) to the surrounding vehicle instincts, which may help emerge safety guidelines. However, studying driving behavior requires high-quality micro-level comprehensive vehicle trajectory data.

To address this need, as a part of the next generation simulation (NGSIM) project (US Department of transportation and federal highway administration, 2007), vehicle trajectory datasets were developed over a longer road space, which has been a prime source for building better understanding on driving behavior throughout the world. In this direction researchers focused on trajectory data for the safety analysis (Calvi, Bella, & D'Amico, 2018; Fitzsimmons, Nambisan, Souleyrette, & Kvam, 2013; Haque, Hadiuzzaman, Rahman, & Siam, 2020; Park, Chen, & Hourdos, 2011; Wei, Li, & Ai, 2009) from the homogeneous traffic conditions.

On the other hand, in Indian traffic conditions prevailing in India and elsewhere, due to the deficiency and complexity in developing trajectory data, driving behavior has not been much explored. Further, due to the variety of vehicle classes and weak lane dripline, even a well-established automated image processing tool is not adequate in tracking vehicle positions over road segments. For these traffic conditions, very few studies (Kanagaraj, Srinivasan, Sivanandan, & Asaithambi, 2015; Raju, Arkatkar, & Joshi, 2019) were reported that have used trajectory data developed using semi-automated image processing tools. After a thorough literature review, it is inferred that there is a real need for developing proactive tools for monitoring the safety of traffic streams that can help identify blackspots in the network and reduce road collisions.

In most cases, after a collision, based on investigative reports, measures are taken aftermath to curb the number of collisions, such as improving geometric design and installing warning signs. However, studying driver behavior to understand the causes of collision is more important as a proactive step. This approach necessitates the use of a high-quality vehicle tracking system over the road sections to capture the vehicle's responses. The development of such a system is quite challenging, particularly for Indian traffic conditions. This study attempts to address this challenge by developing a proactive methodology for monitoring traffic safety.

The next section describes two datasets used in the study: The Indian-traffic dataset and the homogeneous-traffic datasets. The following section describes the proposed methodology, including investigating vehicle-following behavior and developing a safety framework for identifying potential rear-end collisions. Safety analysis of the study sections using the developed framework and the two databases are then presented, followed by a summary and conclusions.

DATASETS

Considering the importance of trajectory data in understanding vehicle-following behavior, driving behavior was evaluated in this study with trajectory data. To better explore vehicle-following behavior, both Indian traffic and homogenous traffic conditions were considered. For Indian traffic conditions, trajectory data from five study sections in India were developed in the present study. For homogenous traffic conditions, the NGSIM trajectory dataset was used. Note that the Indian-traffic dataset was used to investigate vehicle-following behavior and observe the vehicles' hysteresis phenomenon. The NGSIM dataset was used, along with the Indian-traffic dataset, to apply the proposed safety framework.

Indian Traffic Trajectory Dataset

From Indian traffic conditions, five different study sections in India were identified. These include two sections: Ahmedabad-Vadodara Expressway (AVE) and another along Pune-Mumbai Expressway (PME). These are intercity expressways, and the variation in traffic flow over these two sections was observed to be marginal. Unlike other Indian roads, MTW was prohibited on these road sections. The third section was a bridge section located on Maraimalai Adigal Bridge, Chennai. From the Chennai section (CS), open-source trajectory data developed by Venkatesan et al.(Kanagaraj, Asaithambi, Toledo, & Lee, 2015) contained two flow conditions and were used for analysis in the present study.

The last two sections were located on Western Expressway (WE), Mumbai, India, an intra-urban multilane high-speed road. The first section is a 5-lane road, 17.5-m wide (each lane 3.5 m), and a trap length of 120 m was considered a base section. The second section was located on a construction zone located along the same road, where the road width is narrowed from 17.5 m to 10.5 m (5-lanes to 3-lanes) for around 500 m. This section has a trap length of 100 m, precisely around the mid-portion of the construction zone. Snapshots of the study section are shown in Figure 1. Six different vehicle categories were observed over the sections: Motorized three-wheelers (MThW), MTW, Buses, Cars, Trucks, and Light commercial vehicles (LCV).

Further, it can be noted that, in the case of CS, WE, and WE-C, traffic is mixed with the dominant proportion of MTW, cars, and MThW. Unlike the other three sections of mixed traffic, a large traffic flow variation was observed on the WE section. Therefore, the trajectory data were developed at three flow conditions on both sections. It can be noted that driving behavior over the road sections is stochastic. Further recent studies in this direction highlighted the variation in driving behavior over the flow conditions. With this idea, in the present study, trajectory data over various traffic flow conditions at different volume to capacity ratios is used from the study sections.

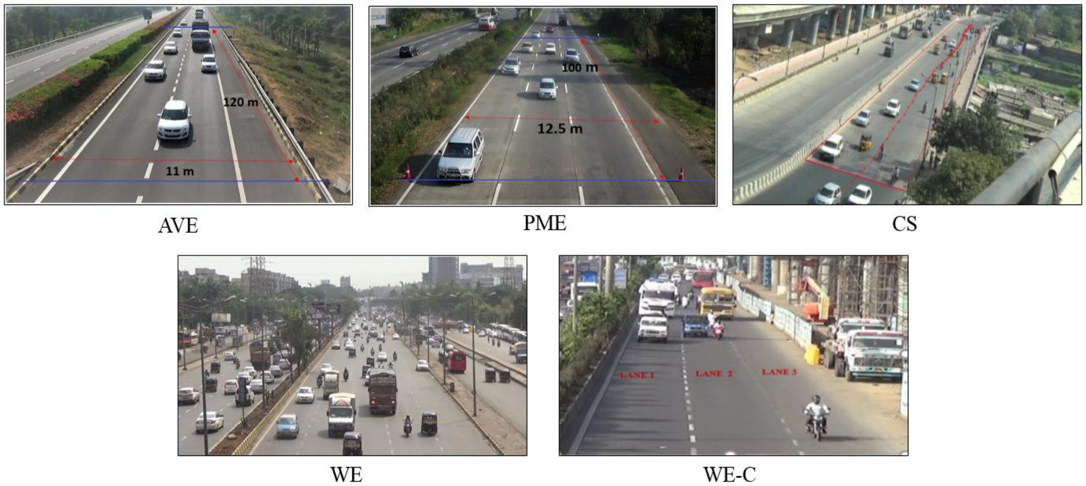


Figure 1 Snapshots of the five study sections

To explore Indian traffic behavior, like NGSIM datasets, high-quality trajectory data was essential. In mixed traffic, the numerous vehicle categories and ensuing lane discipline can result in complex interactions among vehicles. As a result, automation of trajectory data development has not been successful. Even the well-established image processing tools did not perform well in developing trajectory data. A semi-automated image processing tool called traffic data extractor (Vicraman, Ronald, Mathew, & Rao, 2014), was used to overcome this challenge. In this process, using computer mouse clicks, a given vehicle was tracked over the road section with an update interval. Also, smoothening techniques are applied to limit the noise in trajectory data (Raju, Kumar, Reddy, Arkatkar, & Joshi, 2017). Details of the trajectory data for the five study sections are shown in Table 1.

In the case of semi-automated trajectory data extraction from AVE, PME, WE, and WE-C, initially, the study sections are georeferenced. Later with a predefined time update (say 0.1s, 0.3s, 0.5s, 1s), a given vehicle will be tracked over the study section with a unique Id along with its vehicle category. In the AVE and PME, all the vehicles are tracked without much occlusion problems, given the lesser variation in the traffic flow conditions. Simultaneously, inflow 1 and 2 from WE and WE-C, the images' occlusion effect was also minimal due to a vantage position of the installed camera. As a result, all the vehicles in those flow conditions are tracked. Whereas in the case of congested phase, flow 3 from WE, and WE-C some vehicles are found to be hidden behind the other heavy vehicles. Particularly, this is observed, when the trucks are present in the traffic stream; by virtue of its larger dimensions, there may be an occlusion effect. Mainly the occlusion phenomenon is observed with MTW following a truck. However, given the lower composition of trucks (less than 3 percent), the occlusion effect is marginal in affecting the trajectory data's overall accuracy even from the WE and WE-C study locations.

TABLE 1 Details of the trajectory data for Indian traffic conditions

Study Section	Type of Road [a]	Trap Length (m)	Road Width (m)	Traffic Flow Classification (V/C Ratio)	Traffic Composition (%)[c]	No. of Vehicles Tracked	Duration of Trajectory Data (minutes)
AVE	1	120	11	(0.35)	0, 0, 3, 92, 5, 0	359	20
PME	1	100	12.5	(0.67)	0, 0, 8, 82, 10, 0	804	20
CS	2	250	11.2	Flow 1 (0.71)	23, 26, 3, 46, 2, 0	1514	15
				Flow 2 (0.63)	20, 29, 4, 40, 5, 2	1491	15
WE	3	120	17.5	Flow 1 (0.35)	15, 35, 5, 40, 2, 3	1080	15
				Flow 2 (0.71)	20, 29, 2, 45, 1, 3	1715	15
				Flow 3[b]	17, 25, 5, 45, 3, 4	660	10
WE-C	3	100	10.5	Flow 1 (0.42)	15, 27, 8, 42, 5, 3	870	15
				Flow 2 (0.68)	13, 30, 6, 45, 3, 3	1218	15
				Flow 3 (0.91)	10, 35, 5, 45, 2, 3	1312	15

[a] 1= Intercity Expressways, 2 = Urban Arterial, and 3 = Multilane Urban uninterupted faciltiy. [b] Congested conditions;
[c] Traffic composition: MThW, MTW, buses, cars, trucks, LCV.

NGSIM Trajectory dataset

The trajectory data of I-80 and US-101 intercity expressways from the NGSIM project were used in this study. Note that the trajectory data were available for three traffic flow conditions for both sections, and they were referred to herein as Flow 1, Flow 2, and Flow 3 in increasing order of the flow level. On both sections, a high proportion of cars was observed with lane-disciplined movements of vehicles.

METHODOLOGY

Using NGSIM and Indian-traffic trajectory datasets and considering existing research gaps, the present study is carried in two steps. First, the vehicle-following behavior is investigated, and the hysteresis phenomenon among vehicles are identified. Second, based on the hysteresis analysis, a safety framework for identifying potential rear-end collisions is developed and involved three tasks:

1. Identifying the need for modeling follower attention
2. Formulating a new safety measure to understand the attention of the follower better
3. Integrating the new safety measure with distance gap and follower speed

Investigating Vehicle-Following Behavior

To understand vehicle-following behavior, distance gap versus relative speed (follower minus leader speeds) between successive vehicles are plotted for a sample basis from the study sections. From the analysis, the hysteresis phenomenon between vehicles, which represents vehicle-following behavior, was observed. For better understanding, plots of six pairs (as examples) from the NGSIM I-80 section are presented in Figure 2. In general, when a vehicle follows its leader vehicle, it tries to match the leader vehicle speed and maintains a constant distance gap from the leader vehicle. Further due to human activity and lag will lead to fluctuations in distance gaps and relative speeds. To demonstrate this nature, arrows are presented in hysteresis diagrams. In the case of Pairs 1 and 2, the vehicles are showing following good interaction and preferred to maintain a constant distance gap between them. Whereas in Pair 3 and 5, there is a closing process, and giving up behavior can be observed between vehicles, where the distance gap between vehicles varied over 50 m and 25 m, respectively. In Pair 4, the follower initially shows some aggressiveness, which results in decreasing the distance gap. As the follower is closing up, the heeding nature of the follower is depicted and resulted in a decrease in the magnitude of the relative speed.

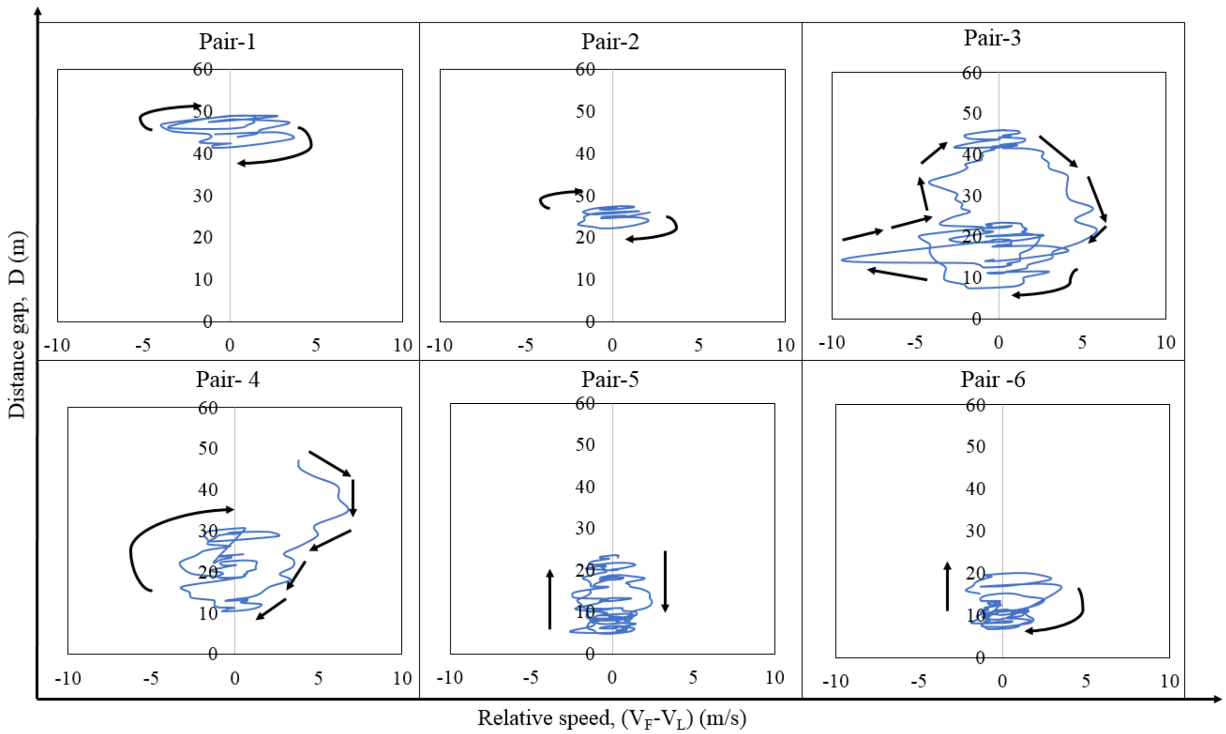


Figure 2 Hysteresis phenomenon between leader-follower pairs

Further, to better understand this hysteresis phenomenon, a python code is scripted. In this code, the lateral overlaps with the subsequent vehicles over the road space are computed. If a vehicle pair is found to have a lateral overlap, the pair will be considered as a leader-follower pair. Then, the distance gaps and relative speeds are computed for the leader-follower pairs and are aggregated for the available traffic flow levels over all study sections, as shown in Figure 3.

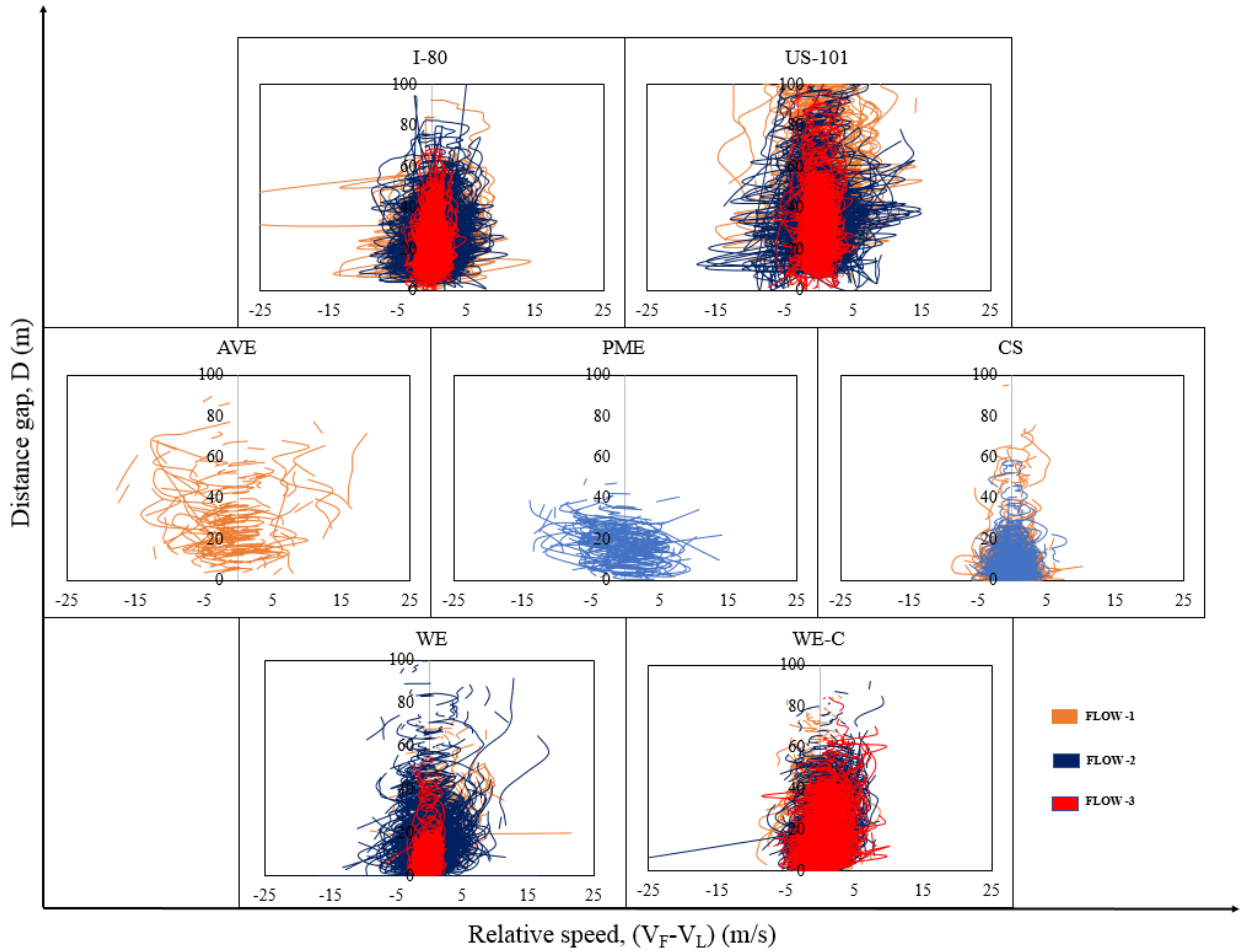


Figure 3 Aggregated hysteresis over the study sections

From the aggregated hysteresis plots, it is observed that in the case of free-flow conditions (mainly Flow 1), a partial hysteresis phenomenon is observed with a wide range of distance gaps and relative speeds. This indicates fewer following interactions among vehicles in free-flow conditions. On the other hand, in Flow 2 over the study sections, a substantial hysteresis phenomenon between vehicles is observed. In Flow 3, which reflects congested (stop-and-go) conditions, the variation in the relative speed in the hysteresis plots is reduced, along with a decrease in the distance gap. Further, the variation of the hysteresis phenomenon exemplifies the variation in driving behavior concerning the change in the traffic-flow level for a given study section.

In Indian-traffic conditions, on intercity expressways (the AVE and PME sections), the variation in the plots is observed in terms of distance gap and relative speed as a traffic flow function. This was higher for the PME section compared with the AVE section. On the other hand, in the WE section, the hysteresis plots become constricted about the y-axis, as traffic flow varies from free-flow to congested-flow conditions. Interestingly, in the WE-C section, since traffic flow is mostly near capacity due to the bottleneck effect, the hysteresis phenomenon has not been visualized much for Flows 1 and 2, as shown in Figure 3 (WE-C). Similar observations are also made in the case of the bridge section.

Developing Safety Framework

New Safety Measure: IHT

Based on the hysteresis analysis over the study sections, a new safety measure was developed. It is visualized that, when a subject follower is closing toward its leader due to its comparative relative speed, at some point time over the space, the follower realizes that he/she is moving closer to the leader and can have a rear-end collision the same speed is maintained. To avoid this, the follower starts matching the leader speed. The time gap available for the follower to mimic its leader to avoid a rear-end collision is termed as instantaneous heeding time (IHT). The definition of *IHT* is depicted in Figure 4a. In this context, to compute the *IHT*, hysteresis plots were examined in detail. It was observed that at the time of heeding, point *a*, the follower just tends to start decreasing its speed, where (V_F – V_L) decreases, to match the leader speed. In this phase, the difference in speed between the vehicles is maximum (positive side). Considering this difference, the *IHT* available for a driver is computed as the slope of the tangent to Point *a*, as shown in Figure 4a. if follower has not paid attention will result in drop of distance gap and end up a rear end collision as depicted with a red line in Figure 4a

Let V_F be the speed of follower at which the follower has perceived its leader that is moving at V_L at a distance gap of *D*. It is noted that, at the time of paying attention, the follower immediately starts dropping its speed, and at that time the follower will have zero acceleration rate. Further in the case of hysteresis at heeding, the relative speed (V_F - V_L) will be positive and is likely to experience a local-maxima as observed in real-field conditions. The time gap, t_g, between the vehicles will be positive. In general, IHT is a time gap between the leader-follower pairs defined, along with specific conditions, as follows,

$$\mathrm{IHT(s)} = \frac{D}{0.278 * (V_F - V_L)};\ \text{when} \begin{cases} Follower\ drops\ its\ speed, V_F(t_n) > V_F(t_{n+1}); \\ \dfrac{\partial(V_F)}{\partial(\mathrm{t})} = 0; \\ V_F - V_L > 0; \\ \dfrac{\partial(t_g)}{\partial(t)} = 0\ (local\ maxima) \\ t_g > 0; \end{cases} \qquad (1)$$

where:

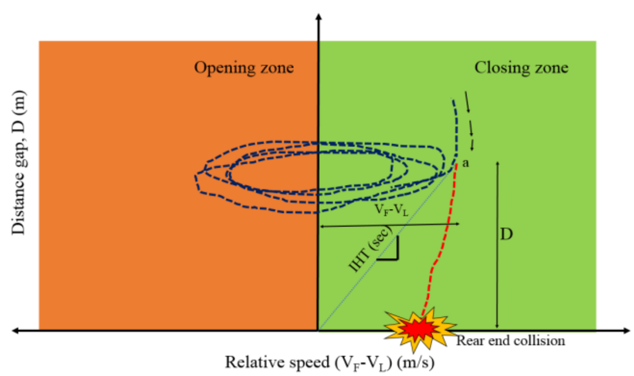
IHT	= instantaneous heeding time (s),
t_g	= time gap (s)
V_F	= speed of the follower (kph)
V_L	= speed of the leader (kph)
D	= distance gap (m)

$V_F(t_n)$ = speed of the follower at time t_n
$V_F(t_{n+1})$ = speed of the follower at time t_{n+1}

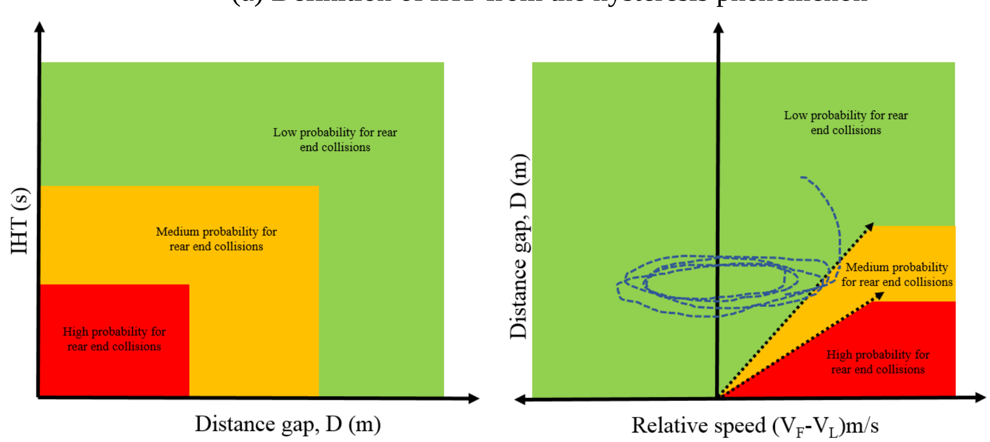
Considering this as a governing principle, an algorithm was developed in the present study and scripted in python based on Equation 1. The variable *IHT* between vehicles was determined using the hysteresis phenomenon derived from the trajectory data over all the study sections.

Need for Considering Follower Speed

From the *IHT* analysis, it can be inferred that the leader-follower pairs with larger *IHT* (more time gap) demonstrate that the follower is more attentive toward the leader instincts and vice-versa. Further, it can be observed that along with *IHT*, the distance gap between the leader-follower pair plays a vital role as an important parameter in assessing potential rear-end collisions. Similarly, the IHT considers the relation between the action points in following conditions and the safety distance in a collision condition (Brackstone & McDonald, 1999; Gipps, 1981). For example, consider Figure 4b which arbitrary boundaries for low, medium, and high probabilities of rear-end collisions. As noted, the probability of rear-end collision is more for pairs with small *IHT* and small distance gaps than that for pairs with the same *IHT* and larger distance gaps. Further, the speed at which the follower decides to decelerate (Point *a*) plays a key role in assessing potential rear-end collisions. For example, consider the following two scenarios:



(a) Definition of *IHT* from the hysteresis phenomenon



(b) Importance of distance gap and *IHT* for rear end collisions

Figure 4 Fundamental relation of *IHT* and distance gap for rear end collisions

Scenario 1: The leader and follower are maintaining speeds of , $V_L = 80$ kph and V_F =100 kph at the time of heeding, at a distance gap *D* = 20 m. Therefore,

$$IHT = \frac{D}{0.278(V_F - V_L)} = \frac{20}{0.278(100-80)} = 3.59\ s$$

Scenario 2: The leader and follower are maintaining speeds of $V_L = 20$ kph and $V_F = 40$ kph at the time of heeding, at a distance gap *D* = 20m. Then,

$$IHT = \frac{D}{0.278(V_F - V_L)} = \frac{20}{0.278(40-20)} = 3.59\ s$$

It is noted that in the preceding scenarios that both *IHT* and *D* are the same, indicating a similar probability for rear-end collisions, according to Fig. 4b. Clearly, there is a limitation to this concept if rear-end collisions are evaluated based only on these two parameters. That is, it is argued that the state at which the follower pays attention to the leader is a key variable in assessing probable rear-end collision. In the present case, the state of the vehicle is represented by the speed of the follower V_F. The conditional probability concepts are used next to formulate the probable rear-end collision using three safety measures *IHT*, *D*, and V_F. Simultaneously, when the leader vehicle moves at high speed, the follower vehicle may tend to maintain a higher distance gap to comprehend the leader vehicle decelerations. In a general context, under a safe scenario, the follower vehicle may decide on a large distance gap. On the other hand, in the case of an unsafe scenario, the follower may end up deciding this with a lesser distance gap.

Integrating Three Safety Measures

Suppose that the critical follower speed, *IHT*, and distance gap for rear-end collisions are given. Then, let P(V_F) be the probability that the follower speed is greater than the critical follower speed, P(*IHT*) be the probability that *IHT* is lesser than its critical *IHT*, and P(*D*) be the probability that the distance gap is less than the critical distance gap. Let P(V_F^c), P(IHT^c), and P(D^c) be the complementary probabilities of the respective events. Further, the probability of each event from the sample space is depicted in the tree diagram shown in Figure 5.

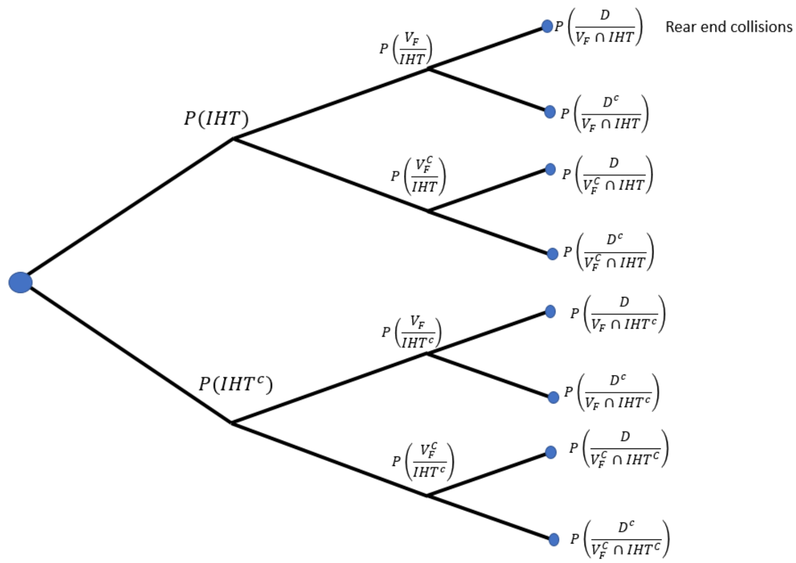


Figure 5 Tree diagram explaining the probability of events in the sample space

The probable rear-end collision between the leader-follower vehicle will be categorized when the IHT is less than the threshold limit, V_F greater than critical speed, and D less than the threshold distance gap. In a mathematical form, these three variables fall under the conditional probability proposition. In line with this, the probability of rear-end collisions is given as $P(V_F \cap IHT \cap D)$. Using the conditional probability concepts, then

$$\begin{aligned} P(V_F \cap IHT \cap D) &= P((V_F \cap IHT) \cap D) \\ &= P(V_F \cap IHT) * P\left(\frac{D}{V_F \cap IHT}\right) \\ &= P(IHT) * P\left(\frac{VF}{IHT}\right) * P\left(\frac{D}{V_F \cap IHT}\right) \end{aligned} \quad (2)$$

$$P(V_F \cap IHT \cap D) = P(IHT) * P\left(\frac{VF}{IHT}\right) * \ P\left(\frac{D}{V_F \cap IHT}\right) \quad (3)$$

Where,

$$P(IHT) = \begin{cases} 1 & \forall \ \ IHT \leq \ IHT_{critical} \\ 0 & \forall \ \ IHT > \ IHT_{critical} \end{cases} \quad (4)$$

$$P\left(\frac{VF}{IHT}\right) = \begin{cases} 1 & \forall \ \ IHT \leq \ IHT_{critical} \quad and \ \ VF \geq \ VF_{critical} \\ 0 & \forall \ \ IHT \leq \ IHT_{critical} \quad and \ \ VF < \ VF_{critical} \\ 0 & \forall \ \ IHT > \ IHT_{critical} \end{cases} \quad (5)$$

$$P\left(\frac{D}{V_F \cap IHT}\right) = \begin{cases} 1 & \forall \ IHT \leq IHT_{critical} \quad and \ VF \geq VF_{critical} \quad and \ D \leq D_{critical} \\ 0 & \forall \ IHT \leq IHT_{critical} \quad and \ VF \geq VF_{critical} \quad and \ D > D_{critical} \\ 0 & \forall \ IHT \leq IHT_{critical} \quad and \ VF < VF_{critical} \\ 0 & \forall \ IHT > IHT_{critical} \end{cases} \tag{6}$$

SAFETY ANALYSIS

Application of the probability concepts in assessing rear-end collisions between vehicles requires critical limits for the parameters. In the available literature, there are no clear findings related to critical limits of V_F, *IHT*, or critical *D* with respect to rear-end collisions. Therefore, according to Shi et al. (Shi, Wong, Li, & Chai, 2018) *TTC* of 2.5 s was regarded as a critical value, and therefore this limit was considered as the critical limit for *IHT*. In addition, based on driving behavior studies (Li, Liu, Wang, & Xu, 2014; Polders et al., 2015), a follower speed of 30 kph and a distance gap of 10 m were taken as the critical limits. Thus, in this study, for a given leader-follower interaction, $IHT \leq 2.5$ s, $D \leq 10$ m, and $V_F \geq 30$ kph will be considered for probabilistic rear-end collisions. Based on these critical limits, the developed framework was tested over the study sections of the NGSIM and Indian-traffic datasets, and the results are shown in Table 2.

From Table 2, it can be noted that the potentiality of rear-end collisions on NGSIM I-80 and US-101 road sections is less, and the traffic stream is found to be safe with negligible rear-end collision instincts. This can be explained as in homogeneous traffic, vehicles maintain enough distance gap and good *IHT* between them, even though they are moving at a higher speed. Similar results are also obtained for the AVE, PME (intercity expressways), and Chennai road (urban arterial) sections.

On the other hand, in the WE and WE-C sections, rear-end collision points are observed. For the WE section, 25 and 59 rear-end collision points are observed at Flows 1 and 2. Interestingly at Flow 3 conditions, no rear-end collision instincts are observed. To better visualize the probable collisions on the study section, the probable collisions are mapped over the study section (WE) for entire flows 1 and 2 individually. Based on the collision points' density, the severity clusters are depicted in terms of contours, as shown in Figure 6. Further, the visualization analysis helps in identifying the risk zones over the study sections, with a reasonable duration of trajectory data. This can be considered as one of the possible pertinent applications for monitoring traffic operations towards enhancing the traffic safety on roadway classes having higher speeds. This is even more important in most of the developing economies due to the presence of different vehicle categories (having varying static and dynamic characteristics) sharing the same space on a given roadway condition.

Whereas in the WE-C section 31, 27, and 15, collision instincts are observed at Flows 1 to 3, respectively. Further, to understand the degradation of safety on the WE and WE-C sections, an investigation was carried out. In both study sections, a predominant portion of MTW was observed. Besides, most of the time, MTW maintained a minimum distance gap from the leaders in the traffic stream. However, due to their size and maneuverability, MTW tended to accept smaller gaps in the traffic stream, and as a result, they were exposed to lesser *IHT* from their followers.

TABLE 2 safety analysis of the study sections based on the demarcated thresholds

Study Section	Flow Level	Rear-End Collision Points	No. of Leader-Follower Interactions
(a) Safety analysis: NGSIM homogeneous lane-based conditions			
I-80	Flow 1	0	954
	Flow 2	0	1857
	Flow 3	0	2674
US-101	Flow 1	2	1154
	Flow 2	0	1958
	Flow 3	4	2876
(b) Safety analysis: Indian traffic conditions			
AVE	-[a]	0	529
PME	-	2	897
CS	Flow 1	2	1254
	Flow 2	0	1159
WE	Flow 1	25	1205
	Flow 2	59	1689
	Flow 3	0	984
WE-C	Flow 1	31	950
	Flow 2	27	1243
	Flow 3	15	1469

[a] No traffic flow data are available for this section.

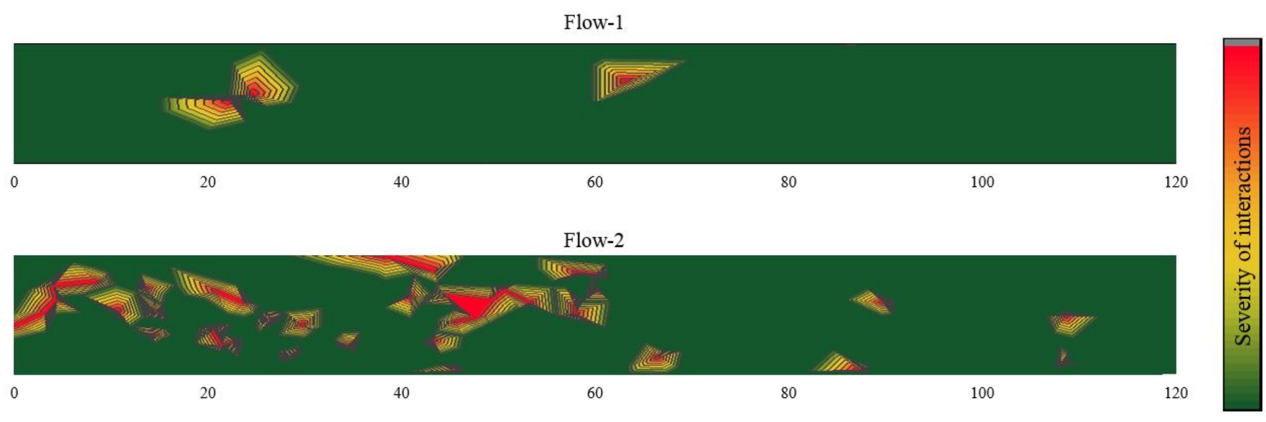


Figure 6 Number of rear-end collision points over the road space on the WE section at Flows 1 and 2. Note: Flow 3 has no rear-end collisions.

From the analysis, it is observed that WE and WE-C tend to have a greater number of probable rear-end collisions than other study sections. This can be attributed to numerous factors, such as road geometry, ongoing construction activity, the proportion of MTWs, etc. Interestingly, from the congested traffic conditions, no probable rear end collisions are observed. In the case of congested conditions in the WE section, both longitudinal and lateral movements of the vehicles were constrained, and as a result, MTW and other vehicles tended to follow their leaders and reduced their speeds. For this reason, Flow 3 of the WE section was found to be safer with no probable rear-end collision. On the WE-C is of bottleneck section. Due to this, the traffic never flows beyond its capacity, resulting in no congested traffic conditions in WE-C. As a result, even in flow 3, around 15 probable collision points are observed.

To understand the vehicles' lateral movement in WE and WE-C, lateral amplitude (Raju, Arkatkar, Easa, & Joshi, 2021) analysis is performed over the vehicle categories and the descriptive statistics as reported in table 3. Lateral amplitude is the measure of lateral weaving of the vehicle over the study sections. From the analysis, it is observed that smaller vehicles, MTW tend to display higher lateral movement when compared to other vehicle categories. Further, in the case of WE, the vehicles' lateral movement increases with the increase in flow conditions. At near stop and go conditions, a downward trend is observed. On the other hand, in the case of WE-C, the lateral amplitude is found to be increased over the flow conditions.

Table 3 Lateral amplitude (m) of vehicles over WE and WE-C study sections

Vehicle category	Parameter	WE			WE-C		
		Flow 1	Flow 2	Flow 3	Flow 1	Flow 2	Flow 3
MTW	Mean (m)	0.9	2.1	1.4	1.1	2.0	2.1
	Std (m)	0.7	1.5	0.9	0.8	1.5	1.3
MThW, CAR	Mean (m)	0.8	1.4	1.1	1.0	1.4	1.5
	Std (m)	0.8	1.2	1.1	0.9	1.0	1.3
BUS, TRUCK, LCV	Mean (m)	0.5	1.4	1.7	0.8	1.3	1.8
	Std (m)	0.2	0.7	1.1	0.5	0.4	1.3

SUMMARY AND CONCLUSIONS

Driving behavior is one of the most sensitive parameters that can be affected by numerous factors and can decisively influence the road network's performance. However, analytical tools for assessing driving behavior in the traffic stream are limited. Given this gap, this study has presented a framework for monitoring safety in the traffic stream, including a new safety measure, and demonstrated the importance of trajectory data in providing a better understanding of driver behavior. Based on this study, the following comments are offered:

- From the individual leader-follower pairs in NGSIM data, a comprehensive hysteresis phenomenon is observed between the leader-follower pairs (Figure 2). This can be mainly attributed to the trap lengths of the NGSIM trajectory data. On the other hand, in the case of Indian trajectory data sets, given the limited trap lengths, the hysteresis phenomenon is witnessed in the aggregated hysteresis plots (Figure 3) for those study sections. Interestingly, with the change in traffic flow conditions, the hysteresis nature between the vehicles is varied. This phenomenon was strongly supported by NGSIM homogeneous-traffic (U.S.) and Indian-traffic trajectory datasets. The phenomenon has inspired the development of the new *IHT* measure in assessing the attentiveness of the subject vehicle towards its leader.

- In the AVE and PME sections, the MTW traffic composition was almost nil and provided an opportunity for testing safety concerning traffic flow levels. It was observed that both sections have very few rear-end collision points. The deterioration in traffic safety in the WE section may not be directly proportional to traffic flow levels. In the case of free-flow conditions (Flow 1) and near-capacity conditions (Flow 2), many data points were observed in the severe and moderate regimes. On the other hand, at congested conditions (Flow 3), the occurrence of rear-end collisions was almost null. The main reason is that in congested conditions, vehicles closely follow one after another, which results in less relative speed between vehicles and greater *IHT* values (greater attention).
- Based on the developed framework, safety in an uninterrupted road section can be monitored on a real-time basis using trajectory data, where safety can be quantified over the road network. With the better availability of new technologies and usage of advanced image processing techniques, the vehicle movement in the traffic network can be monitored, and the trajectory data should be possible to be developed on a real-time mode of traffic operations. Further, keeping this in view, the safety framework adopted in the study can also be embedded in the traffic surveillance systems. Given this, on a real-time basis, the safety over the network could be analyzed more comprehensively. This could be even hold good and prove more promising in monitoring drivers' profile and behavior for formulating better enforcement strategies and policies. Even necessary protective measures can be taken well in advance before the occurrence of any catastrophic event. Further, the study revealed the nature of MTW in degrading safety in the traffic stream, which can be attributed to their high degree of lateral maneuverability as they can switch lateral positions abnormally to escape delay. The vehicles themselves had smaller *IHT* values and lesser distance gaps. For the WE section, at congested conditions, the lateral freedom is arrested, and as a result, safety has improved.
- The methodology can be applied to real-time surveillance, where traffic stream behavior can be monitored and drivers who show aggressive instincts can be easily identified and penalized. For future autonomous and connected vehicles, the developed methodology can be well applied in modeling collision avoidance systems that can be helpful in coding behavioral actions of those vehicles well within the safety limits.
- The critical limits adopted in this study were assumed based on the literature. This assumption may be considered as a limitation of the present work. Future studies to determine appropriate thresholds based on roadway and vehicle characteristics are needed.

LIMITATIONS AND FUTURE SCOPE OF THE WORK

Along with the research findings, the present study has certain limitations, which should be considered in the work's future scope.

- The safety framework presented in the study is only tested with the available trajectory data sets. The present study assumes the thresholds of specific parameters and thereby selected SSMs in analyzing safety at selected roadway sections. However, it is implausible to demarcate the thresholds with the used trajectory datasets. In this direction, for achieving the IHT, VF, and D thresholds, the safety framework must be tested with the historical crash trajectory data. This analysis would help calibrate the threshold limits for the parameters of the safety framework.

- Further, the collision instincts reported in the study is just an ancillary representation of collisions (as a surrogate measure in absence of more reliable historical crash data). It is reported that, in some instants, the surrogate safety methodologies may overpredict the collision occurrence; this can act as a limitation in the present safety framework as well.

- In the present study for the safety analysis, the study assumed a uniform set of thresholds to identify the probable rear end collisions. However, concerning the change in study sections and the flow conditions, the threshold parameters will be varied. Due to this, the probable collisions reported in some of the study sections may vary.

- Along with this, in the present study, explaining the follower vehicle attentions and quantify them, IHT vs. D, are demarcated in a linear form. However, there is no such clear findings or supporting analysis to advocate its linear form. Simultaneously the demarking can be curvy with possible positive and negative slopes. Still, in this direction, few more studies are to be carried in understanding the nature of demarcation.

- Further, the present framework can be explored with a driving simulator experiment. This would help in understanding the subject follower vehicles' attentions towards the leaders. Given this, the safety framework application can be refined further.

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