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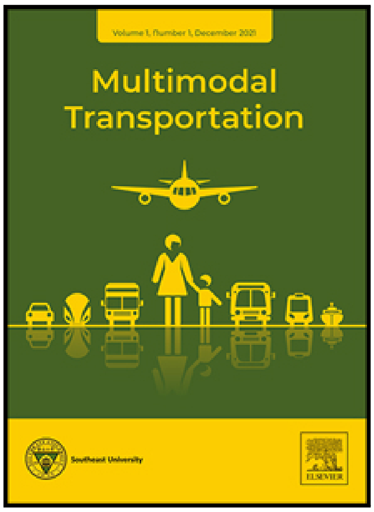

Evaluating Defensive Driving Behaviour Based on Safe Distance Between Vehicles: A Case Study Using Computer Vision on UAV Videos at Urban Roundabout

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Highlights

- A case study of lane indiscipline and heterogeneous traffic of densely populated and developing countries.
- Methodology to assess defensive driving behaviour using UAV videos and computer vision.
- Weighted Safe Distance *WSD* and Weighted Reward for Acceleration *WRA*- Novel surrogate safety measures based on stopping distance, blind spots, and driver's reaction.
- Star rating scheme for evaluating defensive driving behaviour.
- Study collision risk regarding road infrastructure.

Evaluating Defensive Driving Behaviour Based on Safe Distance Between Vehicles: A Case Study Using Computer Vision on UAV Videos at Urban Roundabout

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Abstract

While driving, maintaining a sufficient distance helps reduce collision risk. A time gap of two or three seconds on urban roads from a vehicle ahead is advised in defensive driving. The scenario becomes even more challenging in densely populated and developing countries because of limited road infrastructure, lane indiscipline, and heterogeneous traffic. The safe distance between vehicles and the driver's reaction can be used as surrogate safety measures (SSMs) to evaluate defensive driving behaviour. This paper presents a case study evaluating defensive driving behaviour using the vision-based methodology and UAV video. This paper proposes two novel SSMs based on distance and acceleration and studies defensive driving behaviour, such as "for how long did a vehicle keep driving under another vehicle's blind spots?" and "how is a vehicle driving (an interaction pattern) when another vehicle ahead is in its stopping distance range?." Finally, each driver's star rating depends on their interactions with other vehicles. We observed that around 48% of the vehicles did not follow defensive driving practices. In our vehicle inter-class interaction anal-

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yses, we also found 16.6% Rear-End, 6.3% Side-Swipe, and 1.5% Angled collision risks occurred between car-car, car-car, and 2Wheeler(2W)-car, respectively. Our methodology could help traffic law enforcement agencies and policy-makers elevate road traffic safety by taking counter-measures against the low-star vehicle categories in developing countries. Example videos of star rating are available on XXXXXXX.

Keywords: Blind Spot, Surrogate Safety Measures (SSMs), Collision Risk Assessment, Conflict-based analysis, Defensive Driving Behaviour, Star rating, Unmanned Aerial Vehicles (UAVs)

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1. Introduction

Not maintaining a safe distance could result in various types of collisions. As per MoRTH, 2022 [1], India, the various types of collisions are: Rear-End (Hit from Back), Head-On, Side-Swipe (Hit from Side), Angled (Hit perpendicular/Hit and Run), and With-Parked-Vehicles (Hit with parked vehicles), which contributed to 21.4%, 16.9%, 15.4%, 14.6%, and 3.1% of the total road accidents in 2022, respectively. In densely populated (in terms of the number of road users on any road segment/junction) and developing countries (with limited growth of road infrastructure / limited road infrastructure [2]), such as India, the road traffic condition is complex because of various factors, such as lane indiscipline, faded road markings on urban roads, and heterogeneous traffic [2]. Thus, driving behaviour under such unfavourable/adverse conditions is a crucial driving primitive to study. Defensive driving describes the best practices of foreseeing collisions (mentioned above) despite harmful traffic conditions or the mistakes of others while driving [3], [4], [5], [6], [7]. “Driving behaviour” and “driving style” are generally used interchangeably. Still, the former defines the driver’s reactions to external traffic conditions, while the other refers to how a driver chooses to drive [8]. Therefore, defensive driving behaviour can be evaluated based on the collision's likelihood (or risk) and the driver's reaction [9]. This research evaluates defensive driving behaviour based on the "temporal and spatial proximity of road users to identify conflict and its severity" [9].

In specific scenarios, sudden vehicle breaking is unavoidable; maintaining a safe distance from the vehicle in front (travelling in any direction) while driving could avoid collision. The stopping distance for a vehicle depends on various factors, such as the speed of a vehicle, coefficient of road friction, breaking process, vehicle condition, and perception and reaction time of the driver to apply brake [10], [11]. As per the rule of thumb in defensive driving, a driver should keep at least a time gap of two seconds while driving [3]. Driving in other vehicle's blind spots could also lead to a Side-Swipe collision due to lack of visibility in the blind spot [4]. The blind spot of a vehicle mainly depends on the class of vehicle (design, size, and shape), mirror placement, and driver's height and seating position [12]. The Government of India (GoI) has also taken enforcement measures to avoid such collisions by making mandatory to have the fitment of side, front, and rear under-run protection devices for heavy vehicles and conspicuous reflective tapes to increase visibility at night for all public service vehicles [13]. As per Motor Vehicle Driving Regulations (MVDR), 2017 [14], India, sub-sections 4(8), 17 (1), 17(2), a driver should keep a sufficient distance from a vehicle ahead, and a driver should not apply the sudden brake without a compelling reason when being followed by another vehicle. Such driving behaviour is a punishable offence under the Motor Vehicle Act (MVA) [15] section 190 (2) for violating rules regarding road traffic safety.

Researchers in the intelligent transportation system domain widely use onboard electronic sensors and V2V and V2X technology to collect traffic data and understand driving behaviour [8], [16], [17], [18], [19]. Supporting this requires various resources, such as communication infrastructure, roadside units, and vehicle sensors, which limit its implementation in developing countries. Time-To-collision (TTC) and its variants are widely used time-based SSMs, which measure the time remaining to a conflict if the two vehicles maintain the current speed and direction of travel [9], [20], [21], [22]. These SSMs are generally used to assess the risk of Rear-End collision. However, these cannot be directly applied to angled collisions, which are more relevant in heterogeneous and lane indiscipline traffic conditions.

Recent advancements in UAV and computer vision-based methodologies show promising traffic monitoring and analysis results [2], [23], [24], [25]. Specifically, videos collected using UAV at a shooting angle perpendicular to the road scene (gimbal 90° downwards) inherit several advantages over the other shooting angles and angled traffic cameras or cameras mounted at high-rise buildings [20], [26]. Such UAV videos provide a non-occluded traffic view and the possibility to cover the complete road junction or more areas of the underlying road. Also, it allows computer vision algorithms better to track the vehicles across the complete road junction and extract microscopic and macroscopic traffic parameters [17], [27], [28], [29]. Further, with the help of computer vision techniques, it is possible to derive SSMs from UAV videos for various collisions based on time and distance proximity and deceleration/acceleration profiles [9].

UAV-based naturalistic datasets are publicly available for research work. The HighD dataset [30] is a popular naturalistic driving dataset with videos recorded at six locations on German highways. It includes 1,10,500 vehicle trajectories and functional traffic parameters, such as vehicle class and size, number of neighbouring vehicles, Time-Head-Way (THW) or TTC, vehicle speed, and driving manoeuvres. A similar dataset for a roundabout, known as rounD [31], is also available with vehicle trajectories and other information such as vehicle class, size, speed, and acceleration. Visdrone [32] is another widely used UAV-based dataset for computer vision algorithms training and testing. These are application-specific datasets, as the two former datasets (of German highways and roundabouts) can be directly used to understand driving behaviour (in developed countries). In contrast, the last one is used for training object detection models in computer vision. A UAV-based vehicle dataset with vehicle orientation data for deep learning model training is publicly unavailable.

This paper presents a case study to evaluate defensive driving behaviour based on the likelihood (risk) of collisions and the driver's reaction in lane indiscipline and heterogeneous traffic conditions, using computer vision techniques applied to a UAV video of a self-regulatory road junction in India. The main contributions of our work are as follows:

- A case study of lane indiscipline and heterogeneous traffic (of densely populated and developing countries) at urban self-regulatory road junctions.
- It provides a methodology to study and classify defensive driving behaviour using UAV videos and computer vision.
  - Proposed an automatic vehicle orientation detection method.
  - Defined a safe distance for a vehicle based on stopping distance, blind spot, and collision risk.
  - Proposed novel distance- and acceleration-based SSMs considering the vehicle size.
  - Evaluated defensive driving behaviour through conflict-based analysis using proposed SSMs.
- Studied vehicle interactions and inter-class collision risks using a combination of proposed SSMs.

- Derived an adaptive star rating scheme to evaluate defensive driving behaviour.
- Examined collision risks regarding road infrastructure.
- Provided suggestions for transportation and urban development policies based on inter-vehicle collision analyses and star rating.

2. RELATED WORK

We surveyed various vision-based research works on safe distance-based risk assessment and driving behaviour classification. We have organised the survey according to the research objectives, such as collision risk assessment, developing vision-based SSMs, and understanding and classifying driving behaviour.

Risk assessment based on vehicle manoeuvring helps to evaluate road traffic safety and quantify driving behaviour in terms of safety. In [17], the authors demonstrated the application of UAVs and V2X connectivity to track the movement of vehicles and assess the collision risk at intersections. They used the CenterTrack model to extract the trajectories of vehicles. Then, the authors calculated TTC to determine the collision risk based on vehicle manoeuvring. Data related to TTC was used to estimate the microscopic and macroscopic risk, which could be used to make decisions while driving in connected vehicle environments and help urban planners and transportation managers, respectively. In [20], the authors utilised UAV videos to analyse drivers' lane change-related risk using TTC at interchange merging areas. They used open video processing software Tracker to extract trajectories. In the end, they studied risk based on driving ability, merging speed, and the remaining distance to the end of the acceleration lane. In [29], authors used traffic videos captured by UAV and MATLAB framework to identify potential misbehaviours. Computer-Vision (CV) algorithms from the MATLAB framework extracted critical parameters such as vehicle speed, following distance, lane change, lane change time, and acceleration. Then, the risk associated with manoeuvring is calculated using a weighted risk model.

In [33], authors proposed an Anticipated Collision Time (ACT) (2D TTC) as a safety indicator to evaluate the risk associated with different collisions such as Head-On, Side-Swipe, Rear-End, and Angled collisions. They also derived three other time-based measures from ACT: TEA, TE-ACT, and TI-ACT. They analysed powered two-wheeler safety using ACT measures. They used the SAVETRAX image processing tool to extract vehicle trajectories. In further research [34], using ACT, they evaluated road traffic safety for highways using extreme value theory.

Authors in [23], [24], and [25] studied traffic conflicts at the toll plaza area. They evaluated collision risk in heterogeneous traffic of electronic and manual toll collection vehicles. They used UAV videos and extracted trajectories using OpenCV. They proposed extended TTC [23], independent of the orientation of the approaching vehicle, to calculate collision risk. Then, they analysed the impacts of the toll collection type, target lane and location on safety.

Further, the authors used a random parameters logistic model to quantify the impact of the different factors, such as following the vehicle's travel distance, following the vehicle's initial lane, diverging area, and traffic flow, on vehicle collision risk. Also, they compared the logistic regression model and five typical non-parametric models, including K-Nearest Neighbour (KNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Trees (DT), and Random Forests (RF), to examine the relationship between influencing factors and vehicle collision risk [24]. Further, they discussed the time-varying effects of influencing factors on vehicle collision risk [25].

Bivariate extreme value theory predicts crashes based on safety matrices such as

Time-To-Accident (TA), Post Encroachment Time (PET), minimum TTC (mTTC), and Maximum Deceleration Rate. They used UAV videos and the KLT algorithm to extract trajectories [21].

Research related to vehicle blind spots, associated risk, and analysis is not exploited well. In [35], the authors studied blind spot crashes between trucks and bicyclists. The authors explored the impact of various factors on truck drivers' glance behaviour toward blind spot mirrors when turning right. They found that priority regulation, speed limits, road infrastructure, truck design, driver age, and driver inattention are influencing factors.

Safety space around a vehicle is also considered a safety measure in [26]. Safety space is a buffer around a vehicle with the shape of an approximated half ellipse in front and a rectangular area on the sides. It is a 2D zone around a vehicle, which other vehicles should not invade while driving to avoid conflicts. It is a boundary determined by various factors such as size, velocity, TTC, reaction time, lateral distance from its surrounding vehicles, and the size of other surrounding vehicles. Authors [26] used UAV videos and computer-vision techniques such as SVM, HOG, and the Kalman filter to extract vehicle trajectories.

In addition to collision risk assessment, authors in [22] also considered severe implications of a conflict. They proposed a Conflict Severity Index (CSI) based on crash risk and expected severity. The PET and Δt are used as safety measures to evaluate the crash risk for crossing and rear-end conflicts, respectively—the anticipated loss of kinetic energy after the collision is used to quantify severe implications. Then, CSI is calculated using both crash risk and severity. In [36], the authors proposed a novel risk index related to lane change, which is based on GTTC and change of velocity after a crash occurrence, to evaluate collision and severity risk associated with lane change at expressway weaving segments. Authors in [37] used UAVs to identify conflict points for rear-end, lane change, and crossing situations around a roundabout. They extracted trajectories using the DCF-CSR algorithm and then used conflict data, such as location, direction, and PET, to analyse conflict severity. Analysis and classification of driving behaviours, such as following, aggressive, and manoeuvring-based, serve as a tool for understanding limitations in road infrastructure, installing safety measures, amending traffic rules and regulations, and conducting focused enforcement drives [2]. Driving behaviour analysis helps enhance the ADAS system and road traffic safety. In [27], authors studied Chinese driving behaviour through microscopic and macroscopic traffic parameters, such as traffic flow rate, traffic density, velocity, acceleration, offset from the lane, TTC, and THW during lane changing, extracted from UAV video.

In [38], authors used a safe distance to classify vehicle following behaviour (How is a vehicle following another vehicle ahead?) into three categories: car following, staggered, and following between two vehicles. It is based on the following vehicle's size and extent of overlap between leading and following vehicles. They used a vision-based approach to extract parameters of follower and leader vehicle pairs (class, size, speed, and distance between them) and a multinomial logistic regression model to classify the following behaviour.

Researchers use the term "aggressive" driving behaviour depending on the context. In [39], aggressive behaviour refers to lane changes, whereas in [19] and [40], it relates to road traffic safety. In [39], authors used UAV video and deep learning to determine aggressive lane-change behaviours at an urban signalised intersection. They used "Tracker" software to extract critical parameters such as acceleration, deceleration, lane change (Left/Right), following distance before and after changing lanes, and speed before and after changing lanes. They also used vehicle and driver information along with the above parameters as input to a deep learning network to identify lane-change behaviour, whether aggressive or not. Authors in [40] used a UAV-based dataset of a roundabout to classify driving behaviour in three categories, aggressive, normal, and conservative, in terms of road traffic safety, using a K-means clustering algorithm. Different thirteen volatility measures related to velocity, deceleration and acceleration are used for clustering.

Some researchers also focused on classifying driving behaviour based on the vehicle's manoeuvring style [28], [41], such as going straight and taking left/right turns. Both the approaches in [28] and [41] used UAV videos to extract trajectories. They used the Single Shot MultiBox detector and RetinaNet for vehicle detection, respectively, and the SORT algorithm was used for vehicle tracking. These approaches differ in the output; in the [28], authors identify driving behaviour, whereas, in the [41], they predict driving behaviour. They [28], [41] used the LSTM deep learning model for driving behaviour identification and prediction.

We now summarise the shortcomings of the existing SSMs and methodologies as below:

- SSMs do not consider vehicle class, an essential factor in evaluating defensive driving behaviour in heterogeneous traffic, as the blind spots of the vehicle are dependent on the class of the vehicle.
- They mainly use time-based SSMs, but few works [9], [21] use other distance- and acceleration-based SSMs, which are useful to study vehicle interactions and driver's reactions (evasive actions) [42], [43].
- Extracting vehicle trajectories (including the vehicle's orientation) requires human intervention to some extent [9].
- Vehicle's blind spots have not been considered in assessing collision risk, which

is important to study Side-Swipe collision in lane indiscipline and heterogeneous traffic.

- Defensive driving behaviour in lane indiscipline and heterogeneous traffic has yet to be studied.

Hence, this paper proposes two novel SSMs, Weighted Safe Distance (*WSD*) and Weighted Reward for Acceleration (*WRA*). *WSD* is a distance-based SSM independent of the heading angle of the approaching vehicle. It considers blind spots, stopping distance, and vehicle class. In contrast, *WRA* is an acceleration-based SSM that captures the driver's reaction (evasive actions [9]). Using these SSMs, we propose an adaptive star rating scheme to evaluate defensive driving behaviour, which will help elevate road traffic safety.

3. METHODOLOGY

This section discusses each module of our vision-based methodology to evaluate defensive driving behaviour based on the likelihood of collisions (*WSD*) and the driver's reaction (*WRA*). It starts with data collection using UAV, followed by vehicle detection and tracking. Next is vehicle orientation measurement. Further, it defines three equal-sized zones of blind spots and the stopping distance range of the vehicles. In the end, risk assessment and behaviour classification methods are discussed. Detailed flowchart of the proposed methodology is given in Appendix A.

3.1. Data collection

We chose a self-regulatory urban intersection as a road site for traffic analysis because most road accidents occurred at self-regulatory (uncontrolled) road junctions. We use the DJI Mavic 2 Pro drone to collect traffic videos at a resolution of 3840 x 2160 pixels, at a flight height of 80 to 85 meters, in Ahmedabad city (one of the million-plus cities (population-wise) of India having the highest road accidents [1]), Gujarat, India. The road surface was dry, and the weather was clear.

3.2. Vehicle detection and tracking

Vehicle detection and tracking are preliminary tasks in vision-based traffic analysis. YOLO family models are mostly used as vehicle detection models for UAV-based traffic videos [2], [9]. The latest YOLO models support oriented vehicle detection, but the dataset (for model training) is not publicly available. Hence, we have used YOLOv8 [44], a state-of-the-art model developed by the Ultralytics Company in 2023. YOLOv8 uses CSPDarknet53 as the backbone to harness features efficiently and FPN to extract features on a multi-scale. PANet is used to fuse features from various scales. Also, it uses an anchor-free architecture. These features allow YOLOv8 to detect objects efficiently, irrespective of their sizes. We use the Visdrone 2019 [32] dataset to train YOLOv8. This dataset contains images of two-wheelers, buses, cars, three-wheelers, and vans. Its class-wise distribution is given in [2]. We chose the YOLOv8x model and set the image size to 1280 x 1280 for model training. Visdrone is a skewed dataset; hence, we enable mosaic data augmentation and other transformations, such as scaling and translation. Data augmentation helps to balance skewed datasets and prevents overfitting. YOLO model is trained on NVIDIA Quadro RTX 6000/8000 GPU and achieves 60% mAP@0.5. The YOLO detection model provides a rectangular bounding box (BB) containing a minimum rectangle around an object.

YOLO [44] implementation supports two tracking models, BoT-SORT and ByteTrack, by default. We use the BoT-SORT model to extract vehicle trajectories in traffic video. It uses existing SORT algorithm modules, the Kalman model and the Hungarian algorithm. BoT-SORT also uses low confidence scored detections rather

Figure 1: An example of vehicle detection and tracking. Refer to the track shown by the blue line.

than discarding them, which improves tracking accuracy. Association between detections and predictions is done in two steps: First, high confidence-scored detections are matched with tracklets based on appearance and IoU. Then, low confidence-scored detections are matched with unmatched tracks based on IoU. Various modules of the BoT-SORT tracker are discussed below:

- The Kalman filter models the vehicle's motion in the image plane. It predicts a vehicle's bounding box in the future frame.
- A global motion compensation technique estimates the dynamic motion of the camera. It helps to remove discrepancies related to the dynamic motion of the camera in Kalman's predicted bounding boxes.
- SBS-S50 backbone to extract appearance features.

- Hungarian algorithm for the association between detections and Kalman's prediction based on cosine similarity of appearance features and IoU-based distance.

Figure. 1 gives an example of vehicle tracking.

3.3. Vehicle orientation measurement

To evaluate defensive driving behaviour based on *WSD*, the vehicle's orientation (the heading angle and direction of travel) is required. We propose a novel approach to automatically detect the vehicle's orientation using the appearance features of the vehicle (refer to Figure. 2).

The result of YOLO detection (a rectangle BB) on the image (shown in Figure. 2a) is shown in Figure. 2b. It indicates that the YOLOv8x model cannot capture the vehicle's orientation. Hence, we use the SIFT [45] feature extractor to locate the key points in the vehicle's appearance in the image; refer to Figure. 2c. These key points show the location of extreme intensity change in the image. Therefore, they excluded the background and identified the vehicle's actual location in the image. Then, we recognise the vehicle's heading angle using those key points; refer to Figure. 2d.

We use a simple approach to detect the vehicle's direction of travel based on its trajectory. We calculate the difference between centroids (Δx and Δy) (of the same vehicle) in two consecutive frames, and based on its change in 2D space (image plane), the direction of travel is decided. As shown in Figure. 3, we consider four travel directions (NS, SN, WE and EW). For example, if the vehicle moves from West to East (denoted as WE), the Δx will be positive and equal to or greater than Δy. For other valid options, the relation between Δx and Δy and the direction of travel are shown in Figure. 3. As an example, these values are shown only for the WE direction. Similarly, these values must be assumed for the rest of the directions.

a Cropped image.
b YOLO detection result.
c SIFT keypoints.
d Oriented BB.

Figure 2: Vehicle orientation detection.

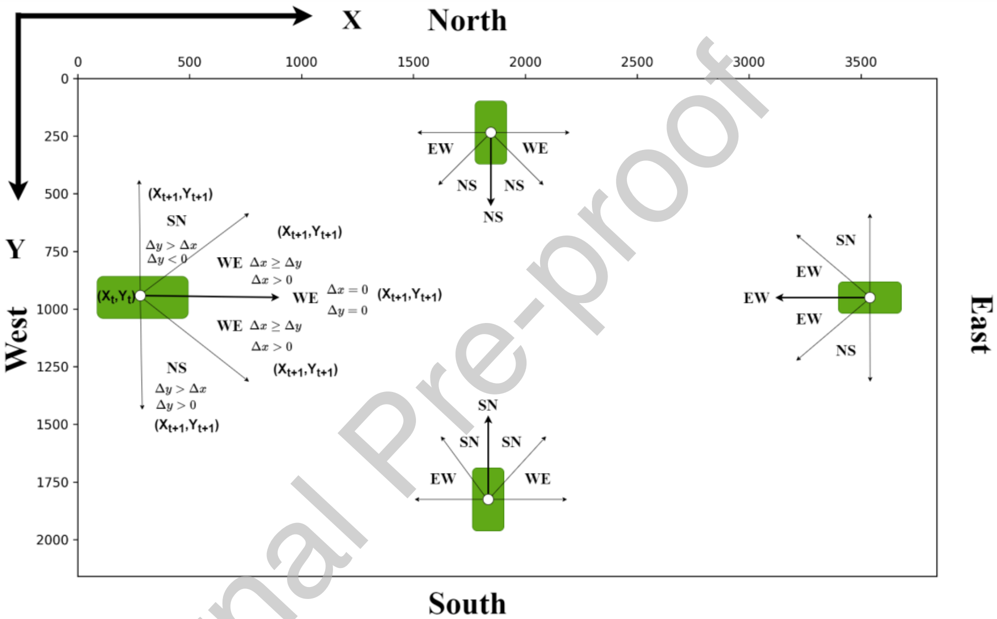


Figure 3: Vehicle's directionality on the image plane.

We calculate the vehicle's heading angle and direction of travel between its two consecutive frames. Hence, the values are prone to measurement noise. The heading angle of the vehicle is calculated using the vehicle's appearance. However, a vehicle's appearance might change during the journey for several reasons, such as driving under the shadow of a tree, which eventually affects the accuracy of the calculated heading angle. We use a 1D Kalman filter to smooth the heading angle values by reducing measurement noise. We use categorical values to denote the vehicle's direction of travel. So, to smooth the directions, we use a Boyer-Moore voting algorithm.

3.4. Definition and risk-based zoning of safe distance

We use blind spots and stopping distance range to define safe distance around a vehicle. We consider the heading angle and class of the vehicle to determine the blind spots and stopping distance range.

Different blind spots are possible in a vehicle, such as A-pillar, front-end, rear-end and side blind spots. These also depend on the vehicle class (design, size, and shape), mirror placement, and driver's height and seating position. This paper focuses on side and A-pillar blind spots. In contrast, front- and rear-end blind spots are indirectly captured using stopping distance range. There is no rule of thumb to determine side blind spots [12], so we chose a 30° side blind spot zone angle for all vehicle classes (as suggested in [12]), with width and length equal to 1 meter and vehicle length, respectively. Also, we chose to place a side blind spot to incorporate A-pillar blind spots. Refer to Figure. 4 for the vehicle's blind spots.

A vehicle's stopping distance depends on the driver's perception and reaction time to apply the brakes, vehicle dynamics, and road conditions. We use Eq. 1 to formulate stopping distance (*SD*) based on the perception and reaction time of the

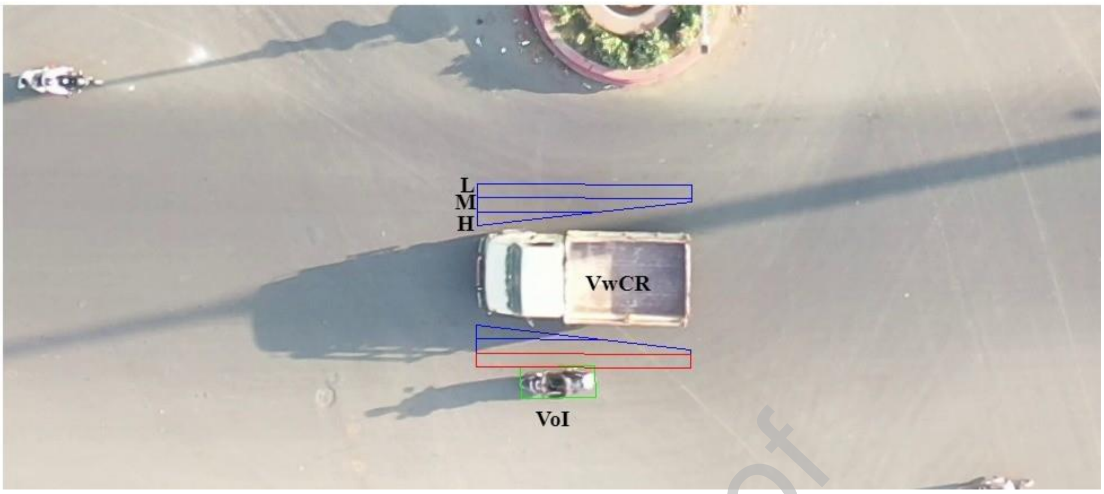


Figure 4: Truck's side blind spots.

driver to apply the brakes and the vehicle's braking distance [46]. We assume the driver is alert and ardent, the vehicle's tyres and brakes are in good condition, and the road surface is dry. We define a stopping distance range (a box) of length as equal to the stopping distance and width as equal to the vehicle size (vehicle class). Refer to Figure. 5 for the stopping distance range of a vehicle.

$$SD = \frac{V_A \times T_R}{3.6} + \frac{K \times V_A^2}{250 \times f} \qquad (1)$$

Where V_A is the velocity of the vehicle (in kmph), T_R is the perception and reaction time of the driver to apply the brake (in seconds), and f is the friction coefficient between the tyres of the vehicle and the surface of the road. K is the factor that is related to vehicle class. We set T_R to 1 second (for alert and ardent drivers) and f to 0.8 (for dry road and good tyres) [10], [11]. In defensive driving practices [3], it is very common to define the same minimum safe distance for all types of vehicles on urban roads, therefore we set $K = 1$.

This paper employs a "zone-based approach" to divide the safe distance into

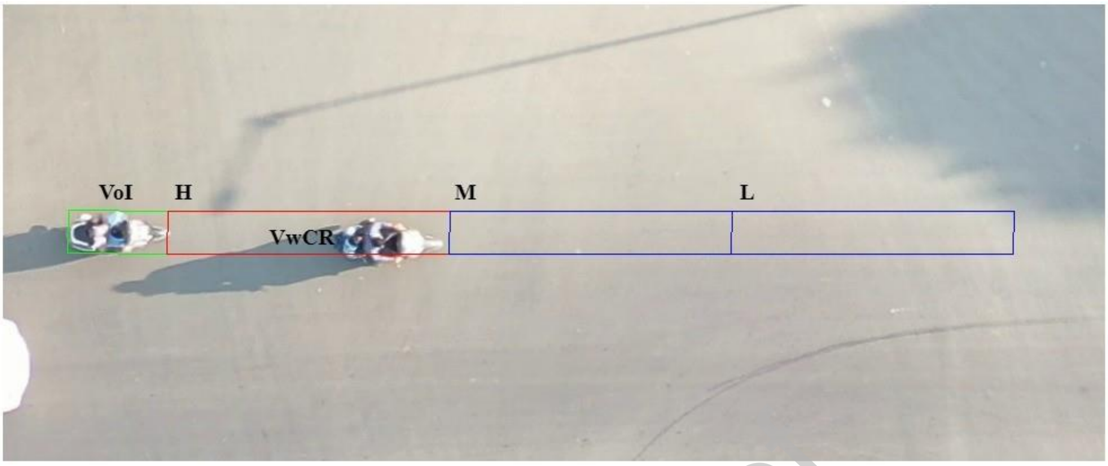


Figure 5: 2W's stopping distance range.

three equal-sized zones and assign weights according to their collision risk. We have defined HIGH (H), MEDIUM (M), and LOW (L) risk zones, and their weights are 1, 2, and 3, respectively. We consider one particular vehicle as the Vehicle of Interest (VoI) whose collision risk we want to calculate and each surrounding vehicle as the Vehicle within Collision Range (VwCR); (refer to Figure. 4 and Figure. 5). If VoI is driving under any of the blind spots of VwCR, the associated risk is assigned to VoI, whereas if VoI is driving such that VwCR is falling under the stopping distance range of VoI, the associated risk is assigned to VoI.

The vehicle's velocity is required to calculate the stopping distance using Eq. 1. We use the centroid difference of a vehicle in two consecutive frames and Ground Sample Distance (*GSD*) to calculate the instantaneous velocity (between two successive frames) of a vehicle according to Eqs. 3-5 [2]. Using Eq. 2 based on UAV camera parameters, *GSD* is derived to establish the pixel-to-actual distance relationship. *GSD* will also be used to map a safe distance from the actual distance (in meters) to the distance in pixels.

$$GSD = \frac{Sensorwidth \times Flightheight}{Focallength \times Imagewidth} \tag{2}$$

$$V_x = \frac{(x_2 - x_1) \times GSD}{t_2 - t_1} \tag{3}$$

$$V_y = \frac{(y_2 - y_1) \times GSD}{t_2 - t_1} \tag{4}$$

$$V = \sqrt{V_x^2 + V_y^2} \tag{5}$$

3.5. Determination of the type of collision risk

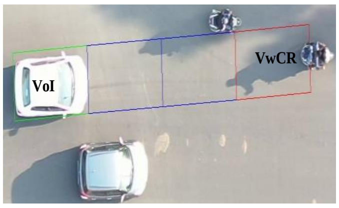
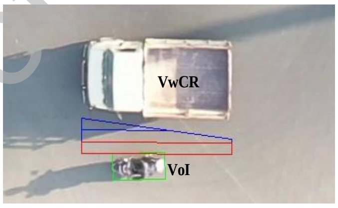
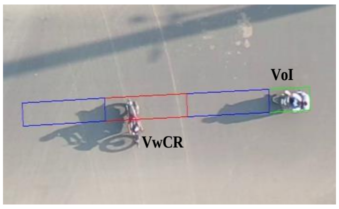
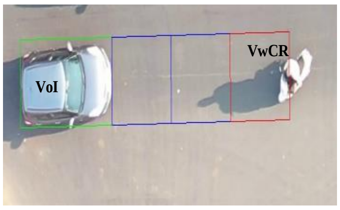
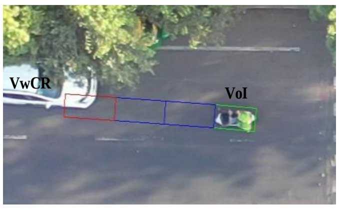
Our proposed methodology is capable of differentiating various types of collision risks. This attribute allows for assessing the risk associated with and analysing defensive driving behaviour according to each collision separately. So, it is possible to reason over those results with road infrastructure. We have defined criteria based on the vehicle's direction of travel (VoI and VwCR) to classify the types of collisions. Blind spots are considered for analysing the Side-Swipe type of collision risk. The stopping distance range is considered for analysing other types of collision risks, such as Angled, Rear-End, and Head-On collision risks (refer to Table 1).

A with-parked-vehicles collision is a collision in which VoI is in motion, and VwCR is a parked vehicle. We considered a parked vehicle based on the definitions in sections 3 and 22 of MVDR [14].

3.6. SSM formulation and Risk assessment

This paper proposes two novel vision-based SSMs to evaluate defensive driving behaviour; one is Weighted Safe Distance (*WSD*), a distance-based SSM calculated based on the interaction between vehicles within the blind spots and stopping distance range of a vehicle. Another is Weighted Reward for Acceleration (*WRA*), an acceleration-based SSM calculated based on the driver's reaction.

Table 1: Criteria for categorizing types of collision risks and related SSMs used in risk assessment.

No.	Type of collision	$Dir_{VoI} \Leftrightarrow Dir_{VwCR}$	SSMs	Example
1	Rear-End	WE⇔WE EW⇔EW NS⇔NS SN⇔SN	WSD_S, WRA	
2	Side-Swipe	⋆	WSD_B	
3	Angled	WE/EW⇔NS/SN	WSD_S, WRA	
4	Head-On	WE⇔EW NS⇔SN	WSD_S, WRA	
5	With-Parked-Vehicles	⋆⋆	WSD_S, WRA	
⋆ *Independent of the direction of VoI/ VwCR*, ⋆⋆ *Depends on the velocity of VwCR*				

3.6.1. Weighted Safe Distance (WSD)

WSD quantifies the interaction between vehicles within the blind spots and stopping distance. It utilises a concept similar to intersection over union to quantify the interaction between 0 and 1. In the case of safe distance, we have two scenarios where associated risk will be assigned to the VoI; the first is interaction with stopping distance range and if the VoI is driving such that VwCR falls under the stopping distance range of VoI. Second is interaction with blind spots and if VoI is driving under any of the blind spots of VwCR. We use the respective vehicle's BB to calculate the intersection between vehicles. In both cases, we have considered the size of the interacting zone and the size of the VoI as a "Union", respectively, as we assign risk to the VoI. Refer to Eq. 6 and Eq. 7 of WSD_S and WSD_B for stopping distance-based and blind spot-related WSD formulation, respectively.

$$WSD_S = \sum_{Z=L,M,H} \left(\frac{Zone_{VoI_Z} \cap BB_{VwCR}}{Size_Z} \right)^{W_Z} \tag{6}$$

$$WSD_B = \sum_{Z=L,M,H} \left(\frac{Zone_{VwCR_Z} \cap BB_{VoI}}{Size_{VoI}} \right)^{W_Z} \tag{7}$$

In Eqs. 6-7, we use weights associated with zones to signify the interaction based on the risk; refer to Figure. 6. For example, more weightage is given to the interaction, which has the same value of IoU but with the different zones H, M and L, in that order. Formulated WSD (Eqs. 6-7) account for conflict probability (collision risk) and severity both by calculating overlap and impact of vehicle interaction (VoI-VwCR) [47].

3.6.2. Weighted Reward for Acceleration (WRA)

As per defensive driving, a driver should accelerate or decelerate (evasive actions [9],[43]) in response to external traffic conditions to avoid collisions. For example, if

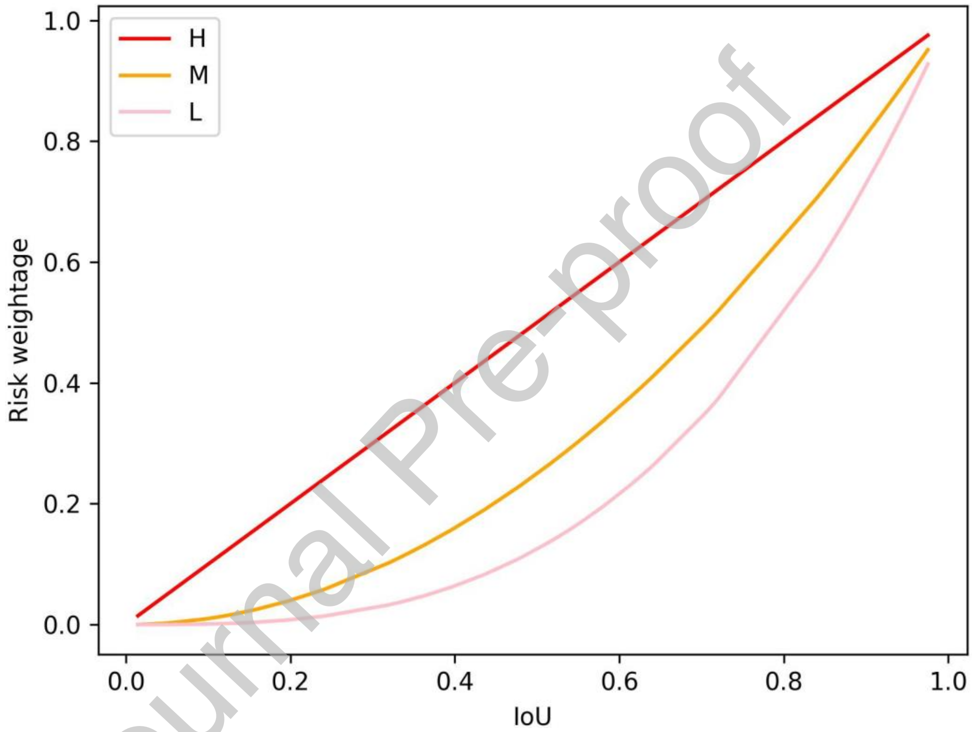


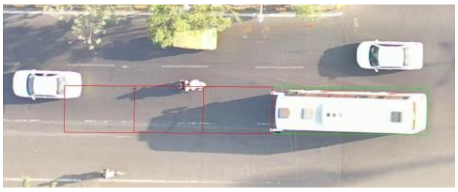
Figure 6: Impact of zone type on risk weightage.

Table 2: Reward/Penalty matrix based on evasive actions

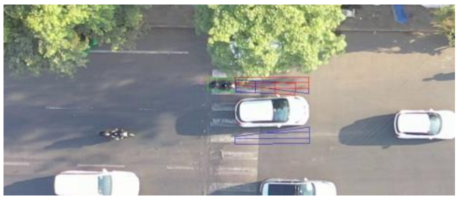
Acceleration (Δ)/ Deceleration (-Δ)		Acceleration/Deceleration magnitude (Δ)		
VoI	VwCR	$\Delta^{VoI}_{t+\delta t} \gg \Delta^{VwCR}_{t}$	$\Delta^{VoI}_{t+\delta t} \ll \Delta^{VwCR}_{t}$	$\Delta^{VoI}_{t+\delta t} \approx \Delta^{VwCR}_{t}$
Δ	Δ	+0.75	+0.50	+0.25
Δ	-Δ	+1.00	+0.75	+0.50
-Δ	-Δ	-0.75	-0.50	-0.25
-Δ	Δ	-1.00	-0.75	-0.50
Note: Values in the first two rows will be interchanged for the Head-On collision.				

a vehicle ahead started decelerating (at time t), then the following vehicle's driver should also begin to decelerate its vehicle (at some time $t + \delta t$) to maintain a safe distance. If the driver does that, we reward that behaviour for evasive actions; otherwise, we penalise it. We have defined the reward/penalty matrix to assign appropriate reward or penalty based on the driver's reaction and the type of collision. We have distributed rewards/penalties uniformly among drivers' various actions. We have considered a single frame difference (δt) to observe the driver's reaction. For Side-Swipe collisions, we use only blind spot-related safe distance to assess the risk. Hence, it is impossible to capture the driver's acceleration reaction for that. We have defined the reward/penalty matrix for the rest, as shown in Table 2.

WRA is calculated based on the weights assigned by the reward/penalty matrix. We use a sigmoid function to assign the associated risk ranging from 0 to 1, related



a Same VoI with multiple VwCRs.



b Same pair of VoI and VwCR.

Figure 7: Examples of multiple interactions simultaneously.

to the driver's reaction; refer to Eq. 8.

$$WRA = \frac{1}{1 + \epsilon^{-reward}} \tag{8}$$

3.6.3. Risk assessment

If VoI does not maintain a safe distance from its surrounding vehicles, it is at risk of collision with VwCR. We determine the type of collision and calculate the risk associated with it. At a time, it is possible to have multiple pairs (denoted as "n" in Eq. 9) of VoI and VwCR, where VoI is the same vehicle (refer to Figure. 7a). Also, an individual pair (where VoI is the same vehicle) is eligible for more than one collision (one from blind spot distance and the other from stopping distance range) (refer to Figure. 7b). So, to calculate risk, a $Risk\ score_t$ for the VoI, we considered all possible collisions at time t (at a particular frame); refer to Eq. 9 and Figure. 7. Moreover, the contributions of the various types of collisions in road accidents are not the same [1], so each collision risk is weighted accordingly (as per Indian statistics for road accidents, from MoRTH report[1]). This attribute of our proposed methodology allows us to calculate risk for any other developing country based on their statistics of road accidents.

$$Risk\_score_t = \sum_{i=0}^{n} (\alpha_{side} \times WSD_B + \alpha_{angled} \times (WSD_S + WRA) + \alpha_{parked} \times (WSD_S + WRA) + \alpha_{rear} \times (WSD_S + WRA) + \alpha_{head-on} \times (WSD_S + WRA)) \quad (9)$$

According to the MoRTH report [1], the contribution of Rear-End (α_{rear}), Head-On collision ($\alpha_{head-on}$), Side-Swipe (α_{side}), Angled collision (α_{angled}), and With-Parked-Vehicles (α_{parked}) is set to 0.214, 0.169, 0.154, 0.146, and 0.031, respectively.

This paper focuses on evaluating defensive driving behaviour. So, we accumulate a $Risk\ score_t$ for a VoI during its complete journey. Then, we normalise that accumulated score by total interactions during the journey. Hence, such a normalised score, independent of the journey time, can be used to evaluate defensive driving behaviour and allows a single measure for analysis. Refer to Eq. 10 for a normalised driver score.

$$Driver\_score_{norm} = \frac{\sum_{journeytime} Risk\_score_t}{\sum_{journeytime} n_t} \quad (10)$$

3.7. Evaluation of defensive driving behaviour

This paper has considered blind spots and the stopping distance range of a vehicle to define a safe distance around the vehicle and derive a driver's score regarding collision risk and the driver's reaction to external traffic conditions. So, it is possible to evaluate defensive driving behaviour based on the factors mentioned above, which helps to describe the defensive driving behaviour of VoI in different driving and collision scenarios, as discussed below.

3.7.1. VoI is driving under a blind spot of the VwCR

Under this driving scenario, VoI drives under the blind spot of the VwCR, which could lead to a Side-Swipe collision. It is a common scenario in developing countries, with lane indiscipline and heterogeneous traffic conditions [2]. Our paper quantifies the driving behaviour of VoI in terms of the length (in meters) of such interaction, which describes, “For how long did VoI keep driving under another vehicle’s blind spots?”—The longer the interaction length (in meters), the higher the (risk) chance of Side-Swipe collision.

3.7.2. VoI is driving such that VwCR falls under the stopping distance range

Here, the VoI can see the VwCR ahead (irrespective of the heading angle of VwCR); based on the VwCR’s movement/action, the VoI accelerates/decelerates and, accordingly, collision risk changes, which describes the defensive driving behaviour of the VoI. This paper uses such interaction (between VoI and VwCR) pattern (of associated collision risk) to study the defensive driving behaviour of the VoI. Moreover, such sequential patterns are treated as time series for analyses. Also, these interaction patterns are not the same length, so resampling to a specific length is needed. The shape of the pattern (“how collision risk changes”) describes defensive driving behaviour. Our paper uses the k-Shape unsupervised clustering algorithm [48], [49] to cluster such sequential patterns. The clustering algorithm identifies the most common shape within those patterns and creates appropriate clusters. Then, the shape within each cluster describes the defensive driving behaviour.

3.7.3. Normalised driver’s score and Star rating scheme

Each driver is assigned a normalised risk score based on the interactions with VwCR during its journey. The higher the risk score ($Driver\_score_{norm}$), the less defensive driving behaviour there is. This paper proposes a Star rating scheme inspired by iRAP methodology [50] to assign a star rating to each driver based on its defensive driving behaviour defined by drivers’ normalised scores. Our proposed star rating scheme gives a star rating to each driver based on the distribution of the normalised driver's score: first, it identifies the average $Driver\_score_{norm}$ score. Then, it divides the distribution around an average score into four ranges, assigning the star rating from 1 to 4, from high-risk to low-risk range. Drivers with zero scores are directly given a 5★. Our star rating scheme is adaptive because the above risk ranges are defined around the average score achieved in road traffic conditions, such as road infrastructure, traffic flow rate, and lane-wise traffic. Ultimately, the distribution of star ratings within each vehicle category is derived, which helps traffic management authorities take counter-measures against the low-star vehicle categories.

4. RESULTS AND DISCUSSION

We tested and validated our defensive driving behaviour evaluation methodology on the traffic video of a multi-lane urban roundabout in Ahmedabad, India, consisting of 17079 frames. This roundabout is prone to several traffic violations (refer to [2], due to several road infrastructure problems). We extracted 1251 trajectories of various road users. The traffic composition (in %) is shown in Figure. 8. We have only considered motorised vehicles in the analysis and evaluation.

4.1. Vision-based traffic data extraction

We have used various vision-based algorithms to extract traffic data from our UAV videos, such as YOLOv8, along with the BoT-SORT for trajectories of vehicles, SIFT features for the heading angle of the vehicle, and UAV calibration for GSD calculation.

We observed that YOLOv8 with BoT-SORT outperformed the YOLOv7 with SORT for vehicle trajectory extraction when we compared it with [2]. We did not have to explicitly merge the broken tracks of a vehicle to get a complete trajectory [2], which allows this methodology to be performed online. After scrutinising YOLO

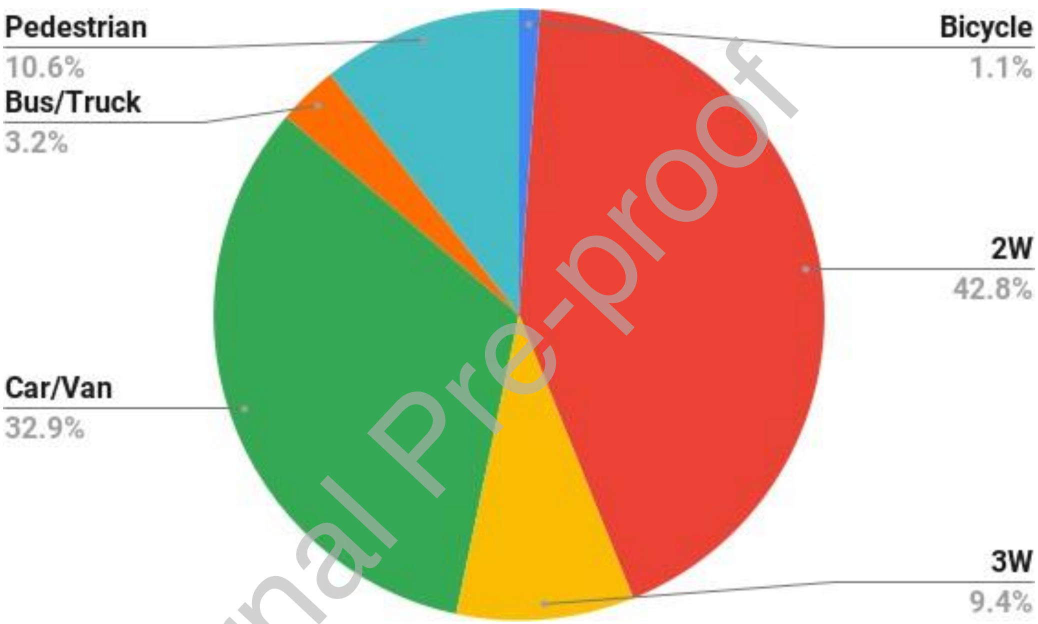


Figure 8: Traffic composition.

detection results, we found that sometimes the bounding boxes did not correctly fit the 3Ws because of the vehicle's shadow. We are using YOLO detection results as input to the SIFT feature extractor to get the vehicle's orientation. So, incorrect YOLO results could lead to wrong orientation calculation. Also, to reduce measurement noise (introduced by YOLO and SIFT results), we used a 1D Kalman filter to smooth the heading angle of the vehicle extracted using SIFT. We represented the vehicle's direction of travel as a categorical value. So, to smooth the directions, we used a Boyer-Moore voting algorithm with a moving window (of size 5).

We have estimated the speed of vehicles using Eqs. 3–5 and calculated vehicle acceleration to quantify the driver's reaction to external traffic conditions. We also used it to estimate the distance (in meters) travelled by a vehicle. Again, we used a 1D Kalman filter to eliminate any measurement noise when calculating the speed of vehicles. In [2], authors discussed errors in *GSD* calculation and their negligible effect on speed estimation when we calculated the vehicle's speed between two consecutive frames.

4.2. Analyses of collision risk

We applied our methodology to our test videos and derived collision risk-related data. The distribution of various types of collision risks based on their occurrences is shown in Figure. 9. We observed that the Rear-End collision risk was the highest, and the MoRTH accidents report [1] corroborates the same. Also, the derived distribution of collision risks (Rear-End, Side-Swipe, and Angled) follows the same order as given in state government road accident data [51]. One of the common reasons for this is that drivers are not following a safe distance from the vehicle ahead. Head-on and With-Parked-Vehicles collision risks are significantly lower, so we will skip them in further analyses. In [2], authors observed vehicles parked near the grocery store

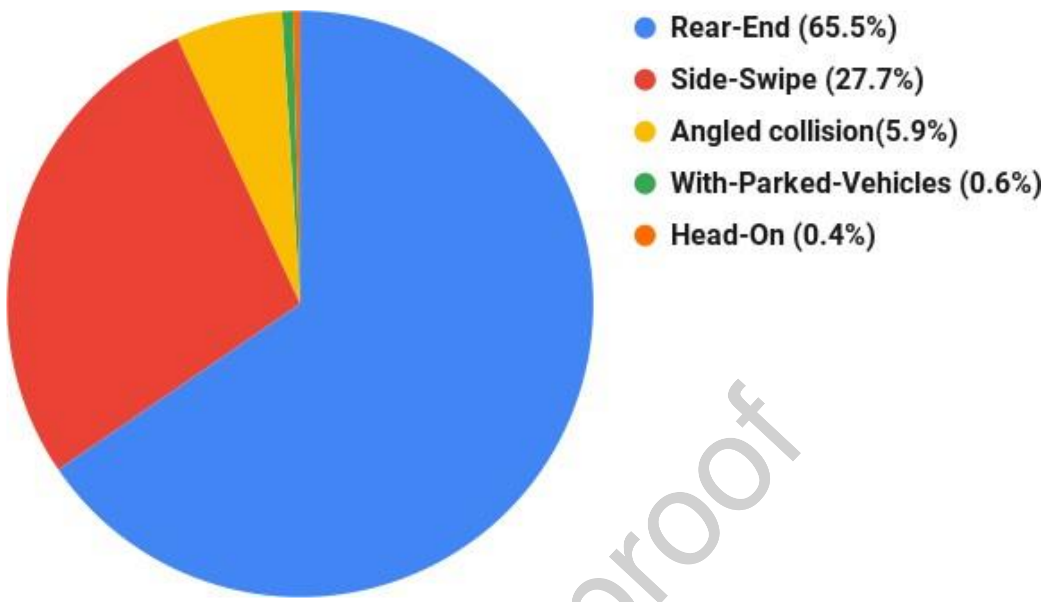


Figure 9: Distribution for various types of collision risks on test data.

responsible for collision risk with parked vehicles.

For the Rear-End, Side-Swipe, and Angled types of collision risks, distributions of (VoI-VwCR) interactions between various classes of vehicles, such as 2W (two-wheeler), 3W (three-wheeler), car/van, and truck/bus, are shown in Figs. 10 to 12. Most Rear-End collision risk interactions occur between car-car, 2W-car, and 2W-2W; refer to Figure.10. Likewise, Side-Swipe collision risk interactions occur between car-car and 2W-car, and cars primarily drive under other vehicles' blind spots; refer to Figure.11. For the Angled collision risk, most interactions occurred between 2W-2W and 2W-car pairs, and 2Ws are responsible for that; refer to Figure.12.

We have plotted the occurrences of VoI-VwCR interactions on the road traffic image (on the road junction) to locate the spatial hot spots of collision risks associated with various collisions. For Rear-End collision risk, more interactions are observed

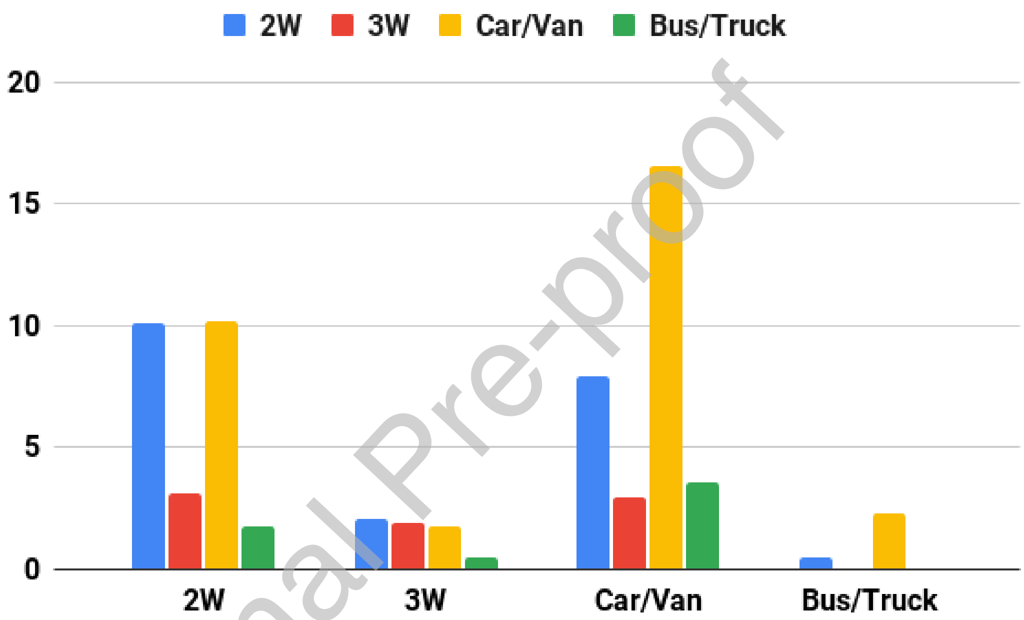


Figure 10: Vehicle inter-class distribution of VoI-VwCR interactions for Rear-End collision risk (in %).

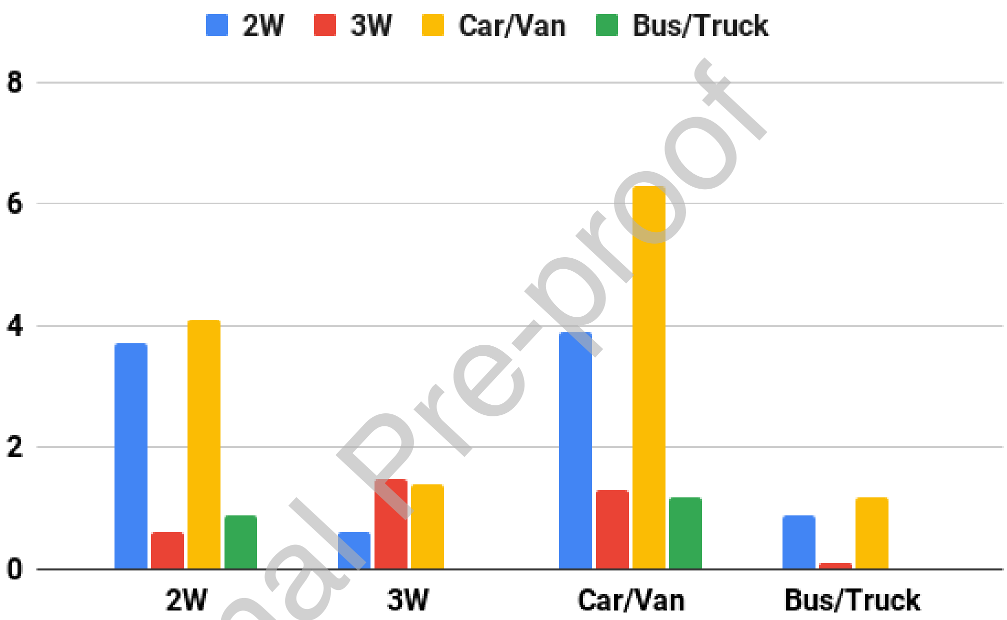


Figure 11: Vehicle inter-class distribution of VoI-VwCR interactions for Side-Swipe collision risk (in %).

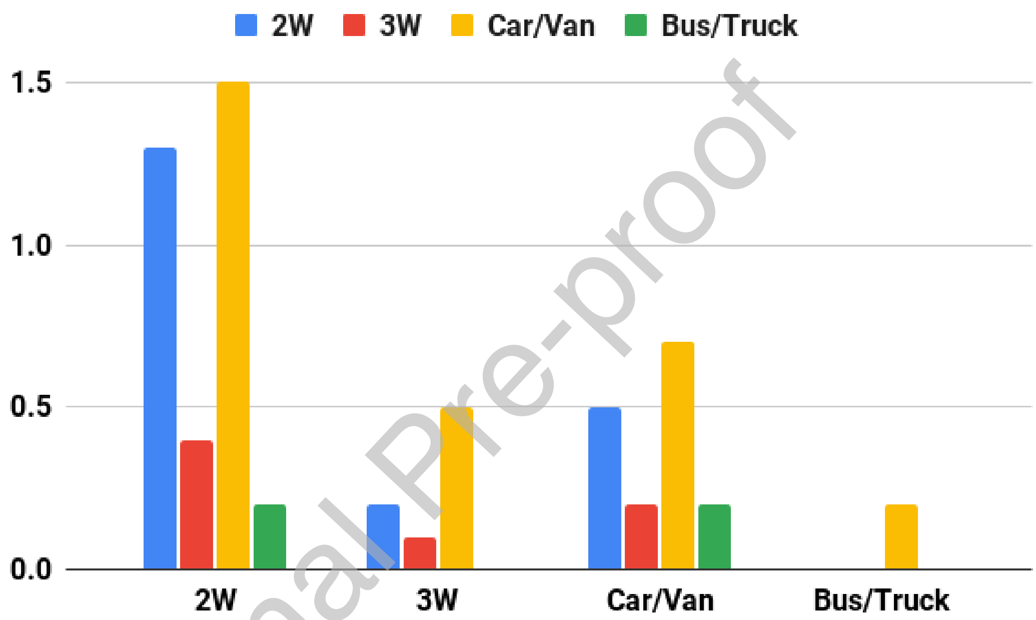


Figure 12: Vehicle inter-class distribution of VoI-VwCR interactions for Angled collision risk (in %).

Figure 13: Occurrences of VoI-VwCR interactions on the road traffic image, for Rear-End collision risk.

at entry points in the west and east directions as shown in Figure.13. It is also the direction of maximum traffic flow [2], which means the majority of vehicles entering the roundabout from either direction are not following a safe distance (i.e. vehicles are entering at speeds higher than the allowed limits; same can be corroborated with [2]). In the case of Side-Swipe collision risk, significant interactions occur around the roundabout (refer to Figure.14), which means vehicles are driving too closely while turning. For Angled collision risk, interactions occur around the roundabout while turning; refer to Figure. 15. Some vehicles do not follow the speed limit while driving within the roundabout [2].

Figure 14: Occurrences of VoI-VwCR interactions on the road traffic image, for Side-Swipe collision risk.

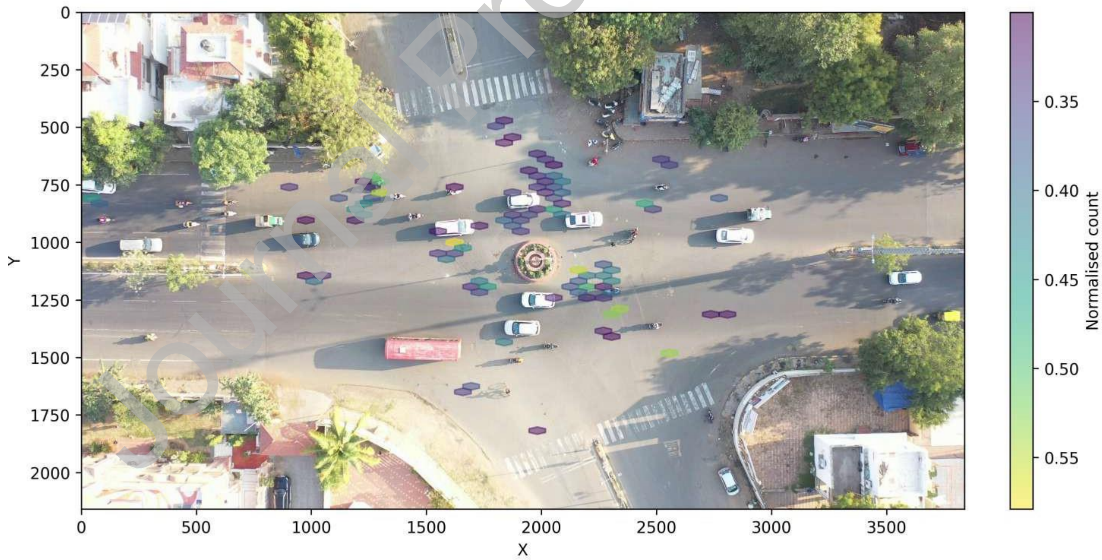


Figure 15: Occurrences of VoI-VwCR interactions on the road traffic image, for Angled collision risk.

4.3. Evaluation of defensive driving behaviour based on blind spots and stopping distance

We can evaluate the defensive driving behaviour of the VoI separately based on blind spots and stopping distance.

4.3.1. Blind spots-based evaluation

We describe the defensive driving behaviour of VoIs based on the question, "For how long did the VoI keep driving under another vehicle's blind spots?" We calculated interaction length in terms of meters based on its average velocity and GSD. We observed that 8.0% of the total vehicles (except parked) drove under another vehicle's blind spots for more than 20 meters (refer to Figure. 16), which is very dangerous and could lead to a Side-Swipe collision.

4.3.2. Stopping distance-based evaluation

When the driver (of VoI) sees another vehicle (VwCR) ahead in its stopping distance range, then how does the driver (of VoI) start reacting in subsequent time steps (a time series pattern of collision risk)? This reaction describes the driver's defensive driving behaviour. We have considered WSD_S and WRA to capture the risk associated with the driver's reaction. We have derived 367 collision risk patterns between VoI-VwCR pairs, with continuous interaction duration of more than one second and average velocity greater than 10 kmph. We then resampled these time series patterns to the same length for clustering based on weighted average length. After resampling, we normalised each pattern based on its mean and standard deviation to improve clustering accuracy. We chose 6 clusters based on the Elbow method. We applied the k-shape algorithm to identify the typical defensive driving behaviour. The line shape in each cluster depicts the driving behaviour of VoI during the interaction with

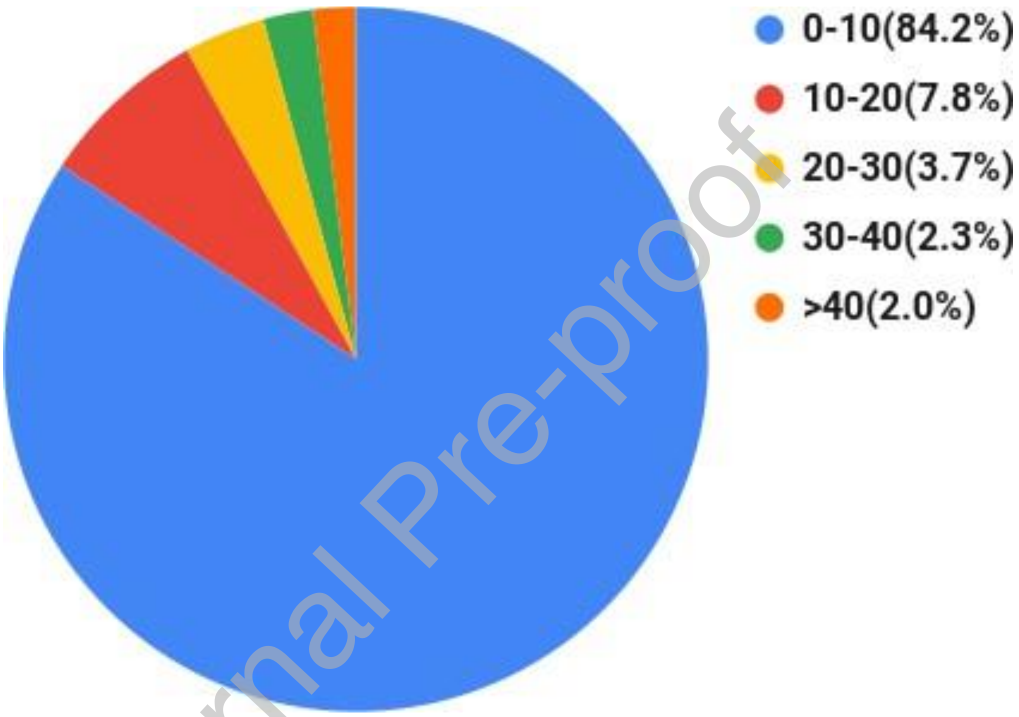
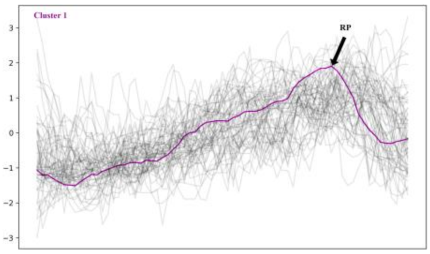


Figure 16: Distribution of distance (in meters) for which VoI keeps driving under another vehicle's blind spots.

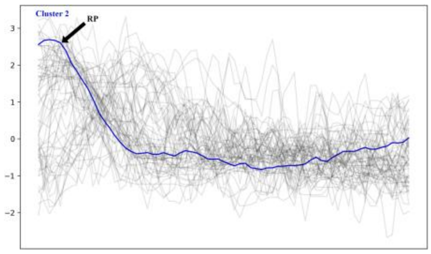
VwCR; refer to Figure. 17. We observed during an interaction that after realising the high risk of collision, the driver (VoI) takes action to avoid a collision. We marked that point as a Realisation Point (RP). We can differentiate/conclude the defensive behaviour based on the change in associated collision risk before and after the RP only if a single RP is present. If multiple RPs exist in the interaction pattern, we consider it inconclusive behaviour (inattentive or nonchalant driving behaviour [2]). We observed that the VoI under 1^{st} cluster (refer to Figure. 17a) is driving such that, initially, the risk gradually increases (driving faster than the VwCR). After the RP, the VoI takes corrective actions, and the risk suddenly decreases. In 2^{nd} cluster (refer to Figure. 17b), the VoI encounters a sudden high collision risk, resulting in RP, and then the collision risk gradually reduces. The sudden collision risk was encountered because of different driving scenarios, such as VoI entering a road junction with other vehicles already present and while VoI/VwCR are taking turns. In the 3^{rd} cluster (refer to Figure. 17c), the collision risk gradually increases and decreases after RP. Other clusters (4, 5 and 6) (refer to Figure. 17d) have multiple RPs, leading to inconclusive behaviour. By visually inspecting videos, we found that to avoid collision, VoIs have intentionally changed their trajectories/lanes (MVDR violations; see [2]) or decreased their velocities (evasive actions); hence, we observed a decrease in the collision risk after RP. Various other possible reasons observed for reducing the collision risk after RP are VoI/VwCR trajectory ends, VoI/VwCR turns, and VwCR increases its velocity or changes its trajectory (VwCR drives away from VoI).

4.4. Defensive driving star rating scheme

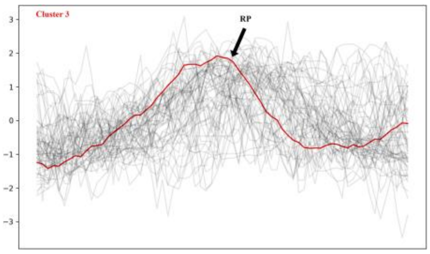
We proposed a star rating scheme to evaluate defensive driving behaviour based on the $Driver\ score_{norm}$. A star rating scheme assigns stars (out of 5) to each VoI based on its defensive behaviour throughout its journey; 5★ indicates safe driving



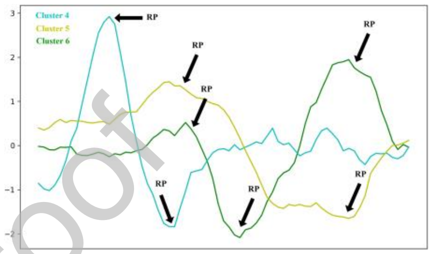
a 1^{st} cluster.



b 2^{nd} cluster.



c 3^{rd} cluster.



d 4^{th}, 5^{th}, and 6^{th} cluster.

Figure 17: Stopping distance-based interaction clustering.

behaviour, whereas 1★ indicates dangerous driving behaviour and others fall between them, in that order. We chose an adaptive star rating scheme, which allows us to rate drivers based on the average score derived from the distribution of the $Driver\ score_{norm}$, as per the road junction under study. We have considered 965 VoIs (except pedestrians and parked vehicles) for the star rating. The distribution of $Driver\ score_{norm}$ for all VoIs is given in Figure. 18. The distribution follows a bell shape; hence, we divided the distribution around an average score into four ranges based on mean and standard deviation, as shown in Figure. 18.

The distribution of VoIs based on star rating is shown in Figure. 19. From Figure. 19, we can say that only half (52%) of the total vehicles (5★) adhere to defensive driving practices (driving safely). Also, it is observed that 6.4% of vehicles (1★) drive very dangerously.

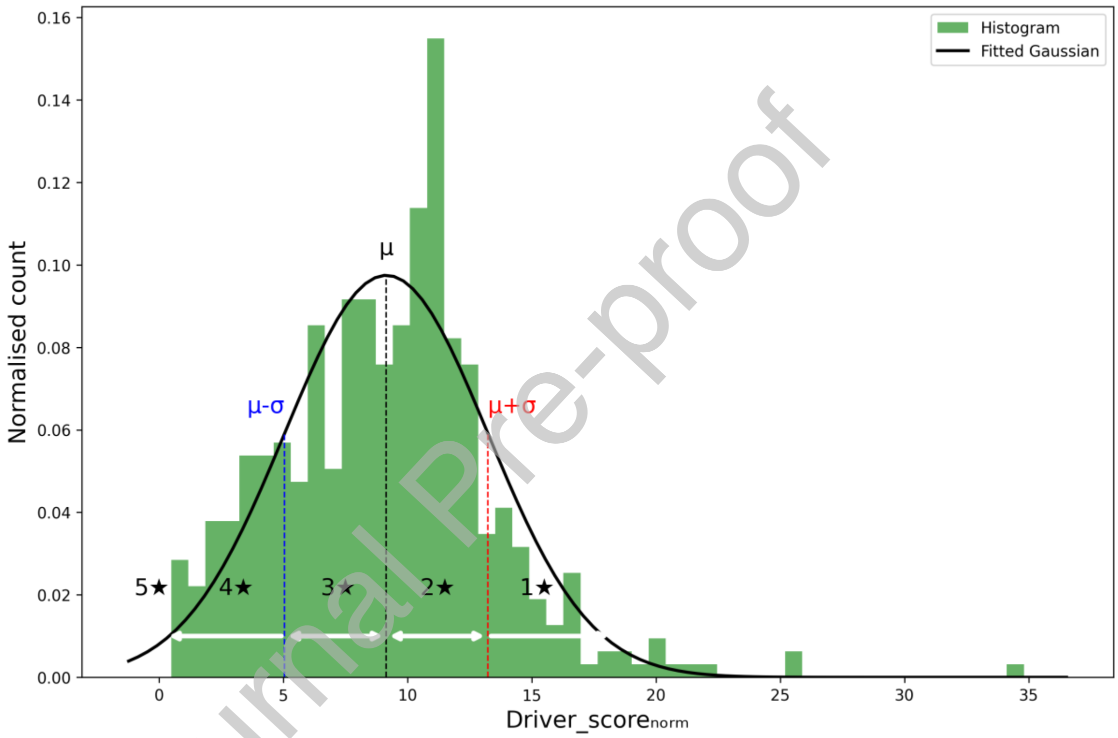


Figure 18: $Driver\_score_{norm}$ distribution.

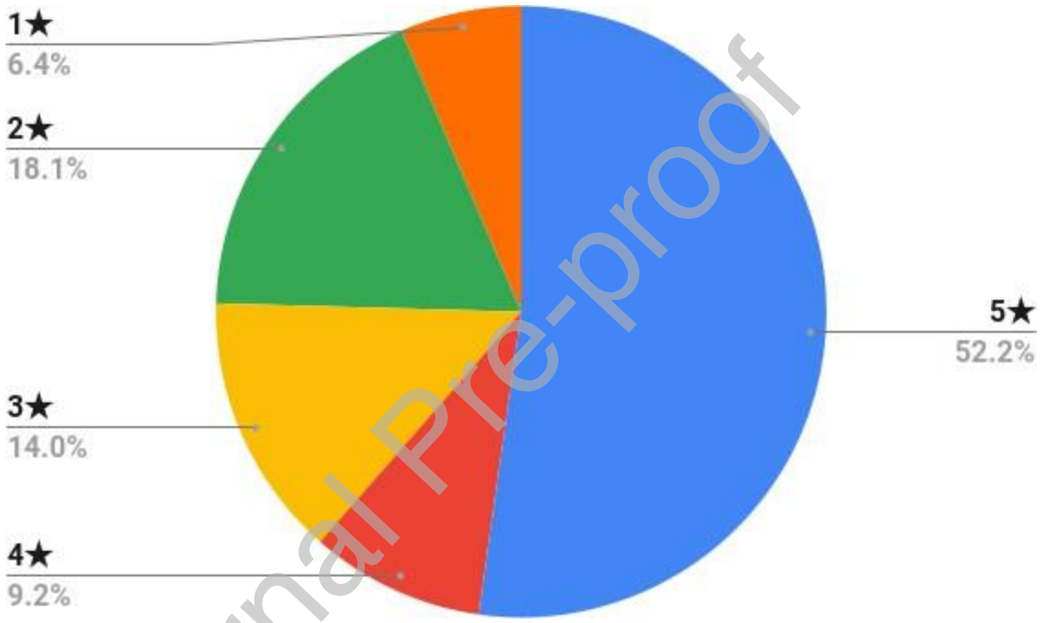


Figure 19: Overall star rating distribution.

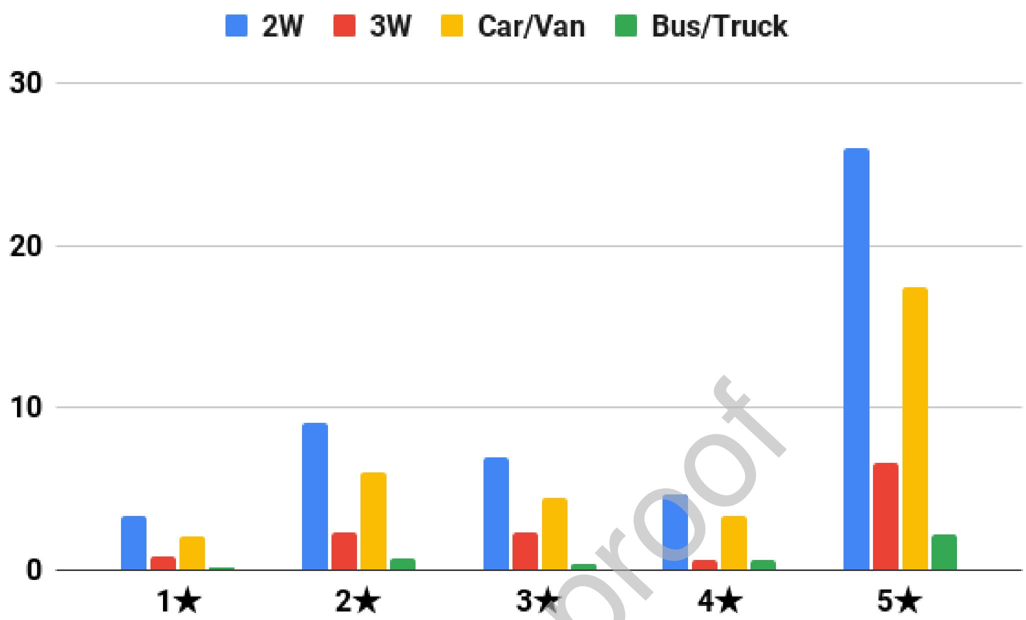


Figure 20: Vehicle class-wise star rating distribution.

In Figure. 20, the vehicle class-wise distribution of star ratings is given. It also shows the order of class-wise safe driving for vehicles in India: 2W (most unsafe), car, 3W, and truck (in that order), which can be corroborated with the MoRTH road accident report [1] and state government road accident data[51].

4.5. Comparison, Advantages, Limitations, and Outcomes

Detailed review of existing SSMs is given in [9], [42], [43]. However, to study defensive driving behaviour, our proposed SSMs are more suitable and differ from others in several ways, such as a) capture more vehicle interactions (driving behaviour) and time exposure to conflict than others (TTC and DRAC) [9], [43]; b) consider the conflict's severity level using overlap and risk weightage (obtained from vehicle trajectories) whereas energy-based SSMs require the knowledge of vehicle mass (cannot obtained from vehicle trajectories) [9]; c) taking into account lateral conflict (Side-Swipe collision) through vehicles' blind spots which other distance-based SSMs do not [43]; d) consider evasive actions using acceleration/deceleration during vehicle interactions which can be added to distance-based (and not time-based) SSMs for better evaluation of driving behaviour [43]; e) taking into account vehicle size whereas other proximity-based SSMs do not consider it [42]; f) no explicit threshold is required to determine conflict/safe state as other time-based SSMs do [9]. g) easy to interpret in lane indiscipline and heterogenous traffic conditions, whereas other proximity-based SSMs have been mainly used for lane-based homogeneous traffic conditions in developed countries [42]. The majority of research work to classify driving behaviour uses onboard electronic sensors, whereas vision-based data (SSMs measurements) are used in crash prediction modelling, collision risk analysis, and driving behaviour models (car-following, lane change) [9], [47], [52]. Our methodology uses a combination of SSMs based on the type of collision to evaluate defensive driving behaviour; it calculates collision risk using SSMs over the journey time of a vehicle, assigns an aggregated risk score to each driver, and then classifies the driver's behaviour using a star-rating scheme.

Now, we discuss the advantages and limitations of our methodology and the outcomes of results obtained through our methodology.

4.5.1. Advantages

(a) Cost-effective solution because a single drone can be re-used (as opposed to mounting numerous CCTVs) to evaluate driving behaviour at various road junctions. Also, the flight height of the drone is adjustable to capture a complete road junction. Top-view (gimbal 90° downwards) from the drone provides a non-occluded view (except trees).

(b) Automatically detect vehicle orientation.

(c) Computationally lightweight method as it uses the direction of travel to determine the type of collision risk, a customizable zone-based approach to define safe distance around a vehicle, and a concept similar to IoU to detect and quantify collision between vehicles.

(d) Adaptive star rating scheme for defensive driving behaviour evaluation.

(e) Could be used to evaluate the defensive driving behaviour in heterogeneous traffic (autonomous and manually driven vehicles).

(f) Could give suggestions to transportation and urban development policies.

4.5.2. Limitations

(a) Data collection using UAVs is only periodic because of limited battery time. Some data collection sites are restricted because of airspace regulations and citizens' privacy [2], [9],[53], [54], [55].

(b) In our methodology, to observe a complete road junction, flying the drone at a higher height is necessary. Hence, 2W and pedestrians become small objects, leading to problems related to small object detection, as discussed in [2], [9].

(c) The SIFT algorithm fails in some cases, such as improper detection by YOLO (where BB also encloses the vehicle's shadow), leading to an imprecise vehicle heading angle [9].

(d) Other manoeuvres, such as intentionally changing lanes to avoid collisions, have yet to be considered while evaluating defensive driving behaviour [9], [43].

(e) Our methodology currently works on recorded UAV video.

4.5.3. Outcomes

Results (vehicle trajectories with orientation, vehicle inter-class collision risk analyses, SSMs-based risk patterns, star rating, and inferences) obtained through our methodology could be helpful to other researchers, traffic law enforcement agencies and policy-makers to further study collisions and driving behaviour, initiate enforcement drives and update driving test procedures, and amend policies for different classes of vehicle, respectively [53]. Some examples are as mentioned here:

(a) educating drivers about defensive driving practices through enforcement drives (sections 138 and 210A of MVA [56]) and driving tests (while issuing driving licenses) (section 15 of CMVR [57]) is necessary. Such rules should be added in section 5 ("Duties of drivers and riders") of the MVDR [14]. Also, the government should provide detailed guidelines for defensive driving. It should be added in section 40 of MVDR [14] as "Knowledge and understanding of defensive driving techniques and practices".

(b) focus should be on 2W while updating the driving test, revising fine amounts (especially over-speeding within the roundabout), and amending urban and transport policies.

(c) Traffic enforcement agencies must strictly act against street vendors/hawkers and illegal parking. In contrast, policy-makers should change related acts/policies such as the Street Vendors Act 2014 [58], National Urban Transport Policy 2014 [59], National Urban Policy Framework 2018 [60], and section 201 of MVA [15], as discussed in detail in [2].

(d) vehicle trajectories data for lane indiscipline and heterogeneous traffic could be valuable to other researchers and traffic management authorities such as

TMICC (under “Data Repository and Analysis” operation) [2], [61], [62] for improving road safety. Also it can be used to calibrate traffic microsimulation models [43].

(e) Recently proposed UAV-based systems such as U-UTM [53] and METRIC [63] could incorporate this methodology to analyse defensive driving behaviour.

5. CONCLUSION

This paper presents a case study (and the methodology) for evaluating defensive driving behaviour based on the safe distance between vehicles using a UAV video of a multi-lane urban roundabout in India. The computer vision techniques used in our work are YOLOv8, BoT-SORT, and SIFT for vehicle detection, vehicle tracking, and determining vehicle orientation, respectively. Our methodology first divides safe distances (blind spots and stopping distance range) into three risk zones (H/M/L) and assigns weights (1/2/3) associated with them. It determines the type of collision risks based on the orientations of the vehicles (VoI and VwCR). Our methodology proposed two novel distance- and acceleration-based SSMs to capture defensive driving behaviour. Then, it checks for the interaction (either with blind spots or stopping distance range) between each pair of VoI and VwCR; if any interaction is found, it calculates the risk associated with that interaction using SSMs. Further, we derive interaction collision risk patterns and calculate the distance for which VoI was driving under the blind spots of VwCRs to evaluate defensive driving behaviour. Also, we studied the collision risks concerning road infrastructure and derived vehicle inter-class interactions for various collision risks. Ultimately, our methodology derives the distribution of normalised driver scores and defines the score ranges based on the average driver score for the star rating. Ultimately, we assigned a star to each driver based on their defensive driving behaviour.

We have studied 965 trajectories of different vehicles: the Rear-End collision risk was most significant, accounting for 65.5% of the total occurrences. We observed the With-Parked-Vehicles and Angled collision risks because of vehicles parked near a grocery store and a hawker standing at the top right corner and top left corner of the roundabout, respectively. Through vehicle inter-class interaction analyses, we found that most collision risks, such as 16.6% Rear-End, 6.3% Side-Swipe, and 1.5% Angled, occurred between car-car, car-car, and 2W-car, respectively. We found that around 8.0% of vehicles were driving under another vehicle's blind spots for more than 20 meters during their journey. We observed that drivers took actions such as decelerating vehicles and intentionally changing their path to reduce collision risk. Around 48% of the vehicles did not follow the defensive driving practices, and 6.4% (1★) drove dangerously.

Results (vehicle trajectories with orientation, inter-vehicle collision risk analyses, SSMs-based risk patterns, star rating, and inferences) obtained through our methodology could help traffic law enforcement agencies and policy-makers elevate road traffic safety.

Future Work

Our proposed methodology has focused on choosing the defensive driving behaviour; for that, we proposed two novel SSMs, but still, there is a scope to improve various modules of the methodology, such as CV techniques, orientation calculation, formulation of SSM, and other defensive driving practices-based evaluation. The problem of broken tracks for the small objects (2W and 3W) could be resolved using more efficient CV techniques. Further, the oriented object detection model can determine the vehicle's orientation more accurately. We have considered only four directions to determine the type of collision risk, which could be further investigated to differentiate between types of collision risks, such as Head-On and Angled. This methodology covered stopping distance and blind spot-based defensive driving practices. However, there is a scope to incorporate others as well. To validate our methodology, we used typical values of parameters (T_R, K, f). These parameters can be varied appropriately for specific/different driver, vehicle, and road conditions [10]. Also, acceleration-based SSM has a scope of modifying the reward/penalty distribution (refer to Table 2) and choosing time difference (δt in Table 2) to formulate the driver's reaction with the help of road traffic safety experts.

Traffic Management and Information Control Centres (TMICCs) are established by the government to support several activities, such as the collection of real-time traffic data and analysis of these data to accomplish the objectives (Obj2-6). Our proposed defensive driving behaviour analysis methodology can be easily plugged into recently proposed UAV-based traffic monitoring systems [53], [63], which are feasible and promising data capturing and analytics solutions for TMICCs and other stakeholders. UAV-based traffic monitoring systems can be improved by incorporating data from other sensors.

Acknowledgement

XXXXX.

Appendix A. Flowchart of the methodology

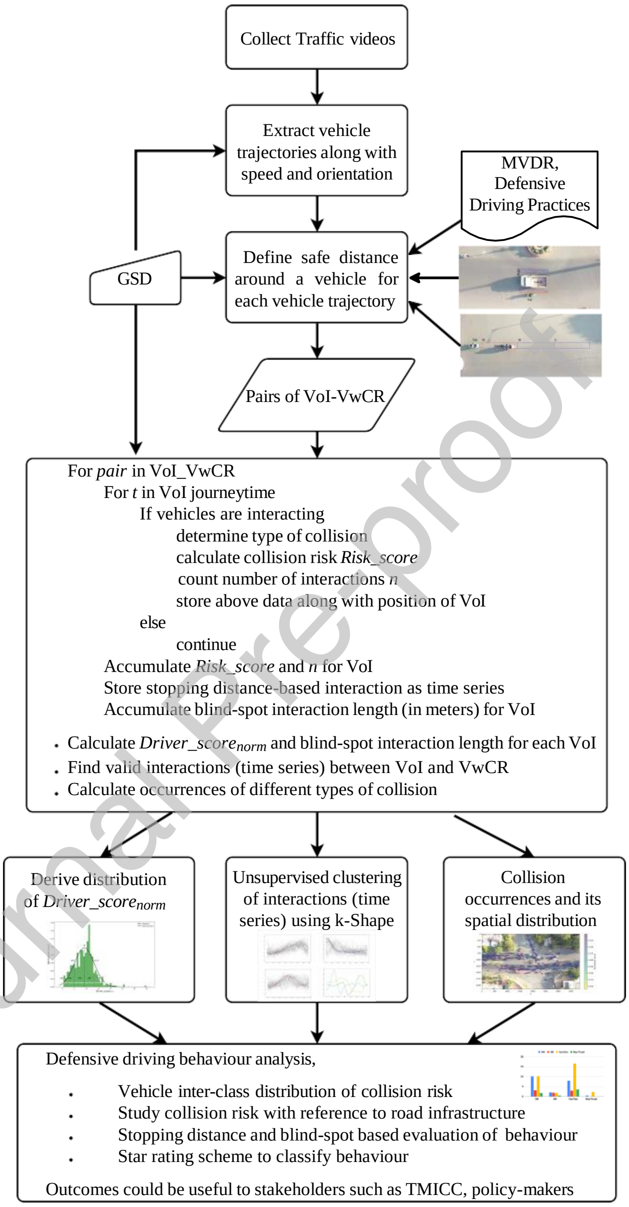


Figure A.21: Flowchart of defensive driving behaviour analysis methodology based on safe distance between vehicles.

Acronyms

1D 1-Dimension. 1

2W Two-Wheelers. 1

3W Three-Wheelers. 1

ACT Anticipated Collision Time. 1

ADAS Advanced Driver-Assistance Systems. 1

ANN Artificial Neural Network. 1

BB Bounding Box. 1

CCTV Closed-Circuit TeleVision. 1

CMVR Central Motor Vehicles Rules. 1

CSI Conflict Severity Index. 1

CV Computer-Vision. 1

DCF-CSR Discriminative Correlation Filter with Channel and Spatial Reliability. 1

DT Decision Trees. 1

FPN Feature Pyramid Network. 1

GoI Government of India. 1

GPU Graphics Processing Unit. 1

GSD Ground Sample Distance. 1

GTTC Generalised Time-to-collision. 1

HOG Histogram of Oriented Gradients. 1

IoU Intersection over Union. 1

KLT Kanade-Lucas-Tomasi. 1

KNN K-Nearest Neighbour. 1

LSTM Long Short-Term Memory. 1

MoRTH Ministry of Road Transport and Highways. 1

mTTC minimum Time-to-collision. 1

MVA Motor Vehicle Act. 1

MVDR Motor Vehicle Driving Regulations. 1

PET Post Encroachment Time. 1

RF Random Forest. 1

RP Realisation Point. 1

SD Stopping Distance. 1

SIFT Scale-Invariant Feature Transform. 1

SORT Simple Online Real-Time. 1

SOTA State-Of-The-Art. 1

SSM Surrogate Safety Measure. 1

SVM Support Vector Machine. 1

TA Time-to-Accident. 1

TE-ACT Time Exposed Anticipated Collision Time. 1

TEA Time of Evasive Action. 1

THW Time-Head-Way. 1

TI-ACT Time Integrated Anticipated Collision Time. 1

TMICC Traffic Management and Information Control Centre. 1

TTC Time-to-collision. 1

UAV Unmanned Aerial Vehicle. 1

V2V Vehicle-to-Vehicle. 1

V2X Vehicle-to-Everything. 1

VoI Vehicle of Interest. 1

VwCR Vehicle within Collision Range. 1

WRA Weighted Reward for Acceleration. 1

WSD Weighted Safe Distance. 1

YOLO You Only Look Once. 1

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