Evaluating the Effects of Cooperative Perception on Avoiding Pedestrian Crashes for Connected and Automated Vehicles

- Using Virtual Simulator to Evaluate the Automated Emergency Braking System for Avoiding Pedestrian Crash at Intersections under the Occluded Conditions

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Abstract

At an intersection, a crash between a pedestrian and a vehicle may occur under the occluded condition. An automated emergency braking (AEB) system could be utilized to actively detect pedestrians and react to avoid potential conflicts. This study contribution is evaluating the effectiveness of the AEB system under occlusion conditions. The braking algorithm was developed in the virtual simulator CARLA to control the ego vehicle. Three occlusion scenarios in which the sensor of the AEB system could not detect the pedestrian if the pedestrian is occluded by a stopping vehicle. The evaluation experiments were conducted at a typical 4-leg intersection considering different motion statuses of the ego vehicle and pedestrian. The effects of field of view (FoV) of the sensor and activation threshold of the AEB system were also explored. The study indicated that the effectiveness of the AEB system could be reduced by the occlusion time. A longer activation threshold is recommended if the pedestrian is potentially occluded for a long time. The effects of other factors such as the speed of the ego vehicle and pedestrian and scenarios were also identified.

1 Introduction

Pedestrian safety is a serious concern. According to the National Highway Traffic Safety Administration (NHSTA), a pedestrian was killed every 85 minutes in traffic crashes in 2019 [1]. The pedestrian deaths accounted for 17% of total crash fatalities, 26% of the pedestrian fatalities happened at intersections [2]. Meanwhile, it was found that the obstruction of drivers' view is one of the most common crash causations for pedestrian crashes [3].

Many studies have been conducted that focused on pedestrian safety. In 2012, Zegeer & Bushell summarized the pedestrian crashes contributing factors into five categories: driver, vehicle, social-demographical or policy, pedestrian, and roadway factors [4]. Among those factors, vehicle speeds are found to have a significant impact on pedestrian safety for both crash occurrence and crash severity. Higher operating speed leads to a longer stopping distance. Thus, vehicles with higher speeds may not be able to stop completely and avoid crashes by emergency brakes. Previous research indicated that the odds of pedestrian fatality increase by 11% for a 1 km/h increment [5]. It was also found that if a pedestrian was hit by vehicles' bumpers, hoods, or the windshield area, the severity of the crash tends to be higher [2]. In 2014, Bertulis and Dulask investigated the relationship between vehicle speeds and yield rate [6]. The results indicated that vehicles with higher speeds are less likely to yield to pedestrians, which is consistent with other studies [7, 8]. Unexpected crossing behavior of pedestrians are also one of the common contributing factors for pedestrian safety critical situations [9], such as running and jaywalking. Meanwhile, it was found that some pedestrians have lower speeds and could not complete crossing before the onset of red signal [10], which could lead to potential conflicts with vehicles.

The advent of Autonomous Vehicle (AV) technologies provides tremendous opportunities to prevent crashes by mitigating human errors. One of these technologies is Automatic Emergency

Braking (AEB), which is expected to benefit pedestrian safety by preventing pedestrian-related crashes. For pedestrian-related situations, if the vehicle sensors detect an imminent collision, the vehicle will begin to brake automatically. Some studied were conducted to estimate the safety benefits of AEB technologies. In 2013, Rosen investigated the impact of AEB systems on both pedestrian and cyclist crashes using real-world crash data. The results indicate that when the system is optimized, the effectiveness can be 52% and 31% for pedestrians and cyclists, respectively [11]. However, the effectiveness of AEB systems is highly influenced by other factors, such as sensors' Field of View (FoV) and the design of the systems [12]. According to previous research, the effectiveness of AEB decreases significantly with the decrease of FoV, as vehicles may not be able to detect dangerous situations in time and have a complete stop before a crash happens [13]. Yue et al. proposed an augmentation function to estimate the crash risk given its time-space-distance relationship with a pedestrian [14]. The crash risk represents the probability of hitting the pedestrian given all the pedestrian's possible random trajectories in the near future. The study demonstrated that an FoV of 50^{o} and a detection range of 40 m would be the minimum requirement to support the augmentation function. Similarly, Zhao et al. reconstructed 40 crash cases based on the collected video data related to taxi-to-cyclists crashes [15]. The results illustrated that an increase of FoV from 50 ° to 90° could avoid 30% more cyclist-related crashes. Meanwhile, the effectiveness of AEB could be various based on when the vehicles start to decelerate automatically and what deceleration rate is employed. The start to brake decisions of the AEB systems usually depend on the Time-to-Collision (TTC) values. When the TTC is lower than the threshold, the vehicle will start to decelerate to avoid the imminent collision. Thus, AEB systems with larger TTC thresholds are found to have higher safety benefits [16].

In recent years, many efforts have been conducted to evaluate the effects of various in-vehicle technologies. Some studies were conducted using naturalistic driving data that were collected in real-life driving conditions. This type of data could capture the drivers' behaviors and some crashes/near-crashes events [17, 18]. In 2020, Seacrist et al. utilized SHRP 2 rear-end striking crashes data to evaluate the effectiveness of AEB for rear-end crashes. This study also found that the increase in vehicle operating speeds has a negative impact on the effectiveness of the AEB system [19]. One of the limitations of naturalistic driving-based studies is that the data collection method is found to be inefficient to obtain sufficient sample sizes for analysis, especially when interaction effects are explored. Hundreds of millions of miles driving may be necessary to assess AVs' safety performance [20]. Another type of method is the driving simulator experiment. Driving simulator experiments are widely utilized to investigate the effects of human factors. In 2017, a driving simulator experiment was conducted to investigate the differences in effects among various types of AEB systems under snow conditions and identified significant differences between males and females [21]. Although the abovementioned methods could be utilized to investigate AV's performance, they have limited capability to explore the relationship between the AV sensors' specifications and the driving performance. An open-source autonomous vehicle simulation platform named "CARLA" was developed in recent years and could be utilized to obtain simulated naturalistic driving data, which provides the flexibility of changing driving environments and sensors' specifications [22, 23]. Thus, it could be employed to identify the impact of AV technologies with different sensor-fusion techniques and AV control algorithms. In 2021, Feng et al. utilized CARLA to build an environment and simulated life-like driving for AVs [20]. The proposed method aims to accelerate the procedure of AV evaluation by reducing the required miles of naturalistic driving. Meanwhile, the CARLA platform can also be extended and employed to test Vehicle-to-Everything (V2X) or Cooperative Driving Automation (CDA) technologies [24, 25].

This study aims to contribute to pedestrian safety from two perspectives: (1) exploring the effectiveness of AEB as an automated function to avoid the pedestrian crashes under the occlusion conditions; (2) using an open-source virtual simulator to integrate the control algorithm and sensor for the evaluation.

2 Methodology

2.1 Virtual simulator

CARLA is an open-source virtual simulator to test automated driving. The CARLA virtual simulator is developed with a client-server architecture with consistent scalability. The server-side is to manage everything related with the Carla simulator such as physical computation, sensor rendering, and updates on different actors. The client-side is developed with the control modules and logic of actors under different scenes and world conditions setting. The control of different agents is based on CARAL API (in python or C++), a layer that connect between server and client. The architecture of the virtual simulator is presented in Figure 1. In general, the simulator includes:

- Traffic Manager (TM). A built-in module controls vehicle in autopilot mode in a simulation with realistic urban traffic conditions. In this study, it is customized with the TTC measurement through Carla python API. TM is running on CARLA's client-side. TM's execution flow divide into stages, each with independent operations and goals. Different agents are controlled by online and offline by setting TM different parameters. For example, vehicle one can be set to a specific speed with autopilot mode by change TM PID control module. TM Vehicle PID Controller is the combination of two PID controllers (lateral and longitudinal) to perform the low-level control of a vehicle from the client-side. It will estimate the vehicle's throttle, brake, and steering inputs to reach a target speed using the TM Motion Planner Stage information.
- Command Array. The Command Array represents the last step in the TM logic cycle. It applies all commands received from all the registered vehicles.
- Agent Lifecycle and State Management (ALSM). It is the first step in the TM logic cycle and provides the context of the current state of the simulation. It will scan the whole simulation world to keep track of all vehicles and pedestrians, and store the position,

velocity, and additional information (such as traffic light influence and bounding boxes) of every vehicle and pedestrian in the simulation state component.

- Path Buffer and Vehicle Tracking (PBVT). It is a data structure that contains the expected path for every vehicle and allows easy access to data during the control loop.
- Sensors. In CARLA, the sensors are a specific kind of actor, which could be attached to different vehicles. The data received through the sensors can be retrieved and stored to ease the process.
- Motion Planner Stage. It makes high-level decisions about how each agent should move.

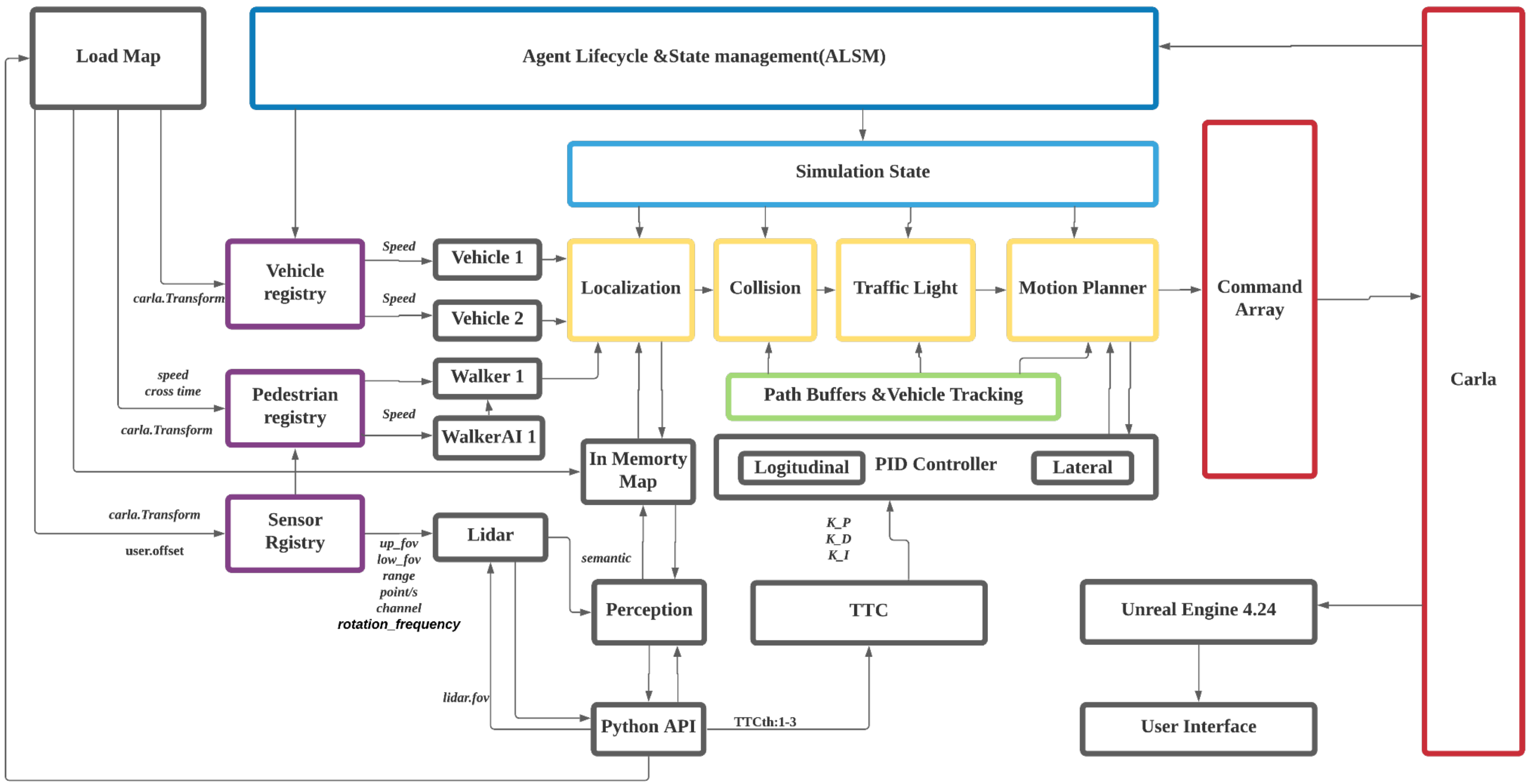


Figure 1 Architecture of the virtual simulator platform

2.2 AEB braking system

The AEB system consists of two main parts: one is the sensor model and the other is the braking strategy. The sensor is mainly responsible for the perception of the surrounding environment in which the ego vehicle is moving. As illustrated in Figure 2, the sensor scans a segment of a circle while transmitting detection rays to detect surrounding objects (e.g., a pedestrian). The minimal distance between the ego vehicle and the moving objects could be used to calculate the time to collision (TTC). The TTC could be applied as a metric to activate the brake signal of the AEB system. Once the TTC is below the specific configurable activation threshold, the AEB system is triggered to react to avoid the potential collision. In this study, the brake system described in the previous study [26] has been adopted. The braking system response consists of a brake delay and the build-up time until the full brake, which could be expressed by the following equation.

$$Deceration\ rate\ (unit\text{:}\ feet/s^2) = \begin{cases} 0; t < 0.25 \\ 65.7(t - 0.25); 0.25s \le t < 0.6s \\ 23; t > 0.6s \end{cases}$$

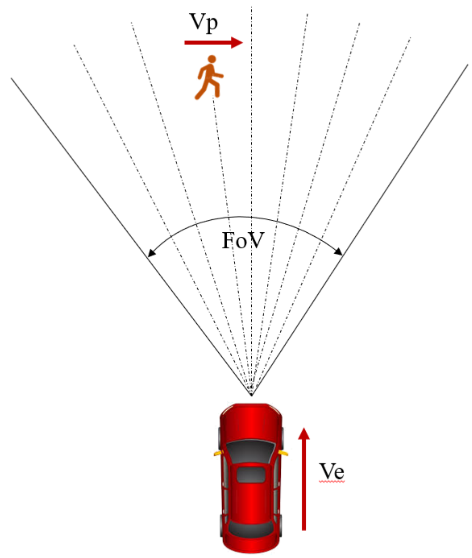
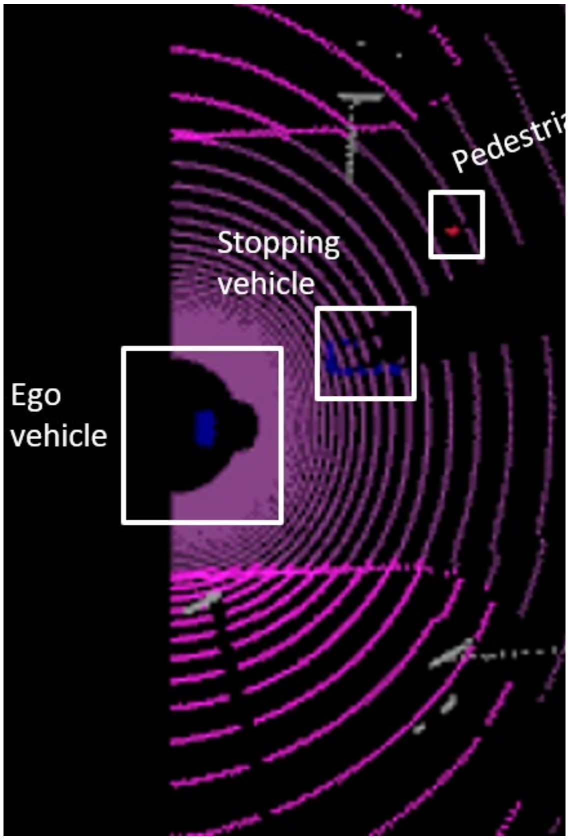
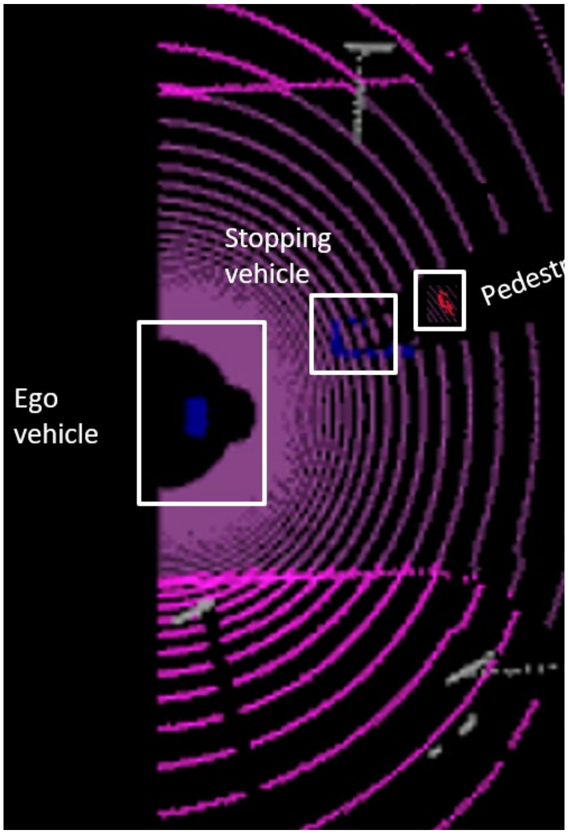


Figure 2 Illustration of pedestrian detection and FoV of sensor

While the effectiveness of the AEB system on avoiding pedestrian crashes has been validated in the previous studies [27], it remains unclear if the pedestrian is occluded by other vehicles. As shown in Figure 3(b), the sensor of the ego vehicle could not detect the pedestrian since the pedestrian is occluded by the stopping vehicle. In that case, there might not be enough time to activate the brake system to decelerate to avoid collisions. Hence, further investigations are needed to explore the effectiveness of the AEB system under the occlusion conditions.





(a) Not occlusion condition (b) Occlusion condition

Figure 3 Illustration of occlusion and not occlusion conditions

2.3 Simulation scenarios

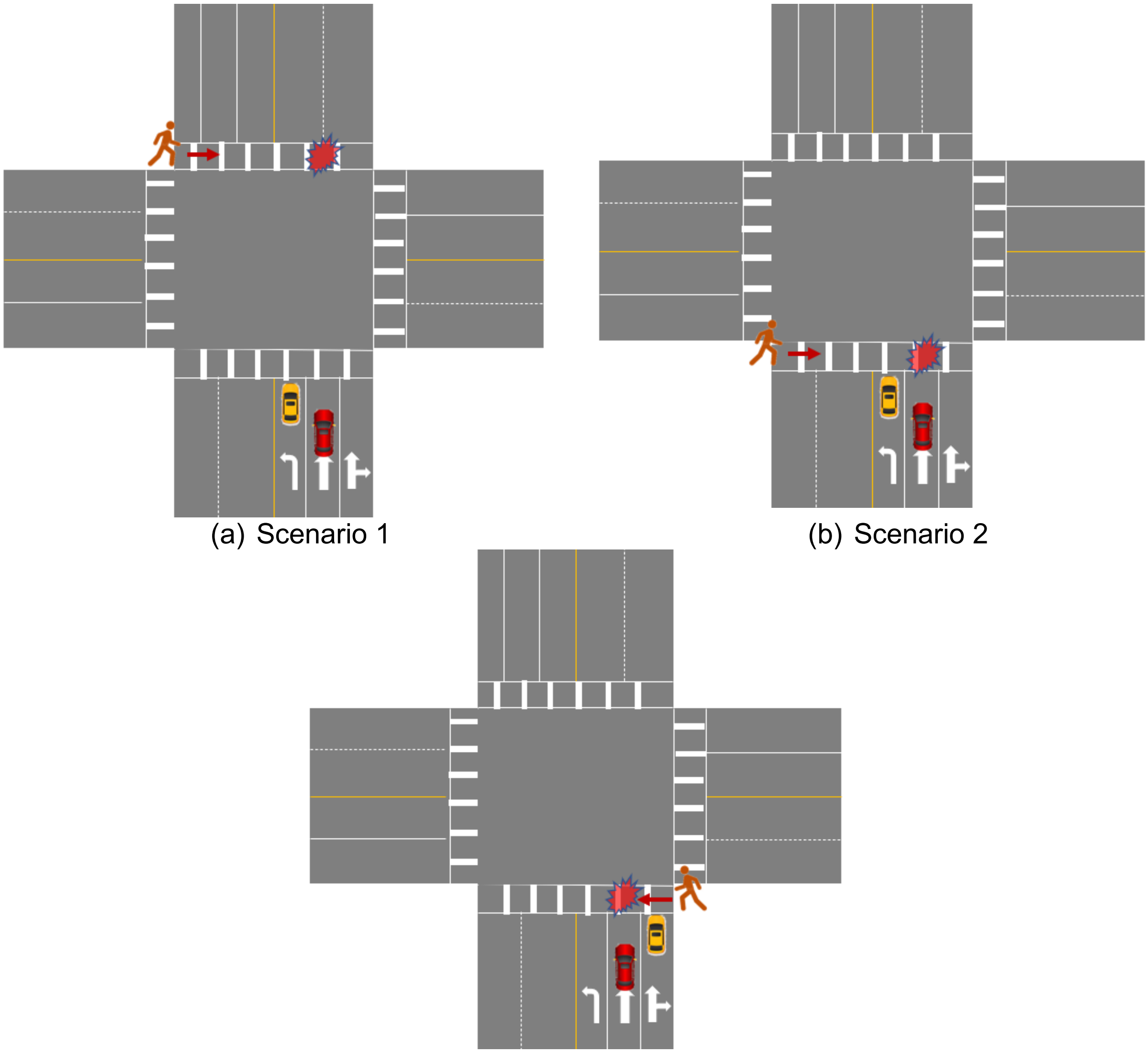
2.3.1 Occlusion scenarios

In this study, three common occlusion scenarios of pedestrians for the through vehicles were investigated based on our previous study about pedestrian crashes [3]. The three scenarios are summarized as follows:

- Scenario 1: the ego vehicle is going through, while a pedestrian is walking on the crosswalk of the ego vehicle's exiting approach and the pedestrian is occluded by a vehicle on the left-turn lane (Figure 4(a))

- Scenario 2: the ego vehicle is going through, while a pedestrian is walking on the crosswalk of the ego vehicle's entering approach and the pedestrian is occluded by a vehicle on the left-turn lane (Figure 4(b))
- Scenario 3: the ego vehicle is going through, while a pedestrian is walking on the crosswalk of the ego vehicle's entering approach and the pedestrian is occluded by a vehicle on the right-turn lane (Figure 4(c))

As illustrated in Figure 4, the pedestrian could be occluded by the stopping vehicle. If occluded, the pedestrian could not be detected by the sensor of the AEB system of the ego vehicle and the braking system would not be activated even reach the threshold. The potential collision points are also highlighted in the figure. In this study, a typical intersection in the Carla map- Town 3 is selected. The entering approach contains three lanes: one is left lane, one is through only lane, and one is through and right lane. The ego vehicle is on the middle lane and it will drive from the upstream to the intersection. It is assumed that the ego vehicle arrives at the intersection during the green time and it will pass the intersection without a stop. In addition, the intersection has crosswalks on which the pedestrian could walking across the intersection. The pedestrian is assumed to crossing the intersection during the red light without seeing the coming through vehicle. Hence, a collision is highly likely to happen and the effectiveness of the AEB system could even be reduced.



(a) Scenario 1 (b) Scenario 2

(c) Scenario 3

Figure 4 Illustration of simulation scenarios

2.3.2 Agents' motion states and system parameters

The development of simulation cases considered the driving speed of the ego vehicle and the crossing speed of the pedestrian in the different study scenarios. As shown in Table 1, six crossing speeds for the pedestrian are simulated, from 2 feet/s to 12 feet/s, similar to the previous study [27]. To simulate different conditions when the ego vehicle has a collision with the pedestrian, an offset time was used to describe when the pedestrian starts to cross the intersection based on the arrival time of the ego vehicle to the collision point. According to the previous study [28], six offset time was used in this study. Six ego vehicle's speed categories from 25 mph and 50 mph, which are the typical driving speed on the partial access-control road. Hence, the total combinations considering the pedestrian speed, ego vehicle speed, and the offset time for the pedestrian to cross are 216 for each scenario.

Table 1 Motion states of ego vehicle and pedestrian

Parameter	Value	Step size	Counts
Pedestrian initial speed (feet/s)	2-12	2	6
Ego vehicle initial speed (through, mph)	25-50	5	6
Offset time for pedestrian to cross (s)	1-6	1	6
Total	-	-	216

As described above, the maximum deceleration rate to achieve the target speed is 3.28 $feet/s^2$. Besides having to brake due to the curve as described above, the braking process would not consider other interactions with the surroundings once activated. The braking system is activated if the time to collision (TTC) reaches the threshold and the pedestrian is not occluded by the stopping vehicle. If the pedestrian is occluded by the stopping vehicle, the activation time of AEB could be delayed. Three TTC thresholds to activate AEB were tested from 1 to 3 seconds. Besides, the sensor's field of view (FoV) could affect the time when the pedestrian could be detected and then affect the activation time if under dangerous condition. Hence, five different angles of FoV were tested. Hence, there are 16 AEB control cases (i.e., 15 with AEB control and 1 without AEB control) included. A total of 10,368 (3 scenarios × 216 motion states ×16 AEB control cases) simulation runs were conducted to evaluate the effects of AEB under occlusion conditions.

Table 2 AEB control cases

Parameter		Value	Step size	Counts
AEB control	Sensor FoV (angle)	60-180	30	5
	TTC threshold to activate AEB (s)	1-3	1	3
No AEB control		-	-	1
Total		-	-	16

The model of the ego vehicle in this study is a typical passenger car that has a length of 16.5 feet and a width of 6.6 feet. The LiDAR sensor locates at the top front part of the ego car 1.6 feet away from the center of the ego vehicle. The sensor parameters in this study were based on as the following:

- Upper FoV: 15°
- Lower FoV: -25°
- Number of channels: 64
- Detection ranges: 300 feet
- Rotation frequency: 20 HZ
- Points per second: 500,000

2.4 Evaluation methods

Different measures were included to evaluate the performance of the AEB system. The output information from the Carla simulation such as agent center position (x, y) in the global coordinate system, agent speeds, yaw angles of the ego vehicle, and vehicle dimension could be used to compute the measures. First, the collisions could be determined by the geometrical overlap of the agent contours, which could be calculated by each time frame. As shown in Figure 5, the position of both the ego vehicle and the pedestrian at the collision time could be identified. By using the geometrical features of the ego vehicle and the pedestrian, the relative impact location to the center of the respective contour edge can be estimated. Besides, the impact speed of the ego vehicle could be obtained for the evaluation as higher speed would result in more severe pedestrian crashes [5]. During the simulation, the information about whether the pedestrian is occluded (i.e., the pedestrian could not be detected by the LiDAR sensor even in the detection range) could be recorded. Hence, the duration of occlusion could be obtained to explore the effects of occlusion on the effectiveness of the AEB system.

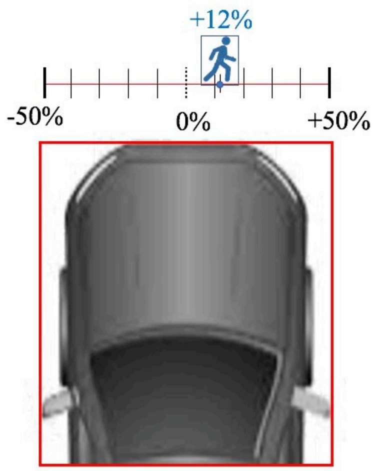


Figure 5 Collision location with the respect to the center of the corresponding contour edge (in %)

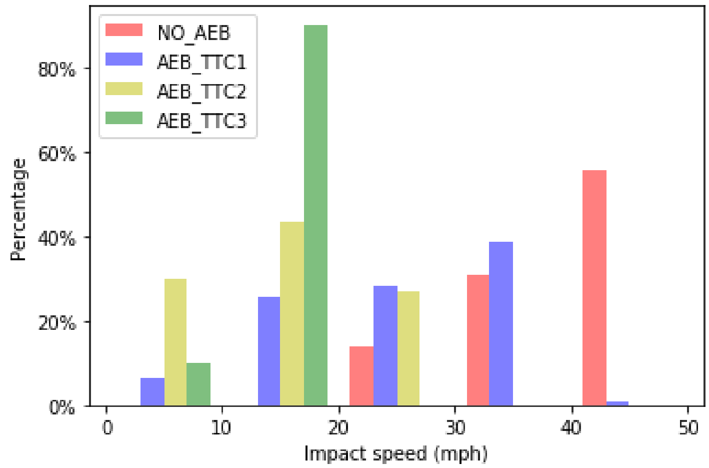
3 Results and discussions

To validate the effectiveness of the AEB under occlusion conditions, the simulation without the AEB braking system was initially simulated as the baseline case. Under this condition, it is assumed that the ego vehicle is not able to react to take any deceleration maneuvers. For each scenario, a total of 3456 simulation runs (216 motion states * 16 AEB control cases) were conducted to reflect different motion statuses of the ego vehicle and the pedestrian. Corresponding to each case without AEB, fifteen simulations with AEB were conducted considering the different FoVs and AEB activate times. Three TTC thresholds to activate AEB were tested. For each threshold, the number of simulation runs is 1,080 (216 motion states * 5 FoV angles) in each occlusion scenario. The percentages of collisions over the simulation cases are summarized in Table 3. Without AEB, more collisions could be found in Scenario 3 (i.e., the pedestrian is occluded by a vehicle at the right side of the ego vehicle). The AEB system could still reduce the number of collisions significantly. With the increase of the activation threshold, more collision could be avoided. If the threshold is 1 second, the ego vehicle would still hit the pedestrian in around 20% of cases.

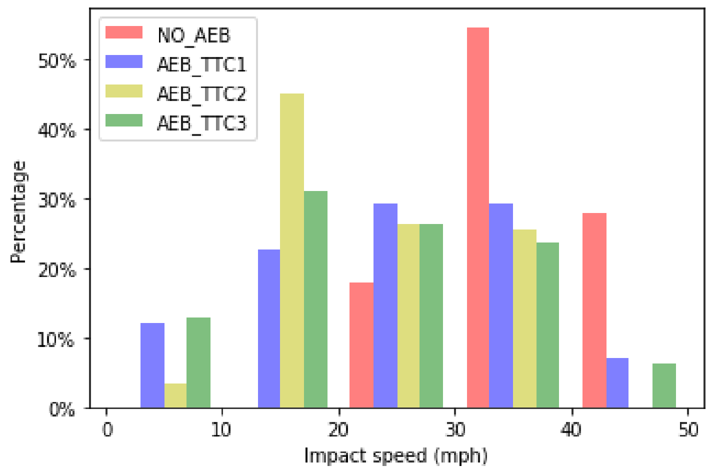
Table 3 Summary of number of collisions under different conditions

Scenario	Measures	Without AEB (number of cases=216)	TTC threshold to activate AEB (AEB_TTC) (number of cases per threshold=1080)		
			1 second	2 seconds	3 seconds
Scenario 1	Percentage	33.80%	18.61%	3.43%	0.93%
	Reduction percentage	-	15.19%	30.37%	32.87%
Scenario 2	Percentage	28.70%	19.35%	13.80%	10.19%
	Reduction percentage	-	9.35%	14.91%	18.52%
Scenario 3	Percentage	50.56%	19.17%	9.17%	5.19%
	Reduction percentage	-	31.39%	41.39%	45.37%

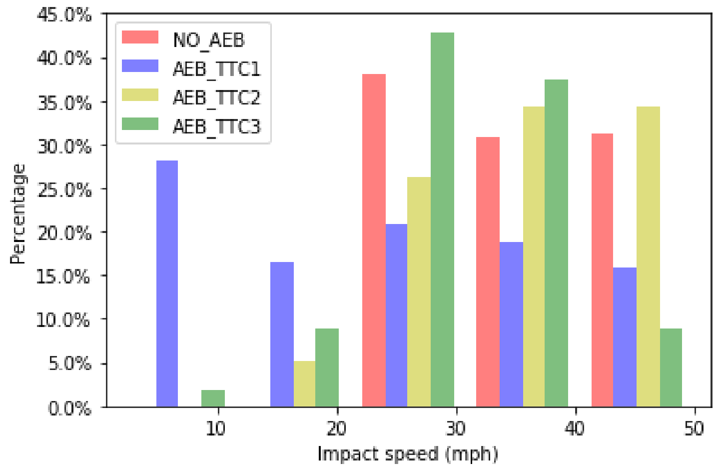
The percentage of the impact speed once a collision occurs between the ego vehicle and the pedestrian was calculated for different AEB control conditions. The results are presented in Figure 6. The figure shows that higher impact speeds could be observed under the no AEB conditions, leading to more severe pedestrian crashes. In the cases when the pedestrian is occluded by the vehicle on the left-turn lane, the impact speeds get reduced with the increase of the activate threshold. However, in the cases when the pedestrian is occluded by the left-turn vehicle, the impact speeds tend to be higher with the increase of the activation time. It is because that it is more dangerous under this case and the cases which are not avoided by the AEB system with a longer activation time are more critical cases with higher initial speeds.



Scenario 1



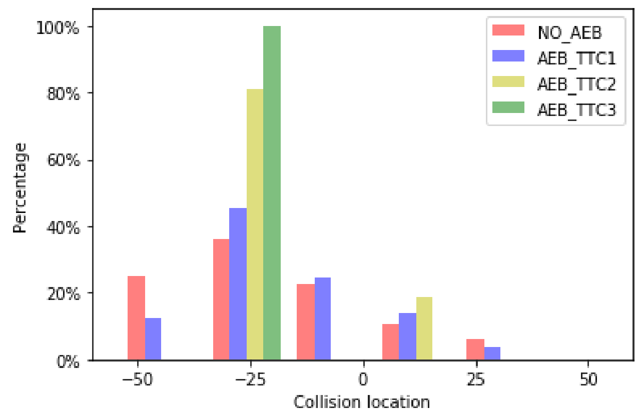
Scenario 2



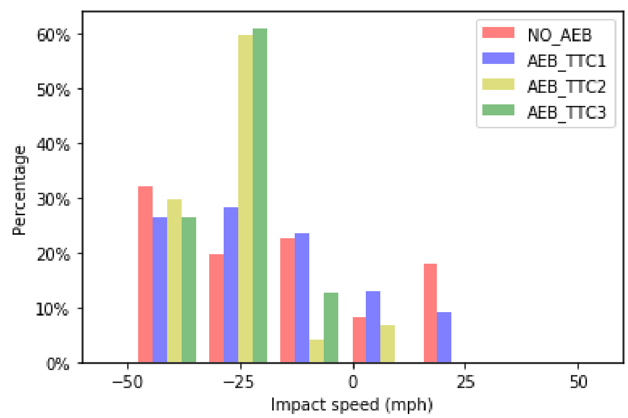
Scenario 3

Figure 6 Distribution of crash speed

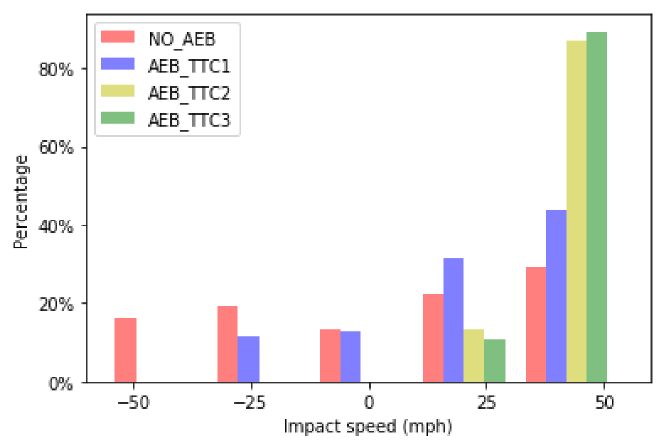
Figure 7 presents the results about the collision location related to the front center of the ego vehicle. The distributions of collision points among different AEB cases in the same scenario are the same. As expected, more collision points are at the left side of the ego vehicle in Scenarios 1 and 2 since the pedestrian crossed the intersection from the left side of the ego vehicle. Similarly, more collision points are found on the right side in Scenario 3.



Scenario 1



Scenario 2



Scenario 3

Figure 7 Normalized collision location to the front center of the vehicle

In the 3 scenarios, there are 73, 62, and 109 cases in which the ego vehicle hit the pedestrian without the AEB system. In the same scenario that the ego vehicle without AEB has a collision with the pedestrian, the AEB could either avoid the collision or reduce the impact speed compared to the condition without AEB. For each scenario, the occlusion time was collected and compared between the 'collision avoided' (i.e., the collision could be avoided by the AEB) and 'collision speed reduced' (i.e., the collision could be avoided by the AEB while the impact speed gets reduced) conditions. ANOVA test has been conducted to compare the occlusion time under the 2 different effect conditions. As shown in Figure 8, the occlusion time is significantly different between the 'collision avoided' and 'collision speed reduced' conditions. Longer occlusion time could be observed for the 'collision speed reduced' conditions. It indicates that the occlusion could make the sensor unable to detect the risky conditions and delay the activation of the AEB braking system. Under the occlusion condition, the effectiveness of AEB could get reduced.

ANOVA test for Scenario 1

	mean of occlusion time (s)	P_value
collision speed reduced	1.910	<0.001
collision avoided	0.527	

ANOVA test for Scenario 2

	mean of occlusion time (s)	P_value
collision speed reduced	1.081	<0.001
collision avoided	0.869	

ANOVA test for Scenario 3

	mean of occlusion time (s)	P_value
collision speed reduced	2.249	<0.001
collision avoided	1.143	

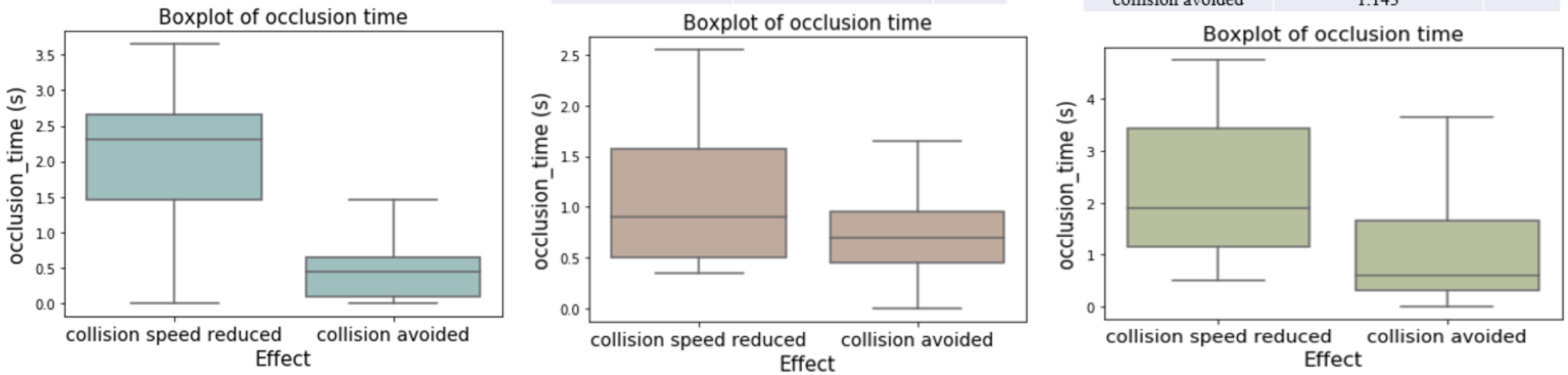


Figure 8 Comparison of occlusion time for different collision avoidance results

As discussed above, for the same condition, the AEB could either avoid hitting a pedestrian or reduce the impact speed if the collision could not be avoided. As the AEB is more effective if the corresponding collision gets avoided, a modeling analysis is conducted to further explore the effects of AEB under different conditions. A binary variable is used to indicate if a collision is avoided (indicator=1) or the impact speed for the collision get reduced (indicator=0). A logistic regression model is estimated to quantify the impact of different factors on the AEB effectiveness including the pedestrian initial speed, ego vehicle initial speed, TTC threshold to activate the AEB, occlusion time, FoV, and scenario. The results are summarized in Table 4. All factors except the FoV are significant in the model. A collision could be more likely to get avoided if the pedestrian walks faster since it takes less time for the pedestrian to cross the intersection and the occlusion time is less. The ego vehicle's speed has the opposite effect on the effectiveness of AEB. The higher speed of the ego vehicle makes it difficult to reduce the speed to avoid collisions. It is expected that the ego vehicle could brake earlier with the longer TTC threshold to activate the AEB and avoid the collision. As discussed above, the effectiveness of AEB gets reduced if the pedestrian is occluded longer. Based on the effects of the TTC threshold to activate AEB and occlusion, a longer TTC threshold is needed if a long occlusion time is expected. Compared to Scenario 1, the effectiveness of the AEB system gets reduced in Scenarios 2 and 3 in which the pedestrian is closer to the stopping vehicle and easier to get occluded.

Table 4 Logistic regression model result for AEB' effectiveness

Variable	**Mean**	**Standard error**	**Z value**	**p_value**
Intercept	1.081	0.490	-2.206	0.0274
Pedestrian's initial speed	0.920	0.109	-8.422	<0.001
Ego vehicle's initial speed	-0.277	0.017	15.906	<0.001
TTC threshold to activate the AEB	1.582	0.104	-15.145	<0.001
Occlusion time	-0.297	0.071	4.189	<0.001
Scenario (reference=scenario 1)				
Scenario 2	-1.868	0.152	12.321	<0.001
Scenario 3	-1.222	0.246	4.967	<0.001

4 Conclusions

This study introduced an open-source approach by using the CARLA virtual simulator to evaluate the effectiveness of the AEB system under the occlusion conditions. The AEB control algorithm was developed in the virtual simulator. The evaluation was conducted by exploring the collision between a pedestrian crossing at the red light and a through vehicle, which is one of the most dangerous conditions at intersections. Three scenarios in which the pedestrian was occluded by a stopping vehicle on either the left-turn or right-turn lane were generated for the evaluation. By considering different motion statuses of the ego vehicle and pedestrian, and the AEB controls, a total of 10,368 cases were generated in the simulation platform. Different measures including the percentage of cases with collisions, impact speed of the collision, and collision locations were adopted to evaluate the effectiveness of AEB under the occlusion condition extensively. The results suggested that the AEB could still effectively avoid collisions between the ego vehicle and the crossing pedestrian. However, the effectiveness of the AEB would get reduced by the occlusion. The longer the pedestrian was occluded by the stopping vehicle, the more the effectiveness of AEB got reduced. The results also suggested that a larger TTC threshold to activate the AEB could improve the effectiveness. In addition, a logistic regression model was developed to explore the effects of other factors. The modeling results suggested that the pedestrian's and ego vehicle's speeds could have significant effects on the effectiveness of the AEB system. Furthermore, different effectiveness of AEB could be found in different occlusion scenarios.

While the effectiveness of the AEB system has been evaluated extensively in this study, the pedestrian is occluded by a stopping vehicle at intersections. The current study could be extended by considering the scenarios in which the pedestrian is occluded by multiple moving vehicles at intersections or crosswalks at segments. Also, since the study confirmed that the effectiveness of the AEB system gets reduced under the occlusion conditions, it is important to explore the cooperative perception to reduce the occlusion through the connected vehicle technology.

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