Situation-Aware Left-Turning Connected and Automated Vehicle Operation at Signalized Intersections

Sakib Mahmud Khan, Ph.D.*
Glenn Department of Civil Engineering
Clemson University
351 Fluor Daniel Engineering Innovation Building, Clemson, SC 29634
Email: sakibk@g.clemson.edu

Mashrur Chowdhury, Ph.D., P.E., F.ASCE
Eugene Douglas Mays Endowed Professor of Transportation and Professor of Automotive Engineering
Clemson University
Glenn Department of Civil Engineering
216 Lowry Hall, Clemson, South Carolina 29634
Email: mac@clemson.edu

*Corresponding author
Word Count: 6,722 words + 1 table (250 words per table) = 6,972 words
Submission date: August 1, 2019
ABSTRACT

One challenging aspect of the Connected and Automated Vehicle (CAV) operation in mixed traffic is the development of a situation-awareness module for CAVs. While operating on public roads, CAVs need to assess the surrounding, especially intentions of non-CAVs. Generally, CAVs demonstrate a defensive driving behavior, and CAVs expect other non-autonomous entities on the road will follow the traffic rules or common driving norms. However, the presence of aggressive human drivers in the surrounding environment, who may not follow traffic rules and behave abruptly, can lead to serious safety consequences. In this paper, we have addressed the CAV and non-CAV interaction by evaluating a situation-awareness module for left-turning CAV operations in an urban area. Existing literature does not consider the intent of the follower vehicle for a CAV’s left-turning movement, and existing CAV controllers do not assess the follower non-CAV’s intents. Based on our simulation study, the situation-aware CAV controller module reduces 40% of the abrupt braking of the follower non-CAVs for the scenario of 600 vphpl on the opposing through movement, compared to the base scenario with the autonomous vehicle without considering the follower vehicle’s intent. For opposite through traffic volumes with 800 and 1000 vphpln, the reduction decreases to 10%. The analysis shows that the average travel time reductions for the opposite through traffic volumes of 600, 800 and 1000 vphpln are 61%, 23%, and 41%, respectively, for the follower non-CAV if the follower vehicle’s intent is considered by a CAV in making a left turn at an intersection.

Keywords: Connected Automated vehicle, Autonomous vehicle, Situation-aware, V2I, aggressive, rear-end
INTRODUCTION

With the emergence of innovative computation and networking solutions, and novel sensor technology, Connected and Automated Vehicle (CAV) will be mainstream in the future transportation system. However, CAVs will have to co-exist with the non-CAVs (i.e., human-driven vehicles) in the foreseeable future, and interacting with humans for the shared roadway spaces can be challenging for CAVs. CAVs are operated by programmable controller software, and the logics embedded in the controller software are based on traffic rules and common driving norms/code of conduct. By default, CAVs are programmed to be ‘defensive’, which implies that the controllers are not allowed to violate any traffic rules. On the contrary, the driving behavior of different human drivers varies significantly. Based on the weather effects, and demography, psychology, and physical condition of the driver, humans can behave significantly different from each other. The driving behavior can also change based on the surrounding road conditions (Ahmed et al., 2019). In terms of aggressiveness, driver behavior can range anywhere from aggressive to non-aggressive and anything in-between. Due to the aggressive nature of human drivers, a human can accelerate/decelerate abruptly, and maintain a very little headway while following vehicles in front of them. This behavior often results in road rages or serious crashes. In urban areas, the presence of traffic signal controls could often lead to aggressive driving behavior. The follower aggressive driver can cause rear-end crashes, if the leading vehicle suddenly decides not to cross the intersection, and applies the brake. Also, if the front vehicle does not make any turn during the permissive phase, the follower aggressive vehicle has to face longer waiting time, and this can lead to road rage.

In this research, we specifically focus on scenarios in an urban Transportation Cyber-Physical Systems (TCPS) environment where CAVs operate in the mixed traffic stream. In an urban TCPS, the physical components include CAV sensors and actuators, traffic signal controllers, roadside units, and video cameras. The cyber components include wireless communication, CAV controller software, and computing software in the roadside unit. Based on the in-vehicle sensor captured data about the surrounding environment, the CAV controller manages the CAV movement. The objective of this research is to design and evaluate a situation-aware CAV controller module, which will operate in response to an aggressive human driver and consider the intent of aggressiveness in the CAV decision-making controller module. As shown in Figure 1, a CAV controller module is developed in this study, which will consider the following vehicle’s intent while making left-turn at an intersection after finding the appropriate gap in the opposite through traffic stream to minimize abrupt braking by the following vehicle, and/or to minimize the waiting time of the following vehicles.

Existing literature does not consider the intent of the follower vehicle for left-turning movement (Wolfermann, Alhajyaseen and Nakamura, 2011; Alhajyaseen, Asano and Nakamura, 2012; Dias, Iryo-Asano and Oguchi, 2017; Gu et al., 2017). Existing CAV controllers do not assess the follower vehicle’s intent. Based on the 28-month Autonomous Vehicle Disengagement Reports Database (September 2014-January 2017), 89% of the total crashes for Autonomous Vehicles
(AVs) occurred at intersections, 69% of the total crashes occurred with AV speed less than 5mph, and 58% of the crashes were rear-end caused by following human drivers (Favarò et al., 2017). A 2016 survey found that 37% of Americans among 2,264 participants were concerned about the interaction of AVs and non-AVs (Cox Automotive, 2016). This research focuses on developing a situation-aware CAV controller module that will enable safe and efficient left-turns at an intersection considering the following vehicle’s aggressiveness. The controller module avoids any abrupt braking incidents of the follower vehicle and minimizes the intersection wait time of the follower. Situation-aware CAVs dynamically identify the intent of the follower vehicle using sensor captured data and adjust speed in real-time to reach the intersection. A video camera at the intersection will monitor the opposite through traffic stream, and using Vehicle-to-Infrastructure or V2I communication, the information will be communicated to the CAVs. In the future, when all vehicles will be connected, the gap information can be derived from the connected vehicle data using Vehicle-to-Vehicle communication. CAVs will identify the appropriate gaps in the opposite through traffic stream and accelerate/decelerate to reach the intersection to capture the appropriate gaps and clear the shared lane, which will be used by the following vehicle to move in through direction and clear the intersection. The following sections discuss related studies, and the evaluation scenario and findings from this research.

![Situation-aware Left-turning CAV Operation](image)

**Figure 1 Situation-aware Left-turning CAV Operation**

**RELATED STUDY**

The following subsections discuss the related studies about driver aggressiveness, rear-end collision mitigation approaches and situation-aware CAVs.

**Driver Aggressiveness Identification**

The aggressive driver behavior was previously studied using data from the smartphone, where the authors identified the acceleration behavior of both aggressive and non-aggressive
drivers to provide feedback in real-time to the corresponding drivers about their driving behavior (Vaiana et al., 2014). The types of aggressive behavior included excess speeding, abrupt braking, lane changes, and aggressive U-turns. The authors in (Vaiana et al., 2014) considered the driver experience and road surface condition to identify the boundary values of acceptable longitudinal and lateral accelerations. The smartphone-based GPS sensor was used to obtain the real-time acceleration rate of the vehicle, and when the acceleration exceeds the allowable threshold, drivers can be alerted about their aggressive behavior in real-time. In another study, the aggressiveness behavior of a subject vehicle was identified based on the vehicle's current lane deviation possibility, speed and estimated collision time with the front vehicle (Kumtepe, Akar and Yuncu, 2016). The authors used both an in-vehicle sensor and camera sensor to collect the required data and trained a machine learning-based classifier (i.e., support vector machine) to identify aggressive driving behavior. The machine learning-based classifier achieved 93% accuracy to classify drivers according to their aggressive driving behavior. Vehicle trajectory data was used in another study, where the authors used relative speed, average speed, distance to leading vehicles, longitudinal jerk and lane change data from the I80 corridors in California to identify driving behavior of a subject vehicle (Cheung et al., 2018). The authors interviewed 100 participants (whose driving data were not included in the I80 database) to identify the driving behavior and level of attentiveness of the subject vehicle driver. The driving behavior identification module was incorporated into a simulated vehicle navigation system to ensure safe navigation. Both speed and lateral and longitudinal acceleration were used to derive the mathematical model of driver aggressiveness in another study, where the authors used real-world data from vehicles (Rodriguez Gonzalez et al., 2014). The authors developed a classifier using Gaussian Mixture Models and maximum-likelihood, which achieved a 92% accuracy to identify each driver’s behavior. In another study, the authors used acceleration and speed of the leading vehicle, and the time gap between the leading vehicle and following vehicle to cluster different driving behaviors (Zhang et al., 2017). Based on the driving behavior and acceleration of the leading vehicle, the car-following behavior was found to be linearly stable. Vehicle data from the I80 corridors in California, available via the Next Generation Simulation database, were used to develop the car-following model. In this research, the driver's intent of the follower vehicle needs to be identified. In an urban TCPS, with the following vehicle’s acceleration/deceleration rate (Wei, Dolan and Litkouhi, 2013; Rodriguez Gonzalez et al., 2014; Zhang et al., 2017), we can directly estimate whether the follower vehicle will slow down while following the leader left-turning CAV. However, time headway is another important parameter (Zhang et al., 2017), as with time headway we can monitor how closely the follower vehicle is following the leader CAV in the urban area. A closely-following follower vehicle is considered to be more aggressive, compared to a follower vehicle maintaining a high headway. Thus we have used both the acceleration of the following vehicle and time headway between the subject vehicle and following vehicle to identify the following vehicle’s aggressiveness in this study.
Rear-end Collision Mitigation

The sudden brake by follower aggressive human drivers can increase the likelihood of rear-end crashes. The aggressive driving behavior (i.e., speeding) was the contributing factor in 26% of all traffic fatalities in 2017 (NHTSA, 2019). For autonomous vehicles, based on the 28-months Autonomous Vehicle Disengagement Reports Database (September 2014-January 2017), 58% of the crashes were rear-ended, where follower vehicles were human-driven (Favarò et al., 2017). In one study, the authors found tactile and audible collision warning systems can reduce the rear-end collision events for human drivers by increasing the brake response time, while the drivers were engaged in a cell phone conversation (Mohebbi, Gray and Tan, 2009). In a similar study, to identify the rear-end collision mitigation method for human drivers, the authors found that the audio and visual warning assisted to release the accelerator faster by the human drivers to avoid a potential rear-end crash (Lee et al., 2002). Due to the faster accelerator release response, drivers could apply brakes gradually to avoid a collision. Another rear-end collision mitigation system for human drivers was the use of green signal countdown timer, which was found to reduce rear-end crashes during the yellow interval (Ni and Li, 2014). The rear-end collision anticipation warning can be provided using vehicle-to-vehicle communication. As the rear-end collision avoidance application needs to satisfy strict delay constraint, the authors in one study developed a rear-end collision avoidance strategy using IEEE 802.11 standard and multi-hop broadcast system (Ye, Adams and Roy, 2008). Using simulated single-lane and multi-lane scenarios, the rear-end crash avoidance strategy reduced almost all rear-end crashes for the following vehicles. AVs still lack a mechanism to avoid rear-end crashes when the follower vehicle is a human driver (Favarò et al., 2017). In this study, we have developed such a control module for left-turning autonomous vehicles to reduce the rear-end crash possibility and reduce road-rage events.

Situation-aware CAV

Earlier research developed the situation-awareness for AVs based on Partially Observed Markov Decision Process, where an autonomous agent chooses a policy for taking an action, without knowing the system state, to maximize rewards (Liu et al., 2015). The authors considered intention recognition and sensing uncertainties in the framework and measured the conflicting vehicle intention with respect to speed. Compared to the reactive approach, the situation-aware autonomous vehicle showed fewer failure rates in different scenarios (such as interacting at roadways with T-intersection and roundabout), meaning autonomous vehicles did not always purposefully give way to the conflicting vehicles. Rather, autonomous vehicles acted proactively to reduce the waiting time. A similar method was used in another research, where the authors used four parameters (i.e., distance to the intersection, yaw rate, speed, and acceleration) to identify each vehicle’s intent at an unsignalized intersection (Song, Xiong and Chen, 2016). The reward function includes reward due to adherence to the traffic law, reduction in travel time and improvement in safety. Using Prescan software, the autonomous vehicles were modeled and using a driving simulator, research participants drove the human-driven vehicles. The analysis showed that, without considering the human intention, the autonomous vehicles were confused about
whether to cross the intersection. In another study, the authors discussed the use of temporal domain prediction instead of spatial domain prediction to predict uncertainty in other agent’s intent (McAree, Aitken and Veres, 2017). For autonomous agents, the authors showed that the required time to reach a destination, and maneuvering time can be designed as a Gaussian distribution. With Monte Carlo simulations, the authors demonstrated that the autonomous vehicle can safely maneuver through roundabouts while considering other vehicle’s predicted position in future times. In order to reduce conflicts among multiple agents, one study investigated the empathic autonomous agent which made decisions based on a utility function (this function depends on the acceptability of any action by all agents, based on the action’s future consequences) of everyone in the driving environment (Kampik, Nieves and Lindgren, 2019). Here, the empathic autonomous agent made the decision which was acceptable to everyone. In another study, autonomous vehicle considered the yielding intent of merging vehicles on the freeway entrance ramp (Wei, Dolan and Litkouhi, 2013). Using the acceleration value of the merging vehicle, the intent of the merging vehicle was recognized. Upon recognizing the intent, an autonomous vehicle would generate candidate strategies to minimize a cost function, which avoids conflict, passenger discomfort, excess fuel consumption, and undesirable operational outcomes. If the merging vehicles did not show the intent to yield, autonomous vehicles would slow down to avoid conflict. In this research, we have developed a situation-aware CAV controller module for one of the most critical interactions between CAVs and follower aggressive vehicles, which results in the most prominent crash type, i.e., rear-end crash, for real-life autonomous vehicles (Favarò et al., 2017).

**SITUATION-AWARE LEFT-TURNING CAV OPERATION**

Steps associated with the situation-aware left-turning CAV operation are shown in Figure 2(a). The situation-aware left-turning CAV operates depending on the surrounding situation, which for this research is an aggressive behavior of the following vehicle. If the following vehicle’s intent is identified, CAV can operate accordingly to prevent or minimize negative consequences, which include abrupt hard braking, and increased waiting time for the follower vehicle. Predicting the future condition of the surrounding traffic helps to take proper actions by an autonomous vehicle. In this case, the opposing traffic stream’s future condition will dictate the availability of the target gap at the intersection when the CAV will arrive at the intersection stop bar to initiate the left-turn maneuver. If the prediction is not accurate, the appropriate gap will not be available for a CAV. Finally, while taking the left turn, the CAV needs to confirm that adequate gaps are there so that there will be no direct conflict with the opposite through traffic stream and the subject CAV. The four steps, as shown in Figure 2(a), are discussed in the later subsections.
(a) Steps for the CAV left turn decision module

(b) Situation-aware left-turning CAV module components

Figure 2 CAV left turn steps and decision module

Figure 2(b) shows the components for the situation-aware control module for left-turning CAVs. The sensors used by this module include a rear-view camera, a GPS sensor, and a V2I...
communication radio. Using these sensors, the intent of the following vehicle (from the rear-view camera) and gaps in the opposite through traffic stream (from V2I communication radio using the analyzed intersection video feed from the roadside unit) are identified. If all vehicles are connected, the gap information can be derived from the connected vehicle data using Vehicle-to-Vehicle communication without any need of cameras installed at an intersection. The GPS sensor is used to identify the location of the CAV. Using the rear-view camera, the relative position of the follower is identified. Based on that the relative position of the follower aggressive vehicle and the CAV’s own position, the position of the follower vehicle is identified. The planning sub-module predicts the future possible gap in the opposite through traffic stream and identifies how CAV should operate in terms of a left turn at an intersection based on the existing road traffic conditions, and traffic signal status, while also considering the speed limit of major and minor streets. This sub-module identifies the final speed to be achieved by a CAV to reach and clear the intersection. Based on the criteria identified by the planning sub-module, the control sub-module runs the optimization to estimate the speed profile to be followed by the CAV.

**Intent Recognition of Following Vehicles**

As discussed earlier, the following vehicle can show either aggressive or non-aggressive behavior. In order to identify the intent, CAVs can consider the data regarding the following vehicle captured by its sensors. Different sensors can be used to obtain data from the following vehicles, and different types of data can be used. These sensors include radar, camera, and LIDAR. In this research, we have considered the following vehicle’s acceleration, and time headway between the CAV and following vehicle to identify the intent of the follower. The CAV follows a decision-making framework, shown in Figure 3(a), for its left-turn maneuver. At first, it detects if there is any follower vehicle. If the follower is present, the CAV sensor captures the data of the relative position of the following vehicle \( \Delta p_{t1} \) at time \( t_1 \). Based on its own position \( p_{t1} \) (captured by the GPS sensor available in the CAV), and \( \Delta p_{t1} \), the position of the follower vehicle \( p_{\text{follow},t1} \) can be estimated using Eq. 1. Using the following vehicle’s position for two consecutive times, \( t_1 \) and \( t_2 \), the speed \( v_{t2} \) at time \( t_2 \) can be estimated using Eq. 2. From the calculated speed \( v_{t2} \), the acceleration \( a_{t2} \) and time headway \( t_h_{t2} \) of the following vehicle at time \( t_2 \) can be estimated using Eq. 3 and 4, correspondingly.

\[
p_{\text{follow},t1} = p_{t1} + \Delta p_{t1} \quad (1)
\]

\[
v_{t2} = \frac{p_{\text{follow},t2} - p_{\text{follow},t1}}{t_2 - t_1} \quad (2)
\]

\[
a_{t2} = \frac{v_{t2} - v_{t1}}{t_2 - t_1} \quad (3)
\]
\[ th_{t_2} = \frac{\Delta p_{t_2}}{v_{t_2}} \]  

(a) Intent recognition framework

(b) Probability of aggressiveness based on acceleration and headway

(c) Probability of non-aggressiveness based on acceleration and headway

Figure 3 Intent recognition framework and the probability of intent
To identify the probability of the follower vehicle’s intent, we have used Bayes Theorem. Equations (Eq. 5 and 6) can be used to derive the probability of aggressiveness (A) or non-aggressiveness (NA) based on the attitude (Att) of the follower.

\[
\Pr(A|\text{Att}) = \frac{\Pr(\text{Att}|A)\Pr(A)}{\Pr(\text{Att}|A)\Pr(A) + \Pr(\text{Att}|\text{NA})\Pr(\text{NA})} 
\]

(5)

\[
\Pr(\text{NA}|\text{Att}) = \frac{\Pr(\text{Att}|\text{NA})\Pr(\text{NA})}{\Pr(\text{Att}|A)\Pr(A) + \Pr(\text{Att}|\text{NA})\Pr(\text{NA})} 
\]

(6)

The assumption is that there is an equal amount of chance for the follower vehicle to be aggressive or non-aggressive. Thus Pr(A) and Pr(NA) is equal to 0.5. In order to get the Pr(A|Att) and Pr(NA|Att), we have considered that the aggressive and non-aggressive behaviors follow the distribution as shown in Figure 3(b) and Figure 3(c), correspondingly. Studies conducted on urban arterials were reviewed to obtain the threshold values for both acceleration and time headway (Michael, Leeming and Dwyer, 2000; Berry, 2010). In an urban area, \(2\text{ms}^{-2}\) acceleration is considered to be aggressive (Berry, 2010). This value is considered as the mean of the Gaussian distribution and the standard deviation is considered to be \(\frac{4}{3}\text{ms}^{-2}\) (when the acceleration is less than \(2\text{ms}^{-2}\)). Beyond the mean acceleration, the follower vehicle will always be considered aggressive. As the CAV will have to decelerate, the follower vehicle should slow down, and the non-aggressive behavior would imply that the follower vehicle is slowing down. Thus, the distribution with the mean deceleration of \(-2\text{ms}^{-2}\) and the standard deviation of \(\frac{4}{3}\text{ms}^{-2}\) is considered as non-aggressive (when the deceleration is higher than the mean). With deceleration less than \(-2\text{ms}^{-2}\), the follower vehicle will always be considered non-aggressive. For time headway, a 1 sec time headway is considered to be the mean of aggressive behavior, while a 2 sec time headway represents a safe or non-aggressive behavior (Michael, Leeming and Dwyer, 2000).

**Prediction of Future Vehicle State of Opposite Traffic Stream**

Once a CAV identifies the intent of the follower vehicle, it will look for an appropriate gap in the opposite through traffic stream. The information about the opposite through traffic stream will be provided by the connected roadside unit, installed at the intersection via Dedicated Short-Range Communication, or DSRC. A camera installed at the intersection can be used to identify the gaps in the opposite through traffic and send them to the connected roadside unit for it to transmit to CAVs. In the future, when all vehicles will be connected, the gap information can be derived from the connected vehicle data using Vehicle-to-Vehicle communication. The assumption in this research is that the opposite through traffic stream will maintain a constant speed while reaching the intersection. However, this assumption is not valid where human drivers can take different actions (i.e., accelerate, lane change) at any given time when they are close to the intersection. Thus, when the CAV is at the intersection with an intent to initiate the left-turn, the gap may not be there. In order to ensure a safe left-turn, the CAV will assess the intersection
condition after reaching the intersection, in real-time, based on the data from the camera about the approaching opposite through traffic stream. Whenever the required gap is available, the CAV will initiate the left turn to safely cross the intersection and clear the path for the following vehicle.

**Opposite Traffic Stream Gap Estimation**

While taking a left-turn maneuver, two scenarios may exist. In the first one CAVs may not need to stop after reaching the intersection if there is a gap in the opposite through traffic stream right at that moment. CAV can take a left-turn without conflicting with any other vehicle after reaching the intersection at a minimum speed. This scenario can be handled by the CAV uninterrupted inflow and outflow speed profile, as shown in Figure 4(a). In the second scenario, the interrupted inflow and outflow speed profile will be active as the CAV will have to stop at the intersection due to the presence of approaching vehicles in the opposing through traffic stream. CAV will wait for the required gap to make a left-turn based on the arriving pattern of the opposing through vehicles and start the left-turn right away when the required gap is available.

(a) Speed profiles for CAV making left-turn
(b) Conflict area for left-turn maneuver

(c) CAV speed adjustment to reach the initial point of deceleration

Figure 4 Movement of CAV making a left-turn

For any two way corridor with ‘m’ number of opposite lanes and ‘n’ number of vehicles at a certain time period on the opposing lanes, the opposite direction lane can be annotated as ‘Opp’, and the same direction shared lane as ‘Same’. For the opposite direction lanes, the vehicles’ state is ‘Pass’ if they pass/clear the conflict area before the CAV is present at the intersection. The ‘App’ state means the vehicle from the opposite direction will approach the intersection conflict area, but it will not clear the conflict area before the CAV clears the conflict area. We have defined lane $\beta \in \{Opp_1, Opp_2, ..., Opp_m, Same\}$, and state $Se(Pass, App)$, and set of all vehicles, $N = \{1, 2, ..., n\}$. We have defined the vehicle sets in TABLE 1 based on the vehicles’ current lane and state (App for vehicles approaching the conflict area, and Pass for vehicles that will pass the conflict area).
**TABLE 1 Vehicle Set Explanation**

| Vehicle Set   | Explanation                                                                 |
|---------------|-----------------------------------------------------------------------------|
| $N_{A,P} := \{x | \beta_x = Opp_1, S_x = Pass, x \epsilon N\}$ | Group of opposing through vehicles in lane 1 that will pass the conflict area when CAV will reach the conflict area |
| $N_{A,A} := \{x | \beta_x = Opp_1, S_x = App, x \epsilon N\}$ | Group of opposing through vehicles in lane 1 that will approach the conflict area when CAV will reach the conflict area |
| $N_{B,P} := \{x | \beta_x = Opp_2, S_x = Pass, x \epsilon N\}$ | Group of opposing through vehicles in lane 2 that will pass the conflict area when CAV will reach the conflict area |
| $N_{B,A} := \{x | \beta_x = Opp_2, S_x = App, x \epsilon N\}$ | Group of opposing through vehicles in lane 2 that will approach the conflict area when CAV will reach the conflict area |
| $N_{C,P} := \{x | \beta_x = Opp_m, S_x = Pass, x \epsilon N\}$ | Group of opposing through vehicles in lane ‘m’ that will pass the conflict area when CAV will reach the conflict area |
| $N_{C,A} := \{x | \beta_x = Opp_m, S_x = App, x \epsilon N\}$ | Group of opposing through vehicles in lane ‘m’ that will approach the conflict area when CAV will reach the conflict area |
| $N_{D,A} := \{x | \beta_x = Same, x \epsilon N\}$ | Group of vehicles following the CAV in the same lane |

Figure 4(b) shows the conflict areas at the intersection for the left-turn maneuver with red bounding boxes. We assume that the CAV will follow a parabolic path while taking the left turn at the intersection. For a typical two-lane corridor, the distance to the conflict area of the opposite first lane from the intersection stop line is $L_2$, and the distance from the intersection stop line to the conflict area of the opposite first lane is $(L_1 + L_2)$, as shown in Figure 4(b). These distances can be computed with the Arc Length (AL) equation of the parabolic path, as shown in Eq. 7.

$$AL = \frac{1}{2}\sqrt{b^2 + 16a^2} + \frac{b^2}{8a} \ln\left(\frac{4a + \sqrt{b^2 + 16a^2}}{b}\right)$$  \hspace{1cm} (7)

For a typical two-lane-two-way corridor, $a$ and $b$ can be calculated as $a = 2.5w_l$ and $b = 3w_l$. $w_l$ is the lane width, and $w_{car}$ is the vehicle width. Here $d_l$ is the distance between the CAV direction stop line and end of the conflict area. We have defined $d_f$ as the distance between the stop line at lanes from which a CAV will start the left turn maneuver and the start of the conflict area. We have defined a distance threshold for both sides of the conflict area compared to the
parabolic path of the CAV. For the start and end of the conflict points, the distance thresholds beyond the CAV’s projected path are $\sigma$ and $\sigma+t$, as shown in Figure 4(b). Considering a two-lane-two-way corridor, both $d_l$ and $d_f$ from Figure 4(b) can be calculated from the following Eq. 8 to 11. Here the first lane means the closest opposite lane for the left-turning CAV, and the second lane means the farthest opposite lane, as shown in Figure 4(b).

\[
d_{l-\text{second lane},i} = 1.41\sqrt{\frac{w_l}{2} - \frac{w_{car,i}}{2}} - \sigma, \ i \in N_{B,p} \tag{8}
\]

\[
d_{f-\text{second lane},i} = 1.41\sqrt{\frac{w_l}{2} + \frac{w_{car,i}}{2}} + \sigma + t, \ i \in N_{B,A} \tag{9}
\]

\[
d_{l-\text{first lane},i} = \sqrt{\frac{w_l}{2} - \frac{w_{car,i}}{2}} - \sigma, \ i \in N_{A,p} \tag{10}
\]

\[
d_{f-\text{first lane},i} = \sqrt{\frac{w_l}{2} + \frac{w_{car,i}}{2}} + \sigma + t, \ i \in N_{A,A} \tag{11}
\]

Optimization of CAV Movement while Avoiding Conflict

Once the follower vehicle intention is known and gaps from the opposite through traffic stream are identified, the CAV controller module needs to estimate its speed profile for the remaining distance. The CAV will follow the speed profile, shown in Figure 4(a), to clear the path for the follower vehicles, or at least to minimize the waiting time for the follower aggressive vehicle. The speed of the turning vehicle can be modeled as a function of time with the polynomial of third-degree (Wolfermann, Alhajyaseen and Nakamura, 2011). The slope of a speed profile means acceleration, and slope of the acceleration profile is called a jerk. For an initial time, $t_o$ we express the speed, acceleration and jerk values as $v_0, a_0$ and $J_0$. We have defined the slopes of the vehicle jerk as $j$. The value of $a_0$ is zero. For any time $t$, the jerk, acceleration and speed can be calculated using the following Eq. 12, 13 and 14, respectively. The same equations can be applied to both inflow and outflow speed profiles.

\[
J_t = J_0 + jt \tag{12}
\]

\[
a_t = a_0 + J_0 t + \frac{1}{2} j t^2 \tag{13}
\]

\[
v_t = v_0 + a_0 t + \frac{1}{2} J_0 t^2 + \frac{1}{6} j t^3 \tag{14}
\]

In order to get the optimal speed profile, the optimization is computed in two steps. In the first step, the inflow speed profile is optimized using the optimized $j$ for the inflow. In the second
step, based on the output of the inflow optimization model, the outflow speed profile is optimized. The input of the optimization model is the initial inflow speed, $v_{o-inflow}$. The speed at which the CAV will reach the intersection needs to be close to zero, so the target speed range is considered to be within 0.1 $ms^{-1}$ to 2.5 $ms^{-1}$. The initial jerk $J_o$ is confined within the boundary of $1.5ms^{-3}$, as that is defined as the limit of the comfortable jerk (Treiber and Kesting, 2013). The boundary values for the slope of jerk ($j_{inflow}$) are derived from (Wolfermann, Alhajyaseen and Nakamura, 2011). The optimization objective, constraints and decision variables are given below.

Optimization objective for inflow:

$$\min (J_{T_{min-inflow}}) \tag{15}$$

Subject to,

$$0.1 ms^{-1} < v_{T_{min-inflow}} < 2.5 ms^{-1}$$

$$-1.5 ms^{-3} < J_{o-inflow} < 1.5 ms^{-3}$$

$$0.1 ms^{-4} < j_{inflow} < 0.8 ms^{-4}$$

$$0 s < T_{min-inflow} < T_{min-inflow,max}$$

$$a_{T_{min-inflow}}=0$$

Decision variables,

$$j_{inflow}, J_{o-inflow}, v_{T_{min-inflow}}, T_{min-inflow}$$

The maximum available time to reach the intersection stop line ($T_{min-inflow,max}$) can vary based on the traffic conditions and geometric characteristics of the corridor. Once the desired target speed ($v_{T_{min-inflow}}$) from the initial optimization is available, the second optimization is conducted for the outflow model. For this outflow, the optimization model is provided in the following Eq. 16. The boundary values for the slope of jerk ($j_{outflow}$) are derived from (Wolfermann, Alhajyaseen and Nakamura, 2011).

Optimization objective for outflow:

$$\min (J_{T_{min-outflow}}) \tag{16}$$
Subject to,

\[ v_{T_{\text{min-outflow}} \text{min}} < v_{T_{\text{min-outflow}}} < v_{T_{\text{min-outflow}} \text{max}} \]

\[-1.5 \, \text{ms}^{-3} < J_0-\text{outflow} < 1.5 \, \text{ms}^{-3} \]

\[-0.2 \, \text{ms}^{-4} < j_{\text{outflow}} < -0.6 \, \text{ms}^{-4} \]

\[ a_{T_{\text{min-outflow}}} = 0 \]

Decision variables,

\[ j_{\text{outflow}}, J_0-\text{outflow}, v_{T_{\text{min-outflow}}}, T_{\text{min-outflow}} \]

The maximum and minimum boundary values of the speed (after entering the side street) to be achieved by the CAVs \( v_{T_{\text{min-outflow}} \text{min}} \) and \( v_{T_{\text{min-outflow}} \text{max}} \) depend on the speed limit of the side street. Once the optimization is done, the distance required to initiate CAV deceleration to reach the intersection stop line \( d_{T_{\text{min-inflow}}} \) can be estimated with the following Eq. 17, where \( d_0 \) is zero.

\[
d_{T_{\text{min-inflow}}} = d_o + v_0 T_{T_{\text{min-inflow}}} + \frac{1}{2} a_o T_{T_{\text{min-inflow}}}^2 + \frac{1}{6} J_0 T_{T_{\text{min-inflow}}}^3 + \frac{1}{24} J T_{T_{\text{min-inflow}}}^4 \]  \hspace{1cm} (17)

The point from which the CAV needs to slow down is shown as ‘Initial Point of Deceleration’ in Figure 4(a). The distance between this initial point of deceleration and the intersection stop line is \( d_{T_{\text{min-inflow}}} \). In order to reach the initial point of deceleration, the CAV adjusts its speed to reach the point soon. The desired speed \( v_{\text{des}} \) to reach the slow down point can be calculated simply by dividing the current distance from the CAV to the initial point of deceleration with the available time. However, \( v_{\text{max}} \) is calculated to create a trapezoidal shape so that the CAV can smoothly increase its speed and slow down, as shown in Figure 4(c). The CAV chooses the appropriate gap which it can utilize so that the speed to reach the initial point of deceleration, \( v_{\text{max}} \) does not exceed the speed threshold (i.e., speed limit + 5 mph).

**CASE STUDY**

We have evaluated the situation-aware left-turning module for CAVs using a case study within a simulated environment. The following subsections discuss the case study area, base scenario, and situation-aware CAV module.
Study Area

A case study is conducted with a simulated intersection from Perimeter Road, Clemson to evaluate the performance of the situation-aware CAV controller module. To simulate the non-CAVs of the mixed traffic stream, we have used Simulation of Urban Mobility (SUMO) software, while to simulate CAVs and communication-infrastructure, we have used Webots. The major corridor of this intersection has two lanes, while the minor corridor has one lane. We have evaluated the simulated network with multiple scenarios while varying the opposite direction traffic. The traffic signal phase for the shared lane is considered to be permissive green, meaning left-turning vehicles need to wait for the appropriate gaps in the opposite through traffic stream. In this experiment, we have restricted the lane-changing capability of the follower vehicle. This scenario simply means that due to the presence of heavy traffic in the same direction, the follower aggressive vehicle cannot make any lane change. The author has considered 600, 800 and 1000 vehicle per hour per lane (vphpln) opposite through traffic. For the non-CAVs, the speed distribution is set up in such a way so that 95% of the vehicles drive within 70%-110% of the speed limit. The speed limit of the corridor is 30 mph. The comparison of the base scenario and situation-aware CAV is conducted based on 10 simulation runs for each scenario with different approaching through traffic volume from the opposite direction.

Base Scenario with Autonomous Vehicle

In this scenario, the AV does not have any communication capabilities and it does not have to consider the following vehicle’s intent (to yield or not yield) to make a left turn at the intersection. The AV uses the front camera to detect the opposite approaching vehicle, and based on the distance between the AV and the opposing vehicles, the AV calculates the gap and evaluates if the gap is acceptable. In a study conducted in California, the authors studied the left-turn gap acceptance value from 1573 observations (Ragland et al., 2006). For human drivers, the authors found that the 15%, 50% and 80% of the accepted gap lengths were 4.1, 6 and 8.6 seconds, respectively. For this study, after trial-and-error with the simulated scenario, we have found 5 seconds is the accepted gap for the AV left-turn maneuver. For gaps less than 5 seconds, a collision occurs between AVs and opposite through non-AVs. In this scenario, the follower vehicle starts the journey after 8 seconds of the leader AV.

Situation-aware CAV

The goal of the situation-aware CAV controller module is to clear the path from the shared lane for an aggressive through vehicle, so that the aggressive driver does not need to apply a hard brake. If no safe gap is available, the CAV will try to clear the path of the aggressive follower vehicle by making a left-turn as soon as possible. We have considered the maximum available time to reach the intersection stop line \( T_{min-inflow,max} \) as 60 seconds for this analysis, and the maximum and minimum boundary values of the target speed (after entering the side street) to be achieved by the CAVs \( v_{T_{min-outflow,min}} \) and \( v_{T_{min-outflow,max}} \) as 6 m/s and 7 m/s.
respectively, based on the minor street speed limit from the study area. In this research, we have used the acceleration of the follower vehicle and time headway between the CAV and follower vehicle to identify the aggressiveness or non-aggressiveness of the follower. The CAV uses a back view camera to capture data related to the following vehicles, following Eq. 1 to Eq. 4. The range of cameras currently used in AVs can be up to 250 meters (Taraba et al., 2018). In this research, we have considered the range to be 200 meters. Figure 5 shows the rear camera window of a situation-aware CAV while tracking the follower vehicle. Similar to the base scenario, here the follower vehicle starts the journey after 8 seconds of the leader CAV. The author has used MIDACO solver to solve the optimization function in real-time (Schlueter et al., 2013).

The arrival time of the vehicles approaching from the opposite through needs to be estimated. Here, one assumption is that a video camera will be installed at the intersection, and it will be used to estimate arrival times of the opposite through vehicles. To identify the start and end of the conflict points in the opposing through traffic stream, σ and t values are considered to be 2 ft. and 4 ft. (Khan, 2019). These small distance thresholds were considered as they provide more gaps for a CAV’s left-turning maneuver that would avoid rear-end crash likelihood with a following aggressive driver. The roadside units, installed at the intersection, will share the camera captured data with the CAV using the V2I communication. The intersection video camera will use V2I communication only to share the information about the approaching through vehicle stream with the CAV. In a previous study, the authors implemented a real-world TCPS application for pedestrian movement detection using a video camera-enabled connected roadside unit (Rahman et al., 2019). The same experimental setup can be used to detect gaps between approaching vehicles on the opposing through lanes. Similar data can be captured through V2V communication if all of the approaching vehicles at the intersection are connected vehicles. After reaching the intersection, a CAV utilizes data from the intersection camera/RSU about the location of the approaching vehicles from the opposite through direction.

ANALYSIS AND FINDINGS

The following subsections discuss the findings for both leader CAV and the follower vehicle.

Abrupt Braking of Aggressive Follower Vehicle

The abrupt braking of the aggressive driver is characterized by a sudden reduction of speed in this research. We have quantified the number of abrupt braking event reduction by the situation-aware CAVs. As shown in Figure 6(a) the situation-aware CAV controller module reduces 40% of the abrupt braking of the follower vehicle for the 600 vphpln opposing through traffic, compared to the base scenario with AV without situation-awareness. With the higher number of opposite through traffic volume (i.e., 800 and 1000 vphpln), the abrupt braking reduction decreases to 10%.
Figure 5 Situation-aware CAV tracking follower vehicle

(a) Abrupt braking reduction by situation-aware CAV
(b) Travel time variations of the leader AV/CAV

(c) Average travel time of the leader AV/CAV
Khan and Chowdhury

(d) Travel time variations of the follower vehicle

(e) Average travel time of the follower vehicle
Figure 6 Evaluation Findings

Travel Time for CAV and Follower Vehicle

We have estimated the travel time for the subject vehicle from the start point of the initial corridor (i.e., the corridor from which the vehicle starts to move to the intersection) to the start point of the target corridor after taking the left turn. As shown with box plots in Figure 6(b), the situation-aware CAV controller module decreases the travel time for the vehicle itself for each scenario compared to the scenario without a situation-aware controller module. Also, for 1000 vphpln opposite through traffic, the travel time distribution is almost the same as the distribution for the 800 vphpln opposite through traffic. This means that the situation-aware CAV controller module can provide the same benefit for the scenarios with high opposite through volume. Figure 6(c) shows the average travel time for both base scenario with AV, and situation-aware CAV. The bold texts inside the columns show the percent reduction of average travel time for the situation-aware CAV compared to the base scenario with an equal number of opposite directional through
traffic. It shows that the average travel time reductions for the 600, 800 and 1000 vphpln scenarios are 54%, 20%, and 38%, respectively. The average travel time savings become steady after 800 vphpln.

Similar results are derived by observing the follower vehicle, as shown in Figure 6(d) and Figure 6(e). The follower aggressive vehicle’s travel time is reduced by the situation-aware CAV controller module for each scenario with different opposite through traffic volumes. In the situation-aware CAV scenario the travel time savings for the follower, compared to the base scenario with AV without situation awareness, are 61%, 23% and 41% for the 600, 800 and 1000 vphpln opposite through vehicle stream, respectively.

**Aggressive Follower Vehicle Progression**

One of the purposes of the situation-aware CAV controller module is to clear the path for the follower aggressive vehicle driver so that the follower vehicle does not need to wait for a long time. The following aggressive vehicle’s progression profile provides a clear picture of the impact of the situation-aware CAV controller module. Figure 6(f) shows the progression of the base AV and situation-aware CAV with time. It is evident from the progressions that the V2I communication enabled situation-aware CAV helps the follower aggressive vehicle to quickly progress through the intersection compared to the base scenario with AV without V2I communication and situational awareness.

**CONCLUSIONS**

The presence of aggressive human drivers in a mixed traffic stream makes the operation of CAVs challenging, as aggressive drivers tend to follow the leader vehicle very closely. Any sudden movement change by a leader CAV has the potential to cause abrupt behavior by the follower vehicle, which may result in road rage and/or a rear-end crash. Also, human drivers often could take unethical advantages of the defensive driving behavior of AVs. If CAVs can act based on surrounding situations, they can mimic human behavior more closely, which will reduce the confusion among the surrounding human drivers about any future actions of CAVs. In this study, the situation-aware CAV uses its own rear camera sensor to identify the following vehicle’s intent. Once the CAV determines that the following vehicle is aggressive, it determines the appropriate gap in the opposite through traffic stream, optimizes the speed profile and increases its speed to reach the initial point of deceleration to initiate the left-turn. If a safe gap is not available when the CAV reaches the approach intersection stop line, the CAV evaluates data from the roadside units about available gaps on the opposing through lanes and prepares to make a left-turn immediately when the required gap is available. The overall decision-making module helps to clear the intersection as soon as possible to reduce the travel time of the following aggressive vehicle.

Based on the analysis conducted in this research, we have found that the situation-aware CAV improves the operational condition compared to the base scenario with only AV (without any V2I communication) for different flow rates in the opposite through vehicle stream. The
situation-aware CAV controller module reduces the number of abrupt braking by 40%, 10% and 10% for opposing through traffic stream with 600, 800 and 1000 vphpln, respectively, compared to the base scenario without situational awareness of AVs. While assessing the travel time reduction, the situation-aware CAV scenario reduces travel time for a CAV, compared to the base scenario with AV, as much as 54%, 20% and 38% for the 600, 800 and 1000 vphpln opposing through vehicles, respectively. Similar improvements are found for the follower vehicles with 61%, 23% and 41% travel time savings for the 600, 800 and 1000 vphpln opposing through vehicles, respectively.

The desired benefit may not be achieved if CAVs cannot be proactive to reduce potential conflicts due to responding to an aggressive follower non-CAV. With an increasing penetration level of CAVs, a cooperative movement can be enabled with CAVs in the opposing traffic stream to help a left-turning CAV find gap if a follower aggressive vehicle is present. Also, the human driver aggressiveness level can vary from person to person. Developing the situation-aware CAV module for a wide range of driver aggressiveness can help CAV take actions based on the characteristics of the specific follower driver. Finally, real-world evaluation of situation-aware CAV controller module presented in this paper should be conducted to validate the operational benefits in real-life.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design, Sakib Mahmud Khan, Mashrur Chowdhury; data collection, Sakib Mahmud Khan; interpretation of results, Sakib Mahmud Khan, Mashrur Chowdhury; draft manuscript preparation, Sakib Mahmud Khan, Mashrur Chowdhury. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

Ahmed, I. et al. (2019) ‘Characterizing Lane Changes via Digitized Infrastructure and Low-Cost GPS’, Transportation Research Record: Journal of the Transportation Research Board. SAGE PublicationsSage CA: Los Angeles, CA, p. 036119811984127. doi: 10.1177/0361198119841277.

Alhajyaseen, W. K. M., Asano, M. and Nakamura, H. (2012) ‘Estimation of left-turning vehicle maneuvers for the assessment of pedestrian safety at intersections’, IATSS Research. doi: 10.1016/j.j.aitssr.2012.03.002.

Berry, I. M. (2010) The effects of driving style and vehicle performance on the real-world fuel consumption of US light-duty vehicles. Massachusetts Institute of Technology.

Cheung, E. et al. (2018) ‘Identifying Driver Behaviors using Trajectory Features for Vehicle Navigation’. Available at: http://arxiv.org/abs/1803.00881 (Accessed: 18 July 2019).

Cox Automotive (2016) Kelley Blue Book | MediaRoom - Special Reports, Kelley Blue Book. Available at: https://mediaroom.kbb.com/future-autonomous-vehicle-driver-study (Accessed: 21
Khan and Chowdhury

July 2019).

Dias, C., Iryo-Asano, M. and Oguchi, T. (2017) ‘Predicting Optimal Trajectory of Left-Turning Vehicle at Signalized Intersection’, in Transportation Research Procedia. doi: 10.1016/j.trpro.2017.03.093.

Favarò, F. M. et al. (2017) ‘Examining accident reports involving autonomous vehicles in California’, PLOS ONE. Edited by X. Hu. Public Library of Science, 12(9), p. e0184952. doi: 10.1371/journal.pone.0184952.

Gu, Y. et al. (2017) ‘Human-like motion planning model for driving in signalized intersections’, IATSS Research. doi: 10.1016/j.iatssr.2016.11.002.

Kampik, T., Nieves, J. C. and Lindgren, H. (2019) ‘Empathic Autonomous Agents’, arXiv preprint.

Khan, S. M. (2019) Connected and Automated Vehicles in Urban Transportation Cyber-Physical Systems. Clemson University.

Kumtepe, O., Akar, G. B. and Yuncu, E. (2016) ‘Driver aggressiveness detection via multisensory data fusion’, EURASIP Journal on Image and Video Processing. Springer International Publishing, 2016(1), p. 5. doi: 10.1186/s13640-016-0106-9.

Lee, J. D. et al. (2002) ‘Collision Warning Timing, Driver Distraction, and Driver Response to Imminent Rear-End Collisions in a High-Fidelity Driving Simulator’, Human Factors: The Journal of the Human Factors and Ergonomics Society. SAGE PublicationsSage CA: Los Angeles, CA, 44(2), pp. 314–334. doi: 10.1518/0018720024497844.

Liu, W. et al. (2015) ‘Situation-aware decision making for autonomous driving on urban road using online POMDP’, in 2015 IEEE Intelligent Vehicles Symposium (IV). IEEE, pp. 1126–1133. doi: 10.1109/IVS.2015.7225835.

McAree, O., Aitken, J. M. and Veres, S. M. (2017) ‘Towards artificial situation awareness by autonomous vehicles’, IFAC-PapersOnLine. Elsevier, 50(1), pp. 7038–7043. doi: 10.1016/J.IFACOL.2017.08.1349.

Michael, P. G., Leeming, F. C. and Dwyer, W. O. (2000) ‘Headway on urban streets: Observational data and an intervention to decrease tailgating’, Transportation Research Part F: Traffic Psychology and Behaviour. doi: 10.1016/S1369-8478(00)00015-2.

Mohebbi, R., Gray, R. and Tan, H. Z. (2009) ‘Driver Reaction Time to Tactile and Auditory Rear-End Collision Warnings While Talking on a Cell Phone’, Human Factors: The Journal of the Human Factors and Ergonomics Society. SAGE PublicationsSage CA: Los Angeles, CA, 51(1), pp. 102–110. doi: 10.1177/0018720809333517.

NHTSA (2019) Speeding | NHTSA. Available at: https://www.nhtsa.gov/risky-driving/speeding (Accessed: 19 July 2019).

Ni, Y. and Li, K. (2014) ‘Estimating Rear-End Accident Probabilities at Signalized Intersections: A Comparison Study of Intersections With and Without Green Signal Countdown Devices’,
Khan and Chowdhury

Traffic Injury Prevention, 15(6), pp. 583–590. doi: 10.1080/15389588.2013.845752.

Ragland, D. R. et al. (2006) ‘Gap acceptance for vehicles turning left across on-coming traffic: Implications for’, in Transportation Research Board 85th Annual Meeting.

Rahman, M. et al. (2019) ‘Real-Time Pedestrian Detection Approach with an Efficient Data Communication Bandwidth Strategy’, Transportation Research Record: Journal of the Transportation Research Board. SAGE PublicationsSage CA: Los Angeles, CA, 2673(6), pp. 129–139. doi: 10.1177/0361198119843255.

Rodriguez Gonzalez, A. B. et al. (2014) ‘Modeling and detecting aggressiveness from driving signals’, IEEE Transactions on Intelligent Transportation Systems. doi: 10.1109/TITS.2013.2297057.

Schlueter, M. et al. (2013) ‘MIDACO on MINLP space applications’, Advances in Space Research. doi: 10.1016/j.asr.2012.11.006.

Song, W., Xiong, G. and Chen, H. (2016) ‘Intention-Aware Autonomous Driving Decision-Making in an Uncontrolled Intersection’, Mathematical Problems in Engineering. Hindawi, 2016, pp. 1–15. doi: 10.1155/2016/1025349.

Taraba, M. et al. (2018) ‘Utilization of modern sensors in autonomous vehicles’, in 2018 ELEKTRO, pp. 1–5. doi: 10.1109/ELEKTRO.2018.8398279.

Treiber, M. and Kesting, A. (2013) ‘Car-Following Models Based on Driving Strategies’, in Traffic Flow Dynamics. doi: 10.1007/978-3-642-32460-4_11.

Vaiana, R. et al. (2014) ‘Driving behavior and traffic safety: An acceleration-based safety evaluation procedure for smartphones’, Modern Applied Science. doi: 10.5539/mas.v8n1p88.

Wei, J., Dolan, J. M. and Litkouhi, B. (2013) ‘Autonomous vehicle social behavior for highway entrance ramp management’, in IEEE Intelligent Vehicles Symposium, Proceedings. doi: 10.1109/IVS.2013.6629471.

Wolffermann, A., Alhajyaseen, W. K. M. and Nakamura, H. (2011) ‘Modeling Speed Profiles of Turning Vehicles at Signalized Intersections’, in 3rd International Conference on Road Safety and Simulation.

Ye, F., Adams, M. and Roy, S. (2008) ‘V2V Wireless Communication Protocol for Rear-End Collision Avoidance on Highways’, in ICC Workshops - 2008 IEEE International Conference on Communications Workshops. IEEE, pp. 375–379. doi: 10.1109/ICCW.2008.77.

Zhang, Y. et al. (2017) ‘A New Car-Following Model considering Driving Characteristics and Preceding Vehicle’s Acceleration’, Journal of Advanced Transportation. doi: 10.1155/2017/2437539.