Physica A 606 (2022) 128083

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Defensive or competitive Autonomous Vehicles: Which one interacts safely and efficiently with pedestrians?

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ARTICLE INFO

Article history:
Received 26 March 2022
Received in revised form 17 July 2022
Available online 22 August 2022

Keywords:
Unsignalized mid-block crosswalks
Autonomous vehicle
Agent-based traffic simulation
Pedestrian safety
Traffic conflict analysis
Traffic crash

ABSTRACT

The emergence of Autonomous Vehicles (AVs) could provoke unexpected challenges in urban traffic environments. One such crucial challenge is the conflicts between pedestrians and AVs, particularly on unsignalized mid-block crosswalks (UMC), where pedestrians are exposed to the AV flow. This study investigates the efficiency and safety performance of a UMC in the presence of both AVs and pedestrians considering the diversities in their behaviors. Through empirical analyses, two pedestrians' crossing decision models are built and four groups of speed profiles are classified. Meanwhile, based on previous literature, defensive and competitive driving strategies are assumed for AVs. The simulation is implemented on an agent-based framework that can dynamically reproduce the kinematic interactions between pedestrians and vehicles. Results indicated that with a reasonable safety margin (2.5 s), percentages of low post encroachment time events for competitive AVs with different pedestrian types are smaller than defensive AVs with differences of 0.2% to 2.9%. The average delays of competitive AVs for all pedestrian types are smaller than defensive AVs with a maximum estimated difference of 39 s. Moreover, the analysis showed that lowering the speed limit may reduce the crash rate of competitive AV up to 0%. It is also found that the pedestrians who make reckless crossing decisions and change their speed drastically during the crossing process are more likely to incur crashes with competitive AVs. Therefore, if pedestrian behaviors can be regulated reasonably, competitive AVs with appropriate parameter settings are most suitable for UMC in the future.

1. Introduction

Statistics suggest that more than 50% of the traffic fatalities are related to vulnerable road users including pedestrians, cyclists, and motorists in 2020 [1]. Installing a refuge island in the middle of the crosswalk is a common approach for improving safety [2]. Federal Highway Administration [3] pointed out that the UMC with refuge island (UMCR) allows

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https://doi.org/10.1016/j.physa.2022.128083
0378-4371/

pedestrians who have crossed the first half crosswalk to wait in protected areas when the latter half is unsafe. On UMCRs, pedestrians only confronts with AVs from one direction and occlusion impacts by opposing vehicles are almost negligible. Therefore, interactions between pedestrians and AVs are simplified so that UMCRs are recognized as the most effective measure to accommodate AVs [4].

However, AVs' performance (especially the safety) in urban areas is a controversial topic [5]. There are some critical issues that must be addressed before AVs can be fully accommodated on UMCRs. The major concern will be the interactions between AVs and pedestrians. To provide suggestions on AVs' behavioral settings, the verification of different driving strategies on UMCRs considering practical problems on UMCRs (e.g., diverse crossing behaviors of pedestrians) are still an open issue in the current research.

Regarding pedestrians, their crossing behaviors are different. For example, reckless pedestrians may cross in a dangerous situation where the vehicle is near and driving at a fast speed, while cautious pedestrians only cross when the vehicle is far away and driving at a slow speed. Pedestrians may cross using a running or walking mode. Previous studies indicated that the average crossing speeds of pedestrians vary in a large range between 0.5 m/s–5.9 m/s [6–8]. Furthermore, some pedestrians may even change their speed drastically, i.e., suddenly switching between walking and running [9]. On the other hand, AVs are driving machines that strictly follow programs that have been established in their control cores. Their safety performance is determined by the behavioral setting. According to [10], AVs may be designed to have defensive or competitive driving strategies. On UMCRs, defensive AVs treat any approaching pedestrians as a potential danger, while competitive AVs tend to find the possibility of quickly passing through without crashes. Possible safety hazards and efficiency problems may exist in scenarios combining various pedestrian behaviors and AV settings. By knowing the reasons for typical issues, corresponding countermeasures can be developed. Therefore, it is necessary to simulate and evaluate AV's driving strategies considering different pedestrian crossing behaviors on UMCRs.

This paper aims to provide suggestions and evidence for the proper AV settings from the viewpoint of practice applications on UMCRs. The safety and efficiency performance of combination scenarios of different AV settings and pedestrians' crossing behaviors will be investigated by simulation experiments. Through this process, the key factors that may incur severe conflict events or even crashes between AVs and pedestrians will be identified. That evidence will help indicate the preferred driving strategy of AVs on UMCRs. Furthermore, corresponding treatments for pedestrians and crosswalks to further ensure basic safety will be proposed.

Three main difficulties to achieve the research objectives should be overcome. First, realistic crossing behaviors of pedestrians, including crossing decisions and crossing speed, should be modeled. Second, reasonable and predictive assumptions on AVs should be given since the current technology of AVs' driving control is still under development. Third, the dynamic pedestrian–vehicle interaction (PVI) should be modeled based on their kinematic relationship.

This paper is structured as follows. Related previous studies are summarized in Section 2. Modeling of pedestrians' and AVs' behaviors are created in Section 3. The PVI framework is described in Section 3 as well. The simulation platform that can realize the proposed framework and scenario settings are introduced in Section 4. The results of experimental data are analyzed in Section 5. In addition, the specific reasons for typical crashes between AVs and pedestrians at UMCRs are discussed in Section 6. Finally, Section 7 summarizes the conclusions, limitations, and future work. Fig. 1 introduces the overall research activity of this study.

2. Literature review

2.1. AVs' behaviors

The reaction time and decision logics of AVs are totally different from human driven vehicles [11]. According to the definition of the National Highway Safety Administration [12], AVs are classified into five levels. Level 5 AVs fully take over the vehicles' operation and can drive in all road conditions, including UMCRs. However, such technologies are far from being achieved. Therefore, the behavior of AVs in this study is assumed based on information from the literature.

In recent years, there has been an active discussion on whether the AV should be defensive or competitive. Camara et al. [13,14] summarized related models that can be applied in AVs for achieving safe interaction processes between pedestrians and AVs. They pointed out that sensing and tracking pedestrians' movements are basic functions for AVs while predicting human maneuvers are advanced models for AVs. If such technologies are good enough to anticipate pedestrian movements, competitive driving will be a possible choice. Otherwise, only defensive driving can be available. Another review study by Zhao et al. [15] compared the competitive and defensive driving strategies. They pointed out that the defensive AVs will be more inclined to give up the right-of-way for ensuring safety and such behavior could lead to poor performance in traffic efficiency, which is in accordance with the results of Pan et al. [16]. On the other hand, competitive AVs will be able to find more passing opportunities by predicting pedestrians' movements. This strategy includes a high risk since pedestrians may behave in ways that defy the anticipation model. Balancing the performance of the two strategies will be the main difficulty for applying AVs to UMCRs. Wang et al. [17] discussed the challenges of putting AVs into practice for pedestrians walking areas. Red lights running, jaywalker, and distraction are major traffic safety problems that should be carefully considered. These issues highlight the necessity to evaluate defensive and competitive strategies for AVs considering the uncertainty of pedestrian behaviors.

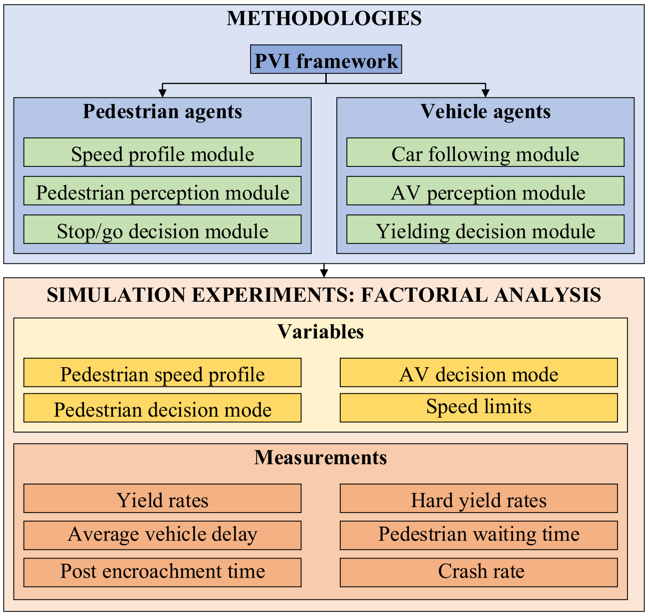

Fig. 1. Conceptual map.

2.2. Pedestrians' behaviors

Understanding how pedestrians walk across the crosswalk (walking speed and decision-making behavior) is the basic step to reproduce conflicts between pedestrians and vehicles. In existing PVI models, pedestrians' walking speeds are usually defined as constant and uniform values for simplification (Gupta et al. 2019). However, Pala et al. [18] analyzed street-crossing behaviors through laboratory experiments by use of the CAVE simulator and the head-mounted display. Their results indicate that the average crossing speed of young participants was 19% greater than old participants. Meanwhile, Iryo-Asano et al. [19], Iryo-Asano and Alhajyaseen [9] modeled the pedestrians speed profiles on crosswalks for reproducing potential conflicts with vehicles. They found that events such as flashing green may trigger pedestrians' speed changes and such behaviors may impact distributions of post encroachment time (PET).

Besides pedestrian speed, the crossing decision has also been widely studied. Alver et al. [20] investigated pedestrians' gap acceptance on UMCs in Izmir city. They found that the critical gaps differed on three survey sites and the maximal difference was 2.1 s. Holland and Hill [21] investigated unsafe crossing behaviors through a simulation study. The results revealed that pedestrians who had driving experience were more likely to take the unsafe cross with a small margin time. Fu et al. [22] established a procedure to evaluate pedestrian safety at UMCs and pointed that the pedestrian's yield decision was highly related to the vehicle's braking distance. Zhang et al. [23,24] surveyed 12 UMCs in China. They found that for multilane crosswalks, the critical gap and PET distributions on each lane are significantly different. From the above studies, it can be concluded that the diversity of pedestrians' behaviors are important and necessary for analyzing safety issues on UMCs.

2.3. PVI modeling

The majority of existing PVI frameworks are based on empirical decision models. Meanwhile, theoretical decision models that reflect the kinematic interactions among multi-agents are limited [25]. Lu et al. [26] proposed a cellular automaton model to simulate the PVI at UMCs. The decision-making models of pedestrians and vehicles were based on two logistic models whose parameters were calibrated with empirical observations. Zhao et al. [27] modeled gap acceptance behaviors for pedestrians by logit models based on the data from 13 UMC in Shanghai. Then, a PVI model based on the proposed logit models was established in a following study [10]. The new PVI model could reproduce the average pedestrian delay with a relative error of 7.8%. The PVI models used in the above studies performed well in reproducing pedestrian and vehicle delays. They cannot, however, simulate real-world conflicts because their decision-making models are all one-kick decision types. Further, the decisions of agents cannot be adjusted over time to account for changing kinematic situations.

There are limited studies on dynamic decision-making procedures of pedestrians and vehicles. For instance, Feliciani et al. [28] improved gap acceptance models by introducing reaction time as an adjustment factor and created a simulation framework for UMCs with dynamic decision modules. This model could reasonably estimate the collision times under different conditions. However, as the reaction time was defined as a parameter on the observed gap, crashes caused by delayed actions could not be reproduced. Zhu et al. [29] proposed an agent-based framework for evaluating pedestrian safety on UMCs which composed of several modules. This model could dynamically update the agents' decisions considering the kinematic interaction between pedestrians and vehicles. Furthermore, the influence of reaction time and visibility could also be reproduced. As the framework is very flexible, each module can be replaced to achieve different research objectives. The current study enhances that framework by including modules on various pedestrian and AV driving behaviors.

3. Methodologies

3.1. PVI framework

This study enhances the basic agent-based framework that was proposed in the authors' previous article [29]. At every time step, each agent obtains the status information (location, speed, acceleration, etc.) from other agents, evaluates potential conflicts, and makes decisions. Agents update decisions with the newly observed information considering the kinematic relationship between pedestrians and AVs. Meanwhile, agents' statuses are determined by the decisions made before. Therefore, the decisions from multiple agents are interactive with each other over time. Moreover, the action is delayed than the corresponding decision with a reaction time. Reaction times for pedestrian and AV agents are symbolized as τ_p and τ, respectively. According to findings of Gorrini et al. [30], pedestrians' crossing can be represented by three phases: approaching, appraising (evaluation of the distance and speed of oncoming vehicles) and crossing. In this framework, pedestrians and AVs behaviors are modeled based on following assumptions.

- Pedestrian agents can decide either to stop or continue walking in every time span when they are in the sidewalk. During crossing, the pedestrian will response to a pre-recorded speed profile. This study does not consider pedestrians' emergency evading behaviors such as stepping back and sudden acceleration in the crosswalk area.
- AVs apply a certain logic to update their decisions (acceleration value) in every time step before passing through the zebra cross based on the current kinematic situation.

Within the framework of this study, new modules are developed for pedestrians' speed profile, pedestrians' stop/go decision, AVs' perception, and AVs' yielding decision.

3.2. Pedestrian agents

For pedestrians on UMCRs, the whole crossing process can be divided into two parts. The first is from the sidewalk to the refuge island followed by the second part from the refuge island to the sidewalk. As shown in Fig. 2, each crossing (from the sidewalk to the median or from the median to the sidewalk) includes three stages, i.e., before the waiting area, in the waiting area, and on the crosswalk. Speed profile module takes effects in stages of "before the waiting area" and "on the crosswalk". When pedestrians are in the waiting area, perception, stop/go decision module, and speed profile module initiate. In order to reproduce realistic behaviors, the speed profile and stop/go decision modules for pedestrian agents are created based on real-world data. For this purpose, field speed data was extracted by image processing from a UMCR in Yaizu City, Japan on November 15th, 2016 (between 14:10–16:30) as shown in Fig. 3. During observation, the road section volume is 868 veh/h (all observed vehicles are not AVs: 495 veh/h from east and 373 veh/h from west). Pedestrian volume during the observation was 270 ped/h (151 veh/h from north and 119 veh/h from south). Since the survey site was near Yaizu railway station, the speed of pedestrian groups varies greatly. Some elder pedestrians walk slowly while some pedestrians ran extremely fast for catching up with trains.

3.2.1. Speed profile module

Extracted spot speeds for 200 pedestrians plotted on space axis with an interval of 0.2 m are shown in Fig. 3(b). This study let each pedestrian agent takes the same speed profile as one of the profiles in Fig. 3(b). The collected pedestrian profiles are classified into four groups based on the speed fluctuations as shown in Fig. 3(c). Great speed difference (GD) is the group of speed profiles in which the difference between the maximum and minimum values of the pedestrian crossing speed is high. The other samples belong to the small speed difference group (SD). The threshold of the speed difference between the two group is 1.535 m/s, which is the 85th percentile value of all populations. 85% of samples are in the SD group SD and 15% are in the GD group. Furthermore, samples in SD are further classified into Low speed (LS) group, Mid-level speed (MS) group, and High speed (HS) group based on the average speed of each speed profile as shown in Fig. 3(d). The two thresholds between these three groups are the 85th percentile value (1.1 m/s) and the 15th percentile value (1.6 m/s) respectively. Therefore, the speed profiles in the SD group are classified as 15% in LS, 70% in MS, and 15% in HS.

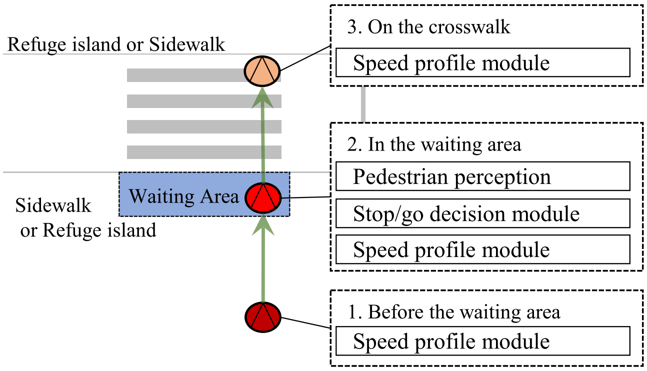

Fig. 2. Modules of pedestrian agents in one crossing (from the sidewalk to the median or from the median to the sidewalk).

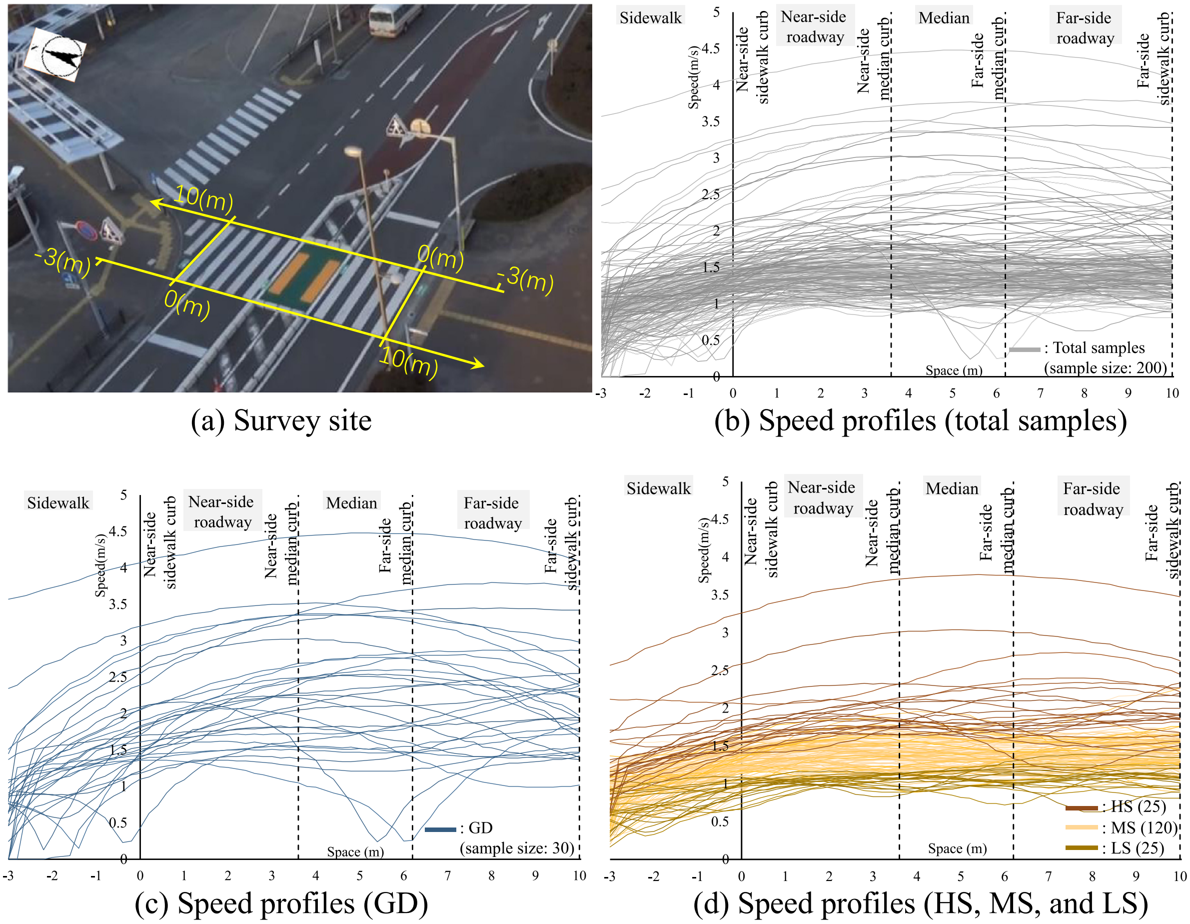

Fig. 3. Survey site and observed speed profiles.

3.2.2. Pedestrian perception and Stop/go decision module

This study does not discuss the impact of visual obstacles. It is assumed that pedestrian agents can perceive other objects within a certain radius. The radius is considered as humans' sight distance (d_p). The V_{ap}, (the speed of approaching vehicle) and D (distance between the pedestrian and the approaching vehicle) at the moment when the subject pedestrian arrived at the waiting area were recorded. The observed points are plotted as shown in Fig. 4. Obviously, pedestrians decide to cross (green points) or wait (red crosses) based on the status of the approaching vehicle. It can be observed that the red crosses are located in the upper left part of Fig. 4, where the V_{ap} is high and D is short. Whereas, the green points are

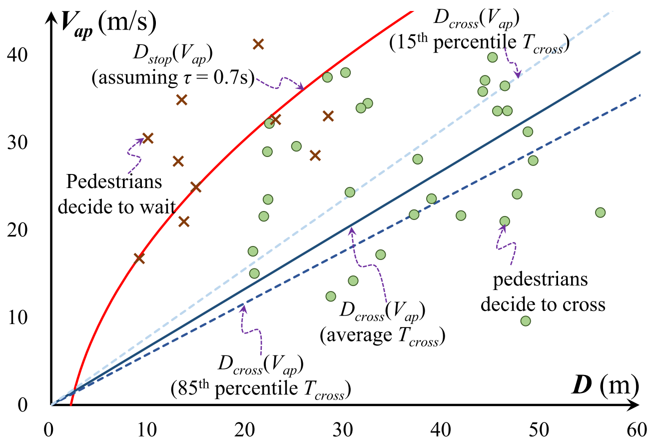

Fig. 4. Traffic conditions (V_{ap} and D) when pedestrians are making decisions.

located in the lower right part of Fig. 4, where the V_{ap} is low and D is long. For better understanding pedestrians' decision-making behaviors, two reference distance values are defined: (a) $D_{cross}(V_{ap})$ is the traveling distance of the approaching vehicle with speed V_{ap} from now until the pedestrian can complete crossing as in Eq. (1); (b) $D_{stop}(V_{ap})$ is the braking distance needed for the approaching vehicle with speed V_{ap} to complete stop as in Eq. (2).

$$D_{cross}\left(V_{ap}\right) = \left(T_{\text{cross}} + \beta_p\right) V_{ap} \tag{1}$$

where T_{cross} is the required time for the pedestrian to leave the conflict zone, and the margin time β_p is the minimum acceptable safe gap time for pedestrians between the pedestrian's leaving the conflict zone and the vehicle's entering the conflict zone. In this study, β_p is assumed to be 1.5 s [31,32].

$$D_{stop}\left(V_{ap}\right) = \text{s}_0 + \tau V_{\text{ap}} + \frac{V_{\text{ap}}^2}{2\text{b}} \tag{2}$$

where s_0 is the minimum stopping distance (m) and b is the braking deceleration (m/s^2). s_0 is 2 m amd b is 4.5 m/s^2 [33,34].

In Fig. 4, Curve of $D_{stop}(V_{ap})$ was plotted assuming τ of human drivers to be 0.7 s [35]. Meanwhile, for each pedestrian the T_{cross} is different. Therefore, Curves of $D_{cross}(V_{ap})$ were drawn with the 15th percentile T_{cross}, the average T_{cross}, and the 85th percentile T_{cross} of total samples, respectively.

As in Fig. 4, it can be observed that the way that pedestrians make decisions differs significantly depending on the statuses of the vehicles. Firstly, only red crosses are distributed above $D_{stop}(V_{ap})$, which represents that approaching vehicles are near and fast. It is impossible to cross safely under such traffic situations. Secondly, several green points and red crosses are located between $D_{cross}(V_{ap})$ (15th percentile T_{cross}) and $D_{stop}(V_{ap})$. Stepping into the crosswalk under these conditions may force approaching vehicles to take emergency brakes, which is a risky decision. Thirdly, only some green points are under $D_{cross}(V_{ap})$ (85th percentile T_{cross}). They represent the situations when the approaching vehicles are far and slow. Pedestrians can complete crossing before the vehicle arrives, which is a safe decision. Based on these findings, three domains are delimited as in Fig. 5. They are Domain A: must wait (the area above $D_{stop}(V_{ap})$); Domain B: dilemma condition (the area below $D_{stop}(V_{ap})$ and above $D_{cross}(V_{ap})$); Domain C: safe to cross (the area below $D_{cross}(V_{ap})$). Then, two stop/go decision modules are assumed according to the three domains as shown below.

• High priority sense (HPS) module

These pedestrians think that they are endowed with high priorities on the crosswalk. They decide to cross once they confirmed that the status of the approaching vehicle is in the domain of 'dilemma condition' or 'safe to cross', as shown in Fig. 5(a).

• Conservative (C) module

This type of pedestrian makes cautious decisions. Pedestrians keep waiting unless they confirmed that the approaching vehicles in the domain of 'safe to cross' as shown in Fig. 5(b).

3.3. AV agents

As shown in Fig. 6, after AVs passed the crosswalk, they only need to follow the leading vehicle ahead. Therefore, only the car following module comes into play in this stage. In the stage of "before passing the crosswalk", four modules take effect. Two types of AVs are assumed, namely the defensive AVs that tend to prevent all potential danger against uncertainties, and the competitive AVs that are always seeking the possibility of increasing driving efficiency. The main difference between them is considered in yielding decision modules.

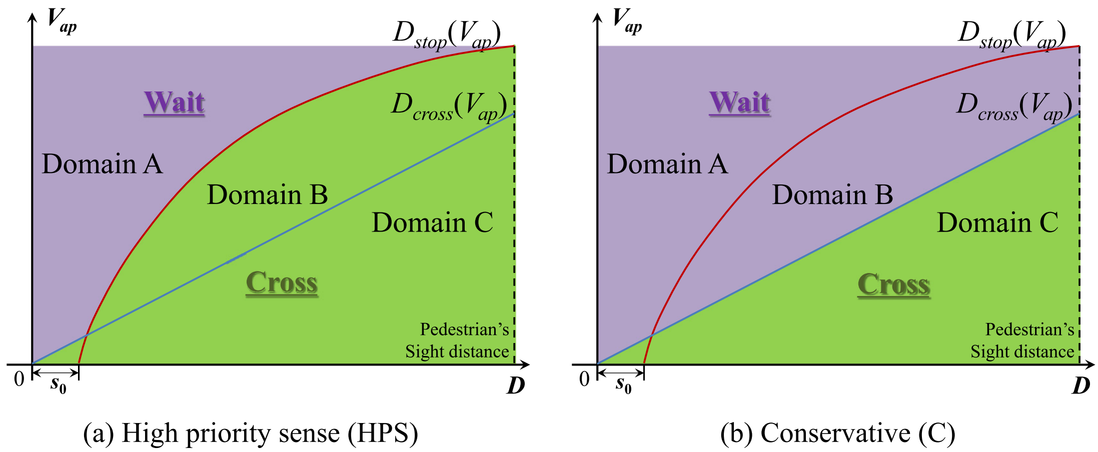

Fig. 5. Diagram of pedestrian stop/go decision modules.

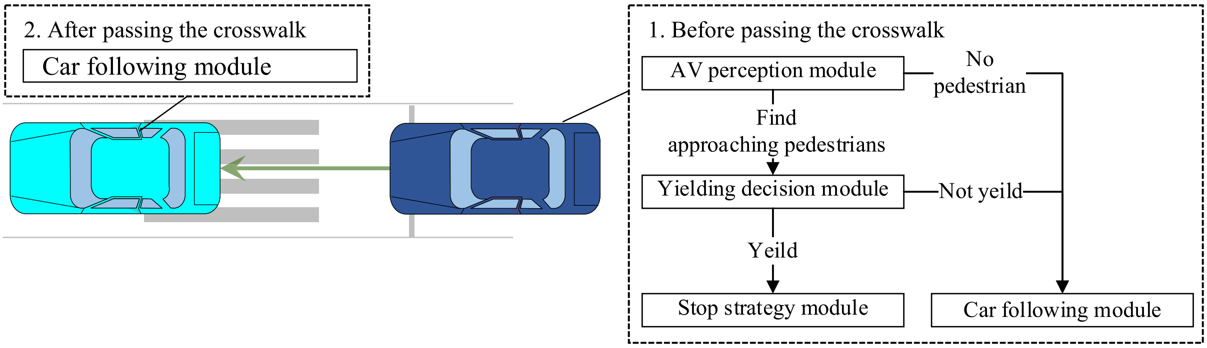

Fig. 6. Modules of AV agents.

3.3.1. Car following module

A car following module was introduced in the driving mode to ensure the safe headway to the leading vehicle. The Intelligent driver model (IDM) [34] was selected in this study due to its robustness. The simplest form of the IDM is described in Eqs. (3) and (4).

$$\begin{cases} \dfrac{\mathrm{dx}_{IDM}\,(\mathrm{t}+\tau)}{\mathrm{dt}} = \mathrm{v}_{IDM}\,(\mathrm{t}) \\ \dfrac{\mathrm{dv}_{IDM}\,(\mathrm{t}+\tau)}{\mathrm{dt}} = a\left(1-\left(\dfrac{v\,(t)}{v_0}\right)^{\delta}-\left(\dfrac{s*(v\,(t)\,,\Delta v\,(t))}{s\,(t)}\right)^{2}\right) \end{cases} \tag{3}$$

$$s*(v\,(t)\,,\Delta v\,(t)) = s_0 + v\,(t)\,T + \frac{v\,(t)\,\Delta v\,(t)}{2\sqrt{ab}} \tag{4}$$

where a is the maximum vehicle acceleration (m/s^2); Δv(t) is the speed difference between the subject and leading vehicle at time t (m/s); T is the minimum time headway (s), v_0 is the desired speed and equal the road speed limits in this study and δ is the acceleration exponent.

3.3.2. AV perception module

The main task of the AV perception module is to obtain pedestrians' status within the detection radius (d_{AV}). The size, speed, and position of AVs and pedestrians will be reconstructed in a two-dimensional space as shown in Fig. 7. Firstly, if the AV is not the first vehicle before the stop line, the AV simply follows the leading vehicle. Secondly, a judgment area that includes the whole crosswalk and a certain area of the sidewalk is defined for AVs. Pedestrians who are detected in the judgment area will be further considered for the yielding decision module.

3.3.3. Yielding decision module

The safety situation of each pedestrian will be evaluated based on the obtained information from the AV perception module. Two types of yielding decision modules are built for representing defensive and competitive driving strategies. It

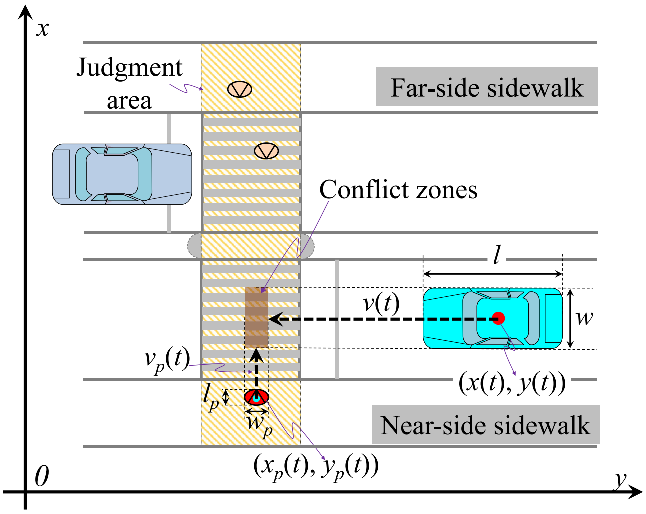

Fig. 7. Two-dimensional coordinate in AV perception module.
Notes At time t, coordinates of the pedestrian and the AV are $(x_p(t), y_p(t))$ and $(x(t), y(t))$. For the pedestrian, the vertical length is l_p (m), the horizontal width is w_p (m) and the speed is $v_p(t)$. For the AV, the length is l (m), the width is w (m), and the speed is $v(t)$.

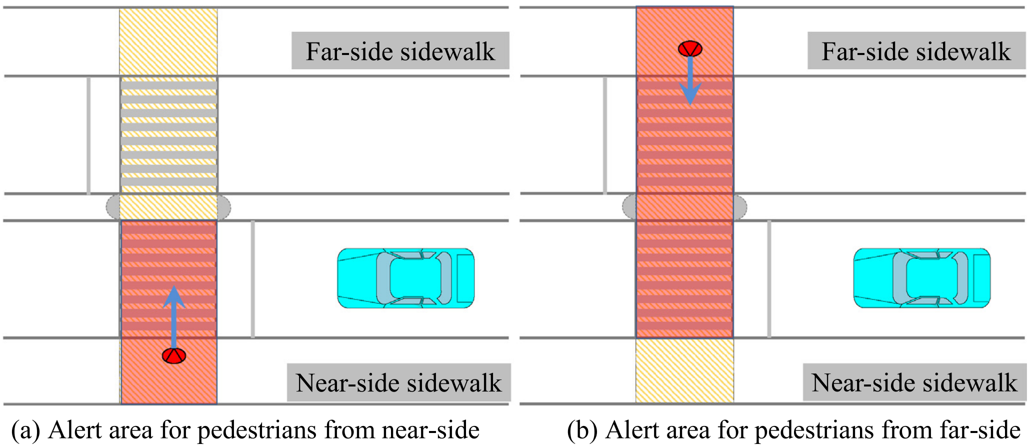

Fig. 8. L1 yielding decision module.

is important to note that the modules in the following sessions are introduced taking one pedestrian as an example. However, AVs may encounter multiple pedestrians simultaneously on the UMCRs. In this study, AVs will repeat the same calculation for all detected pedestrians and evaluate the safety for each of them. Then decisions are made for the pedestrian who is in the most risky situation for the AVs.

In some situations, pedestrians will give way to AVs. It will be unnecessary and meaningless for AVs to yield for those pedestrians. In this study, such a situation happens if the following two conditions are satisfied: (a) the pedestrian is on the sidewalk or refuge island; (b) The approaching speed and distance of the AV to the pedestrian are in the domain of 'must wait' as in Figure . Then the algorithm will shift to the car following module instead.

• Level 1 (L1): defensive AVs

The majority of current AVs are operated by applying defensive driving strategies [13]. In this study, if the considered pedestrian is walking toward or on the crosswalk, the pedestrian will be marked as an unsafe pedestrian. This alert will not be relieved until the pedestrian finishes crossing. As shown in Fig. 8, specific alert areas are delineated for pedestrians from near-side and far-side crosswalks separately. If AVs find any pedestrian walking in such areas, AVs will stop.

• Level 2 (L2): competitive AVs

The safety margin based decision module, previously proposed by Zhu et al. [29], reproduces the decision-making behaviors of drivers who compete for the right of way with pedestrians on UMCs. This module is introduced to simulate the yielding decision module of competitive AVs. The yielding decision module of L2 AV will generate two options as well: yield or not yield. For each pedestrian, the conflict zone is the area enclosed by extension lines of the AV's and the pedestrian's borders as in Fig. 7. In this study, the L2 AVs are always finding the fastest path to pass all conflict zones while keeping basic safety margins with approaching pedestrians.

An approximate optimization iteration procedure [36] is adopted to achieve this objective. At each time step, AVs evaluate the feasibility of full-speed driving. If the path of full-speed driving is in conflict with any anticipated pedestrian trajectory, AVs implement the stop strategy module. Otherwise, they initiate the car-following module. This procedure repeats again in every time step until the AV passes the crosswalk. The kinematic situations between pedestrians and AVs change dynamically over time. AVs may find opportunities to leave in another time step when they are braking to yield. Similarly, the chance of quickly passing that has been obtained before may become invalid in the other time step as well.

The margin time β_{AV} is the defined minimum acceptable safe buffer time between trajectories of AV and pedestrian. If the time interval between the anticipated occupying time of the pedestrian and the AV is larger than the safety margin time β_{AV}, it means the assumed full speed passing path is feasible. This logic is described through Equations (5) and (6). If both Equations (5) and (6) are satisfied, the algorithm will shift to the car following module. Otherwise, the stop strategy module will be implemented.

$$t_{AV,leave}^{ant}(t) + \beta_{AV} \geq t_{ped,enter}^{ant}(t) \tag{5}$$

$$t_{ped,leave}^{ant}(t) + \beta_{AV} \geq t_{AV,enter}^{ant}(t) \tag{6}$$

Where $t_{AV,enter}^{ant}(t)$ and $t_{AV,leave}^{ant}(t)$ are the time for the AV to enter and leave the conflict zone which is anticipated by the AV at time t assuming it drives in the full-speed mode (s); $t_{ped,enter}^{ant}(t)$ and $t_{ped,leave}^{ant}(t)$ are the time for the pedestrian to enter and leave the conflict zone which is anticipated by the AV at time t assuming the pedestrian does not change the walking speed (s). For the detailed calculation process of the four values, please refer to [29].

3.3.4. Stop strategy module

The stop strategy mainly considers the impacts of pedestrians and leading vehicles. Regarding the first issue, AVs will slow down gently as much as possible for ensuring the comfort of passengers. Also, for avoiding interfering with the pedestrian flow, AVs will attempt to stop at the stop line. However, if the distance is insufficient, the AV will implement an emergency brake with a deceleration rate b. As for the second issue, AVs' deceleration should not be smaller than the value required by the car-following module. The stop strategy is defined through Eqs. (7) and (8).

$$dec\,(t+\tau) = \max\left(-\frac{dv_{IDM}\,(t+\tau)}{dt},\quad dec_{ped}\,(t)\right) \tag{7}$$

$$dec_{ped}\,(t) = \begin{cases} \dfrac{v\,(t)^2}{2\,(d_{sl}\,(t) - \tau v\,(t))} & d_{sl}\,(t) > \tau v\,(t) \\ b & d_{sl}\,(t) \leq \tau v\,(t) \end{cases} \tag{8}$$

where $dec(t)$ is AV's deceleration at time t; $dec_{ped}(t)$ is the required deceleration for the AV to yield approaching pedestrians t; $d_{sl}(t)$ is the distance between the AV's front bumper and the stop line at time t.

4. Simulation experiments

4.1. Simulation platform

A platform was built for the surveyed UMCR as shown in Fig. 9. In order to create a high possibility of conflicts between AVs and pedestrians, heavy pedestrian volume is assumed. The AV volume is low for avoiding long queues at the stop line. Agents' behaviors reproduced through the Simulation of Urban MObility (SUMO) 1.7.0 [37] and Python 3.8. The simulation step length is 0.1 s. In every step, the speed and position of all agents will be uploaded from SUMO to Python by a traffic control interface function (TraCI). The algorithm of each module is calculated in Python and the action indication will be sent back to SUMO through TraCI. SUMO implements action orders and updates agents' statuses in the next step. Meanwhile, trajectories of all agents will be recorded and evaluation indexes such as the PET can be calculated.

4.2. Scenario settings

Parameters of AV and pedestrian agents are given in Tables 1 and 2. The choice set for pedestrian types includes eight options (HPS(GD), HPS(HS), HPS(MS), HPS(LS), C(GD), C(HS), C(MS), and C(LS)). The choice set for AV types includes three options (L1, L2(1.5 s), and L2(2.5 s)). Meanwhile, two levels of speed limits (30 and 40 km/h) are assumed for the UMCR. In total, 48 (8 × 3×2) scenarios were created for simulation experiments. For each scenario, three simulation repetitions were performed and each round lasts for 2.5 h. The first 30 min were warm-up time and the subsequent 2 h were the measurement period. The final result of each scenario considered the average values of the three rounds.

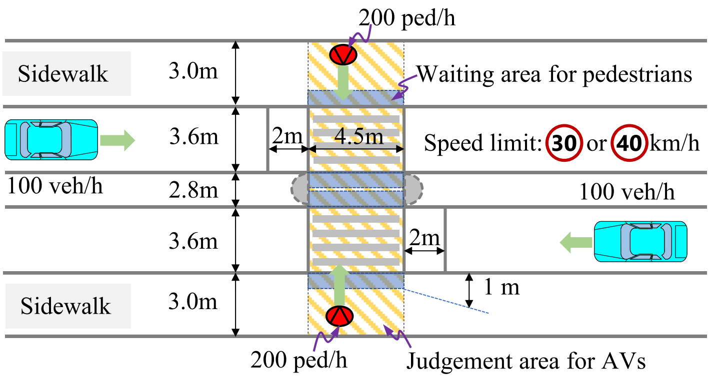

Fig. 9. Simulation platform.

Table 1
Parameters or AV agents (see [13,14,33,34,38]).

Parameters	AV agents		
d_{AV} (m)	100 [13, 14]		
τ (s)	0.1 [13, 14]		
a (m/s^2)	2.0 [38, 34]		
b (m/s^2)	4.5 [38, 34]		
δ	4.0 [33, 34]		
T (s)	1.0 [33, 34]		
s_0 (m)	2.0 [33, 34]		
l (m)	4.8**		
w (m)	2.0**		
Yielding decision module	L1*	L2*	L2*
β_{AV} (s)		1.5*	2.5*

Notes: *: values are determind based on assumption; **: values are determined based on observation;

Table 2
Parameters for pedestrian agents (see [28,31,32,35]).

Parameters	Pedestrian agents
d_p (m)	60 [28]
τ_p (s)	0.4 [35]
β_p (s)	1.5 [31, 32]
l_p (m)	0.75**
w_p (m)	0.4**
Stop-go decision module	HPS or C*
Speed profile module	GD, LS, MS, or HS*

Notes: *: values are determind based on assumption; **: values are determined based on observation;

5. Simulation results

5.1. Yield rates and hard yield rates

The conflict events between pedestrians and approaching AVs (conflict event, hereinafter) are determined based on the following requirements. (a) Each event happened between one pedestrian and one AV; (b) the AV should be the first approaching vehicle on the near-side lane of the pedestrian; (c) the pedestrian should be ahead of the AV and within AV's detection range. Since vehicles and pedestrians were randomly generated, the number of conflict events for each scenario is around 4200 (between 4151 to 4276). The yield rate is defined as the ratio of "the total number of conflict events in which the pedestrian crosses before the AVs" to "the total number of conflict events".

Firstly, it can be observed that yield rates of L1 AVs to all types of pedestrians are almost 100% which is in accordance with the settings of the defensive strategy, as shown in Table 3. L2 may compete for the right of way with pedestrians so that the yield rates of all L2 scenarios are lower than L1. Secondly, in L2 scenarios, yield rates to C type pedestrians are lower than HPS (Table 3). By checking the simulation record, it is found that, unlike HPS pedestrians' reckless crossing

Table 3
Results of yield rates.

		Speed Limit: 40 km/h			Speed Limit: 30 km/h		
		L1	L2(1.5 s)	L2(2.5 s)	L1	L2(1.5 s)	L2(2.5 s)
C	GD	92.12%	30.15%	32.02%	92.67%	32.09%	35.67%
	LS	93.34%	28.21%	33.01%	93.68%	33.31%	33.97%
	MS	94.51%	31.97%	35.55%	89.05%	34.88%	38.74%
	HS	96.12%	36.99%	38.14%	92.86%	40.00%	48.09%
HPS	GD	96.01%	45.71%	38.03%	94.98%	48.07%	51.79%
	LS	91.41%	37.41%	40.73%	95.68%	41.41%	48.07%
	MS	94.54%	51.24%	52.36%	93.71%	55.06%	60.95%
	HS	97.22%	60.31%	66.59%	96.94%	64.52%	69.98%

Table 4
Results of hard yield rates.

		Speed Limit: 40 km/h			Speed Limit: 30 km/h		
		L1	L2(1.5 s)	L2(2.5 s)	L1	L2(1.5 s)	L2(2.5 s)
C	GD	55.20%	10.50%	13.44%	58.59%	12.16%	17.50%
	LS	60.45%	11.20%	14.52%	63.92%	13.86%	16.66%
	MS	57.34%	9.92%	13.30%	53.40%	11.90%	17.86%
	HS	52.80%	10.36%	12.54%	49.29%	11.60%	20.64%
HPS	GD	57.60%	17.10%	17.10%	57.95%	20.16%	30.09%
	LS	60.97%	15.91%	19.68%	67.20%	18.45%	30.24%
	MS	55.46%	16.83%	20.28%	55.46%	20.90%	37.82%
	HS	49.47%	18.60%	22.44%	48.00%	21.45%	41.30%

decision, C pedestrians may hesitate to cross in some situations which may give the passing opportunity to L2 AVs. Such phenomena frequently happen when the speed limit is 40 km/h. Thirdly, the result also indicates that yield rates of L2 (2.5 s) scenarios are higher than L2 (1.5 s). This can be explained that as the safety margin (β_{AV}) of the AV reduces the number of events where the AV should yield to pedestrians also reduces. This finding also reveals that by enlarging the β_{AV} of AVs the yield rate can be increased. Moreover, especially with C pedestrians, yield rates become lower as the speed of pedestrians reduces from HS to LS in L2 scenarios. The reason is that competitive AVs may find the passing chance more easily as LS pedestrians spend more time on the sidewalk.

The yielding can be divided into hard and soft yielding. Hard yielding refers to the event where the vehicle stops completely for giving way to pedestrians. Soft yielding refers to the event that the vehicle yields to pedestrians without a complete stop. The hard yield rate is the ratio of "the number of hard yield events" to "the total number of conflict events". As shown in Table 4, for both speed limits of 40 km/h and 30 km/h, L1's hard yielding rate is extremely larger than the one of L2. The hard yielding rate of L2 (2.5 s) is higher than the one of L2 (1.5 s). Furthermore, with the increase of the pedestrian speed, the hard yield rates of L2 AVs to HPS increase slightly. This is because high pedestrian speed leads to more yielding events (Table 3), which drives the increase of hard yield events as well. HS and HPS pedestrians spent less time in the sidewalk and made reckless crossing decisions even when L2 AVs is near. Such aggressive behaviors left less buffer time for L2 AVs to change motion plans and catch them off guard. Therefore, cases, where AVs applied emergent brakes to evade crashes with pedestrians, happened more frequently. In contrast, the hard yielding rates in L1 scenarios increases as the pedestrian speed decreases. For L1 AV, the yield rate is already saturated for L1 AVs. Whereas, as low-speed pedestrians spend more time in the alert area of L1 AVs letting more AVs stop until the pedestrian passed so that hard yield rates increases.

5.2. Average vehicle delay and pedestrian waiting time

Vehicle delay is the time difference between the actual travel time and the travel time under ideal road conditions (no pedestrian influence, maximal speed) for the assumed roadway (200 m). The results of the average vehicle delay are shown in Table 5. It can be observed that the average delay of the L1 AV is significantly higher than L2 AV whereas the delay of L2 (2.5 s) is slightly higher than L2 (1.5 s) with an average difference of 1.5 s. Meanwhile, the average delay of scenarios with a speed limit of 30 km/h is higher than those with a 40 km/h speed limit. Their average difference between them is 5.5 s which almost equals the delay caused by the different speed limits. In addition, the average delay of the L1 AV with C type pedestrians is higher than that with HPS. C pedestrians may wait longer on the sidewalk until the AV slows down to the speed that satisfies pedestrians' crossing requirements. In this regard, C pedestrians spend more time

Table 5
Results of average vehicle delay.

		Speed Limit: 40 km/h			Speed Limit: 30 km/h		
		L1	L2(1.5 s)	L2(2.5 s)	L1	L2(1.5 s)	L2(2.5 s)
C	GD	15.50	2.00	2.72	19.37	7.52	8.83
	LS	41.91	1.86	2.76	44.31	7.45	8.59
	MS	20.42	1.85	2.81	24.04	7.64	9.30
	HS	9.28	2.23	3.20	14.27	7.79	8.50
HPS	GD	10.38	3.11	4.05	17.52	8.37	9.46
	LS	31.90	5.14	7.80	38.77	10.86	13.97
	MS	15.87	4.25	5.73	20.65	9.19	11.03
	HS	7.87	3.09	3.91	12.64	8.54	9.62

Notes: Results of scenarios whose speed limits are 30 km/h include 6s delay due to the speed difference (200m roadway is assumed)

Table 6
Results of pedestrian waiting time.

		Speed Limit: 40 km/h			Speed Limit: 30 km/h		
		L1	L2(1.5 s)	L2(2.5 s)	L1	L2(1.5 s)	L2(2.5 s)
C	GD	0.82	8.23	3.63	0.70	7.71	2.98
	LS	0.68	8.74	3.37	0.58	7.44	3.09
	MS	0.71	7.71	3.24	0.81	7.26	2.74
	HS	0.81	6.64	3.10	0.89	6.18	2.01
HPS	GD	0.70	5.40	2.76	0.76	5.08	1.43
	LS	0.72	6.61	2.36	0.53	5.93	1.52
	MS	0.80	4.83	1.82	0.79	4.44	0.90
	HS	0.83	4.11	1.37	0.89	3.71	0.64

on decision-making than HPS. However, L1 AVs' will always wait for the whole crossing process, which contributes to a lot of delay for themselves. On the contrary, the average delay of the L2 AV with C pedestrians is lower than it with HPS. This is because the yield rate of L2 to C pedestrians is lower than it to HPS. In addition, it can be observed that the delay of L1 AV with LS pedestrian is extremely larger compared to other scenarios. LS pedestrians spend more time on crosswalks. Therefore, there is a high probability that new pedestrians will arrive during the crossing of the last pedestrian and L1 AV may Table 5. Results of average vehicle delay wait for multiple consecutive pedestrians. Considering this finding, we infer that applying the defensive strategies may lead to heavy congestions at UMCRs.

The average pedestrian waiting time is the accumulative time when the pedestrian speed is 0 m/s. The result is shown in Table 6. It can be found that the average pedestrian waiting time in L1 scenarios is lower than 1 s and extremely smaller than it in L2 scenarios. As for the L2 scenarios, the average pedestrian waiting time in L2 (2.5 s) is lower than that in L2 (1.5 s). It indicates that for the interferences from AV to pedestrians, L2(1.5 s)>L2(2.5 s)>L1. In addition, for L2 scenarios, the average waiting time of C pedestrians is 1.5–3.0 s longer than it of HPS pedestrians, which reveals that the interferences from L2 AVs to C pedestrian are greater than HPS.

5.3. Percentage of short post encroachment time (%SPET)

At the UMCR, PET is defined as the global time difference between the next vehicle entering the conflict zone and the subject pedestrian leaving the conflict zone. As the PET becomes smaller, the conflict is more likely to cause a crash. As an example, PET distributions of HPS(GD) pedestrians with all types of AV are illustrated in Fig. 10. It is found that the PET distribution of L2 (2.5 s) is similar to the distribution of L1. The distribution of L2 (1.5 s) is obviously located leftward of those two, especially when PETs is between 1.5 s and 3 s.

Low PET cases should be paid more attention. It has been widely recognized in previous studies, e.g., [39]; Zhang et al. 2017, that PET $= 2$ s is an important threshold for analyzing conflicts between pedestrians and vehicles. The cumulative probabilities of low PET events (PET ≤ 2 s) are abbreviated as %SPET and the results are shown in Table 7. Firstly, it can be observed that there is almost no difference in scenarios with L1 AVs (%SPETs of most cases are smaller than 3%). Secondly, for scenarios of L2 AVs, %SPET s of HPS are higher than the %SPET s of C. Also, among the three AV types, the %SPETs of L2(2.5 s) are the lowest, and those of L2(1.5 s) are the highest. Especially in scenarios with C pedestrians, %SPETs of L2(2.5 s) are smaller than 1%, whereas, %SPETs of HPS(GD)-L2(1.5 s) are 10.2% (speed limit is 40 km/h) and 8.9% (speed limit is 30 km/h). This finding indicates that by enlarging the β_{AV}, AVs' safety performance can be improved. It also means for

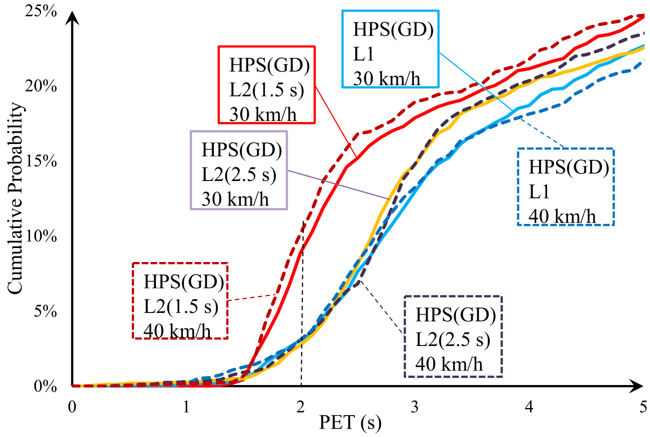

Fig. 10. Example of PET distributions (pedestrians: HPS(GD)).

Table 7
Results of %SPET.

		Speed Limit: 40 km/h			Speed Limit: 30 km/h		
		L1	L2(1.5 s)	L2(2.5 s)	L1	L2(1.5 s)	L2(2.5 s)
C	GD	3.47%	4.79%	0.89%	2.96%	3.63%	0.87%
	LS	3.02%	2.46%	0.56%	2.63%	1.45%	0.26%
	MS	3.53%	3.96%	0.71%	3.14%	2.19%	0.32%
	HS	3.62%	4.72%	0.72%	3.96%	3.46%	0.64%
HPS	GD	3.11%	10.17%	3.10%	3.06%	8.90%	2.75%
	LS	3.20%	7.25%	2.19%	3.37%	7.00%	2.59%
	MS	3.50%	8.25%	2.41%	2.97%	7.72%	2.64%
	HS	3.94%	10.11%	2.82%	3.43%	8.40%	2.83%

competitive AVs with a small safety margin, pedestrians who make reckless crossing decisions and change their speed drastically are the most contributing to severe conflicts with AVs. In addition, it can be observed that %SPETs of scenarios with the 40 km/h speed limit are higher than those under the 30 km/h speed limit for the majority of scenarios (except C(HS)-L1, HPS(LS)-L1, HPS(LS)-L2(2.5 s), HPS(MS)-L2(2.5 s), and HPS(HS)-L2(2.5 s)), which reveals that speed reduction can be a possible treatment to improve safety.

6. Discussion on crashes

6.1. Crash rate

The crash rate is defined as the ratio of "the number of crashes" to "the number of pedestrian crossings" and that can be considered as an important index for evaluating pedestrian safety. Table 8 compares the observed crash rates in the simulation runs. Based on the simulation data, crashes happened only in the scenarios of HPS(GD)-L2(2.5 s)-40 km/h, HPS(GD)-L2(1.5 s)-30 km/h, and HPS(GD)-L2(1.5 s)-40 km/h. All these scenarios are with L2 AVs and HPS(GD) pedestrians. It reveals that reckless crossing decisions, changing speed greatly, and competitive driving strategy may cause crashes. Moreover, crash rates of HPS(GD)-L2(1.5 s)-30 km/h and (HPS(GD)-L2(2.5 s)-40 km/h are 50% lower than HPS(GD)-L2(1.5 s)-40 km/h. Meanwhile, the crash rate of HPS(GD)-L2(2.5 s)-30 km/h is zero. It indicates that reducing speed limits and large safety margin time can be effective methods to avoid crashes for competitive AVs.

6.2. Crash reasons in simulation

The process of the typical crash in the simulation is analyzed and illustrated in Fig. 11. In the beginning, there is a pedestrian walks slowly toward the crosswalk. The approaching AV decides to keep the current speed (40 km/h) for passing through the conflict zone before the pedestrian. In this plan, the safety margin between AVs' leaving time and pedestrian's entering time will be 1.9 s (>1.5 s). At time t_1, the pedestrian steps into the waiting area. She/he decides to cross since the pedestrian perceives that the AV will yield and give the right of way on time. Therefore, at time t_2 (τ_p after

Table 8
Results of accident rate.

		Speed Limit: 40 km/h			Speed Limit: 30 km/h		
		L1	L2(1.5 s)	L2(2.5 s)	L1	L2(1.5 s)	L2(2.5 s)
C	GD	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
	LS	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
	MS	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
	HS	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
HPS	GD	0.000%	0.255%	0.126%	0.000%	0.128%	0.000%
	LS	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
	MS	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
	HS	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%

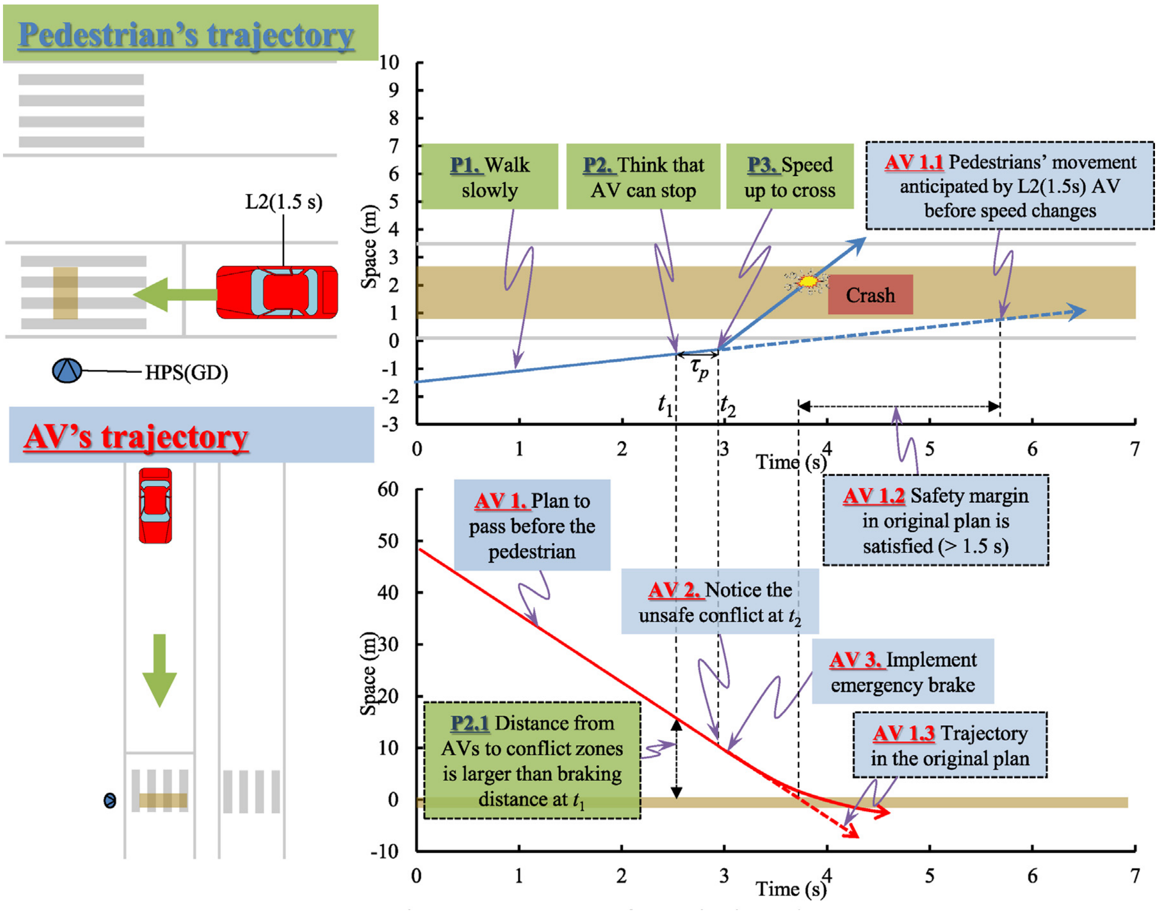

Fig. 11. Process of a typical crash.

the time t_1), the pedestrian boosts her/his speed suddenly and steps into the crosswalk. The AV detects that it will have a crash with the pedestrian. Even though the AV implements the emergency brake, it is already too late to avoid the crash.

The occurrence of such crashes is also because this framework only considered the pedestrians' decisions in the waiting area. In reality, when pedestrians are on the crosswalk, they may change their speed or even step back after they notice the danger. However, it is inevitable that some pedestrians may fail to react appropriately to avoid the crash due to distraction or other reasons, or even due to their belief in the AVs' abilities to stop even in such critical situations. Those pedestrians may have insufficient observations when they are on the crosswalk. For preventing crashes from happening, the following treatments are proposed for the pedestrian sides: (1) delimiting auxiliary decision area with color pavement (if AVs are running toward the crosswalk in such area, pedestrians are suggested to wait); (2) Educating pedestrians not to switch between running and walking arbitrarily during the crossing.

7. Conclusions and future work

This study aims to provide suggestions and evidence for the proper AV settings on UMCRs considering various crossing behaviors of pedestrians. Two driving strategies were assumed, namely defensive and competitive driving strategies, for AVs on UMCRs. Also, different pedestrian behaviors including decision-making and speed profiles were modeled through analyzing real-world data. Scenarios combining different AV strategies (i.e., defensive (L1) or competitive (L2)), pedestrians' crossing decisions (i.e., Cautious (C) or High Priority Sense (HPS)), pedestrians' crossing speed profiles (i.e., Great speed Difference (GD), Low Speed (LS), Mid-level Speed (MS), or High speed (HS)), and speed limits (40 km/h or 30 km/h) were designed and compared by simulation experiments.

It is found that defensive AVs (L1) had a good safety performance on the UMCR. That is, the %SPET was around 3% and the crash rate was 0%. Also, L1 AV was found to have less interference with pedestrians. The average pedestrian waiting time was less than 1 s and the yield rate is almost 100%. However, as the result indicated, the key drawback of L1 AVs was the efficiency. The average vehicle delay was even exceeded 40 s when they encountered slow and conservative pedestrians. Regarding the competitive AV, they displayed good performances in terms of efficiency. The average vehicle delays were between 1.8 s and 13.9 s for different types of pedestrians. Whereas, competitive AVs with small safety margin time were found to be dangerous for pedestrians. Under the speed limit of 40 km/h, the %SPET of L2 (1.5 s) was 10.17% and the crash rate was 0.26% when pedestrians were reckless and changed speed drastically. Also, the L2 (1.5 s) had a significant influence on pedestrians' crossing. The yield rate could even be 28% when pedestrians were conservative and walking at low speed. The average pedestrian waiting times were between 4.1 s and 8.7 s for different types of pedestrians. However, if the AV safety margin time is increased to 2.5 s, the safety and efficiency performance could be well balanced. For L2 (2.5 s) AV, the average pedestrian waiting times were decreased to between 0.6 s and 3.6 s. Its %SPETs were less than 3.1% which was even better than L1 AVs. Also, its crash rate equals 0% under the speed limits of 30 km/h. Therefore, it can be concluded that competitive AVs with a large safety margin can find safe and proper gaps to pass through UMCRs which are wasted by defensive AVs. As a result, they can ensure the basic safety requirements compared to the competitive AVs with small safety margin and have a better efficiency performance than the defensive AVs.

These findings indicate that competitive AVs with appropriate parameters are more suitable for UMCs than defensive AVs in the future. Finally, a typical crash process in the simulation was analyzed to identify the critical factors leading to safety hazards. Corresponding treatments were proposed for further enhancing the safety performance of competitive AVs: (1) for AV side, firstly is to increase safety margin time; secondly to decrease the road speed limit; thirdly advanced detection technology that can help AV identify risky pedestrians are expected to be applied, such as artificial intelligence [40]; (2) for pedestrian side, firstly guiding pedestrians to make the right decisions, for example, delimiting the risk area in the roadway before the crosswalk in which if AVs are running toward the crosswalk, pedestrians are suggested to wait and secondly to educate pedestrians for avoiding drastic behavioral changes while crossing such sudden crossing with high speed.

Still, there are several limitations in this study such as the realism of pedestrian behaviors should be further considered for reproducing more real conflicts. Firstly, pedestrians' visual fields and AVs' scanning areas may be obscured by objects in the surrounding environment (such as trees, poles, and buildings) and bodies of opposing vehicles. In such circumstances, influenced visibility may increase the crashes as well. Therefore, the occlusion effect is also an important aspect that should be included for testing the feasibility of driving strategies. Secondly, in the crosswalk area, the speed profile model only applied the pre-recorded projection speed in the crossing direction and those data profiles were collected from one crosswalk with typical geometry in Japan. On one hand, pedestrians' lateral movements and speed changes when reacting to approaching vehicles during crossing may also influence the safety performance. For this sake, a comprehensive pedestrian behavior model considering interaction force and psychological factors should be developed [41–44]. On the other hand, unsignalized crosswalks are seldomly used in Japan and the majority of unsignalized crosswalks only have one lane in each direction. It is quite challenging for us to have diverse data currently. Therefore, we also plan to seek international cooperation to expand our database for achieving data diversification in the future.

CRediT authorship contribution statement

Hong Zhu: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Wael Alhajyaseen:** Conceptualization, Writing – review & editing, Writing – original draft, Project administration, Funding acquisition. **Miho Iryo-Asano:** Conceptualization, Writing – review & editing, Writing – original draft, Project administration, Funding acquisition. **Hideki Nakamura:** Conceptualization. **Charitha Dias:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This publication was made possible by the Qatar–Japan Research Collaboration Application Award [M-QJRC-2020-8] from Qatar University. The statements made herein are solely the responsibility of the authors. This research is supported by The Kurata Grants No. 1397 of Hitachi Global Foundation.

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