Journal of Intelligent and Connected Vehicles
2023, **6**(2): 91–101
https://doi.org/10.26599/JICV.2023.9210008

Research Article

Hybrid cooperative intersection management for connected automated vehicles and pedestrians

Pinlong Cai[1], Jia He[2,✉], Yikang Li[1]

[1]*Shanghai Artificial Intelligence Laboratory, Shanghai 200232, China*
[2]*Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology, Beijing 100124, China*

Received: December 13, 2022; Revised: February 11, 2023; Accepted: May 10, 2023

ABSTRACT: Connected Automated Vehicles (CAVs) have drawn much attention in recent years. High reliable automatic technologies can help CAVs to follow given trajectories well. However, safety and efficiency are hard to be ensured since the interactions between CAVs and pedestrians are complex problems. Thus, this study focuses on cooperative intersection management for CAVs and pedestrians. To avoid the effects of uncertainty about pedestrian behaviors, an indirect way is to use pedestrians' signal lights to guide the movements of pedestrians, and such lights with communication devices can share information with CAVs to make decisions together. In time domains, a general conflict-free rule is established depending on the positions of CAVs and crosswalks. Geometric analysis with coordinate calculation is used to accurately determine the feasible vehicle trajectories and the reasonable periods for signal lights turning green. Four control strategies for the same conditions are compared in simulation experiments, and their performances are analyzed. We demonstrate that the proposed cooperative strategy not only balances the benefits of vehicles and pedestrians but also improves the traffic efficiency at the intersection.

KEYWORDS: connected automated vehicle, intersection, pedestrian, crosswalk, cooperative management

1 Introduction

In the traffic field, artificial intelligence and communication technologies significantly change road transportation. Nowadays, many institutes and companies focus on the design and manufacture of automated vehicles. High-level automated vehicles will run on the road in the foreseeing future, which can also be called Connected Automated Vehicles (CAVs). CAVs can sense and share dynamic traffic information in large-range areas, plan their trajectories, and achieve their maneuvers automatically.

The applications of CAVs integrate many emerging technologies (Rashidi et al., 2020). Many sensors are applied to perceive information about static road environments and dynamic traffic states. Massive perceptual data help CAVs to make wise decisions by themselves without the interference of human beings. Thus, planning for CAVs is a vital technical direction to improve road traffic systems. According to different purposes, planning includes three types (González et al., 2015). The first type is mission planning, which aims to find the most efficient routes to bring passengers from origins to destinations. The traffic states of local road networks are usually concerned with mission planning to save time and energy. Behavior planning is the second type to decompose the planned mission and achieve several specific vehicle motion behaviors, including car following, lane changing, and turn corners. The third type is trajectory planning to find the optimal or near-optimal trajectories for CAVs. The vehicle controllers can manipulate motions to follow these trajectories. Thus, trajectory planning focuses on the microscope motions, which helps CAVs to provide passengers with safe, efficient, and comfortable travel experiences.

To share information on the roads, Vehicle-to-Everything (V2X) communication is an important technology. Recently, researchers have summarized that the V2X communications of intersection management have different structures, including centralized structures, decentralized structures, and distributed structures (Zhong et al., 2020). The communication structure determination is beyond the scope of this study. The communication quality within the control ranges is usually assumed to be guaranteed. Under such an assumption, plenty of studies focus on cooperative control for CAVs at intersections (Cai et al., 2019; Chai et al., 2018; Li et al., 2018; Meng et al., 2017; Tachet et al., 2016), road segments (Jiang et al., 2021; Rios-Torres and Malikopoulos, 2017), etc. Intersection management is one of the most challenging tasks because of the complex motion coupling among CAVs. Signal Time Assignment (STA) is not suited for CAVs at all because of its waste of passage time. Traditional intersection management needs to make changes to cater to the applications of CAVs.

A typical method called Autonomous Intersection Management (AIM) was proposed in 2004 (Dresner and Stone, 2004). First, it permits CAVs to submit their requests to the controllers before they enter the junctions of intersections, and then they can receive reasonable time slots for their crossing from the controllers. However, as the AIM is supported by the "First Come, First Severed" (FCFS) policy, it cannot get satisfactory results. Levin et al. (2016) illustrated that the AIM system with the FCFS policy had worse control effects compared to the common STA method in some specific conditions. In recent years, with the

✉ Corresponding author.
E-mail: hejia@bjut.edu.cn

清華大学出版社 Tsinghua University Press | IEEE

enhancement of computing power, many researchers attempt to optimize the enter or exit sequences of CAVs, which is regarded as an NP-hard problem. They proposed nonlinear programming problems with constraints to describe the CAVs-involved intersection management. The solutions to such non-convex problems are hard to be obtained by mathematical derivation. Thus, many numerical methods are proposed to get near-optimal solutions, such as Monte Carlo Tree Search (MCTS) (Mirheli et al., 2018; Xu et al., 2019) and graph-based method (Ge et al., 2021; Xu et al., 2018). These numerical solutions can assign vehicle orders well and enhance the efficiency of intersections, whereas these models hardly consider the crossing of pedestrians to lead to more idealized results than practical applications.

The motions of CAVs are dynamic processes that relate to vehicle kinematic constraints. Researchers optimize the trajectories to achieve the objectives of energy-saving and comfort. Malikopoulos et al. (2018) summarized multiple situations of vehicle motion at intersections and then gave the analytical solutions based on the optical control theory. Bichiou and Rakha (2019) estimated vehicles' arrival time and optimized vehicle trajectories using Pontryagin's minimum principle to solve the Lagrange functions with constraints. These analytical solutions provide CAVs with precise trajectory guidance to cross the intersections. One of the vital points of these studies is to identify the constraints related to the conflict-free rule at intersections. However, compared to simplified scenarios in these studies, the setting of green time for pedestrians' crossing will inevitably add extra delays to the trajectory optimization process of CAVs.

Although many existing methods have been proposed to manage the intersections for CAVs, they hardly consider the influences of other traffic participants. The interactions between CAVs and other traffic participants play significant roles in research and practical applications (Rasouli et al., 2020). Therefore, intersection management for CAVs needs to be enhanced. The newest study proposed an automated pedestrian shuttle to carry pedestrians cross the street within an AIM system, whereas the strategy greatly changes the existing pedestrian traffic rules (Wu et al., 2022).

This study attempts to analyze the mutual interference between CAVs and pedestrians at intersections and to give a more realistic crossing efficiency evaluation. In most cases, we must set crosswalks at all entrances of intersections for pedestrians and bicycles to cross the roads. For simplicity, bicycles are considered to cross the roads like pedestrians, which are included in the pedestrian flows. Moreover, the interaction among pedestrians at crosswalks is ignored. Thus, this study proposes an efficient hybrid cooperative intersection management method for CAVs and pedestrians.

Unlike the connectivity of CAVs, pedestrians cannot easily exchange information with vehicles or infrastructure. We use the signal lights for pedestrians only, namely pedestrian lights, which have red and green lights for guidance. CAVs need to cooperate with the assignments of pedestrian lights to ensure safety and efficiency. In this study, different assignments are studied in detail. The first type of STA has fixed cycles used for zebra crossings. The second type is used for pelican crossings, where pedestrians can control the pedestrian lights. In this way, the STA has variable cycles. The pedestrian lights can be controlled adaptively, relying on the pedestrians' demands. Three main contributions of this study are described as follows.

1) A general conflict-free rule for CAVs and crosswalks with green lights on is proposed. To avoid conflicts between CAVs and pedestrians, the CAVs are banned to go through crosswalks when their corresponding pedestrian lights are green. Thus, if the green lights for crosswalks turn on, the virtual entities appear in the same positions, considered in the trajectory planning of CAVs. Such constraints may increase delays for CAVs compared to simplified scenarios without considering pedestrians.

2) Cooperative optimization for pedestrian lights and CAVs to minimize the total delays. Several intersection strategies are proposed. This study balances CAVs and pedestrians to reasonably assign the crossing time to both sides. The influences of several significant parameters are analyzed through simulation experiments.

3) Different strategies are compared for the same conditions at the intersection to show their advantages and disadvantages. For different considerations of the vehicle or pedestrian priority, appropriate strategies and evaluation indicators can be determined in targeted manners.

The rest of this paper is organized into the following sections. Section 2 describes the concerned problem at intersections. Section 3 provides a general conflict-free rule for CAVs and pedestrians by geometric analysis. Section 4 introduces the logic of cooperative intersection management. Section 5 describes the experiments and gives some discussions about significant parameters. Section 6 concludes this study.

2 Problem statement

In the cooperative vehicle infrastructure system, with the help of roadside devices with mobile edge computing services, CAVs can not only make joint decisions with other vehicles to obtain near-optimal trajectories but also cooperate with pedestrian lights to avoid collisions with pedestrians. We study a hybrid cooperative intersection management strategy that provides near-optimal trajectories for multiple vehicles and reasonable green time for pedestrian lights. In this study, we assume CAVs can pass accurately according to the planned trajectories. Pedestrians can pass crosswalks at green time, and the minimum length of green time ensures that pedestrians can cross the intersection safely.

A typical four-way intersection is studied in this study, shown in Fig. 1. According to the white signs with arrows at each entrance, vehicles can go straight in two lanes, turn left in the

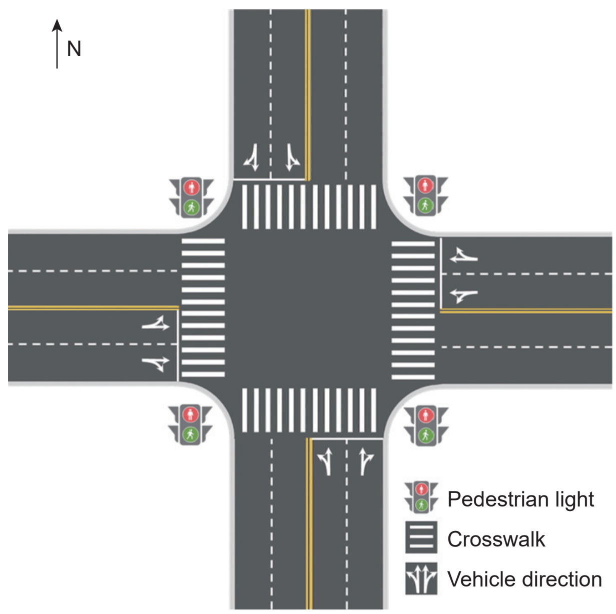


Fig. 1 Exhibition of the studied intersection.

inside lane, and turn right in the outside lane. The crosswalks are placed beside the stop line at all entrances. Vehicles must pass through the crosswalks before they enter the junction and after they leave the junction. The pedestrians controlled by pedestrian lights can walk on the crosswalks when the corresponding lights turn green. Differently, vehicles cross the intersections by cooperative trajectory planning. We assume that all the vehicles studied in this study are CAVs, and the pedestrian lights can share information with CAVs to make decisions together.

3 General conflict-free rule

3.1 Preset vehicle trajectories

The trajectories of straight-going direction are easily obtained since they are straight lines. Besides, Bezier curves are chosen to fit the trajectories to ensure vehicles to achieve their travels smoothly by turning left and turning right within the intersection. A Bezier curve is determined by several control points (Prautzsch et al., 2002) and the equation of the Bezier curve depends on the Bernstein polynomials of degree n shown as Eq. (1):

$$B(u) = \sum_{i=0}^{n} \binom{n}{i} P_i (1-u)^{n-i} u^i \tag{1}$$

where P_i is the coordinate of i^{th} control point. The number of control points is $n+1$. In this study, we use the four-order curve function with five control points to fit the trajectories. $B(u)$ is the coordinate of interpolation point within the trajectory and $u \in [0, 1]$. Especially, when $u = 0$, $B(0) = P_0$; when $u = 1$, $B(1) = P_n$.

In Fig. 2a, aiming at a left-turning trajectory, we select five control points, of which the points A and B are in the center line of the arrival lane belonging to the western approach of the intersection, the points D and E are in the center line of the departure lane belonging to the southern exit of the intersection, and the point C is in the center of the junction. Similarly, a right-turning trajectory is controlled by five points shown in Fig. 2b, of which the points A and B are in the center line of the arrival lane belonging to the western approach of the intersection, the points D and E are in the center line of the departure lane belonging to the northern exit of the intersection, and the point C is the common point between the center lines of these two lanes. In this way, we can also preset trajectories of other directions within the intersection.

3.2 Conflict-free rule for vehicles

To avoid conflicts among vehicles, a rigid safety constraint needs to be satisfied, meaning that all vehicles cannot occupy the same position at intersections. In this study, we use rectangular shapes to describe vehicle contours. Thus, the conflict-free rule is equivalent to a no-overlap rule among vehicle contours, and the two cases are shown in Fig. 3. The safety distance among CAVs can be closer than human-driving vehicles since CAVs are usually considered to have shorter reaction time and lower estimation errors than human-driving vehicles (Yu et al., 2021). In this study, the vehicle contours also consider the extra safety margin around the contours.

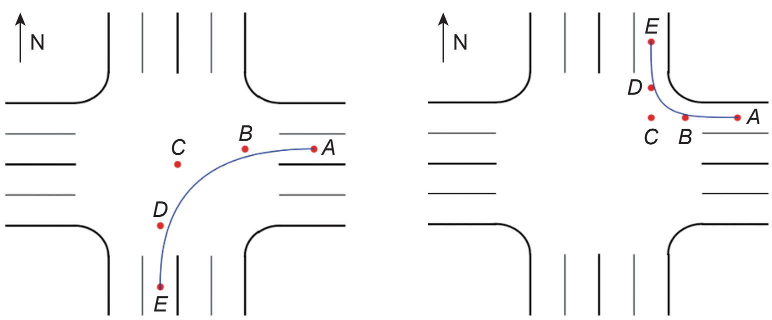
The overlap includes two situations. First, at least one vertex of one vehicle is in the contour of the other vehicle. Second, none of the vertexes is in the contour of the other vehicle, whereas overlap exists. By common sense, the second situation always occurs after the first situation during collision processes. Thus, we only consider avoiding the first situation. To precisely analyze the collisions at intersections, a coordinate system is defined for the study zone. Hence, we can get the vertex coordinates of each vehicle contour. A vector-multiplication-based geometric method is used to judge whether a point is in a rectangle, of which the discriminant is shown as Eq. (2):

$$\begin{cases} (\boldsymbol{AP} \times \boldsymbol{AD}) \cdot (\boldsymbol{CP} \times \boldsymbol{CB}) < 0 \\ (\boldsymbol{BP} \times \boldsymbol{BA}) \cdot (\boldsymbol{DP} \times \boldsymbol{DC}) < 0 \end{cases} \tag{2}$$

where $\boldsymbol{AP}$, $\boldsymbol{AD}$, $\boldsymbol{CP}$, $\boldsymbol{CB}$, $\boldsymbol{BP}$, $\boldsymbol{BA}$, $\boldsymbol{DP}$, and $\boldsymbol{DC}$ are vectors in Fig. 4. The sign "$\times$" represents the outer product operation between two two-dimensional vectors. The sign "$\cdot$" is the norm of a vector. The first inequality of Eq. (2) is to judge whether the point P is between the family of parallel lines AD and BC. The second inequality is to judge whether the point P is between the family of parallel lines AB and CD. As the area of the rectangle $\square ABCD$ is bounded by two families of parallel lines, the point P cannot be inside of the rectangle $\square ABCD$ when one of two inequalities of Eq. (2) is satisfied.

3.3 Virtual entity for crosswalk

At common intersections, all vehicles pass through crosswalks when they arrive and leave intersections. Pedestrian lights are always placed on the roadside to give permission or prohibition indications for pedestrians to avoid collisions with vehicles. When a pedestrian light turns green, CAVs cannot go through their corresponding crosswalk. Benefiting from the technology of V2X communication, CAVs can receive the signal information far away from the crosswalk. CAVs can plan their trajectories to avoid passing through crosswalks when the green lights are on. CAVs are expected to have high velocities and reduce occupation time when they travel during intersection junctions through trajectory planning. The control of pedestrian lights also cannot have conflicts with vehicles that have already planned their trajectories. Here, the conflict-free rule for vehicles is extended to suit general conflict-free cases among more traffic participants.



(a) A left-turning trajectory (from A to E) (b) A right-turning trajectory (from A to E)

Fig. 2 Control points and Bezier curves.

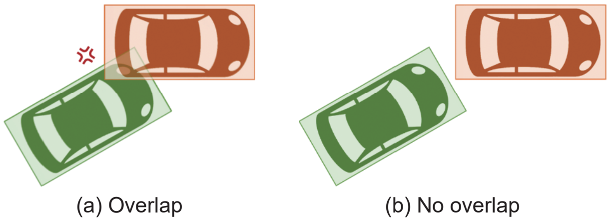


Fig. 3 Overlap and no overlap between the two vehicles.

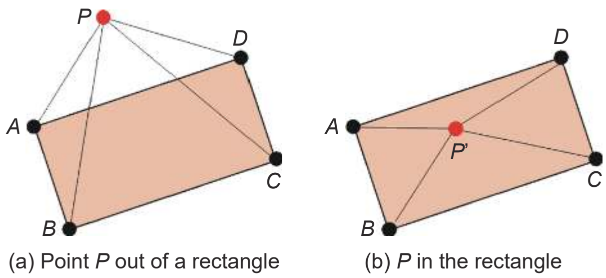


Fig. 4 Relationship between the point P and the rectangle $\square ABCD$.

Considering the interaction between vehicles and pedestrians, we propose virtual entities to ensure the safety of pedestrians when they cross the roads during green time. The virtual entities refer to the space positions occupied by crosswalks during the green time, which participate in cooperative processes with multiple vehicles. If the traffic light of a crosswalk turns green, then a virtual entity with a two-dimensional shape appears in the perceived results of CAVs within the communication range. A virtual entity is like an obstruction with a rectangle shape covering the crosswalk, and it also occupies a certain space during green time, as shown in Fig. 5. The interaction modeling of vehicles and pedestrians is realized by the cooperative control design for vehicles and pedestrian lights, and the conflicts between them are avoided through the allocation of spatiotemporal resources in the intersection. Note that there is no conflict among virtual entities themselves.

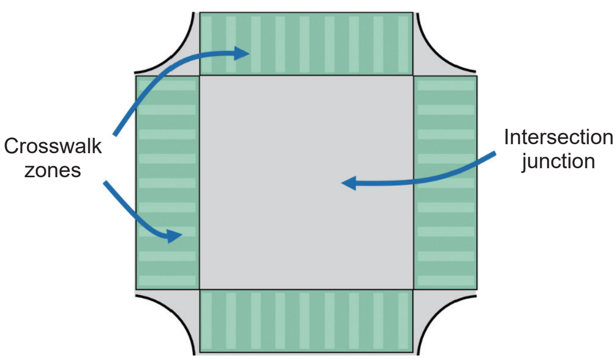


Fig. 5 Virtual entities of crosswalks during green time.

4 Cooperative intersection management

4.1 Area division at roads of entrances

With the help of the communications between CAVs and pedestrian lights, we assume that the vehicles can adjust their velocities before they enter the junction. To obtain high crossing efficiency, the occupation time of vehicles in the junction should be as little as possible. We assume that the velocities are expected to be optimal before CAVs arrive at stop lines. Thus, the states of vehicles before crosswalks are definite. However, since the time allowed for vehicles to arrive at the intersection needs to be negotiated, vehicles need to adjust their speed at the entrance roads.

We divide the entrance roads of the intersection into decision zones and adjustment zones. The lengths of decision zones are related to the V2X communication abilities and the computation abilities for cooperation. If the studied physical ranges of intersections are fixed, then the lengths of decision zones can be determined by the lengths of the adjustment zones on the same lanes. The minimum lengths of adjustment zones are changeable, depending on the number of vehicles in the zones. Due to the limitation of maximum acceleration and deceleration, vehicles need enough space to adjust their speed to meet the requirements of reaching the intersection at the specified time. When no vehicle is in the adjustment zone, the minimum length of the adjustment zone is the sum of the distances required for a vehicle to decelerate from the state with the optimal speed to stop and to accelerate from the stopped state to the state with the optimal speed. When several vehicles enter the adjustment zone, it is necessary to maintain safe headways between vehicles, so the length of the adjustment zone needs to extend the sum of these safe headways.

An example is given in Fig. 6. If the maximums of acceleration and deceleration are priori conditions, then the minimum length of an adjustment zone (L_{AZ}) is derived as Eq. (3):

$$L_{\mathrm{AZ}} = \frac{v_{\mathrm{o}}^2}{2d_{\max}} + \frac{v_{\mathrm{o}}^2}{2a_{\max}} \tag{3}$$

where v_{o} is the optimal velocity, $d_{\max}$ is the maximum deceleration, and $a_{\max}$ is the maximum acceleration. However, if the delays of vehicles are unavoidable, they may wait in lines before they enter the junction. If vehicles exist in an adjustment zone, the length of the adjustment zone needs to be expanded to ensure that the subsequent vehicles have no risk of rear-end collisions. Thus, a new definition of the length of the adjustment zone (L'_{AZ}) is shown as Eq. (4):

$$L'_{\mathrm{AZ}} = L_{\mathrm{AZ}} + \sum_{i=0}^{m} L_i + m\delta \tag{4}$$

where m is the number of vehicles already existing in the adjustment zone, L_i is the length of vehicle i, and δ is the safety margin among the vehicles. The second and third items on the right side of Eq. (4) are the sum of the safe headways between vehicles that are within the adjustment zone. As shown in Fig. 6, the critical point is used to distinguish the decision zone and the adjustment zone. When a vehicle enters the adjustment zone, its trajectory is determined by the proposed cooperative logic, and other vehicles or virtual entities need to avoid conflicts with the determined trajectory in the subsequent decision-making processes. Thus, if vehicles arrive at critical points, they need to make decisions for planning their trajectories during their travels within the intersection area.

If there are no delays for vehicles, they can pass through the adjustment zone with the optimal velocity. However, delays are often inevitable in most cases. Vehicles may stop and wait in the adjustment zone when the delays are large enough. These constraints are provided for the trajectory optimization process, which can refer to related research (Malikopoulos et al., 2018; Wang et al., 2020).

4.2 Cooperative logics

This study researches the cooperative vehicle infrastructure logic in the intersection to determine the reasonable vehicle trajectories

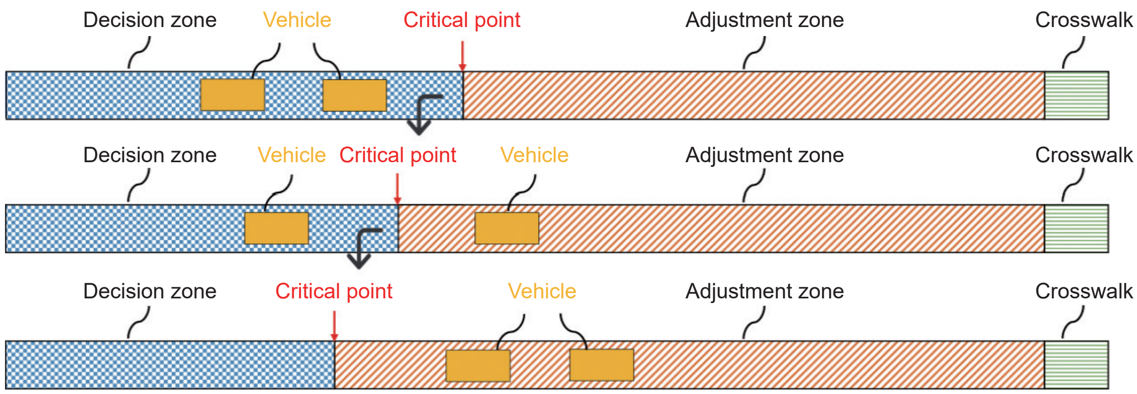


Fig. 6 Dynamic length of the adjustment zone.

and the green time of the pedestrian lights. The cooperative process can be divided into two phases: a distributed triggering mechanism and a centralized decision-making mechanism. The distributed trigger mechanism means that the executions of cooperative decision-making processes can be triggered by both CAVs and pedestrians, when CAVs reach critical points or pedestrian lights request turning green. The centralized decision-making mechanism means that global cooperative decisions and scheduling are operated through roadside devices with mobile edge computing services, and then send the decision-making results to vehicles and pedestrian lights. Through this cooperative process, the vehicles obtain near-optimal trajectories, and the pedestrian lights obtain reasonable green time assignment. Although the decision processes of cooperation are continuous in the time domain, the practical applications should be discrete. In each time step, the traffic participants can operate the cooperation.

The green time setting for pedestrian lights has significant effects on the trajectories of vehicles. Different control mechanisms of pedestrian lights lead to different situations in the decision process. The fixed STA with a fixed cycle is commonly used in urban zebra crossings. Undoubtfully, the fixed STA has the highest priority to generate several virtual entities of crosswalks that interfere with the decisions of vehicles. Differently, the facilities of pelican crossings have irregular cycles because the lights are actuated by pedestrians. Considering the cooperative management between CAVs and pedestrians, a new control way for pelican crossings is proposed in this study.

Depending on the demands of pedestrians and vehicles, the control strategy of pedestrian lights can be actuated automatically. Benefiting from roadside devices, e.g., cameras and lidars, the number of pedestrians waiting on roadsides can be detected by these sensors. Then, a threshold is set for making decisions. If the number of pedestrians waiting on roadsides is larger than its threshold, then the pedestrian lights get the qualifications to participate in a cooperative decision-making process with CAVs. A larger threshold requires more pedestrians waiting on the roadsides, which causes a low frequency of green lights and brings about large delays of pedestrians. However, it avoids creating numerous entities of crosswalks that affects CAVs' crossing. Thus, the threshold determination should balance the rights of the way between vehicles and pedestrians to get satisfactory results. The related flowchart is shown in Fig. 7. If the number of pedestrians does not reach the threshold, the cooperative decision-making process is conducted for CAVs when any vehicles arrive at the critical points.

4.3 Determination of decision-making order

Due to the limited spatiotemporal resources of the intersection, conflicts between vehicles and pedestrians always exist. By adjusting the occupation time of vehicles and virtual entities in the intersection area, the conflict decoupling in the time dimension is realized. Related to the right-of-way regulation, if a vehicle is permitted to pass through the stop line at the intersection, then it can pass through the intersection without conflicts. Thus, we need to determine when vehicles can pass through the stop line. The situations for pedestrian lights are similar. For several vehicles and pedestrian lights, we need to obtain appropriate time considering the conflict-free rule. Thus, the significant decision variables are the time when vehicles arrive at the intersection and the time when pedestrian lights turn green. The constraints to be satisfied

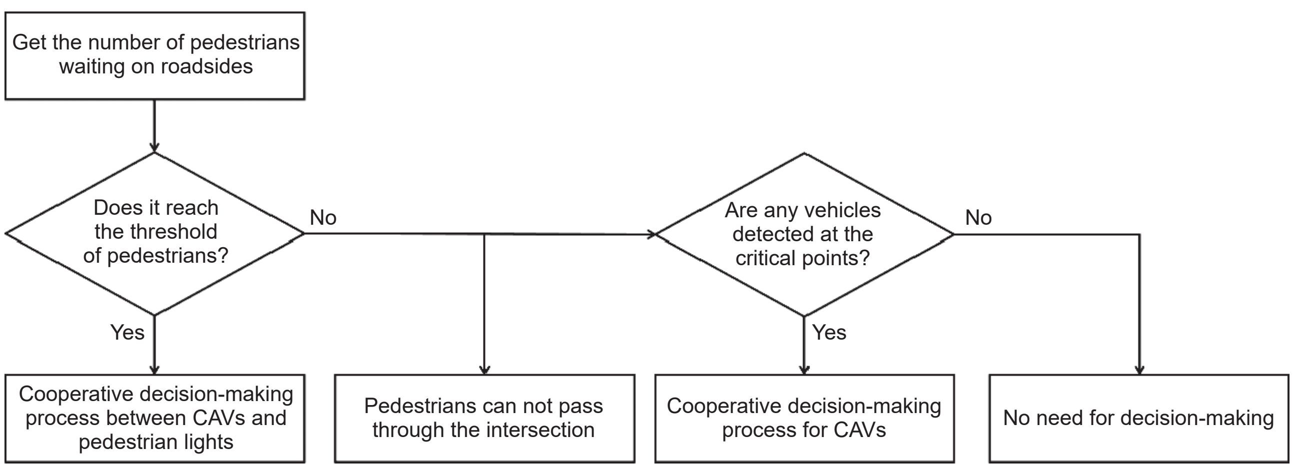


Fig. 7 Flowchart of cooperation between CAVs and pedestrians.

https://doi.org/10.26599/JICV.2023.9210008

are that the trajectories of different vehicles do not conflict with each other, and cannot invade the virtual entities so that both vehicles and pedestrians can safely pass through the intersection.

In the intersection, different traffic participants compete for limited spatiotemporal resources, and pedestrian lights can represent the benefits to pedestrians. To meet the conflict-free rule, it is necessary to consider the priorities among traffic participants to decide whether to pass or yield for them. The priority is determined by optimizing the decision-making order, similar to the right-of-way regulation for different participants. The participants in the lower order succumb to the participants in the higher order, that is, when potential conflicts may occur, the participants in the lower order need to adjust their strategies. Thus, we propose an MCTS-based decision-making method that can optimize the decision-making order and improve overall traffic efficiency. For vehicles and pedestrian lights, the earlier decision-making order means higher priority, that is, the right to access the intersection with less delay. A general rule for such a step-by-step decision-making process is given here. If some participants get the decision orders ahead of the trigger, their allocations are unchanged. Otherwise, the participants with the decision orders behind the trigger will be reallocated spatiotemporal resources in subsequent time steps. Vehicles should pass successively through decision zones, adjustment zones, and crosswalks. The vehicles within decision zones are considered as the participants for cooperation. The optimized order of vehicles to plan trajectories can be obtained by various methods, including enumeration methods, graph-based methods, and MCTS.

In Algorithm 1, the MCTS is selected in this study to optimize the decision orders between vehicles and pedestrian lights. The MCTS method includes the following steps. First, a tree structure needs to be generated and the solutions of the candidate orders can be received by the information of the links from the root node to the leaf nodes. Second, at each iterate process, using the Upper Confidence Bound (UCB) as the measure index to choose the children nodes step by step until a new order is generated. Third, the node weights are updated according to the delay of the order. More details about MCTS can refer to related work (Browne et al., 2012).

Algorithm 1: Decision order optimization by MCTS.

Generate a tree structure, and each node includes two parameters, that is, average delay and visited times;
Initialize the delay set as D_{opt} according to the order following by the FCFS rule, and then update the parameters of related nodes in the tree;
while maximum iterate time does not reach **do**
  Generate a new order according to the tree by the UCB method;
  Calculate the delay D_{new} according to the new order and update the parameters of related nodes in the tree;
  if $D_{\text{new}} < D_{\text{opt}}$ **then**
    update D_{opt} by D_{new} and record the new order for optimized order;
  end
end
Determine occupations of pedestrian lights and CAVs with orders ahead of the trigger of the cooperation.

4.4 Decision-making process of pedestrian lights

The behaviors of pedestrians are controlled by pedestrian lights. If the pedestrian lights turn green, then pedestrians can cross the road. It often costs periods of time for decision-making to change lights because the pedestrian lights cannot conflict with the trajectories of vehicles already in the adjustment zone. According to the conflict-free rule, the occupations of participants are rectangles, including vehicles and the virtual entities of crosswalks. A tuple composed of the coordinates of four vortexes can be used to indicate the position of a rectangle in the intersection area. At time step t, an occupation set $S(t)$ is used to record these tuples. The control rule of a pedestrian light is shown in Algorithm 2. A decision for the pedestrian light means to determine the appropriate time for the pedestrian light turning green. At initialization stage, expected start time indicates the time that the pedestrian light requests to participate in a cooperative decision-making process (if the number of pedestrians waiting on roadsides is larger than its threshold). As the description in Section 3.3, the virtual entity of a crosswalk appears when the pedestrian light turns green. It must not conflict with the existing occupations in $S(t)$. Otherwise, the extra delay Δt is added to postpone the start time of the green light.

Algorithm 2: The occupation time determination of a pedestrian light.

Initialize the expected start time t_0, initial delay $d = 0$, and green time T;
while no decision **do**
  Check whether conflicts occur or not according to the occupation set $S(t)$, where$t \in [t_0, t_0 + T]$;
  if any conflicts occur **then**
    Add the extra delay by $d \leftarrow d + \Delta t$;
    Update the start time by $t_0 \leftarrow t_0 + d$;
  else
    A decision for the pedestrian light is made;
  end
end
Record the occupation time of the pedestrian light to update $S(t)$, where $t \in [t_0, t_0 + T]$.

4.5 Decision-making process of CAVs

Similarly, the trajectory determination of CAVs should consider the conflicts with existing occupations. The decision-making process of a CAV is shown in Algorithm 3. A decision of trajectory for the CAV means to determine the appropriate time for the vehicle entering intersection zone and its spatiotemporal trajectories within the adjustment zone and the intersection zone. First, the expected entry time and the delay are initialized. The expected entry time indicates the earliest time for the vehicle to pass through the stop line with the optimal velocity. The preset trajectory in the junction is determined according to Section 3.1. Then, the trajectory can be calculated in the discrete-time domain. If the trajectory conflicts with the existing occupations, then the extra delay Δt is added to postpone the entry time until no conflict occurs.

Algorithm 3: The trajectory determination of a CAV.

Initialize the expected entry time t_0 and the initial delay $d = 0$;
Determine the preset trajectory according to its origin and direction;
while no decision **do**
  Set the first time step $t \leftarrow t_0$;

while the end of the route has not been reached **do**
Calculate the next position at time step $t+1$ based on its position at the previous time step t by following the preset trajectory;
Update time step by $t \leftarrow t+1$;
end
Check whether conflicts occur or not according to the occupation set $S(t)$, where $t \in [t_0, t)$;
if any conflicts occur **then**
Add the extra delay by $d \leftarrow d + \Delta t$;
Update the entry time by $t_0 \leftarrow t_0 + d$;
else
A decision of trajectory for the CAV is made;
end
end
Record the occupation of the CAV within the trajectory to update $S(t)$, where $t \in [t_0, t_0 + T]$.

5 Experimental evaluation

5.1 Simulation setup

Several simulation experiments are conducted to evaluate the proposed method and discuss the influence of significant parameters on results. Table 1 lists the general information on simulation experiments. Referring to Highway Capacity Manual (Transportation Research Board, 2010), pedestrian flows at intersections are usually less than 1,000 p/h. Thus, we set the studied pedestrian flows of one entrance as 300, 500, 700, and 900 p/h for different conditions. As the vehicle capacity of a single lane in an urban highway is approximately 2,000 v/h, the capacity of one lane at one entrance is approximately 500 v/h due to the shared crossing within the four-way intersection. Benefiting from the technologies of automated driving and cooperative intersection management, the CAV capacity can be larger than 500 v/h. Thus, we set the vehicle flows of a single lane as 500, 1,000, 1,500, and 2,000 v/h for different conditions. The arrival rates of vehicles and pedestrians follow the Poisson distribution in our simulation experiments. The traffic flows are generated randomly, and the same random seeds are used in comparative experiments to ensure consistency. The running time is set to 300 s for each experiment. Considering the vehicle directions of all lanes, the occupations of vehicles following their trajectories are exhibited in Fig. 8. The lengths of trajectories can be obtained by the numerical integration method.

5.2 Performance index

Table 1 General information of simulation experiments

Item	Setting
Time step interval	0.1 s
Width of each lane	3 m
Width of each crosswalk	2 m
Length of each vehicle	4 m
Width of each vehicle	2 m
Maximum acceleration of vehicles	3 m/s^2
Maximum deceleration of vehicles	3 m/s^2
Maximum velocity of vehicles	20 m/s
Safety margin among vehicles	0.2 m
Minimum crossing velocity of pedestrians	1 m/s
Range of the intersection	1,200 m × 1,200 m

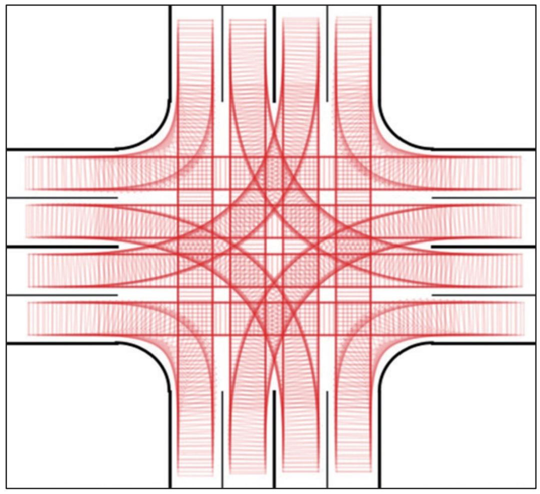


Fig. 8 All the occupations of vehicles follow their trajectories.

To enhance the efficiency at intersections, we need to minimize the delays of vehicles and pedestrians. The delays of them are the difference between real travel time and the ideal travel time at intersections. The evaluating indicators include the average Delay of Pedestrians (DP) and the average Delay of Vehicles (DV). For a vehicle i at an intersection, its ideal travel time is defined as the length of its route through the intersection divided by its optimal velocity. Thus, the delay of the vehicle is defined as Eq. (5):

$$\mathrm{DV}_i = T_i - \mathrm{IDT}_i = (t_{i,\mathrm{exit}} - t_{i,\mathrm{arrival}}) - L_i/v_0 \quad (5)$$

where DV_i is the delay of the vehicle i, T_i is the actual travel time, and IDT_i is the ideal travel time. The actual travel time T_i can be obtained by subtracting the arrival time $t_{i,\mathrm{arrival}}$ (when the vehicle is generated at the beginning of the decision zone) from the exit time $t_{i,\mathrm{exit}}$ (when the vehicle arrives at the beginning of the departure lane). L_i is the length of its route from the beginning of the decision zone to the beginning of the departure lane. v_0 is the optimal velocity. In this study, we define that all vehicles have the same value of optimal velocity. The item of L_i/v_0 in the Eq. (5) gives the calculation of IDT_i. The delays of pedestrians are defined by the lengths of their waiting time beside crosswalks, which are the differences between the time when pedestrians enter the crosswalk (when the corresponding pedestrian lights turn green) and the time when pedestrians are generated beside the crosswalks. The delay of the pedestrian j is defined by DP_j, which is the waiting time before the pedestrian light turns green. Combining DV_i and DP_j, the performance index of the intersection management system is the Weighted Average Delay (WAD) defined as Eq. (6):

$$\mathrm{WAD} = (1-\lambda)\sum_{i=1}^{M}\mathrm{DV}_i + \lambda\sum_{j=1}^{N}\mathrm{DP}_j \quad (6)$$

where M and N are the number of vehicles and pedestrians at the intersection during the study period, receptively, which can be obtained by counting the flows in the experiments. λ is a weight coefficient to trade off two components.

5.3 Results and analysis

Different intersection managements are compared in this study and their description are as follows. A video of visual traffic simulations is provided at https://www.youtube.com/watch?v=CQB_4sQHVxk&t=2s to assist in understanding.

1) Fixed STA for both CAVs and pedestrians (STA-B): The

Tsinghua University Press | IEEE

yellow time between two successive phases is set at 2 s. The launch time of CAVs at the beginning of green time is ignored because they can get the signal information in advance and have little reaction time. In each phase of the cycle, vehicles from the two lanes of one entrance can cross the intersection, and pedestrians can pass through the crosswalk of the next entrance in an anti-clockwise direction. Due to the high velocity of vehicles at intersections, the traffic flow of a single lane is much larger than in previous conditions. Thus, the traffic efficiency of pedestrians is a significant factor of STA. The green time is calculated according to the length of crosswalks and the minimum velocity of pedestrians. In this way, the green time is determined as 12 s to ensure safe crossing for pedestrians. During a period of green time, considering the space occupation of pedestrians, the maximum crossing number of pedestrians is 15. Note that the interactions between right-turning vehicles and pedestrians are ignored in the simulation experiments of the STA-B.

2) Fixed STA for pedestrians and cooperation for CAVs (STA-P): Pedestrians should obey the control of STA, whereas CAVs can cross the intersection by the hybrid cooperative intersection management and follow the FCFS principle. Moreover, the STA for pedestrians is set in advance, and the arriving vehicles must avoid conflicts with the crosswalks when their corresponding lights are green. Like the STA-B, the length of green time must ensure that pedestrians can cross the intersection safely, so the green time is also set as 12 s.

3) The cooperation for CAVs and pedestrians with FCFS (CO-FCFS): Although the STA for pedestrians also exists, its cycle is not fixed. CAVs and pedestrians participate in the cooperative decision-making process. All participants follow the FCFS principle, and the conflicts between vehicles and virtual entities of crosswalks must be avoided.

4) The cooperation for CAVs and pedestrians with MCTS (CO-MCTS): CAVs and pedestrians participate in the cooperative decision-making process. The MCTS method is used to optimize the decision order of CAVs and pedestrians. The parameter λ in Eq. (6) is involved in the node weight update process in the MCTS method. To treat CAVs and pedestrians equally, λ is set as 0.5.

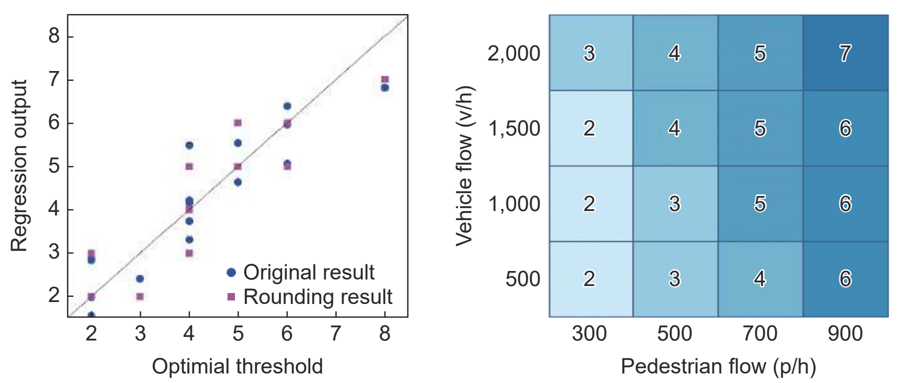
The threshold determination for actuating pedestrian lights to participate in the cooperation is analyzed in Fig. 9. Different values of pedestrian flows and vehicle flows are set in experiments. Under each traffic condition, we can get the average delays of vehicles and pedestrians with the threshold ranging from 1 to 10. According to the delays, the optimal thresholds are chosen under the different traffic conditions. Without loss of generality, multiple linear regression is conducted. Here, two flows are used for the independent variables and the threshold is used for the dependent variable. The form of multiple linear regression is shown as Eq. (7):

$$y = a_1x_1 + a_2x_2 + a_3 + e \tag{7}$$

where y is the threshold, and x_1 and x_2 are the pedestrian flow and the vehicle flow, respectively. The values of x_1 and x_2 are transformed into the range of [0, 1] divided by 3,600. Through the experiment, we can get $a_1 = 23.85$, $a_2 = 3.06$, and $a_3 = -0.85$. e is the fitting bias. The comparisons between optimal thresholds and regression outputs are shown in Fig. 9a. The rounding function is used to process the original results to get integers. As the traffic flow increases, the optimal thresholds become large. A large threshold means longer waiting time for pedestrians and less delay for vehicles. Thus, the thresholds are determined by trading off the benefits between pedestrians and vehicles. These values are used in later simulation experiments for the CO-FCFS and the CO-MCTS. Considering the traffic conditions in this study, we determine the optimal thresholds given in Fig. 9b. The optimal threshold ranges from 2 to 7. For instance, when the vehicle flow is 2,000 v/h and the pedestrian flow is 900 p/h, the optimal threshold is determined as 7. In this case, if the pedestrians waiting on the roadside at an entrance are up to 7, the pedestrian light is actuated to become the trigger of cooperation.

The STA method is used to allocate time and resources for different entrances and crosswalks, and the number of green lights is usually less than two. Differently, the number of green lights under the hybrid cooperative intersection management can be set flexibly. The Maximum of Green Lights (MoG) has a high impact on traffic efficiency. We set the MoG ranging from 1 to 4 and operate the simulations receptively. The results are shown in Fig. 10. In this case, λ in Eq. (6) is 0.5. When the MoG is 1, the pedestrians have larger delays than the other cases. Although it would bring benefits to vehicles, the whole delay measured by WAD is much larger than that in the other cases yet. As the MoG increases from 2 to 4, the DP and the DV slightly decrease.

The largest MoG is the best choice for cooperative management. In the view of pedestrians, a large MoG means that the occupation time of green lights increases, and the waiting time of pedestrians decreases. In the view of vehicles, virtual entities of crosswalks are obstructions for vehicles, and vehicles coming from a half number of directions are interfered by them. When the MoG is large, the number of simultaneous green lights is as large as possible for pedestrians crossing the intersection from several entrances. In other words, pedestrians should cross the road at the same time as possible. In such situations, the time periods with no green light may be extended, reducing the influence of virtual entities on vehicles. Thus, the MoG is set as 4 in the following



(a) Linear regression for thresholds (b) Optimal thresholds in different conditions

Fig. 9 Threshold determination for actuating pedestrian lights.

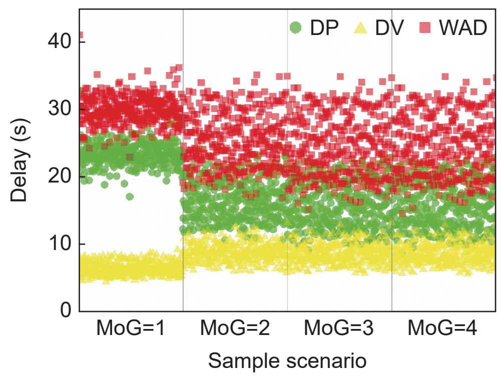


Fig. 10 Performances with the MoG changing.

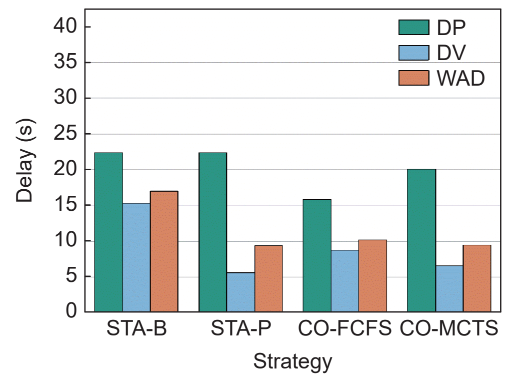


Fig. 11 Comparison among four strategies.

experiments.

The results of simulation experiments under different demands are shown in Table 2. Four strategies are compared under several flows of pedestrians and vehicles. The worst performances of both DPs and DVs are obtained under the control of the STA-B since the control logic does not consider the dynamic traffic demands. Although the STA-P leads to the largest DPs like STA-B, it brings about the least DVs in many conditions. The comparison between the STA-B and the STA-P illustrates that hybrid cooperative intersection management improves the traffic efficiency for vehicles at the intersection.

Under the control of the CO-FCFS, if the number of pedestrians waiting beside the road is larger than the threshold, then the lights turn green in a short time. Thus, the CO-FCFS gives priority to pedestrians. As pedestrians benefit from the CO-FCFS, the DPs decline sharply. In most conditions, the CO-FCFS performs well to ensure low values of DPs, whereas it leads to extra delays for vehicles.

Unlike the STA-P and the CO-FCFS, the CO-MCTS permits complete cooperation between pedestrians and vehicles. The CO-MCTS balances the benefits of these two participants and gives trade-off results. Thus, in most conditions, CO-MCTS have the second least DPs and DVs. It is interesting to note that the CO-MCTS performs the best for vehicles under low demands. Thus, benefiting from the cooperation, the CO-MCTS mitigates the interference of green lights in vehicle flows.

The average results of all demands are shown in Fig. 11. In the view of pedestrians, the CO-FCFS brings about the least average DP and the CO-MCTS brings about the second least average DP, which means that pedestrians can benefit from cooperative management to reduce their delays. In the view of vehicles, the average DV declines sharply under the control of the STA-P compared with the STA-B. Besides, the CO-MCTS leads to the second least average DV. Although the STA-P and the CO-MCTS have the least values of WAD, the CO-MCTS brings balanced results to the two traffic participants.

The performances by WAD under different demands are shown in Fig. 12. Different tendency occurs for four strategies. Under the low pedestrian flows and the high vehicle flows, the STA-P brings about better performances. The dominant factor of the STA-P is the length of green time, which has a significant influence on the vehicles. As the DVs are always less than the DPs (Table 2), high demands for vehicles can reduce the WAD statistically. Differently, under the other three control strategies, the more demands of both pedestrians and vehicles, the worse performances in the simulation experiments. An interesting conclusion is illustrated that no matter how many pedestrian flows they are, the CO-MCTS has the best performance under the low vehicle flows (500 and 1,000 v/h), and the STA-P is the best choice under the high vehicle flows (1,500 and 2,000 v/h). The results can give guidance to select reasonable strategies for different traffic conditions.

Table 2 Results of simulation experiments under different demands

Pedestrian flow (p/h)	Vehicle flow (v/h)	STA-B		STA-P		CO-FCFS		CO-MCTS	
		DP (s)	DV (s)	DP (s)	DV (s)	DP (s)	DV (s)	DP (s)	DV (s)
300	500	21.77	13.96	21.77	4.99	10.60	6.92	12.00	3.90
300	1,000	21.77	14.88	21.77	5.41	13.08	8.20	16.04	6.17
300	1,500	21.77	15.73	21.77	5.82	15.29	9.74	20.55	8.69
300	2,000	21.77	16.70	21.77	6.28	20.55	9.30	26.87	8.82
500	500	21.94	13.96	21.94	4.99	11.66	7.41	13.61	3.88
500	1,000	21.94	14.88	21.94	5.41	13.92	8.75	17.99	6.24
500	1,500	21.94	15.73	21.94	5.82	17.62	8.65	23.35	7.04
500	2,000	21.94	16.70	21.94	6.28	19.94	10.52	26.74	9.54
700	500	22.41	13.96	22.41	4.99	11.90	7.56	14.14	4.00
700	1,000	22.41	14.88	22.41	5.41	15.33	7.65	21.76	4.93
700	1,500	22.41	15.73	22.41	5.82	17.34	9.15	23.83	7.35
700	2,000	22.41	16.70	22.41	6.28	19.73	11.11	24.07	9.87
900	500	23.41	13.96	23.41	4.99	13.20	6.72	18.48	3.16
900	1,000	23.41	14.88	23.41	5.41	15.12	7.99	19.77	5.13
900	1,500	23.41	15.73	23.41	5.82	17.34	9.66	21.66	7.62
900	2,000	23.41	16.70	23.41	6.28	20.88	10.64	20.20	9.18

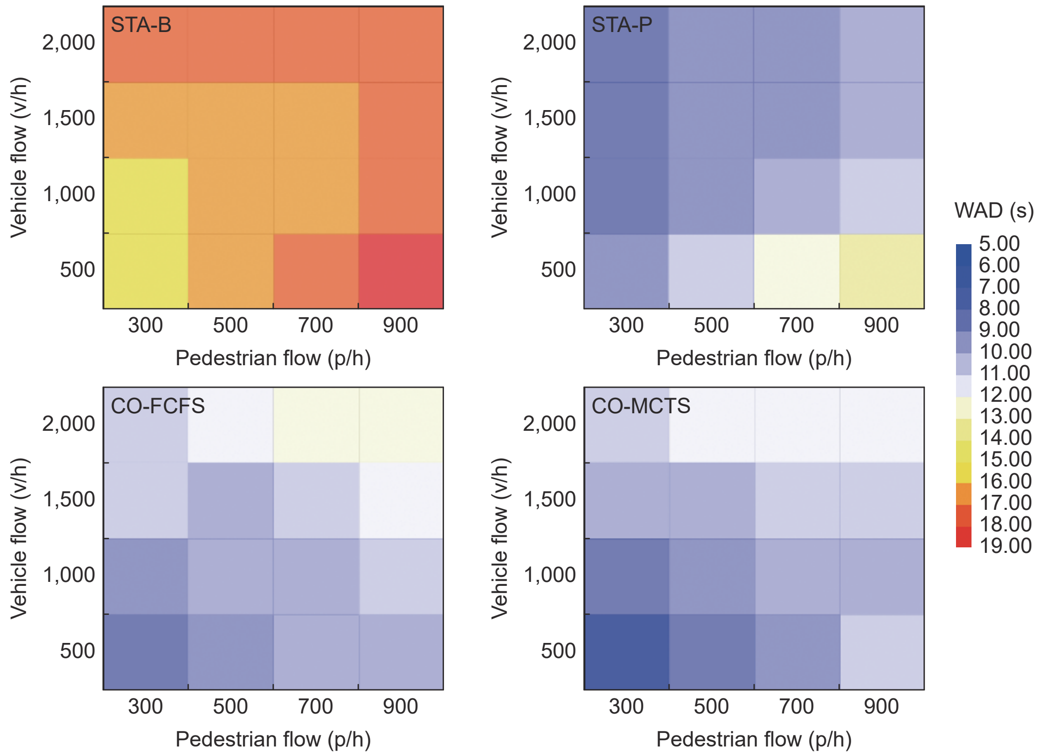


Fig. 12 Performances by WAD under different demands.

As the weighted sum of DV and DP relies on the value of Eq. (6), different considerations may result in different choices. Usually, vehicles can carry one or more passengers, so vehicles should be given priority over pedestrians. However, in some conditions, pedestrian priority is reasonable, e.g., commercial streets and scenic spots. In these conditions, the vehicles are encouraged to yield to pedestrians, so the value of λ is supposed to be larger than 0.5.

6 Conclusions

This study researches the hybrid cooperative intersection management and focuses on the cooperation between vehicles and pedestrians. We describe the general conflict-free rule in detail, of which the conflicts or not can be identified explicitly based on the geometric methods. A virtual entity method is proposed to determine the outlines for crosswalks when pedestrian lights turn green. The conflicts between vehicles and virtual entities must be avoided under cooperative intersection management. An MCTS method is used to optimize the decision order of CAVs and pedestrians considering different cooperative triggers.

Four strategies, the STA-B, STA-P, CO-FCFS, and CO-MCTS, are compared in simulation experiments. The STA-B has the largest delay for vehicles and pedestrians since it cannot adaptively adjust the crossing priorities for traffic participants according to their demands. Under the high demands of pedestrians and low demands of vehicles, the STA-P is in favor of vehicles that can cross intersections by cooperation, whereas the CO-FCFS gives more priority to pedestrians. When pedestrians and vehicles are treated equally, the STA-P and the CO-MCTS have the least weighted sum of delays. Moreover, the CO-MCTS and the STA-P are suitable for conditions with low vehicle flows and high vehicle flows, respectively. In most conditions, the CO-MCTS balances the benefits of these two participants and gives trade-off results.

Besides CAVs, vehicles with different levels of intelligence and networking technologies may share the road. Thus, the cooperation between mixed vehicle flows and pedestrian flows will be further studied in the future.

Acknowledgements

This work was supported by the Science and Technology Commission of Shanghai Municipality (Nos. 22YF1461400 and 22DZ1100102) and the National Natural Science Foundation of China (No. 72001007).

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

Bichiou, Y., Rakha, H. A., 2019. Developing an optimal intersection control system for automated connected vehicles. IEEE Trans Intell Transp Syst, 20, 1908–1916.

Browne, C. B., Powley, E., Whitehouse, D., Lucas, S. M., Cowling, P. I., Rohlfshagen, P. *et al.*, 2012. A survey of Monte Carlo tree search methods. IEEE Trans Comput Intell AI Games, 4, 1–43.

Cai, P. L., Wang, Y. P., Lu, G. Q., 2019. Intersection self-organization control for connected autonomous vehicles based on traffic strategy learning algorithm. In: 19th COTA International Conference of Transportation Professionals, 5551–5562.

Chai, L., Cai, B., Wei, S. G., Wang, J., Wang, H., 2018. Connected and autonomous vehicles coordinating approach at intersection based on space-time slot. Transp A Transp Sci, 14, 929–951.

Dresner, K., Stone, P., 2004. Multiagent traffic management: A reservation-based intersection control mechanism. In: Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems, 530–537.

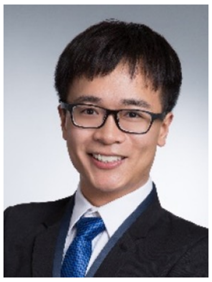
Ge, Q., Sun, Q., Wang, Z., Li, S. E., Gu, Z., Zheng, S., *et al.*, 2021. Real-time coordination of connected vehicles at intersections using graphical mixed integer optimization. IET Intell Transp Syst, 15, 795–807.

González, D., Pérez, J., Milanés, V., Nashashibi, F., 2015. A review of motion planning techniques for automated vehicles. IEEE Trans Intell Transp Syst, 17, 1135–1145.

Jiang, Z., Yu, D., Zhou, H., Luan, S., Xing, X., 2021. A trajectory optimization strategy for connected and automated vehicles at junction of freeway and urban road. Sustainability, 13, 9933.
Levin, M. W., Boyles, S. D., Patel, R., 2016. Paradoxes of reservation-based intersection controls in traffic networks. Transp Res A, 90, 14–25.
Li, B., Zhang, Y., Zhang, Y., Jia, N., Ge, Y., 2018. Near-optimal online motion planning of connected and automated vehicles at a signal-free and lane-free intersection. In: 2018 IEEE Intelligent Vehicles Symposium (IV), 1432–1437.
Malikopoulos, A. A., Cassandras, C. G., Zhang, Y. J., 2018. A decentralized energy-optimal control framework for connected automated vehicles at signal-free intersections. Automatica, 93, 244–256.
Meng, Y., Li, L., Wang, F. Y., Li, K., Li, Z., 2017. Analysis of cooperative driving strategies for nonsignalized intersections. IEEE Trans Veh Technol, 67, 2900–2911.
Mirheli, A., Hajibabai, L., Hajbabaie, A., 2018. Development of a signal-head-free intersection control logic in a fully connected and autonomous vehicle environment. Transp Res C, 92, 412–425.
Prautzsch, H., Boehm, W., Paluszny, M., 2002. B-spline techniques. In: *Bézier and B-Spline Techniques*. Prautzsch, H., Boehm, W., Paluszny, M., Eds. Berlin, Heidelberg: Springer, 77–89.
Rashidi, T. H., Najmi, A., Haider, A., Wang, C., Hosseinzadeh, F., 2020. What we know and do not know about connected and autonomous vehicles. Transp A Transp Sci, 16, 987–1029.
Rasouli, A., Tsotsos, J. K., 2020. Autonomous vehicles that interact with pedestrians: A survey of theory and practice. IEEE Trans Intell Transp Syst, 21, 900–918.
Rios-Torres, J., Malikopoulos, A. A., 2017. Automated and cooperative vehicle merging at highway on-ramps. IEEE Trans Intell Transp Syst, 18, 780–789.
Tachet, R., Santi, P., Sobolevsky, S., Reyes-Castro, L. I., Frazzoli, E., Helbing, D. *et al.*, 2016. Revisiting street intersections using slot-based systems. PLoS One, 11, e0149607.
Transportation Research Board, 2010. *Highway Capacity Manual*, 5th edn. Washington, DC: The National Academies Press.
Wang, Y., Cai, P., Lu, G., 2020. Cooperative autonomous traffic organization method for connected automated vehicles in multi-intersection road networks. Transp Res C, 111, 458–476.
Wu, W., Liu, Y., Hao, W., Giannopoulos, G. A., Byon, Y. J., 2022. Autonomous intersection management with pedestrians crossing. Transp Res C, 135, 103521.
Xu, B., Li, S. E., Bian, Y., Li, S., Ban, X. J., Wang, J., *et al.*, 2018. Distributed conflict-free cooperation for multiple connected vehicles at unsignalized intersections. Transp Res C, 93, 322–334.
Xu, H., Zhang, Y., Li, L., Li, W., 2019. Cooperative driving at unsignalized intersections using tree search. IEEE Trans Intell Transp Syst, 21, 4563–4571.
Yu, H., Jiang, R., He, Z., Zheng, Z., Li, L., Liu, R., *et al.*, 2021. Automated vehicle-involved traffic flow studies: A survey of assumptions, models, speculations, and perspectives. Transp Res C, 127, 103101.
Zhong, Z., Nejad, M., Lee, E. E., 2020. Autonomous and semiautonomous intersection management: A survey. IEEE Intell Transp Syst Mag, 13, 53–70.

Pinlong Cai received his Ph.D. degree in traffic information engineering and control from Beihang University, Beijing, China, in 2020. From 2016 to 2017, he was a Research Assistant with the Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences. From 2020 to 2021, he was a Standard & Strategy Engineer in ZTE Corporation. He is currently a Research Scientist in Shanghai AI Laboratory. His research interests include data modelling, decision intelligence, and cooperative vehicle infrastructure system (CVIS).

Jia He received his Ph.D. degree from the School of Economics and Management, Beihang University, Beijing, China, in 2018. He is currently working as a lecturer at College of Metropolitan Transportation, Beijing University of Technology. His research interests include traffic flow theory (car-following model and lane-changing model), driver's route choice behavior, and electric vehicle charging facility location model.



Yikang Li received his B.S. degree in electronic engineering from Tsinghua University, Beijing, in 2016 and his Ph.D. degree in electronic engineering from The Chinese University of Hong Kong, in 2020. From 2019 to 2021, he was a Deputy Director of R&D on autonomous driving with Sensetime Technology Ltd. Since June 2021, he has been a Research Scientist with Intelligent Transportation Research Center, Shanghai AI Laboratory, China. He has published several papers on CVPR/ICCV/ECCV/NeurIPS. His research interests include the 3D scene understanding, multi-modal fusion, scene reconstruction, autonomous driving simulation, and decision intelligence.