2021 IEEE Intelligent Transportation Systems Conference (ITSC)
Indianapolis, USA. September 19-21, 2021

A hierarchical planning framework of the intersection with blind zone and uncertainty

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2021 IEEE International Intelligent Transportation Systems Conference (ITSC) | 978-1-7281-9142-3/21/$31.00 ©2021 IEEE | DOI: 10.1109/ITSC48978.2021.9564821

***Abstract*— It is important for autonomous vehicles to plan at the unsignalized intersection due to the uncertainty of visible vehicles and phantom vehicles in the blind zone. This paper proposes a hierarchical framework to optimize the left-turn planning at the intersection to solve this problem. The framework is composed of a higher-level candidate paths selector and a lower-level Partially Observable Markov Decision Process planner. All possible vehicle distributions in the blind zone are represented in the form of a set, which makes the method have the good universality. The simulation experiments show that autonomous vehicle can pass the intersection safely and efficiently.**

I. Introduction

Autonomous driving still face various challenges in complex scenes. The planning layer of autonomous driving is one of the major modules in the autonomous vehicles system. It needs to select the best action according to the information considering the uncertainty of other visible vehicles and the potential blind zone risk (in Figure 1). The unsignalized intersection is a critical and dangerous scene for autonomous vehicles.

The uncertainty about the surrounding traffic and the risk of blind zone have been focused on the unsignalized intersection. For the blind zone problem, references [1]–[3] use artificial intelligence methods to learn driving behaviors in blind zone from human driving data, and to plan the trajectory. The geometric modeling method [4] can also considerc the blind zone risk and it is highly dependent on the established model. It has limitations because of the uncertainty. For the uncertain intention of others at the intersection, graph search methods [5]–[7] are considered for planning. But the complexity and rapid changes of the intersection make the flexibility insufficient. The Partially Observable Markov Decision Process (POMDP) method [8]–[10] has become an emerging technology to solve the problem in autonomous driving. POMDP method is capable of performing human-like behavior at the unsignalized intersection. One of the blind zone risk or uncertain intention is considered in these previous researches, and few of them are considered together. However, in the actual intersection, both of them are existing, and both will cause potential danger to the driving safety.

Reference [11] uses a hierarchical framework to solve the uncertainty of visible vehicles at the intersection. This hierarchical framework improves the efficiency of autonomous vehicle at the intersection. However, it only focuses on the uncertain intention of vehicles, we improve it to take blind zone risk into consideration. The method is more adaptive and universal. It can also be generalized to the intersection of various situations. The autonomous vehicles will continuously collect the information about its surroundings for subsequent action when the framework works. The hierarchical framework method can improve the commuting efficiency in the case of autonomous vehicle passing the intersection safely. This paper provide a less conservative but safer strategy. It presents a new method to solve the problem of passing the unsignalized traffic intersection. Major contributions of this paper are as follows:

- Considering both the uncertain intention of other vehicles and the risk of blind zone.
- Various situations of vehicles in the blind zone are represented. This method is adaptive.
- The higher-level framework designs the turning points and candidate paths, while the lower-level framework uses Frenet coordinates to reduce the dimension of the problem. The model improve traffic efficiency.

The rest section of the paper is as follows. Section II will introduce the framework of the hierarchical planning method. Section III will introduce the principle of the POMDP method and the process of modeling. Section IV will introduce the construction of the simulation scene and the analysis of the simulation results, and Section V will give

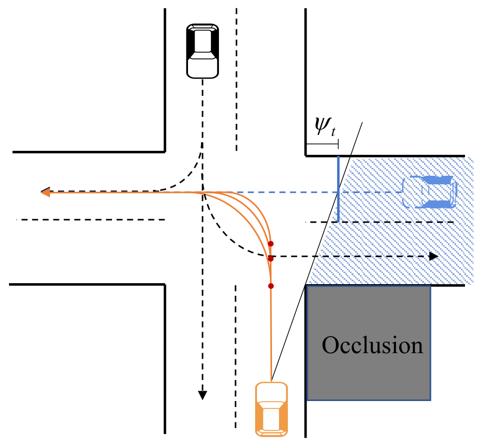

Fig. 1. Autonomous vehicle's decision making and planning of turning left. The vehicle in yellow represents the autonomous vehicle, the vehicles in black represent visible vehicles of uncertain intention, the vehicle in blue represent phantom vehicle may be in the blind zone.

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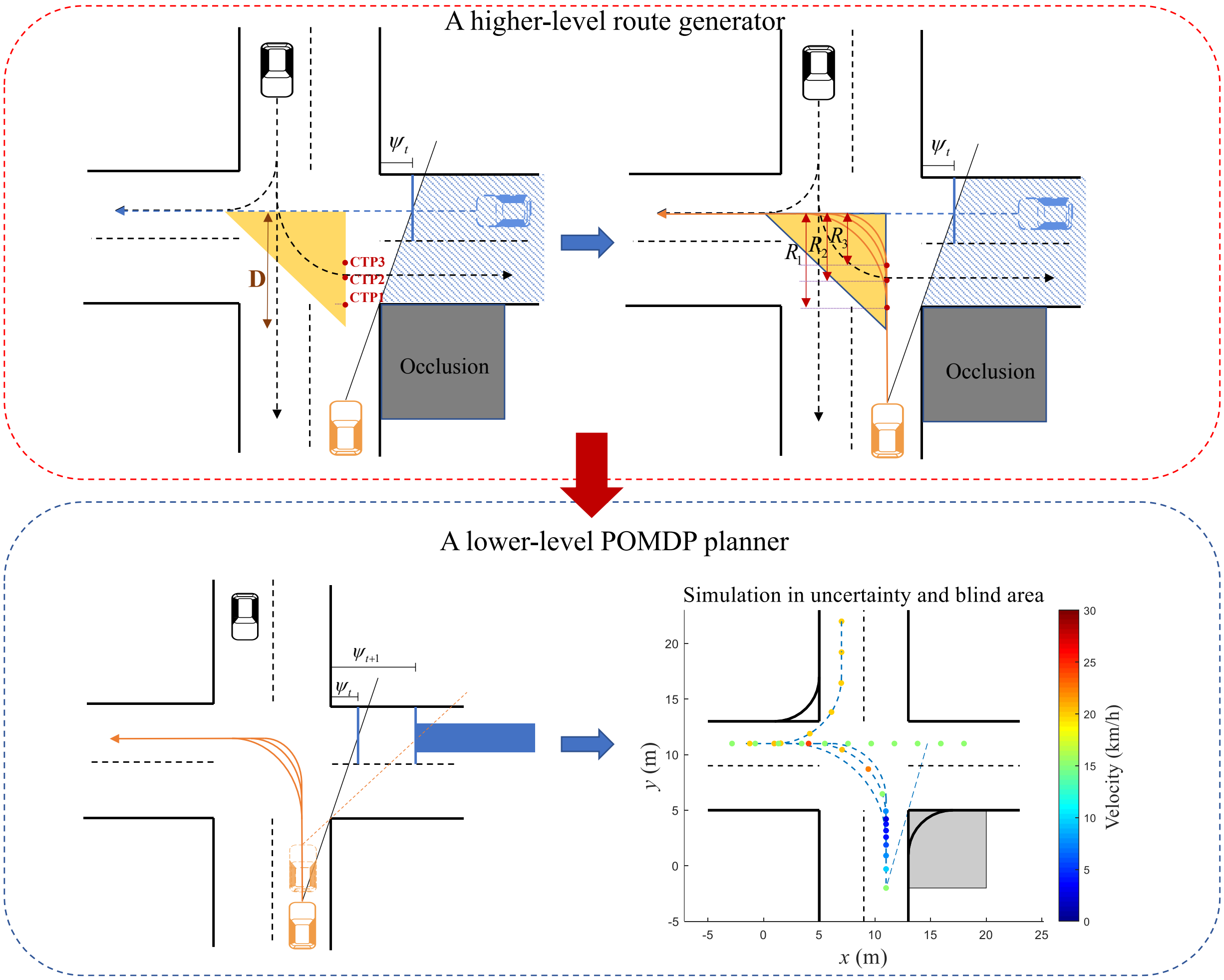

Fig. 2. The hierarchical framework model

a brief conclusion and future work.

II. Overview Of Hierarchical Planning Framework

The planning framework of the unsignalized intersection is shown in Figure 2, consisting of a higher-level candidate paths generator and a lower-level path and speed planner.

A. Generation of higher-level paths

1) The generating idea and rationality of candidate paths: When experienced drivers drive a vehicle to turn left at an intersection, they often creep-and-go, and then start to turn the steering wheel quickly in an appropriate position to complete the turning operation. The method of generating candidate paths is inspired by turning left of human-driven vehicle. This not only makes the left-turn planning of the autonomous vehicle more human-like, but also helps the surrounding drivers to predict the behavior of autonomous vehicle better. The method of generating the candidate paths based on critical turning point (CTP) refers to [11], which is suitable for the intersection of any shape. In addition, this paper calculates the dataset [12]. Based on this, we extract the left-turn trajectory area, which is the range area for vehicles to turn left. And we denote the length of the critical area as D shown in Figure 2. The trajectory of turning left is composed of two straight lines and a quarter arc. The starting point of the straight line before entering the intersection is defined as the start point. The start of the arc is defined as the turning point. The end point of the second straight line is defined as the target point. Given that the human drivers will slam the steering wheel at some point and begin to complete the steering when making a left turn, the position of CTP is defined as $d_i = r_i D\,,\ i = 1, 2, 3$, where d_i is the distance from the start point to the turning point. d_i is calculated by a ratio r_i. In this paper, the existence of turning points and the selection of ratio are determined by the data.

2) Determination of candidate paths: As shown in Figure 2, the turning radius of each trajectory is determined by the ratio r_i and the critical side length D, as shown in the formula:

$$R_i = (1 - r_i)D\,, \quad i = 1, 2, 3 \tag{1}$$

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The candidate paths are generated in the Cartesian coordinates system. Then they are converted to Frenet coordinates.

B. Determination of lower-level framework

Once the candidate paths are generated, they are provided to the lower-level planning framework. A POMDP model is used for the speed planning and path selection. Partial observability of the environment is taken into account by the model, such as the uncertain driving intention of other vehicles and the information of whether there is a vehicle in the blind zone. The modeling of POMDP will be explained in Section III. For the three candidate paths, the optimal strategy are used to choose the best path, and the third path will be selected by default if ego vehicle driving to the end.

III. POMDP Modeling Method

This section firstly introduces the general formula and principle of POMDP. Then it details the problem of the POMDP modeling process and each part of the content.

A. Partially observable Markov decision process

POMDP is composed of a set of $(S, A, O, T, Z, R, b_0, \gamma)$, in which the definition of state set S, action set A, transition probabilities function T and reward function R are the same as Markov decision process. The hidden state of the system assumed by POMDP can be estimated from the observation set O. The observation function $Z(s', a, o) = f(o|s', a)$ represents the probability of observing some observation O after taking an action a and ending with a new state s'. $T(s, a, s') = f(s'|s, a)$ is the transition probability function from state s to a new state s'. $R(s, a)$ is the reward for selecting action a in state s. Besides, a discount factor $\gamma \in (0, 1)$ is used when the sequence of actions is of infinite length. The goal is to choose an appropriate sequence of actions that maximizes its expected total reward. The belief state describes the probability distribution of all possible states. The initial belief of the agent is b_0.

POMDP calculates an optimal strategy that maximizes the total expected reward of the agent. A policy of POMDP $\pi : B \to A$ is mapping $b \in B$ to action a. The solution of POMDP is the optimal strategy, as shown in the formula:

$$\pi^* = \arg\max_{\pi} \left(E\left[\sum\nolimits_{t=0}^{\infty} \gamma^t R(s_t, \pi(b_t)) | b_0, \pi \right] \right) \quad (2)$$

B. Environment and state space

The state of POMDP model includes ego vehicle, observable vehicles and vehicles in blind zone. For visible oncoming vehicle, it is assumed to move only longitudinally along the route, but which route will be chosen is uncertain by ego vehicle. The state space of the model is defined as a combination of the states of all vehicles, and there are explicit (observable) and implicit (non-observable) states in the states set. The state is represented as

$$s = [s_0, s_k, \cdots, s_p, \cdots]^T \quad (3)$$

where the states of s_0 describes ego vehicle, the states of s_k, $k = 1, \cdots, K$ describe surrounding visible vehicles, the states of s_p, $p = K + 1, \cdots, K + P$ describe phantom vehicles in blind zone. The state of ego vehicle can be defined as

$$s_0 = [l_0, v_0, r_0]^T \quad (4)$$

The states of surrounding visible vehicles can be defined as

$$s_k = [l_k, v_k, r_k]^T \quad (5)$$

Phantom vehicles in blind zone can be defined as

$$s_p = [l_p, r_p, c_p]^T \quad (6)$$

The candidate paths of ego vehicle are generated by the higher-level, and the paths are free of static obstacle collision. With the proposed hierarchical framework, only the longitudinal speed along the path needs to be optimized in the lower-level model. The candidate paths for vehicles are converted from Cartesian coordinates to Frenet coordinates [13], so the coordinates and speed of each vehicle can be defined in terms of less state quantities. l represents the longitudinal length in the Frenet frame with its origin at the start of the certain route r. v represents the speed of the vehicle. r represents the chosen route of the ego vehicle, and c is a boolean variable that indicates whether there are any vehicle in the blind zone.

C. Observation and action model

For the observation model, it is assumed that there is no sensor noise in the scene, and the observation set can be expressed as $o = [o_0, o_1, \cdots, o_K, o_{K+1}, \cdots, o_{K+P}]$. Ego vehicle is a direct mapping from state to observation, and it knows all its states. The route of the observable oncoming vehicle is unknown, and visible vehicle's observation is $o_k = [x_k, y_k, v_k]$. For the phantom vehicle that may exist in the blind zone, observation is considered as the actual field of view on the given route: $o_p = [\psi_p, r_p]$. The ego vehicle's actions are defined in a two-dimensional space, including acceleration action a_v from $-4\ \mathrm{m/s^2}$ to $4\ \mathrm{m/s^2}$ with a step of $1\ \mathrm{m/s^2}$ and a boolean type of action a_l (0 or 1) whether to slam the steering wheel to turn left. In this case, the planning problem of turning left at the intersection becomes a problem of longitudinal speed planning and candidate paths selection, which reduces the dimension effectively.

D. Representation of phantom vehicles in the blind zone

For the vehicles in the blind zone, the distribution and number of vehicles cannot be observed accurately, and it is difficult to represent all possible vehicle distributions in the blind zone. In this case, a worst-case scenario is assumed, and the boundaries of the blind zone and field of view are constantly updated as the ego vehicle drives. According to reference [13], phantom vehicles are defined. If phantom vehicles exist, it is assumed to be at the most edge of the blind zone and driving 10 percent above the road speed limit. Moreover, it is assumed that the phantom vehicle in the blind zone is infinite long. In this way, the possible existence of phantom vehicles in the blind zone is considered in the reachable set. In the initial state, a phantom vehicle is

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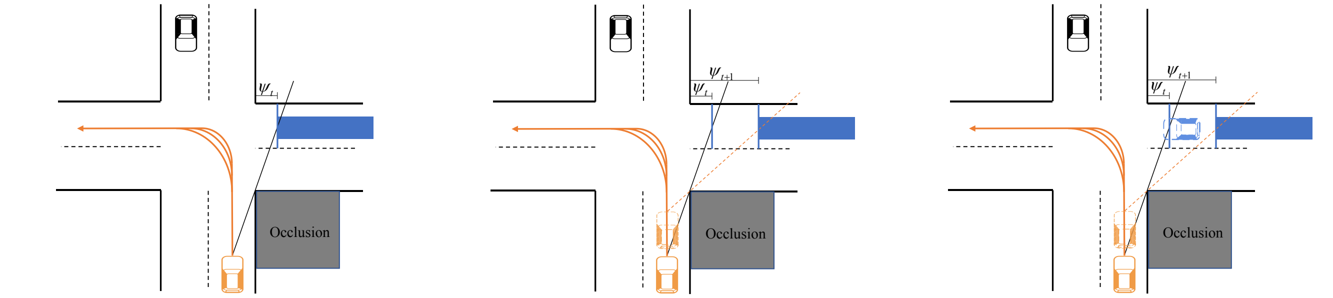

(a) a phantom vehicle is assumed to exist at the boundary of the blind zone

(b) there are no phantom vehicles in the field of view

(c) there are phantom vehicles in the blind zone and they appear in the field of view

Fig. 3. Representation of the phantom vehicles

assumed to exist at the boundary of the blind zone in Figure 3(a). If there is no vehicle in the updated field of view at the next moment, an infinite long phantom vehicle will be placed at the boundary of the next blind zone. With the uncertain phantom vehicles in the blind zone, the only correct and safe action to do is to make a left turn when you have an enough field of view or when the blind zone has no effect on the ego vehicle. Referred to [13], the traffic density is defined as the uniform probability distribution in the shaded area, and the Bernoulli distribution is used to update the probability of vehicles in the blind zone:

$$P_{\phi}(\Delta\psi) = \begin{cases} 0, & \Delta\psi \leq 0 \\ \frac{\Delta\psi}{\omega}, & 0 < \Delta\psi \leq \omega \\ 1, & \Delta\psi > \omega \end{cases} \tag{7}$$

where ω is the length of the interval of per vehicle, and traffic density is defined as the average number of vehicles per 100 meters.

E. Transition function

The transition model can be defined on Frenet coordinates, and vehicles are assumed to drive on a predefined route. For ego vehicle, the transition function is

$$s_0{}' = s_0 + v_0\Delta t + 0.5 a_v \Delta t^2 \tag{8}$$

Besides, the vehicle needs to decide which turning point ($a_l = 1$) to turn left. For visible vehicles, the transition function is similar with ego vehicles:

$$s_k{}' = \begin{bmatrix} l_k{}' \\ v_k{}' \\ r_k{}' \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} l_0 \\ v_0 \\ r_0 \end{bmatrix} + \begin{bmatrix} 0.5\Delta t^2 \\ \Delta t \\ 0 \end{bmatrix} a_k \tag{9}$$

For phantom vehicles in the blind zone, there are no phantom vehicles in the field of view in Figure 3(b). The function is

$$s_p = [l_p, r_p, c_p]^T = [\max(\Psi_l, \Psi_l{}'), r_p, c_p]^T \tag{10}$$

In the case of $c_p = 1$, there are phantom vehicles in the blind zone, and phantom vehicle appear in the field of view partly.

$$s_p = [l_p, r_p, c_p]^T = [\min(\Psi_l, \Psi_l{}') - 1.1 \cdot v_{\max} \cdot \Delta \mathrm{t}, r_p, c_p]^T \tag{11}$$

If there are phantom vehicles in the blind zone and they appear in the field of view, then we consider whether there are new phantom vehicles in the blind zone of the next field of view in Figure 3(c).

F. Reward model

Define the reward in a given state:

$$R = R_v + R_c + R_g + R_r + R_m + R_a \tag{12}$$

where

$$R_v = \begin{cases} -100\,|V - v_{ref}|\,, & V \leq v_{ref} \\ -100(V - v_{ref})^2, & otherwise \end{cases} \tag{13}$$

indicates that the speed of ego vehicle should be closer to the reference speed on the reference route. $R_c = -200000$ is the reward function when the ego vehicle have a collision with other vehicles. $R_g = 400000$ is the reward when the target point is reached. If ego vehicle goes in reverse on the route, then $R_r = -30000$ is added to R. The reward R_m encourages the vehicle to travel closer to the target point so that the vehicle can choose a better route. If the acceleration at the previous moment is opposite to this at the current moment, $R_a = -500$ is given, indicating that the vehicle needs to drive more smoothly and comfortably within a reasonable range.

IV. SIMULATIONS

In the simulation scenario, an oncoming vehicle follows a preset path toward an unsignalized intersection, but the intention of the oncoming vehicle is unclear to the ego vehicle. In addition, there is a vehicle in the blind zone driving along the preset trajectory and approaching the intersection. The ego vehicle do not know whether there is a vehicle in the blind zone. The experiment simulates six specific conditions in the unsignalized traffic intersection. The color of each point indicates the speed of the vehicle at the current point. As the field of view becomes larger, the vehicle in the blind zone is gradually found by the ego vehicle. Monte Carlo search tree method is implemented in this experiment. Each sampling time interval is 0.5 s.

In the experiments in Figure 4, the oncoming visible vehicle pass through the intersection at a high, medium and low

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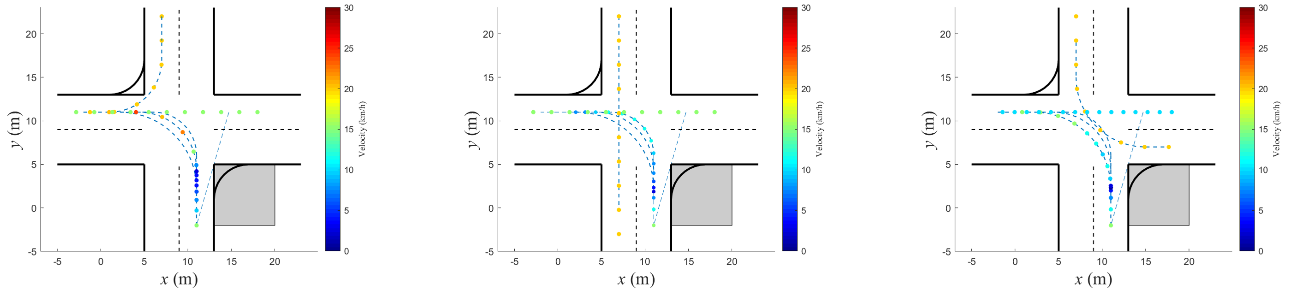
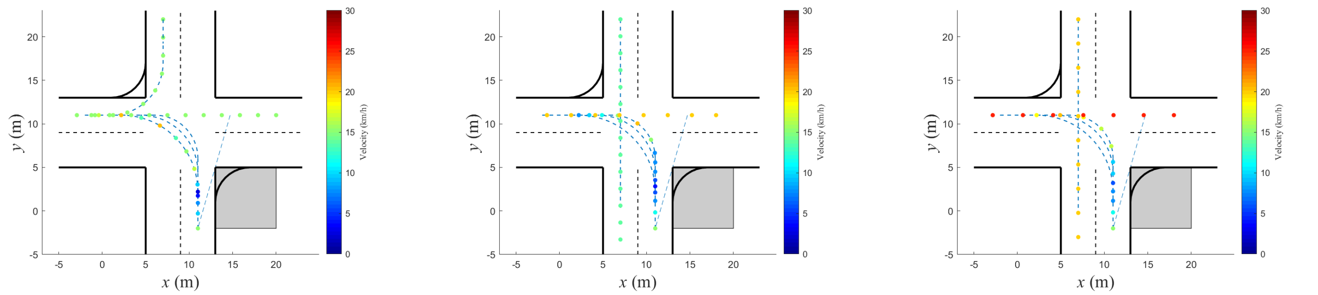


(a) Visible vehicle turns right at a high speed (b) Visible vehicle goes straight at a high speed (c) Visible vehicle turns left at a high speed



(d) Visible vehicle turns right at a medium speed (e) Visible vehicle goes straight at a low speed (f) Visible vehicle goes straight at a high speed

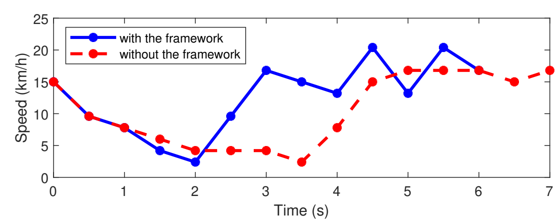
Fig. 4. Simulations of the model. The color of each point indicates the speed of the vehicle at the current point. Dotted lines for autonomous vehicle represent candidate paths generated by the higher-level framework. Dotted lines for the visible vehicle represents different intention. The grey shading cause blind zone for autonomous vehicle.

speed, and experiments simulate different scenarios of the oncoming visible vehicle. Besides, experiments compare the scene of phantom vehicles driving out of the blind zone at a higher speed and a lower speed in the six specific conditions. The ego vehicle chooses different driving strategies with different driving intention of the oncoming visible vehicle. In these cases, the autonomous vehicle will slow down and creep at the beginning due to the probability of the phantom vehicle in the blind zone and the uncertain intention of oncoming vehicle. It is not until the field of view becomes larger and the driving intention towards the vehicle becomes clear that the autonomous vehicle will speed up and make other strategies.

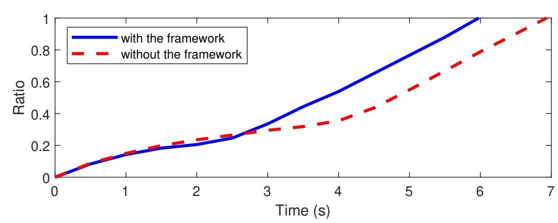
When the oncoming vehicle turns right at a slower speed and will cause a great impact on the ego vehicle, the speed of the ego vehicle in Figure 4(d) will be lower than the speed of the left turn in Figure 4(a). When the oncoming vehicle runs straight, the ego vehicle will choose the third route in Figure 4(b) and 4(e). Although the length of the third route is the longest, it can avoid the scope of collision with the vehicle and improve the traffic efficiency.

When the phantom vehicle in the blind zone becomes visible and passes the intersection at a higher speed with a less impact on the ego vehicle, the vehicles will pass the intersection at a higher speed in Figure 4(f) when turning left compared with Figure 4(b). This experiment validates that the method is safe and feasible.

The experiment shown in Figure 5 proves that the intersection planning using the hierarchical framework planner is highly efficient. The figure compares the difference in speed



(a) Speed comparison diagram with and without a hierarchical framework



(b) Driving ratio comparison diagram with and without a hierarchical framework

Fig. 5. Comparison of speed and efficiency with and without the hierarchical method

and driving ratio with and without the use of a hierarchical framework. The plan without the hierarchical framework is just generated by two straight lines and a quarter arc. Since the length of the two paths is not consistent, the driving ratio is used as one of the indicators of driving efficiency. The ratio is defined as the longitudinal distance traveled by the autonomous vehicle to the total length of the turning. Compared with the other method, the results show that using the hierarchical method reduces the two steps size, which

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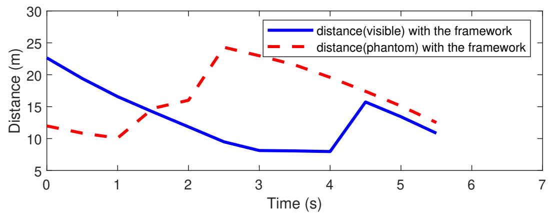
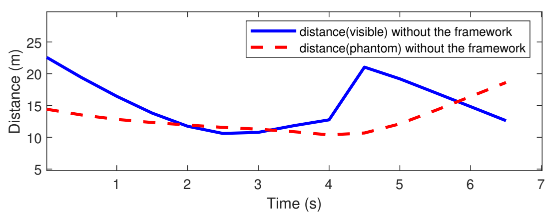
is about one second. It can be analyzed from the speed comparison diagram. With the existence of the layered frame, the hierarchical method can choose to replace a path, while another method without the hierarchical framework can only stay in the blocked area for about 2 seconds at a very low speed.



(a) Distance between ego vehicle and other vehicles with the framework



(b) Distance between ego vehicle and other vehicles without the framework

Fig. 6. Comparison of safety with and without the hierarchical method

Figure 6 shows the distance between the ego vehicle and the visible vehicle, and the distance between the ego vehicle and the phantom vehicle with and without the hierarchical framework. It can be found that the ego vehicle can safely pass the intersection regardless of whether the hierarchical framework is used. In combination with Figure 5 and Figure 6, it can be found that ego vehicles can safely and efficiently pass the intersection by using the hierarchical framework. Generally, the autonomous vehicle will enter the intersection at a relatively high speed. And it will creep at a lower speed initially, as whether there is a vehicle in the blind zone and the intention of the oncoming vehicle are uncertain. With the increasing of field view in blind zone and the intention of the oncoming vehicle, the autonomous vehicle will adopt a safe and more efficient strategy to cross the intersection.

V. CONCLUSIONS

In this paper, a hierarchical framework based on the POMDP method is proposed at the unsignalized traffic intersection to solve the problem of the invisible phantom vehicle in the blind zone and the uncertain intention of the visible vehicle. Experimental results show that the hierarchical framework can pass through the intersection safely and efficiently.

In the future, the uncertain intention of pedestrians and the smoothness of autonomous vehicle will be taken into consideration.

ACKNOWLEDGMENT

This work was supported in part by the National Natural Science Foundation of China under Grant No. 61773291 and 61973239.

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