

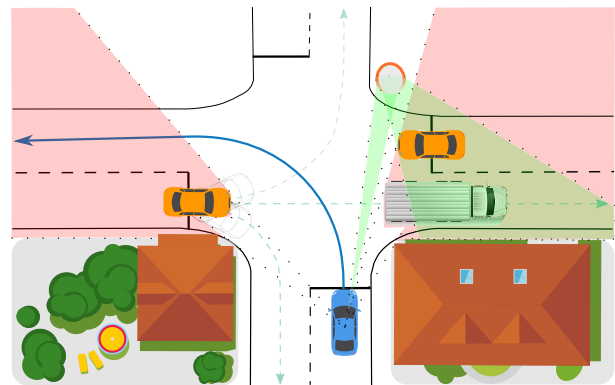
Traffic Mirror-Aware POMDP Behavior Planning for Autonomous Urban Driving

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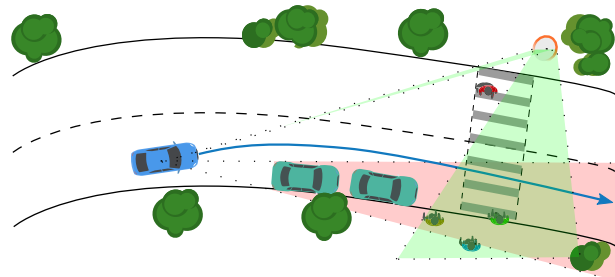
Abstract—Driving autonomous vehicles safely through a complex urban environment remains a difficult task. The sensor limitations, as well as the various occlusions in the urban environment caused by static and dynamic objects, make the decision-making task even more complex. To improve the autonomous vehicle’s ability to handle various occlusion driving scenarios, we propose a behavior planner with traffic mirror awareness based on the partially observable Markov decision process (POMDP). Our approach is based on the concept of phantom road users, which allows us to reason about the potentially occluded traffic participants and estimate the appearance probability in risky areas based on contextual information. A confidence modifier is introduced to either increase or decrease the appearance probability by utilizing the uncertain road users tracking results from available traffic mirror detections. Furthermore, we present an active traffic mirror perceiving method for encouraging the ego vehicle to explore the environment and plan driving policies that support perception. Finally, in the POMDP model, the detected real road users and inferred phantom traffic participants are represented in the state space. The driving policies are obtained by using the anytime Monte Carlo tree search (MCTS) algorithm to solve the POMDP model online. In various simulation scenarios with static and dynamic obstacles in an urban environment, the proposed approach is compared to the baseline approach. Our planner successfully uses the uncertain objects tracking information from traffic mirrors and provides safer and more efficient driving policies.

I. INTRODUCTION

Autonomous driving in urban scenarios is difficult due to its complex road topology, uncertain sensory information, unknown intentions with other road users during the interaction, and the limited field of view (FoV) caused by static and dynamic obstacles. The decision-making module of the autonomous vehicle should be able to infer the risk posed by occlusion areas and provide safe and efficient driving policies. In complex urban areas with limited visibility, traffic mirrors are often placed by local authorities to reduce the risk of traffic accidents. A traffic mirror, also known as a security mirror or a road safety mirror allows drivers and pedestrians to better understand their surroundings and see around blind corners or other obstructions. They can be helpful at intersections, roads or parking areas where there are either natural or manufactured obstructions (see Fig. 1). Traffic mirrors are beneficial



(a) The ego vehicle intends to turn left at an occluded intersection.



(b) The ego vehicle drives through a partially occluded road section with a crosswalk.

Fig. 1: Two driving scenarios in an urban environment in the presence of occlusions caused by buildings, parked cars or moving trucks. Traffic mirrors are found at the corner of an intersection (a) and on the other side of a road (b), and their information is used to increase the FoV. Red areas indicate the occluded area of the ego vehicle, whereas green areas show observed regions of the traffic mirror.

for humans. Utilizing traffic mirror information within autonomous vehicles could expand the FoV.

Some works have been proposed in recent years to investigate the decision-making algorithms with occlusion-awareness for autonomous vehicles. Reachability analysis was used in some studies to assess the collision risk posed by potentially occluded traffic participants in the occluded regions [1]–[3]. Learning-based methods have also been investigated to learn driving strategies for handling occlusion scenarios rather than manually defining rules. [4]–[6]. Recently, due to the increased computational power and further development of solving libraries [7]–[9], the partially observable Markov decision process (POMDP) has become an emerging method for decision-making for

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autonomous driving under uncertain intentions of traffic participants [10]–[12]. Several POMDP planners with occlusion awareness have also been proposed to consider potentially occluded vehicles and pedestrians with increased occlusion scenario coverage [13]–[19].

In addition to occlusion-aware decision-making and motion planning methods, studies are focusing on improving occlusion-awareness in the prediction module of the autonomous vehicle. Formal set-based prediction is used to predict a set of occupancies for both detected and occluded road users [20], [21]. Reference [22] utilizes contextual information to estimate the emergence probabilities of the hidden pedestrians. Furthermore, some researchers have proposed methods for perceiving traffic mirrors and tracking dynamic objects based on detected traffic mirrors. Based on camera images, either traditional computer vision methods such as Gaussian filters [23] or convolutional neural network (CNN)-based approaches [24], [25] are used to detect traffic mirrors. The Kalman filter and optical flow are used for tracking objects moving direction, i.e., whether objects are approaching or receding from the observer [23], [25]. According to our research, no prior work investigates how to incorporate perceived uncertain traffic mirror information into the decision-making method for autonomous vehicles in the presence of occlusions.

In previous studies [10]–[19], the ability of POMDP-based behavior planners for autonomous driving is improved by integrating more sources of uncertain information, such as uncertain measurements, uncertain intentions of traffic participants, and uncertain appearance of occluded road users. In this study, we further expand an occlusion-aware POMDP behavior planner [19] to handle occlusion scenarios where uncertain information can be derived from traffic mirrors. First, high-risk areas where road users are very likely to appear such as intersections and bus stops are identified from the high-definition (HD) map. Next, the status of phantom road users is estimated, including the location, orientation, and likelihood of appearing in high-risk regions. Following that, a confidence modifier is modeled based on the detected traffic mirror and its observed lane or areas as well as the directions of tracked hidden road objects. The confidence modifier is then integrated into the POMDP observation model to increase or decrease the appearance probability of phantom road users in high-risk areas based on whether the tracked road users are close to or far away from the ego vehicle. The appearance probability of phantom road users is sampled for constructing the belief tree.

Furthermore, we present an active mirror perceiving method to encourage the ego vehicle to actively explore the environment and gain more information when the traffic mirror is temporarily occluded by dynamic obstacles. This method first searches the HD map for relevant traffic mirrors based on the ego mission. For every relevant traffic mirror, three-dimensional observability checks are performed between the ego vehicle position and the position of the relevant traffic mirror in the current and the future time steps while constructing the belief tree. The result of the checking

is combined with the reward function to encourage the ego vehicle to keep relevant traffic mirrors visible. Finally, through the belief tree, the driving policies that maximize accumulated rewards are obtained.

The main contributions of this study are:

- a concept for using perceived traffic mirrors and uncertain objects tracking information as a confidence modifier,
- the combination of the confidence modifier and a phantom road user concept in a POMDP-based behavior planning to enable the autonomous vehicles to benefit from the uncertain traffic mirror information,
- an active mirror perceiving method combined with POMDP behavior planning for encouraging the autonomous vehicle to plan driving policies that maintain traffic mirror observability.

The remainder of this study is structured as follows. In Section II, the concept of this work is described in detail. In Section III, evaluation results are provided. In Section IV, conclusions and future work are presented.

II. TRAFFIC MIRROR-AWARE POMDP BEHAVIOR PLANNER

This study focuses on designing a behavior planner for an autonomous driving system to handle occlusion driving scenarios in the urban environment by incorporating uncertain tracking information from traffic mirrors. The POMDP behavior planner generates longitudinal driving policies in each planning cycle to control the ego vehicle along a planned mission path.

This section first introduces the general theory of POMDP and how to use the POMDP formulation to model a driving scenario. Following that, we revisit the observation model from our previous study [19], which consists of observing real traffic road users as well as the context-based appearance probability of potentially occluded road users such as vehicles and pedestrians. Furthermore, we introduce a confidence modifier that is based on the object detection result from available detected traffic mirrors to influence the appearance probability of hidden road users. Then, the modification of context-based appearance probability with a confidence modifier is explained in detail. Finally, with a further definition of transition and reward model, the POMDP is solved using the Monte Carlo tree search (MCTS) method [8].

A. POMDP Preliminaries

A POMDP is a probabilistic method that models the sequential decision process of a system (often denoted as agent) under uncertain conditions. A POMDP is defined by the tuple $(S, A, O, T, Z, R, \gamma)$ where S, A, O represent the state, action, and observation spaces, respectively. The transition model T is a conditional probability function $T(s, a, s') = P(s' | s, a)$ modeling the probability of a system transition from the state $s \in S$ to the state $s' \in S$ when action $a \in A$ is executed. Similarly, the observation model Z is a conditional probability function $Z(o, a, s') = P(o | s', a)$ describing the

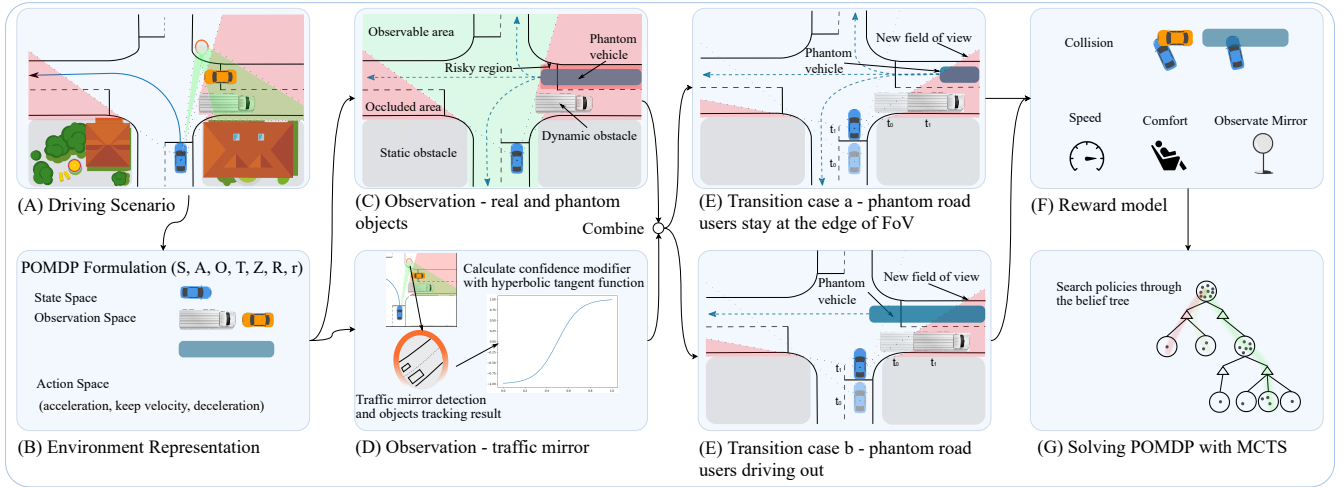


Fig. 2: The process of traffic mirror-aware POMDP behavior planning.

probability of receiving observation $o \in \mathcal{O}$ after taking action $a \in \mathcal{A}$ and transitioning to state $s' \in \mathcal{S}$. The reward $R(s, a)$ is the immediate reward generated by performing the action $a \in \mathcal{A}$ from the state $s \in \mathcal{S}$. Finally, a factor $\gamma \in [0, 1)$ discounts future rewards [26].

In a partially observable environment, the agent has only partial knowledge of the system state. Hence, a belief state $b(s)$ is maintained to reflect its internal knowledge of the system and estimates the true state. The policy $\pi : \mathcal{B} \rightarrow \mathcal{A}$ is a mapping from a belief $b \in \mathcal{B}$ to an action $a \in \mathcal{A}$. Therefore, the solution to a POMDP problem is an optimal policy π^* that maximizes the expectation of accumulated reward over time:

$$\pi^* = \arg \max_{\pi} E \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(b_t)) \mid b_0, \pi \right]. \quad (1)$$

B. Environment Representation

1) *State and observation space representation*: As shown in Fig. 2 A and B, the state space and observation space in the urban driving environment are defined in the same manner, containing the ego vehicle state, real and phantom road users. Phantom objects represent potentially existing vehicles and pedestrians in occluded areas. The ego vehicle state contains its Cartesian position, orientation, velocity, and mission route. Similarly, the state of real and phantom road users includes information such as their location, direction, and speed. Their intentions, such as driving routes or a set of potential pedestrian navigation goals, are partially observable variables that must be considered as internal beliefs and inferred from observation and interaction history.

2) *Action space*: The presented approach is focused on planning longitudinal driving policies on the collision-free path regarding static obstacles. Possible driving behaviors $B = \{acceleration, keep\ velocity, deceleration\}$ of the ego vehicle in longitudinal direction are represented by a set of acceleration values: $A = \{+1.5\ m/s^2, 0\ m/s^2, -1.5\ m/s^2\}$.

C. Observation Model for Real and Phantom Road Users

1) *Observation of real road users*: All the observable variables in the observation space can be directly updated from sensor measurements, including the position and velocity as well as the orientation of the ego vehicle and other real traffic participants. The noise of sensor measurements can also be considered during the update of observation. Unknown intentions are inferred by the autonomous vehicle's prediction module, which is updated each time after receiving new measurements.

2) *Observation of phantom road users*: Phantom objects are potentially occluded traffic participants in roads or areas that cannot be observed directly. This section will briefly recall the concept of phantom road users, including phantom vehicles [16], [17], and phantom pedestrians [19].

Phantom road users can suddenly come out from occluded areas and represent a collision risk with the ego vehicle. Their appearance from unobservable regions must be justified and factored into the planning process. To model the phantom road users, two steps are taken: the creation of phantom traffic participants and the estimation of their appearance probability.

In the first step, unobservable areas are calculated considering occlusions due to static and dynamic obstacles. High-risk areas are further selected from unobservable areas where road users are more likely to appear. Finally, for each high-risk area, phantom road users are generated at the edge of the ego vehicle's FoV. As shown in Fig. 2 C, the state of a phantom road user is similar to that of a real road user, including position, velocity, orientation, and intentions.

In the second step, the appearance probability $P_a(d, u)$ of each phantom traffic participant is reasoned using Eq. 2. The min operator is introduced to guarantee the boundary of the appearance probability to be $P_a(d, u) \leq 1$.

$$P_a(d, u) = \min((P_{env}(d) + P_{FoV}(u)), 1). \quad (2)$$

The appearance probability $P_a(d, u)$ consists of two parts: a location-relevant part $P_{env}(d)$ and a dynamic part $P_{FoV}(u)$.

As shown in Eq. 3, $P_{env}(d)$ describes the appearance probability depending on the location of the occlusion area. The distance d measures the distance between the location of a phantom road user to the considered occlusion area. The initial environmental probability K_{env} and a distance threshold D_s are applied to represent the situations that pedestrians are more likely to appear near high-risk regions such as crosswalks, bus stops than on roads.

$$P_{env}(d) = \max \left(\left(K_{env} \frac{D_s - d}{D_s} \right), 0 \right). \quad (3)$$

The probability $P_{FoV}(u)$ captures the change of appearance probability with regards to the change of the FoV of the ego vehicle in the future. With a wider FoV, the ego vehicle has a better chance of spotting a previously unseen road user. The unobservable area or lanes are assumed to have a normal distribution of phantom traffic participants. As shown in Eq. 4, u is the change of the FoV in meters, and L defines the length within which one phantom road user is expected to be observed.

$$P_{FoV}(u) = \begin{cases} 0 & , \text{ for } u \leq 0 \\ \frac{u}{L} & , \text{ for } u > 0 \text{ and } u < L \\ 1 & , \text{ for } u \geq L. \end{cases} \quad (4)$$

D. Observation Model for Traffic Mirror

1) Confidence modifier for existing object probability:

The perception module of an AV system provides observation of traffic mirrors as well as object tracking information. Some research focuses on improving estimation and tracking results based on camera data, whereas our primary focus is on utilizing uncertain traffic mirror information for behavior planning. Ideally, a perception system should be able to observe the traffic mirror's location and match it within the map. Furthermore, it would provide perceived dynamic road users with detailed information such as position, velocity, directions etc. In this case, considering these tracked objects in the behavior planning module is straightforward since we can model the objects in the state space. However, tracking and providing dynamic road users' position, velocity, and direction through traffic mirrors based solely on camera images is difficult, because traffic mirrors are typically small in size, and minor uncertainties in mirror position and orientation have a large impact on the tracking result.

Instead of overloading the perception system to provide this information, we propose a concept that will reduce the difficulty of perceiving and tracking objects from traffic mirrors, as illustrated in Fig. 2 D. The concept is comprised of three steps. In the first step, the location of the traffic mirror and all its observing lanes or risk areas, such as crosswalks are stored in the HD map. The location of the traffic mirror and its associated observing lanes are then provided online to the perception and behavior planning module in the second step. The relevant traffic mirror regarding the ego vehicle's navigation path and the information of which lane it observes is identified. In the next step, the perception module is responsible for estimating

whether objects move close to the ego vehicle or cross the risk area based on the camera data. The detection result is defined as the detection probability $0 \leq P_m \leq 1$, which denotes the confidence of an object that approaches the observation area of the traffic mirror.

2) *Modification of phantom object's appearance probability with traffic mirror observation:* In this step, we calculate a confidence modifier $P_{cm} \in [-1, 1]$ according to the detected probability P_m using a hyperbolic tangent function,

$$P_{cm} = \tanh(5 \cdot (P_m - 0.5)). \quad (5)$$

The confidence modifier P_{cm} is applied to enlarge or reduce the context-based appearance probability P_a :

$$P_{a_modified} = \max(0, \min(1, P_a(d, u) + P_{cm})). \quad (6)$$

With this extension, the information additionally provided from the traffic mirror detection module can be taken into account. If the detection probability is high, the confidence modifier P_{cm} is close to 1. The modified appearance probability $P_{a_modified}$ can be increased up to 1. The opposite occurs if the detection module does not detect any road users in the hidden area. The confidence modifier calculated by Eq. (5) is around -1 , which will reduce the $P_{a_modified}$ to 0. Another benefit with this extension is that, as long as the detection is very uncertain, P_m is around 0.5. The confidence modifier P_{cm} results in 0, which does not influence the context-based appearance probability P_a .

E. Transition Model

We apply a point mass dynamic model in Eq. 7 as the motion model of the ego vehicle to update the new state along with the mission path in Frenet coordinates [27], where l' denotes the new location of the ego vehicle along the mission path r' of the ego vehicle and v' is the updated ego velocity.

$$\begin{bmatrix} l' \\ v' \\ r' \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} l \\ v \\ r \end{bmatrix} + \begin{bmatrix} \frac{1}{2} \Delta t^2 \\ \Delta t \\ 0 \end{bmatrix} a. \quad (7)$$

For the transition model of other real road users, we use the motion predictions delivered from the prediction model of the ego vehicle according to the corresponding time step.

The state transition of phantom objects depends on the sampled result of the final appearance probability $P_{a_modified}$ after considering the traffic mirror detection. A sample is drawn according to $P_{a_modified}$ each time when the transition of phantom objects is needed. When the sample result is zero, the phantom road user does not appear from the occlusion area. It is updated at the edge of the new FoV in the next time step, as shown in Fig. 2 E case a. When the result is one, indicating that the phantom object comes out from the occluded region (see Fig. 2 E case b), a constant velocity model is applied:

$$l'_i = l_i + v_{\max} \cdot \Delta t, \quad (8)$$

Algorithm 1: Traffic mirror observability check

Input : Current ego states s_{ego} , Next ego states s'_{ego} , Relevant traffic mirror list \mathcal{M} , Object list \mathcal{S}'

Output: Traffic mirror observation flag f_o

```
1 foreach relevant traffic mirror  $m_i \in \mathcal{M}$  do
2    $b_{ego} \leftarrow \text{egoToMirrorPolygon}(s'_{ego}, m_i)$ 
   foreach object  $s_{object} \in \text{object list } \mathcal{S}'$  do
3      $b_i \leftarrow \text{buildBoundingBox}(s_{object})$ 
4     if  $\text{isIntersecting}(b_{ego}, b_i)$  then
5       return FALSE
6     end if
7   end foreach
8 end foreach
9 return TRUE
```

where v_{\max} represents the speed limit of the driving lane according to the HD map. $v_{\max} = 1.25 \text{ m/s}$ is applied to represent the normal walking speed of pedestrians. The phantom road user will only move forward along the path within a planning cycle as long as it is outside of the occlusion region.

F. Reward Function

The reward function of this study includes the objectives safety, speed, comfort, and mirror observation:

$$R = R_{\text{collision}} + R_{\text{speed}} + R_{\text{comfort}} + R_{\text{observation}}. \quad (9)$$

We performed several simulations to determine weights for the reward function.

1) Rewards regarding safety, speed, and comfort:

To consider safety, we assign a large negative reward $R_{\text{collision_real}} = -100000$ when the ego vehicle has collisions with other traffic participants. The collision with phantom road users is penalized with a different negative reward $R_{\text{collision_phantom}} = -10000$.

The ego vehicle is also encouraged to maintain the desired velocity v_{desired} following its mission:

$$R_{\text{speed}} = \begin{cases} -200 \cdot (v_{\text{desired}} - v_0), & \text{if } v_{\text{desired}} \geq v_0 \\ -2000 \cdot |v_{\text{desired}} - v_0|, & \text{otherwise.} \end{cases} \quad (10)$$

To obtain comfortable driving policies, changing acceleration is penalized with $R_{\text{comfort}} = -300 \cdot a^2$.

2) *Reward for active traffic mirror perceiving:* We introduce an active mirror perceiving method to encourage the ego vehicle to keep observing the traffic mirror. The idea is that the ego vehicle has access to the HD map and thus knows the position of all relevant traffic mirrors along the ego navigation path. Algo. 1 shows the process of traffic mirror observability check. A polygon between the ego vehicle and the traffic mirror (as shown in Fig. 2 A), is built for every relevant traffic mirror when the ego vehicle approaches it (line 1 to 2). Three-dimensional checks are performed using the polygon and bounding boxes from all static and

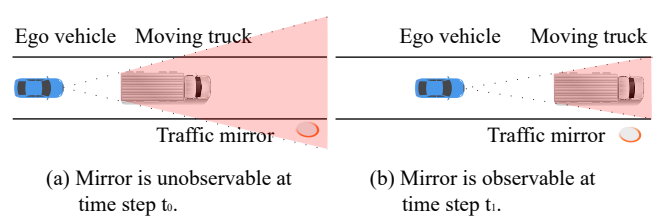


Fig. 3: (a): Ego vehicle cannot observe the mirror, since the mirror is occluded by the moving truck. (b): Ego vehicle is able to observe the mirror.

dynamic objects (line 3 to 8). Finally, the checking result f_o indicates whether the traffic mirror is observable. Fig. 3 shows an example of the traffic mirror which is occluded by a dynamic truck in the first time step and is observable by the ego vehicle in the next time step. The check result f_o is considered in the active mirror perceiving reward $R_{\text{observation}}$:

$$R_{\text{observation}} = \begin{cases} -500 \cdot v_{\text{ego}}, & \text{if } f_o = \text{FALSE} \ \& \ v_{\text{ego}} > 5\text{m/s}, \\ 0, & \text{otherwise.} \end{cases} \quad (11)$$

G. Solving POMDP Model

We apply the TAPIR toolkit [8] to solve the POMDP model. The TAPIR toolkit is implemented in C++ which is capable of handling large continuous state spaces in real-time. The POMDP model is solved online by constructing a belief tree based on the Monte Carlo tree search process. At the beginning, an initial state is sampled as the root of a belief tree to represent the current state of the environment. The belief tree τ is extended further by sampling episodes containing belief, action, reward, and observation. The optimal sequence of actions is searched through the belief tree which maximizes the accumulated rewards. As a result, the search space is limited to the reachable states from the current belief space, allowing TAPIR to provide near-optimal policy within a specified search time online. In this study, we applied varying time steps to utilize the better prediction quality closer to the current observation while achieving a total planning horizon of 10 seconds: $[\Delta t_0 \dots \Delta t_3, \Delta t_4 \dots \Delta t_7, \Delta t_8, \Delta t_9] = [0.5 \text{ s} \dots 0.5 \text{ s}, 1.0 \text{ s} \dots 1.0 \text{ s}, 2.0 \text{ s}, 2.0 \text{ s}]$.

III. EVALUATION

In this section, we use a proprietary simulator to evaluate our approach under various challenging occlusion scenarios in the urban environment. Evaluation results are recorded in video¹. The goal of this research is to incorporate traffic mirror data into the behavior planning module. Thus, in the simulator, we set up a simple perception module for observing simulated traffic mirrors, which provide information about observed lanes as well as the probability of oncoming objects on the observed lanes. The surrounding road users are controlled based on predefined behaviors

¹Video: <https://github.com/GitChiZhang/GT-POMDP>

TABLE I: Applied parameters in the simulation.

Parameter	Value	Parameter	Value
Planning Frequency	2 Hz	Planning Horizon	10 s
Discount Factor γ	0.95	Maximal Tree Depth	10
Scenario B: $V_{vehicle}$	6.5 m/s		
Scenario D: $V_{pedestrian1}$	2.0 m/s	$V_{pedestrian2}$	2.0 m/s
Scenario E: $V_{leading\ vehicle}$	5.0 m/s		

in the simulation to have a fair comparison between different planning approaches. The parameters applied in the simulation are chosen to compare different planning behaviors (see TABLE I).

Our generic occlusion- and traffic mirror-aware POMDP behavior planner is denoted as GT-POMDP. We set up another version of the planner (GTM-POMDP) that also takes into account whether the ego vehicle can observe the traffic mirror by including a reward for encouraging traffic mirror observation. We contrast our approaches with two other approaches. The GO-POMDP from our previous study [19] is a POMDP-based behavior planner that can handle intersections and crosswalks regarding potentially occluded vehicles and pedestrians but cannot use the information provided by the traffic mirror. We consider it as a baseline method. As the ground truth, we established another strategy, V2X-POMDP, which has access to all environmental information, including all occluded traffic participants.

A. Occlusion in Unsignalized Intersection

In scenario A shown in Fig. 4, the ego vehicle intends to turn left in an unsignalized intersection occluded by a building. A traffic mirror is placed at the street that point to the occluded lanes. In scenario B, we additionally set up a moving vehicle driving toward the intersection in the occluded area to evaluate how the planners react to vehicles that suddenly appear. Because there are no other vehicles on the occluded lanes, V2X-POMDP accelerates and drives through the intersection, as illustrated in Fig. 5. Our GT-POMDP approach utilizes traffic mirror data to determine whether or not a vehicle is in an oncoming lane. So, it

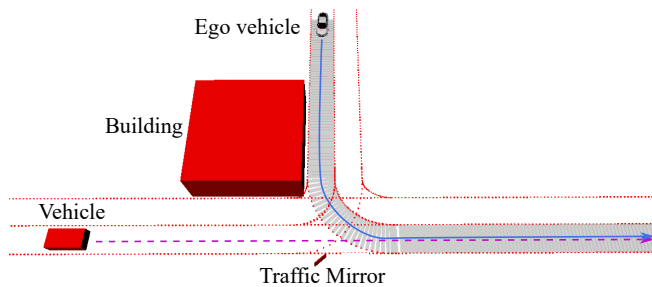


Fig. 4: Scenario A: The ego vehicle intends to turn left in an empty unsignalized intersection with occlusion caused by a building. Scenario B: Additionally, a dynamic vehicle is approaching the intersection.

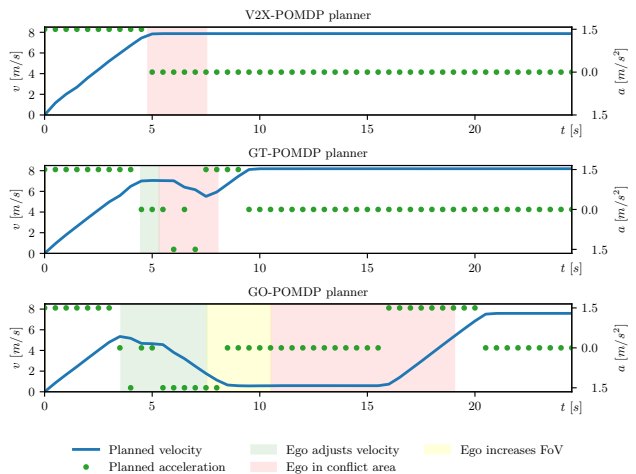


Fig. 5: Comparison of planned driving strategies for handling the occluded intersection (scenario A).

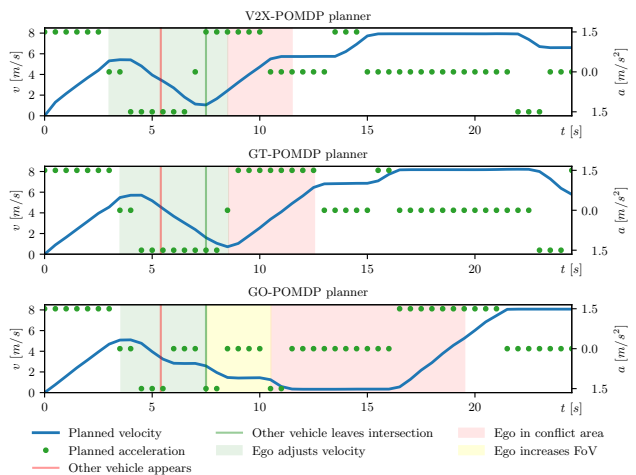


Fig. 6: Comparison of planned driving strategies for handling the occluded intersection with a dynamic vehicle (scenario B).

maintains a relatively high speed through the intersection. In contrast, GO-POMDP decelerates and creeps forward with low speed to increase the FoV so that it can safely drive through the intersection.

If there is a vehicle hidden in the occluded area that approaches the intersection in scenario B, GT-POMDP in Fig. 6 shows comparable performance to V2X-POMDP. It slows down and waits for the vehicle that has higher priority. After the other vehicle leaves the conflict area at time $t = 7.52$ s, GT-POMDP enters the intersection at $t = 8.56$ s and accelerates as long as the mirror provides high confidence that no vehicles are in the blind spot. GO-POMDP again drives slowly to increase the FoV when handling the occluded scenario.

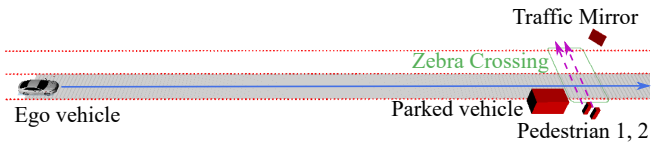


Fig. 7: Scenario C: Ego vehicle driving through a crosswalk with occlusion caused by a parked vehicle. Scenario D: Two pedestrians intend to cross the road, but their views are blocked.

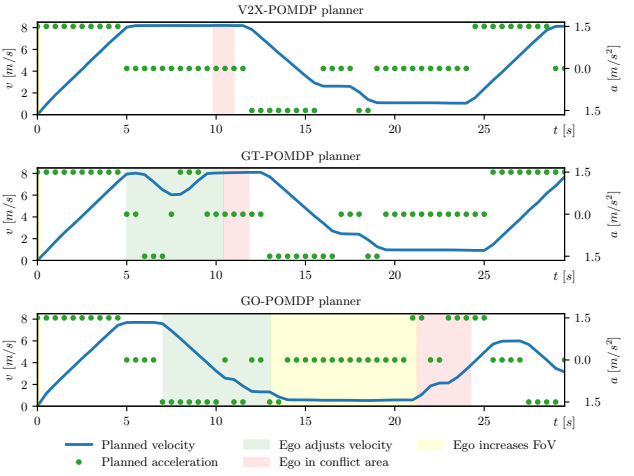


Fig. 8: Comparison of planned driving strategies for handling the occluded crosswalk without pedestrians (scenario C).

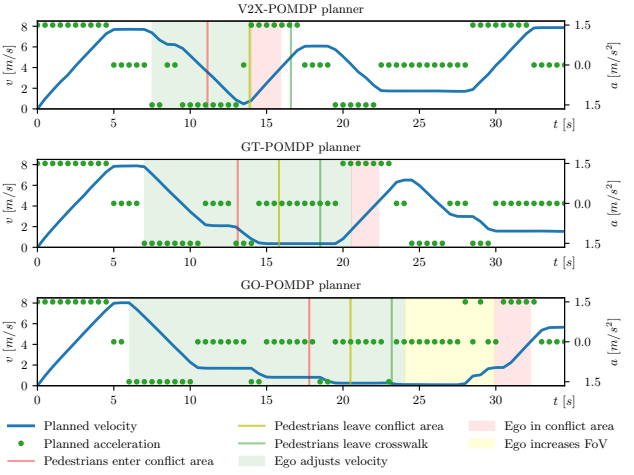


Fig. 9: Comparison of planned driving strategies for handling the occluded crosswalk with crossing pedestrians (scenario D).

B. Occlusion in Crosswalk

We present a crosswalk scenario in Fig. 7 to evaluate our approach’s performance in the presence of an occluded risk area where pedestrians may cross the street. Scenario C is without pedestrians, whereas in scenario D, two pedestrians will cross the street when the ego vehicle is near the

crosswalk. It can be seen in Fig. 8 that GT-POMDP stops decelerating at time $t = 7.47 s$ and decides to cross the crosswalk due to the awareness of the low appearance risk of pedestrians in the occluded area. Without this knowledge provided by the traffic mirror, GO-POMDP needs to behave more cautiously.

The result for scenario D shown in Fig. 9 shows a similar reaction of GT-POMDP like V2X-POMDP. When pedestrians cross the street, the ego vehicle has already slowed down to a reasonable speed and let them cross first. Compared to GO-POMDP, GT-POMDP drives through the occluded intersection faster.

C. Occluded Traffic Mirror

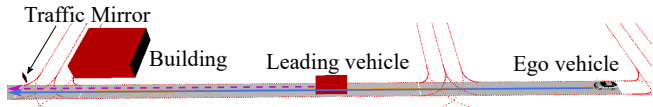


Fig. 10: Scenario E: Ego vehicle is approaching a slow truck. The traffic mirror is blocked by the truck.

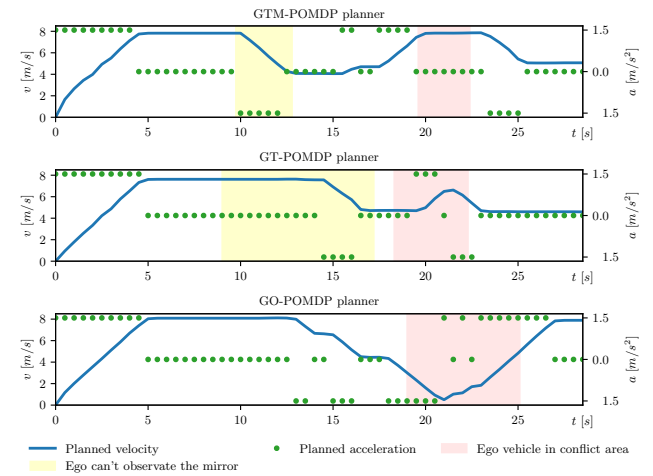


Fig. 11: Comparison of planned driving strategies for handling the occluded intersection with occluded traffic mirror (scenario E).

Finally, we set up a challenging scenario in Fig. 10 to demonstrate the capability of our planner where a static building occludes the intersection, and a moving truck in the front of the ego vehicle limits more FoV of the ego vehicle. Even the traffic mirror is occluded by the truck when the ego vehicle approaches the occluded area.

The acceleration and velocity profiles are shown in Fig. 11. To keep observing the traffic mirror, the GTM-POMDP starts to slow down at time $t = 10.1 s$ and tries to keep a large distance to the leading truck. The GTM-POMDP has more time to observe the traffic mirror before entering the conflict area of the intersection. The GT-PMODP is not aware of the traffic mirror, resulting in a late slow down before entering the intersection. Furthermore, GTM-POMDP has a shorter period that is obstructed from viewing the traffic

mirror. GO-POMDP shows a more conservative driving style compared to both GT-POMDP and GTM-POMDP.

IV. CONCLUSION AND FUTURE WORK

This study presented a traffic mirror-aware behavior planner based on the POMDP model for handling urban driving scenarios under visibility limitations. Our approach generates phantom traffic participants in risky occluded areas and reasons their appearance probability based on contextual information and available uncertain traffic mirror detections. The evaluations show that using traffic mirror detection allows our planner to drive more safely and efficiently in the presence of occlusions in intersections and crosswalks. Because of the active traffic mirror perceiving method, our planner can take into account the current and future observability of the traffic mirror and drive slower to better observe the traffic mirror and gain more information.

In the future, we would like to expand our concept by utilizing a V2X module that provides measurements of dynamic road users with uncertainty in unobservable areas.

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