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Virtual Obstacle for a Safe and Comfortable Approach to Limited Visibility Situations in Urban Autonomous Driving

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François Aioun², Franck Guillemard²

Abstract—Path planning algorithms for autonomous vehicles need to account for safety and comfort, more so, in scenarios where the possibility of casualties are higher due to increased traffic frequency and limited visibility. In this paper, we discuss the idea of a virtual obstacle deployed at occluded scenarios to avoid a potential collision or severe deceleration of the ego-vehicle. Urban scenarios like intersections, roundabout and merging are experimented. Results of simulating the integration of virtual obstacle with the trajectory planning algorithm, are analyzed in detail comparing speed and acceleration profiles.

I. INTRODUCTION

The challenge of fully autonomous driving has been approached by numerous researchers in academia and industry alike, during the last decades. Although there has been noteworthy progress during the period, the problem remains largely unsolved for the edge cases because of factors such as the unpredictability of traffic, limited sensor range and interaction with human drivers.

Some of the most complex driving scenarios are the intersections and roundabouts where the uncertainty factor is high, especially with the presence of an occlusion blocking the view of the ego-vehicle (EV). These occlusions are generally due to infrastructures like buildings or large parked vehicles, which severely impede visibility. In these situations, other vehicles may not be perceived by the EV, thus increasing the risk of accidents. In this paper, we propose a solution to evade the occlusion based uncertainties. Whenever the EV is approaching a limited visibility situation, it has to adapt to a suitable speed to be able to react to potentially incoming vehicles. Our idea is to generate a *virtual obstacle* at the edge of visibility to create a constraint for the motion-planning algorithm of the EV and thus ensure a comfortable and safe approach.

We discuss in detail our approach towards different scenarios in the following sections. After talking through the related work carried out on the same issue so far in Section II, we proceed to explain the concept of the virtual obstacle in Section III. Simulation setup and results are analyzed in detail in Section IV. After an overview of limitations, we conclude on the paper in Section V.

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II. RELATED WORKS

A great deal of work has been carried out by researchers in the past decade towards the improvement of path planning approaches, more specifically in risk assessment and addressing uncertainty issues. Katrakazas et al. [1] widely scrutinize various planning techniques like RRT or A* with an emphasis on planning with obstacle prediction and decision making. The article briefs on research implementing techniques such as POMDP (Partially Observable Markov Decision Process) which transform the state space into belief space and cost based approaches to choose the trajectory satisfying the limits of safety and comfort.

Hallerback et al. [2] suggest a simulation based toolchain for cooperative automated vehicles, where a number of metrics like TTC (time to collision), TTB (time to brake) and false positive rate were iterated to identify critical scenarios in day to day driving, and tested with X-in-loop test benches to simulate a real world proving ground.

Yu et al. in [3] address the limited sensor range and large occlusions in urban environments. The authors propose to predict the risk caused by unobserved regions as opposed to a baseline method, which only predicts the distribution of risk caused by unobserved vehicles. Collision rates are reduced by almost 5 times in comparison to a baseline method, with augmented driving comfort.

Data driven approaches to solve the occluded intersections were discussed in [4] by Isele et al. The authors investigated the idea of training the Deep Q-network (DQN) models and comparing them with a standard TTC algorithm, and generated metric scores like collision and success percentages, average time for iteration and braking. While the results stated that deep learning reinforcement approach was able to generate exploratory behaviors to fully understand the scene, therefore overcoming limitations of rule-based methods, there was still the shortcoming of *out of sample* cases, which can only be solved by extensive mining of large variety of datasets.

More relevant works addressing occlusion issues are [5] and [6], both employing probabilistic methods of risk assessment. In [5], Lee et al. propose a PCV, Potential Collision Vehicle, which could be outside the field of view and assess the collision probability rate as a function of the speed of the ego-vehicle. In [6], McGill et al. discuss the idea of risk modelling on the basis of a Bayesian probabilistic model, more specifically applicable to intersections with an occluded view. Risk is quantified on the basis of visibility and a *nudge*

and clear policy is seen, where the ego-vehicle gradually nudges into the intersection to gain visibility at a lower speed. When enough visibility is obtained, the EV accelerates to avoid a potentially incoming vehicle moving at maximum speed, whose presence is judged by probability as well.

The need for being safe but not overcautious and to avoid unnecessarily slowing down was studied by Naumann et al. in [7], where the conflict zones were assessed for occupancy probability and stronger potential decelerations were avoided by analysis of reachability and cost based trajectory calculations.

In [8], Orzechowski et al. propose a similar idea of a Virtual Obstacle, where any area outside the field of view is considered ambiguous and is therefore considered as an occlusion. The implementation is on the basis of the idea of reachable sets and safe state estimation with comfort and safety constraints verified through bounding boxes. Although this can ensure a safe approach, a lot of computational time and effort could be at stake.

We present in this paper, the concept of a Virtual Obstacle beyond visibility, only with respect to the identified priority lanes in some critical urban cases, thus narrowing down the issue.

III. VIRTUAL OBSTACLE IN LOW-VISIBILITY SITUATIONS

The virtual obstacle principle is designed to be integrated in the motion planning algorithm proposed by [9]. In the following sections, relevant details of the planning algorithm are provided and the virtual obstacle concept is presented.

A. Trajectory planning algorithm

The local motion planning algorithm used in this work consists of multiple steps presented in Figure 1a. The first step is to generate multiple geometric paths that the ego-vehicle could follow, represented in Figure 1b. These paths are composed of a transition part which brings the ego-vehicle to a given lateral offset from the center of the lane, followed by a parallel part which keeps this offset constant. The geometric paths are then fixed, and a speed profile is defined on each path with respect to static and dynamic objects in the environment. The speed profile is initialized with the maximum legal speed, provided by an upstream decision module. Then, each position of the path is checked to ensure that it does not overlap with a static obstacle, and if so, a stop point is introduced on the path to reduce the speed and avoid the collision. After this, a time-based trajectory is generated from the path and the speed profile on a given time horizon T , and each future position of the ego-vehicle is compared with the predicted positions of the other moving obstacles detected in the scene. If an overlap is detected in the predicted configurations of the vehicles, the speed profile is also adjusted to make the vehicle stop before the collision. Finally, the best trajectory is selected from the set of generated trajectories by computing a cost function based on comfort and efficiency. This algorithm is applied in a reactive way, such that this process is repeated at regular time steps.

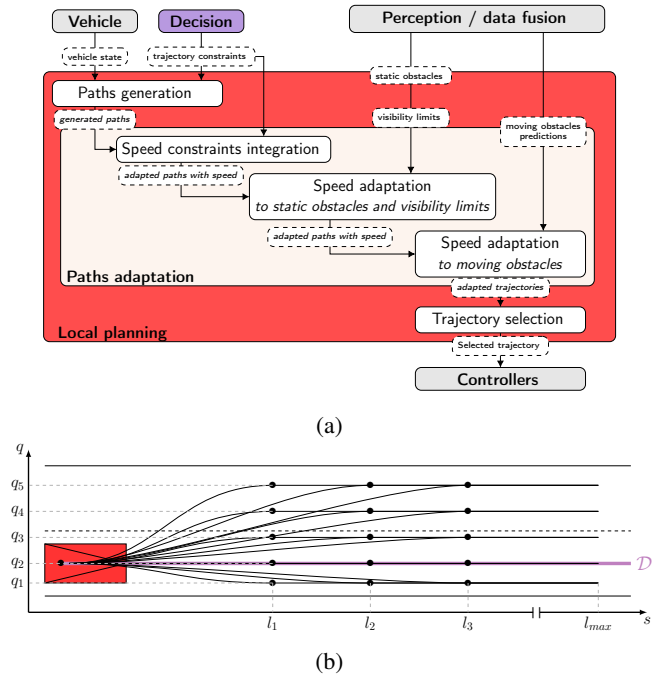


Fig. 1: Illustration of the motion planning organization and paths shape. a) Local trajectory planning organization, b) Shape of the generated paths (see [9] for more details)

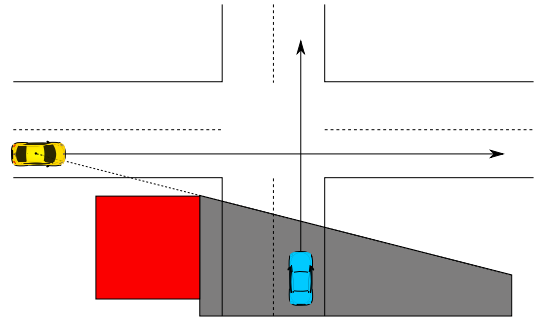


Fig. 2: Illustration of a potentially critical case: the visibility of the ego-vehicle (yellow) in the left branch is limited by the building (red) and can't see the potential vehicle (blue) coming from the bottom branch, which has the right of way.

As described here, this algorithm checks only the planned path of the ego-vehicle with respect to the environment and the other vehicles which are detected. When dealing with occlusions, it is then possible to detect that the path will leave the visibility limits, which can be represented as a static obstacle. However, it is not possible to account for a potentially unseen vehicle, which could have priority over the EV. On European roads, this is the typical case of a crossing with a building hiding a part of the lane coming from the right, on which vehicles have the right of way, as illustrated in Figure 2. To have a safe approach of the crossing, the ego-vehicle should slow down while getting closer to the intersection, until it has enough visibility to guarantee that it can cross the road safely.

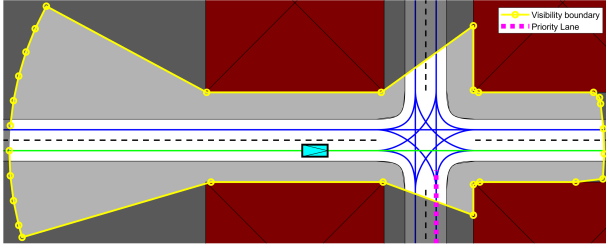


Fig. 3: Bird-eye view representation of a situation, with the visibility boundary (yellow) and the identified priority lane (dotted magenta).

B. Virtual Obstacle principle

As explained in the previous paragraph, the motion planning algorithm generates trajectories adapted only to what was seen in the environment. Hence, we propose to generate a virtual obstacle which will be added to the list of the perceived obstacles, such that the ego-vehicle can adapt its speed when approaching the crossing.

We suppose that the perception systems of the ego-vehicle are able to determine the *visibility boundary* projected on a bird-eye view, as illustrated in Figure 3. This visibility boundary could be obtained from lidar or radar sensors by projecting the point clouds on the ground and processing the result to compute the boundary. We also suppose that a representation of the local road network is available, and that the upstream decision module identifies the *priority lane* to which the ego-vehicle should potentially give way.

The idea of the virtual obstacle is to constantly suppose that a hidden vehicle is located just at the edge of the visibility boundary, and that this vehicle continues on the road at the maximum speed allowed in the current context. This represents the first vehicle that could reach the intersection and thus cross the path of the ego-vehicle – under the assumption that this other vehicle respects the maximum speed limit. Any other vehicle, with an initial position further away from the intersection, or with a lower speed, will reach the intersection and cross the ego-vehicle’s path later in time.

Consequently, to safely enter the crossing, the ego-vehicle must ensure that it can pass *before* this virtual obstacle. In this case, it means that even if a vehicle suddenly appears, the ego-vehicle will have enough time to safely evade the crossing. If this safety condition is not met, then the ego-vehicle should plan to stop before the crossing. The intersection will then be approached with a reduced speed which guarantees that if a vehicle suddenly appears, the ego-vehicle will be able to stop and avoid a collision.

Although this constraint may seem conservative, it should be noted that the planning algorithm is reactive, meaning that the computed trajectory is updated at regular time steps. This way, when the ego-vehicle approaches the intersection, in most cases the visibility will increase until it becomes long enough to allow the ego-vehicle to cross, as will be shown in Section IV

C. Virtual Obstacle construction

To integrate this virtual obstacle into the motion planning algorithm, a predicted trajectory for this obstacle must be defined over the time horizon T .

First, the initial position X_{VO} of the virtual obstacle is determined by computing the intersection between the visibility boundary and the priority lane, both given as a set of segments. Since the virtual obstacle is supposed to be completely hidden, the position X_{VO} corresponds to the front of the vehicle. Therefore, the polygonal representation of the virtual obstacle computed at position X_{VO} must be designed accordingly.

Then, the trajectory can be extrapolated by propagating X_{VO} in the road network at the determined speed v_{VO} . The distance s crossed by a vehicle in a time t is given by Equation (1), when assuming a constant speed v_{VO} .

$$s(t) = \int_0^t v(u)du = \int_0^t v_{VO}du = v_{VO} \times t \quad (1)$$

This equation can then be used to compute the position of the virtual obstacle at each time t_i (corresponding to the discretization of the time horizon T used in the motion planning algorithm), by computing the point X_{VO}^i located at the curvilinear distance $s(t_i) = v_{VO} \times t_i$ from X_{VO} when following its lane in the road network.

As explained before, the ego-vehicle can only pass before the virtual obstacle. This constraint is represented by considering that once the virtual obstacle has reached the position X_{VO}^i at time t_i , this position remains occupied from t_i to the end of the time horizon T . Since the motion planning algorithm will check for overlaps between the expected position of the ego-vehicle and the virtual obstacle at each time t_i , the polygonal representation of the virtual obstacle at time t_i is defined such that it covers all the positions $X_{VO}^j \forall j \leq i, j \geq 0$.

This representation of the virtual obstacle is interesting because, thanks to its geometrical representation, it can be used in any situation with a limited visibility, independently of the shape of the intersection or the local maximum speed. The representation can also be directly processed by the planning algorithm as an extra obstacle, which is added to the list of real obstacles, such that all constraints are considered at the same time. Finally, the required visibility range to be able to cross the intersection is implicitly determined by the planning algorithm, which checks if the planned trajectory can pass before the Virtual Obstacle or not, by taking into account all the other constraints, such as the initial speed, limited accelerations and other vehicles.

Compared to [7], our approach implicitly allows the EV to cross without computing explicit maximum speeds or distances to the conflict zones. Our polygonal representation also seems simpler to implement than the one used by [8], since we can use a simple rectangle to represent the obstacle at each position X_{VO}^i .

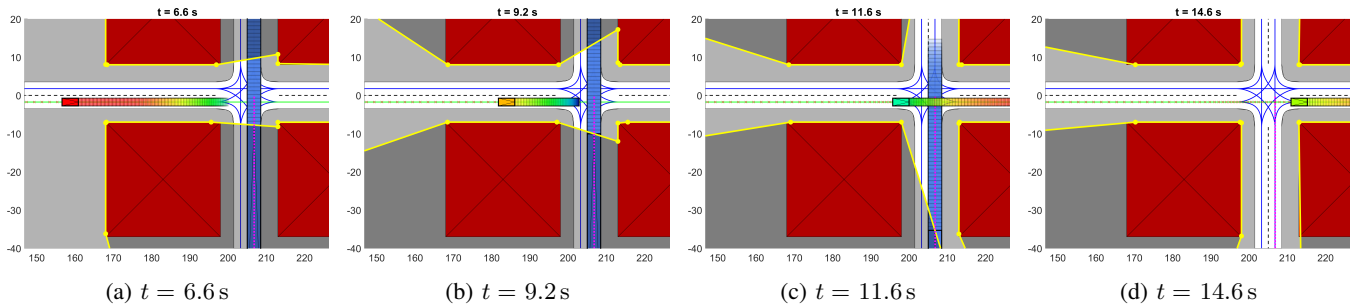


Fig. 4: Evolution of the visibility and the virtual obstacle (blue vertical rectangle) generated in Scenario 1. The trajectory planned for the ego-vehicle (red on the left) is represented with a color ramp, where low speeds are represented in blue and high speeds in red.

IV. SIMULATION RESULTS

Simulations integrating this virtual obstacle concept have been conducted to show its efficiency in various low-visibility urban situations. In these situations, the virtual obstacle is generated and provided to the motion planning algorithm, which is not specifically adapted for these situations.

A. Simulation setup

In the proposed simulations, the ego-vehicle has to follow the *mission path*, represented in green in the different following illustrations. A 360° visibility with a 100 m range is assumed. Occluding obstacles, such as buildings or big parked vehicles, are represented in the scenarios as red polygons, such that the visibility boundary around the ego-vehicle can be computed by raycasting from its position. The priority lane is manually defined as a predefined set of points on an existing lane. Automatically inferring the priority rules at an upcoming intersection should be carried out by the upstream decision module, which is out of the scope of this paper and therefore not considered here.

The algorithm is implemented on MATLAB/Simulink. In these simulations, the ego-vehicle is assumed to perfectly follow the trajectory provided by the planning algorithm. No vehicle model or controllers are implemented in order to study only the results of the planning algorithm. The time horizon T used in the planning algorithm is 5 s. The comfort deceleration bound is defined at -2 m s^{-2} , and the maximal bound at -10 m s^{-2} . The maximum speed for these simulations is set to 10 m s^{-1} . The shape of the roads is designed to be similar to real-world situations.

This work does not focus on computation time since the goal is to increase safety. In the proposed scenarios, only one virtual obstacle is generated and follows one specific path, which requires low processing times.

B. Scenario 1: Intersection without a real moving obstacle

In this first scenario, we consider a four-branches intersection with buildings limiting the view in each corner. The ego-vehicle is alone in the scenario, without a real obstacle, in order to assess the impacts of the virtual obstacle generation on its behavior. The resulting trajectory planned for the

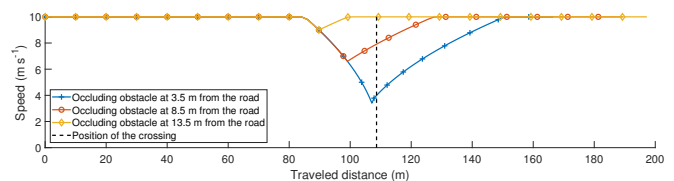


Fig. 5: Resulting speed profile in Scenario 1 with different positions for the building

EV is presented at different times in Figure 4. The EV is seen to adapt its speed profile smoothly as it approaches the intersection since it observes the presence of a virtual obstacle on the priority lane, represented in purple. After the progressive deceleration, which ensures the safety of the EV for any unseen vehicles beyond the visibility, the EV starts gradually accelerating once it gains enough visibility into the priority lane.

Since the position of the building directly impacts the visibility, which is a primary factor affecting the speed profile of the ego-vehicle, multiple simulations are done varying its position. The building is placed at different distances from the intersection to illustrate the effects of the visibility on the ego-vehicle's behavior. The resulting speed profiles are shown in Figure 5. It can be observed that, the further away then building is from the intersection, the lesser time it takes for the EV to cross the intersection. Since the visibility into the priority lane improves quickly when the building is far from the intersection, the EV crosses without being overcautious.

C. Scenario 2: Intersection with a real moving obstacle

A real moving vehicle is simulated in this scenario corresponding to a real life situation, to show the interest of the virtual obstacle. This vehicle is supposed to travel at maximum lane speed, and is placed in the priority lane such that both the EV and the real obstacle reach the intersection at the same time if they drive at a constant speed. The real obstacle is hidden by the building and can't be detected before a certain time. Therefore, if the EV keeps its initial speed, it will be already close to the intersection when the real obstacle is perceived. This should cause a sharp deceleration and thus extreme discomfort to avoid the collision,

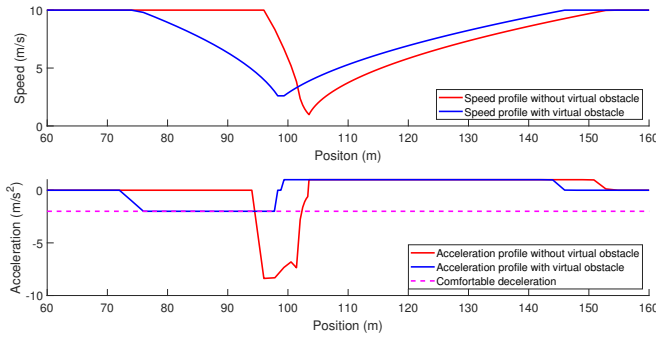


Fig. 6: Comparison of acceleration and speed profiles in Scenario 2

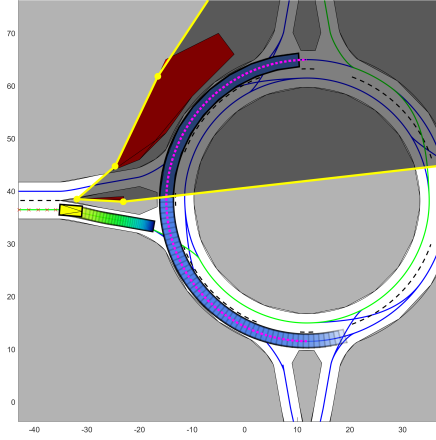


Fig. 7: Virtual Obstacle illustration at a roundabout (Scenario 3)

and even potential safety issues depending on the braking capabilities. With the integration of the virtual obstacle, the ego-vehicle should be able to anticipate the presence of a dynamic obstacle, thus gradually slowing down. Therefore, when the real obstacle is detected, the speed of the EV is consistent with a safe and comfortable braking.

The simulation is carried out for this scenario and the results are seen in Figure 6. As expected, without considering the virtual obstacle, a late and strong deceleration is produced. With the consideration of the virtual obstacle, the ego-vehicle starts decelerating earlier, stays within the lower limit of comfort deceleration, regaining the maximum velocity quicker as well.

D. Scenario 3: Roundabout scenario

This scenario examines the behaviour of EV at the roundabout, more commonly seen in European roads. Here, the visibility of the EV is limited by an obstacle, like a bush, just before entering into the roundabout, and by another obstacle close to the priority lane. A real obstacle is also added such that it will conflict with the ego-vehicle.

As seen in Figure 7, the shape of the virtual obstacle is designed to have a curvature similar to that of the lane. Its length is defined to cover all the positions of the obstacle

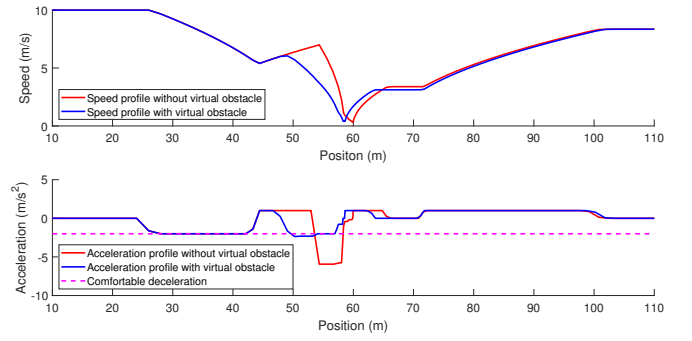


Fig. 8: Comparison of acceleration and speed profiles in Scenario 3

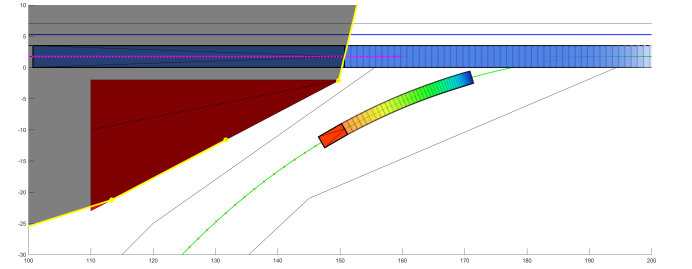


Fig. 9: Virtual Obstacle at a merging situation (Scenario 4)

in the time horizon, with respect to the maximum speed assumed in the curve given by Equation (2). a_{lat} represents the assumed comfort lateral acceleration, and κ represents the curvature of the outer ring of the roundabout.

$$v_{max} = \sqrt{\frac{a_{lat}}{|\kappa|}} \quad (2)$$

Therefore, the length of the virtual obstacle is given by Equation (3).

$$l_{VO} = T \times v_{max} \quad (3)$$

If multiple intersection points are detected, the closest one from the mission path is chosen and the virtual obstacle is set to begin from this point. The EV can be seen to gradually advance in its path until it gains better visibility and finally accelerates again when it gains complete visibility of the lane and notices that any moving obstacle can be evaded with a safe distance between them.

Figure 8 presents the resulting speed and acceleration profiles. As can be seen, when the EV does not consider the virtual obstacle, it accelerates before entering the roundabout, and then applies a strong braking when the real obstacle is detected. As expected, when the virtual obstacle is considered, the speed is reduced in advance in a comfortable manner, leading to a safe approach of the intersection.

E. Scenario 4: Merging scenario

In this scenario, the EV is set to merge with limited visibility, as shown in Figure 9. Here again, a real obstacle is introduced, and the scenario is simulated with and without

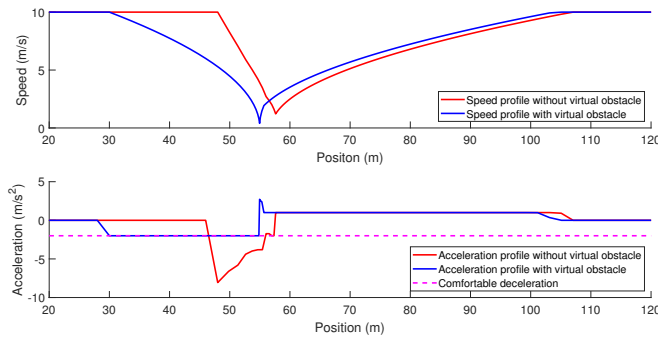


Fig. 10: Comparison of acceleration and speed profiles in Scenario 4

considering the virtual obstacle. Figure 10 presents the resulting speed and acceleration profiles.

Without considering the virtual obstacle, the real obstacle is detected very late, thus the acceleration profile can be seen to reach deceleration values very close to the maximal bound. When the virtual obstacle is considered, the comfortable deceleration is steadily maintained until the real obstacles has passed and enough visibility is obtained.

F. Limitations

Although we have a safe approach with the virtual obstacle principle successfully addressing multiple urban scenarios within a given testing framework, this approach has some limitations.

First, by assuming that the moving obstacle travels in a given direction at a set maximum speed, any intention uncertainty has been ignored at the intersection. The unseen vehicle on the right lane does not necessarily have to travel straight through the intersection as seen before, it can take a left or a right turn. Since this is assumed to be a non-signalized intersection, it does not only increase the collision probability but also complicates the decision for the EV. The approach to solving the intentional uncertainty could be by using methods like Kalman filter derivatives, to gain a more comprehensive picture at intersections.

For the concept of virtual obstacle to be successfully implemented, it demands a previous knowledge of the lanes and thus it could face limits on unknown terrain where mapping hasn't been done yet. Another major concern is the case where the visibility would be severely limited, leading to a complete stop for the EV. Very large occluding obstacles and vehicles parked very close to intersections are commonly seen in dense urban areas, which block the visibility onto the priority lane and lead to a dead stop for the EV. Since the EV cannot move any further, it cannot have more visibility on the priority lane, and consequently will remain blocked at that position. A similar behavior could be observed with a long platoon of vehicles passing through the right lane, and the EV eventually slows down until it comes to a stop, not being able to gain any more visibility. These dead-end cases could be approached by probabilistic or data-driven approaches, or by a hybrid approach which could be activated in these conflict zones.

A strategy to increase the field of view by safely orienting the ego-vehicle in a way to maximize visibility was seen in [10]. Model Predictive Control could be implemented to recover from a blind spot and a receding horizon. And if the autonomous vehicle does not have enough information to take a decision to advance, even after integrating these alternative approaches, the back-up option could be to return the control to the human driver.

V. CONCLUSION

In this paper, we presented the idea of a virtual obstacle to address the limited visibility intersections and similar scenarios ensuring a safe approach. The consideration of virtual obstacle clearly improve the ego-vehicle's reaction to any unseen incoming obstacles. Test cases where collision is imminent or an emergency stop is to be employed were improved when the virtual obstacle was considered, by decelerating in an anticipated and comfortable fashion. A smoother velocity profile was seen, thus enhancing comfort by staying within the recommended limits. The anticipation of the presence of a real obstacle, and the use of an extended virtual obstacle in order to account for any initial position and velocity of a potentially hidden vehicle, result in a safe and comfortable trajectory at the limited visibility zones.

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