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Predictive Trajectory Planning in Situations with Hidden Road Users Using Partially Observable Markov Decision Processes

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***Abstract*— State of the art emergency brake assistant systems solely based on sensor measurements reduced the number of traffic accidents and casualties drastically in recent years. In order to be able to react on road users who elude a vehicle's field of view because of sensor limits or occlusions, this paper presents an approach to anticipate potential hidden traffic participants in occluded areas in the decision making process of an autonomous vehicle. A Partially Observable Markov Decision Process is used to determine the vehicle's longitudinal motion. Observations are made using the vehicle's field of view. Therefore the field of view is calculated with a generic model of a sensor setup in dependence of the current or the predicted environment. In this way, the vehicle can either observe that it detects a previously hidden road user or receives information that the road is clear. In total, that allows the vehicle to better anticipate future developments. Therefore, assumptions about vehicles that may be located in hidden areas need to be made. We demonstrate the approach in two scenarios. Firstly in a scenario, where the vehicle has to move cautiously into the intersection with a minimum number of actions and secondly in a typical scenario for urban traffic. Evaluation shows, that the approach is able to anticipate hidden road users correctly and act accordingly.**

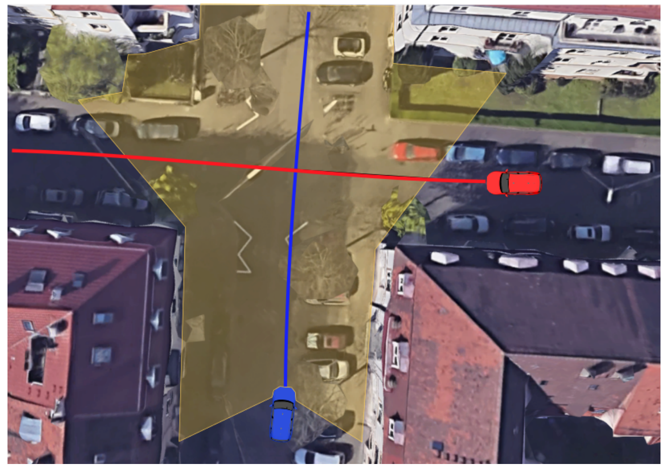

Fig. 1: The ego vehicle depicted in blue approaches an unsignalized intersection. The other traffic participant (red) can not be seen by the ego vehicle because a building limits the ego vehicle's field of view (yellow) [image @ Google Maps, 2019, location: Karlsruhe, Germany, accessed: 24 January 2019]

I. Introduction

New driving assistant systems are constantly being developed to reduce the number of traffic accidents in every day traffic. Systems like adaptive cruise control (ACC) or emergency brake assists for avoiding rear-end collisions are deployed in normal off-the-shelf vehicles nowadays. These systems are all directly based on sensor perceptions. However, in 2017 14.9%[1] of all traffic accidents including pedestrians in Germany were caused because pedestrians suddenly emerged from behind obstacles. Additionally, 14.5%[1] of accidents between vehicles occurred because of vehicles that failed to yield the right of way and another 15.7%[1] occurred while turning or while entering the road from driveways. It is expected that a considerable part was caused because the other vehicle could not be detected in time. So it has to be noted that collisions often occur with traffic participants that have not been detected in time, because of sensor limitations, occluded streets or hidden driveways. Fully autonomous vehicles are faced with the same challenge of ensuring safety at all time. To achieve this goal without resorting on fully conservative behaviour, uncertainties about high-level features like future motion or intentions of other traffic participants need to be taken into account. Therefore it is strongly suggested that new methods of dealing with these uncertainties need to be developed on the way to a fully autonomous driving vehicle.

Fig. 1 shows an exemplary situation. The autonomous vehicle (blue) approaches an intersection, where incoming lanes can not be observed completely because of buildings and parked vehicles. Thus, it can not detect the other vehicle (red), which has priority at the intersection. To anticipate such traffic participants a more sophisticated approach is necessary that considers meta information like the road network topology and the prediction of the environment. A predictive behavior of automated vehicles also leads to a more explainable and comprehensible behavior for other road users. People for example approach intersections like the one in Fig. 1 by anticipating another vehicle, but they also know from experience that there is a chance that they do not have to stop and accelerate again from a halt. In autonomous driving, a common approach to deal with such scenarios is the worst case assumption. That makes the vehicle stop at each intersection even if it is not necessary, what may lead to inexplicable behavior for on board passengers or following drivers. Therefore a foresighted planning process that considers future developments of a scene in dependence of the behavior of each road user is necessary.

Vehicle-to-x communication allows vehicles to receive information, they are not able to perceive themselves. As a result automated vehicles would be to safely manage all situations in which their own sensors are not sufficient. How-

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ever, not every vehicle and especially not every road will be equipped with these technologies. So, these open challenges still need to be solved in order to achieve fully autonomous vehicles, that manage arbitrary situations themselves.

Therefore, we present a probabilistic planning approach that is able to handle aforementioned situations safely in an anticipatory planning process. We address the challenge of potentially appearing road users using a Partially Observable Markov Decision Process (POMDP). During the planning process the autonomous vehicle is able to consider future observations in dependence of the current and predicted environment. To determine, what the vehicle will see, we use a generic representation of the vehicle's sensor setup to calculate its field of view. In total, the combination of the field of view and assumptions about hidden vehicles leads to a more foresighted and anticipating planning process.

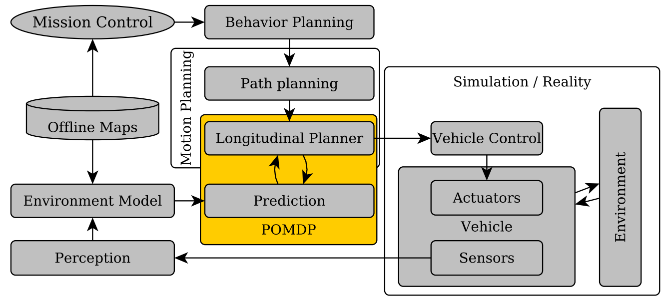


Fig. 2: The general framework including necessary components (middle and left) and the application system (right). An environment model is built from sensor measurements combined with offline maps. This environment model contains information about objects in the scene as well as the road network and is further used in the POMDP. The POMDP includes the longitudinal planning and the prediction.

II. Related Work

Many works tackle the problem of handling uncertainties in the decision making process for autonomous vehicles. They differ in the nature of the uncertainties considered as well as in the approach applied. A common approach to cope with uncertainties is to measure the criticality of a situation using metrics like time to collision or distance to collision. In [2] the authors propose a particle-based approach for the assumption of hidden vehicles. They use the road topology to predict particles along the road network. Lidar measurements are used to evaluate if the particle is visible or not. At intersections, the times required for the ego vehicle and the potential other vehicle to reach the crossing point are used to determine the maximum velocity of the ego vehicle.

Hoermann et. al [3] introduce an approach based on object prediction for already discovered objects as well as an occupancy grid based prediction for unknown road users. The prediction is used to determine occupied sections along a precalculated discretized path for merging into a road.

Both approaches do not take into account that the field of view of the ego vehicle is going to change while making progress. In the worst case this can lead to a standstill.

The approach of Brechtel et al. [4] on the other hand considers future developments of a scene by using a POMDP for the longitudinal planning. They show the benefits in a lane merging scenario with limited sight. Occlusions are determined by checking the direct line of sight between two road users. However, the number of traffic participants must be known a priori as the representation of the scene is learned beforehand and the policy is determined offline.

The use of POMDPs for decision making in autonomous driving is becoming more and more popular, as the solvers for POMDPs have made great progress in recent years. Although the Partially Observable Markov Decision Process was first described in 1965 in [5], solvers that are suitable for real time planning of complex scenarios like autonomous driving were long missing. When solving a POMDP, it has to be distinguished between online and offline solving. Offline solvers are able to determine an optimal policy for an arbitrary initial belief, whereas online solvers try to seek the optimal immediate action for the current belief. Latest state-of-the-art solvers include the Randomized Belief-Space Replanning (*RBSR*, 2010) [6] and Monte Carlo Simulation based approaches like Partially Observable Monte-Carlo Planning (*POMCP*, 2010) [7], Monte Carlo Value Iteration (*MCVI*, 2011) [8], the Determinized Sparse Partially Observable Tree (*DESPOT*, 2013) [9] and the Adaptive Belief Tree (*ABT*, 2013) [10] algorithm. In particular, the latter two approaches and their extensions were applied in applications in the context of autonomous driving recently. For example, the *ABT* algorithm is used in [11] for behavior planning at intersections. The authors in [11] consider unknown intentions of other road users, but non-visible vehicles are not taken into account. It is shown that the approach is able to guess the hidden intentions of other road users and to react accordingly. A similar scenario is investigated in [12] by Liu et al. using *DESPOT*. The POMDP is used for the longitudinal planning of the ego vehicle using a small set of discrete actions. By observing the velocity of other traffic participants, their behavior is estimated.

In this work, the Toolkit for Approximating and Adapting POMDP Solutions in Real-Time *TAPIR* [10] is used. The toolkit is based on the *ABT* algorithm. Thereby a belief is formed as a set of particles that represent the probability distribution over the assumed state of the environment. Belief updates are conducted using particle filter techniques. The belief tree is built from a set of sampled episodes that comprise of a sequence of quadruples of encountered states, actions, observations and rewards starting from an initial belief. For further details the user is referred to [10] and [13].

III. Concept

The approach presented here, is able to consider an arbitrary number of hidden traffic participants in the decision making process for an autonomous vehicle. Fig. 2 shows an overview of the overall architecture. It is worth mentioning that the localization is not shown because it is assumed to be known and therefore not part of the concept. The application system in the right part of Fig. 2 can either be a real test vehicle or modeled in the simulation. It comprises of the real or modeled world including streets and objects such as other road users or pedestrians and the ego vehicle that interacts with the environment.

In the left and middle part of Fig. 2, the components involved in the predictive planning approach are depicted. On the top level of the planning process, the mission control determines an optimal route to the desired destination. Therefore the mission control uses offline maps. These offline maps are also taken into account, when building the environment model. This model includes information about all objects, either tracked or detected by the perception module or contained in the maps, and the road network topology. The environment model can also be extended by further information like crosswalks, pedestrian crossings or driveways.

The previously determined route sets the boundary conditions for the following behavioral planning step. The behavior planning proposes how the vehicle should act to reach the target position through high level behaviors like lane changes, overtaking or following the vehicle in front. To execute the behavior, a valid trajectory has to be determined in the underlaying motion planning unit. The behavior addressed here is to follow the current lane and at the same time be aware of potential dangerous situations caused through hidden traffic participants.

The proposed motion planning process is separated into two parts, a path planning step and a longitudinal planning step. First, a valid path is planned for the ego vehicle. The path meets requirements for collision avoidance with static obstacles, lane markings and meets kinematic constraints. The path planner is designed to keep to the center of the current lane of the ego vehicle if possible. By separating the motion planning, the decision making problem degenerates into a one-dimensional problem. In literature, this procedure is known as “path-velocity decomposition” [14].

The longitudinal planning is done in a POMDP. Thereby, the longitudinal planning and the prediction unit are strongly interdependent as future developments are directly accounted for in the planning process. This way also uncertainties about these future developments are regarded. In this work, uncertainties in the form of the existence of hidden traffic participants are addressed. The new planning concept considers not only the current field of view of the ego vehicle, but also the field of view in future steps. This is achieved by a generic sensor setup that enables the agent to obtain observations in dependence of actions taken previously and the development of the environment. The solution of the POMDP provides an optimal action for the ego vehicle in dependence of the current state of the environment. Here, actions are described by set of longitudinal acceleration and deceleration values.

The POMDP model including necessary space and model definitions is explained in detail in the next section.

IV. POMDP Model for Longitudinal Planning

In the following the general concept of POMDPs is shortly addressed, followed by the definitions of the used spaces, models and reward function.

A. Partially Observable Markov Decision Process

A Partially Observable Markov Decision Process is defined by the tuple $(\mathbb{S}, \mathbb{A}, T, \mathbb{O}, Z, R, b_0, \gamma)$ comprising of the set of all possible states $s \in \mathbb{S}$, the set of possible actions $a \in \mathbb{A}$ and the set of possible observations $o \in \mathbb{O}$. The transition probability $T(s', s, a) = P(s'|s, a)$ describes the probability of ending in state s' when executing action a in the current state s. Hereby, the Markov assumption ensures, that the future state s' solely depends on the current state s and action a. Conversely, this means that all necessary information must be contained in the state s. When choosing action a in state s the agent receives the reward $R(s, a)$. These rewards are discounted using the discount factor $\gamma \in [0, 1)$ to favor early decisions by giving them greater weights. At an infinite horizon the discount factor is also necessary for a solution to be found at all. In contrast to a Markov Decision Process (MDP) the state of the environment is not perfectly known. That is because not every state is directly observable. For that reason the true state is estimated by a belief $b \in B$. To update the current belief b the agent receives an observation o in dependence of the action taken previously. The probability of making observation o in the new state s' after taking action a is described by $Z(o, s', a) = P(o|s', a)$. The goal of solving a POMDP is to find an optimal policy π that maximizes the expected sum of rewards for the initial belief b_0

$$V_\pi(b_0) = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(b_t))\right]. \tag{1}$$

B. State Space

A state $s \in \mathbb{S}$ needs to contain all information to predict future states to keep to the Markov property. Information that never changes during the planning process, can be seen as static background knowledge [4] and must therefore not be part of the state space as it might be accessed at any time. Static background knowledge thus contains information about the road network topology and its geometry and static objects like buildings or parking vehicles.

Hence, a state $s \in \mathbb{S}$ comprises of the combined state vectors of the n traffic participants involved and the ego vehicle

$$s = [s_0, s_1, ..., s_n]^\top, \tag{2}$$

where

- s_0 is the state of the ego vehicle and $s_i,\ i \in \{1, ..., n\}$ represents the state of one of n additional road users.
- n is assumed to be sufficiently large to account for an arbitrary number of possibly appearing traffic participants.
- $s_i = [x_i, y_i, v_i, r_i]^\top,\ i \in \{0, ..., n\}$ is the state of vehicle i. The position of the vehicle is given by the cartesian coordinates (x_i, y_i). v_i represents the absolute

velocity along the vehicle's route r_i. A route consists of a sequence of *lanelets* [15]. *Lanelets* are based on the principal, that roads can be split into single lanes, which are either oncoming lanes or point in the same direction. Lanes are segmented in connected sections called *lanelets*. Hence, a route is built from a sequence of lane segments. For further details on *lanelets*, the reader is referred to [15].

The state space S is continuous, because the positions and velocities of all traffic participants and of the ego vehicle are continuous as well. To account for uncertain measurements of visible other traffic participants in the initial belief b_0, additive noise could be added to their position or velocity.

C. Observation Space

The observations space $\mathbb{O}$ is modeled almost identical to the state space S. As well as a state s, an observation $o \in \mathbb{O}$ comprises of the individual observations o_i of each vehicle so that

$$o = [o_0, o_1, ..., o_n]^\top, \text{ with} \tag{3}$$

$$o_i = [x_i, y_i, v_i, r_i]^\top, \ i \in \{0, ..., n\}. \tag{4}$$

For the special case, that traffic participant i is assumed to be occluded, an observation $o_i = o_{occluded}$ is added. If a potential traffic participant is neither directly visible nor assumed to be in an occluded region, it is considered not to be a part of the current scene. That road user is observed with the observation $o_{invisible}$.

In total, the set of possible observations results to

$$o_i \in \mathbb{S} \cup \{o_{occluded}, o_{invisible}\}. \tag{5}$$

The process of making an observation is explained in detail in the observation model IV-F.

D. Action Space

In contrast to the state and observation spaces, the action space A is discrete. A discrete set of finite actions is sufficient to represent all desired behaviors like stopping in front of an intersection, following a vehicle in front or accelerating to a desired velocity. Thereby, only the action of the ego vehicle can be determined while solving the planning problem. Actions of other road users need to be inferred through observations. Because the lateral behavior for the ego vehicle is already determined in the route and path planning steps, the set of actions solely consists of a number of acceleration and deceleration values. The set has to contain at least one action to represent acceleration and another one to represent deceleration. In addition, a third one is required to maintain the current velocity. The upper size of the set of actions is not limited, but it should be noted that a larger size leads to a significant increase in complexity and computing time.

E. Reward Function

The reward function is used to describe the agent's desired behavior. As mentioned above, the agent receives the reward $R(s, a)$, when it executes action a in state s. The result of the planning process has to satisfy safety criteria as well as comfort or economical criteria. Thus, the reward function is split into different components

$$R(s, a) = R_{goal}(s) + R_{col}(s) + R_v(s) + R_{action}(a). \tag{6}$$

The agent receives the reward R_{goal}, when reaching the goal. Goals are often described semantically, for example to cross the intersection safely. Furthermore, the main objective of an autonomous vehicle is to minimize the risk of collisions, while keeping to the traffic rules. Because of that, the agent receives a high negative reward R_{col} for collisions. R_{col} can also be used for violations of traffic rules or when leaving the road or lane. But in this work, the agent always keeps to precalculated path, so the vehicle always stays in the desired lane. Comfort and efficiency aspects are modeled using R_{action} and R_v to penalize high acceleration or deceleration with high costs. Additionally, R_v also leads the ego vehicle to keep to a desired velocity and might be used to have the agent decrease the velocity in curves to reduce lateral accelerations. In order to weight speed oversteppings more strongly than if the speed is below the reference velocity v_{ref} the following cost term is used

$$R_v(s) = \begin{cases} -k_1 \cdot (v_{ref} - v_0), & \text{if } v_0 \leq v_{ref} \\ -k_2 \cdot (v_0 - v_{ref}), & \text{else }, \end{cases} \tag{7}$$

where v_0 is the velocity of the ego vehicle and $k_1 < k_2$.

F. Observation model

Making an observation when dealing with concealed areas strongly depends on the vehicle's field of view. Therefore we are going to explain the generation of the field of view in detail in the next section. Afterwards the observation model itself is explained.

1) Field of View: In autonomous driving, different kind of sensors are used to perceive the environment. For example lidar sensors, radar sensors or cameras. In order to keep the approach independent of the used sensor concept, a generic model of a sensor setup is used to determine the field of view.

Therefore each sensor is described by its position and orientation in regard of the vehicles reference point and by its opening angle and maximum range. In addition, the world is assumed to be two-dimensional and so are the sensor models. That is because the motion of all participants is two-dimensional. Obstacles, that are above or below the assumed plane, can be projected into the plane to be accounted for in the process. The number of obstacles, that are regarded when the field of view is determined, is limited to the number of objects that the ego vehicle might collide with or that block the field of view of one of the sensors. The generic model of the sensor setup could also be used to represent sensors under poor conditions, such as cameras at night where only the area illuminated by the headlights is visible.

The vehicle used in this work is equipped with a total of five lidar sensors as depicted in Fig. 3. The sensors are chosen to be of the same kind. The sensor setup is based on a reduced configuration of our test vehicle.

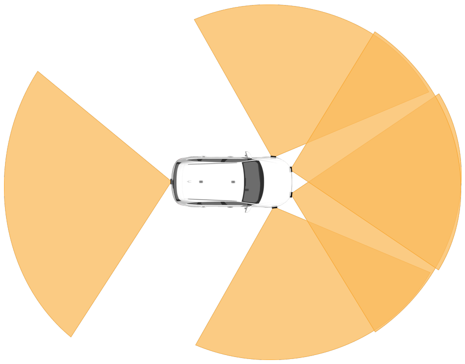


Fig. 3: Modeled sensor setup of the vehicle. The vehicle is equipped with five lidar sensors. A single sensor at the rear, two at the front and one left and one right each.

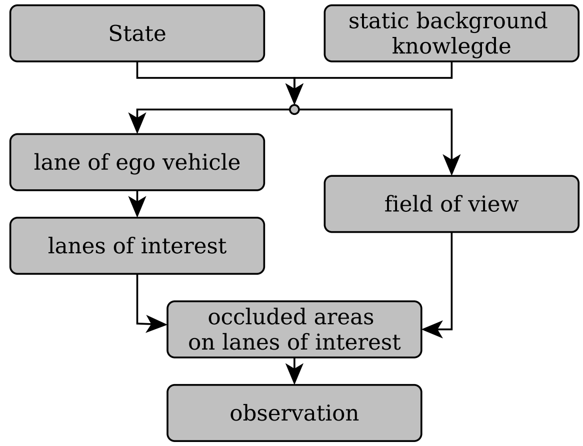


Fig. 4: Sequence of the observation model. In dependence of the state of the environment and the static background knowledge containing maps and static objects, the field of view and occluded areas on lanes of interest are determined in order to receive a observation.

The vehicle's field of view is created as the union of the single sensors field of view. The union hereby does not have to be a single area. It might also be represented by a set of areas like it is shown in Fig. 3. In order to calculate a sensor's field of view, an algorithm based on ray casting is used [16]. First, rays are sent out repeatedly in discretized steps for the whole opening angle. The starting point and the direction of the rays are determined by the mounting position and orientation of the sensor. The endpoint of a ray is either determined by the specified maximum sensor range or if the ray hits an obstacle beforehand. The resulting polygon of the field of view is created by combining all end points and the start point in an ordered way.

The resulting representation of the environment is a two-dimensional world, where obstacles are represented as polygons, visible areas are those areas that build the field of view and the rest is considered to be occluded.

2) Making an observation: The process of making an observation is shown in Fig. 4. Whereas the state of the ego vehicle is assumed to be perfectly observable, the current field of view needs to be taken into account in order to observe the states of the other traffic participants. So, the current field of view is calculated first as described earlier using the information about the current states of all known vehicles and adding static obstacles from the static background knowledge, that are not included in the state. The dimensions of other vehicles are assumed to be equal to the ego vehicle's dimensions. It is to be mentioned that the assumed vehicles themselves can also cause occlusions.

Afterwards, the state of the ego vehicle is used to determine the current ego lane. Then, all lanes of interest are determined using knowledge about the road network topology. Lanes of interest can be manifold. In general they include lanes, that are prioritized over the lane of the ego vehicle or, when regarding non-compliant behavior of other traffic participants, all oncoming, merging or crossing lanes. When regarding not only intersection scenarios but dangerous situations in general, also not visible courtyard exits or pedestrian crossings along the ego vehicle's path are of interest. In our context the lanes of interest are limited to lanes that the ego vehicle must yield to in order to stick to the traffic rules. As mentioned above, we represent lanes based on the concept of *lanelets*. In order to yield to a road user on a prioritized lane, only the *lanelets* before and in the intersection need to be considered.

In the next step, concealed areas on all lanes of interest are calculated using the set of determined lanes and the current field of view. There are three cases that need to be distinguished:

1) When a road user is detected in the field of view, its position and velocity is measured with small additive Gaussian distributed noise to account for sensor inaccuracies. A traffic participant is considered to be visible, if an arbitrary piece of it is located in the field of view. The route of other road users can be observed, because it is assumed that vehicles will follow the *lanelet* with the closest distance to the corresponding center line. Measurements of different vehicles are modeled to be independent.
2) If there is an occluded area with a certain minimum size on a lane of interest, a potentially hidden vehicle can be observed with the observation $o_{occluded}$. Nevertheless, there is the chance that no vehicle is located in the occluded area. Therefore the observation $o_{occluded}$ is made with a probability $P(o_{occluded}|s', a) \leq 1$. $P(o_{occluded}|s', a)$ depends on various aspects like the traffic density or the distance to the vehicle at front. The traffic density in itself is dependent on the type of road, area and time of day. A value of $P(o_{occluded}|s', a) = 1$ yields a worst case assumption. Here, we solely consider values of $P(o_{occluded}|s', a) <$ 1. The velocity of a hidden vehicle can not be measured and it is therefore assumed to arrive at the intersection at the same time as the ego vehicle, as long as the vehicle's velocity still is plausible. More precisely, the velocity must be in a certain range. For example, it is not assumed for a road user to appear at a significantly

excessive speed.

3) All remaining road users are given the observation $o_{invisible}$.

The concept can be extended to account for pedestrians e.g. by using maps containing sidewalks. Areas of interest are then determined as areas where pedestrians are expected to cross or walk on the road.

G. Transition model

The transition model describes the dynamics of the system and the effect of the chosen actions. The state at time step $t+1$ of the ego vehicle is predicted based on the chosen action a and its current state at time step t with the step size T. As all vehicles are predicted along their current route, the prediction can be executed in one dimension by predicting the current progress d of vehicle i along its route r_i

$$\begin{bmatrix} d \\ v \end{bmatrix}_{t+1} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} d \\ v \end{bmatrix}_{t} + \begin{bmatrix} \frac{1}{2}T^2 \\ T \end{bmatrix} a \; . \tag{8}$$

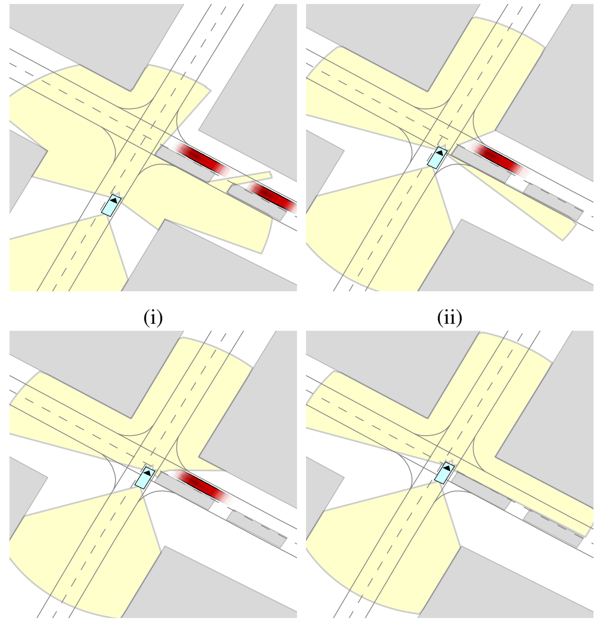
For other road users than the ego vehicle, a constant velocity prediction with additive noise on both the position and the velocity is applied instead of applying an action term, because their actions can not be determined in the planning process. A state $s_i \in \mathbb{S}$ can be obtained by reconverting the position d along the corresponding route r_i with the geometry of the route back to a cartesian position. The absolute velocity is independent of the frame.

To achieve a larger planning horizon or to reduce the number of planning steps for a given planning horizon, the step size T can be varied. As described in [4], a time step of at least $0.2\ s$ is necessary to achieve good simulation results. To avoid the tunneling effect, where two road users pass each other in between one time step, we also apply intermediate collision checking steps.

V. Evaluation

The presented approach was evaluated in multiple scenarios at an intersection with different initial conditions and types of occlusion of which two are presented here. Thereby, the self-driving ego vehicle is approaching unsignalized intersections. For the evaluation, a simulation framework for traffic scenarios is used, which was developed at our institute [17]. The scenarios are built from real scenes, where hidden vehicles are expected. The simulation also allows to vary the ratio of simulation time to actual elapsed time to evaluate the setup in a closed loop without delays due to the demanding calculation of the solution of the POMDP.

The sight of the road coming from the right is limited through occlusions by the surrounding buildings or static obstacle. The agent has to yield to vehicles coming from the right, but has the right of way over vehicles coming from the left. Therefore the ego vehicle needs to take into account, that there might be a vehicle on the prioritized lane, that it has to yield to, even if it does not see the other vehicle during the approach. Since the goal of the ego vehicle is to traverse the intersection safely, the agent receives a high reward when it has accomplished to reach the target position behind the intersection. The current action for the agent is calculated online and executed afterwards.



(i) (ii) (iii) (iv)

Fig. 5: The temporal development of a scenario with heavy occlusion through two parking vehicles. The ego vehicle is shown in blue, other road users in red, static obstacles in grey and the field of view in yellow. These colors are also used in Fig. 8. (i) $t = 14\ s$: The ego vehicle approaches the intersection and assumes vehicles in the occluded areas. (ii) $t = 17.5\ s$: The ego vehicle decelerates and enters the intersection. (iii) $t = 20\ s$: Slowly feeling its way into the intersection, aware of potential approaching vehicles. (iv) $t = 21.5\ s$: Reaches critical point where it either has to make a full stop or to accelerate. As the sight is clear, the ego vehicle crosses the intersection.

The behavior of other traffic participants is modeled by the intelligent driver model [18] and they do not act cooperatively or assume incompliant behavior of other road users, especially the ego vehicle. At intersections, the other road users randomly turn or follow straight. Because road users from the right are on a prioritized lane, the ego vehicle has to yield either way.

In the first scenario, shown in Fig. 5, the agent approaches a road with two parked vehicles on the right lane of the prioritized road, blocking the view on the incoming lane. The goal for the ego vehicle is, as mentioned above, to cross the intersection safely. The agent can choose from three actions only ($a \in \mathbb{A} = \{D = -2.0\ \frac{m}{s^2}, M = 0.0\ \frac{m}{s^2}, A = 1.0\ \frac{m}{s^2}\}$). The velocity profile and the actions taken by the agent are depicted in Fig. 6. While approaching the intersection, the agent keeps to a reference velocity of 6 $\frac{m}{s}$. As the ego vehicle has to assume that there are other road users in the concealed areas, the agent decelerates. When it arrives at the intersection, it slowly moves forward, knowing that it is able to peek into the prioritized lane at a certain point. The ego vehicle thereby keeps a velocity allowing it to come to a halt at any time. Assuming a worst case scenario, the agent would be stuck behind the parking car, blocking not only vehicles behind it but also vehicles coming from the left side. When

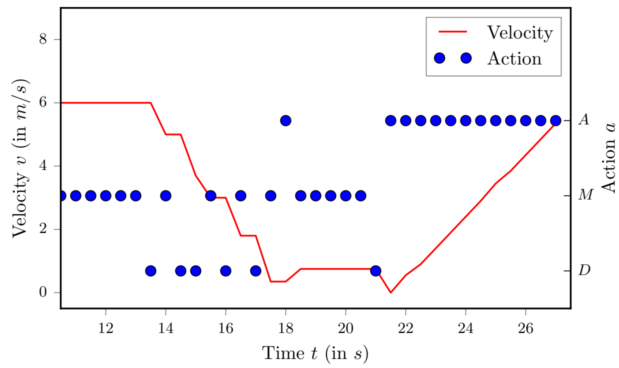


Fig. 6: Velocity and action profile for a scenario with heavy occlusions due to two parked vehicles. The agent can choose between three different actions shown in blue ($D = -2.0\ \frac{m}{s^2}, M = 0.0\ \frac{m}{s^2}, A = 1.0\ \frac{m}{s^2}$). He decelerates first, then moves slowly into the intersection and accelerates as it registers that the intersection is clear.

finally arriving at the critical point, the agent receives the observation, that there is no vehicle coming from the right and the agent accelerates to traverse the intersection.

The second scenario is a common scenario for urban traffic, especially in residential areas with a lot of parked vehicles and no traffic lights. The ego vehicle again approaches an intersection. It is able to observe the intersection at a certain distance before the entry as can be seen in Fig. 8. This time, the agent is able to choose from four actions comprising a strong and a slight deceleration with $a \in \mathbb{A} = \{SD = -3.0\ \frac{m}{s^2}, D = -1.0\ \frac{m}{s^2}, M = 0.0\ \frac{m}{s^2}, A = 1.0\ \frac{m}{s^2}\}$. The corresponding profiles of the current velocity and the actions taken over time are shown in Fig. 7.

In the beginning, the ego vehicle approaches the intersection with the desired velocity of 8 $\frac{m}{s}$. No other vehicles are visible in the intersection yet, but the ego vehicle is still away far enough. When approaching the intersection, it assumes

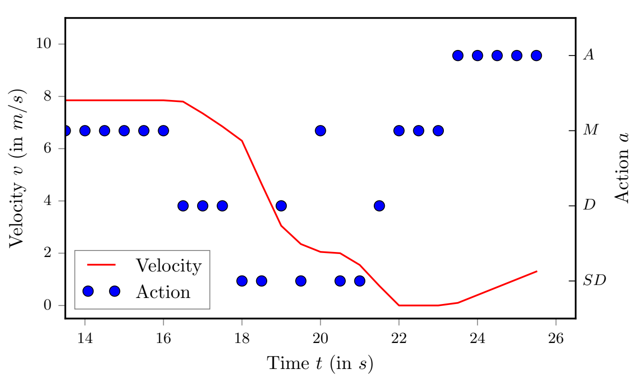
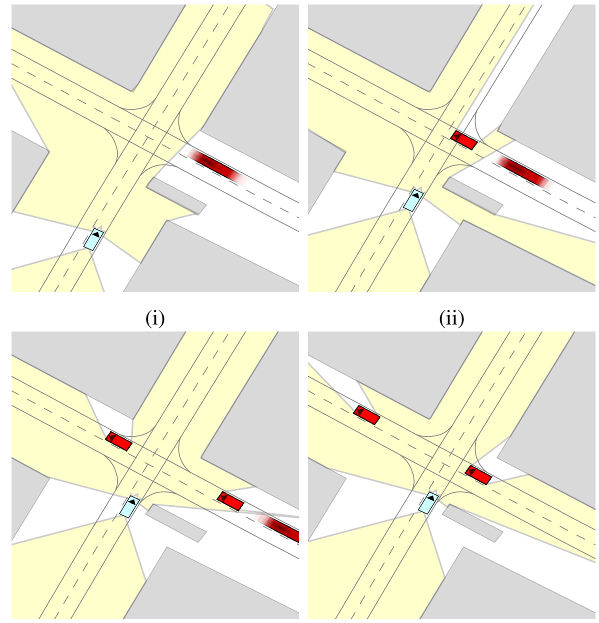


Fig. 7: Velocity and action profile for scenario with two hidden vehicles. Actions are shown with blue dots. Hereby, A is accelerating with 1.0 $\frac{m}{s^2}$, SD strong deceleration with $-3.0\ \frac{m}{s^2}$, D deceleration with $-1.0\ \frac{m}{s^2}$ and M to maintain the current velocity. The velocity of the ego vehicle is shown in a red line. The ego vehicle solely decelerates as much as required to be able to yield an appearing vehicle at every time and decelerates strongly, when it perceives another vehicle.



(i) (ii) (iii) (iv)

Fig. 8: The temporal development of a scenario with two hidden vehicles coming from the right. The sight is blocked by a parked vehicle. (i) $t = 17\ s$: The ego vehicle approaches the intersection and assumes a vehicle in the concealed area. (ii) $t = 18.5\ s$: The beforehand invisible road user enters the intersection. Another vehicle is assumed behind it. (iii) $t = 20\ s$: The second vehicle is detected by the ego vehicle and the ego vehicle comes to a halt. (iv) $t = 21.5\ s$: The ego vehicle waits for all road users to pass and has full sight of the intersection to cross it safely.

an other vehicle coming from the right. Since the agent knows, that there is the chance to accelerate immediately after he made the observation that the intersection is clear when passing the parked vehicle, he only decelerates slightly. Because he is aware that he can still come to a halt on time, when he decelerates strongly after observing an incoming vehicle, the agent does not decelerate strongly right away to avoid a high negative reward for decelerating to strong for nothing. Unfortunately a vehicle is appearing from the right and the agent has to decelerate strongly, hoping to be able to pass right behind the vehicle. Therefore it does not come to a halt and decelerates only as much as required. When it detects the second vehicle approaching, the ego vehicle stops at the intersection and waits for the other road users to pass before crossing the intersection safely.

The evaluation shows that the proposed concept is able to cope with severe occlusions with a minimum number of actions without ending in a deadlock situation. The second scenario shows that the concept leads to a foresighted behavior at the intersection. The behavior resembles human behavior when approaching intersections with limited sight.

VI. Conclusions and Future Work

In this paper we presented a novel POMDP model for predictive trajectory planning suitable to safely manage situations with occlusions. The novel approach allows the consideration of an arbitrary number of visible and not visible traffic participants. A generic sensor setup is used to calculate the field of view in dependence of the current state of the environment to generate new observations. The evaluation showed that the vehicle is able to deal with heavy occlusions, where current metrics or planner based on worst case assumptions would cause a stand still. In a second scenario it was demonstrated that an increase in the size of the action set leads to more foresighted behavior. The direction for further evaluations is indicated. In both scenarios, the vehicle successfully manages to cross the intersection safely.

In the future, we plan to incorporate further information about the probability of the existence of other traffic participants. Context information can be used to infer the existence of other road users as well as context related traffic densities. In addition, the runtime performance is going to be optimized in order to apply it on our real test vehicle. Therefore especially the generation of the field of view needs to be more efficient since it requires the majority of the calculation time. In addition, the evaluation on a real test vehicle requires a suitable environment to track both, the ego vehicle and hidden vehicles. Such an infrastructure is provided in the Test Area Autonomous Driving Baden-Württemberg [19] and we aim to evaluate the system there. When changing the angle of view, not only the ego vehicle has difficulty seeing others, but also vice versa. So, the approach can easily be extended to also consider not compliant road users and road users that are not able to spot the ego vehicle on time.

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