

Safe but not Overcautious Motion Planning under Occlusions and Limited Sensor Range

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Abstract—For a successful introduction of fully automated vehicles, they must behave both provably safe but also convenient, i.e. comfortable and not overcautious. Given the limited sensing capabilities, especially in urban scenarios where buildings and parking vehicles impose occlusions, this is a challenging task. While recent approaches gave first ideas for boundary conditions of safe behavior, an approach for convenient motion planning that fulfills these constraints is still an open issue. Therefore, we utilize and enhance safety approaches for occlusion handling in order to facilitate comfortable and safe motion planning. We consider worst case assumptions, arising from potential objects at critical sensing field edges, along with their probability. With this information, we can ensure to not act overcautiously while still moving provably safe. The potential of our approach is shown in a modified CommonROAD scenario.

Index Terms—Automated vehicles, occlusions, field of view, provable safety, motion planning, behavior generation.

I. INTRODUCTION

Automated driving is gaining more and more attention in the public, as automated vehicles slowly start populating the roads. The combination of adaptive cruise control and lane keeping assist already gives a first impression on how fully automated vehicles take over control. In the currently available automation level, however, the driver must continuously monitor the system due to safety reasons.

One key issue that is not yet solved is the limited sensor range due to the measurement principle, adverse environmental conditions, or occlusions. The current field of view has to be taken into account for safety reasons, but also to ensure comfort, avoiding unexpected and harsh reactions. Some parts of the sensing horizon can be neglected due to physical reasons, such as parts behind a guard rail. Other parts can be neglected as they are implicitly considered in the motion planner: In many approaches, new obstacles are treated by frequent replanning. Assuming absence of wrong-way drivers, being able to stop within the sensing horizon can already ensure safety.

For the comfort consideration, it is particularly interesting to look at the probability of objects being at the edge of the field of view. In this work, we are proposing an approach for reacting convenient, i.e. safe and comfortable but not overcautious, to occlusions. The approach is based on our

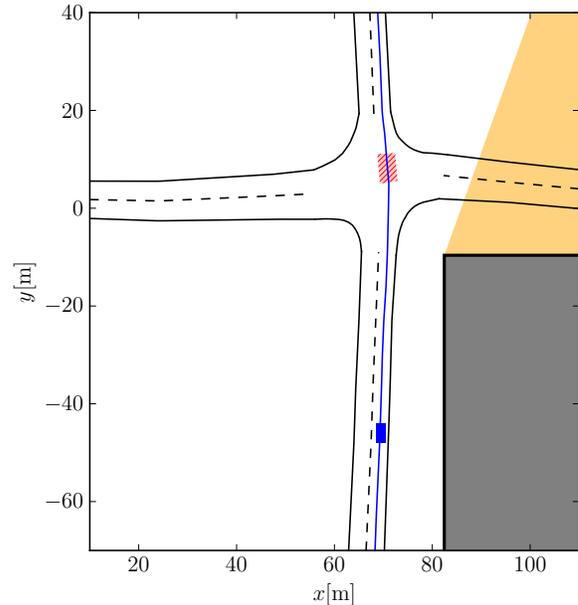


Fig. 1: A modified *CommonROAD* [1] scenario with severe occlusions due to a building (grey). The orange area is obscured for the sensors of the automated vehicle driving along its desired path (blue). However, there is a conflict zone (red) due to intersecting paths with vehicles coming from the occluded area. Using this information is essential for safe and comfortable motion planning.

recent work [2], where we presented a probabilistic cooperative planning framework considering possible violations of the model compliance as well as intention uncertainties.

The main contributions are

- 1) a method to analyze the safety of a given trajectory with respect to occlusions,
- 2) a method to estimate the risk and severity of a potential emergency braking due to an object behind an occlusion and
- 3) a probabilistic framework to determine convenient behavior in presence of occlusions.

The basic idea of the framework is that a safe emergency maneuver must be possible to avoid potential collisions with any object that could be hidden by the occlusion. Yet, uncomfortable emergency maneuvers are acceptable if the probability is sufficiently low. Thus, wrong probability estimates only affect comfort, not safety.

The remainder of this paper is structured as follows: In the next section, we shortly review the related work. In Section III, we start with preliminary considerations, before

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presenting our new approach in Section IV. In Section V, we evaluate the approach in a modified *CommonROAD* [1] scenario. Finally, we conclude our work in Section VI.

II. RELATED WORK

While the goal of this paper is to provide a comfortable and comprehensible motion plan that is still provably safe, previous work mainly focused on comfort while minimizing some risk measure, as Orzechowski et al. [3] point out in detail. Recently, Bouton et al. [4] also presented an approach treating occlusions in a POMDP. While the approach is promising regarding the computational feasibility of occlusion treatment with POMDPs, it does not guarantee or focus on safety. Tas et al. [5], on the other hand, focused on safety but not on comfort.

Bouraine et al. [6] give a so-called *passive safety guarantee*, meaning that if a collision occurs, the robot is at rest. While this might work for unstructured environments, it is insufficient for structured environments like road traffic, where certain traffic participants have the right of way over others. Rather, guaranteeing to yield the right of way is an essential component of road traffic safety. Therefore, we adopt the notion of *blame* from Shalev-Shwartz et al. [7], meaning that self-driving cars will never *cause* an accident. This notion is also followed by the reachable set approach of Althoff et al. [8], which Orzechowski et al. [3] recently expanded by occlusion consideration.

III. PRELIMINARY CONSIDERATIONS

The key issue when facing occlusions and limited sensor range is that within the occluded area, there might be static and/or dynamic objects that have to be considered for motion planning.

A. Integration into probabilistic planning

As motivated in our previous work [2], potential uncertainties from perception and prediction are crucial to the motion planning problem. In order to be able to cooperate with other traffic participants, some estimate of their intention, for example whether they want to turn right or go straight at an intersection, is necessary. In order to get this estimate, we need to have measurements for this object beforehand. Wherever our sensing is limited, e.g. due to occlusions, we must consider hypothetical objects within those areas. Thus, dealing with this incomplete information is the first step in motion planning, before any object intention consideration and possible cooperative motion planning.

B. Focus on junctions

While a potential cooperation with a hypothetical object contains too large uncertainties for a meaningful result, cases with less uncertainty are more meaningful: Specifically interesting are those sensing edges that hide potential objects that have priority over us, such that we would have to yield, as cooperation is rare in these cases and can be neglected. The most obvious case is an object in our lane, where we have to avoid a rear-end collision, also with limited sensing

range, for example due to dense fog. Another common case is a junction, where objects on some lanes have the right of way over others.

In structured environments, traffic can be separated into lanes and we can identify overlapping parts with the lanes of others as potential collision zones or conflict zones, as explained in-depth in our previous work [9]. In cases, where we have to give way to potentially occurring traffic participants from occluded areas, safety can be ensured by two conditions:

- C1 We can ensure to come to a safe state before a conflict zone.
- C2 We can ensure to legitimately pass the conflict zone, i.e. come to a safe state after the conflict zone without risking a collision inside.

The union of those conditions must be a hard constraint to every safe planner. The overall reaction time from the appearance of an object to the actual response of the actuators must of course be incorporated in the constraints. They can be reformulated to *As long as we cannot ensure a safe trajectory through a conflict zone, we have to ensure the reachability of a safe state before it.*¹

Traveling at the edge of these conditions, however, condition C1 means that we react to occlusions late and with maximum deceleration (a) until condition C2 is fulfilled, or even worse, (b) until we come to a full stop, if an object appears and condition C2 remains unfulfilled. Thus, traveling at the edge of these conditions leads to unpleasant motion plans. In order to plan convenient trajectories in the presence of occlusions and limited sensor range, we apply the key idea of our recent work [2]: We look at possible reactions to potentially occurring objects along with their probability.

C. Prerequisites

As input to our motion planning module, we need information about lanes, conflict zones, the traffic rules as well as static obstacles that cause occlusions, such as buildings. All this information can be derived from a *lanelet2*-map [10]. Then of course, we must be localized inside the map, and we need critical sensing edges and the predicted occupancy that arise from those [3]. This input is supposed to be *probably approximately correct* [11], in order to guarantee a reasonable level of safety, as Shalev-Shwartz et al. motivate [7]. Further, we need information about the traffic density of those lanes, that cause the predicted occupancy, in order to decide how likely it is that condition C2 remains unfulfilled as we actually detect objects at the critical sensing edges.

IV. APPROACH

As motivated in our previous work [2], motion planning algorithms should distinguish between safety, which has to be proven, and comfort, where uncomfortable motion is sometimes okay, if it prevents permanent overcautious

¹The special case of carefully advancing into conflict zones is neglected for now.

behavior. This also facilitates methods for the comfort planner, that do not give guarantees regarding feasibility and/or convergence speed, such as sampling.

As stated previously, we explicitly consider occlusions and limited sensor range: When planning our future motion, we look at where and when we could sense previously occluded objects, and how we would have to react, along with the probability of those hypothetical cases. We assume that we do not influence the occurrence probability or the behavior of objects in the relevant occluded areas, as they have priority over us. Still, theoretically, we would have to consider the probability of all possible trajectories of others at any time along with the probability of their occurrence. The expected cost would then be computed as

$$G_{\text{occl}}(\mathbf{x}_{\text{ego}}) = \sum_{\mathbf{x}_{\text{other}}} p(\mathbf{x}_{\text{other}})G(\mathbf{x}_{\text{ego,react}}) \quad (1)$$

for every set of trajectories of possibly occluded objects $\mathbf{x}_{\text{other}}$ along with their probability $p(\mathbf{x}_{\text{other}})$ (including $\mathbf{x}_{\text{other}} = \{\}$) and the respective reaction of the ego vehicle $\mathbf{x}_{\text{ego,react}}$.

A. Simplified reaction model

Since neither the data collection nor the cost computation is feasible for this general case, we further simplify our consideration. In most parts of the road network, traffic can be separated into lanes. At junctions, overlapping lanes can be identified as conflict zones. Thus, the path for following a particular route in the road network is rather predefined, which motivates the use of path-velocity decomposition, as introduced by Kant and Zucker [12]. Therefore, our scope of action lies in determining a velocity profile along the path. In the following, we denote the path with s , the velocity with v and the longitudinal acceleration along the path with a .

a) Safe state before the conflict zone (C1): Determining safe states in road traffic is a separate research topic, which is further discussed by Shalev-Shwartz et al. [7]. In the remainder of this paper, we consider stopping in a lane as safe, as long as we are outside of any junction, which we think is reasonable for urban areas. With this, we can identify the last possible safe stop in front of conflict zones. Knowing this position, we can infer a maximum feasible velocity, for which we are still able to reach the safe state in front of the conflict zone. Let this last safe position be in a distance of $d_{\text{safe}} \geq 0$ from the conflict zone. Further, let s_{ego} be the position along the path with respect to the conflict zone, as in Fig. 2. For positions $s_{\text{ego}} \leq -d_{\text{safe}}$, the double integrator equations

$$\begin{aligned} s_{\text{brake}} &= v_{\text{max, safe}} \cdot (t_{\text{r}} + t_{\text{brake}}) + \frac{1}{2}a_{\text{brake}}t_{\text{brake}}^2 \\ &\stackrel{!}{=} |s_{\text{ego}}| - d_{\text{safe}} \end{aligned}$$

and

$$v_{\text{brake}} = v_{\text{max, safe}} + a_{\text{brake}}t_{\text{brake}} \stackrel{!}{=} 0$$

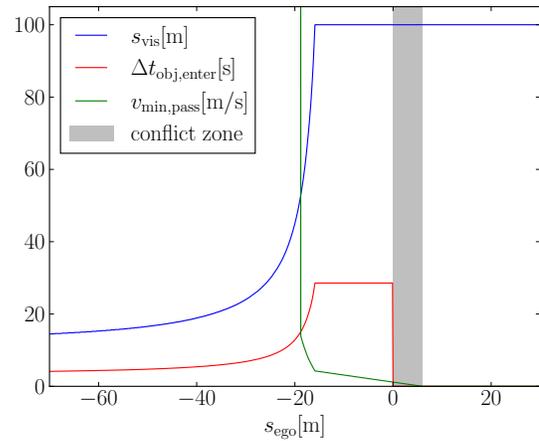


Fig. 2: Exemplary visualization of the velocity that ensures safe passing before a potentially occurring object for the scenario of Fig. 1, assuming $\text{TZC}_{\text{min}} = 2\text{s}$.

yield

$$v_{\text{max, safe}}(s_{\text{ego}}) = a_{\text{brake}}t_{\text{r}} + \sqrt{(a_{\text{brake}}t_{\text{r}})^2 - 2a_{\text{brake}} \cdot (|s_{\text{ego}}| - d_{\text{safe}})}$$

with the reaction time t_{r} and the maximum brake deceleration a_{brake} .

b) Safely passing the conflict zone (C2): On the other hand, as stated in the previous section, as soon as we can ensure to legitimately pass the conflict zone, the trajectory is safe w.r.t. the conflict zone, such that we do no longer react to potentially occurring objects regarding this conflict zone. For this case, we can again compute the velocity profile $v_{\text{min, pass}}(s_{\text{ego}})$, above which a reaction has probability zero, assuming that occurring objects drive with a maximum velocity v_{max} , and that we did not violate their right of way if the time of zone clearance, i.e. the time between we leave and they enter, is larger than TZC_{min} . The relevant variable here is the earliest possible entrance time of a hypothetical object $\Delta t_{\text{obj, enter}}$. This variable can be retrieved from the set based prediction as in Orzechowski et al. [3], however, the maximum processing time from occurrence to the detection of potential objects, the so-called perception delay $t_{\text{perc_delay}}$, must be taken into consideration. With the length of the conflict zone along our path $s_{\text{ego, cz}}$, the minimal velocity to pass is

$$v_{\text{min, pass}}(s_{\text{ego}}) = \frac{s_{\text{ego}} + s_{\text{ego, cz}}}{\Delta t_{\text{obj, enter}} - t_{\text{perc_delay}} - \text{TZC}_{\text{min}}} \quad (2)$$

It is visualized in Fig. 2.

Note, that if slower vehicles are detected, which block the full lane, this $v_{\text{min, pass}}(s_{\text{ego}})$ can even be reduced. This rare case, however, is not further considered in the remainder of this work.

c) Irrelevant objects: Still, given a certain velocity of an object appearing at the sensing edge, we would not react if being sufficiently far from the conflict zone. Rather, with limited sensing along a prioritized lane, it is likely that a

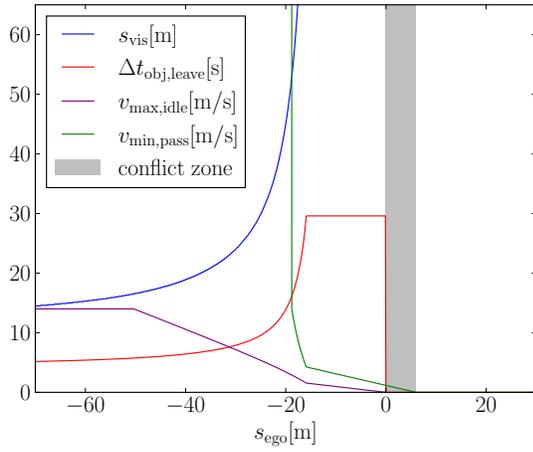


Fig. 3: Exemplary visualization of the velocity below which we would not react to an occurring object for the scenario of Fig. 1, assuming the object drives at least $v_{\min} = 0.9v_{\text{speedlimit}}$.

sensed object will already have left the conflict zone far before we arrive, unless we are fairly close to the conflict zone. Thus, just sensing an object does not necessarily mean that our current planned trajectory is affected at all. For the scenario from Fig. 1, the velocity profile $v_{\max,\text{idle}}(s_{\text{ego}})$ under which an occurring object does not affect the planned trajectory² is visualized in Fig. 3, assuming that occurring objects drive with a minimum velocity $v_{\text{obj},\text{min}}$ with respect to the lane coordinates. The time after which a hypothetical object will have left the conflict zone is $\Delta t_{\text{obj},\text{leave}}(s_{\text{ego}}) = \frac{s_{\text{vis}}(s_{\text{ego}}) + s_{\text{obj},\text{cz}} + l_{\text{max,obj}}}{v_{\text{obj},\text{min}}}$, with our visibility along the objects' lane up to the beginning of the conflict zone s_{vis} , the length of the conflict zone $s_{\text{obj},\text{cz}}$ and the maximum object length $l_{\text{max,obj}}$. The maximum speed up to which we would enter the conflict zone comfortably after the hypothetical object is $v_{\max,\text{idle}}(s_{\text{ego}}) = \frac{s_{\text{ego}}}{\Delta t_{\text{obj},\text{leave}}(s_{\text{ego}}) + \text{TZC}}$ with the desired time of zone clearance TZC .

d) *Single reaction:* With these considerations, we can eliminate particular trajectories for others from equation (1), and reduce it to a single reaction consideration

$$G_{\text{occl}}(\mathbf{x}_{\text{ego}}) = (1 - p(\text{react}))G(\mathbf{x}_{\text{ego}}) + p(\text{react})G_{\text{react}}(\mathbf{x}_{\text{ego}}) \quad (3)$$

where $1 - p(\text{react})$ is the probability that we can drive trajectory \mathbf{x}_{ego} without hindrance. This reaction is only pursued in the area between $v_{\max,\text{idle}}$ and $v_{\min,\text{pass}}$. In other words, there are parts of the trajectory that are considered independent of occurring objects $\mathbf{x}_{\text{ego}}^{\text{fix}}$.

For the cost computation of $G_{\text{react}}(\mathbf{x}_{\text{ego}})$, we can take advantage of the fact that the reactions always intend a full stop in front of the conflict zone. As the waiting time as well as the subsequent starting are independent of the reactive deceleration, the cost can be split into

$$G_{\text{react}}(\mathbf{x}_{\text{ego}}) = G(\mathbf{x}_{\text{ego}}^{\text{fix}}) + G_{\text{decel}}(\mathbf{x}_{\text{ego}}) + G_{\text{wait}} + G_{\text{start}} \quad (4)$$

²assuming no acceleration after sensing an object

with the waiting cost G_{wait} and the starting cost G_{start} being independent of the specific deceleration implied by \mathbf{x}_{ego} . Consequently, for the choice of the trajectory \mathbf{x}_{ego} , we only have to consider the deceleration phase.

The maximum deceleration that might be needed is caused by an object that appears just before we can switch to condition C2, neglecting the planning delay $t_{\text{plan_delay}}$. The latter delay can be incorporated in the calculation of $v_{\min,\text{pass}}$:

$$v'_{\min,\text{pass}}(s_{\text{ego}}) = \frac{s_{\text{ego}} + s_{\text{ego},\text{cz}}}{\Delta t_{\text{obj},\text{enter}} - t_{\text{delay}} - \text{TZC}_{\min}} \quad (5)$$

with $t_{\text{delay}} = t_{\text{perc_delay}} + t_{\text{plan_delay}}$. Mathematically, the point of maximum deceleration $a_{\max,\text{brake}}$ is the intersection of our planned trajectory with $v'_{\min,\text{pass}}(s)$. For an equally distributed object occurrence, the mean expected deceleration cost is defined by

$$\begin{aligned} G_{\text{exp,decel}} &= \frac{1}{t_{\text{total}}} \int_{t \in T} G(a_{\text{brake}}(s_{\text{ego}}(t))) dt \\ &= \frac{1}{t_{\text{total}}} \int_{t \in T} G\left(\frac{v^2(t)}{2s_{\text{ego}}(t)}\right) dt \end{aligned}$$

with the times where reactive braking is possible T and the length of T being t_{total} .

We assume that the planned acceleration is not smaller than the deceleration needed for a stop $a_{\text{ego}}(t) \geq a_{\text{brake}}(t) \forall t \in T$. A violation of this assumption facilitates stopping before the latest possible safe stop, which is not meaningful in our case. With this assumption we know that $a_{\text{brake}}(t)$ is monotonic over t . Thus, we can over-approximate $G_{\text{exp,decel}}$ by subdividing T into N time intervals and choosing the right bound for every subdivision:

$$G_{\text{exp,decel}} < \frac{1}{t_{\text{total}}} \sum_{n=1}^N (t_n - t_{n-1}) \cdot G(a_{\text{brake}}(s_{\text{ego}}(t_n))). \quad (6)$$

Note, that a longer interval for possible braking reduces the expected cost from braking, but does not change the occurrence probability, as discussed earlier. Note further, that by using analytically computed trajectories for this reactive braking maneuver, the planning delay, and thus the expected cost for reactive braking can be reduced. Also, for occluded areas that are far away from the conflict zone, a full deceleration is unlikely. Rather, during replanning, a comfortable passing between two obstacles without coming to a full stop is chosen.

B. Occupancy probability

Having an estimate for $G(\mathbf{x}_{\text{ego},\text{react}})$, the probability of this reaction is to be estimated. While a profound probability estimation lies outside the scope of this paper, we briefly explain an exemplary calculation. The occupancy of a specific conflict zone can be monitored, yielding a binary occupancy function over time. With this, we can compute all time gaps in-between two objects. From those time gaps, we have to subtract twice the desired time of zone clearance, as we want to keep a safe distance to our predecessor and our successor. From the remaining gap, we now have to subtract

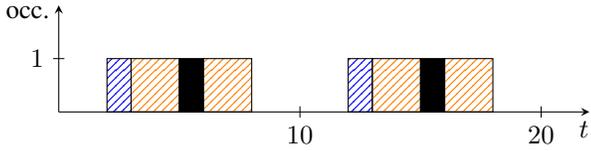


Fig. 4: Occupancy of a conflict zone: The time in which the zone is occupied by another traffic participant (black) is surrounded by a zone clearance time (orange). Additionally, the expected time that is needed to pass the zone is marked in blue. The remaining time is the potential scope for our traversal.

our estimated zone passing time. The remaining gap is the potential scope for our traversal, cf. Fig. 4.

$$t_{\text{gap,scope}} = t_{\text{gap}} - 2\text{TZC} - t_{\text{pass,ego}} \quad (7)$$

Neglecting further information that we could gain from observing the conflict zone, the probability that we can unaffectedly pass it is

$$p(\text{react}) = 1 - \frac{\sum_{\text{gaps}} t_{\text{gap,scope}}}{t_{\text{total}}} \quad (8)$$

In the following, the probability is assumed to be given and constant for a certain planning time. Further, the ego vehicles actions do not affect this probability, i.e. changes in the probability due to future observations are independent of the ego action.

C. The pass through decision

In the presented approach, the decision to pass a conflict zone is always implicitly taken. If, however, an object occurs before we have reached condition C2, we abort the maneuver and yield to this object. The previously explained cost computation facilitates a comfortable switch to this yield maneuver. Note, that safety is never put at risk using this method, as we only chose trajectories that always fulfill the union of conditions C1 and C2.

D. Several occlusions leading to one safe stop

Several occlusions that are not related to each other, i.e. that are statistically independent, but lead to the same conflict zone, require special treatment. An example would be Fig. 1 with another building on the left, such that the lane from left to right is occluded as well. For statistically independent events A and B , we know that $P(A \cap B) = P(A)P(B)$. As the reaction is the same for both events (deceleration for the same safe stop), we can only react once. Thus, the probability of reacting to A or B is not statistically independent. As A and B are equally distributed over certain times $T_A = [t_A^{\text{begin}}, t_A^{\text{end}}]$ and $T_B = [t_B^{\text{begin}}, t_B^{\text{end}}]$, we can subdivide the events into time intervals arbitrarily. Assuming that $t_A^{\text{end}} < t_B^{\text{begin}}$, this means that a reaction to event B only has the probability $P(\bar{A})P(B)$. In general, we can define disjunct time intervals T_1, T_2, \dots where only A is possible, only B is possible, both at the same time are possible or where none is possible, and compute the respective probabilities P_1, P_2, \dots

of the joint event $(A \cap B)$ with $0 \leq P_n \leq 1$. The probability of a reaction P_n^{react} in T_n can then be computed via

$$P_n^{\text{react}} = \left(1 - \sum_{m=0}^{n-1} P_m^{\text{react}}\right) \cdot P_n \quad (9)$$

with $\sum_n P_n^{\text{react}} = 1 - P(A \cap B)$.

As stated earlier, small decelerations far away from the conflict zone are not pursued up to a full stop, but a new plan with the detected object is made. Thus, the single reaction policy might be violated for far away occluded areas. To avoid using heuristics or a threshold for those cases, we over-approximate P_n^{react} by P_n .

E. Occlusions of consecutive conflict zones

For consecutive conflict zones, more specifically conflict zones with consecutive safe stop areas, the reaction differs. The occurrence probability is also assumed to be statistically independent. As the plan for a successive conflict zone is only pursued if no reaction is caused by the previous conflict zone, the concatenation of the events is not further considered. Thus, the cost weighted with its probability can simply be added to the cost calculation.

V. RESULTS AND EVALUATION

In order to evaluate our approach, we chose the scenario from [3], which represents a real world scenario with actually existing occlusions: It is a modified version of the *CommonROAD* [1] scenario *DEU_Ffb-1_1_T-1*.

In the scenario, we approach a junction, where we have to yield to crossing traffic. The lane coming from the right, however, is occluded by a building. Since we know the layout of the junction, we can infer the conflict zone and the position for the latest possible safe stop in front of it³. With this information, we can compute the maximum possible velocity for condition C1. Also, as the building is mapped in our lanelet2-map, we can infer the occlusion along the path beforehand. From these sensing edges, we can infer the occupancy prediction as in Orzechowski et al. [3] and from the latter, we can compute the minimum required velocity to safely pass, according to condition C2.

Now, we look for the best trajectory, given certain occupancy probabilities and certain actual occupancies, using jerk sampling. Unsafe trajectories that violate the safety conditions C1 and C2 at the same time are discarded. As baseline, we implemented the method of Orzechowski et al., but disregarded the jerk constraint. The values were chosen as in [3]: A fail-safe deceleration of $4 \frac{\text{m}}{\text{s}^2}$ and maximum comfortable acceleration of $2 \frac{\text{m}}{\text{s}^2}$. Note that, as a zone clearance time was not considered here, this approach might still violate the right of way of others, even though it is provably safe.

While the baseline always reacts with a sharp deceleration, independent of the occupancy probability, our approach takes advantage of the latter: If we are sure, that the junction

³In this case, we have to stop before entering the junction, and must not stop in the lane crossing from left to right.

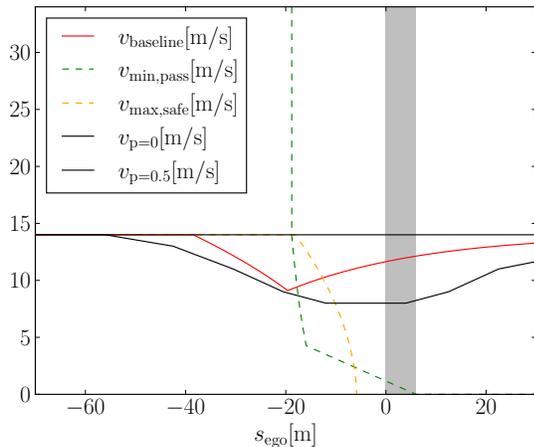


Fig. 5: Planned trajectories for the scenario from Fig. 1. While the baseline [3] acts without considering the occupancy probability, the proposed approach plans constant velocity (upper black) when expecting a free intersection and decelerates early (lower black) when expecting occupancy.

will be free ($p(\text{react}) = 0$), we just have to make sure that we do not risk a collision. As, in the given scenario, a transition from condition C1 to condition C2 is possible at the maximum velocity, there is no need to decelerate at all. On the other hand, if there is a lot of traffic ($p(\text{react}) = 50\%$), we decelerate early and comfortably. This behavior is similar to the one of human drivers, behaving differently depending on how likely it is, that there actually is a relevant object in the occluded area. The results are plotted in Fig. 5. Note that as we always check for a safe transition from condition C1 to condition C2, safety is never put at risk, and wrong probability estimates $p(\text{react})$ only affect the comfort of driven trajectories.

VI. CONCLUSIONS AND FUTURE WORK

In this paper we have presented an approach for safe but at the same time not overcautious motion planning under occlusions and limited sensor range. To the best of the authors' knowledge, this is the first approach that optimizes passenger comfort while being provably safe.

Focusing on junctions, we first derived a method to analyze the safety of given trajectories with respect to occlusions, based on reachability analysis. Next, we derived a method to estimate the expected cost caused by potentially occurring objects. In this method, we apply path velocity decomposition for our own trajectory, which is well-suited for intersection scenarios. Combined with traffic flow information of the respective junctions, we can determine the expected cost of a trajectory as weighted sum of the cost if we can pursue the trajectory and the cost for the reaction to an occurring object.

We show the performance and the potential of our approach by comparing it to the recently presented method of Orzechowski et al. [3]: The shown trajectories reflect a human-like behavior, risking stronger potential decelerations, the less likely they are.

Future work should include carefully advancing into conflict zones, as permitted by the traffic rules, in case of a severe occlusion where a safe transition is not possible otherwise. Further, as occlusions of potential objects can also be inferred if we have the right of way, we can deduce areas where other objects could carefully advance into our lane. This information must also be included to facilitate safe motion planning in all scenarios.

ACKNOWLEDGEMENTS

We gratefully acknowledge support of this work by the Tech Center a-drive, the Profilverein Mobilitätssysteme Karlsruhe and by the Deutsche Forschungsgemeinschaft (German Research Foundation) within the Priority Program "SPP 1835 Cooperative Interacting Automobiles".

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