Tackling Existence Probabilities of Objects with Motion Planning for Automated Urban Driving

Ömer Şahin Taş and Christoph Stiller

Abstract—Motion planners take uncertain information about the environment as an input. The environment information is most of the time noisy and has a tendency to contain false positive object detections, rather than false negatives. The state-of-the-art motion planning approaches take uncertain state and prediction of objects into account, but fail to distinguish between their existence probabilities.

In this paper we present a planning approach that considers the existence probabilities of objects. The proposed approach reacts to falsely detected phantom objects smoothly, and in this way tolerates the faults arising from perception and prediction without performing harsh reactions, unless such reactions are unavoidable for maintaining safety.

I. INTRODUCTION

Automated driving needs to employ various sensor modalities to meet the requirements for driving. The redundant sensor information is processed in different modules and the divergence in the subsequent measurements is typically represented probabilistically. The resulting data is then fused either by a temporal filtering intrinsically, e.g. [1], or as a single shot with subsequent temporal filtering, e.g. in grid maps [2], [3]. In any case, the fusion may generate false negatives, and more frequently false positive objects in order to avoid any severe consequences. The output of the fusion is then processed in scene understanding module and the predicted motion of the objects is transmitted to the motion planner [4]. A motion planner takes all the objects and considers the uncertainties associated to them by treating these as hard or soft constraints.

The object list transmitted to the planner may contain a false-positive object, i.e. a phantom object, close to the ego vehicle (see Fig. 1). Independent of the existence probability of the phantom object, this will trigger either braking or swerving on a multi-lane road. On the other hand, the low existence probability of the phantom may diminish completely within the next couple updates of the perception. This typically corresponds to durations smaller than half a second [5], [6]. In such, braking or swerving will be discarded eventually, leading to instable behavior.

Tackling phantom objects can be done in different layers of an automated vehicle. This can be done either by a module that is closely related to the perception or fusion, e.g. [7] or by a centralized plausibility module, e.g. [4]. Another approach is to consider the problem from the end-side: how urgent is it for the motion planner to react to the object? The answer of this question depends both on the existence probability of the object and on its pose-based prediction uncertainty. Our motion planning approach fundamentally considers these two aspects and tolerates faulty detections by degressively postponing evasive actions by expecting the perception system to deliver more precise results over time. In this sense, we tackle the existence probability of objects from the motion planning perspective for the first time.

The rest of the paper is structured as follows: we classify the uncertainty types in Section II since understanding the source and types of uncertainties that propagate in an automated vehicle is essential. Then, in Section III we present the state-of-the-art solvers that use distinct modalities to deal with those uncertainties and describe their limits. Our motion planner has certain input requirements on the predicted object list. In Section IV we briefly describe these requirements. We then continue with Section V in which we present the problem formulation to tackle existence probabilities in planning. The resulting nonlinear optimization problem can be solved with different approaches. We give an overview on this in Section VI. We conclude the paper and summarize the key aspects in Section VII.
II. Types of Uncertainties in Automated Driving

The uncertainties are either due to noisy measurements, or the obscurity of the future, or the occlusions. In a robotic system, these uncertainties yield to three main classes of problems:

1) Uncertainty in pose
2) Uncertainty in prediction
   a) Maneuver classes
   b) Profile of maneuvers
3) Uncertainty in existence
   a) Field-of-view (fov)
   b) Phantom detections.

The uncertainty in pose covers the position and velocity uncertainty of the ego vehicle and other participants. This type of uncertainty is typically represented with a probability distribution, e.g. normal distribution.

The second class, the uncertainty in prediction, comprises distinct semantic maneuver classes together with their motion profiles. Representing this type of uncertainty is quite difficult as it is highly related with types of objects, e.g. pedestrians, bicycles, motorbikes, trucks, unclassified etc. Each one of these classes introduces different maneuver classes, depending on the current traffic scene and the interactions. In unstructured environments or for some object types in structured environments, a semantic classification of maneuvers is not even possible. It must be underlined that the uncertainty in pose is covered by this type uncertainty while planning motion over a horizon.

The uncertainty in existence is the type of uncertainty, which this paper focuses on. It reflects the uncertainty of an object to exist, either at the outside borders of fov, or even inside the fov. Following the notion presented in [8], we refer to the objects at the border of fov as hypothetical object. However, we refer to any object suspected to be a non-object as a phantom object. We assume the existence probability of objects to remain constant over planning horizon.

III. Existing Planners that Consider Uncertainty

Planning safe maneuvers while considering uncertainty is a profound topic of motion planning research for automated driving.

Motivated from robotics applications, early automated vehicle motion planning methods penalized the probability of being in the space of other objects while planning a path [9]. Safe intersection crossing with probabilistic risk indicators is tackled in [10]. Recent works have focused on occlusions and considered the objects that could emerge behind the visible field. Orzechowski et. al. used reachable sets [11] for dealing with occlusions in a safe way [12]. Another work investigated the risk associated with occlusions and limited sensor range and sampled particles to get an estimation of it [13]. They used the risk for planning smooth motion. Tas et. al. calculated the limits that can be reached by an object while considering normal distributed sensor information. They solved the resulting problem with an optimization-based solver [8].

Gritschneider et. al. focused on interaction uncertainties in a Markov Decision Process (MDP) and chose the high-level behavior actions that are sent to the motion planner [14]. Among distinct maneuver options, the planner considered undecided cases as well. But it failed to consider the uncertainties in state and maneuver intentions of other vehicles. Zhan et. al. used the planning approach developed by Ziegler et. al. [15], and proposed to plan maneuvers that are optimal for undecided cases [16]. In their paper, they neither specified the optimization method nor the details of how to handle the cost terms and constraints of the optimization problem. Apart from this work, Tas et. al. used the same approach to deal with the same problem [17]. In their paper, they described how the parameter transition of maneuvers can be handled while solving the optimization problem. They further proposed to consider the entropy of predicted maneuver intention of the other vehicle, and executed the best maneuver that satisfied a threshold on entropy.

Partially Observable MDP (POMDP) methods consider the state as a probability distribution and perform predictions on the motion of other vehicles while planning over a horizon. Although these are very well suited for motion planning problems of automated vehicles, they are very complex to solve in real-time [18]. Even though early applications on automated driving scenarios were scene-specific [19], recent sampling-based solvers are able to tackle scenario-independent problems in real time without any training [20]. Hubmann et. al. use POMDPs to deal with all types of uncertainties except the existence uncertainty of phantom objects [21]. Based on our definitions, they use the term “phantom object” to tackle hypothetic objects that could be at the boundaries of the visible field. Another recent work focuses on uncertainties resulting from occlusions, limited sensor range, probabilistic prediction and unknown intentions by using model predictive control [22]. They used inverse reinforcement learning for learning the cost function.

IV. Requirements on Predicted Outputs

The planner requires predicted motion of other participants over the planning horizon and the existence of these objects as an input. As outlined in Section II, the an object has uncertainties regarding type information, existence probability, maneuver classes, and the profile of these classes.

The profile is required to be represented as truncated normal distribution. The reason for choosing normal distribution is its ease of computation, eventually causing the problem to remain quadratic. The mean value of the distribution can be obtained from an arbitrary prediction algorithm, either model based or learning based [23]. The calculation of variance is not straightforward due to the constraints employed by a truncation. An overview is provided in [24]. Together with

1Etymologically we find the use of “phantom” more appropriate than the use of “ghost” for this type of uncertainty.
type information, every maneuver class creates a modus in a multi-modal truncated normal distribution.

V. Tackling Uncertainties for Safe Planning

We solve the motion planning problem for a kinematic vehicle model by transforming it into an optimization problem [15]. Our previous work has already developed the approach presented in [15] further by integrating safe stops while considering perception uncertainties, limited visible field and uncompliant behaviors [8]. Our follow-up work has resolved situations in which the intention of other vehicles are unclear by analyzing undecided cases about the maneuver intention of others and executing neutral motion plans [17]. Here we build upon these by tackling phantom detections. We briefly present the fundamentals from those papers and elaborate these for handling phantom objects.

A. Baseline

For a motion to be optimal, we seek for smooth control inputs. This can be achieved by penalizing jumps in acceleration values of a maneuver \( m \in \mathcal{M} \) over a planning horizon \( T \). A discrete representation of such a functional with stepwidth \( \Delta t \) by \( N \) points using forward differences minimizes the sum

\[
J^d(x_0, x_1, \ldots, x_{N-1}) = \sum_{i=0}^{N-4} L(x_i, x_i^d, x_i^{dd}, x_i^{ddd}). \tag{1}
\]

The variable \( x_i = [x_i, y_i]^T \) represents \( i \)th motion support point corresponding to the position values in Cartesian coordinates, \( L \) is a function comprising cost terms minimizing value or range residuals (see [17] and [25] for details), the superscript ‘\( d \)’ indicates that the variable is a discretized approximation.

The modules of an automated vehicle have delays and the motion is not planned instantaneously. Therefore, to maintain temporal consistency during replanning, some motion support points are taken from the previously planned motion. We denote the index until which the previous motion is kept fixed with the subscript ‘pin’. The visualization is given in Fig. 2a after the time \( t_{\text{pin}} \), a motion is calculated. If replanning is performed in constant time intervals, only the part between the time interval \( t \in [t_{\text{pin}}, t_{\text{2pin}}] \) of the motion planned at \( t_0 \) will be executed. The support points between \( t \in [t_{\text{2pin}}, T] \) is replanned during the next planning instance, i.e. at \( t_{\text{2pin}} \) (see Fig. 2b).

Until now, the motion for a single maneuver \( m \) is considered. An automated vehicle typically has to consider maneuvers of different homotopy classes and choose one of them according to utility and safety reserves [26]. Even though a variety of maneuver alternatives are possible, the promising maneuvers in most cases reduce to two, i.e. the behavior planner might in some cases be undecided between two maneuver options. We denote two maneuvers of different homotopy classes with \( m_1 \) and \( m_2 \). Almost every motion planning algorithm plans these alternatives separately (see Fig. 2c).

Another option is to plan these maneuvers in a combined fashion [16], [17]. In this way, the optimization parameter vector becomes

\[
X = \begin{pmatrix}
X_0, \ldots, X_{\text{pin}},& X_{\text{pin}+1}, \ldots, X_{2\text{pin}}, \\
\text{pinned} & \text{shared} \\
X_{2\text{pin}+1}, \ldots, X_N, & X_{N+1}, \ldots, X_{2N-n_{\text{pin}}}
\end{pmatrix}.
\]

This allows to consider both homotopy classes simultaneously and results in a motion that is tailored for undecided cases: the motion is equally optimal for \( m_1 \) and \( m_2 \) (see Fig. 2d). The implementation details for constructing
constraints and calculating the cost are provided in [17]. Although this approach is advantageous for considering uncertainties, such a computation has an increased complexity: \(2N - 2n_{\text{pin}}\) number of free variables are optimized instead of \(N - n_{\text{pin}}\), and the matrices of the minimization problem are not diagonal anymore.

**B. Maintaining Safety**

A set of rules for an automated vehicle to plan a safe motion is provided in Responsibility Sensitive Safety model (RSS) [27]. In the context of continuous replanning, we consider a planned motion safe if it is able to reach a safe state after executing the motion interval that is kept fixed in the subsequent instance. In the notation presented in the previous subsection, the motion in \(t \in [t_{\text{pin}}, t_{\text{stop}}]\) must ensure the presence of safe maneuvers.

These safe maneuvers can either be full braking actions, or swerve maneuvers, or a combination of them. For urban environments, we treat full braking actions \(m_Z\) as safe maneuvers and ensure the presence of them by introducing an inequality constraint. The full stop point \(t_{\text{stop}}\) along the path must remain lower than the lower bound of the truncated normal distribution representing the position of the closest object \(o\) for timesteps

\[
\delta_i - t_{\text{stop}} \geq 0, \forall i \in \{n_{\text{pin}}, \ldots, 2n_{\text{pin}} - 1\}. \tag{3}
\]

In case of limited visibility, we consider hypothetic objects at the end of the visible field as described in [8]. Unless a vehicle is percepted, we treat the hypothetic vehicle to be uncompliant to the traffic rules, and approach the intersection while reserving a full braking maneuver that comes to a full stop before this zone. Once a vehicle is percepted, if its yield intention becomes clear by reducing its speed so that it can come to full stop before colliding, we remove the constraint applied on the planner.

**C. Maintaining Comfort**

All of the motion support points have an influence on comfort. The change in lateral and longitudinal acceleration is considered as a cost summand to yield a comfortable ride [15]. Besides this, we soft constrain the collision uncertainty with the objects by calculating cumulative distribution function (cdf). We take truncated normal distributed position predictions (see [17]). The error function (erf) is used in the calculation of cdf. We use an efficient numerical approximation of the erf that is presented in [28, p. 214].

**D. Interacting with Unknown Maneuver Intentions**

Our planner considers two maneuver alternatives while interacting with other traffic participants. This number can be increased at the cost of solving problems in a parallel way. In some cases, the maneuver intention of others is unclear and it is beneficial to perform a neutral maneuver, as described in Section [17]. Our approach presented in [17] selected the maneuver yielding the lowest cost among the alternatives that have an entropy lower than a certain threshold.

Note that such interactions can also be considered as a further comfort term, because they estimate the further evolution of the current situation and subsequently serve for adapting the speed.

**E. Tackling Existence Probabilities**

Objects inside the object list sent to the planner must be processed carefully. Independent of the value of existence probability, the safety conditions provided in the Section [V] must be met. If no immediate evasive action is required, we follow a strategy derived from undecided case.

Considering the situation depicted in Fig. 1 lets assume the existence probability of the red vehicle \(p(\alpha_{\text{red}})\) to be 0.21. The red vehicle is likely to be a phantom and hence, no immediate reaction \(m_Z\) is required as the potential phantom object is enough away, i.e. \(l_B(t_{\text{pin}}) > l_{\text{stop}}(t_{\text{pin}})\). In such a case, the planner has two maneuver alternatives: \(m_A\) and \(m_B\). The weight of the cumulative cost terms \(J_A\) and \(J_B\) are \(w_B = p(\alpha_{\text{red}})\) and \(w_A = 1 - p(\alpha_{\text{red}})\) respectively. The total cost \(J^d\) is calculated as

\[
J^d(x_0, x_1, \ldots, x_{2N-n_{\text{pin}}}) = w_A J_A^d(x_0, \ldots, x_N) + w_B J_B^d(x_0, \ldots, x_{2pin}, x_{N+1}, \ldots, x_{2N-n_{\text{pin}}}). \tag{4}
\]

The resulting maneuver is a weighted combination built according to the existence probability of the phantom object. In this way, the planner reacts to the object smoothly, without initiating harsh braking maneuvers.

**VI. SOLVING THE NONLINEAR OPTIMIZATION PROBLEM**

Formulation of the optimization problem is presented in Section [V] The resulting problem has a quadratic objective function and is constrained nonlinearly.

Finding a local optimum of such a nonlinear program is difficult. The main competing approaches are the Active Set Methods and the Interior Point Methods. Both allow the use of inequality constraints, whereas the main distinction between them is in the way they handle the constraints [29].

Active Set Methods guess which of inequality constraints are binding, i.e. active and neglect the non-binding ones during a single iteration. Hence, active set works on the smaller space of the remaining constraints. This allows these type of solvers, such as Sequential Quadratic Programming (SQP) methods, to scale very well with a large number of constraints.

The Interior Point Methods, on the other hand, treat inequality constraints as equality constraints by introducing slack variables. However, such an approach increases the computational cost. Therefore, interior point methods are preferred if the nonlinear problem is constrained with only a small number of constraints.

Simulations have revealed that in complex intersections with occlusions the constraints shrink the solution space considerably. In these cases, the convergence and the quality of the solution depends strongly on initialization. The initialization must satisfy all the constraints. Otherwise, a feasible solution might not be found. For this reason, we initialize the problem with full braking applied at \(t_{\text{pin}}\).
In our previous work, we solved the optimization problem by utilizing the nonlinear least-squares solver Ceres [30]. In the work that focused on safe and comfort, we were able to obtain results in less than 100ms [8]. In the work that focused on undecided maneuvers, the solution time increased to 300ms, for the same planning horizon $T$ value [8]. However, when we utilize the solver to the problem stated in this paper, the planner sometimes fails to find a solution. This highlights the need to use a SQP solver, which is tailored for the needs of constrained optimization and matches with the discussion presented in [31].

VII. CONCLUSIONS AND FUTURE WORK

The existing literature focuses on developing new motion planning algorithms with different modalities. However, the biggest challenge here is to tolerate the faults in perception. While the literature has overseen this need, our research focused on developing a motion planner to compensate the faults in perception.

In this paper, we categorized types of uncertainties influencing the motion of an automated vehicle. We clarified the reasons of these uncertainties and defined the underlying causes. Based on this, we considered existence probabilities of objects in planning by inspecting the motion reserve to activate evasive actions. This allowed us to tolerate faulty detections of phantom objects. With our previous work, we were able to present a motion planner that could deal with all types of uncertainties while ensuring safety.

Future work will focus on developing a SQP solver with automatic differentiation feature. There is not any off-the-shelf solver available for this task, and therefore it is left for future work. Developing such a solver could be topic of applied numerical analysis rather than a motion planning problem for automated driving, as well. The utilization of such a solver would allow more frequently replanning, resulting lower dead time and hence allowing to drive at higher speeds. Once the solver is developed, on-vehicle experiments by injecting phantom objects into the perception pipeline of our automated vehicle BERTHAONE is planned [25].

REFERENCES

[1] B. Duraisamy, T. Schwarz, and C. Wohler, “On track-to-track data association for automotive sensor fusion,” Int. Conf. Inform. Fusion, 2015.
[2] S. Richter and S. Wirges, “Fusion of range measurements and semantic estimates in an evidential framework,” Technisches Messen, vol. 86, pp. 102–106, 2019.
[3] S. Steyer, G. Tanneister, and D. Wollherr, “Grid-Based Environment Estimation Using Evidential Mapping and Particle Tracking,” IEEE Trans. Intell. Veh., pp. 1–1, 2018.
[4] Ö. Ş. Taş, S. Hörmann, B. Schaufele, and F. Kuhnt, “Automated Vehicle System Architecture with Performance Assessment,” in Proc. IEEE Intell. Transp. Syst. Conf., 2017, pp. 1–8.
[5] F. Yin, D. Makris, and S. Velastin, “Real-time ghost removal for foreground segmentation methods,” in IET Electron. Lett., 2008, pp. 1351–1353.
[6] M. Kocamaz, “Drive labs: Tracking objects with surround camera vision,” Jun 2019, Date retrieved: January 10, 2020. [Online]. Available: https://news.developer.nvidia.com/drive-labs-tracking-objects-with-surround-camera-vision/
[7] D. Barnes, W. Maddern, and I. Posner, “Find Your Own Way: Weakly-Supervised Segmentation of Path Proposals for Urban Autonomy,” in Proc. IEEE Int. Conf. Robot. and Autom., 2017, pp. 203–210.
[8] Ö. Ş. Taş and C. Stiller, “Limited Visibility and Uncertainty Aware Motion Planning for Automated Driving,” in Proc. IEEE Intell. Veh. Symp., 2018, pp. 1171–1178.
[9] W. Xu, J. Pan, J. Wei, and J. M. Dolan, “Motion planning under uncertainty for on-road autonomous driving,” in Proc. IEEE Int. Conf. Robot. and Autom., 2014, pp. 2507–2512.
[10] G. R. de Campos, A. H. Runarsson, F. Granum, P. Falcone, and K. Alenljung, “Collision avoidance at intersections: A probabilistic threat-assessment and decision-making system for safety interventions,” in Proc. IEEE Intell. Transp. Syst. Conf., 2014, pp. 649–654.
[11] M. Althoff and S. Magdici, “Set-based prediction of traffic participants on arbitrary road networks,” IEEE Trans. Intell. Veh., vol. 1, no. 2, pp. 187–202, 2016.
[12] P. F. Orzechowski, A. Meyer, and M. Lauer, “Tackling occlusions & limited sensor range with set-based safety verification,” in Proc. IEEE Intell. Transp. Syst. Conf., 2018, pp. 1729–1736.
[13] M.-Y. Yu, R. Vasudevan, and M. Johnson-Roberson, “Occlusion-aware risk assessment for autonomous driving in urban environments,” IEEE Robot. and Autom. Lett., vol. 4, no. 2, pp. 2235–2241, 2019.
[14] F. Gritschneder, P. Hatzelmann, M. Thom, F. Kunz, and K. Dietmayer, “Adaptive learning based on guided exploration for decision making at roundabouts,” in Proc. IEEE Intell. Veh. Symp., 2016, pp. 433–440.
[15] J. Ziegler, P. Bender, T. Dang, and C. Stiller, “Trajectory planning for Bertha — a local, continuous method,” in Proc. IEEE Intell. Veh. Symp., 2014, pp. 450–457.
[16] W. Zhan, C. Liu, C.-Y. Chan, and M. Tomizuka, “A non-conservatively defensive strategy for urban autonomous driving,” in Proc. IEEE Intell. Transp. Syst. Conf., 2016, pp. 459–464.
[17] Ö. Ş. Taş, F. Hauser, and C. Stiller, “Decision-Time Postponing Motion Planning for Combinatorial Uncertain Maneuvering,” in Proc. IEEE Intell. Transp. Syst. Conf., 2018, pp. 2419–2425.
[18] C. H. Papadimitriou and J. N. Tsitsiklis, “The Complexity of Markov Decision Processes,” Math. of Operations Res., vol. 12, no. 3, pp. 441–450, 1987.
[19] S. Brechtel, T. Gindele, and R. Dillmann, “Probabilistic decision-making under uncertainty for autonomous driving using continuous pomdps,” in Proc. IEEE Intell. Transp. Syst. Conf., 2014, pp. 392–399.
[20] M. Egorov, Z. N. Sunberg, E. Balaban, T. A. Wheeler, J. K. Gupta, and M. J. Kochenderfer, “POMDPs: j: A framework for sequential decision making under uncertainty,” The J. of Mach. Learn. Res., vol. 18, no. 1, pp. 831–835, 2017.
[21] C. Hubmann, N. Quetschlich, J. Schulz, J. Bernhard, D. Althoff, and C. Stiller, “A POMDP Planner Maneuver For Occlusions in Urban Scenarios,” in Proc. IEEE Intell. Veh. Symp., 2019, pp. 2172–2179.
[22] L. Sun, W. Zhan, C.-Y. Chan, and M. Tomizuka, “Behavior planning of autonomous cars with social perception,” in Proc. IEEE Intell. Veh. Symp., 2019, pp. 207–213.
[23] S. Lefèvre, D. Vasquez, and C. Laugier, “A survey on motion prediction and risk assessment for intelligent vehicles,” Robomech Journal, vol. 1, no. 1, p. 1, 2014.
[24] D. Simon, “Kalman filtering with state constraints: a survey of linear and nonlinear algorithms,” IET Control Theory & Appl., vol. 4, no. 8, pp. 1303–1318, 2010.
[25] Ö. Ş. Taş, N. O. Salscheider, F. Poggenhans, S. Wieges, C. Bundera, M. R. Zofka, T. Strauss, J. M. Zöllner, and C. Stiller, “Making Bertha Cooperate - Team AnnieWAY’S Entry to the 2016 Grand Cooperative Driving Challenge,” IEEE Trans. Intell. Transp. Syst., vol. 19, no. 4, pp. 1262–1276, April 2018, Date of Publication: 02 October 2017.
[26] P. Bender, O. Ş. Taş, J. Ziegler, and C. Stiller, “The combinatorial aspect of motion planning: Maneuver variants in structured environments,” in Proc. IEEE Intell. Veh. Symp., 2015, pp. 1386–1392.
[27] S. Shailev-Shwartz, S. Shammah, and A. Shashua, “On a formal model of safe and scalable self-driving cars,” 2017.
[28] W. H. Press, S. A. Teukolsky, B. P. Flannery, and W. T. Vetterling, Numerical Recipes in Fortran 77: The Art of Scientific Computing, Cambridge University Press, 1992.
[29] J. Nocedal and S. Wright, Numerical Optimization. Springer Science & Business Media, 2006.
[30] S. Agarwal, K. Mierle, and Others, “Ceres solver,” http://ceres-solver.org.
[31] D. Lenz, T. Kessler, and A. Knoll, “Stochastic model predictive controller with chance constraints for comfortable and safe driving behavior of autonomous vehicles,” in Proc. IEEE Intell. Veh. Symp., 2015, pp. 292–297.