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A Non-Conservatively Defensive Strategy for Urban Autonomous Driving

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Abstract— **From the driving strategy point of view, a major challenge for autonomous vehicles in urban environment is to behave defensively to potential dangers, yet to not overreact to threats with low probability. As it is overwhelming to program the action rules case-by-case, a unified planning framework under uncertainty is proposed in this paper, which achieves a non-conservatively defensive strategy (NCDS) in various kinds of scenarios for urban autonomous driving. First, uncertainties in urban scenarios are simplified to two probabilistic cases, namely passing and yielding. Two-way-stop intersection is used as an exemplar scenario to illustrate the derivation of probabilities for different intentions of others via a logistic regression model. Then a deterministic planner is designed as the baseline. Also, a safe set is defined, which considers both current and preview safety. The planning framework under uncertainty is then proposed, in which safety is guaranteed and overcautious behavior is prevented. Finally, the proposed planning framework is tested by simulation in the exemplar scenario, which demonstrates that an NCDS can be realistically achieved by employing the proposed framework.**

I. INTRODUCTION

Urban autonomous driving is very challenging since the host vehicle has to handle various kinds of scenarios and the behaviors of other road participants are highly unpredictable. Variations in intentions of others [1][2] and uncertainties in subsequent motions [3] may lead to different decisions and resultant motions taken by the host autonomous vehicles. Typically, the relationship between decision-making and motion planning is hierachical [4]. However, for autonomous vehicles in dynamic environment, taking an immediate action does not mean that it has to immediately make a final decision among possible future actions. Tentative actions are commonly seen in human driving, which is ambiguous and allows the diversification of possible subsequent actions that can be transitioned smoothly in the future. The following challenging urban driving scenarios are provided to illustrate why decision-making for ambiguous intentions of others can be incorporated in motion planning by taking actions tentatively, which enables a non-conservatively defensive strategy (NCDS).

Scenario 1: Avoiding violation vehicles at intersections. Careless drivers may violate stop signs or red lights and cause fatal accidents [5]. In order to be defensive to red light runners, Google programmed a short pause after light turning green before its car proceeds into the intersection [6]. Also, stop sign violation is not an extremely rare behavior in real world traffic. Google self-driving car was crashed by a car violating stop sign in February 2015 [7]. When observing a vehicle that may run the stop sign or red light with high speed and low deceleration, an autonomous vehicle should be prepared to avoid a possible crash. However, it does not mean that the autonomous vehicle should slow down prematurely to make a yielding decision. If the violation probability is relatively low, it can maintain its speed as long as its braking capability can allow it to stop timely before reaching the conflict region.

Scenario 2: Roundabout entering. When an autonomous vehicle is entering a roundabout, some vehicles in the roundabout may act aggressively to deter the host vehicle from merging but other non-aggressive vehicles may slow down and yield to the host vehicle [8]. It was observed in the test in Parma [9] that the VisLab autonomous car, when entering a roundabout, acted conservatively so that there were long pauses and unnecessary stops before proceeding even though the other vehicle in the roundabout had already started to turn into other road branches. Therefore, in planning to enter the roundabout given the uncertainties above, an autonomous vehicle does not have to decide immediately whether to merge before or after the other vehicle in the roundabout coming to its entrance point. It can just keep a proper speed and further observe the motion of the vehicle in the roundabout, and make final decisions when it has to.

Scenario 3: Four-way-stop intersection entering. At a busy four-way-stop intersection, an autonomous vehicle can hardly move forward if it strictly obeys the rule and behave cautiously, waiting behind the stop bar for its turn. This case was observed in a demonstrated situation that the Google self-driving car faced. Google decided to enable the car to move forward a little to show its determination to go. In fact, the principle behind such human-like behavior can be explained as follows. It is possible that all vehicles from other approaches of the intersection may yield. Hence the host vehicle can start to accelerate and show its intention to go first. However, to stop again and yield to others is still possible in case any of them shows stronger determination so that the host vehicle has to yield.

Scenario 4: Lane change. When an autonomous vehicle is changing lane, other vehicle may speed up to prevent it from cutting in. Drivers of large vehicles on the target lane tend to assume that the autonomous vehicle would not risk to cut in closely, so that they just maintain the speed

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anyway. That was how the accident happened on the Google car on February 2016 [10]. Moreover, another vehicle may be merging into the same lane from the other side at the same time [11]. Therefore, an autonomous vehicle should be prepared to change back to its original lane when such threats appear. Starting the movement to change lane is also a tentative motion and the final decision does not need to be made at that point.

In all the aforementioned scenarios, autonomous vehicles should execute a defensive driving strategy to avoid possible collisions when potential threats exist. However, the current demonstrated design of autonomous vehicles is often overly cautious and sometimes behaves unhuman-like in real world scenarios in order to guarantee safety. Such conservative behaviors will degrade the driving quality and may still jeopardize safety when the behaviors are not expected by other road participants. To address this problem, we propose that autonomous vehicles need a unified planning framework to handle uncertainties in various kinds of urban driving scenarios when the decision and action are tentative, so that the driving strategy is defensive enough to guarantee safety even when others are violating traffic rules, and yet not too conservative to degrade driving quality.

In literature, partially observable Markov decision process (POMDP) was used extensively in autonomous driving for decision making and planning under uncertainty [12][13]. However, there is no guarantee for the planned trajectories to be collision-free within a specific preview horizon regarding each possible intention of the others. In this paper, we emphasize on the guarantees of the safety of the autonomous vehicle even when the others choose the worst case behavior.

The rest of this paper is organized as follows. Section II models the behavior of others via simplifying the uncertainty quantification and providing the model in an exemplar scenario. A non-conservatively defensive strategy (NCDS) is detailed in Section III. A deterministic planner is designed as a baseline. Then a safe set is defined, and a unified planning framework under uncertainty is proposed. Then Section IV gives illustrative examples, and Section V concludes the paper.

II. Behavioral Modelling

In this section, we model the behavior of other road participants via calculating the probabilities of the cases that lead to passing and yielding decision of the host autonomous vehicle. A logistic regression model is then provided for an exemplar scenario to get the probabilities of other vehicles to violate the stop sign or not.

A. Simplified uncertainty quantification

In order to define the boundary for moving obstacles at each future time step, the behaviors of other road participants within the preview horizon should be predicted, which are full of uncertainties in urban driving scenarios. In fact, it is beyond the scope of this paper to model all uncertainties in object detection, intention recognition and motion prediction in various kinds of urban driving scenarios. In the following we will discuss how the uncertainty quantification can be simplified to facilitate decision-making and motion planning.

Although a road participant may exhibit varying intentions and there can be uncertainties in recognizing the object, an autonomous vehicle typically has just two choices in the current preview horizon – passing or yielding. This simplified description is applicable to various kinds of urban driving scenarios, such as merging into a roundabout, passing through an intersection, changing into another lane, or yielding to crossing pedestrians. [1]

Uncertainties originating from different causes can be combined. For instance, uncertainties from both perception and intention recognition systems may co-exist on whether an object is a pedestrian and whether the pedestrian intends to cross the street. For the yielding case, the motion planner only considers the probability of the event that the object is a pedestrian and the intention of the pedestrian is to cross the street. The passing case then encompasses the remaining possibilities.

For the potential threats beyond the field of view, prior knowledge is used to obtain the probabilities. The probabilities are constant over time until the view reveals the suspected region. When more information becomes available, then the probability assessment is updated.

In summary, by observing the motions of other road participants with contextual information, the probabilities for an autonomous vehicle to pass and yield are obtained, which are denoted as $P(\text{pass})$ and $P(\text{yield})$, respectively. Then under each case, the worst possible boundaries generated by the motion are constructed as the predicted motion. Although it is possible for weird behaviors to happen, the bounds we introduced are meaningful as 1) they are reasonable assumptions anticipated by human drivers; and 2) they cover cases with low probability.

Specific models and learning methods based on different approaches can be adopted to quantify the uncertainties and create constraint boundaries for different road participants under various conditions. In the next subsection, a possible method to model the uncertainties in an exemplar scenario is shown as an example.

B. An exemplar scenario

The exemplar scenario we use is a two-way-stop intersection, which is shown in Fig.1. The autonomous vehicle V1 (red car) holds the right of way, and the other vehicle V2 approaching the stop sign (orange car) is expected to stop. We model the behavior of V2 to calculate the violation probability.

We carried out a field observation effort at a real-world intersection to collect motion data of vehicles approaching

[1] The significance of solving the problem with two cases is not reduced by the fact that multiple moving objects may exist and possible decisions may not be limited to just two cases. Usually, they can be clustered and two best decisions can be created for the proposed framework to plan motions. Also, the accidents and overly conservative behaviors of autonomous vehicles mentioned in Section I were all caused by inappropriate motions with two ambiguous decisions. Moreover, the framework has the potential to be extended to handle more than two cases.

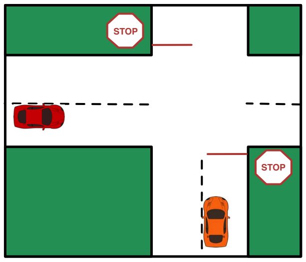


Fig. 1. A two-way-stop intersection

stop bars. Features including distance to the stop bar d_{stop}, velocity $\dot{d}_{\text{stop}}$ and acceleration $\ddot{d}_{\text{stop}}$ are chosen to represent the motions. Sample data is illustrated in Fig.2.

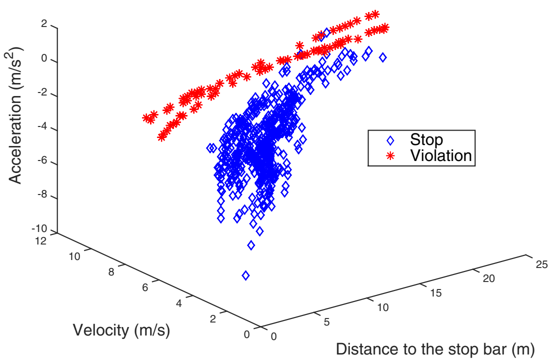


Fig. 2. Visualized 3D taining data

Among the V2 motions observed from the field data, slight rolling stop motions are frequently observed, which are labeled and grouped together with the full-stop motions as "stop cases" in Fig.2. The reason we regard slight rollings as cases that V1 can pass is that drivers of those slight rolling vehicles are likely paying attention to the cross traffic and are ready to stop if a vehicle holding the right of way appears [14].

A logistic regression model is employed to obtain the probabilities to quantify the uncertainty based on the motion features of V2, which can be written as

$$
\begin{aligned}
P(\text{pass}|z) &= \frac{e^{-\beta^T z}}{1+e^{-\beta^T z}}, \\
P(\text{yield}|z) &= 1 - P(\text{pass}|z),
\end{aligned}
$$

where

$$
z = \begin{bmatrix} d_{\text{stop}} & \dot{d}_{\text{stop}} & \ddot{d}_{\text{stop}} & 1 \end{bmatrix}^T,
$$

the passing case corresponds to stop of V2 and yielding case corresponds to violation of V2. The vector β is obtained by maximizing the log likelihood based on the Newton-Raphson method.

For the passing case, no blocking line is created. For the yielding case, blocking lines are created for V1 in a time period from the earliest possible time for V2 to enter the conflict region to the latest possible time for V2 to leave the conflict region.

III. Non-Conservatively Defensive Strategy

In this section, a non-conservatively defensive driving strategy (NCDS) is proposed for urban autonomous driving scenarios, which is defensive to deal with potential threats to guarantee safety, but not overly conservative to degrade driving quality.

A. Deterministic planner

In this section, a spatiotemporal trajectory planner in deterministic environments is designed by adopting a modified receding horizon optimization framework [15], which is solved by sequential quadratic programming. $q_i = [x_i \quad y_i]^T$ is the position vector of the autonomous vehicle at time step i, where x_i and y_i depicts the position of the center of the vehicle rear axle. Suppose T_p is the whole planning time horizon, t is the current time step. Typically, the planner optimizes the motion within the whole time horizon $q_{t+1:t+T_p} = \left[q_{t+1}^T, q_{t+2}^T, \ldots, q_{t+T_p}^T\right]^T$.

Note that the position vector q_t is not the full state of the vehicle at time step t. The full state s_t of the vehicle should contain at least two more position vectors backward, that is $s_t = \left[q_{t-2}^T, q_{t-1}^T, q_t^T\right]^T$. Then velocity and acceleration can be obtained via backward differences. For the optimization at each time step t, s_t is used as the initial value so that the velocity, acceleration, yaw angle, as well as jerk and yaw rate at $t+1$ can be calculated.

The objectives contain five aspects to enhance driving quality and follow traffic rules. Taking into account factors such as comfort, smoothness and fuel consumption, we penalize accelerations, jerks, and yaw rates in J_1, J_2, and J_3, respectively. The expressions can be found in [15]. Position errors relative to the desirable traffic-free reference path are penalized as

$$
J_4\left[q_{t+1:t+T_p}\right] = \sum_{i=t+1}^{t+T_p} d\left(q_i\right)^2,
$$

where $d(q_i)$ is the distance from the position at the ith time step to the desirable traffic-free reference path. In order to enhance time efficiency and avoid overspeed, velocity errors relative to the desirable traffic-free reference velocity are penalized as

$$
J_5\left[q_{t+1:t+T_p}\right] = \sum_{i=t+1}^{t+T_p} \left\| v_{\text{limit}} V\left(q_i\right) - \dot{q}_i \right\|^2,
$$

where $V(q_i)$ is the unit tangent vector of the reference path for q_i. After defining the five aspects above, we can express the cost function of the optimization as a weighted sum, that is,

$$
J\left[q_{t+1:t+T_p}\right] = \sum_{j=1}^{5} w_j J_j\left[q_{t+1:t+T_p}\right].
$$

In order to guarantee the feasibility of the planned trajectory according to the vehicle kinematics and dynamics, we constrain curvatures and accelerations of the vehicle. The curvature constraints can be written as

$$|\kappa_i| \leq \kappa_{\max}, \quad i = t+1, ..., t+T_p. \tag{1}$$

For dynamics constraints, [15] used a tire friction circle as the acceleration constraints, which is shown in Fig.3(a). Such constraints miss a key element of vehicle dynamics, which is the limitation of engine traction when accelerating the vehicle. In fact, maximum traction acceleration $a^+_{\max}$ is much smaller than the absolute value of maximum brake deceleration $a^-_{\max}$ typically. Therefore, a better approximation of the vehicle dynamics constraints is proposed in this paper, which is shown in Fig.3(b). In the forward-rearward direction, the maximum acceleration is $a^+_{\max}$, and the maximum deceleration is $a^-_{\max}$. Therefore, the radius of the acceleration circle is $r_a = \left(a^+_{\max} + a^-_{\max}\right)/2$, and the distance from the origin to the center of the circle is $c_a = \left(a^-_{\max} - a^+_{\max}\right)/2$. Then the acceleration constraint circles can be written as

$$\|\ddot{q}_i + c_a V\left(q_i\right)\|^2 \leq r_a^2, \quad i = t+1, ..., t+T_p. \tag{2}$$

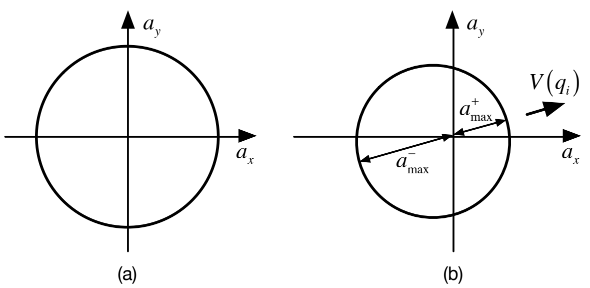


Fig. 3. Acceleration circles

Collision avoidance for moving and static obstacles is another aspect of hard constraints to consider in order to guarantee driving safety and traffic rule adherence. We will not dive into the details since it is not the core scope of this paper. Instead, we will only give a brief description here. We use the bounds of moving obstacles obtained in the Section II, as well as information on road structure and static obstacles to create lines for collision avoidance checking. A vehicle body can be represented into several circles, and the created lines are used to bound the centers of the circles. Therefore, the constraints can be expressed as

$$g_k\left[c_j\left(q_i\right)\right] \leq 0, \quad i = t+1, ..., t+T_p, j = 1, ..., n_{\text{cir}}, \tag{3}$$

where $c_j\left(q_i\right) = \left[x_{c_j(q_i)}\ y_{c_j(q_i)}\right]^T$ is the center of the jth circle at the ith time step, and $g_k\left[c\right]$ is a linear combination of x_c and y_c with bias representing the kth line created.

After defining all constraints and objectives, the planning problem in deterministic environments can be written as

$$\begin{aligned} \min_{q} \quad & J\left[q_{t+1:t+T_p}\right], \\ \text{s.t.} \quad & \text{Constraints (1)-(3).} \end{aligned}$$

B. Safety assessment under uncertainty

Safety is the top priority in autonomous driving, which should be guaranteed. However, conservative definitions of safety may lead to overcautious behaviors. In this paper, we exploit the feasibility of vehicle kinematics and dynamics to extend the safe set of an autonomous vehicle, so that NCDS can be achieved.

The definition of safety should contain current safety and preview safety. Current safety means that the current state is collision-free. Preview safety means that given the current state as the initial state, a sequence of motion exists, which is feasible and collision-free for a specific length of preview horizon T.

Suppose s_t is the current state of the autonomous vehicle, and $E \in \{\text{pass, yield}\}$ represents the case. We first define current safe set under each case, that is,

$$\mathcal{S}_E^{\text{curr}} = \left\{s_t \middle|\ q_t \text{ satisfies } (3)_E\right\},$$

where Constraints $(3)_E$ are the collision avoidance constraints constructed under the passing or yielding case. Next the preview safe set under each case is defined in terms of preview horizon T, that is,

$$\mathcal{S}_E^{\text{prev}}\left(T\right) = \left\{s_t \middle| \exists\ q_{t+1:t+T} \text{ s.t. } (1), (2), \text{ and } (3)_E\right\}.$$

Since the collision avoidance constraints do not need to be considered when the probability of the case goes to zero, the overall safe set in terms of T under each case can be written as

$$\mathcal{S}_E\left(T\right) = \begin{cases} \mathcal{S}_E^{\text{curr}} \cap \mathcal{S}_E^{\text{prev}}\left(T\right), & P\left(E\right) > 0 \\ \mathcal{U}, & P\left(E\right) = 0 \end{cases}$$

where $\mathcal{U}$ is the whole state space.

Finally, the overall safe set (zone) of the autonomous vehicle in terms of T can be defined as

$$\mathcal{S}\left(T\right) = \mathcal{S}_{\text{pass}}\left(T\right) \cap \mathcal{S}_{\text{yield}}\left(T\right).$$

Then $s_t \in \mathcal{S}\left(T\right)$ can be interpreted as that safety is guaranteed within the preview horizon T with state s_t.

C. Planning framework under uncertainty

Next we will illustrate how the probability of each case, namely $P\left(\text{pass}\right)$ and $P\left(\text{yield}\right)$, can be utilized in a unified trajectory planning framework under uncertainty so that NCDS can be achieved. In the receding horizon optimization framework, although the vehicle trajectory is planned in a relatively long preview horizon, the autonomous vehicle only executes the first (few) motion(s) planned. To be ready to deal with varying cases in the future, different long-term motions should be planned, but the short-term motion should be consistent for different future cases since the motion executed at the next time step should be determined.

Therefore, the following position vector is created, which contains short-term motion with horizon T_1, as well as long-term motions for each case with preview horizon T_p. The vector can be expressed as

$$q = \left[q^T_{t+1:t+T_1}, \left(q^{\text{pass}}_{t+T_1+1:t+T_p}\right)^T, \left(q^{\text{yield}}_{t+T_1+1:t+T_p}\right)^T\right]^T,$$

which is the position vector to be optimized in our planning framework under uncertainty. Then for each case the position vector for the whole preview horizon is

$$q_{t+1:t+T_p}^{E} = \left[q_{t+1:t+T_1}^{T}, \left(q_{t+T_1+1:t+T_p}^{E} \right)^{T} \right]^{T},$$

in which $E \in \{\text{pass, yield}\}$.

Then the optimization problem can be formulated as

$$\begin{aligned} \min_{q} \quad & \sum_{E \in \{\text{pass, yield}\}} P(E)\, J\left[q_{t+1:t+T_p}^{E} \right] \\ \text{s.t.} \quad & (1) \text{ and } (2) \text{ for } q_{t+1:t+T_p}^{E},\ \forall E \in \{\text{pass, yield}\}, \\ & (3)_E \text{ for } q_{t+1:t+T_p}^{E},\ \forall E \in \{\text{pass, yield}\}. \end{aligned}$$

to minimize the expected cost. The position vector for each case should satisfy feasibility constraints, as well as the collision avoidance constraints for each case, respectively.

It can be easily proved that with preview horizon T_p, by executing the next position vector q_{t+1} obtained, the state of next time step is in the safe set with $T_p - 1$ preview horizon, that is,

$$s_{t+1} \in \mathcal{S}(T_p - 1).$$

Therefore, the driving strategy based on the proposed planning framework is defensive if potential threats exist.

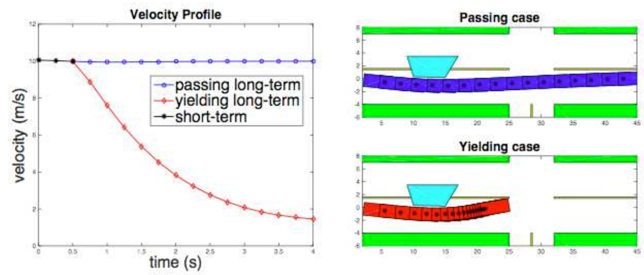
Moreover, the driving strategy will not overreact to potential threats with low probability since the cost for yielding case $J\left[q_{t+1:t+T_p}^{\text{yield}} \right]$ only minimally influence the total cost. In fact, the long-term motions under each case are voting as part of the cost function to decide the short-term motion to execute at the next time step. The voting outcome depends on the probability of each case. Decision-making is incorporated in the planning framework, and the final decision is not made immediately until it needs to be. This is the reason why the strategy is not conservative.

IV. Illustrative Examples

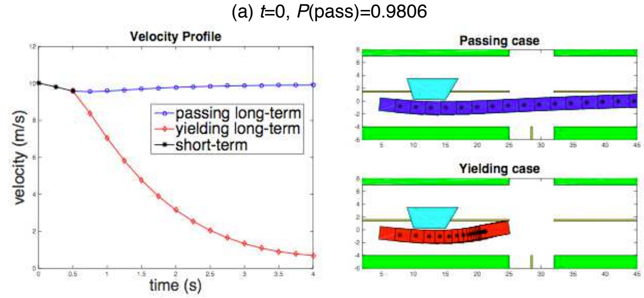
In this section, examples are shown to illustrate the capability of the proposed planning framework to achieve NCDS. We used the two-way-stop scenario in Fig.1 to show how the probabilistic threats were handled. The logistic regression model described in Section II B and trained by the empirical data was used to obtain $P(\text{pass})$ and $P(\text{yield})$, which was updated at every time step. We also created static obstacles invading the travel lane of the host vehicle to test the collision avoidance capability and smoothness with lateral motions.

The sampling time of the receding horizon optimization is $h = 0.25$ s. The horizon of planning at each time step is $T_p = 4$ s. The short-term horizon is $T_1 = 0.5$ s. Rectangle was used to represent the vehicle body. $v_{\text{limit}} = 10$ m/s, $\kappa_{\max} = 0.2$ m^{-1}, $a_{\max}^{+} = 4$ m/s^2 and $a_{\max}^{-} = 8$ m/s^2.

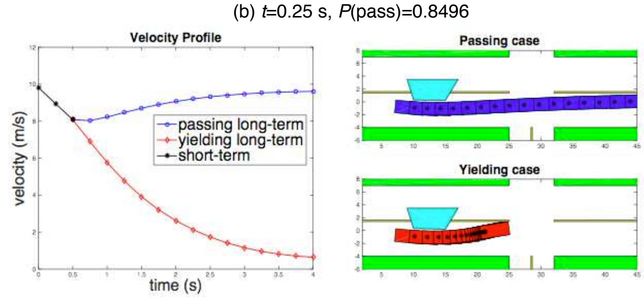
First a sequence of violation motions in our dataset was used to test the defensive capability of the planning framework and corresponding results are shown in Fig.4. When the violating vehicle was relatively far away from the stop bar, $P(\text{pass})$ was still as high as 0.9806. However, as the distance becomes smaller but the velocity was still high and there was hardly any deceleration, $P(\text{pass})$ went down rapidly at each sample point as $[0.8496, 0.3801, 0.0594, 0.0049, 0.0003, 0, 0, ...]$. The planned motions and velocity profiles at the first four time steps are shown in Fig.4 with corresponding timestamps and probabilities. The final executed motions and velocity profiles are shown in Fig.6(a).



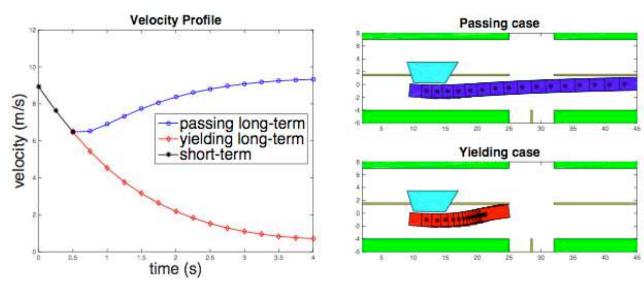
(a) t=0, P(pass)=0.9806



(b) t=0.25 s, P(pass)=0.8496



(c) t=0.5 s, P(pass)=0.3801

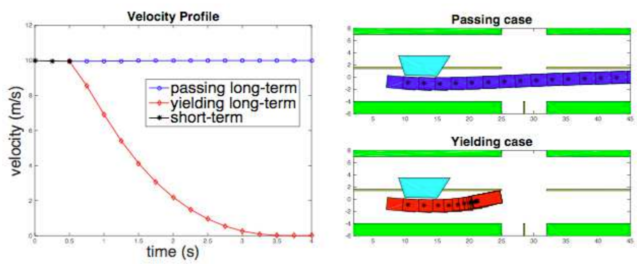


(d) t=0.75 s, P(pass)=0.0594

Fig. 4. Planned motions and velocity profiles at the first four time steps under yield case

The results proved several aspects of capabilities of the planning framework. First, the trajectory was very smooth even with lateral motions, and the speed did not exceed the speed limit. Also, collision avoidance and feasibility were guaranteed within the preview horizon. Moreover, the vehicle tried to keep at the center of its lane.

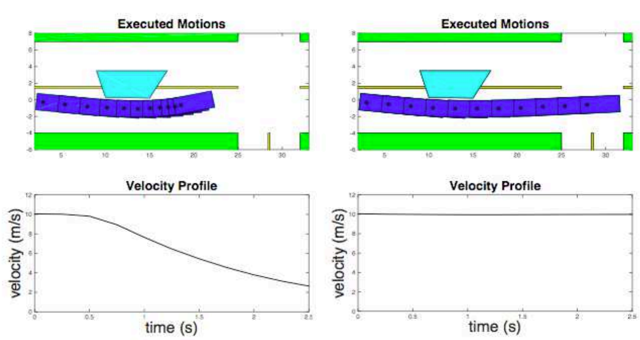
By comparing the planning results with different probabilities, we can explain the principle of our planning framework intuitively. In the velocity profiles, the black lines are the short-term motions which will be executed for the next time step. The blue line represents the long-term motion under the passing case and the red line corresponds to the yielding case. When $P\,(\text{pass})$ is close to 1, the planner tends to keep the current speed which increases the cost under the yielding case. When $P\,(\text{pass})$ becomes smaller, the planner tends to slow down and the deceleration is higher which increases the cost under the passing case.



t=0.5 s, *P*(pass)=0.9992

Fig. 5. Planned motions and velocity profiles at one step under pass case

Next a sequence of stop motions in our dataset was used to test the non-conservative capability of the planning framework. The probabilities at sample points were $[0.9696, 0.9992, 0.9999, 0.9998, 1, 1, ...]$. When the vehicle was relatively far away from the stop bar, the high speed made $P\,(\text{pass})$ a little smaller than 1, which imitated the threat with low probability. As it started to decelerate, the probability went to 1. The planned motions and velocity profiles at one step are shown in Fig.5. with corresponding timestamp and probability. The final executed motions and velocity profiles are shown in Fig.6(b). In the results we can see that the potential threat with very low probabilities does not influence the speed of the vehicle meaningfully, which makes the strategy non-conservative. However, safety is always guaranteed since the long-term motion under yielding case ensures safety at each time step.



(a) Yielding case (b) Passing case

Fig. 6. Executed motions under each case

V. Conclusion

A unified planning framework under uncertainty was proposed in this paper for urban autonomous driving, which can achieve NCDS for various kinds of scenarios. Based on the deterministic planner designed, as well as the probability under each possible case obtained by behavioral modelling, trajectories were planned to avoid overcautious behavior and to guarantee safety via defensive behavior. Two-way-stop intersection was used as an exemplar scenario to show the capabilities of the proposed planning framework. The results demonstrated that based on the proposed planner, the autonomous vehicle can guarantee safety even when others are violating traffic rules, and the host vehicle does not overreact to threats with low probabilities. For future studies, various urban driving scenarios will be used to test the capabilities of the proposed planning framework to achieve a driving strategy which is defensive, but not overly conservative.

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