Toward Safe, Feasible and Human-Like Motion Generation for Urban Autonomous Driving

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Abstract

Motion prediction and motion planning problems are deeply interconnected for urban autonomous driving. In this project, we target the problem of safe, feasible and human-like motion generation. A non-conservatively defensive strategy (NCDS) is proposed, which is defensive under the worst case to guarantee safety, but not conservative so as to degrade driving quality and generate behaviors which are not human-like. A planning framework based on NCDS is constructed, which generates desirable tentative actions by incorporating decision-making and planning in a variety of challenging urban driving scenarios. Also, a prediction framework based on NCDS is proposed, which can obtain most possible future motions of others under each intention, and the intention probabilities without training a behavioral model with collected data. Preliminary results of safe and feasible motion generation via deep net are also illustrated in the report.

1 Overview

Motion prediction of other vehicles and motion planning of the host vehicle are closely related to each other. Motion prediction is a stochastic version of motion planning, and the mechanism of motion planning should be considered to predict the motion of others. Correspondingly, motion planning is to choose the best among motions predicted by others, and how others expect the motion of the host vehicle should be considered. Due to the inherent connection of prediction and planning, we handle the two problems together as motion generation. Motions generated by prediction and planning should be 1) safe to avoid collisions, 2) feasible according to the vehicle kinematics and dynamics, and 3) human-like to be not overly conservative to enhance driving quality. In order to achieve safe, feasible and human-like motion generation, a non-conservatively defensive strategy (NCDS) is proposed. It is a driving strategy which is defensive under the worst case to guarantee safety, but is not conservative so as to degrade driving quality. NCDS can be applied to decision-making and motion planning, as well as intention recognition and motion prediction.

When NCDS is applied to decision-making and planning, a unified planning framework under uncertainty can be constructed in various kinds of urban driving scenarios. In the planning framework, feasibility and safety are guaranteed by providing the limits steering angle, tire friction and engine traction, as well as by checking collisions under the worst case, such as violations or aggressive behaviors of others. However, overly conservative actions are avoided by exploiting the probabilities of possible intentions of others to form an expected cost, which comprehensively considers time-efficiency, comfort, road structure and traffic rules under each case. The probabilities are obtained by behavioral models trained by real world motion data.

In practical, we cannot collect large amounts of motion data and training behavioral models for all scenarios which might be encountered by autonomous vehicles. An intention recognition and motion prediction framework is required to handle uncommon scenarios so that probabilities and most possible predicted motion of each possible intention of others can be obtained. The NCDS we proposed can also be used to approximate the intention probability and predict most possible motion without training behavioral model with motion data.
Motions generated by NCDS are human-like with guarantee on safety and feasibility. Our ongoing exploration is to obtain the driving policy of human drivers via incorporating the domain knowledge and mechanism we have already know, with powerful representation capabilities of deep net, to generate safe, feasible and human-like motions. We train the policy net with an evaluation function which includes the cost function of the proposed planner with receding horizon optimization, as well as barrier functions containing constrains for safety and feasibility.

2 Planning framework based on NCDS

In this section, we will illustrate our concept of NCDS by using a two-way-stop intersection as an exemplar scenario (shown in Figure 1(a)). The more detailed mathematical derivation and technical approaches, which cover a variety of scenarios, have been documented in a paper to appear in IEEE ITSC 2016:


![Figure 1: (a) A two-way-stop intersection. (b) Motion data collection at a stop-sign intersection. (c) Visualized 3D training data.](image)

In Figure 1(a), the autonomous vehicle V1 (red car) holds the right of way, and the vehicle V2 approaching the stop sign (orange car) should stop. We model the behavior of V2 to calculate the stop-sign violation probability via a logistic regression model trained by data visualized in Figure 1(c). This data set was collected by a field observation experiment by monitoring the movements of vehicles as they approached a stop sign (shown in Figure 1(b)). As shown in Figure 1(c), there were a sequence of cases with the approaching vehicle violating or stopping for the stop sign. A logistic regression analysis led to an empirical data of the probability of stop-sign violation. P(pass) denotes the probability that V2 will not violate and V1 can pass. When V2 was relatively far away from the stop bar, P(pass) was still as high as 0.9806. However, as the distance of V2 to the stop line becomes smaller but the velocity of V2 was still high and there was hardly any deceleration, P(pass) went down rapidly at each sample point as \([0.8496, 0.3801, 0.0594, 0.0049, 0.0003, 0, 0, \ldots]\).

To further illustrate the outcome of trajectory planning of the autonomous vehicle, we devise a driving scenario to show the evolution of planned motions as V1 moves toward an intersection. In this scenario, a static obstacle partially blocking the travel lane of V1 was added, as shown in Figure 2. V1 not only needs to take into account the task of collision avoidance as it moves into the intersection, it also must steer clear of and go around the static obstacle. The planned motions and velocity profiles at the first four time steps are shown in subplots (a) to (d) of in Figure 2 with corresponding timestamps and probabilities.

1This section presents a joint work with contributions from Changliu Liu and Ching-Yao Chan.
The results proved several aspects of capabilities of the planning framework. First, the trajectory was very smooth even with lateral motions to steer clear of the static obstacle, and the speed did not exceed the speed limit. Additionally, 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, the principle of the NCDS can be understood 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. 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 verifies safety at each time step, which renders the strategy defensive.

Next, an extreme case was used to push the vehicle to the limit of its dynamics to show the effectiveness of the acceleration circle designed to constrain dynamics. In this case, the field of view of the autonomous vehicle was limited by parked vehicles near the intersection. Hence, it could not see a violating vehicle approaching the intersection with high speed. When the autonomous vehicle entered the intersection, it detected the violating vehicle. In Figure 3, we define the

![Velocity Profile and Motion Diagram](image-url)

**Figure 2:** Planned motions and velocity profiles at the first four time steps under yield case

**Figure 3:** Motions and velocity profile to avoid being crashed by a violating vehicle with high speed.
time instant at $t = 0$ when the autonomous vehicle was able to react to the violating vehicle. Based on the worst possible motion predicted, the autonomous vehicle had to leave the intersection before $t = 1$ s, or it will be impacted on its side by the violating vehicle. To make the maneuver of the autonomous vehicle more complicated, a parked van was placed at the far side of the intersection and another static obstacle partially blocked the lane, as shown in Figure 3.

The planning results are illustrated in Figure 3. In this situation, the autonomous vehicle had to speed up to avoid the collision. From the velocity profile, we can see that the autonomous vehicle succeeded to avoid all possible collisions and the planned trajectory was feasible. At the fourth time step in the planned motion, which corresponded to $t = 1$ s, the rear end of the vehicle was out of the intersection region. Also, the slope of the velocity profile during acceleration was approximately $4 \text{ m/s}^2$, and that during deceleration was approximately $-8 \text{ m/s}^2$, both of which were bounded as what we set for the planning framework.

3 Prediction framework based on NCDS

As is shown in the previous section, NCDS can be applied to a decision-making and planning framework to find desirable motion of the next step given intention probabilities and current motion. It is also possible to apply NCDS to find intention probabilities given the motions of the current and previous step of others, to construct a intention recognition and motion prediction framework without training a behavioral model with large amounts of data.

We use an exemplar scenario shown in Figure 4(a) to illustrate the concept, in which a target vehicle is cutting-in from street parking. The target vehicle may keep accelerating to force the host vehicle to decelerate, or it may stop soon if the driver sees the host vehicle is approaching with relatively high speed. We assume that the host autonomous vehicle has never been trained with any model which can obtain the intention probability of the target vehicle in such scenario. Figure 4(b) shows the real motion of the target vehicle. The acceleration was fairly aggressive and finally it stopped. In the following we will show how to obtain the intention probabilities and predict possible future motions of the target vehicle via NCDS.

![Figure 4: (a) A scenario with cutting-in vehicle from street parking. (b) Real motion of the target vehicle](image)

The most possible future motions of each possible case can be predicted by the deterministic planner. Desirable driving qualities are achieved with the prerequisite that feasibility and obstacle avoidance for the specific case are guaranteed. The results are shown in Figure 5. Next we will show how intention probabilities are obtained via NCDS.

We assume that the human driver in the target vehicle is executing NCDS. The motion of the target vehicle at each time step can be regarded as the desirable tentative action planned by the human driver from the previous time step. By executing the current desirable tentative action, for each case, distances can be formed between the optimal trajectory given the current motion and the optimal trajectory given the previous motion. Therefore, the probabilities in the mind of
the human driver, which form the expected cost to obtain the current motion of the target vehicle, can be reflected by the relative magnitude of the distances for each case.

As is shown in Figure 6(a), the acceleration is relatively aggressive, and the distances between the predicted motion given the current motion \((t = 0.25 \text{ s})\) and the predicted motion given the previous motion \((t = 0)\) are equally small. Hence, the probabilities of each intention are as equal. Then the distance for the going case becomes relatively larger than that for the stopping case, and the probability of the stopping case becomes higher correspondingly (shown in Figure 6(b-d)).

Comparing to the computation of NCDS for planning, that of NCDS for prediction can be much less since 1) the preview horizon can be shorter, 2) the optimization is for each deterministic case, and 3) the optimal prediction of the previous step can be used recursively.

### 4 Safe and feasible motion generation via deep net

We used a lot of domain knowledge in the design of planning and prediction framework based on NCDS. Still, there were lots of hand designs on representing the world model and motions of each objects. Our ongoing work is to incorporate

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2This section presents a joint work with contributions from Jiachen Li and Yeping Hu.
powerful representation capability of deep net with the domain knowledge we have to generate motions which is safe, feasible and human-like. With the proposed planning and prediction framework based on NCDS, we also get a good infrastructure to simulate vehicle motions and training the deep net.

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\begin{align*}
\text{min } & f_0(x) \text{ (driving cost)} \\
\text{s.t. } & f_i(x) \leq 0, i = 1, \ldots, n \text{ (safety and feasibility)} \\
\end{align*}
\]

Figure 7: (a) Architecture of supervised learning with optimal planner. (b) Architecture of our training

An intuitive idea is supervised learning (shown in Figure 7(a)), that is, to use an optimal planner to generate expert motions and minimize the evaluation function with \( L_2 \) norm. However, using \( L_2 \) norm as the training evaluation cannot guarantee safety and feasibility, which is the prerequisite of the motion generation. For constrained optimization, people may use a differentiable barrier function to construct an unconstrained optimization. We are trying to use the cost function with differentiable barrier functions to incorporate the domain knowledge in the optimal planner (in Figure 7(b)), to train our neural net approximate the performance of the optimal planner and not to output motions which are infeasible or unsafe.

We first used a simple intersection scenario (shown in Figure 8(a)) to show some preliminary results. We used a two-layer fully connected net to generate a sequence of one-dimensional positions of the vehicle within the preview horizon. The input of the net is the current position, velocity, acceleration and time for the target vehicle to leave the conflict region. We penalize longitudinal acceleration and jerk, as well as difference to the speed limit. Acceleration is bounded to guarantee feasibility and the host vehicle cannot enter the conflict region until the target vehicle leaves.

After training, we randomly generate a set of input within a specified range, and plot the position, velocity, acceleration and jerk with the output sequence (in Figure 8(b)). As is shown in the results, the safety and feasibility constraints are satisfied. The target vehicle left the conflict region when \( t = 7 \), and the host vehicle did not pass the point \( x = 0 \) until \( t \geq 7 \). The acceleration had saturation at \( 4 \text{ m/s}^2 \), which was set in the constraints. Also, the neural net can generate smooth motion since acceleration and jerk are penalized. The vehicle tends to accelerate since low speed is penalized.
The proposed approach is not successful all the time, and we may encounter problems such as dead reLU and gradient explosion. We are still on the way to explore and update the approach. Also, note that this is just a toy example to test the idea. A quadratic programming (QP) solver is enough to solve the problem in real time, and we do not need to employ a deep net. The approach will be extended to two-dimensional motions of the vehicle with complicated scenarios, where deep net may possibly be needed.