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Joint Decision Making and Motion Planning for Road Vehicles Using Particle Filtering

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Abstract: This paper describes a probabilistic framework for real-time, joint decision making and trajectory generation of road vehicles. The selection of desired lane and state profile is posed as a stochastic nonlinear estimation problem. The nonlinear estimator is integrated with a sampling-based motion planner that computes candidate paths and corresponding state trajectories, while accounting for obstacle motion. The motion planner is implemented in receding horizon and repeatedly replans, based on stored candidate trajectories. A simulated autonomous highway-driving example illustrates how vehicle dynamics is naturally handled in the framework. The results show that the framework is capable of making effective online decisions and computing safe trajectories.

Keywords: path planning, trajectory planning, vehicle dynamics, optimal estimation

1. INTRODUCTION

Decision making and motion planning are two key components for future generations of advanced driver-assistance systems (ADAS). Based on driver desires and current and predicted information, decision making concerns selecting the desired lane and velocity profile. In semi-autonomous mode, decision making can also include decisions about whether to assist the driver or take control over the car. Motion planning, on the other hand, addresses generation of suitable trajectories. Decision making and planning is sometimes modeled separately, but can also be considered jointly (Carvalho et al., 2015). In recent literature, model-predictive control (MPC) is a popular choice (Di Cairano et al., 2013; Carvalho et al., 2015; Ali et al., 2013) for designing ADAS, because it naturally provides a framework for performing joint decision making and trajectory generation. However, MPC is not a stand-alone component for solving the motion-planning problem, since it typically requires a precomputed reference trajectory.

Sampling-based methods, such as rapidly exploring random trees (RRTs) (LaValle, 2006; Karaman and Frazzoli, 2011), are popular and reliable methods for path planning in robotic applications, because they guarantee to provide a path whenever it exists. Traditional RRTs rely on random sampling of the state space. Each generated sample is checked for collision, typically assuming a static environment; if the sample location is collision free, it is added as a node, and collision-free connections are made to surrounding nodes for tree expansion. However, to include dynamics, or even kinematics, is nontrivial. Despite this, sampling-based approaches have been successfully used for motion planning of automotive systems in some cases, both in simulation and experiment. In (Hwan Jeon et al., 2013), time-optimal minimization of a hairpin turn was considered. Full-scale field tests for an online RRT have been performed in (Kuwata et al., 2009). There, an input-based RRT that samples position references to a tracking controller was developed. The method uses the tracking controller to connect position references to each other, thereby generating drivable paths between points. In (Arslan et al., 2016), the approach in (Kuwata et al., 2009) was extended to optimal motion planning.

In this paper, we propose a sampling-based, probabilistic framework for joint decision making and motion planning applied to road vehicles. RRTs are commonly used as path planners by generating samples such that the state space is covered uniformly, and do not include decision making. Our motion planner is entirely simulation based and complex vehicle dynamics is therefore naturally included, unlike most other sampling-based approaches. Here, the vehicle dynamics is modeled using a nonlinear single-track chassis model that incorporates combined-force modeling, seven states in total. Commonly, sampling-based planners generate random states and then connect these through approximate solutions to two-point boundary value problems, which is computationally prohibitive in automotive applications. In contrast, the proposed planner generates random inputs. This reduces the search space from the dimension of the state space to the dimension of the input space (i.e., from seven to two for the considered model), simplifying real-time implementation. In addition, our approach includes decision making in the planner already in the sampling phase. The input samples are guided to distinct lanes and velocity sets using particle filtering (Doucet et al., 2001; Gustafsson, 2010). This can be seen as a de-randomizing step. The proposed planner computes several sets of trajectories that can be used for decision making. Our approach draws inspiration from (Gustafsson et al., 2012; Eidehall and Petersson, 2008), where sequential Monte Carlo is used for threat assessment. This paper extends the application domain of sequential Monte Carlo to motion planning of road vehicles. The approach is explained and demonstrated using a simulated highway-driving example in different scenarios, such as overtaking of vehicles and in case of obstructed lanes.

2. VEHICLE MODELING

The model used in the motion planning is a nonlinear single-track model with lumped right and left wheels; for more model details, see (Berntorp, 2014). Fig. 1 shows the notation and

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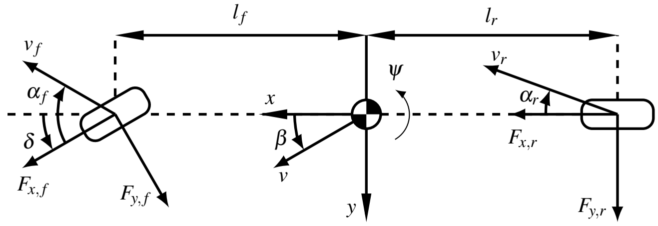

Fig. 1. Notation and geometry of the single-track chassis model used in the motion planning.

geometry. The chassis model has three degrees of freedom, two translational and one rotational:

$$\begin{aligned} \dot{v}_X - v_Y\dot{\psi} &= \frac{1}{m}(F_{x,f}\cos(\delta) + F_{x,r} - F_{y,f}\sin(\delta)), \\ \dot{v}_Y + v_X\dot{\psi} &= \frac{1}{m}(F_{y,f}\cos(\delta) + F_{y,r} + F_{x,f}\sin(\delta)), \\ I_{zz}\ddot{\psi} &= l_fF_{y,f}\cos(\delta) - l_rF_{y,r} + l_fF_{x,f}\sin(\delta), \end{aligned} \tag{1}$$

where m is the vehicle mass; I_{zz} is the vehicle inertia about the z-axis; $\dot{\psi}$ is the yaw rate; δ is the steer angle; v_x, v_y are the longitudinal and lateral velocities at the center of mass; l_f, l_r are the distances from the center of mass to the front and rear wheel base; and $\{F_{x,i}, F_{y,i}\}_{i=f,r}$ are the longitudinal and lateral tire forces acting at the front and rear wheels, respectively.

Slip angles α_f, α_r are introduced following (Pacejka, 2006) and are described by

$$\alpha_f := \delta - \arctan\left(\frac{v_y + l_f\dot{\psi}}{v_x}\right), \tag{2}$$

$$\alpha_r := -\arctan\left(\frac{v_y - l_r\dot{\psi}}{v_x}\right). \tag{3}$$

The lateral nominal tire forces—that is, the forces under pure slip conditions—are computed with a simplified Magic-Formula model (Pacejka, 2006),

$$\begin{aligned} F_{y,i}^0 = \mu_{y,i}F_{z,i}\sin\Big(C_{y,i}\arctan\big(B_{y,i}\alpha_i \\ - E_{y,i}(B_{y,i}\alpha_i - \arctan(B_{y,i}\alpha_i))\big)\Big), \end{aligned} \tag{4}$$

$$F_{z,i} = mg(l - l_i)/l, \ i = f, r, \text{ where } l = l_f + l_r. \tag{5}$$

The simplification in (4) lies in that since a single-track model is used, the tire models are assumed symmetric in α_i. Furthermore, μ denotes the friction coefficient and B, C, and E are model parameters. Combined slip is modeled using the friction-ellipse concept:

$$F_{y,i} = F_{y,i}^0\sqrt{1 - \left(\frac{F_{x,i}}{\mu_{x,i}F_{z,i}}\right)^2}, \tag{6}$$

where $F_{y,i}^0$ is computed using (4), given the longitudinal force.

There are different options for choosing inputs to the vehicle model. Here, we have opted for using the steer rate $\dot{\delta}$ and longitudinal acceleration a_x as inputs. The choice of steer rate and acceleration implies that the resulting steer angle and velocity are continuous. Furthermore, it is straightforward to impose constraints on the inputs in the sampling phase with this choice of inputs, ensuring that the computed trajectories provide a smooth and safe ride. We model the steer dynamics as an integrator, but it is straightforward to include more complex dynamics. The acceleration is translated to longitudinal forces by assuming that the front and rear wheel axle provide longitudinal forces that are proportional to the length from the respective center of mass, that is,

$$F_{x,f} = ma_xl_r/l, \quad F_{x,r} = ma_xl_f/l.$$

Thus, the total number of states are

$$x = \begin{bmatrix} X & Y & \psi & \dot{\psi} & v_x & v_y & \delta \end{bmatrix}^{\mathrm{T}}, \tag{7}$$

where the Cartesian positions X and Y relate to the mass center in the vehicle frame as

$$\begin{aligned} \dot{X} &= v_x\cos(\psi) - v_y\sin(\psi), \\ \dot{Y} &= v_x\sin(\psi) + v_y\cos(\psi), \end{aligned}$$

and the inputs are

$$u = \begin{bmatrix} a_x & \dot{\delta} \end{bmatrix}^{\mathrm{T}}. \tag{8}$$

In the following, we will compactly write (1)–(8) as

$$\dot{x} = f(x, u). \tag{9}$$

There are sources of uncertainty in this model. Mass and tire parameters are not exactly known and inputs are uncertain. However, the range of these uncertainties can typically be specified; for example, the inputs are bounded by their allowed ranges and it is more likely that the inputs are close to zero than saturating for normal driving. The uncertainties are therefore modeled by introducing stochastic process noise w acting on the inputs and states. Standard choices for noise distributions are Gaussian or uniform distributions. Other examples are given in (Gustafsson et al., 2012; Eidehall and Petersson, 2008).

3. JOINT DECISION MAKING AND TRAJECTORY GENERATION

Many sampling-based path planners find geometric paths based on a snapshot of the environment and are applicable in quite general scenarios (LaValle, 2006). However, they often ignore the equations of motion. For automotive systems, the vehicle dynamics significantly restricts the reachable set and should therefore be accounted for. An approach to incorporate equations of motion is to sample inputs and propagate through the system model (Hsu et al., 2002; Frazzoli et al., 2002). While this often works well, it can be very inefficient in certain scenarios, because it does not utilize structure in the motion-planning problem.

3.1 Task Specification

In many motion-planning problems there are certain specifications that should be fulfilled. In RRT, specifications are handled by appropriate choice of cost function, evaluated among all feasible paths. This can lead to inefficiency and poor performance in certain applications. While specifications on path level can be accounted for, it is hard to incorporate specifications on general variables while preserving convergence guarantees. In our approach, we model specifications as probabilistic constraints on the allowed motion and therefore only generate samples that are consistent with the specifications. To exemplify, when considering vehicle motion planning, possible specifications are:

- Stay on the road
- Maintain a desired velocity profile
- Drive smoothly, that is, prioritize small steer rates
- Keep safety distance to surrounding obstacles

Specifications are modeled as constraints by introducing them as desired outputs y_d as functions of the states,

$$y_d = h(x). \tag{10}$$