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Receding horizon maneuver generation for automated highway driving

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ABSTRACT

This paper focuses on the problem of decision-making and control in an autonomous driving application for highways. By considering the decision-making and control problem as an obstacle avoidance path planning problem, the paper proposes a novel approach to path planning, which exploits the structured environment of one-way roads. As such, the obstacle avoidance path planning problem is formulated as a convex optimization problem within a receding horizon control framework, as the minimization of the deviation from a desired velocity and lane, subject to a set of constraints introduced to avoid collision with surrounding vehicles, stay within the road boundaries, and abide the physical limitations of the vehicle dynamics. The ability of the proposed approach to generate appropriate traffic dependent maneuvers is demonstrated in simulations concerning traffic scenarios on a two-lane, one-way road with one and two surrounding vehicles.

1. Introduction

Besides increasing transport efficiency and driver convenience, automated driving is expected to enhance traffic safety. On highways, a high percentage of traffic accidents and fatalities is caused by human errors in lane change and overtake maneuvers (van Schijndel et al., 2011). Advanced Driver Assistance Systems (ADAS) such as Adaptive Cruise Control (ACC) and collision warning with auto brake have been shown to have a positive impact on traffic safety (Neale et al., 2005). Thus, the introduction of fully automated systems, capable of safely and autonomously performing lane change and overtake maneuvers on highways, is expected to further contribute to increase traffic safety.

Highways are structured environments with relatively simple and easily maintainable traffic rules. As such, the driving task is quite straightforward, i.e. maintaining a desired velocity while avoiding collision conflicts with surrounding vehicles, and respecting the traffic rules. Hence, in this paper the problem of determining how a vehicle should behave with respect to surrounding vehicles on highways is stated as an obstacle avoidance path planning problem. Several approaches to path planning with obstacle avoidance have been proposed where the most common include, but are not limited to, grid/graph-based methods e.g. Astar and Dstar (Ferguson, Likhachev, & Stentz, 2005; Ziegler, Werling, & Schröder, 2008), randomized sampling-based methods e.g. Rapidly exploring Random Trees (RRTs) (Karaman & Frazzoli, 2011; Kuwata et al., 2008), Artificial Potential Fields (APFs) (Khatib, 1986), and cost- and utility-based functions (Wei, Dolan, & Litkouhi, 2010; Wang, Yang, & Yang, 2009).

In grid/graph-based and randomized sampling-based methods, the state space is divided into grid cells or graph nodes which can be assigned obstacle and goal dependent costs, thus allowing the path planning algorithms to find collision free paths by exploring the grid map or graph tree. However, the algorithms can require significant computer resources since the number of grid cells or graph nodes grows exponentially with the dimension of the state space. Moreover, optimality guarantees of these algorithms are only ensured up to the grid/graph resolution.

The general idea of APFs for path planning is to consider the vehicle as a particle moving in a force field where obstacles generate repulsive artificial potentials while goal locations are represented as attractive potentials. Despite the method's popularity, APFs do have several drawbacks, including local minima and oscillatory behavior. Many of the successful applications are therefore restricted to environments where objects move at relatively low velocities, where the path planning is performed in order to achieve some well-defined motion task, or where the APF is used as a mean of reacting to unexpected obstacles.

Similar to APFs, cost- and utility-based functions are commonly used due to their straightforwardness and simplicity. By e.g. adding a cost term that increases when obstacles are in close proximity, collision free paths can be determined. However, these types of cost functions and constraints are normally non-linear and/or non-convex, thus providing no guarantee of generating an optimal solution. Further, utility- and cost-based approaches do not normally include

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a search through the configuration space but rather use the cost functions or constraints as a mean of determining which maneuver to perform within a limited set of predefined paths.

Although the above mentioned approaches for path planning with obstacle avoidance do provide good results in a number of applications, they also come with various drawbacks where the main is the trade-off between required computational resources and solution optimality. Further, many of the commonly used obstacle avoidance path planning methods lack formal stability analysis and verification methods and thereby rely heavily on extensive simulation testing. It is therefore desirable to formulate the obstacle avoidance path planning problem as a low complexity problem within a framework where stability analysis and verification tools exists.

In this paper, the obstacle avoidance path planning problem is formulated as a Model Predictive Control (MPC) problem (Mayne et al., 2000). In the MPC path planning framework, a path is found as the solution of a constrained optimal control problem over a finite time horizon. In particular, a cost function is minimized subject to a set of constraints including the vehicle dynamics, design and physical constraints, and additional constraints introduced to avoid collision with surrounding vehicles. The constrained optimal control problem is solved in receding horizon, i.e. at every time step the problem is formulated over a shifted time horizon based on new available sensor measurement information. The main advantage of resorting to such a formulation is that collision avoidance is guaranteed, provided that the optimization problem is feasible. However, collision avoidance constraints generally result in mixed-integer inequalities (Borrelli et al., 2006), which may lead to prohibitive computational complexity that prevents the real-time execution of the path planning algorithm (Wei, Zefran, & DeCarlo, 2008). A particular optimal control path planning algorithm is therefore generally tailored to a certain traffic situation or maneuver (e.g. Attia et al., 2012; Daniel et al., 2011).

To accommodate both collision avoidance constraint satisfaction and low computational complexity, in this paper, the collision avoidance constraints are formulated as affine combinations of the vehicle states and inputs. By exploiting the highway structure, two methods that affinely express the collision avoidance constraints are presented. Thus, the need of mixed-integer inequalities is eliminated and the resulting optimization problem is a standard convex Quadratic Program (QP) that can be solved in real-time by using efficient solvers (e.g. Mattingley & Boyd, 2012). The general idea behind the affine formulation of the collision avoidance constraints was first introduced in Nilsson et al. (2013), and the proposed approach has been shown to produce paths which can be tracked by a four-wheel vehicle model in real-time in Nilsson et al. (2014). This paper extends the results presented in Nilsson et al. (2013, 2014) by providing further details regarding the affine formulation of the collision avoidance constraints and by applying the MPC path planning algorithm to more complex traffic situations involving two surrounding vehicles.

The remainder of the paper is organized as follows: in Section 2 the standard MPC problem formulation is introduced, while Section 3 presents the considered obstacle avoidance path planning problem. Section 4 describes the vehicle dynamics model, and the physical and design constraints to which it is subjected. In Section 5 the affine formulation of the collision avoidance constraints is introduced, and the MPC path planning problem is formulated. Simulation results are presented in Section 6, and conclusions are stated in Section 7.

2. Preliminaries

Consider the linear, time-invariant, discrete time system

$$x_{t+1} = Ax_t + Bu_t, \tag{1}$$

where

$$x \in \mathcal{X} \subseteq \mathbb{R}^n, \quad u \in \mathcal{U} \subseteq \mathbb{R}^m, \tag{2}$$

are the state and input vectors respectively, and $\mathcal{X}$ and $\mathcal{U}$ are polytopes containing the origin. Without loss of generality, assume that the control objective is to control the state of system (1) to the origin, while fulfilling the state and input constraints (2).

Consider the following cost function:

$$J(x_t, \mathcal{U}_t) = \|x_{t+N}\|_P^2 + \sum_{k=0}^{N-1} \|x_{t+k}\|_Q^2 + \|u_{t+k}\|_R^2, \tag{3}$$

where $\mathcal{U}_t \triangleq [u_t^T, \dots, u_{t+N-1}^T]^T$, $\|x\|_Q^2 \triangleq x^T Q x$ denotes the weighted, squared 2-norm, $N \in \mathbb{N}^+$ is a finite, discrete time horizon called *the prediction horizon* and $P \in \mathbb{R}^{n\times n}, Q \in \mathbb{R}^{n\times n}, R \in \mathbb{R}^{m\times m}$ are weighting matrices. In MPC, at every time instant t, the following finite time, constrained optimal control problem is formulated and solved:

$$\min_{\mathcal{U}_t} J(x_t, \mathcal{U}_t) \tag{4a}$$

subject to

$$x_{t+k+1} = Ax_{t+k} + Bu_{t+k}, \tag{4b}$$

$$x_{t+k} \in \mathcal{X}, \quad k = 0, \dots, N, \tag{4c}$$

$$u_{t+k} \in \mathcal{U}, \quad k = 0, \dots, N-1, \tag{4d}$$

and the control input is the state feedback law $u^*(x_t)$ obtained from the first element of the solution $\mathcal{U}_t^*$ to the problem (4). The problem (4) is solved in *receding horizon*, i.e. every time instant the problem (4) is formulated and solved based on the current state x_t, over a shifted time horizon. If the sets $\mathcal{X}$ and $\mathcal{U}$ in (4c)–(4d) are convex, then the MPC problem (4) can be equivalently rewritten as a standard QP problem

$$\min_{\mathcal{U}_t} J = \tfrac{1}{2} w^T H w + d^T w \tag{5a}$$

subject to

$$H_{in} w \le K_{in}, \tag{5b}$$

$$H_{eq} w = K_{eq}, \tag{5c}$$

with $w \triangleq [\mathcal{U}_t, x_t^T, \dots, x_{t+N}^T]^T$. The QP problem (5) is convex if the matrix H is symmetric and positive semi-definite.

3. Problem statement

The problem of autonomous highway driving is considered as the problem of controlling the motion of the ego vehicle, E, in order to maintain a desired velocity while avoiding collisions with the surrounding vehicles, S_j, $\forall j = 1, \dots, q$, where q is the number of surrounding vehicles. As an example, consider the highway traffic scenario consisting of E, and two surrounding vehicles, S_1 and S_2, as shown in Fig. 1. In the scenario, S_1 is driving ahead of E in the same lane, and S_2 is traveling in the left adjacent lane. In the described traffic situation, E could either

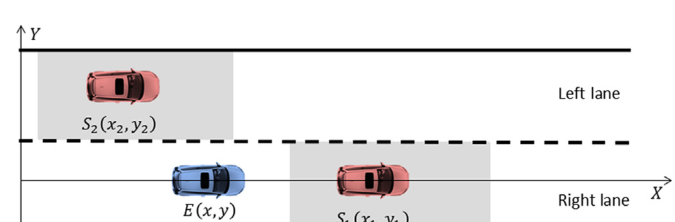

Fig. 1. Vehicles traveling on a road with two lanes. The ego vehicle (E) is shown in blue and the surrounding vehicles (S_1 and S_2) in red. The gray boxes around S_1 and S_2 indicate safety critical regions which E should not enter. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)