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Autonomous driving motion planning with obstacles prioritization using lexicographic optimization

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ABSTRACT

There are driving situations that avoiding all obstacles is infeasible. In such situations, an autonomous vehicle should avoid vulnerable obstacles like pedestrians. In this paper, a motion planning method is presented that avoids obstacles according to their priority orders. The method utilizes a model predictive controller with obstacle constraints and applies lexicographic optimization to the controller to prioritize the constraints, and subsequently, prioritize the obstacles. The proposed method is simulated on a high fidelity CarSim vehicle model. The results show that when avoiding all obstacles is not feasible, the proposed method avoids the obstacles with the highest priority orders.

1. Introduction

National Highway Traffic Safety Administration (Singh, 2015) reports the driver as the critical reason of 94% of crashes involving light vehicles from 2005 to 2007. Autonomous vehicles are being developed in the hope that they reduce the number of crashes by removing drivers. However, becoming involved in some crashes is inevitable for autonomous vehicles. Goodall (2014a, b) expresses three groups of reasons for autonomous vehicles' crashes. First, an autonomous vehicle system is imperfect and occasionally fails. Second, even if autonomous vehicles are perfect, they should drive in a mixed human-driven traffic. Human drivers have unpredictable driving behaviors, and avoiding all of their possible movements is impossible (Benenson, Fraichard, & Parent, 2008). Third, even in a road with only perfect autonomous vehicles, the vehicles would face wildlife, pedestrians, and bicyclists, which have unpredictable behaviors too. Because of the mentioned reasons, some crashes are unavoidable for autonomous vehicles.

Autonomous vehicles are expected to respond properly in a situation that a crash is imminent. Drivers might panic in such a situation and usually are not blamed for it, but autonomous vehicles cannot use this excuse (Goodall, 2016). One example of such a situation is when a deer is on the middle of the road at a distance that the vehicle cannot stop behind the deer if it brakes, but it can swerve to avoid the deer (Lin, 2016). In this situation, a driver might decide to brake, which will result in a crash and a possible injury of the passenger. The driver would not be blamed for this decision, but the decision is not acceptable for an autonomous vehicle since not programming the vehicle to swerve is construed as negligence (Goodall, 2016).

Many factors like the type of the objects around the vehicle, the road structure, and the conditions of the road sides are important in making decisions for a scenario with an imminent crash. In the deer scenario mentioned above, the deer is on the road, but the vehicle has enough space on the road beside the deer to swerve. Therefore, swerving is more reasonable since it is less costly compared to braking. An alternative scenario is when there is not enough space beside the deer for the vehicle to swerve safely, and moving to the road sides can damage the vehicle. In this scenario, swerving and moving to the road sides is more reasonable since it only damages the vehicle and is less costly compared to braking. Another alternative is a similar scenario when the deer is replaced by a squirrel. In this situation, crossing over the squirrel is more reasonable since it has no harm or damage to the passengers and the vehicle and is less costly.

There are many scenarios where a crash is imminent, and even unavoidable. In these scenarios, autonomous vehicles are expected to consider priorities of the obstacles and find the maneuver with the minimum cost based on these priorities. There are some works in the literature that prioritize driving rules. Castro, Chaudhari, Tumova, Karaman, Frazzoli, and Rus (2013) and Tumova, Hall, Karaman, Frazzoli, and Rus (2013) introduce algorithms for motion planning of autonomous cars that minimize the violation of a set of prioritized driving rules, e.g. avoiding traveling on the sidewalk has priority over avoiding moving on the wrong direction. However, to the best knowledge of the author, except for Rasekhipour, Khajepour, Chen, and Litkouhi (2017), there is no

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work in the literature on prioritizing obstacles in planning autonomous cars' trajectory.

The obstacles' priorities should be considered in the motion planning module since it is the module in autonomous vehicles that considers obstacles in its planning. Many motion planning techniques are developed for autonomous road vehicles; interpolating curve planners, graph-search planners like A*, sample-based planners like Rapidly-exploring Random Tree (RRT), and optimization planners like Model Predictive Controller (MPC). Among the motion planning techniques, an MPC has the advantage of systematically handling vehicle future predictions and constraints of vehicle and obstacles in planning the optimal trajectory.

Motion planning MPCs avoid obstacles with two approaches. One approach is to generate a repulsive force that keeps the vehicle away from the obstacle. This method is performed by adding a repulsive Potential Function (PF) to the optimization cost function. Abbas, Milman, and Eklund (2014) and Gao, Lin, Borrelli, Tseng, and Hrovat (2010) include hyperbolic PFs of the distance from the obstacle, and Park, Kim, Yoon, Kim, and Yi (2009) and Yoon, Shin, Kim, Park, and Sastry (2009) include parallax PFs in the MPC cost function. The resulted cost functions are nonlinear and nonconvex, and require solving nonlinear optimization problems. Rasekhipour et al. (2017) consider hyperbolic PFs for non-crossable obstacles and exponential PFs for crossable obstacles, and approximate the nonlinear PFs by convex quadratic functions to make the MPC a convex quadratic MPC.

Another approach to perform obstacle avoidance task is constraining the vehicle to remain in the obstacle-free area. The essence of an obstacle-free area is nonconvex, and the area can be generated by nonconvex constraints. Liu, Jayakumar, Stein, and Ersal (2016) generate a safe area in the LIDAR detection area. The safe area is the semicircle detection area cut by obstacles. Gotte, Keller, Hass, Glander, Seewald, and Bertram (2015) constrain the vehicle out of the circle around each obstacle. Gao, Gray, Tseng, and Borrelli (2014) constrain the vehicle out of the ellipse around each ellipsoidal obstacle. Liao and Hedrick (2015) consider the obstacles as rectangles and use mixed integer constraints to keep the vehicle in the obstacle-free area. Frasch, Gray, Zanon, Ferreau, Sager, Borrelli, et al. (2013) also consider obstacles as rectangles but use nonlinear constraints to generate the obstacle-free area.

MPC problems with nonconvex constraints are nonlinear and have high calculation costs. Several works investigate convex alternatives for the problem. Some researches only control the lateral motion of the vehicle for obstacle avoidance and assume to know the longitudinal motion prior to obstacle avoidance. They grid the obstacle-free space for prediction time steps based on the longitudinal motion. For each prediction time step, they constrain the vehicle's lateral position to an available convex lateral space at the corresponding grid (Brown, Funke, Erlien, & Gerdes, 2016; Erlien, Fujita, & Gerdes, 2013; Gray, Gao, Hedrick, & Borrelli, 2013; Gray, Gao, Lin, Hedrick, & Borrelli, 2013; Liniger, Domahidi, & Morari, 2015). The method is useful for situations that only the lateral motion is planned by the motion planning module. Some papers generate a convex safe envelope based on the driving mode, and plan the longitudinal and lateral motions to keep the vehicle in the safe envelope (Schildbach & Borrelli, 2015; Suh, Kim, & Yi, 2016a; Suh, Yi, Jung, Lee, Chong, & Ko, 2016). These methods keep a predefined envelope structure for each driving mode, and therefore, lose a large portion of the obstacle-free area. Some other papers consider a linear constraint for each obstacle. Nilsson, Falcone, Ali, and Sjöberg (2015) generate a linear constraint with a constant slope for each obstacle. However, because of the constant slope, the constraint compromises between having enough space for passing an obstacle on its side and having enough space for stopping behind the obstacle. Carvalho, Gao, Lefevre, and Borrelli (2014) generate a constraint based on the Signed Distance (SD) of the vehicle and the obstacle, and linearize the constraint around the predicted states. This method generates a linear constraint with slopes based on the relative position of the vehicle and the obstacle, and solves the problems existing for the constraints presented by Nilsson et al. (2015).

As mentioned, to the best knowledge of the authors, the autonomous cars' trajectory is planned based on obstacles' priorities only in Rasekhipour et al. (2017). In Rasekhipour et al. (2017), the first obstacle avoidance approach is used, and different kinds of PFs are utilized for different kinds of obstacles to prioritize obstacles based on the necessity of avoiding them. The obstacles are categorized as crossable obstacles, which are preferred but not required to be avoided such as a bump, and non-crossable obstacles, which are required to be avoided such as a car or a pedestrian. Exponential PFs are assigned to crossable obstacles and hyperbolic PFs are assigned to non-crossable obstacles to prioritize them based on the necessity of avoiding them. However, Rasekhipour et al. (2017) does not prioritize non-crossable obstacles while crashing into different non-crossable obstacles also have different costs, e.g. crashing into a pedestrian is more costly than crashing into a car.

In this paper, the second obstacle avoidance approach is used to prioritize non-crossable obstacles. Obstacle constraints are applied to non-crossable obstacles, which are generated based on the linear constraints introduced in Carvalho et al. (2014). Priorities on non-crossable obstacles are implemented on the motion planning MPC by prioritizing the obstacles constraints. The obstacle constraints are prioritized in the motion planning MPC using Lexicographic Optimization (LO).

LO is a method to prioritize objective functions of an optimization problem. Generally, an optimization problem with multiple objective functions does not have a solution that minimize all the objective functions. A weighted sum of the objective functions can be solved to find a pareto-optimal solution of the problem (Boyd & Vandenberghe, 2004). If an objective function has a priority over another objective function, this method is not appropriate, since it does not necessarily minimize the objective function with the higher priority order. Using LO, it is possible to consider priorities on the objective functions (Freuder, Heffernan, Wallace, & Wilson, 2010). It finds the optimal solution set of an objective function in the optimal solution set of the objective function with the higher priority order. The optimal solution of the objective function with the lowest priority order is the optimal solution of the problem.

In an MPC problem, where constraints can cause infeasibility, slack variables are added to the constraints to avoid infeasibility. Terms containing slack variables are also added to the objective function to penalize constraint violations. Priorities can exist on the constraints, i.e. violating some constraints can be less favorable than violating other constraints. LO can include the priority order of the constraints in the MPC problem by prioritizing the penalizing terms of the constraint violations (Kerrigan & Maciejowski, 2002).

In this paper, LO is applied to an MPC motion planning to prioritize the obstacle constraints. Using this method, in a situation that avoiding all obstacles is not possible, the MPC finds the solution that avoids the obstacles with the highest priority orders. Besides, the method presented in this paper avoids only non-crossable obstacles. Therefore, the method used in Rasekhipour et al. (2017) is also implemented in this paper for avoiding crossable obstacles.

The rest of the paper is organized as follows. Section 2 presents vehicle dynamics, vehicle constraints, potential field, and obstacle avoidance constraints and introduces the MPC for the motion planning problem. Section 3 expresses LO approach for prioritizing constraints in an MPC, and introduces the LO-based motion planning MPC for prioritizing obstacles. Section 4 shows the simulation results for some test scenarios. Section 5 concludes the paper.

2. MPC motion planning

This paper focuses on the motion planning module of an autonomous vehicle. This module plans the trajectory for the autonomous vehicle so that it avoids obstacles, complies with road regulations, follows the desired commands, and provides the passengers with a smooth ride. It is assumed that the module receives information of the obstacles (Hu, Paisitkriangkrai, Shen, van den Hengel, & Porikli, 2016), road (Jung,