

Vehicle Automatic Lane Changing based on Model Predictive Control

Zheng Wang, Weiwen Deng, and Sumin Zhang
State Key Lab of ASCL, Jilin University

Jianpeng Shi
Dongfeng Motor Corporation

ABSTRACT

In this paper, we present a model predictive controller for the autonomous vehicle lane-change maneuver. Firstly, an optimal trajectory is generated by polynomial, then, utilize it as the reference trajectory of the controller. It is well known that vehicle with nonholonomic constraints can not be feedback stabilized through continuously differentiable, time-invariant control laws. One of the advantages of MPC is the ability to handle constraints in a straightforward way. Quadratic programming is used to solve a linear MPC by successive linearization of an error model of the vehicle. Due to that the vehicle dynamics model is used, in order to prevent optimal solution cannot be obtained within the prescribed time, the relaxation factor in the objective function.

CITATION: Wang, Z., Deng, W., Zhang, S., and Shi, J., "Vehicle Automatic Lane Changing based on Model Predictive Control," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 9(1):2016, doi:10.4271/2016-01-0142.

INTRODUCTION

In the last decade, significant advances on research and commercial purposes focused on intelligent vehicle have permitted to improve the safety in both urban and highway roads. Automated driving vehicles have many complex operations like changing lanes on a highway, leaving the road, or overtaking another vehicle on a two-way road [1]. In this paper, we will focus on the trajectory tracking of this third maneuver.

Automated vehicle overtaking consists of two lane changes—one from the right to the left lane of the road, and the other is to return to the right lane after passing. Figure 1 illustrates an overtaking maneuver, which is composed of a (left) lane change, lane keeping and a (right) lane change, the combination of the two atomic submaneuvers. In this paper, we simplified the lane changing environment, reference lane-change trajectory is generated.

Although there are many issues of the automated driving vehicle control research, they can be expressed as two main elements: driving strategies of the surrounding environment and the appropriate behavior of the vehicle. In addition, the two issues need that automated driving vehicle should be controlled like human driver or better than that [2].

PID control algorithm, sliding mode control algorithm and other control algorithms are now commonly used, but they depend on the parameters and the environment. Because the tracking algorithm based on model predictive control for the forecast of the future trajectory and the ability to deal with multi-objective constraints is strong, so it gradually becomes the hot research spot.

The model of a vehicle is nonlinear. Although nonlinear model predictive control has been well developed, the computational effort necessity is much higher than the linear version. In nonlinear model predictive control, there is a nonlinear programming problem to be solved on-line, which is nonconvex and has a larger number of decision variables, and a global minimum is in general impossible to find [3].

We proposed a strategy to overcome at least one part/parts of these problems. The fundamental idea consists of using a successive linearization approach, as briefly outlined in [3], yielding a linear, time-varying description of the system being solved through linear MPC. Then, considering the control inputs as the decision variables, it is possible to transform the optimization problem in a quadratic programming problem. Since this is a convex problem, QP problems can be solved by numerically robust solvers which lead to global optimal solutions. Model predictive control instabilities caused by a short predictive horizon can be stabilized using a predictive contractive constraint for a linear predictive control system with softening constraints [4].

The paper is structured as follows. Section II introduced a simplified lane changing scene and generated static reference trajectory. In section III Lane changing trajectory tracking controller is designed. Simulations are conducted and presented in Section IV followed by conclusions in Section V.

TRAJECTORY PLANNING

Lane change situations are various. In this paper we consider the simple lane-change [5]. We do not take into account the changing driving environment, thus, the trajectories are stationary in nature.

The trajectories are The controller system controls the vehicle to track the desired trajectory based on the optimal preview control method which is a simple and effective approach.

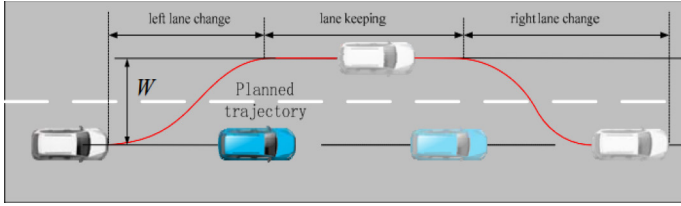


Figure 1. An overtaking maneuver consists of two atomic sub-maneuvers

Trajectory of lane-change behavior consists of two parts, path and speed. We assume that the velocity is constant or small variation in a lane changing process, so the lane-change behavior is completely determined by the path. The vehicle with continuous lateral acceleration.

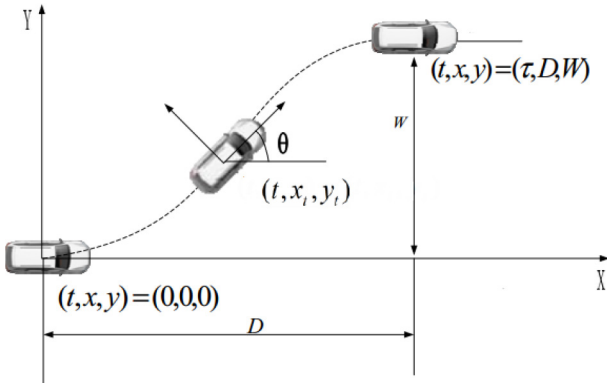


Figure 2. (Left) lane change as one of the atomic sub-maneuvers

Figure 2 shows a typical and complete left lane change maneuver. Its trajectory can be mathematically expressed as a polynomial curve:

$$\begin{aligned} x(t) &= a_3 t^3 + a_2 t^2 + a_1 t + a_0 \\ y(t) &= b_3 t^3 + b_2 t^2 + b_1 t + b_0 \end{aligned} \quad (1)$$

(x, y) is the vehicle mass center coordinates, tangent value of the heading angle φ is $\frac{dy}{dx}$. The boundary conditions at both initial and final x can be listed below as:

$$y(0) = 0, y(\tau) = W, \dot{y}(0) = 0, \dot{y}(\tau) = 0 \quad (2)$$

$$x(0) = 0, x(\tau) = D, \dot{x}(0) = 0, \dot{x}(\tau) = u \quad (3)$$

Thus, the parameterized curve can be given by:

$$\begin{aligned} x(t) &= 2(u\tau - D)(t/\tau)^3 - 3(u\tau - D)(t/\tau)^2 + ut \\ y(t) &= -2W(t/\tau)^3 + 3W(t/\tau)^2 \end{aligned} \quad (4)$$

The planned trajectory on a maneuver, followed by trajectory tracking, greatly influences vehicle dynamic performance in terms of comfort, handling and stability, and driving efficiency. To quantify these, a cost function is introduced, which takes into account the magnitude of the vehicle acceleration and the time duration to complete the maneuver:

$$J = w_1 a^2 + w_2 \tau^2 \quad (5)$$

where w_1 and w_2 are the two weighting factors and a is the maximum total vehicle acceleration:

$$a = \max(\sqrt{\ddot{x}^2 + \ddot{y}^2})|_{t=0 \sim \tau} \quad (6)$$

we aim to minimize the cost function:

$$\min J = \min \left[w_1 a^2 + w_2 \left(\frac{3W^3 a}{u^4} + \frac{11.4\sqrt{3}W^2}{u^2} + \frac{5.76W}{a} \right) \right] \quad (7)$$

By solving the above, we can obtain the optimal values of both a^* , τ^* :

$$\tau^* = \frac{\sqrt{3}W^{3/2}}{u^2} \left(\frac{5.76w_2W}{2w_1} \right)^{1/6} + 2.4\sqrt{W} \left(\frac{5.76w_2W}{2w_1} \right)^{-1/6} \quad (8)$$

$$a^* = \left(\frac{5.76w_2W}{2w_1} \right)^{1/3} \quad (9)$$

Further, the optimal value of the vehicle travel distance D can be obtained approximately:

$$D^* = 2.4u\sqrt{W} / \sqrt{a^*} \quad (10)$$

Since the lane width W is generally known, thus, the optimal trajectory under a given vehicle speed u can be derived to meet the optimal requirements on both vehicle performance and driving efficiency:

$$\begin{aligned} x(t) &= 2\sqrt{3} \frac{W^{3/2}\sqrt{a^*}}{u^2} \left(\frac{t}{\tau^*} \right)^3 - 3\sqrt{3} \frac{W^{3/2}\sqrt{a^*}}{u^2} \left(\frac{t}{\tau^*} \right)^2 + ut \\ y(t) &= -2W \left(\frac{t}{\tau^*} \right)^3 + 3W \left(\frac{t}{\tau^*} \right)^2 \end{aligned} \quad (11)$$

Figure 3 shows an example of optimal lane change maneuvers. With this method, by varying the two weighting factors w_1 and w_2 , different trajectories can be generated to meet different requirements in terms of vehicle performance or turning efficiency.