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Study on Vehicle Lateral Control for Backward Driving

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***Abstract*—In this paper, we study the vehicle lateral control for backward driving. While the path tracking algorithms for forward driving have been studied extensively, backward driving control of an autonomous ground vehicle has received less attention. The vehicle backwards is harder than driving forwards because of the non-minimum phase system and the limitation of the dynamic lateral motion model by the tire model assumption. Towards a fully autonomous driving, the backward driving should be considered in the steering control system. Therefore, we compare the lateral control methods for the backward driving and analyze the path tracking results. Comparison of each method is simulated by using MATLAB and CarSim simulator.**

***Keywords*—Autonomous ground vehicle, Path tracking, Backward driving**

1. Introduction

The lateral control of an autonomous vehicle researches has been studied extensively over the past two decades and many path tracking control algorithms have been developed. The methods using the road geometry, i.e. Stanley[1] and Pure-pursuit[2] are the popular classes of path tracking methods found in robotics. The idea of the Stanley method is to command the steering angle by a control input that yields both the lateral deviation and the heading angle error that converges to zero. The Pure-pursuit is developed for nonholonomic ground vehicles and it computes the angular velocity command that moves the vehicle from its current position to reach some look-ahead point in front the vehicle. There are also path tracking algorithms using artificial intelligence approach based on a Fuzzy-logic set of rules which imitate the human driving skills[3]. And the simplified vehicle system model using a kinematic bicycle model based method[4] and the optimal control method[5] using the dynamic bicycle model have been studied. However, although these algorithms may work well in the forward driving, there are insufficient researches and the performance analyses in backward driving. Besides, compared with the forward driving studies, the backward driving researches have been mainly conducted on parking situations and few studies on the backward driving have been reported. Therefore, the backward driving should be considered in path tracking algorithms for a variety of situations toward the realization of autonomous driving.

Sometimes drivers have to drive backwards, for example, in the narrow region or indoor environments. The path tracking performance of the backward paths should be guaranteed as well as that of the forward paths. Therefore, the evaluation and studies on the limitation of the path tracking algorithms for the backward driving are necessary.

In prior studies on the backward driving, such as [6] and [7], they designed the controller using the similarity between a boat and the car driven backwards. In [8], they proposed the preview control based on a nonlinear kinematic model of the vehicle. Though these methods presented some results of the backward path tracking, to realize precise control of an autonomous ground vehicle, various tracking approaches should be studied. Therefore, it is important to analyze the representative control methods considering backward driving situations and the path tracking performance. We simulated the backward driving using the Stanley method, the Pure pursuit method and the optimal control method using the dynamic bicycle model on the Double Lane Change scenario(ISO 3888) and difficulties in the backward driving are addressed through comparing three methods.

In this paper, we assume that the planned path is already given by the path planner. We present results with respect to the lateral control of a backward driven front-steering vehicle. The paper is organized as follows. In the second section, backward driving control methods are briefly described and the difficulties in backward driving are discussed in Section 3. The simulation test environment is presented in Section 4 and we conclude in Section 5.

2. Driving control methods

2.1. Stanley method

The Stanley method is a geometric path tracking algorithm used by Stanford Universitys autonomous vehicle entry in the DARPA Grand Challenge, 2005. This method uses a nonlinear function of the lateral distance error, e_{fa}, which is measured from the center of the front wheel to the nearest path point and a heading error(θ_e) with respect to the target point. The resulting control law is given as

$$\delta(t) = \theta_e(t) + \arctan\Big(\frac{ke_{fa}(t)}{v_x(t)}\Big), \tag{1}$$

where k is a gain parameter which represents the convergence speed of the lateral error with the vehicle longitudinal velocity at the front wheel, v_x.

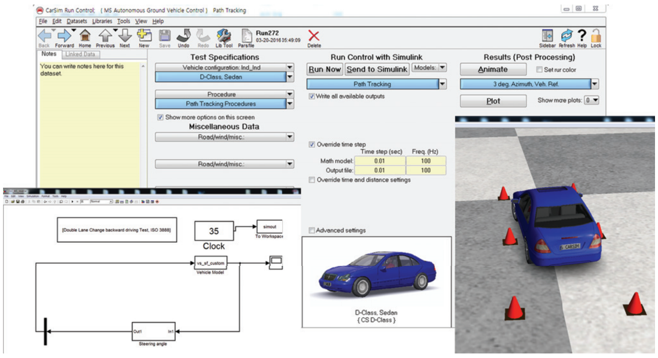


Fig. 1: Simulation environments

2.2. *Pure pursuit method*

The Pure pursuit method is based on simple geometric considerations as follows. Target path is tracked by repeatedly fitting with the instantaneous circular arcs with respect to vehicles rear axle location and a goal point, while vehicle moves forward. The steering angle can be computed by the goal point location and the angle, α, between the vehicles heading vector and the look-ahead vector. By these criteria, the resulting control law is given as

$$\delta(t) = \arctan\left(\frac{2L\sin(\alpha(t))}{l_d}\right), \tag{2}$$

where l_d is the look-ahead distance and L is the look-ahead length.

2.3. *Models based state feedback control methods*

There are two types of models of the vehicle lateral control; the kinematic and the dynamic model. In this paper, we used only the dynamic lateral motion model for the simulation. In order to formulate the state equation, state equation with the dynamic models is defined with respect to the road. For designing a Linear Quadratic Regulator(LQR) with the state equation, $x(k)$ is the state variable and we used the state feedback control is

$$\delta(k) = -K_x x(k). \tag{3}$$

K_x is the optimal state feedback gain and it can be obtained by solving the Riccati equation to minimize the objective cost function:

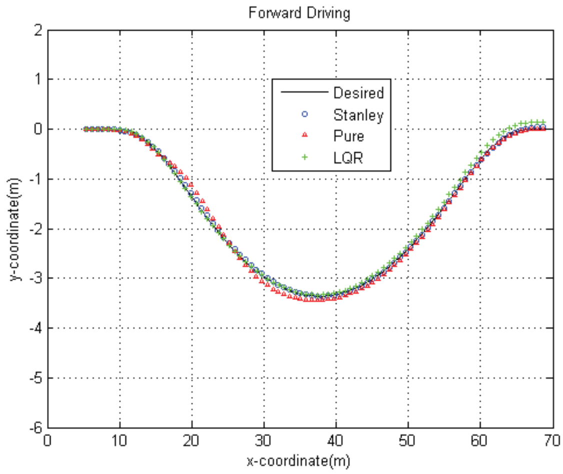
$$J = \sum_{k=0}^{\infty} x(k)^T Q x(k) + \delta(k)^T R \delta(k). \tag{4}$$

Q is a diagonal weighting parameter matrix with an entry for each state and R is a weighting parameter with respect to the control effort contributing to the cost function.

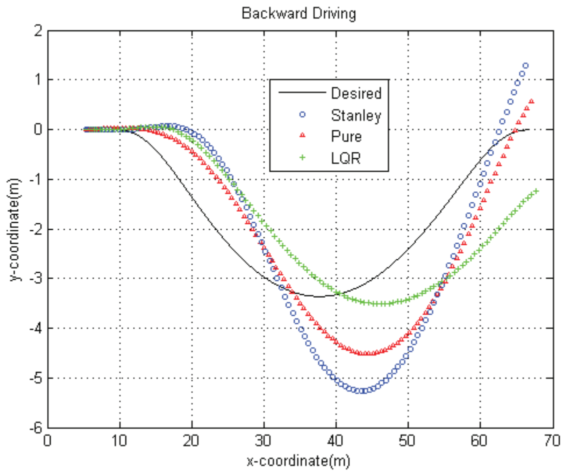
3. Simulation and Discussion

3.1. *Simulation environments*

To provide the comparison of the control methods, we implemented each algorithm by using Matalb/Simulink and



(a)



(b)

Fig. 2: The comparison of methods: Stanley, Pure pursuit and LQR; (a) Forward driving (b) Backward driving

Carsim simulator, as shown in Fig. 1. A path used in the simulation is Double Lane Change (ISO 3881). To show difference control properties between the forward driving and backward driving, the backward driving were simulated using same parameter values in the forward driving. And the velocity of the vehicle in simulations was a constant value. First, the comparison result of the path tracking driving forwards is shown in Fig. 2(a). As shown in the figure, three algorithms work well in the forward driving. However, as shown in Fig. 2(b), one can observe that the deviation from the desired path is significantly large for backward driving. Among these algorithms, the Pure-pursuit shows better performance than others. RMS lateral error distances are as follows (RMS errors(m): Stanley = 1.2134, Pure pursuit = 0.9371, LQR = 1.0168). Because the Pure pursuit uses look-ahead distance, the response to the variation of the path is faster than the other algorithms. The Stanley method shows the significant

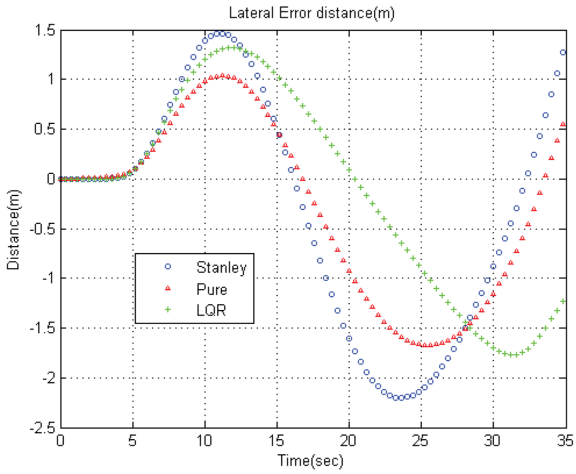


Fig. 3: Lateral Distance Error(m)

overshoot. This is because compared to the Pure pursuit algorithm and the LQR, the Stanley method uses the lateral displacements in front axle with respect to the target point.

If all methods in this simulation consider the various velocity of the vehicle, one can get better performance. Also, the improved performance of the path tracking can be obtained with the adequate adaptive tuning of the look-ahead distance. However, this approach requires parameter tuning by trial-and-error.

3.2. Difficulties in backward driving

There are mainly two types of difficulties in realizing the backward driving.

A. Non-minimum phase system: Difficulties in backward maneuvers were analyzed by a previous study[8]. A transfer function from the steer at the front axle of the vehicle to the lateral deviation in front axle with respect to the target point has an unstable zero at right-half-plane(RHP) of the complex plane. This is a kind of the non-minimum phase systems. The unstable zero cannot be canceled with any controller poles. As an alternative, in order to avoid the non-minimum phase system, the desired steering angle can be calculated by the rear axle of the vehicle. This kind of a improved way of the Stanley method might be better than an original way of the Stanley. However, the approach violates inherent constraints of the Stanley method such as steering angle and lateral displacement assumptions. Though the improved method for Stanley method is not verified by any proof, the method considering the lateral displacement between the vehicles rear axle and the target paths can be an alternative path tracking approach than the method considering the lateral displacement between the vehicles front axle and the target paths.

B. Tire model assumption at a low speed: The backward driving at a low speed eliminates some challenges with respect to the dynamic properties of the vehicle, but it can introduce other problems in designing for the lateral controller. The dynamic bicycle model for the vehicle lateral control starts to break down at very slow speed or parking maneuvers. As shown in Fig. 3, the LQR shows the significant deviation. The model utilizes a linear tire model to consider forces between the wheel and ground and it uses a slip angle estimation term which has the velocity in the denominator. At low speed range, this type of the model is inadequate even for stop-and-go scenarios. (5) is formulated by the small angle theory applied to the slip angle at rear tires, α_r.

$$\alpha_r = \arctan(\frac{v_y - l_r r}{v_x}). \tag{5}$$

v_y and v_x are the lateral velocity and the longitudinal velocity at the center of the gravity of the vehicle, respectively. l_r is the length from the center of the gravity of the vehicle to the rear axle of the vehicle and r is the angular rate about the yaw axis. At very low speeds, the tire model which has a velocity at denominator is the singular point by this assumption. The assumption about the relationship between the cornering stiffness and the lateral tire force is broken sequentially. In order to address this singular problem, the fundamental analysis for the path tracking methods using the dynamic vehicle model is necessary.

4. Conclusion

We describe methods of the vehicle lateral control and difficulties for the backward driving. Using three methods, we present the simulation results with respect to the lateral control of a backward driven front-steering vehicle. By virtue of these results, there are two useful knowledges in the design of the vehicle backward lateral controller. First, the desired steering angle should not be calculated with respect to the front axle of the vehicle. Second, if one uses the vehicle lateral motion model at a low speed, the consideration of the slip angle assumption is necessary. Our future work will address the backward driving with the consideration of driving stabilities using Model Predictive Control method.

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