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Trajectory planning and tracking control for autonomous lane change maneuver based on the cooperative vehicle infrastructure system

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ABSTRACT

Lane change maneuver is one of the most conventional behaviors in driving. Unsafe lane change maneuvers are key factor for traffic accidents and traffic congestion. For drivers' safety, comfort and convenience, advanced driver assistance systems (ADAS) are presented. The main problem discussed in this paper is the development of an autonomous lane change system. The system can be extended applied in intelligent vehicles in future. It solves two crucial issues – trajectory planning and trajectory tracking. Polynomial method was adopted for describing the trajectory planning issue. Movement of a host vehicle was abstracted into time functions. Moreover, collision detection was mapped into a parameter space by adopting infinite dynamic circles. The second issue was described by backstepping principle. According to the Lyapunov function, a tracking controller with global convergence property was verified. Both the simulations and the experimental results demonstrate the feasibility and effectiveness of the designed method for autonomous lane change.

1. Introduction

1.1. Problem and motivation

Lane change maneuvers are one of the most conventional behaviors in driving. It is defined transfer of a host vehicle from the current lane to the next adjacent lane. To perform a lane change, drivers have to collect a large amount of information, such as velocity and distance between the host vehicle and vehicles in the target lane, traffic flow and road traffic environment information related to facilities. The decision of lane change is made on condition that the safe gap between vehicles is satisfied according to human driver experience. Actually, the process of a lane change involves environmental information collection and analysis, opportunity judgment, trajectory generation, collision detection, conflict processing and etc. According to past research, lane change and lane merge maneuvers account for approximately 5% of total crashes and as high as 7% of total crash fatalities (Habel & Schreckenberg, 2014; Rodemerk, Habenicht, Weitzel, Winner, & Schmitt, 2012). At present, traffic accidents related to lane change on highway account for a considerable proportion. From the Netherlands's transportation statistics, 12.6% of all traffic accident are caused by lane change (Bax, Leroy, & Hagenzieker, 2014). In Canada, 9.8% of crash fatalities result from lane change (Amin, Zareie, & Amador-Jiménez, 2014). In the United States, from 1994 to 2005, there were 13,939 traffic accidents caused by lane change and 24,565 killed (Kretschmer, Neubeck, & Wiedemann, 2005).

In developing countries such as India, Brazil and China, the problem gets worse. In China, traffic accidents caused by lane change are on the rise. Depending on the report from the China's Highway Traffic Safety Administration, massive traffic accidents caused by lane change are outstanding. Especially, more than 60% of the traffic accidents on the freeway are related to lane change (Li, Wu, Xu, & Lin, 2014). It is obvious that traffic accidents caused by lane change occur frequently. Thereby, how to improve safety for lane change has become an urgent issue to be dealt with.

Recently, traffic safety administration agencies and automobile companies focus more on reducing the number of lane change crashes. Traffic safety administration agencies are actively finding a solution to the issue that can regulate driving behavior by encouraging safer driving actions. For instance, through public advertisement or publicity board, the serious consequences in lane change crashes are emphasized. Also, notes on lane change safety

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are repeated. Some agencies in China use large variable message board (VMB) for freeways to remind drivers to reduce the number of lane change in accident high-risk or heavy-traffic areas.

On the other hand, the automobile companies have an urgent interest in utilizing high technology to provide lane change assistance for drivers. With the increase in the wide application of sensor technology in automobiles, advanced driver assistance systems (ADAS) have been implemented in recent years. The development of ADAS to aid in driving-related tasks has a crucial role to play in the automotive field. For more lane change safety, the lane change assistance system will become one of the most significant parts of the ADAS.

1.2. Related works

As discussed above, ADAS are developed to assist human drivers. One of the main objectives of the technology has been to increases driver awareness by providing useful information. Over the last years, ADAS have obtained a large number of research achievements. There are some examples of lane detection and lane keeping assistance (LKA) (He, McCarley, & Kramer, 2013; Lefevre et al., 2014; Son, Yoo, Kim, & Sohn, 2015), and obstacles detection and avoidance in the vehicle's path such as either vehicles (Hassannejad, Medici, Cardarelli, & Cerri, 2015) or pedestrians detection (Alahi, Bierlaire, & Vandergheynst, 2014; Sermanet, Kavukcuoglu, Chintala, & LeCun, 2013), adaptive cruise control (ACC), stop&go, autonomous parking or other elements, like traffic lights on roads (Diaz-Cabrera, Cerri, & Medici, 2015). ADAS are onboard vehicle systems which concentrate on the driving process. Of all examples, LKA and ACC are becoming the highest potential technologies in ADAS. The former was regarded as an extension of cruise control (CC). Drivers can set a specified driving velocity in advance with CC in which the vehicle is capable of following a leading car on freeways by controlling the throttle and brake pedals, i.e., longitudinal control. On the other hand, in essence, LKA, which remains one of the toughest challenges in the development of ADAS, is lateral control for vehicle. It is designed to alert the driver when the system detects that the vehicle is about to deviate from a lane. Complete lateral vehicle control has still to be addressed by the automotive companies.

Compared with the achievements achieved in ADAS, the research on lane change safety lags behind. In all maneuvers, lane change is one of the most complexes since both lateral and longitudinal control need to be considered. Drivers have to consider several factors affecting safety. These factors include, speed and position of the subject vehicle and vehicles in the target lane, geometric characteristics of the road, vehicle characteristics, and others. Due to the significance of the lane change safety, recent literature has been devoted to four main aspects of lane change, i. e., lane change warning, lane change behavior, lane changing trajectory planning and lane change control.

- Lane change warning

According to the ISO Standard 17387, Lane Change Decision Aid System (LCDAS) consist of three different types of warning systems – Blind Spot Warning (BSW), Vehicle Proximity Warning (VPW), and lane change warning (LCW). In BSW systems, there is a warning message triggered in case that any obstacles intervene into drivers' blind spots or areas. VPW systems are capable of recognizing approaching vehicles from behind in adjacent lanes. LCW systems are considered as a hybrid system, which has the function of both BSW systems and VPW systems. Based on the Standard, some studies have been conducted. For instance, in Shiller, Prasanna, and Salinger (2008), a collision warning approach due to neighboring traffic is presented. Based on the concept of velocity obstacles, it designed to alert the driver of a potential front collision and against attempting a dangerous lane change maneuver. To avoid false alarms in lane changes, prediction of a lane-change maneuver is needed. In Schmidt, Beggiato, Hoffmann, and Krems (2014), obtained early predictors by analyzing 3111 lane changes with regard to speed, secondary task engagement, turn signal usage, and steering wheel angle. Tomar et al. proposed a strategy for warning and intervention to assist the driver in a lane change maneuver (Tomar, Verma, Kushwah, & Tomar, 2013). The strategy consists of a relative motion estimator and supervisor. To assess the threat in a lane change situation, vehicle sensor information and rear-side radar sensor information have been combined in the relative motion estimator. In our work, we have not considered this approach, since our technique, which is not only warning for lane change, focus on how to accomplish autonomous lane change.

- Lane change behavior

Many research works like (Guo, Wan, Zhao, Wang, & Li, 2013; Zheng, Suzuki, & Fujita, 2014) have been conducted in lane change behavior. These studies show that the drivers' decision to change lanes is associated with driver characteristics, driver attitudes (such as aggressive behavior) and depends on many factors. In Gipps (1986) designed a lane changing model that was implemented in a microscopic traffic simulator. In a recent study Hou, Edara, and Sun (2015), have developed a genetic fuzzy model to predict merging behavior of drivers at lane drops. Xiaorui and Hongxu (2013) established a lane change model integrated with the car following behavior. The model considers kinematic behavior of the lane-changing vehicle in the case of acceleration. In Zheng, Ahn, Chen, and Laval (2013) presented a method to explore diverse components of lane changes impacts- anticipation process, relaxation process and change in driver characteristics induced by lane changes. Laval and Daganzo (2006) proposed a model to consider the drop in discharge rate at bottlenecks due to lane-change maneuvers. It provides simulations that appear to replicate empirical results observed from fixed-point detectors in their studies. These models stated above have been proposed to acquire the accurate way to describe a lane change maneuver. However, none of them were designed for use in a real-time lane changing assistance system that advises drivers of when it is safe or unsafe to merge.

- Lane changing trajectory planning

A predefined trajectory must be presented to track during the lane change maneuver. Accordingly, trajectory planning is an extremely significant issue in the topic of autonomous lane change maneuver. Its main aim is to generate a trajectory from current lane to goal lane that satisfies some limitations or objectives, like acceleration, joint jerk, minimization of time interval, vibration, collision avoidance criteria or other dynamic constraints.

There are numerous experiences in lane changing trajectory planning. Classical trajectory planning strategies, such as road map, cell decomposition and potential field methods are frequently mentioned in robot field. Nevertheless, they have the possibility of getting stuck in local minima. Furthermore, it takes an extremely long time to reach global minima in the case of too many parameters. Actually, trajectory planning for a lane change is always simple. The existing methods are on various types of curves – circular (Kim, Oh, Suk, & Tsourdos, 2014), harmonic (Zhang, Chen, & Shen, 2013), polynomial (Rossi & Savino, 2013) and line segments (Vale, Fonte, Valente, & Ribeiro, 2014). In Ioannou (2013), lane change patterns of each driver are modeled with a hidden Markov model (HMM). From the HMM, vehicle trajectories are selected in a maximum likelihood criterion at random lane-changing time and state duration. On the other hand, the trapezoidal acceleration curve trajectory was proposed to generate the least possible lateral acceleration for lane changes (Soudbakhsh, Eskandarian, & Chichka, 2013). In Soudbakhsh et al. (2013), three different path planning methods- state lattice, predictive constraint-based planning and spline based on search tree -are evaluated. In Hidalgo-Martínez, Sanmiguel-Rojas, and Burgos (2014), a path planner based Bézier curve which enables the anti-collision behavior of vehicle is presented.

In spite of these developments, the latest trends have been focused on planning based on cooperative technologies (Behere, Törngren, & Chen, 2013; Pérez, Milanés, Godoy, Villagrá, & Onieva, 2013). In our work, in the framework of cooperative technologies, a trajectory planner based the polynomial for lane change maneuver was presented since the polynomial curve has the advantage of continuous curvature and simplicity. Moreover, the algorithm does not consume much computation time.

- Lane change control

To accomplish the autonomous lane change, a controller should be developed to track the predefined trajectories according to the vehicle states and road information. Many different controlling algorithms for trajectory tracking have been proposed in prior studies. Bayar (2013) designed a traditional PID controller for trajectory tracking, not only because of its simple structure and easy implementation but also because of its acceptable tracking performance. However, the controller is not satisfactory for applications that require high tracking accuracy. Guo, Ge, Yue, and Zhao (2014) reported the trajectory tracking controller of closed-loop control structure is derived using integral backstepping method to construct a new virtual variable. The Lyapunov theory is utilized to analyze the stability of the proposed tracking controller. In Du, Wang, and Chan (2014), a model predictive controller is calculated by reducing the complexity of the system model. The predictive controller allows full control of acceleration/deceleration as well as providing a decision variable regarding preferred lane at each time instance. In Berntorp, Olofsson, Lundahl, and Nielsen (2014), an optimal trajectory based on minimization of yaw acceleration was derived, and the simulation and comparative analysis were also done with different speed values. Ying, Mei, Song, and Liu (2014) studied the longitudinal and lateral coupling control for vehicle platoon lane changing by sliding mode method. In Ren, Zhang, and Wang (2014), a two-layer nonlinear adaptive steering controller is designed that allows tracking the desired trajectories. The adaptive controller is capable of dealing with parameter uncertainties with its self-organizing ability. However, this entails a high computational cost. And more importantly, in spite of the fact that the above controller can track the predefined trajectories, both passengers' comfort and vehicles' characteristics are ignored.

1.3. Contribution

The main contribution of this paper is to develop a trajectory planning algorithm for autonomous lane change. It is based on polynomials because polynomial curve has the advantage of continuous curvature and simplicity. Another important advantage of the method over other methods is that it yields much safer trajectories with a lower computational cost. In addition, collision detection strategies are taken into account in this planner. Collision-free trajectories can be generated easily by mapping the obstacles into a parameter space.

As an additional contribution, a study is presented in the development of the tracking controller for trajectories for lane change maneuver. It is designed by using the backstepping method. The convergence of the controller is proven by the Lyapunov stability theory. The controller considers not only passengers' comfort, but vehicles' characteristics.

We tested our proposed the trajectory planning algorithm and the tracking controller for trajectories to verify their performance. This study includes simulation and experimental analyses.

The remainder of the paper is organized as follows. Section 2 describes the kinematics model for a lane change. The collaborative strategy for a lane change is discussed in Section 3. Section 4 introduces trajectory representation and generation for the lane change scenario. Section 4.1 presents a trajectory generation method for the case without a front vehicle. Section 4.2 describes the trajectory generation algorithm with a front vehicle. Section 5 introduces tracking control of reference trajectories. Section 6 shows the simulation and experimental results and provides information about the experimental platform. Conclusions are presented in Section 7 that indicate future directions for the research.

2. Kinematics model for lane change

2.1. Vehicle kinematics and tracking error model

This work deals with the trajectory tracking problems of the kinematic car-like model shown in Fig. 1, with a nonholonomic constraint that restricts the wheels to roll with no slip. The vector $p_c = (x_c, y_c, \theta_c, \delta_c)$ denotes the configuration of the vehicle, where (x_c, y_c) is the location of the midpoint of the rear axle, θ_c is the angle between the x-axis and a reference line on the vehicle frame and δ_c is the steering angle. The subscript c stands for 'current'.

Let $u_c = (v_c\ \omega_c)$ be a controlling vector. The kinematics model for the vehicle-based point $M$is shown in Eq. (1). The vehicle's motion state during lane changing is shown in Fig. 2. Assuming $p_r = (x_r\ y_r\ \theta_r)^T$ is the vehicle's reference posture, where $(x_r\ y_r)$ and θ_r stand for the posture vector, the coordinates of reference point N and the orientation angle, respectively.

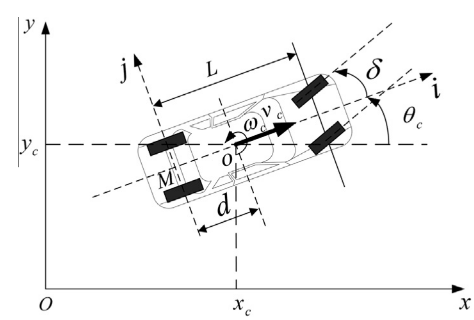


Fig. 1. The definition of WCS and VCS.

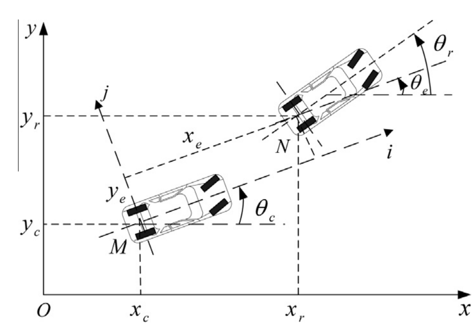


Fig. 2. Current and reference posture of a vehicle in the WCS.

$$\dot{p}_c = \begin{bmatrix} \dot{x}_c \\ \dot{y}_c \\ \dot{\theta}_c \end{bmatrix} = \begin{bmatrix} \cos\theta_c & 0 \\ \sin\theta_c & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_c \\ \omega_c \end{bmatrix} \tag{1}$$

The motion error of the vehicle $p_e = (x_e\ y_e\ \theta_e)^T$ is represented by Eq. (2).

$$p_e = \begin{bmatrix} x_e \\ y_e \\ \theta_e \end{bmatrix}_{(M,i,j)} = \begin{bmatrix} \cos\theta_c & \sin\theta_c & 0 \\ -\sin\theta_c & \cos\theta_c & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_r - x_c \\ y_r - y_c \\ \theta_r - \theta_c \end{bmatrix}_{(o,x,y)} = J_1 \cdot q_e \tag{2}$$

Therefore, the derivative equations of the position error of the vehicle can be derived as (Hung, Hedrick, & Tomizuka, 1994).

$$\dot{p}_e = \begin{bmatrix} \dot{x}_e \\ \dot{y}_e \\ \dot{\theta}_e \end{bmatrix} = \begin{bmatrix} \omega_c y_e - v_c + v_r \cos\theta_e \\ v_r \sin\theta_e - \omega_c x_e \\ \omega_r - \omega_c \end{bmatrix} \tag{3}$$

2.2. Tracking problem definition

As indicated by Eq. (3), the tracking control for the designed trajectory has to take the two states of vehicle into consideration: the posture of the reference vehicle $p_r = (x_r, y_r, \theta_r)$ and the current position $p_c = (x_c, y_c, \theta_c)$. Accordingly, the tracking control for a trajectory can be converted based on the fact that, within the arbitrary initial errors, the control vector of the input $u_c = (v_c\ \omega_c)$ should be selected to track the posture of the reference vehicle $p_r = (x_r, y_r, \theta_r)$ and the current position $p_c = (x_c, y_c, \theta_c)$, and additionally to keep (x_e, y_e, θ_e) bounded and $\lim_{t\to\infty}\left\|(x_e\ y_e\ \theta_e)^T\right\| = 0$.

3. Collaborative strategy for lane change

The environmental information collected from a single vehicle is ultimately quite limited. Therefore, the latest trends have been dedicated to vehicle–vehicle-infrastructure communication (V2X). Using V2X techniques, cooperative trajectory planning can be performed for a lane change. In such a mechanisms, the state messages between vehicles, including information about coordinate position, velocity, and posture, can be broadcasted. For each vehicle, there is one local trajectory planner corresponding to its knowledge base. In a lane change, the trajectory planning not only observe the individual vehicle's behavior but also consider the driving state of other vehicles. The cooperative mechanism for a lane change is illustrated in Fig. 3.

4. Trajectory representation and generation for the lane change scenario

To seek a feasible trajectory and to keep the vehicle running smoothly in a lane change scenario, we introduced some basic principles for the trajectory planning (Feng, Rongben, & Ronghui, 2008):

- The trajectory is continuous.
- The first derivative and second derivative of the trajectory are continuous and also bounded.
- The trajectory can be generated easily and quickly.
- The trajectory should be reasonable and possible to execute.
- The trajectory should avoid rough output from the lane change controller.

Based on the cooperative mechanism described in Section 3, we accomplish trajectory generation and collision detection for a lane change. Our current work has been performed for two different situations: with and without a front vehicle.

4.1. Trajectory generation without a front vehicle

In this scenario, we assume that the host vehicle C_0 performs a lane change with a certain longitudinal velocity $\dot{x}$. As shown in Fig. 4, if there are no front vehicles in the current and adjacent lane,

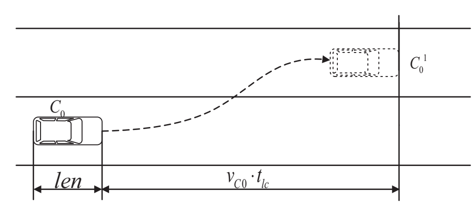


Fig. 4. Lane change scenario without a front vehicle.

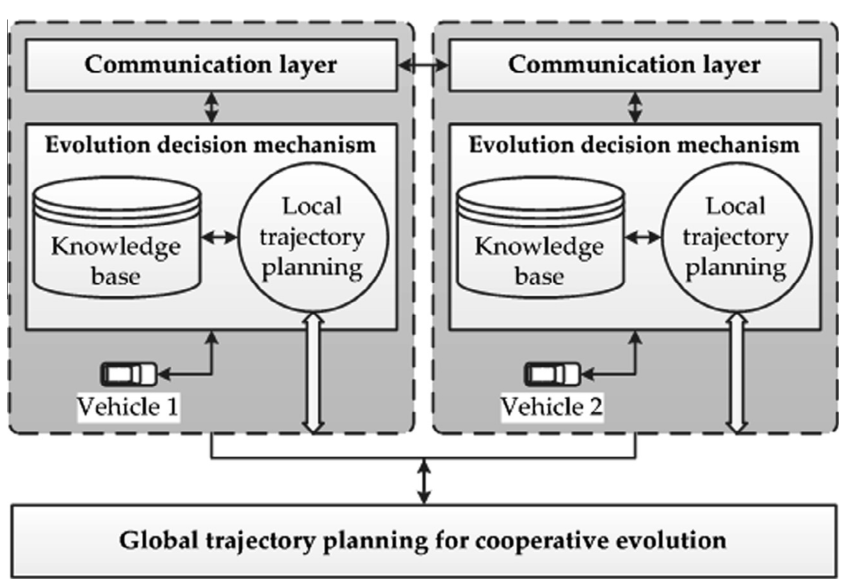


Fig. 3. Mechanism of coevolution for a lane change.

the time t_{lc} to complete the lane change depends on the driver's comfort. We can easily conclude that the trajectory planning for a lane change can be converted into an issue of solving for boundary conditions. Specifically, our aim is to select a trajectory that links the given start points and the target points and makes the vehicle move smoothly between the two end points. While there are numerous approaches to solving the trajectory generation problem, some require a large amount of computational power. At worst, this may result in a trajectory that is not smooth.

In our approach, a polynomial algorithm is used to determine the trajectory. In this method, the polynomial, which has some significant advantages over simple high-degree polynomials such as those used in Lagrange interpolation (Jalali, Piltan, Gavahian, & Jalali, 2013), is selected. It is capable of ensuring the smoothness of the trajectory because its performance is twice differentiated. Moreover, it only requires a small number of points to generate the trajectory. The following describes the details of the approach.

According to the vehicle's initial errors and target state, the lane change trajectories are generated to reach the adjacent lane at a specified time. By using function $f(x,y,t)$ to describe the trajectory for a lane change, we try to select some trajectory from a certain class of functions, which depends on lane structure and, simultaneously, illustrates the dynamic characteristics of the vehicle from the initial and the target position. Based on this rule, a polynomial is selected to construct the class of functions for the lane change. Specifically, the 5th-degree polynomial is applied in x and y directions, as shown in Eq. (4)

$$\begin{cases} f(x,t) = \sum_0^5 a_i * t^i \\ f(y,t) = \sum_0^5 b_i * t^i \end{cases} \tag{4}$$

We obtain Eqs. (5) and (6) by taking the first derivative and the second derivative of Eq. (4).

$$\begin{cases} \dot{f}(x,t) = \frac{d\left(\sum_0^5 a_i * t^i\right)}{dt} \\ \dot{f}(y,t) = \frac{d\left(\sum_0^5 b_i * t^i\right)}{dt} \end{cases} \tag{5}$$

$$\begin{cases} \ddot{f}(x,t) = \frac{d\left(\sum_0^5 a_i * t^i\right)}{d^2 t} \\ \ddot{f}(y,t) = \frac{d\left(\sum_0^5 b_i * t^i\right)}{d^2 t} \end{cases} \tag{6}$$

Let the initial and target state vectors be

$$\vec{S}_0 = (x_0, \dot{x}_0, \ddot{x}_0, y_0, \dot{y}_0, \ddot{y}_0)$$

and

$$\vec{S}_t = (x_t, \dot{x}_t, \ddot{x}_t, y_t, \dot{y}_t, \ddot{y}_t),$$

where x, $\dot{x}$, $\ddot{x}$, y, $\dot{y}$ and $\ddot{y}$ are the longitudinal displacement, longitudinal velocity, longitudinal acceleration, lateral displacement, lateral velocity and lateral acceleration of the vehicle, respectively. Substituting the two state vectors into Eqs. (4)–(6), the Eqs. (7) and (8) are obtained.

$$\begin{bmatrix} f_0(x,t) & \dot{f}_0(x,t) & \ddot{f}_0(x,t) & f_t(x,t) & \dot{f}_t(x,t) & \ddot{f}_t(x,t) \end{bmatrix}^T = T_{6\times 6} * A^T \tag{7}$$

$$\begin{bmatrix} f_0(y,t) & \dot{f}_0(y,t) & \ddot{f}_0(y,t) & f_t(y,t) & \dot{f}_t(y,t) & \ddot{f}_t(y,t) \end{bmatrix}^T = T_{6\times 6} * B^T \tag{8}$$

where

$$A^T = (a_5, a_4, a_3, a_2, a_1, a_0)$$

$$B^T = (b_5, b_4, b_3, b_2, b_1, b_0)$$

$$T_{6\times 6} = \begin{bmatrix} t_0^5 & t_0^4 & t_0^3 & t_0^2 & t_0^1 & 1 \\ 5t_0^4 & 4t_0^3 & 3t_0^2 & 2t_0^1 & 1 & 0 \\ 20t_0^3 & 12t_0^2 & 6t_0^1 & 2 & 0 & 0 \\ t_t^5 & t_t^4 & t_t^3 & t_t^2 & t_t^1 & 1 \\ 5t_t^4 & 4t_t^3 & 3t_t^2 & 2t_t^1 & 1 & 0 \\ 20t_t^3 & 12t_t^2 & 6t_t^1 & 2 & 0 & 0 \end{bmatrix}$$

A trajectory is created by solving Eqs. (7) and (8). The details of the algorithm are provided in Section 5.

4.2. Trajectory generation for a vehicle with one front vehicle

If there is a vehicle in front of the host vehicle C_0 during the lane change, a collision will probably take place because the previous algorithm does not take the obstacle vehicle into consideration. At the start of the lane change, the host vehicle C_0 and the front vehicle C_3 are positioned as shown in Fig. 3. The initial velocities of host vehicle C_0 and front vehicle C_3 are v_{C0}^0 and v_{C3} respectively. The distance SS between the two vehicles can be selected experimentally. It is assumed that vehicle C_3 drives forward at a constant speed in the current lane and that vehicle C_0 shifts to the adjacent lane at the planned acceleration. After a lane change lasting t_{lc} seconds, the vehicles C_0 and C_3 respectively arrive at positions C_0^1 and C_3^1, as shown in Fig. 5. Δ_1 is the longitudinal space between the two vehicles C_0 and C_3.

5. Trajectory generation

As shown in Fig. 5, by analyzing the area between vehicles C_0 and C_3, the longitudinal displacements of vehicles C_3 and C_0 during the lane change can be determined using Eqs. (9) and (10).

$$S_{C3}^1 = v_{C3} \cdot t_{lc} \tag{9}$$

$$S_{C0}^1 = len + SS + v_{C3} \cdot t_{lc} - \Delta_1 - len \tag{10}$$

The trajectory planning method for a vehicle with one front vehicle is based on Section 4.2 mentioned above. If we increase the order of one of the polynomials, the trajectory will be changed, which is useful for giving more freedom to generate a collision-free trajectory.

$$\begin{cases} f(x,t) = \sum_0^6 a_i * t^i \\ f(y,t) = \sum_0^5 b_i * t^i \end{cases} \tag{11}$$

$$\begin{cases} \dot{f}(x,t) = \frac{d\left(\sum_0^6 a_i * t^i\right)}{dt} \\ \dot{f}(y,t) = \frac{d\left(\sum_0^5 b_i * t^i\right)}{dt} \end{cases} \tag{12}$$

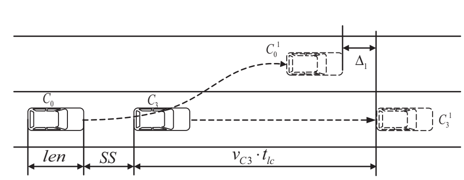


Fig. 5. The area between vehicles C_0 and C_3.

$$\begin{cases} \ddot{f}(x,t) = \frac{d\left(\sum_0^6 a_i * t^i\right)}{d^2 t} \\ \ddot{f}(y,t) = \frac{d\left(\sum_0^5 b_i * t^i\right)}{d^2 t} \end{cases} \tag{13}$$

We increase the polynomial degree of the x direction because the changing range of the longitudinal velocity of the vehicle is larger than that of the lateral velocity, often 2 to 5 times larger. In this way, we simplify the generation of the trajectory of the lane change. Specifically, a 6-degree polynomial in the $x$direction and 5-degree polynomial in y direction are selected to model the trajectory of the lane change. We use Eqs. (11)–(13) to represent the longitudinal and lateral displacement, velocity and acceleration, respectively.

By substituting the initial conditions of the vehicle from Eq. (11) into Eq. (13), we deduce Eqs. (14) and (15).

$$\left[f_0(x,t) \quad \dot{f}_0(x,t) \quad \ddot{f}_0(x,t) \quad f_t(x,t) \quad \dot{f}_t(x,t) \quad \ddot{f}_t(x,t)\right]^T = T_{6\times7} * A^T \tag{14}$$

$$\left[f_0(y,t) \quad \dot{f}_0(y,t) \quad \ddot{f}_0(y,t) \quad f_t(y,t) \quad \dot{f}_t(y,t) \quad \ddot{f}_t(y,t)\right]^T = T_{6\times6} * B^T \tag{15}$$

Here,

$$A^T = (a_6, a_5, a_4, a_3, a_2, a_1, a_0) \tag{16}$$

$$B^T = (b_5, b_4, b_3, b_2, b_1, b_0) \tag{17}$$

$$T_{6\times7} = \begin{bmatrix} t_{ini}^6 & t_{ini}^5 & t_{ini}^4 & t_{ini}^3 & t_{ini}^2 & t_{ini} & 1 \\ 6t_{ini}^5 & 5t_{ini}^4 & 4t_{ini}^3 & 3t_{ini}^2 & 2t_{ini} & 1 & 0 \\ 30t_{ini}^4 & 20t_{ini}^3 & 12t_{ini}^2 & t_{fin} & 2 & 0 & 0 \\ t_{fin}^6 & t_{fin}^5 & t_{fin}^4 & t_{fin}^3 & t_{fin}^2 & t_{fin} & 1 \\ 6t_{fin}^5 & 5t_{fin}^4 & 4t_{fin}^3 & 3t_{fin}^2 & 2t_{fin} & 1 & 0 \\ 30t_{fin}^4 & 20t_{fin}^3 & 12t_{fin}^2 & t_{fin} & 2 & 0 & 0 \end{bmatrix} \tag{18}$$

$$T_{6\times6} = \begin{bmatrix} t_{ini}^5 & t_{ini}^4 & t_{ini}^3 & t_{ini}^2 & t_{ini} & 1 \\ 5t_{ini}^4 & 4t_{ini}^3 & 3t_{ini}^2 & 2t_{ini} & 1 & 0 \\ 20t_{ini}^3 & 12t_{ini}^2 & t_{fin} & 2 & 0 & 0 \\ t_{fin}^5 & t_{fin}^4 & t_{fin}^3 & t_{fin}^2 & t_{fin} & 1 \\ 5t_{fin}^4 & 4t_{fin}^3 & 3t_{fin}^2 & 2t_{fin} & 1 & 0 \\ 20t_{fin}^3 & 12t_{fin}^2 & t_{fin} & 2 & 0 & 0 \end{bmatrix} \tag{19}$$

6. Calculation of 'distance to obstacle'

By analyzing Eqs. (14)–(19), we find out that 13 parameters are undetermined in matrix A. However, the initial and target conditions of the vehicle only provide 12 equations. Hence, the obstacle avoidance algorithms should work cooperatively with trajectory generators. We have to introduce the 'distance to obstacle' to solve the indeterminate equation.

There are numerous approaches to calculating the distances to obstacles (Wang, Yang, & Yang, 2013; You, Wang, & Zhang, 2013). Most of them suppose that the host vehicle and the obstacle are circular objects with minimum radii that include all of the physical boundaries, as shown in Fig. 6. Under this assumption, the aim of the obstacle avoidance algorithm is to find a purely reactive heading reference to achieve the goal coordinates while avoiding obstacles with as great a distance as possible (Sezer & Gokasan, 2012).

Using the distance-to-obstacle geometry in Eq. (20), d is illustrated in Eq. (21).

$$dis = \sqrt{(x_{C0} - x_{C3})^2 + (y_{C0} - y_{C3})^2} \tag{20}$$

$$\Rightarrow d = dis - \sqrt{(x_{C0} - x_{C3})^2 + (y_{C0} - y_{C3})^2} \tag{21}$$

The two vehicles do not collide if $d > 0$. Thus, the obstacle avoidance problem is now equivalent to obstacle avoidance for points in Cartesian space. This guarantees a trajectory without collision if any gap is calculated. Otherwise, a collision risk exists due to the physical dimensions of the vehicles and obstacles. At present, one commonly used method is to surround the obstacle vehicles with a circle, as illustrated in Fig. 7. Actually, these approaches simplify the yield of the collision–free trajectory. However, these designed trajectories are obviously conservative because part of the non-vehicle region is included. It is difficult to seek a smooth trajectory if the host vehicle is close to the obstacle vehicles in the lane change scenario.

7. Collision avoidance

As shown in Fig. 8, we choose a dynamic circle with a diameter equal to the width of the vehicle, and we construct the region by using the circle to sweep along the vehicle length. Hence, a vehicle can be represented by an infinite number of circles.

The centers of the dynamic circles are given by Eq. (22).

$$\begin{cases} x = x_r + u_x(x_f - x_r) \\ y = y_r + u_y(y_f - y_r) \end{cases} \tag{22}$$

In this equation, $u_x \in [0,1]$, $u_y \in [0,1]$, x_r, x_f, y_r and y_f are the lateral coordinate of the rear dynamic circle, the lateral coordinate of the front dynamic circle, the longitudinal coordinate of the rear dynamic circle and the longitudinal coordinate of the front dynamic circle, respectively. By substituting the initial and target conditions of the vehicles, we can describe the other undetermined coefficients using the linear combination of a_6, as shown Eq. (23). Furthermore, a_i is a function of time t.

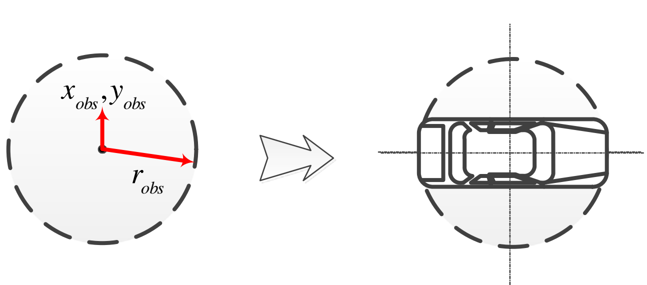


Fig. 6. How to abstractly represent a vehicle as a circle.

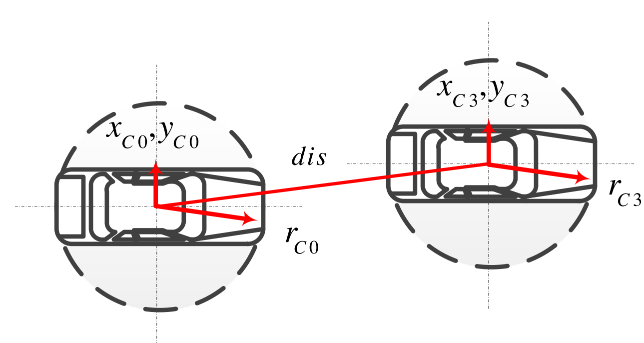


Fig. 7. Distance between two vehicles.

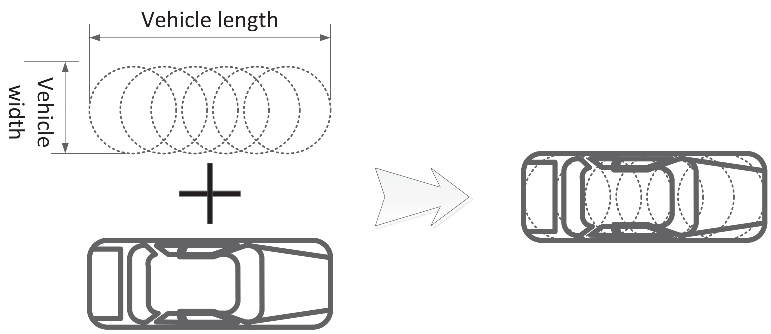


Fig. 8. Vehicle model based on infinite dynamic circles.

$$a_i = p_i + q_i a_6 \quad i = 1, 2 \ldots 5 \tag{23}$$

It is obvious that the conditions of collision avoidance should satisfy the rule shown in Eq. (24) during the entire lane change procedure.

$$(x_{c0} - x_{c3})^2 + (y_{c0} - y_{c3})^2 > (R_{c0} + R_{c3})^2 \tag{24}$$

Substituting Eq. (22) into Eq. (24), we obtain the following equation:

$$\begin{aligned}&[x_{c0r}(t) + u_{c0x}(x_{c0f}(t) - x_{c0r}(t)) - x_{c3r}(t) - u_{c3x}(x_{c3f}(t) - x_{c3r}(t))]^2\\ &\quad + [y_{c0r}(t) + u_{c0y}(y_{c0}(t) - y_{c0r}(t)) - y_{c3r}(t) - u_{c3y}(y_{c3f}(t) - y_{c3r}(t))]^2\\ &\quad > (R_{c0} + R_{c3})^2\end{aligned} \tag{25}$$

Eq. (25) is can be simplified because of the smaller lateral angle of the vehicle in a normal lane change scenario.

$$\begin{aligned}&[x_{c0r}(t) + u_{c0x}(x_{c0f}(t) - x_{c0}r(t) - x_{c3r}(t) - u_{c3x}(x_{c3f}(t) - x_{c3r}(t))]^2\\ &\quad + [y_{c0r}(t)]^2\\ &\quad > (R_{c0} + R_{c3})^2\end{aligned} \tag{26}$$

The equation above can be rewritten by using Eq. (27).

$$\alpha^2 a_6^2 + \beta a_6 + \gamma > 0 \quad \alpha \neq 0 \tag{27}$$

According to the analysis of the characteristics of the quadratic polynomial, the conditions of collision avoidance for the vehicles are such that the value of a_6 should be selected outside of the two roots of Eq. (28):

$$a_6 < \frac{-\beta - \sqrt{\beta^2 - 4\alpha^2\gamma}}{2\alpha^2} \cup a_6 > \frac{-\beta + \sqrt{\beta^2 - 4\alpha^2\gamma}}{2\alpha^2} \tag{28}$$

To illustrate the procedure, we give an example for the selection of a_6 in Section 6.2.

5. Tracking control of the reference trajectory of the vehicle

According to the kinematics model for a lane change and the control law design based on the backstepping method (Attia, Orjuela, & Basset, 2014; Takemura, Nakamura, & Ishiguro, 2011; You, Wang, Zhang, & Xiong, 2008), the error component x_e is regarded as a virtual control input, and the new virtual variables are denoted by Eq. (29).

$$\hat{x}_e = x_e - a_1 f(k\omega_c) y_e \tag{29}$$

where $f(k\omega_c)$ is the hyperbolic tangent function, and $a_1 f(k\omega_c) y_e$ is virtual feedback of controller. Let control input u_c make $\hat{x}_e \to 0$, the new virtual control input is defined in Eq. (31).

$$\forall a_1 \in (0, +\infty) \quad f(k\omega_c) = \tanh(k\omega_c) = \frac{1 - e^{-2k\omega_c}}{1 + e^{-2k\omega_c}} \tag{30}$$

$$x_e \to a_1 f(k\omega_c) y_e \tag{31}$$

Provided that $\theta_e \to 0$, according to the second equation of Eq. (3), we define the following equation.

$$\dot{y}_e \to -a_1 \omega_c f(k\omega_c) y_e \tag{32}$$

As for the theory of solving differential equations, the solution of equation, such as Eq. (33), is simplified to Eq. (34), i.e., $x(t)$ converges to zero asymptotically.

$$\dot{x} = -ax \quad (a > 0) \tag{33}$$

$$x(t) = x_0 e^{-at} \tag{34}$$

According to the characteristics of hyperbolic tangent function, it implies $\omega_c f(k\omega_c) \geqslant 0$ as ω_c and $f(k\omega_c)$ are in the same sign. Therefore, y_e converges to zero asymptotically as $t \to \infty$. Through further deduction, provided y_e converges to zero, Eq. (31) → 0, x_e also converges to zero. Accordingly, the control law of tracking trajectory mainly focuses on seeking control input $u_c = (v_c\ \omega_c)$ to make x_e converge to $a_1 f(k\omega_c) y_e$ and $y_e \to 0$.

Above implies that if $a_y > 0$, $p_e = (\hat{x}_e, y_e, \theta_e)^T = 0$ as $V = 0$; $p_e \neq 0$ as $V > 0$, i.e., Eq. (35) is positive definite.

Lyapunov candidate function is developed in Eq. (35).

$$V = \frac{1}{2}\hat{x}_e^2 + \frac{1}{2}y_e^2 + \frac{2}{a_y}[1 - \cos(\theta_e/2)] \tag{35}$$

From Eqs. (3) and (29), the following equation is deduced.

$$\dot{\hat{x}}_e = \dot{x}_e - a_1 f'(k\omega_c) k\dot{\omega}_c y_e - a_1 f(k\omega_c) \dot{y}_e \tag{36}$$

$$\begin{aligned}\dot{V} &= x\dot{\hat{x}}_e + y_e\dot{y}_e + \frac{\dot{\theta}_e}{a_y}\sin(\theta_e/2)\\ &= \hat{x}_e[-v_c + v_r\cos\theta_e - a_1\left(1 - f^2(k\omega_c)\right)k\dot{\omega}_c y_e - a_1 f(k\omega_c)\\ &\quad \times (-\omega_c x_e + v_r \sin\theta_e)] - a_1\omega_c f(k\omega_c) y_e^2 + \frac{1}{a_y}\sin(\theta_e/2)\\ &\quad \times [\omega_r - \omega_c + 2a_y y_e v_r \cos(\theta_e/2)]\end{aligned} \tag{37}$$

where

$$f'(k\omega_c) = \left[1 - f^2(k\omega_c)\right] \tag{38}$$

After taking the derivative of Eq. (36) and substituting Eq. (3), we obtain Eq. (37).Provided v_r, $\dot{v}_r$, ω_r and $\dot{\omega}_r$ are bounded $(\forall t \in [0, +\infty))$. Moreover, v_r, ω_r are not zero simultaneously. We choose the following controlling law.

$$\left.\begin{aligned}&\omega_c = \omega_r + 2a_y y_e v_r \cos(\theta_e/2) + a_0 v_r \sin(\theta_e/2)\\ &v_c = v_r\cos\theta_e + a_1 f(k\omega_c)\omega_c x_e - a_1 f(k\omega_c) v_r \sin\theta_e +\\ &a_x x_e - a_1 a_x f(k\omega_c) y_e - a_1 k\left(1 - f^2(k\omega_c)\right)\dot{\omega}_c y_e\end{aligned}\right\} \tag{39}$$

where $a_0 > 0,\ a_1 > 0,\ a_x > 0,\ a_y > 0,\ k > 0$. Substituting Eq. (39) into Eq. (35), we obtain Eq. (40).

$$\dot{V} = -a_x\hat{x}_e^2 - a_1\omega_c f(k\omega_c)y_e^2 - \frac{a_0}{a_y}v_r \sin^2(\theta_e/2) \tag{40}$$

Because $a_0,\ a_1,\ a_x,\ a_y \in (0, +\infty),\ \omega_c f(k\omega_c) > 0$, we know that $\dot{V} \leqslant 0$. Specifically, $\dot{V}$ is a negative, definite and continuous function because V of the Lyapunov function is positive, definite and bounded, which shows that $\hat{x}_e^2(t),\ y_e^2(t),\ \omega_c f(k\omega_c)y_e(t)$ and $\sin^2\theta_e/2$ converge to zero asymptotically as $t \to \infty$. Additionally, $x_e \to a_1 f(k\omega_c)y_e$ as $\lim_{t\to\infty}\hat{x}_e = 0$. Under the conditions that v_r and ω_r are not zero simultaneously, and assuming $\omega_c f(k\omega_c)y_e(t) \to 0$, we can deduce that $y_e \to 0$. Based on the above analysis, $x_e \to 0$. According to the Lyapunov stability criterion, the state vector $(x_e, y_e, \theta_e)^T$ is bounded and $\lim_{t\to\infty}\left\|(x_e\ y_e\ \theta_e)^T\right\| = 0$ when using the control input developed in this paper.

As for the kinematic characteristics of the lane change process, if system errors remain high, the control input $u_c = (v_c\ \omega_c)$ generated from the control law developed in our paper may exceed the scope of the maximum velocity $u_{\max} = (v_{\max}\ \omega_{\max})$ or the

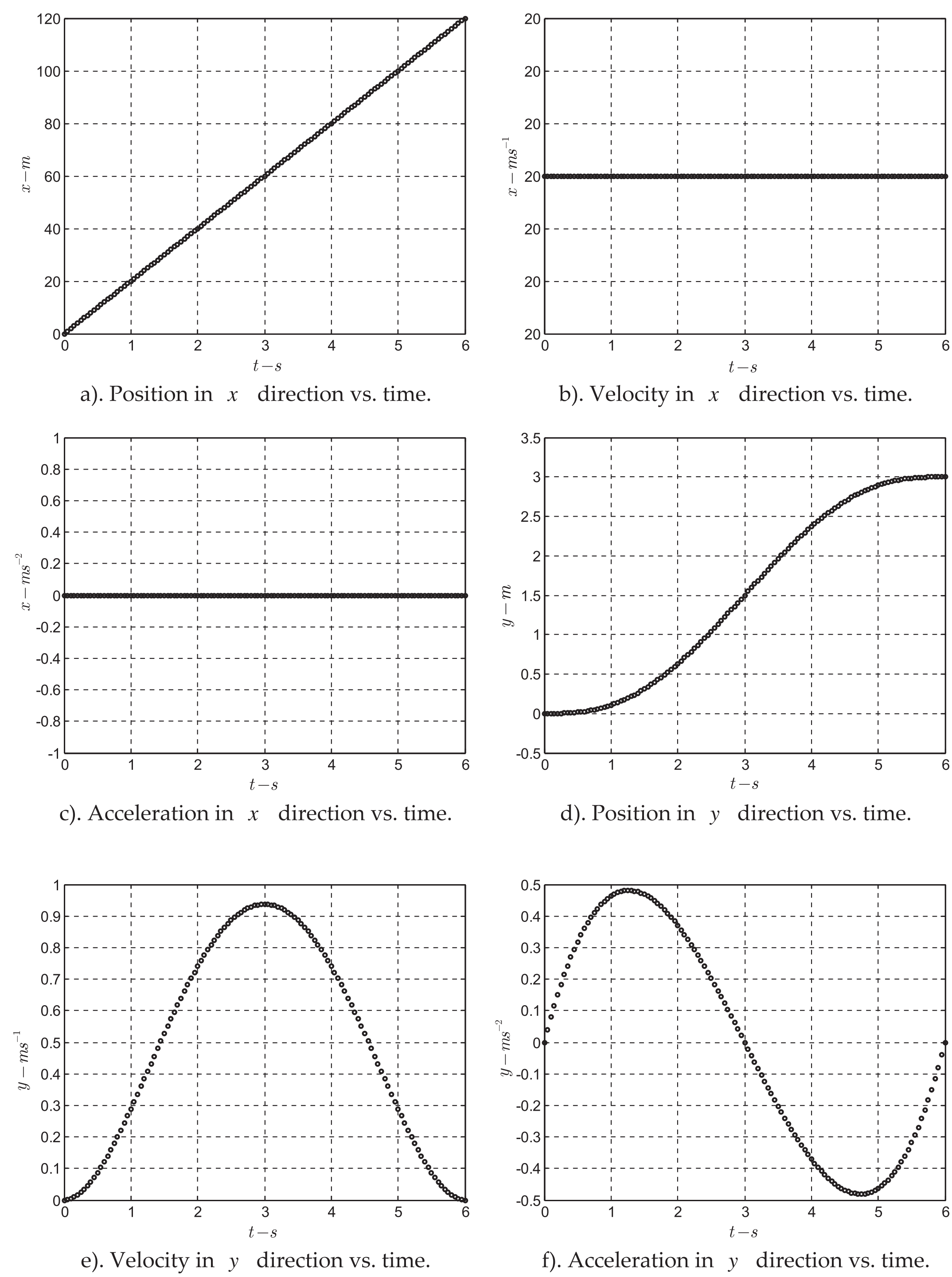


Fig. 9. Positions, velocities and accelerations of the host vehicle during a lane change without a front vehicle.

maximum acceleration ($\dot{v}_{\max}\ \dot{\omega}_{\max}$) of the vehicle. Therefore, we introduce the following control mechanics to avoid a slip between the wheel and the ground.

$$\omega_c = \begin{cases} \omega_c & |\omega_c| < |\omega_{\max}| \\ \omega_{\max} & |\omega_c| \geqslant |\omega_{\max}| \end{cases} \tag{41}$$

$$v_c = \begin{cases} v_c & |v_c| < |v_{\max}| \\ v_{\max} & |v_c| \geqslant |v_{\max}| \end{cases} \tag{42}$$

6. Experimental results

To validate the correctness and effectiveness of the control algorithm, a simulation was performed for a 4-wheeled vehicle in MATLAB/Simulink. It is more meaningful to select the parameters of the control law. In particular, parameter k influences the smoothness of the hyperbolic tangent function. Larger values of k cause $f'(k\omega_c)$ converge to zero faster. The control parameters were selected as $(a_1, a_x, a_y, a_0, k) = (1.5, 2.5, 0.2, 2.5, 6.8)$. The following figures represent the simulation results of the two trajectories.

6.1. Example 1

Assume a vehicle (host vehicle) running at $\dot{x} = 20\ \mathrm{m\ s^{-1}}$ performs a lane change at time $t = 0$ s and completes it at $t_{lc} = 6$ s. Assume that the vehicle accomplishes the lane change when both the longitudinal and lateral accelerations are 0. The width of each lane is 3 m. Hence, the initial and final states of the vehicle are

$$\vec{S}^{initial} = (x_0, \dot{x}_0, \ddot{x}_0, y_0, \dot{y}_0, \ddot{y}_0) = (0, 20, 0, 0, 0, 0)$$

$$\vec{S}^{final} = (x_t, \dot{x}_t, \ddot{x}_t, y_t, \dot{y}_t, \ddot{y}_t) = (120, 20, 0, 3, 0, 0)$$

By solving Eqs. (7) and (8), the trajectory is obtained, as shown in Fig. 10. Fig. 9(a)–(f) show the position in the x direction vs. time, the velocity in the x direction vs. time, the acceleration in the x direction vs. time, the position in the y direction vs. time, the velocity in the y direction vs. time, and the acceleration in the y direction vs. time, respectively. According to Figs. 9 and 10, the generated trajectory results obviously have a continuous curvature outline (see Fig. 11).

6.2. Example 2

Assume a vehicle (host vehicle) running at $\dot{x} = 20\ \mathrm{m\ s^{-1}}$ performs a lane change at time $t = 0$ s. At the same time, there is another vehicle running at $\dot{x} = 20\ \mathrm{m\ s^{-1}}$ in front of the host vehicle. Assume that the host vehicle executes the lane change and finally adjusts its velocity to that of the front vehicle, which is one of most important principles in cooperative driving. After time $t_{lc} = 6$ s, both the longitudinal and lateral accelerations of the host vehicle are 0. Hence, the initial and final states of the vehicle are

$$\vec{S}^{initial} = (x_0, \dot{x}_0, \ddot{x}_0, y_0, \dot{y}_0, \ddot{y}_0) = (0, 20, 0, 0, 0, 0)$$

$$\vec{S}^{final} = (x_t, \dot{x}_t, \ddot{x}_t, y_t, \dot{y}_t, \ddot{y}_t) = (140, 20, 0, 3, 0, 0)$$

Obviously, selecting $a_6 = -0.025$ will bring about a collision at time $t = 3s$ between the host vehicle and the obstacle vehicle. Conversely, a collision-free trajectory is generated if a_6 is selected outside the two roots of Eq. (27). For example, selecting $a_6 = 0.015$ yields a collision-free trajectory. Obviously, the selection of collision-free trajectories is not complicated since the obstacles are mapped into some parameters space–space $a_6 - t$. Fig. 12(a)–(f) show the position in the x direction vs. time, the velocity in the x direction vs. time, the acceleration in the x direction vs. time, the position in the y direction vs. time, the velocity in the y direction vs. time, and the acceleration in the y direction vs. time, respectively. Based on Figs. 12 and 13, it is clear that the generated trajectory results have a continuous curvature outline. As expected, the collision avoidance algorithm results in a smooth trajectory.

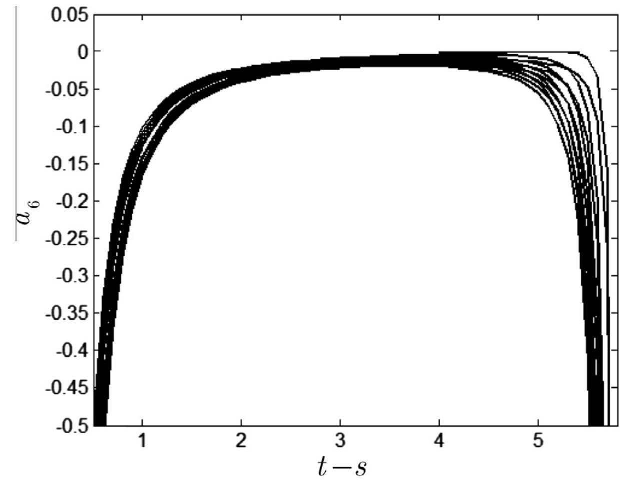


Fig. 11. $a_6 - t$ space.

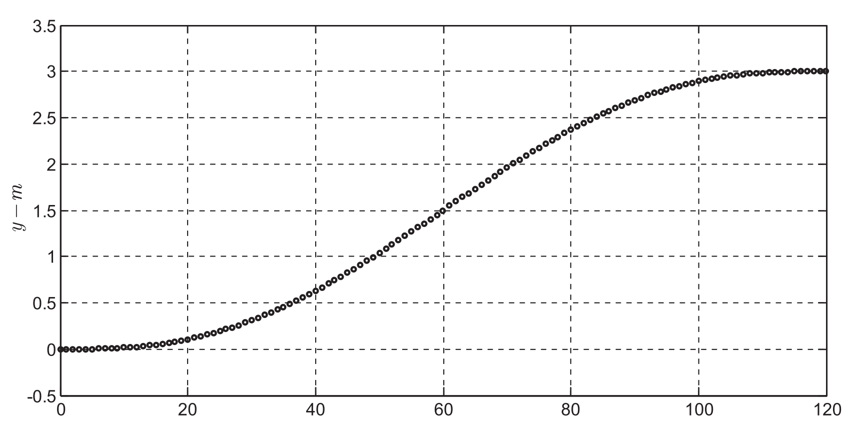


Fig. 10. Trajectory of a lane change without a front obstacle vehicle.

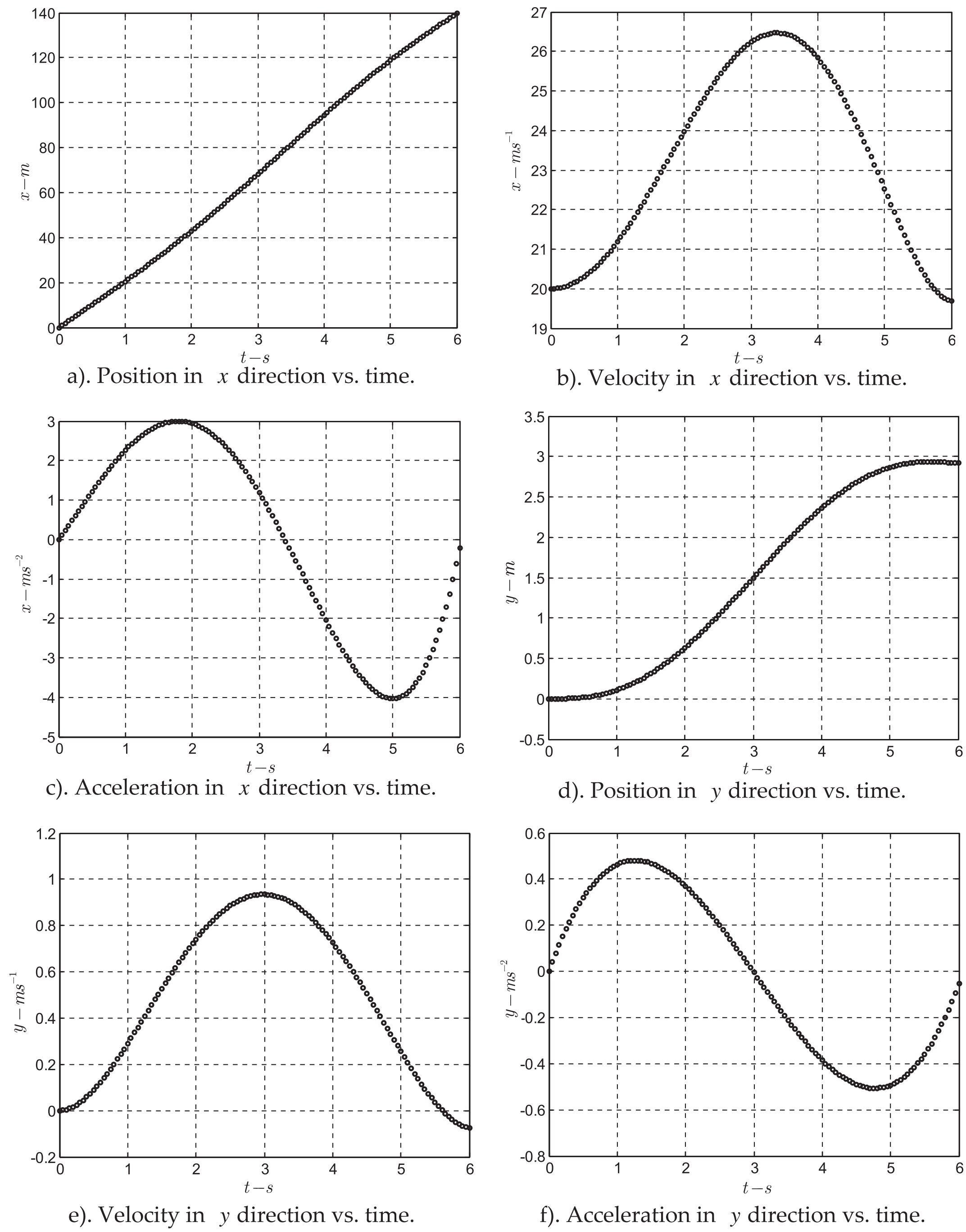


Fig. 12. Positions, velocities and accelerations of the host vehicle during a lane change with a front vehicle.

6.3. Tracking a straight line

Tracking a straight line is a simple case for the vehicle. Here, for simulation, we assume a straight line. It is further assumed that the initial state of vehicle is

$(x_e, y_e, \theta_e) = (10\ m, 3\ m, \pi/3\ rad).$

The straight line reference trajectory to be tracked is given by $y = x$. The simulation results for tracking a straight line are shown in Fig. 14.

6.4. Tracking a circle

The simulation results for tracking a circle are shown in Fig. 15. We selected the desired circle trajectory

$x^2 + y^2 = 40^2$

with the initial state of the vehicle

$(x_e, y_e, \theta_e) = (15\ m, 3\ m, \pi/3\ rad).$

The reference linear velocity is selected to be $v_r = 5$ m/s, and the angular velocity ω_r updates with each change of posture.

6.5. Experimental platform

After developing the algorithm for trajectory generation and tracking and successfully running the simulations, we experimentally validated our control algorithm on an intelligent vehicle (IV), the 'DLUT-IV'. DLUT-IV is a fully intelligent ground vehicle with sensors for localization and mapping, real-time industrial personal

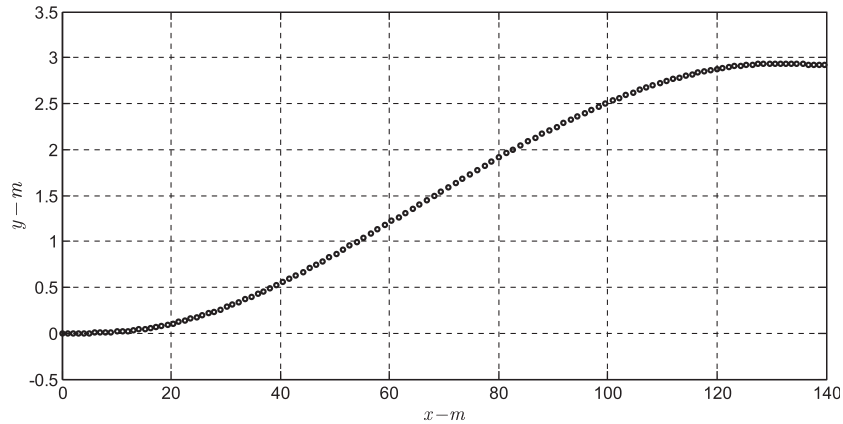
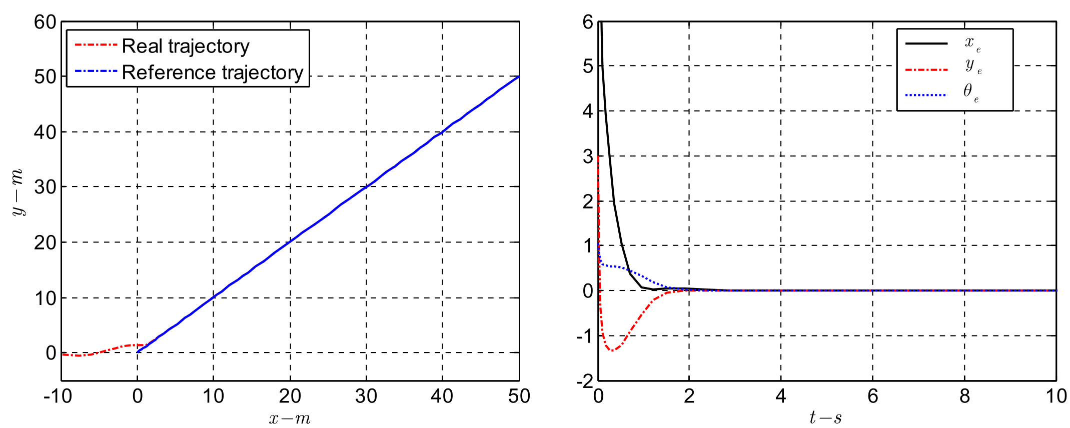


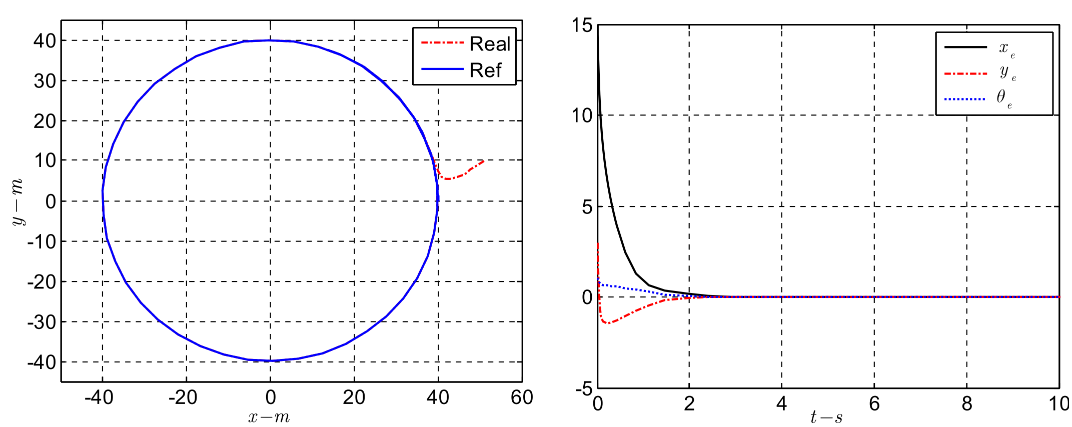
Fig. 13. Trajectory of a lane change with a front obstacle vehicle.



a). Simulation of tracking a line

b). Tracking errors

Fig. 14. Trajectory tracking of a straight line and the resulting tracking errors.



a). Simulation of tracking a circle

b). Tracking errors

Fig. 15. Trajectory tracking of a circle and the associated tracking errors.

computers and drive-by-wire capability. Fig. 16 shows the sensors mounted on the DLUT-IV. The vehicle is 1.5 m wide and 4.8 m long. It weighs approximately 1450 kg and can accommodate 4 people. Like ordinary vehicles, it has two rear-driving wheels and two front wheels with a maximum steering angle, δ, of 21.5°. It is equipped with a 196 kW gasoline engine that can drive the vehicle up to 80 km h^{-1}.

All of the computer and sensor systems and their communication protocols are illustrated in Fig. 17. Because the sensors have different communication protocols, in-vehicle communication is performed via CAN, Ethernet, RS232 and 1394 firewire. More information about the hardware and software structure of the experimental platform can be found in.

6.6. Tracking experiments for the lane change trajectory

Based on the simulations of a straight line and a circle discussed in sub-sections 6.3 and 6.4, it is concluded that the IV with the

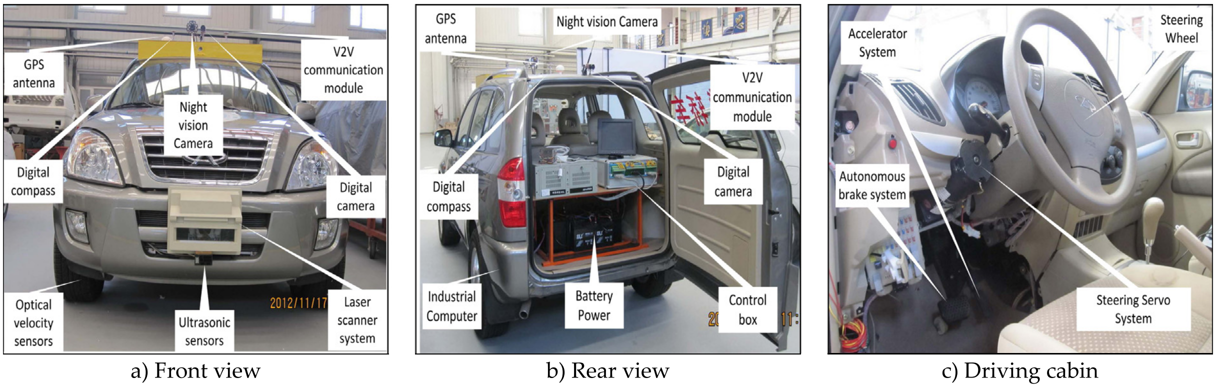


Fig. 16. Experimental setup: fully intelligent DLU-IV with sensors and actuator.

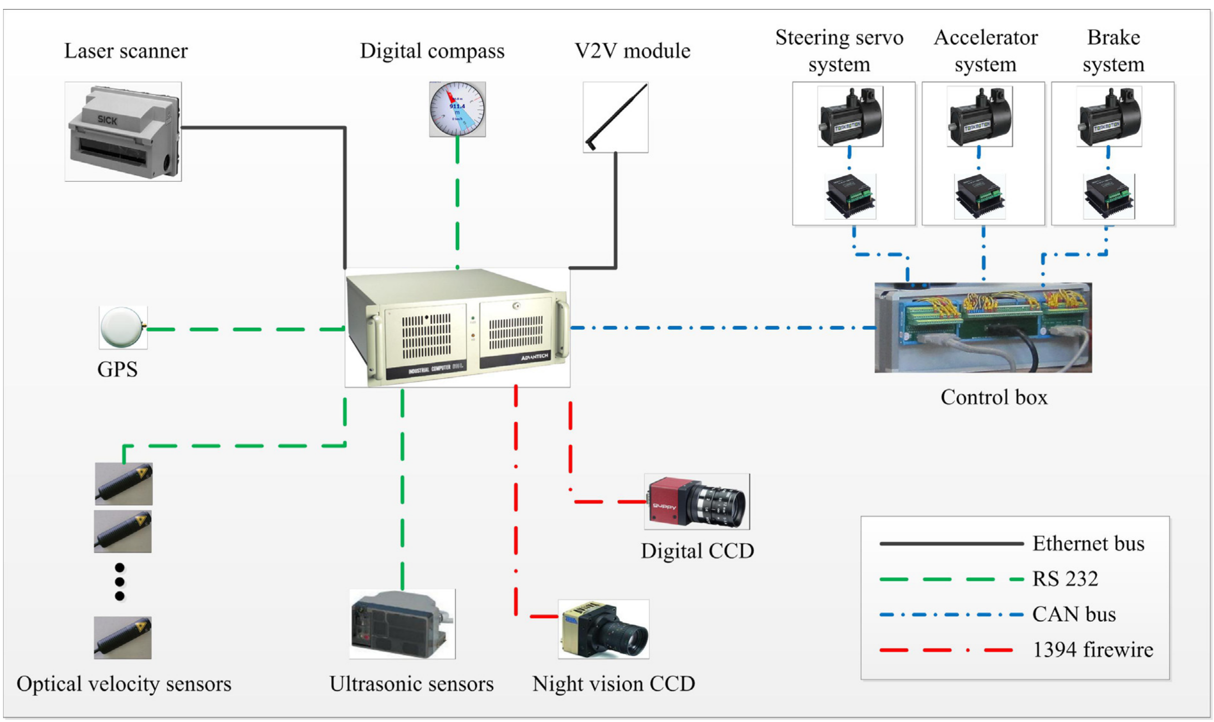


Fig. 17. Sensors, computer system and communication system in the DLU-IV.

designed controller is capable of globally asymptotically tracking the desired trajectories. All of the simulation results use the same controller parameters $(a_1, a_x, a_y, a_0, k) = (1.5, 2.5, 0.2, 2.5, 6.8)$. Based on the simulation results, tracking experiments for lane change trajectory were carried out to determine the effectiveness of the controller.

It is extremely significant that each vehicle in the lane change scenario can be coordinated. The vehicles and infrastructure can be linked by using V2X. Information about posture from the vehicles and about the environment is shared. Based on this scheme, a cooperative decision can be made for the lane change, which includes steps of trajectory planning, collision avoidance, movement coordination and controller design.

The case of lane change by two vehicles is analyzed to determine the performance of the cooperative strategy. Because testing behaviors such as 'avoid collision with the front vehicle' or 'lane change to the right lane' requires at least two vehicles, our experiments have paid attention to testing the trajectory tracking and obstacle-vehicle avoidance behaviors. In the case under discussion, the host vehicle is tested and found to have a minimum speed of 10 km/h and a maximum speed of 20 km/h. The maximum turning rate of the vehicle is 3° s^{-1}. The initial and final states of the host vehicle are

$$\vec{S}^{initial} = (x_0, \dot{x}_0, \ddot{x}_0, y_0, \dot{y}_0, \ddot{y}_0) = (0, 12, 0, 0, 0, 0)$$

and

$$\vec{S}^{final} = (x_t, \dot{x}_t, \ddot{x}_t, y_t, \dot{y}_t, \ddot{y}_t) = (110, 12, 0, 3.75, 0, 0).$$

The different parameters used in the experiments are specified according to characteristics of the DLUT-IV. They are described in

Table 1
Parameter ranges for characteristics of the DLUT-IV.

v_{x_max}	$\dot{v}_{x\_max}$	v_{y_max}	$\dot{v}_{y\_max}$	δ_{max}	$\dot{\delta}_{max}$
20 m s^{-1}	1 m s^{-2}	1.2 m s^{-1}	0.6 m s^{-2}	21.5°	3° s^{-1}

Table 1. At the start of the lane change, the spacing between the host and the obstacle vehicle is 15.2 m. The time for the lane change is approximately 8 s. The communication range is about 300 m, and the data sent is received by the other vehicle with a delay of one update period.

When the host vehicle makes a lane change request by using v2X and the remote center approves the request, the lane change can be carried out by the host vehicle. Fig. 18 shows the experimental results following the planned trajectory. In the plot, it can be noted that the host vehicle runs forward 110 m by the end of the lane change (after 8 s). Moreover, the lateral displacement is 3.75 m. Obviously, the host vehicle crosses into the adjacent lane. In addition, the experimental results for longitudinal displacement, longitudinal velocity, lateral displacement and lateral velocity of the host vehicle are reported in Fig. 20. Snapshots of the experimental lane change with a front vehicle are presented in Fig. 20. The subplots show that the host vehicle is capable of tracking the pre-established trajectory and advancing side-by-side with the obstacle vehicle in an adjacent lane at the end of the process. There is no collision between the host and obstacle vehicle. The process benefits from the contributions of the cooperative technology (see Fig. 19).

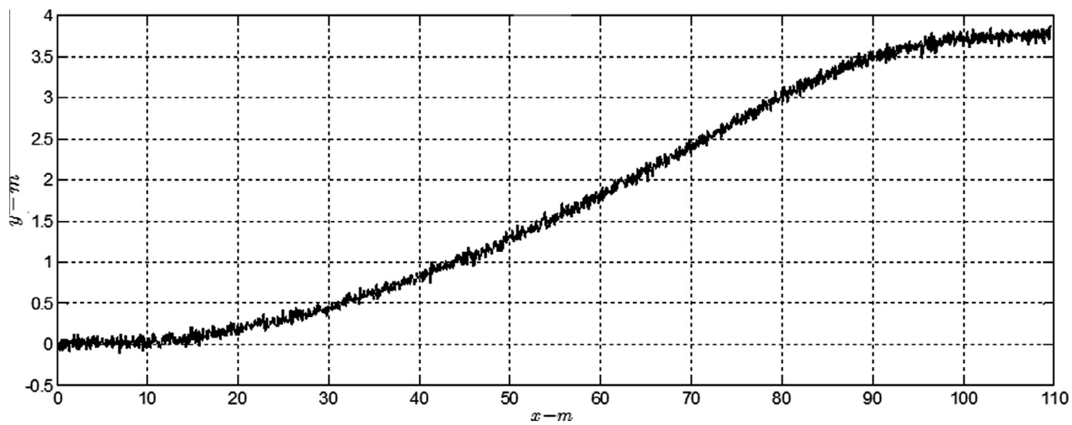


Fig. 18. Trajectory of the lane change with a front obstacle vehicle.

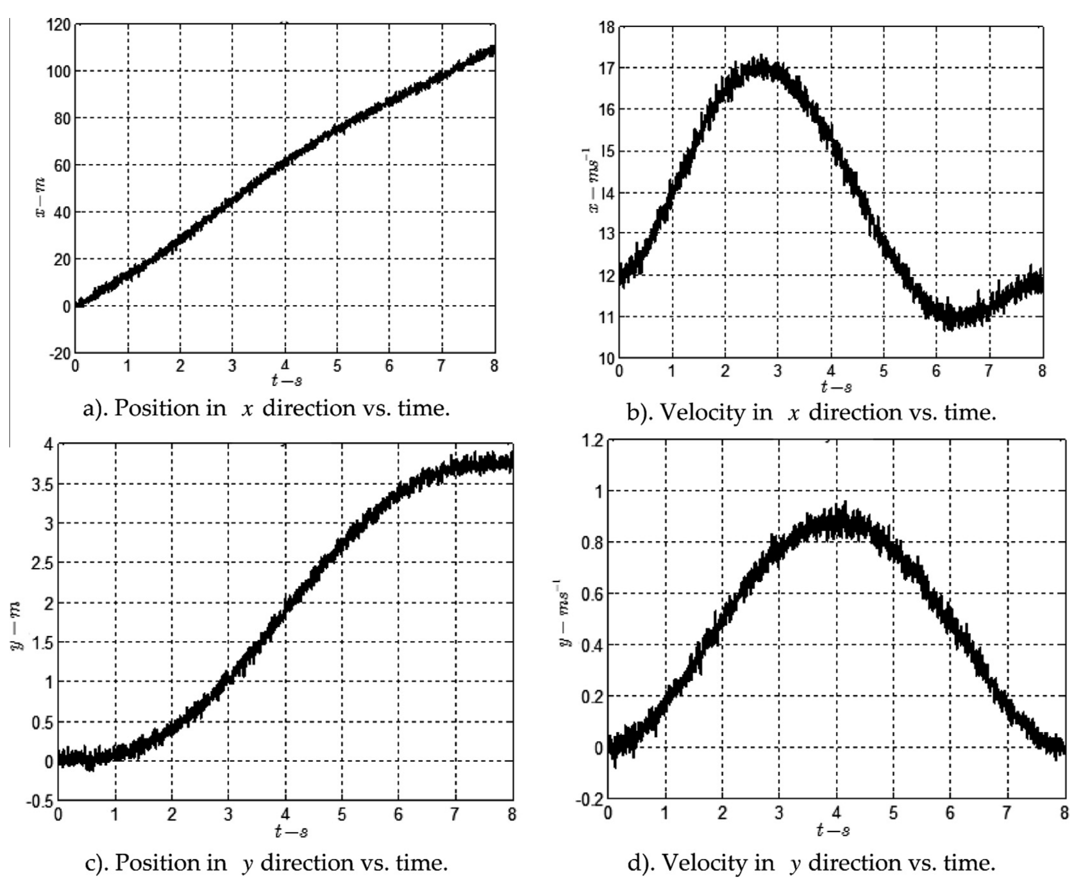


Fig. 19. Positions and velocities of the host vehicle during a lane change with a front vehicle.

Fig. 20. Snapshots of the lane change experiment with a front vehicle.

7. Conclusions

Lane change maneuvers are one of the most conventional behaviors in driving. Unsafe lane change maneuvers could result in road traffic accidents and the following congestion and delay. The main issue discussed in this paper is the development of a lane change assistance system. The system contains two core modules – trajectory planning and trajectory tracking. The former is based on the characteristics of polynomials. It abstracts the lateral and longitudinal movement of the host vehicle as functions of time in Cartesian Coordinates system. Also, in order to yield a collision-free trajectory, a method based on infinite dynamic circles is introduced to detect collision during lane change. The latter is based on the backstepping principle. It designs a tracking controller, proven to possess global convergence ability by Lyapunov stability theory.

The main contribution of the system is the design algorithm to generate trajectories during lane changes. Most authors have dealt with the trajectory planning using road-map, cell decomposition, HMM, and circular. As a novelty, the planning process is based on polynomials due to the fact that a polynomial curve has the advantage of continuous curvature and simplicity. It abstracts movement of a host vehicle into functions of time. Collision detection is performed through the application of infinite dynamic circles. The selection of collision-free trajectories is transformed into an easy work because the obstacles are mapped into parameters space. Simulation and experiments have been conducted to demonstrate the effectiveness of the proposed trajectory planning method.

Another significant contribution to the system is the ability to track the predefined trajectories for autonomous lane changes Maneuver. The tracking controller is based on backstepping principle. It is capable of ensuring global convergence property during lane change. In addition, as for the kinematic characteristics of the host vehicle and passengers' comfort, the output of the controller is limited to avoid a slip between wheels and ground. Simulation and experimental results demonstrate that this controller can guarantee the convergences of relative position tracking errors.

Although achieved results are promising, the developed system is far from the practical application for which the scenario lane change in the paper is rather simple and 100% reliability is needed. Further analysis and improvement are required. There are several directions for future research. One is to develop an autonomous lane change system that is capable of 100% accuracy. Another is to utilize this technique for more complex scenarios, such as those involving multiple vehicles. For example, there may be front vehicles and behind vehicles in the current lane or in the neighboring lane. The third one is to explore new trajectory prediction methods based on trajectories data collected in real driving conditions during lane changes with instrumented vehicles. This will fully take the human drivers' personal habits of driving into account.

As discussed above, lane change maneuvers are one of the most common driving behaviors. And unsafe lane changes cause many road traffic accidents. Accordingly, to improve safety of lane changes, the proposed system in this paper can be integrated into an ADAS. Although further studies on this system are needed, it still has a promising potential for many applications. For example, this system can evaluate driving risks for lane changes using trajectories generated. On the other hand, the system can be installed on intelligent vehicles: this algorithm could be integrated with other algorithms which typically operate on intelligent vehicles, such as lane keeping and adaptive cruise control, providing the capability of exiting from a vehicle platoon or merging to a vehicle platoon. By using this system, driving fatigue and inattentions could be effectively reduced. Additionally, the system could take actions on behalf of the driver to avoid traffic accidents in case of emergency. Finally, the proposed system is a feasible ADAS for translation into integrated circuits such as a field-programmable gate array (FPGA). Such an implementation will extend the application of the presented system-not only in highways, but also city expressway.

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