Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 52-8 (2019) 422–427

A Path Planning Method for Vehicle Overtaking Maneuver Using Sigmoid Functions

Xujiang Huang, * **Wenzhe Zhang, Pu Li**

* *Process optimization Group, Institute of Automation and Systems Engineering, Technische Universitt Ilmenau, POBOX 100565, 98694 Ilmenau, Germany (e-mail: xujiang.huang; abebe.geletu; pu.li@tu-ilmenau.de).*

Abstract: Geometric curves are mostly applied as guidance for lane-keeping and lane-changing motions. In this work, we explore the capabilities of using sigmoid functions in vehicle overtaking scenarios. Such curves are parameterized based on the current relative distance and speed concerning the preceding vehicle. Besides, the overtaking decision, i.e., whether to change lane or not, can be determined by using a piecewise function in the planning module. Then, model predictive control (MPC) is applied to track the generated overtaking path. Case studies including two scenarios, i.e., preceding vehicle driving at constant and varying speed, show that the proposed control framework is capable of self-decision making and handling overtaking maneuver effectively.

Keywords: Overtaking maneuver, path planning method, sigmoid function, model predictive control

1. INTRODUCTION

Over the last few years, autonomous driving has been one of the most interesting topics in the automotive industry due to its potential capabilities of increasing the traffic efficiency and decreasing the traffic accidents. Potential automatic lane-keeping functions, such as the adaptive cruise control (ACC) and the lane-keeping assist (LKA), have been widely employed as a driving-assistant function Watanabe et al. (1995); Pohl and Ekmark (2003). To complete the evolutionary transition, an autonomous lane-changing function is indispensable to perform special driving activities, such as at highway entry and exit, platoon merging and leaving, and vehicle overtaking.

Several studies have recently been made to address the trajectory planning problem for lane-changing using the state-based scheme. A detailed review refers to Katrakazas et al. (2015). Given the initial or current state, the planning problem is solved using a geometric or model-based approach. In the geometric method, a specific pattern of the geometric curve, such as arcs, clothoids, polynomial spirals and spline curves, is predetermined to ensure smooth motions. Then, the velocity and acceleration profile related to the curve is calculated by tracking the reference trajectories or by minimizing a cost function. In Petrov and Nashashibi (2014), an adaptive nonlinear controller was designed to follow reference trajectories described by a polynomial function for overtaking. A three-phase overtaking maneuver is realized by tracking the virtual reference points attached to the overtaken vehicle. In Delsart et al. (2009); Cong et al. (2010), a second or fourth order polynomial trajectory is optimized according to a customized cost function. In Ziegler et al. (2014); Hardy and Campbell (2013), multiple traffic participants were considered by constructing driving corridors as constraints for the curvature. The complexity of the optimization problem increases as more constraints are included. For a model-based method, model predictive control (MPC) is favored due to its advantages on an explicit inclusion of variable constraints. Within MPC, at each time instant, an optimal trajectory over a finite time horizon is generated by solving an open-loop optimization problem considering vehicle dynamics, vehicle capabilities and variable boundaries introduced by the road and traffic participants. In Nilsson et al. (2015), the trajectory plan was made by solving a quadratic programming (QP) problem, where collision avoidance constraints were formulated as affine combinations of the vehicle state and input variables. In Nilsson et al. (2016); Mads et al. (2013), a corridor path was formulated as constraints in the optimization problem. However, an adaptive path planning strategy considering the impact of relative velocities between two vehicles has not been comprehensive discussed in the references.

In this work, we propose to derive the overtaking maneuver with two stages: path planning and path tracking. In the path planning, the reference path is generated together with the overtaking decision on whether to make the lane-changing maneuver or not according to the relative speed between the ego and preceding vehicle. Namely, the reference path is adjusted itself according to this relative speed. For example, the path switch to the adjacency lane when the ego vehicle is faster than the preceding one. Otherwise, the reference path remains in the current

⋆ The authors would like to thank the Audi AG for the equipment and technical support during the Audi Autonomous Driving Cup 2017 competition. This support is gratefully acknowledged.

10.1016/j.ifacol.2019.08.098

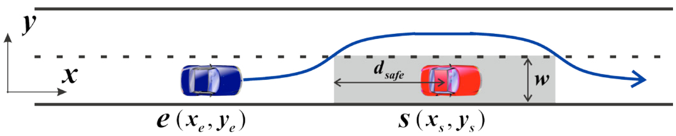

Fig. 1. An overtaking scenarios involved with two vehicles e and s. The overtaking path (blue) should avoid to enter the forbidden area (gray) around s.

lane, i.e., lane-keeping mode. To achieve this adaptive lane-changing strategy, the path is constructed with two sigmoid functions parameterized by the relative speed and pre-defined minimum safe distance. After that the reference path will be fed to the tracking controller, which the real-time nonlinear model predictive control (NMPC) is adopted in this work.

The paper is organized as follows. Section 2 introduced the control architecture for the vehicle overtaking function. In Section 3 and 4, the proposed path planning method using sigmoid function and path tracking function implemented with NMPC trajectory are described. In Section 5, the experiment results including two overtaking scenarios are presented. The conclusions and future work are given in Section 6.

2. PROBLEM DEFINITION

In this study, we consider an overtaking scenario involved with two vehicles. As seen in Fig. 1, the ego vehicle (blue), denoted as e, is governed by the approach developed in this study. The preceding vehicles (red) in the originating (right) lane is denoted as s. All the symbols or parameters associated with the vehicles are denoted by a subscript $i \in \{e, s\}$. We define a forbidden area around s. As seen in Fig.1, this forbidden area is a rectangular, in which a safe distance d_{safe} is defined for longitudinal direction and w (i.e., width of the lane) for lateral direction. A sequence of reference points (x_{ref}, y_{ref}) are generated from the image processing. The path planning algorithm is responsible for the calculation of the lateral coordinates y_o for lane changing and give the control inputs in the form of speed v_e and δ_e

For the purpose of observing ego and neighboring vehicles' states (i.e., position and speed), we assume that the vehicle is equipped with internal sensors (i.e., wheel encoder and IMU) and external sensors (i.e., radars, Vehicle-to-Vehicle (V2V) communication modules).

The schematic architecture of the control system considered in this study is illustrated in Fig. 2.
V2V communication receives the the longitudinal coordinate x_s and the cruise velocity v_s of s in real-time.
Lane detector generates the reference points (x_{ref}, y_{ref}) of the current lane for lane-keeping function. The implementation of the lane detector is beyond this paper and will not be discussed.
Path planning determines a geometric curve, describing the overtaking motions. In this work, the curve is parameterized based on sigmoid functions. A sequence of lateral coordinates y_o is interpolated with the longitudinal reference points x_{ref} from lane detector.
Path tracking is responsible for tracking the overtaking path x_{ref}, y_o considering both overtaking path and cruise

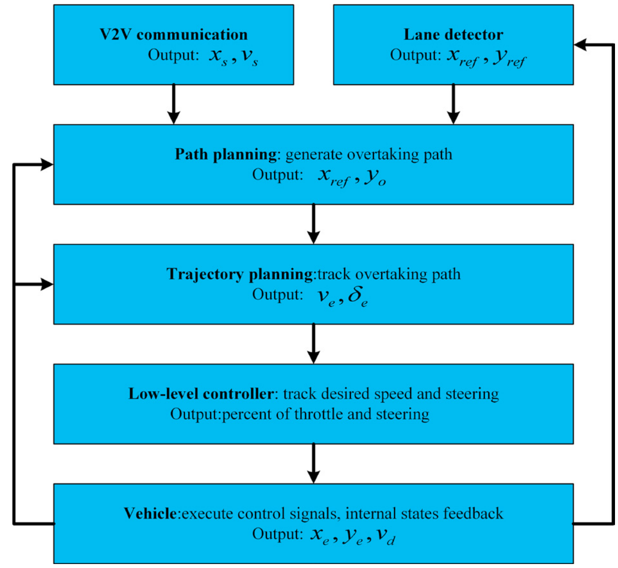

Fig. 2. System architecture

velocity. A model predictive control (MPC) framework is adopted for on-line implementation.
Low-level controller is responsible for the direct control of the motion of e. It is directly connected to the actuators and is supposed to be able to track the speed v_e and steering angle δ_e appropriately.
Vehicle is the controlled object. Information from internal sensors is processed in localization function, which delivers a proper estimation of the current position of (x_e, y_e). The desired cruise velocity is denoted as v_d.

3. PATH PLANNING BASED ON SIGMOID FUNCTIONS

In this paper, we propose a path planning method based on sigmoid functions. The shape of the overtaking path is determined with pre-defined parameters considering the aspects of collision avoidance and driving comfort. Assume e remains at a constant cruise speed v_d, an overtaking maneuver is only necessary when the speed of s is lower than e and impedes its travel efficiency.

3.1 Construction of overtaking path

A sigmoid function is a mathematical function which is continuous, monotonic, differentiable, and constrained by a pair of horizontal asymptotes. The formula of a normal sigmoid function is described as:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

where $x \in \Re$ and $S(x) \in (0, 1)$.

As seen in Fig. 3(a), the shape of the sigmoid function (1) is similar to the lane change curve in an overtaking maneuver. Two horizontal asymptotes represent the centerlines of originating and destination lanes.

To reshape (1) with the road geometry and avoid collision with s, a sequence of transformation operations, i.e., *reflection*, *stretch*, *translation* and *addition*, are performed.

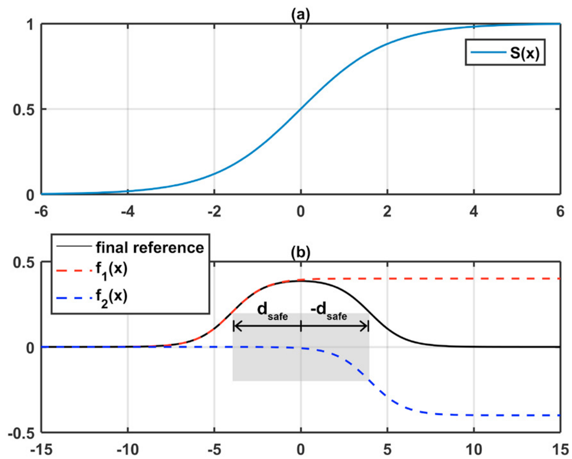

Fig. 3. (a) Sigmoid function with variable $x \in (-\infty, +\infty)$. (b) Overtaking path (black) composed of y_1(red) and y_2(blue). $w = 0.4$, $d_{safe} = 4$ and $\mu = 1$.

First, we formulate two sigmoid functions y_1 and y_2, which represent the lateral coordinates of left and right lane change movements, and state as follows:

$$y_1(x_1) = \frac{w}{1 + e^{-x}} \tag{2}$$

$$y_2(x_2) = \frac{-w}{1 + e^{-x}} \tag{3}$$

where the sigmoid functions are stretched with a scalar factor w so that the lane change curve terminate at the center of the destination lane. $y_2(x)$ is reflected around x-axis for right lane change when s is overpassed.

As mentioned in Section II, e is only allowed to have a longitudinal relative distance with s smaller than d_{safe} when it departures from the originating lane. Therefore, we define x_1, x_2 as follows:

$$x_1 = \frac{1}{\mu}(\Delta x + d_{safe}) \tag{4}$$

$$x_2 = \frac{1}{\mu}(\Delta x - d_{safe}) \tag{5}$$

where (4) and (5) are translated with a displacement distance of $+d_{safe}$ and $-d_{safe}$, respectively. $\Delta x = x - x_s$ and $\Delta y = y - y_s$ are the relative distance between e and s in the longitudinal and lateral directions, respectively.

To construct a complete overtaking path, the lateral coordinates of the entire overtaking movements are computed with the addition of (2) and (3):

$$y_o = y_1 + y_2 + y_l \tag{6}$$

where y_l is the lateral coordinate of the centerline of the originating lane.

Remark 1. Parameter μ determines the slope of the lane change movements and has to be defined properly. As shown in Fig. 4, a gentle lane change curve with large μ may result in a long occupation time on both lanes. However, a lane change curve with small μ is too aggressive to have a comfort driving experience.

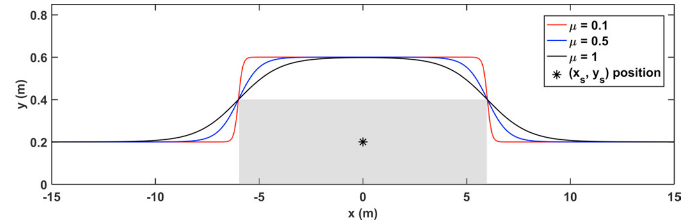

Fig. 4. Overtaking paths with different parameters $\mu \in \{0.1, 0.5, 1\}$. In this case, $d_{safe} = 6$, $w = 0.4$ and $y_l = 0.2$.

3.2 Piecewise function for collision avoidance and decision making

To guarantee a safe path overpassing s, we define d_{safe} as:

$$d_{safe} = \Delta v t_s \tag{7}$$

where $\Delta v = v_d - v_s$ is the relative velocity between s and e. The time interval t_s is a quantified criterion, namely, the time-to-collision (TTC) defined as the reaction time of human drivers.

To describe the overtaking decision based on the relative speed between e and s, the safe distance d_{safe} in Eqs. (4) and (5) is defined as a piecewise function and given as:

$$d_{safe} = \begin{cases} 0 & \text{if } \Delta v \leq 0 \\ \Delta v t_s & \text{otherwise} \end{cases} \tag{8}$$

where the first part holds $d_{safe} = 0$ when $v_d \leq v_s$. Then, x_1 and x_2 have the same value in (4) and (5). Then, (3) is simply a reflection of (2) around x-axis. Consequently, $y_o = y_l$ and no overtaking maneuver will be performed. In the second part, d_{safe} increases linearly with Δv when e is faster than s. A distance gap emerges between (2) and (3) so than s can be overpassed without collision.

Due to the symmetric property of the sigmoid function, the left-change path is neutralized by the nearby right-change path when the relative velocity is slight. For instance, when $0 < \Delta v < 0.5$, the shift of the lateral coordinates in the reference path is not enough, i.e., $y_o < w$. Moreover, the size of the resulting distance gap is insufficient to overpass s without collision. Although this phenomenon can be eliminated by changing μ, the resulting path leads to an undesirable lateral movement as discussed in Remark 1. Thus, we introduce an additional term d_{min} for compensation:

$$d_{min} = \begin{cases} 0 & \text{if } \Delta v \leq 0 \\ d_c & \text{otherwise} \end{cases} \tag{9}$$

where d_c is the minimum overtaking distance during parallel driving in the left lane for overpassing the preceding vehicle. Then,

$$x_2 = \frac{1}{\mu}(x_{ref} - x_s - d_{safe} - d_{min}) \tag{10}$$

It can be seen that d_{min} is also limited at 0 when $v_d \leq v_s$, but it will switch to d_c when e is faster than s. The red path in Fig. 5 indicates a successful overtaking maneuver after the compensation.

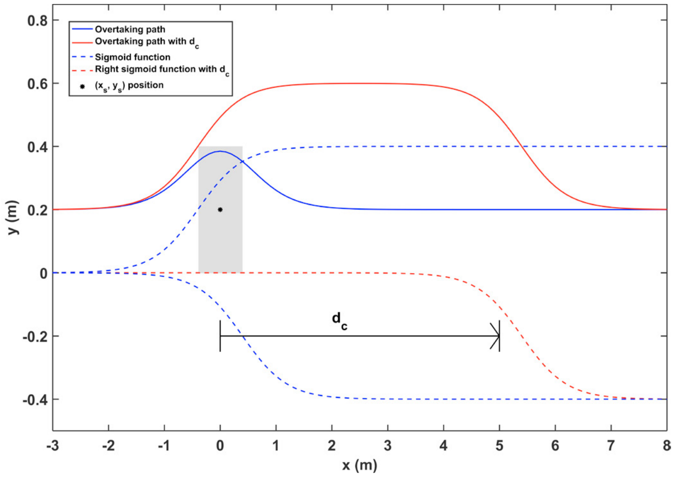

Fig. 5. Overtaking path (blue) determined with relative speed $\Delta v = 0.2m/s$, TTC $t_s = 2s$ and $d_{safe} = 0.4$. The path (red) with compensation part is carried out with $d_c = 5m$.

4. PATH TRACKING USING NONLINEAR MODEL PREDICTIVE CONTROL

In general, NMPC works by repeatedly solving (i.e., at every sampling time) a finite dimensional nonlinear programming (NLP) problem considering the current state as the initial state x_0 of the problem. The predicted states and controls are continually updated to take account of the most recent target and measured data. For each prediction, the solution of the NMPC problem is a sequence of optimal control inputs, which minimizes an objective function and leads the vehicle towards the desired behavior. At time $t = t_0$ the NMPC problem is solved and the actuator applies only the first element of the optimal control input computed for the time $t = [t_0, t_f]$. After that, the prediction horizon is receded, the current state is measured (or estimated) using sensors (or observers), and the NMPC problem is solved again using the measured (or estimated) state as initial state. This process is repeated iteratively while the system is in operation.

4.1 Optimal path tracking problem

This work considers nonlinear dynamic optimization problems of the form

$$\min_{u(t)} \left\{ J = \int_{t_0}^{t_f} L(x(t), u(t))dt \right\}$$

subject to:

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t), p, t),\ x(t_0) = x_0, \qquad (11)\\ x_{min} &\leq x_i(t) \leq x_{max},\ \text{for } i = 1, \ldots, n_x \\ u_{min} &\leq u_j(t) \leq u_{max},\ \text{for } i = 1, \ldots, n_u \\ t &\in [t_0, t_f], \end{aligned}$$

where $x(t) \in \Re^{n_x}$ represents the vector of state variables and $u(t) \in \Re^{n_u}$ is the control vector. The time-independent parameters are defined as $p \in \Re^{n_p}$. The initial state $x(t_0)$ is supposed to be known and fixed. The final state $x(t_f)$ may be fixed or free. The time horizon is defined as $t \in [t_0, t_f]$, with initial time t_0 and terminal time t_f. The function $f : \Re^{n_x} \times \Re^{n_u} \times \Re^{n_p} \times [t_0, t_f] \rightarrow \Re^{n_x}$ as well as the objective function J are assumed to be twice differentiable.

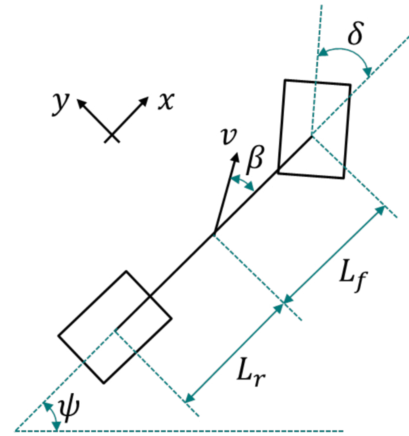

Fig. 6. Kinematic vehicle model

The differential states and control variables are bounded as indicated by the box-constraints.

The objective function is designed to track the overtaking path generated in the path planning module and stated as:

$$\begin{aligned} L(x(t), u(t)) = &a_1(x_i(t) - x_{ref}(t)^2 + a_2(y(t) - y_o(t))^2 \\ &+ a_3(v(t) - v_d(t))^2 \end{aligned} \qquad (12)$$

where parameters a_1, a_2, a_3 are the positive weighting factors which reflect the user-defined path tracking behaviors.

The mathematical model for this vehicle (see in Fig. 6) is formulated as a kinematic bicycle model (Rajamani (2011)) and stated as

$$\dot{x}(t) = v(t) \cdot \cos(\psi(t) + \beta(t)) \qquad (13a)$$

$$\dot{y}(t) = v(t) \cdot \sin(\psi(t) + \beta(t)) \qquad (13b)$$

$$\dot{\psi}(t) = \frac{v(t)}{L_f + L_r} \cdot \tan(\delta(t)) \qquad (13c)$$

$$\beta \approx \frac{L_r}{L_f + L_r} \cdot \delta(t) \qquad (13d)$$

where $\beta(t)$ denotes the sideslip angle [rad], $\psi(t)$ is the heading angle [rad], $v(t)$ - velocity [m/s] and $\delta(t)$ - steering angle [rad] are contained in the control input $u(t) = [v(t), \delta(t)]$. $x(t)$ and $y(t)$ are longitudinal and lateral coordinates in [m] and locate on the center of gravity point (COG) of the vehicle body. L_f and L_r are the front and real axle length with respect to the COG.

4.2 Numerical implementation

To solve the dynamic optimization problem (11), the combined multiple-shooting and collocation (CMSC) method is applied for transformation into a finite-dimensional NLP problem Tamimi and Li (2010); Drozdova et al. (2016); Lazutkin et al. (2015). The time horizon $[t_0, t_f]$ is divided into N intervals, and in each interval, the state variables are treated using the multiple-shooting method. The resulted NLP problem is solved using IPOPT software Wächter and Biegler (2006).

5. EXPERIMENTAL VERIFICATION

We consider two scenarios in the case studies. Scenario 1 presents an overtaking maneuver when the preceding s

drives at a constant speed. Scenario 2 presents an overtaking maneuver, during which s increases its speed linearly. The parameters settings for experiments are shown in Table. 1 and 2. Because of the mechanical limitations and safety considerations, the steering angle and speed are constrained between a suitable range. The upper and lower bound of the steering angle are non-symmetric according to the measures conducted from experiments.

Table 1. Parameters settings for path planning

Sigmoid parameter	$\mu = 0.1$
Safety time [s]	8
Safety distance [m]	0.6
Lane width [m]	0.45

Table 2. Parameters settings for NMPC

Predictive horizon	$N = 12$
Sample time [ms]	$\Delta t = 100$
Speed [m/s]	$v \in [0, 1]$
Axel length [m]	$L_f = L_r = 0.18$
Steering angle [rad]	$\delta \in [-0.46, 0.49]$
Weighing factor	$a_{1,2,3} = [1, 10, 10]$

Our experiments were carried out based on a Audi Q2 model car (scale 1:8) equipped with an Intel Core i3-6100T CPU (3.2 GHz). The path planning and control frameworks are developed under the software platform Automotive Data- and Time-triggered Framework (ADTF).

5.1 Scenario 1: Preceding vehicle with constant velocity

In scenarios 1 (see in Fig. 7), the cruise speed of e and s maintain at 0.6 m/s and 0.4 m/s, respectively. When the relative distance Δx decreases to $d_{safe} = \Delta v t_s = 0.2\,\mathrm{m/s} \times 8\,\mathrm{s} = 1.6\,\mathrm{m}$, the lane-changing maneuver is initiated and e departures from the origination lane. When the relative distance reached 2.2 m, which is the same as designed with $d_c = 0.6\,\mathrm{m}$ and $t_s = 8\,\mathrm{s}$, vehicle e returns back to the right lane and the overtaking maneuver is accomplished. The measuring speed of e shows slight fluctuation during lane changing processes, since the front wheels steer properly to track the overtaking path.

Since the tracking of x_{ref} is less emphasized regarding the weighting factors defined in the objective function, the NMPC trajectory deviated earlier than the reference path. Moreover, it can be seen that the reference path and corresponding NMPC trajectory show slight tremble during the lane-changing process, since the IMU sensor cannot track the position precisely due to limited accuracy and unexpected disturbance. Also, the behaviors of the steering angle oscillates due to the actual road condition and the mechanical properties of actuators.

5.2 Scenario 2: Preceding vehicle with linearly increasing velocity

In scenario 2 (see in Fig. 8), the cruise velocity of s increases linearly from 0.5 m/s to 1.0 m/s, while e is set with a cruise speed at 1.0 m/s. Therefore, vehicle e initiates the lane-changing maneuver since the cruise velocity of e is larger than s at the beginning. Meanwhile, vehicle s starts to accelerate and reaches around 1.0 m/s at $t = 12\,\mathrm{s}$, which is the same desired cruise velocity of e. Then,

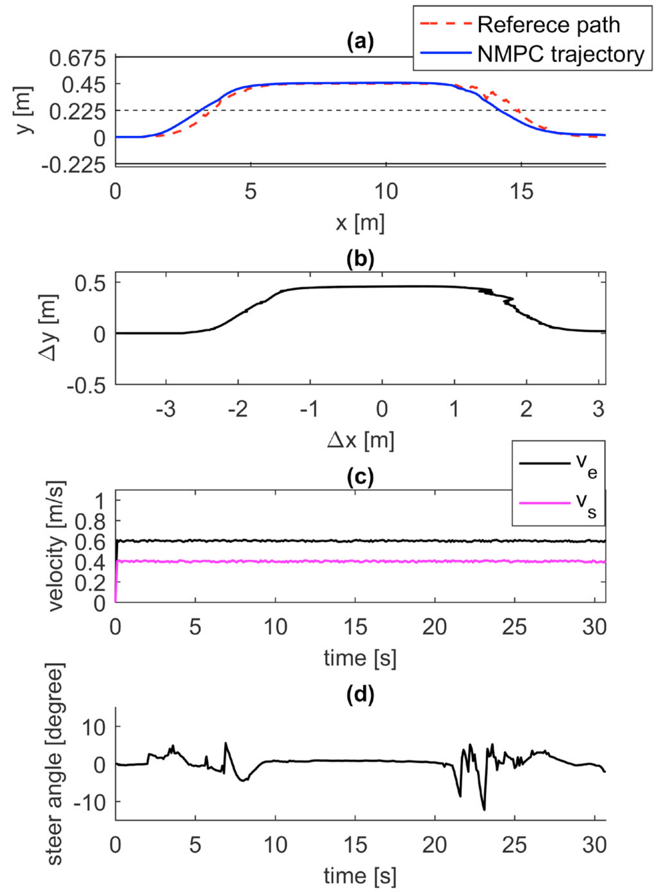

Fig. 7. (a) Reference path (red) and NMPC trajectory (blue) in global coordinates. (b) Relative distance between e and s in both longitudinal and lateral directions (c) Actual speeds of e (black) and s (pink). (d) Steering angle of e.

vehicle e returns back to the right lane indicating to give up overtaking. The relative distance between two vehicles remains no less than 1 m (seen in Fig. 8(b)), which indicates that a safe relative distance is successfully maintained. The non-smooth of the relative distance in Fig. 8b is caused by the measuring error in the IMU sensor. The velocity of e is compromised around 0.9 m/s, since the weighting factors makes a trade-off between the tracking accuracy of the overtaking path and the desired velocity. Besides, the magnitude of the oscillation in steering angle is greater than the one in scenario 1 due to the non-smooth lane-changing path.

6. CONCLUSION AND FUTURE WORK

In this work, we proposed a path planning method based on sigmoid functions for autonomous overtaking maneuver. The reference path is determined whether and how to overtake according to the relative distance and the relative speed (considering the desired cruise speed) between two vehicles. The parameters are determined concerning safety issues, i.e., the quantified TTC criterion. The overtaking decision is inherited from a piecewise function. The experimental results show that the proposed control architecture can handle the overtaking maneuver with a constant velocity of the preceding vehicle properly. Besides, it shows that

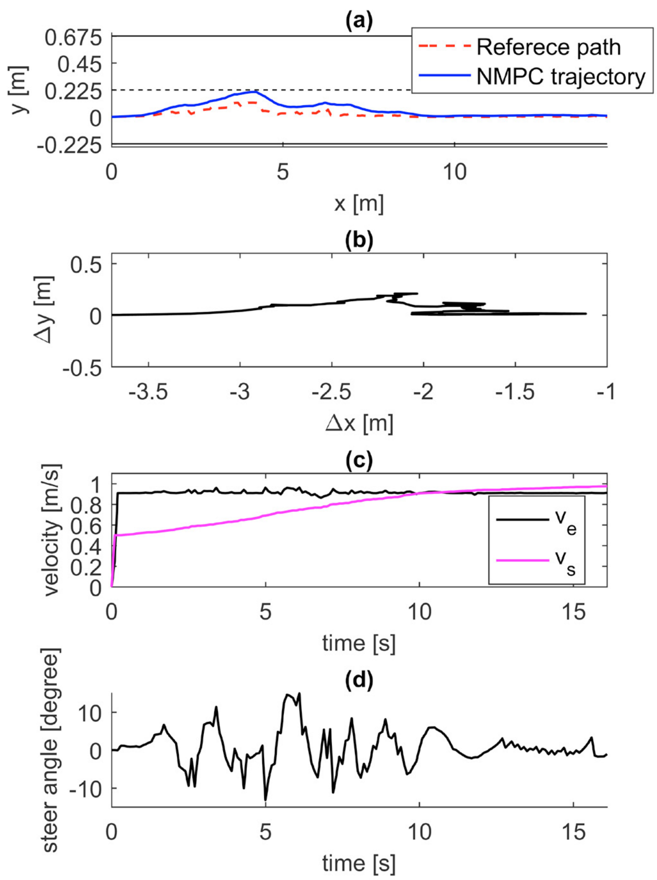

Fig. 8. (a) Reference path (red) and NMPC trajectory (blue) in global coordinates. (b) Relative distance between e and s in both longitudinal and lateral directions (c) Actual speeds of e (black) and s (pink). (d) Steering angle of e.

it can also handle the situation when the preceding vehicle changes its velocity (speeds up) during the overtaking process. When the preceding vehicle is faster, the reference path steers the vehicle back and overtaking maneuver is given up.

Until now, we have considered only one surrounding vehicle as the potential overtaken objects while multiple surrounding vehicles exist in real traffic situations. Meanwhile, surrounding vehicles may perform unexpected acceleration or deceleration behaviors rather than linear speed changing. These complicated scenarios will be addressed in our future work. Also, the overtaking scenarios in the curved road shall also be considered in the future experiments.

REFERENCES

Cong, Y., Sawodny, O., Chen, H., Zimmermann, J., and Lutz, A. (2010). Motion planning for an autonomous vehicle driving on motorways by using flatness properties. In *2010 IEEE International Conference on Control Applications*, 908–913.

Delsart, V., Fraichard, T., and Martinez, L. (2009). Real-time trajectory generation for car-like vehicles navigating dynamic environments. In *Proceedings of the 2009 IEEE International Conference on Robotics and Automation*, ICRA'09, 2257–2262. IEEE Press, Piscataway, NJ, USA.

Drozdova, E., Hopfgarten, S., Lazutkin, E., and Li, P. (2016). Autonomous driving of a mobile robot using a combined multiple-shooting and collocation method. *IFAC-PapersOnLine*, 49(15), 193 – 198, 9th IFAC Symposium on Intelligent Autonomous Vehicles IAV 2016.

Hardy, J. and Campbell, M. (2013). Contingency planning over probabilistic obstacle predictions for autonomous road vehicles. *IEEE Transactions on Robotics*, 29(4), 913 – 929.

Katrakazas, C., Quddus, M., Chen, W.H., and Deka, L. (2015). Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. *Transportation Research Part C: Emerging Technologies*, 60, 416 – 442.

Lazutkin, E., Geletu, A., Hopfgarten, S., and Li, P. (2015). An analytical hessian and parallel-computing approach for efficient dynamic optimization based on control-variable correlation analysis. *Industrial & Engineering Chemistry Research*, 54(48), 12086–12095.

Mads, D., Nosratinia, M., Keshavarz, M., Sundstrm, P., Philippsen, R., Eidehall, A., and Dahln, K.M. (2013). On path planning methods for automotive collision avoidance. In *Intelligent Vehicles Symposium (IV), 2013 IEEE*, 931–937.

Nilsson, J., Brnnstrm, M., Fredriksson, J., and Coelingh, E. (2016). Longitudinal and lateral control for automated yielding maneuvers. *IEEE Transactions on Intelligent Transportation Systems*, 17(5), 1404–1414.

Nilsson, J., Falcone, P., Ali, M., and Sjberg, J. (2015). Receding horizon maneuver generation for automated highway driving. *Control Engineering Practice*, 41, 124 – 133.

Petrov, P. and Nashashibi, F. (2014). Modeling and Nonlinear Adaptive Control for Autonomous Vehicle Overtaking. *IEEE Transactions Intelligent Transportation Systems*, 15(4), 14.

Pohl, J. and Ekmark, J. (2003). Development of a haptic intervention system for unintended lane departure. Technical report, SAE Technical Paper.

Rajamani, R. (2011). *Vehicle dynamics and control*. Springer Science & Business Media.

Tamimi, J. and Li, P. (2010). A combined approach to nonlinear model predictive control of fast systems. *Journal of Process Control*, 20(9), 1092 – 1102.

Wächter, A. and Biegler, L.T. (2006). On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. *Mathematical Programming*, 106(1), 25–57.

Watanabe, T., Kishimoto, N., Hayafune, K., Yamada, K., and Maede, N. (1995). Development of an intelligent cruise control system. In *Steps Forward. Intelligent Transport Systems World Congress*, Volume 3.

Ziegler, J., Bender, P., Dang, T., and Stiller, C. (2014). Trajectory planning for bertha a local, continuous method. In *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 450–457.