Received December 9, 2020, accepted December 16, 2020, date of publication December 25, 2020, date of current version January 6, 2021.
Digital Object Identifier 10.1109/ACCESS.2020.3047385

An Adaptive Motion Planning Technique for On-Road Autonomous Driving

XIANJIAN JIN[1,2], (Member, IEEE), ZEYUAN YAN[1], GUODONG YIN[3], (Senior Member, IEEE), SHAOHUA LI[4], AND CHONGFENG WEI[5]
[1]School of Mechatronic Engineering and Automation, Shanghai University, Shanghai 200072, China
[2]State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun 130022, China
[3]School of Mechanical Engineering, Southeast University, Nanjing 211189, China
[4]State Key Laboratory of Mechanical Behavior and System Safety of Traffic Engineering Structures, Shijiazhuang Tiedao University, Shijiazhuang 050043, China
[5]Department of Mechanical and Construction Engineering, Northumbria University, Newcastle NE1 8ST, U.K.

Corresponding authors: Xianjian Jin (jinxianjian@yeah.net), Guodong Yin (ygd@seu.edu.cn), and Shaohua Li (lishaohua@stdu.edu.cn)

This work was supported in part by the National Science Foundation of China under Grant 51905329, in part by the Foundations of State Key Laboratory under Grant KF2020-26, and in part by the National Key Research and Development Program of China under Grant 2016YFB0100906.

ABSTRACT This paper presents a hierarchical motion planning approach based on discrete optimization method. Well-coupled longitudinal and lateral planning strategies with adaptability features are applied for better performance of on-road autonomous driving with avoidance of both static and moving obstacles. In the path planning level, the proposed method starts with a speed profile designing for the determination of longitudinal horizon, then a set of candidate paths will be constructed with lateral offsets shifting from the base reference. Cost functions considering driving comfort and energy consumption are applied to evaluate each candidate path and the optimal one will be selected as tracking reference afterwards. Re-determination of longitudinal horizon in terms of relative distance between ego vehicle and surrounding obstacles, together with update of speed profile, will be triggered for re-planning if candidate paths ahead fail the safety checking. In the path tracking level, a pure-pursuit-based tracking controller is implemented to obtain the corresponding control sequence and further smooth the trajectory of autonomous vehicle. Simulation results demonstrate the effectiveness of the proposed method and indicate its better performance in extreme traffic scenarios compared to traditional discrete optimization methods, while balancing computational burden at the same time.

INDEX TERMS Autonomous driving, motion planning, path generation, obstacle avoidance.

I. INTRODUCTION

The aim of motion planning for autonomous driving is to find a feasible sequence of control inputs to drive the vehicle from its initial state to the goal state within environmental and physical constraints. Considerable emphasis should be paid on safety as well as driving comfort because of higher speed in autonomous driving than in the field of mobile robots. The motion planning problem of autonomous driving is usually decomposed into a global reference path planning level and a local motion planning level for computational efficiency in handling the changing traffic environments in various on-road scenarios [1].

The task of global path planner is to find a feasible path to the destination in the perceived environment with a certain update frequency, and a long enough forward prediction horizon of the global path should be achieved for safety guarantee. A variety of methods have been proposed to address this problem. Potential fields were created for rapid response and easy execution, but would suffer from local minimal, and variants of potential fields focus on handling this drawback [2], [3]. Graph-searching-based algorithms such as Dijkstra and A∗ algorithms family have been successfully implemented in the DARPA Challenge [4], [5] in semi-structured environments [6], and in parking lots [7]. Sampling-based methods have also proven to be efficient in path planning, among them the rapidly exploring random tree (RRT), together with its variants, is one of the most popular algorithms in the last decades [8], [9]. Curve interpolation has been proved a practical technique for reference path generation. Polynomials [10], [11], Bezier curves [12], and B-splines [13] have all been used by scholars, among them, Clothoids [14]

The associate editor coordinating the review of this manuscript and approving it for publication was Shihong Ding.

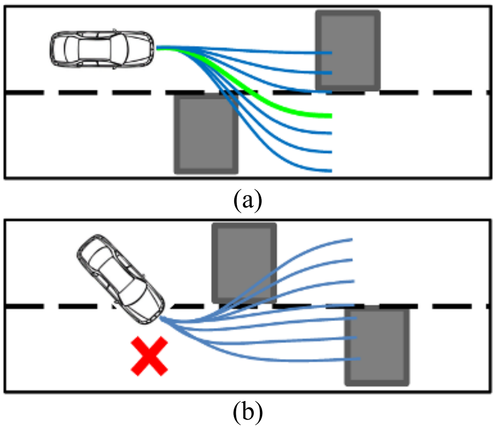


FIGURE 1. Typical failure condition of traditional discrete optimization method. (a) An optimal reference path can be found from the candidate set, (b) All candidate paths fail for collision checking.

stand out for its easy calculation of curvature. Numerical optimization based methods aim to minimize or maximize a function subject to different constrained variables [15], [16], also is often used to smooth previously computed path [17].

In the local motion planning level, a shorter local path aligning with the proposed global reference path should be constructed efficiently and a corresponding control sequence will be calculated by the tracking controller to drive the autonomous vehicle. There is actually no clear distinction between global and local planners in terms of planning algorithms. As the local planners are mainly designed to meet the real-time planning needs for addressing the planning problem in the changing traffic environments, we found in our simulations that decreasing the planning horizon of the global planner could complete the same task. Among various approaches, discrete optimization method is a practical alternative, which is a modification of numerical optimization methods that constructs a finite set of candidate paths, usually by interpolating curves in discrete time or space domain, in terms of traffic environments, and the optimal one will be selected for tracking based on a certain evaluation criterion [18], [19]. However, limited by the local shapes of interpolated curves, it is easy for the planner to get into trouble when the vehicle is close to the surrounding obstacles, which we call it a near-obstacle planning trouble, as is shown in Figure 1. For the path tracking and lateral stability controller, some advanced control methods have been developed, such as pure pursuit tracking control and model predictive control [20], [21], robust control [22]–[24], fuzzy control [25], sliding mode control [26]–[28], adaptive control [28], [29], non-smooth control [30], disturbance decoupling control [31], other nonlinear control [32], which have shown promising perspective in vehicle engineering application. In this study, we consider that our main objective tends to develop trajectory planning technique for on-road autonomous driving, hence the path tracking control is simplified, we employ a modified pure pursuit tracking controller for forward simulation to obtain a feasible control sequence of the vehicle and further smooth the path simultaneously.

This paper tries to present a local motion planning method with adaptability features to better handle the near-obstacle planning trouble. The logical idea of our method to ensure the success rate of planning lies in that the possibility of finding a feasible path will be increased when adjusting the state of ego vehicle in a safe range, where the shapes of corresponding planned candidate paths could be modified so as to be feasible. That means the local planning should focus on handling the nearing obstacles when needed, and the ego vehicle is expected to slow down for safety guarantee.

The framework of our method includes a global path planner, a local path planner and a local tracking controller. First, a global reference path is obtained by an upper level module based on the traffic environment. Then the local planner decomposes the trajectory planning problem that, a set of candidate paths will be generated with different lateral offsets shifting from the proposed global path for lateral planning and a speed profile aligning with the aforemen-tioned candidate paths will be designed for longitudinal control. After that an optimal path will be selected for tracking in terms of the pre-designed cost functions. Finally, a modified pure pursuit based tracking controller is applied to obtain a feasible control sequence and further smooth the trajectory of the autonomous vehicle. The global planner is not discussed in this paper, the maps and the global reference paths used in this paper are pre-defined in our simulations as various structured roads and their centerlines, respectively. The main contributions of this paper are listed as follows:

1) The adaptability features of our method is achieved by a well-designed coupling framework of the lateral planning and longitudinal control strategies. The speed profile design is first performed in trapezoidal forms, the result of which is then used for the generation of the spatial candidate paths. After that, path evaluation will be carried out by pre-defined cost functions and the optimal one will be selected for tracking control to obtain a feasible control sequence. If all current candidate paths fail, the longitudinal horizon for generating spatial paths will be re-determined and speed references will be updated accordingly in two different strategies according to the traffic conditions, namely a multi-stage planning framework is presented here.

2) An efficient Clothoid interpolation method applied for local smooth candidate paths generation, a lazy collision checking approach implemented to guarantee safety and the triggered mechanism in the multi-stage planning strategies all contribute to the balance between planning performance and computational efficiency.

3) Performing better in terms of planning quality and computational burden compared to traditional methods, the excellent coupled manners in our approach makes the local planner adaptively handle both static and moving obstacles in various on-road driving scenarios without the intervention of a high level decision module.

The remainder of this paper is organized as follows. Section II describe the multi-stage planning framework. Section III presents the simulation results and discussion on

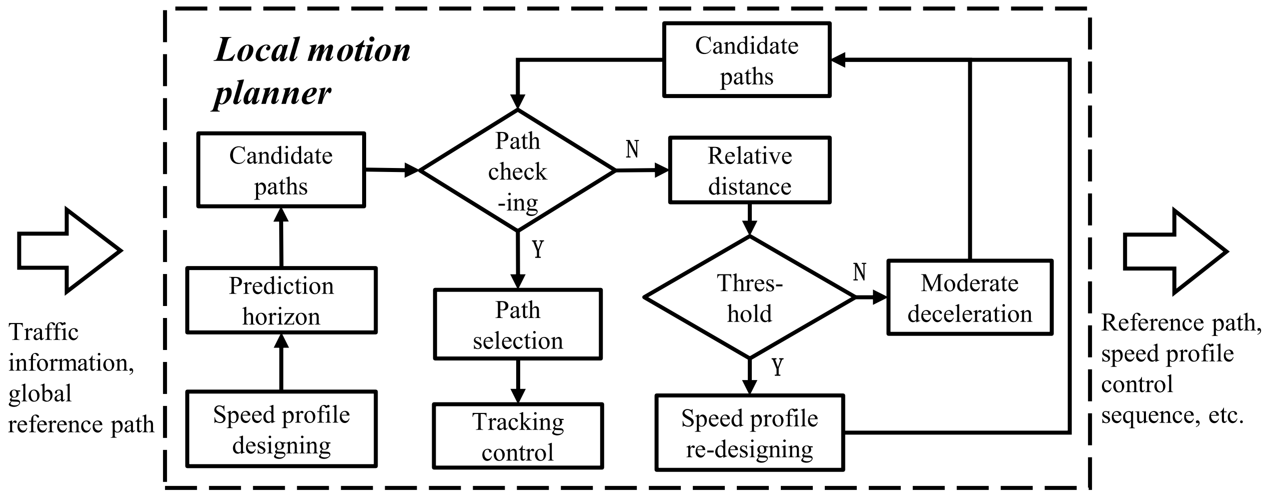


FIGURE 2. Overall framework of our planning strategies.

the features of our approach. Section IV concludes the paper and suggests future work.

II. MOTION PLANNING WITH ADAPTIVE STRATEGIES

In similar traditional approaches, spatial local candidate paths are generated by coupling a set of pre-defined discrete longitudinal horizons and lateral offsets shifting from the global reference path and velocity references aligning with candidate paths will be generated afterwards. Restrictions on geometric shapes and lack of spatial adaptability to the changing traffic environment make traditional candidate paths perform poorly especially in complex scenarios. When current planning fails, ego autonomous vehicle will probably execute uncomfortable or even unnecessary drastic brake operations until next feasible planning result occurs, which obviously impacts the performance of autonomous driving.

Our approach sets apart from traditional ones that the longitudinal horizon is determined by a pre-designed trapezoidal speed profile. By applying our multi-stage planning strategy, generation of spatial candidate paths, along with corresponding velocity references, can be performed adaptively in each planning cycle, which increases the success rate of planning without bringing much computational burden. The overall planning strategy of the proposed method is shown in Figure 2.

A. DETERMINATION OF LONGITUDINAL HORIZON

Different from traditional discrete planning method, our approach starts with a speed profile designing in time domain. There is no doubt that speed design has a great influence on driving safety and comfort. Acceleration limited by path curvature and vehicle physical constraints, speed limits by traffic rules and safety should all be considered in designing the speed profile.

Basically the speed profile used in this paper consist of a rising line representing acceleration from current speed, a horizontal line denoting constant-speed driving and a descending line for deceleration until stopping. We design our speed reference by first determining current speed v_{car}, speed limit v_{max}, acceleration limit a_{acc} and deceleration limit a_{dec} of the ego vehicle and planning time horizon $T_{planning}$, then a trapezoidal speed profile can be constructed into two fundamental types as shown in Figure 3 (a) and (b). The main difference between the two speed profile is whether speed limit is activated because acceleration is terminated once reaching the speed limit. The speed design shown in Figure 3 can be described as follows.

$$v = a_{acc}t + v_{car}, \quad t \in [0, T_{acc}] \tag{1}$$

$$v = v_{\max}, \quad t \in [T_{acc}, T_{dec}] \tag{2}$$

$$v = a_{dec}t - a_{dec}T_{planning}, \quad t \in \left[T_{dec}, T_{planning}\right] \tag{3}$$

Equations (1), (2) and (3) describe the acceleration, speed maintaining and deceleration stage, respectively, where v is the designed speed reference, T_{acc} is the acceleration time, T_{dec} is the deceleration time. The planned time horizon $T_{planning}$ is a pre-defined parameter. The deceleration stage is a must in every speed profile for safety guarantee, which means T_{dec} can be first calculated by v_{max} and a_{dec}. Then T_{acc} can be determined in terms of current speed v_{car}, speed limit v_{max} and deceleration stage (3) if needed. For simplicity, a_{acc} and a_{dec} are set as constants 1m/s^2 and -5m/s^2, respectively, both within the vehicle physical performance.

Obviously, the area lies between the speed lines and axis is the wanted longitudinal horizon to generate the spatial candidate paths, when applying a series of lateral offsets aligning with global reference geometry at the same time, in a planning cycle, and evaluation of paths and collision checking can be conducted afterwards.

When all the generated candidate paths are judged as infeasible, the longitudinal horizon will be re-determined in terms of relative distance between ego vehicle and the nearest obstacle, and the speed profile will be re-designed accordingly. In this stage, judgement will be first made whether the proposed relative distance is longer than that of executing a moderate braking operation to stop from current speed. If not, the longitudinal planning horizon will be set as the calculated

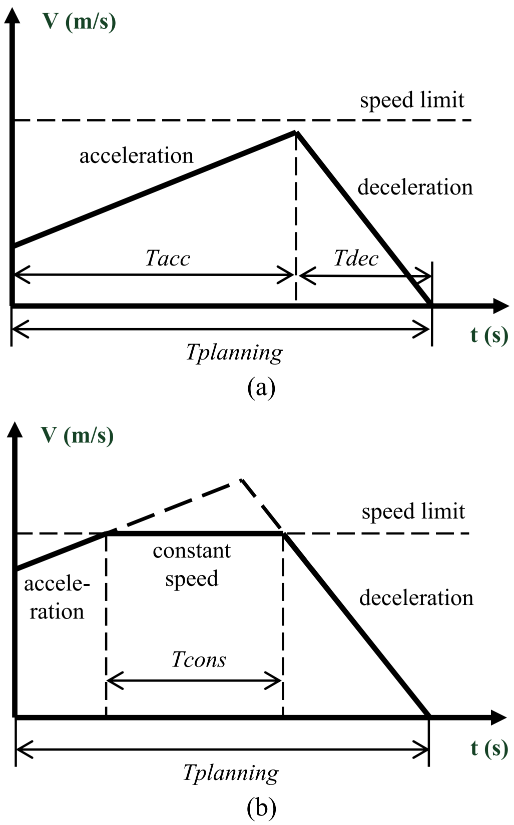


FIGURE 3. Speed profiles design. (a) Speed profile design with a small initial velocity, (b) Speed profile with a bigger initial velocity.

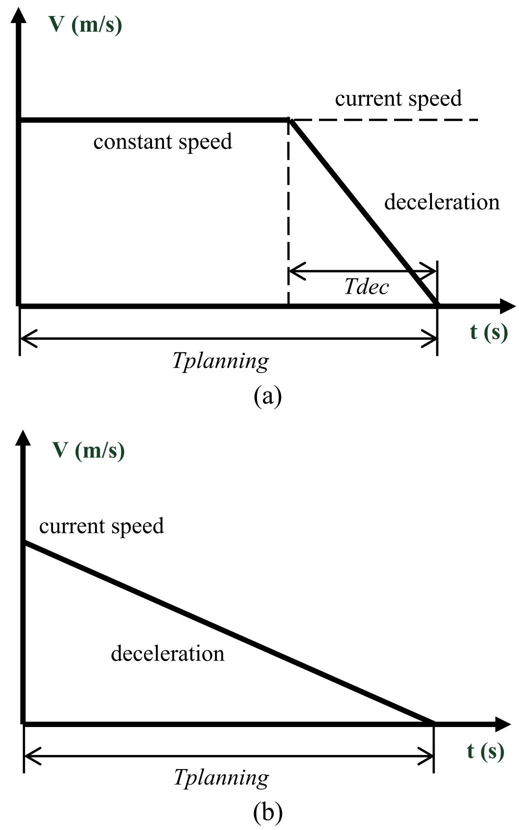


FIGURE 4. Speed profiles re-design. (a) Speed profile re-design when candidate paths fail in the first stage, (b) Speed profile of moderate deceleration when candidate paths fail in the second planning stage.

area enclosed by axis and speed curve in Figure 4 (b), and an a_{dec} deceleration operation will be conducted to ensure the vehicle stop before completely executing the planned trajectory, thus safety is guaranteed. Otherwise, the horizon will be set as the proposed relative distance and a speed profile replacing v_{max} with v_{car}, as is shown in Figure 4 (a), will be applied for longitudinal control. The moderate deceleration profile can be described as follows

$$v = a_{com}t + v_{car}, \quad t \in \left[0, T_{planning}\right] \tag{4}$$

where a_{com} is the moderate deceleration value set as -2 m/s^2, which is thought to be a comfortable braking operation during driving.

Remark 1: We find the key of getting out of traditional planning trouble is to choose a proper longitudinal horizon for the generation of spatial candidate paths. Increasing the number of discretion of longitudinal horizons in traditional methods is considered as an easy way to improve the planning performance, however, computational burden will be considerably increased as more spatial paths will be generated and evaluated, and the real-time demand for the local planner will probably be harmed as a result. Thus, we innovatively adjust the longitudinal horizons by a multi-stage strategy coupling the speed profile design and relative safety distances between ego vehicle and obstacles. Compared to traditional methods, the triggered mechanism in our multi-stage planning strategy deactivates the re-planning steps when unnecessary, thus the computational efficiency can be improved.

B. SAFETY GUARANTEE

There is no doubt that safety is a leading demand in motion planning of autonomous driving. Traditional discrete optimization methods take safety into account by generation of collision-free spatial reference paths with a set of fixed forward prediction horizon along with different lateral offsets shifting from the base references. When the candidate paths become infeasible, the ego vehicle tends to execute a drastic deceleration to avoid collision until a feasible reference is successfully obtained in the next several planning cycles, guiding the vehicle to its new destination. Obviously, safety can be guaranteed within the above closed-loop planning strategy.

In our method, safety is guaranteed by three mechanisms. Firstly, like what is in traditional methods, periodically updated candidate paths generated by lateral offsets and adaptively chosen longitudinal horizons are combined with cost functions for evaluation to keep a proper distance between the vehicle and obstacles. Secondly, each speed profile is designed with an end speed of zero that guarantees the vehicle could stop safely at the end if executing one whole feasible local trajectory. Thirdly, once a judgement is made that the vehicle is too close to the nearest obstacle according to its driving performance, a moderate deceleration that ensures stopping before colliding into the obstacle will be conducted. The relative distance threshold can be easily calculated as follows

$$L_{relative} \geq \frac{1}{2} v_{car} T_{planning} \tag{5}$$

where $L_{relative}$ denotes the distance between ego vehicle and the nearest obstacle. The right part of inequality (5) denotes the expected driving distance in the moderate deceleration stage described by equation (4) in a local planning cycle, and the left part of inequality (5) is the changing relative distance between ego vehicle and nearest obstacle. As is illustrated in Section II. A, judgement will first be made whether the relative distance is longer than moderate braking distance, to determine the planning strategy chosen in next stage, and inequality (5) gives an easy but practical calculation of this threshold.

C. LOCAL PATH GENERATION

In this paper we employ an efficient Clothoid interpolation method for local path generation. The position and heading angle of ego vehicle and the destination are required to construct the local paths. Another advantage of this interpolation method is that due to the features of Clothoid curves, curvature of the generated paths is easy to obtain for the following feasibility checking procedure. The general parametric form of a Clothoid spiral curve is as follows

$$x(s) = x_0 + \int_0^s \cos\left(\frac{1}{2}\kappa'\tau^2 + \kappa\tau + \theta_0\right) \mathrm{d}\tau \tag{6}$$

$$y(s) = y_0 + \int_0^s \sin\left(\frac{1}{2}\kappa'\tau^2 + \kappa\tau + \theta_0\right) \mathrm{d}\tau \tag{7}$$

where s is the arc length, (x_0, y_0) denotes the starting position, θ_0 is the initial heading angle, $\kappa' t + \kappa$ is the linearly varying curvature, and $0.5\kappa'\tau^2 + \kappa\tau + \theta_0$ is the heading angle at arc length s. The determination of the parameters θ_0, κ and κ' are related to the choice of points and heading angles at both ends of the curve.

In this paper, the starting point and heading angle are the current vehicle position and heading angle, respectively. The end points are determined by the longitudinal planning horizon and several specified lateral offsets, which may be modified according to different road width. The end heading angles are the same as that of the forward predicted destination point on the global reference path. An efficient method proposed in [14] to calculate a curve satisfying (6) and (7) with minimum positive length between its two ends fits well in our approach. Typical resulting paths can be seen in Figure 5.

D. PATH SELECTION

After the generation of candidate paths, we should choose the optimal path among them as reference for the tracking control. Driving comfort and energy consumption are the two main concern in our cost function designing. Curvature is applied as a representation of comfortability for computational efficiency, which is defined as follows

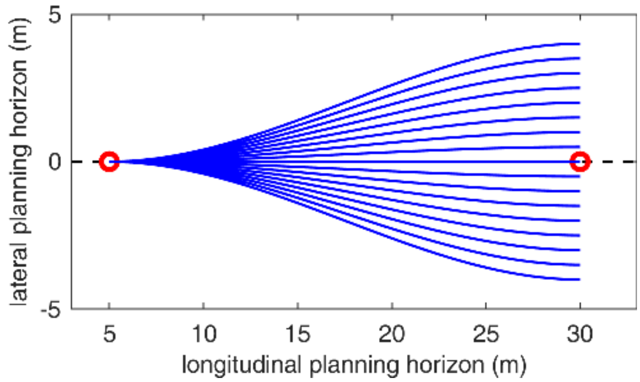


FIGURE 5. Illustration of generated candidate paths based on the end lateral offsets. Left red circle is the initial position and right red circle is the predicted goal position on the reference path.

$$f_{com}(r_i) = \int \kappa_i^2(s)\mathrm{d}s \tag{8}$$

here we denote that the number of candidate paths generated is i, and $f_{com}(r_i)$ is the driving comfort cost for the i-th candi-date path, $\kappa_i(s)$ denotes the curvature of r_i at arc length s.

As fewer steering operations mean less energy consumed, our second cost function is designed to make the vehicle drive along the global reference path as much as possible.

$$f_{ene}(r_i) = d(r_i) \tag{9}$$

where $f_{ene}(r_i)$ is the driving comfort cost for the i-th candidate path, $d(r_i)$ denotes the accumulated lateral offsets shifting from the global reference of i-th path based on lateral planning and a speed profile aligning for longitudinal control. In this way, operations that deviate from the global reference path will be punished to reduce unnecessary steering operations. It should be mentioned that in some conditions driving with a moderate deviation from the reference line actually achieves the best smoothness, which means curvature can also be an evaluation criterion for energy consumption. The total cost function is designed as follows

$$f(r_i) = k_1 f_{com}(r_i) + k_2 f_{ene}(r_i) \tag{10}$$

where $f(r_i)$ is the total cost of the i-th candidate path, k_1 and k_2 are two weight factors adjusting the smoothness of resulted references. Note that weight factor k_1 has a greater influence on path selection than $k_{2,}$ here two weight factors k_1 and k_2 are set as 0.2 and 0.8 in term of experience and online test, respectively.

Remark 2: It can be seen that the feasibility is not considered in the aforementioned cost function designing, because a lazy collision checking strategy is applied here. Candidate paths are firstly evaluated and sorted by calculated costs, then path checking for collision risk and curvature limit is carried out on the sorted candidates, to make sure the feasibility, and a candidate path will be selected as final reference path once passing the checking, leaving the rest ones unchecked. Thus, the number of execution of path checking procedures can be slightly reduced, compared to attach the collision test as part of the cost functions, so as to obtain better computational efficiency as well as keep path quality.

E. LOCAL TRACKING CONTROLLER

In this paper, we employ a modified pure pursuit tracking controller for forward simulation to obtain a feasible control sequence for the vehicle and further smooth the path at the same time. The bicycle model simplified from a front-wheel steering Ackerman vehicle is employed to predict trajectory in a certain time period and run the forward simulation. The kinematic model is in the following form

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} \cos\varphi \\ \sin\varphi \\ \tan\delta_f/L \end{bmatrix} v \tag{11}$$

where x and y are the coordinates of the center point of the rear axle, φ denotes the heading angle of vehicle in regard to the x-axis, L is the vehicle wheelbase and δ_f denotes the front wheel steering angle. Longitudinal speed v and front wheel steering angle δ_f are the two control inputs to the system.

For the purpose of avoiding abrupt change in the control input of δ_f, its incremental form is employed in calculation.

$$\delta_f = \delta_{f0} + \int_0^t \dot{\delta}_f dt \tag{12}$$

where δ_{f0} denotes the initial steering angle of the front wheel and t is the simulation time.

The tracking controller for active steering calculation derived from [9,10] is presented as

$$\delta(t) = \tan^{-1}\left(\frac{2L\sin(\alpha(t))}{l_d}\right) \tag{13}$$

where l_d denotes the look-ahead distance, which is the Euclidean distance between current state and the excepted tracking state. L is the wheelbase of the vehicle. α is the relative angle between current heading angle and the excepted tracking one. δ is the calculated steering angle of front wheels. Note that here the tracking controller in equation (13) is usually used to path tracking control for trajectory planning researches, the effectiveness of controller has been proved in theory [9], [10]. The vehicle runs forward at a constant speed and steering angle is calculated and executed at a certain frequency. Finally, a feasible control sequence and a corresp-onding smooth trajectory will be obtained.

III. SIMULATION AND DISCUSSION

To verify the effectiveness of our approach, challenging traffic conditions for static and moving obstacles avoidance scenarios are applied. Road shapes and global reference paths are manually predesigned. In the resulting plots, the ego vehicle is simplified as a point, static obstacles are described by red hollow circles, moving obstacles and their trajectories are shown in filled red circles and red lines, respectively. The dashed dark lines are the centerline of the road, namely the global reference path. Road edges are described by black straight lines or cubic splines. The solid blue curve sets denote planned local candidate paths when the proposed adaptive planning horizon method is triggered. The solid green curves are the trajectories of ego vehicle. The initial speed of ego vehicle is 6 m/s and the speed limitation is 10 m/s, and the curvature limit of candidate paths is 0.1 m^{-1}.

A. STATIC OBSTACLES AVOIDANCE

Two simulations with different global references are made for verification of static obstacles avoidance. A comparison of simulation results between traditional discrete method and our approach can be seen in Figure 6. In Figure 6 (a), the difference in vehicle trajectories between the two methods is small, where successful planning is carried out. The ego vehicle executed a smooth trajectory on a curved road with avoidance of several static obstacles. It also shows a good tracking performance that, ego vehicle could quickly return to the center reference path once completing a lane-change maneuver for obstacle avoidance. Figure 6 (b) describes the driving speed during execution, gentle deceleration in our approach can be seen clearly compared to traditional method. The blue candidate paths are those generated by our approach and pink ones are by traditional method, obviously our planning strategies shows better choice of the planning horizons and corresponding speed profiles, as a result better driving comfort can be obtained while successfully completing the same task with traditional method. It should be noted that the deceleration stage designed in (1), (2) and (3) will generally not be activated, because planning failure tends not to mean there is actually no way for the vehicle to go with application of discrete optimization-based planning methods. We find the planning performance largely is limited by the shapes of candidate paths in every planning cycle, when the vehicle could safely adjust its location for new planning, feasible reference paths probably could be found in the next few new planning cycles. This is actually where the logic of our planning strategies lies in.

To underline our planning technique characteristic, Figure 7 shows the simulation result of static obstacle avoidance in a challenging condition. In Figure7(a), (b), (c), we use the different x-axles of distance and time to describe resulting trajectory of ego autonomous vehicle, speed statistics of ego vehicle during execution, and front wheel steering statistics of ego vehicle respectively. In this scenario, a group of densely arranged obstacles will make ego vehicle conduct a zigzag driving, meanwhile the speed should be slowed down within handling and safety. As expected, traditional discrete planning fails here without applying of extreme parameter settings, while our approach performs well. The trajectory of ego vehicle is described in Figure 7 (a). The solid blue curves are notations of where the adaptive re-planning is executed. It can be seen this mechanism is triggered mainly when the vehicle is close to the static obstacles, which is just a common dilemma for traditional planners. By tracking the newly planned shorter reference path while conducting a moderate brake operation, the ego vehicle could

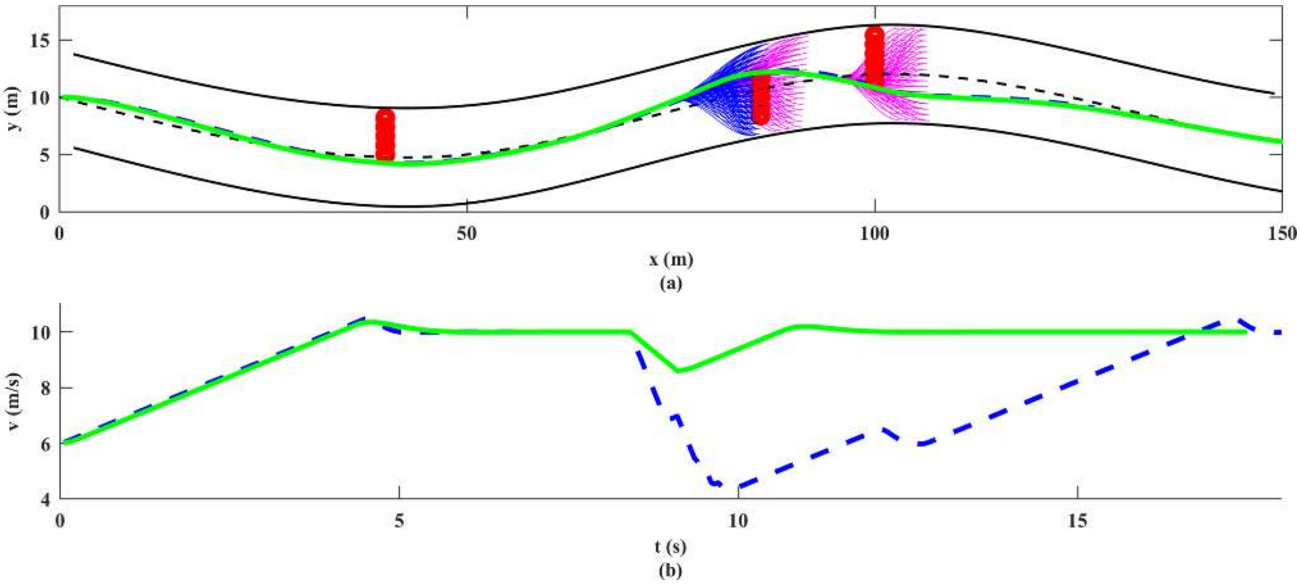


FIGURE 6. Simulation result of comparison between traditional discrete method and our approach. (a) Resulting trajectory of ego autonomous vehicle, traditional method (dashed blue) and our method (solid green), the solid blue curve sets illustrate the reference paths generated when near-obstacle trouble occurred and our adaptive planning strategies activated, correspondingly the purple ones were generated by traditional method, (b) Speed comparison of ego vehicle during driving, traditional method (dashed blue) and our method (solid green).

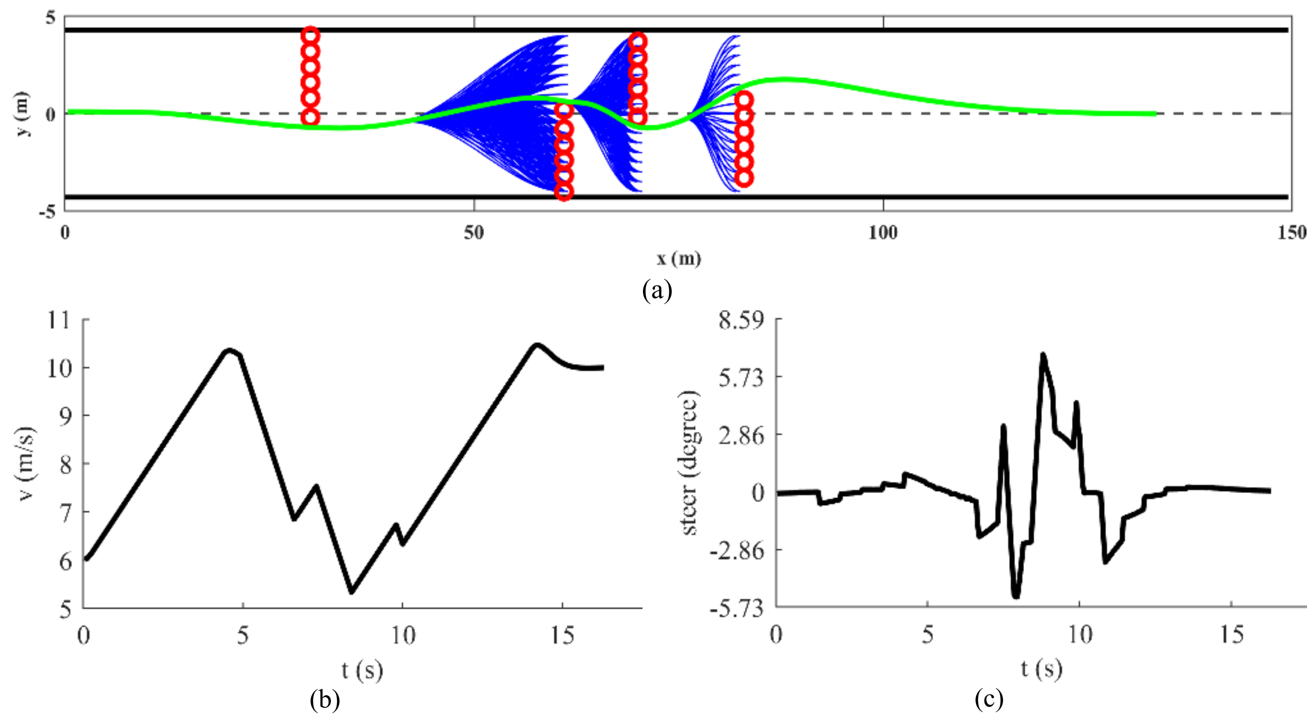


FIGURE 7. Simulation results of challenging static obstacles avoidance. (a) Resulting trajectory (solid green) of ego autonomous vehicle, solid blue curve sets are candidate path generated by the proposed strategies, (b) Speed statistics of ego vehicle during execution, (c) Front wheel steering statistics of ego vehicle during execution.

be safely guided to regions where new feasible planning probably occurs, and autonomous driving thus can be continued. As is shown in Figure 7 (b) and (c), by applying our adaptive planning strategies, the ego vehicle handles the challenging traffic condition with proper speed and steering operations within physical constraints. After successfully avoiding all static obstacles, the ego vehicle is able to turn right in time and continue to drive along the reference centerline.

B. AVOIDING BOTH STATIC AND MOVING OBSTACLES

Avoiding static and moving obstacles simultaneously would be a challenging task for autonomous driving. A scenario of this condition is designed in Figure 8 (a), where the moving

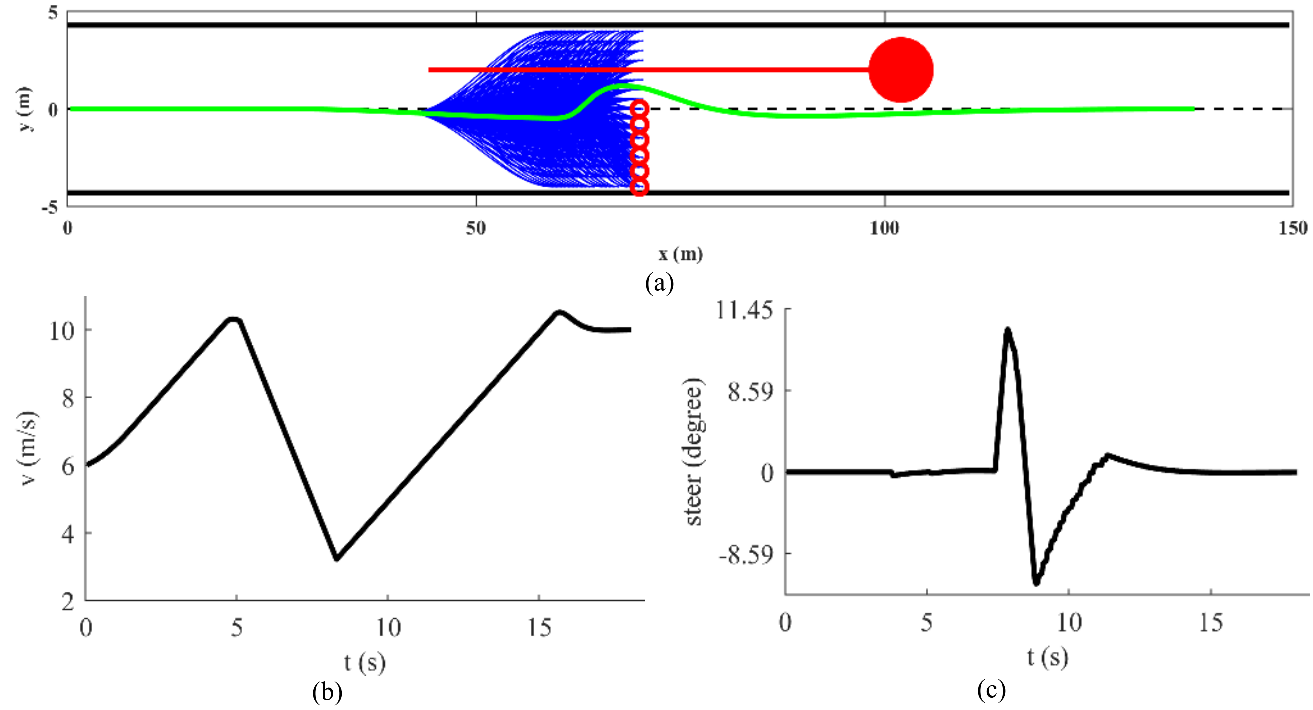


FIGURE 8. Simulation results of both static and moving obstacles avoidance. (a) Resulting trajectory (solid green) of ego autonomous vehicle, solid blue curve sets are candidate path generated by the proposed strategies, (b) Speed statistics of ego vehicle during execution, (c) Front wheel steering statistics of ego vehicle during execution.

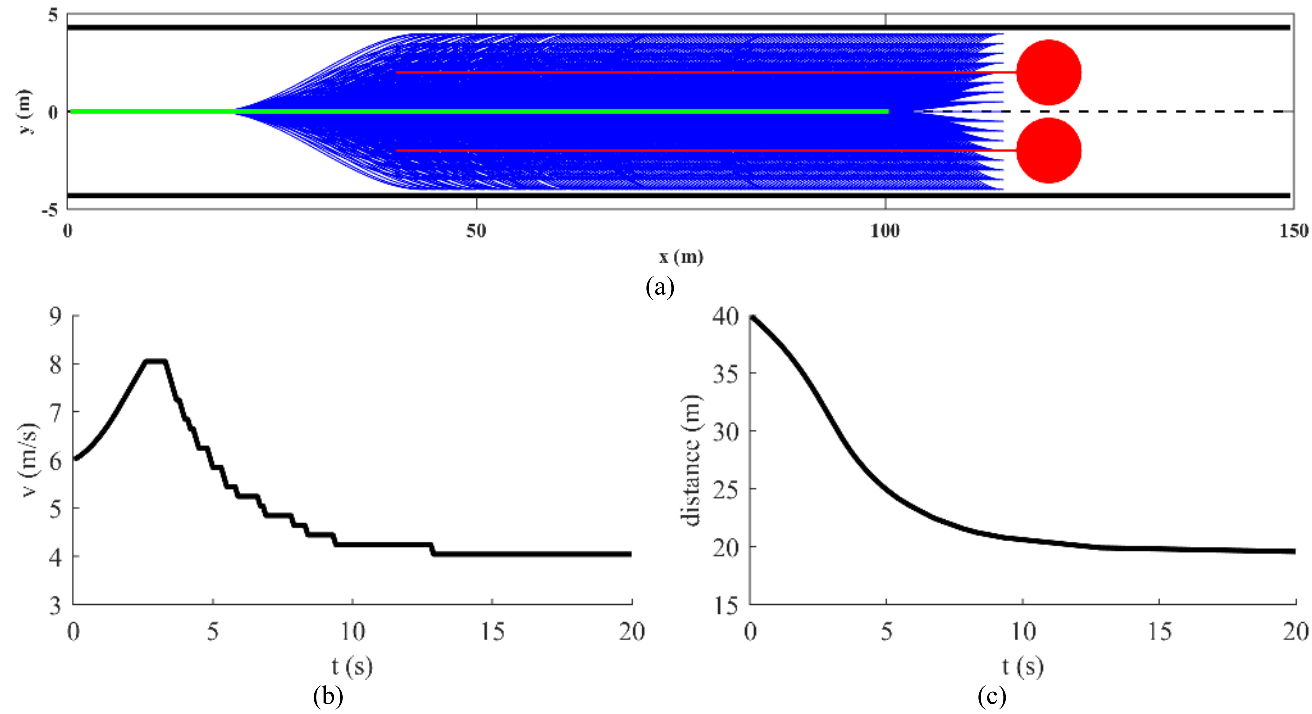


FIGURE 9. Simulation results of moving obstacles avoidance. (a) Resulting trajectory (solid green) of ego autonomous vehicle, solid blue curve sets are candidate path generated by the proposed strategies, (b) Speed statistics of ego vehicle during execution, (c) Relative distance between moving obstacles and ego vehicle during execution.

and static obstacles happen to block the whole road when the ego vehicle approaches. Obstacle in the upper lane moves at a constant speed of 4 m/s, which means a passable space will occur a few seconds later. It is required that the planning strategy should make the vehicle slow down to wait for a left lane-change opportunity. The changing planning horizon described by blue solid curves can be seen during execution, where the ego vehicle was slowed down until a lane-change room occurred and static obstacle avoidance was successfully carried out afterwards. Steering statistics in Figure 8 (b) and speed curve in Figure 8 (c) have confirmed the driving strategy. Trajectory shown in Figure 8 (a) indicates the ego vehicle easily completed the challenging task.

C. MOVING OBSTACLES AVOIDANCE

In the scenario shown in Figure 9, since the scenario simulates two obstacles move forward with a constant speed 4 m/s, steering angle is replaced by relative distance between moving obstacles and ego vehicle during execution. It is set that the ego vehicle has no room for overtaking and should slow down to follow the moving obstacles. As Figure 9 (a) shows, adaptive planning horizon has continuously been used since the ego vehicle has been close enough to the moving obstacles. Figure 9 (b) shows the speed statistics, and Figure 9 (c) describes the relative distance between them. Obviously, the ego vehicle successfully slowed down to the speed of moving obstacles while maintaining a rational relative distance of about 20 m.

D. PERFORMANCE EVALUATION

Simulations were run on a computer with an Intel Core i7-6700HQ and 16GB RAM. In the simulations above, 17 candidate paths were generated in each planning cycle, which is a most rational choice balancing success rate and computational efficiency in our traffic scenarios. The average execution time of our local motion planner in a cycle is 16 ms, meeting the real-time requirements.

Benefit from the implementation of adaptive planning horizon, our motion planner can actively handle various traffic scenarios without the intervention of a high-level decision module. Simulation results also proved that it works well even under challenging traffic conditions.

IV. CONCLUSION

This paper presents a hierarchical motion planning method for autonomous driving on structured roads with avoidance of both static and moving obstacles. The proposed method starts from designing a speed profile for the determination of the planning horizon. Then an efficient Clothoid interpolation method is applied for the generation of local candidate paths with a set of end points lateral offsets. After that paths will be evaluated by cost functions considering driving comfort and energy consumption and checked for feasibility. When all candidate paths fail, a re-planning procedure using a changing horizon in terms of relative distance between ego vehicle and nearing obstacles will be triggered for higher planning success rate as well as driving safety. Our approach stands out for the adaptively determined longitudinal horizon that make the planning better performance especially in challenging traffic environments, without the help of a decision module. Compared to similar traditional planners, our method considerably reduces the number of local candidate paths to obtain a better computation efficiency. Feasibility constraints are considered both in the path planning and tracking procedure. Moreover, since the path tracking control is simplified in this study, we will further research adaptive motion planning technique with advanced path tracking control methods such as adaptive control for on-road autonomous driving vehicle application.

REFERENCES

[1] D. Gonzalez, J. Perez, V. Milanes, and F. Nashashibi, "A review of motion planning techniques for automated vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 1135–1145, Apr. 2016.

[2] Y. Rasekhipour, A. Khajepour, S.-K. Chen, and B. Litkouhi, "A potential field-based model predictive path-planning controller for autonomous road vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 5, pp. 1255–1267, May 2017.

[3] Y. Huang, H. Ding, Y. Zhang, H. Wang, D. Cao, N. Xu, and C. Hu, "A motion planning and tracking framework for autonomous vehicles based on artificial potential field elaborated resistance network approach," *IEEE Trans. Ind. Electron.*, vol. 67, no. 2, pp. 1376–1386, Feb. 2020.

[4] C. Urmson, J. Anhalt, D. Bagnell, C. Baker, and M. Gittleman, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 425–466, Aug. 2008.

[5] D. Ferguson, T. M. Howard, and M. Likhachev, "Motion planning in urban environments," *J. Field Robot.*, vol. 25, nos. 11–12, pp. 939–960, Nov. 2008.

[6] D. Dolgov, S. Thrun, M. Montemerlo, and J. Diebel, "Path planning for autonomous vehicles in unknown semi-structured environments," *Int. J. Robot. Res.*, vol. 29, no. 5, pp. 485–501, Apr. 2010.

[7] X. Zhang, A. Liniger, A. Sakai, and F. Borrelli, "Autonomous parking using optimization-based collision avoidance," in *Proc. IEEE Conf. Decis. Control (CDC)*, Miami Beach, FL, USA, Dec. 2018, pp. 4327–4332.

[8] S. Karaman and E. Frazzoli, "Sampling-based algorithms for optimal motion planning," *Int. J. Robot. Res.*, vol. 30, no. 7, pp. 846–894, Jun. 2011.

[9] L. Ma, J. Xue, K. Kawabata, J. Zhu, C. Ma, and N. Zheng, "Efficient sampling-based motion planning for on-road autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1961–1976, Aug. 2015.

[10] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, and K. Lau, "Stanley: The robot that won the DARPA grand challenge," in *DARPA Grand Challenge*. Berlin, Germany: Springer-Verlag, 2007, pp. 1–43.

[11] K. Yang and S. Sukkarieh, "An analytical continuous-curvature path-smoothing algorithm," *IEEE Trans. Robot.*, vol. 26, no. 3, pp. 561–568, Jun. 2010.

[12] Y. Kwangjin, D. Jung, and S. Sukkarieh, "Continuous curvature path-smoothing algorithm using cubic B zier spiral curves for non-holonomic robots," *Adv. Robot.*, vol. 27, no. 4, pp. 247–258, Mar. 2013.

[13] T. Maekawa, T. Noda, S. Tamura, T. Ozaki, and K.-I. Machida, "Curvature continuous path generation for autonomous vehicle using B-spline curves," *Comput.-Aided Des.*, vol. 42, no. 4, pp. 350–359, Apr. 2010.

[14] E. Bertolazzi and M. Frego, "Fast and accurate clothoid fitting," 2012, *arXiv:1209.0910*. [Online]. Available: https://arxiv.org/abs/1209.0910

[15] J. Ziegler, P. Bender, T. Dang, and C. Stiller, "Trajectory planning for Bertha—A local, continuous method," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2014, pp. 450–457.

[16] X. Hu, L. Chen, B. Tang, D. Cao, and H. He, "Dynamic path planning for autonomous driving on various roads with avoidance of static and moving obstacles," *Mech. Syst. Signal Process.*, vol. 100, pp. 482–500, Feb. 2018.

[17] M. Zucker, N. Ratliff, A. D. Dragan, M. Pivtoraiko, and S. S. Srinivasa, "CHOMP: Covariant Hamiltonian optimization for motion planning," *Int. J. Robot. Res.*, vol. 32, nos. 9–10, pp. 1164–1193, Aug. 2013.

[18] M. Werling, J. Ziegler, S. Kammel, and S. Thrun, "Optimal trajectory generation for dynamic street scenarios in a Frenét frame," in *Proc. IEEE Int. Conf. Robot. Automat.*, Anchorage, USA, May 2010, pp. 987–993.

[19] J. Zhou, H. Zheng, J. Wang, Y. Wang, B. Zhang, and Q. Shao, "Multi-objective optimization of lane-changing strategy for intelligent vehicles in complex driving environments," *IEEE Trans. Veh. Technol.*, vol. 69, no. 2, pp. 1291–1308, Feb. 2020.

[20] K. Liu, J. Gong, A. Kurt, H. Chen, and U. Ozguner, "Dynamic modeling and control of high-speed automated vehicles for lane change maneuver," *IEEE Trans. Intell. Vehicles*, vol. 3, no. 3, pp. 329–339, Sep. 2018.

[21] J. Suh, K. Yi, J. Jung, K. Lee, H. Chong, and B. Ko, "Design and evaluation of a model predictive vehicle control algorithm for automated driving using a vehicle traffic simulator," *Control Eng. Pract.*, vol. 51, pp. 92–107, Jun. 2016.

[22] X. J. Jin, G. Yin, and N. Chen, "Gain-scheduled robust control for lateral stability of four-wheel-independent-drive electric vehicles via linear parameter-varying technique," *Mechatronics*, vol. 30, pp. 286–296, Sep. 2015.

[23] X. Jin, G. Yin, C. Bian, J. Chen, P. Li, and N. Chen, "Gain-scheduled vehicle handling stability control via integration of active front steering and suspension systems," *J. Dyn. Syst., Meas., Control*, vol. 138, no. 1, Jan. 2016, Art. no. 014501.

[24] X. Jin, Z. Yu, G. Yin, and J. Wang, "Improving vehicle handling stability based on combined AFS and DYC system via robust Takagi-Sugeno fuzzy control," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 8, pp. 2696–2707, Aug. 2018.

[25] Z.-M. Li, X.-H. Chang, and J. H. Park, "Quantized static output feedback fuzzy tracking control for discrete-time nonlinear networked systems with asynchronous event-triggered constraints," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Aug. 15, 2019, doi: 10.1109/TSMC.2019.2931530.

[26] S. Ding and S. Li, "Second-order sliding mode controller design subject to mismatched term," *Automatica*, vol. 77, pp. 388–392, Mar. 2017.

[27] L. Liu, S. Ding, and X. Yu, "Second-order sliding mode control design subject to an asymmetric output constraint," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, early access, Sep. 4, 2020, doi: 10.1109/TCSII.2020.3021715.

[28] L. Liu, W. X. Zheng, and S. Ding, "An adaptive SOSM controller design by using a Sliding-Mode-Based filter and its application to buck converter," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 67, no. 7, pp. 2409–2418, Jul. 2020.

[29] X. Jin, G. Yang, X. Chang, and W. Che, "Robust fault-tolerant H_∞ control with adaptive compensation," *Acta Automatica Sinica*, vol. 39, no. 1, pp. 31–42, Jan. 2013.

[30] Q. Meng, T. Zhao, C. Qian, Z.-Y. Sun, and P. Ge, "Integrated stability control of AFS and DYC for electric vehicle based on non-smooth control," *Int. J. Syst. Sci.*, vol. 49, no. 7, pp. 1518–1528, Apr. 2018.

[31] Q. Meng, Z.-Y. Sun, Y. Shu, and T. Liu, "Lateral motion stability control of electric vehicle via sampled-data state feedback by almost disturbance decoupling," *Int. J. Control*, vol. 92, no. 4, pp. 734–744, Apr. 2019.

[32] S. Ding, W. Chen, K. Mei, and D. J. Murray-Smith, "Disturbance observer design for nonlinear systems represented by input–output models," *IEEE Trans. Ind. Electron.*, vol. 67, no. 2, pp. 1222–1232, Feb. 2020.

XIANJIAN JIN (Member, IEEE) received the Ph.D. degree from the Department of Vehicle Engineering, Southeast University, Nanjing, China, in 2017.

From 2016 to 2017, he was a joint Ph.D. Researcher with the Department of Mechanical and Aerospace Engineering, The Ohio State University, Columbus, OH, USA. He is currently an Assistant Professor with the School of Mechatronic Engineering and Automation, Shanghai University, Shanghai. His current research interests include vehicle dynamics and control, advanced electric vehicles, and intelligent and connected vehicles. He is the invited reviewer over 40 international SCI journals (more than ten IEEE Transactions). He is a Lead Guest Editor of *Mathematical Problems in Engineering* and a Young Editor of the *International Journal of Hydromechatronics*.

ZEYUAN YAN received the B.S. degree in vehicle engineering from the Wuhan University of Technology, Wuhan, China, in 2020. He is currently pursuing the M.S. degree with the School of Mechatronic Engineering and Automation, Shanghai University, Shanghai.

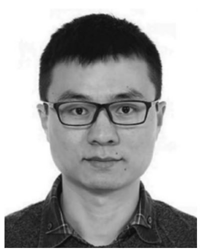
His current research interests include trajectory generation and path planning for autonomous vehicles.

GUODONG YIN (Senior Member, IEEE) received the Ph.D. degree from the Department of Vehicle Engineering, Southeast University, Nanjing, China, in 2007.

From 2011 to 2012, he was a Visiting Scholar with the Department of Mechanical and Aerospace Engineering, The Ohio State University, Columbus, OH, USA. He is currently a Professor with the School of Mechanical Engineering, Southeast University, Nanjing. His current research interests include vehicle dynamics and control, connected vehicles, and multiagent control. He is an Associate Editor of the *Journal of Mechanical Engineering*.

SHAOHUA LI received the Ph.D. degree from the Department of Vehicle Engineering, Beijing Jiaotong University, Beijing, China, in 2009.

From 2014 to 2015, she was a Visiting Scholar with the Department of Mechanical Engineering, Purdue University, West Lafayette, IN, USA. She is currently a Professor with Shijiazhuang Tiedao University, China. Her research interests include vehicle system dynamics and vibration control and intelligent control.



CHONGFENG WEI received the B.S. degree in computational and applied mathematics and the M.S. degree in vehicle engineering from Southwest Jiaotong University, Chendu, China, in 2009 and 2011, respectively, and the Ph.D. degree in mechanical engineering from the University of Birmingham, Birmingham, U.K., in 2015.

After two and a half years Postdoctoral research period, he joined the School of Mechanical Engineering, Shanghai Jiao Tong University, as an Assistant Professor (tenure-track). He then moved to the Institute of Transport Studies, University of Leeds, as a Research Fellow, in 2018. He is currently a Senior Lecturer with the Department of Mechanical and Construction Engineering, Northumbria University, Newcastle, UK. His current research interests include decision making and control of intelligent vehicles, human-centric autonomous driving, cooperative automation, and dynamics and control of mechanical systems. He is an Associate Editor of IEEE Open Journal of Intelligent Transportation Systems.