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Vision article

# Trajectory planning and tracking for autonomous overtaking: State-of-the-art and future prospects

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A B S T R A C T

Trajectory planning and trajectory tracking constitute two important functions of an autonomous overtaking system and a variety of strategies have been proposed in the literature for both functionalities. However, uncertainties in environment perception using the current generation of sensors has resulted in most proposed methods being applicable only during low-speed overtaking. In this paper, trajectory planning and trajectory tracking approaches for autonomous overtaking systems are reviewed. The trajectory planning techniques are compared based on aspects such as real-time implementation, computational requirements, and feasibility in real-world scenarios. This review shows that two important aspects of trajectory planning for high-speed overtaking are: (i) inclusion of vehicle dynamics and environmental constraints and (ii) accurate knowledge of the environment and surrounding obstacles. The review of trajectory tracking controllers for high-speed driving is based on different categories of control algorithms where their respective advantages and disadvantages are analysed. This study shows that while advanced control methods improve tracking performance, in most cases the results are valid only within well-regulated conditions. Therefore, existing autonomous overtaking solutions assume precise knowledge of surrounding environment which is not representative of real-world driving. The paper also discusses how in a connected driving environment, vehicles can access additional information that can expand their perception. Hence, the potential of cooperative information sharing for aiding autonomous high-speed overtaking manoeuvre is identified as a possible solution.



## Contents



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## 1. Introduction

Modern cars are equipped with various sensors and electronic systems to reduce the workload of a driver by providing emergency assistance (e.g., ABS, traction control, stability control, etc.), ADAS (e.g., cruise control, lane keeping, crosswind assistance, blind spot detection, etc.), and navigational assistance (e.g., trip planning, route selection, regular traffic update, etc.). However, the next generation of intelligent vehicles are expected to have increased capabilities which allow automated manoeuvring in various driving scenarios (Eskandarian, 2012; Gordon & Lidberg, 2015). Overtaking is one of the most common driving manoeuvre and any vehicle capable of end-to-end autonomy must have the ability to determine if, when, and how to perform this driving task.

Overtaking is a complex driving task as it involves both lateral and longitudinal motions of an overtaking vehicle (subject vehicle) while avoiding collisions with a slower moving vehicle (lead vehicle) (Milanés et al., 2012). Additional complexity arises due to different environmental conditions (e.g., road legislations, visibility, weather, etc.) and diversity of road-users (e.g., small cars, buses, trucks, etc.) (Vanholme, Gruyer, Lusetti, Glaser, & Mammar, 2013). Typically, an overtaking manoeuvre is considered successful on proper completion of three sub-manoeuvres namely, (i) lane change to overtaking lane, (ii) pass lead vehicle(s), and (iii) lane change back to original lane (Petrov & Nashashibi, 2014). The lane change sub-manoeuvre which indicates the start and the end of an overtake can be classified under two categories; (i) Discretionary Lane Change (DLC) and (ii) Mandatory Lane Change (MLC) (Moridpour, Rose, & Sarvi, 2010). A DLC sub-manoeuvre is performed when the immediate traffic situation in the faster lane is deemed to be better than the current lane and thus, the lane change is performed in anticipation of an improvement in the immediate driving conditions. On the other hand, an MLC sub-manoeuvre is performed due to compulsion arising from traffic rules (e.g., stalled vehicle, need to follow desired route, etc.). Moreover, the lane change to return back to the original lane can also be either DLC or MLC based on traffic conditions in each lane, legislation, etc. thus, transforming an overtaking manoeuvre into a complex task of dynamically choosing the best driving lane based on (i) legislation, (ii) driving intentions, and (iii) instantaneous traffic situation. This inference that the choice of lane is affected by both; (i) driving intention, and (ii) neighbourhood traffic conditions was verified in Toledo, Koutsopoulos, and Ben-Akiva (2003) using an integrated model (combining MLC and DLC) for lane changing behaviour based on gap acceptance (lead and lag gap). Therefore, it is noted that due to the dynamic nature of driving environments (i.e., traffic conditions in original and fast lane, speed limits, road conditions, etc.) overtaking is not standardised manoeuvre and thus, each overtaking manoeuvre in real-world scenarios is unique. This uniqueness arises from variations in number of overtaken vehicles, duration of overtake, relative velocity between concerned vehicles, distance between concerned vehicles, etc (Baber, Kolodko, Noel, Parent, & Vlacic, 2005; Hegeman, Brookhuis, & Hoogendoorn, 2005; Kesting, Treiber, & Helbing, 2007; Motro et al., 2016; Shamir, 2004; Thiemann, Treiber, & Kesting, 2008; Vlahogianni, 2013; Webster, Suzuki, Chung, & Kuwahara, 2007). For an autonomous vehicle, feasibility of an overtaking manoeuvre is evaluated on the basis of safety based on subject vehicle's states as well as surrounding information leading to a discrete outcome for making tactical decisions (i.e., either perform lane-change or do not perform lane change) which form a part of planning and decision making process. A variety of techniques for decision making are available in literature with (i) multi-level decision trees (Claussmann, Carvalho, & Schildbach, 2015), (ii) probabilistic weighted comparison of concurrent goals (Ardelt, Coester, & Kaempchen, 2012), and (iii) higher award seeking Markovian Decision Process algorithms (Ulbrich & Maurer, 2015) being among the prominent methods.

A schematic representation of an overtaking manoeuvre is shown in Fig. 1 with each sub-manoeuvre labelled with roman numerals. As discussed above, the lane change back to the original lane depends on the traffic conditions and thus both possibilities are depicted in the schematic. Despite the innumerable variations present due to the factors discussed above, overtaking manoeuvres can be classified under the four categories listed below (Hegeman et al., 2005):

- Normal: The subject vehicle approaches the lead vehicle and waits for a suitable opportunity to perform the manoeuvre.
- Flying: The subject vehicle does not adjust its longitudinal velocity and is directly able to overtake the lead vehicle.
- Piggy backing: The subject vehicle follows a preceding vehicle as they both overtake the lead vehicle.
- $2^+$: The subject vehicle overtakes two or more lead vehicles in a single manoeuvre.

For the aforementioned scenarios, the duration of a completed overtake has been found to be in the range of 5.4 to 12.5 s (subject to dynamic nature of the surrounding traffic and environment) using recording the trajectories of vehicles on typical European highways (Jong, Park, Chao, & Yen, 2016; Kanaris, Kosmatopoulos, & Ioannou, 2001; Khodayari, Ghaffari, Ameli, & Flahatgar, 2010; Milanés et al., 2012; Valldorf & Gessner, 2005; Vlahogianni, 2013; Wan, Raksincharoensak, Maeda, & Nagai, 2011). Performing an autonomous overtaking manoeuvre based on any of scenarios mentioned above within a given time range requires accurate information of surrounding environment, traffic, and weather conditions along with sophisticated sensing and perception, planning, and control systems (Chu, Lee, & Sunwoo, 2012). The surrounding environment of a vehicle is populated by different features; (i) permanent (road and lane limits), (ii) slowly changing (e.g., temporary speed limits, road works, traffic density, etc.), and (iii) fast changing (surrounding vehicle velocity, position, heading, etc.). A modern day vehicle uses a host of on-board sensors to discern the environment and the placement of an on-board sensor suite used to perform this task can be seen in Fig. 2. The information from these sensors is combined and used for tasks such as; (i) classify objects, (ii) track stationary and moving obstacles, (iii) identify safe driving zones, etc. Currently, there are some production vehicles that utilise vehicle-to-everything (V2X) information to provide updates on permanent (e.g., road and lane limits, road inclination, etc.) or slowly changing features (e.g., temporary speed limits, road works, traffic updates, etc.) of surrounding environment via a combination of cellular data and Local Dynamic Map (LDM) updates. However, despite an elaborate sensor suite and first generation V2X communication systems the capabilities of the contemporary autonomous vehicles is limited to low-speed overtaking. This is due to limitations such as; (i) range of sensors, (ii) blind spots, (iii) small timescales for predicting motion of traffic participants, (iv) sensor imperfections, and (v) possible V2X network outages. The combination of one or more of these limitations result in significant uncertainty while planning complex highway manoeuvres (e.g., overtaking) which span several seconds at high-speeds (Aeberhard et al., 2015; Son, Kim, Lee, & Chung, 2015). Moreover, unless all the traffic participants are connected and autonomous the uncertainty arising from predicting the motion of traffic vehicles cannot be brought down to negligible levels even with the advent of perfect on-board sensors and/or V2X communication network. Thus, predicting the motion of traffic participants for risk assessment forms a vital part of manoeuvre planning and this domain has witnessed a lot of research and a large number of techniques are present in literature. The different methods for motion planning for intelligent

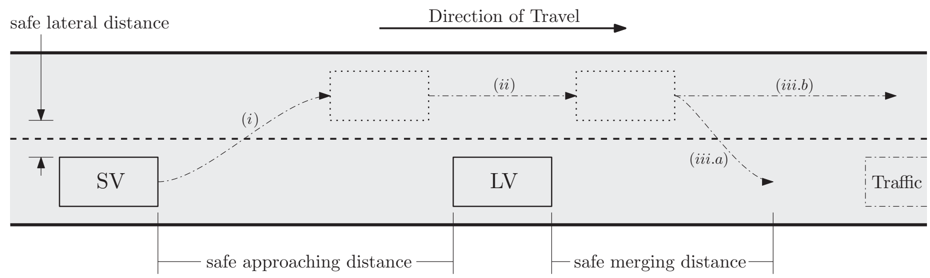


**Fig. 1.** Basic schematic of an overtaking manoeuvre. *Note:* Different sub-manoeuvres are (*i*) lane-change; (*ii*) pass lead vehicle; (*iii.a*) merge back into original lane; (*iii.b*) continue in faster lane to pass traffic.

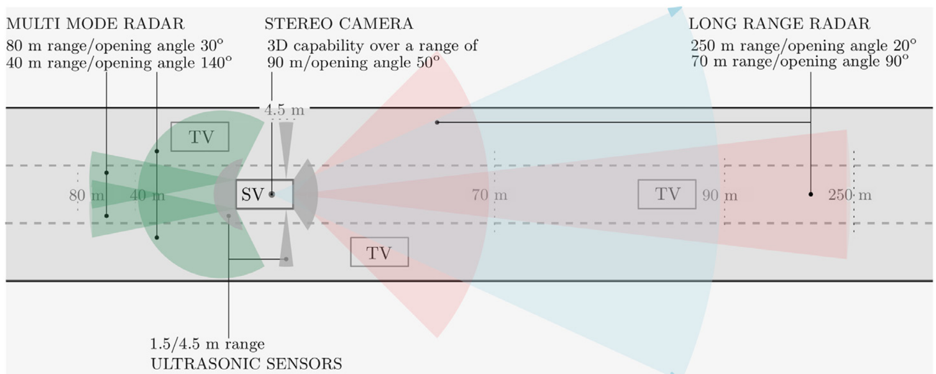


**Fig. 2.** Visibility of an autonomous vehicle. *Note:* SV: Subject Vehicle, TV: Traffic Vehicle. Sensor performance specifications are based on Radar, 2018.

autonomous vehicles based on abstraction levels of traffic motion are classified as; (i) Physics-based (Schubert et al., 2011; Schubert, Richter, & Wanielik, 2008; Schubert, Schulze, & Wanielik, 2010), (ii) Manoeuvre-based (Eggert, Klingelschmitt, & Damerow, 2015), and (iii) Interaction-aware (Bahram, Hubmann, Lawitzky, Aeberhard, & Wollherr, 2016; Lawitzky et al., 2013). A comprehensive survey discussing the advantages and limitations of each of these techniques is presented in Lefèvre, Vasquez, and Laugier (2014) and an interested reader is directed towards it.

Recent research has highlighted the potential use of off-board information via V2X communications in expanding the sensory and perception horizon of a vehicle through the communication systems (Andrews, 2012; Guzzella, 2009; Luo, Xiang, Cao, & Li, 2016). In the context of autonomous overtaking, initial research has been largely focused on the integration of V2X information to: (i) manoeuvre feasibility check, and (ii) decision making stages (Hegeman et al., 2005; Luo et al., 2016; Motro et al., 2016). However, the potential enhancements that can be achieved in trajectory planning and trajectory tracking of an overtaking manoeuvre by exploiting V2X information are yet to be studied. In this paper, a review of various techniques for trajectory planning and trajectory tracking for autonomous overtaking systems is presented. The aim of this paper is twofold: (i) to gain insight on techniques suitable for autonomous overtaking systems, and (ii) to investigate how V2X information can enhance both trajectory planning and tracking techniques of an autonomous overtaking system.

The paper is structured as follows: Section 2 introduces the system overview of an autonomous driving system and discusses how a 2-tier control architecture can be used to perform autonomous overtaking. In Section 3, an extensive literature review of trajectory planning methods used for generating overtaking trajectories is presented. Comparison of key aspects pertaining to vehicle models and a review of different control strategies for trajectory tracking applications is performed in Section 4. Finally, the concluding remarks are presented in Section 5.

## 2. System architecture

An autonomous overtaking manoeuvre requires consideration of a variety of factors such as subject vehicle states and constraints, lead vehicle states, environment limits, safety, and comfort. An overview of an intelligent autonomous driving system capable of performing autonomous overtaking is shown in Fig. 3. For an autonomous vehicle to successfully perform different tasks (e.g., lane change, pass lead vehicle, and merge) pertaining to overtaking, it is expected that the vehicle can carry out each sub-task within the sensing and perception, planning, and control blocks. Sensing and perception includes gathering information about the driving conditions to determine if and when the conditions are favourable to perform the overtaking (Kanaris et al., 2001). An autonomous vehicle utilises information from on-board sensors (Radar, LiDAR, camera, etc.) and/or off-board information via V2X communications to generate a real-time environmental representation (Kim, Kim, Park, Jung, & Yi, 2016), see Fig. 3. The main objectives of the sensing and perception system are lane-level localisation, neighbouring vehicle detection, static obstacle/constraint detection and safe drivable area representation (Kim et al., 2016).

The planning module utilises the perception information along with the subject vehicle states and dynamic constraints to compute safe collision free local trajectory for the subject vehicle at each time instant (Katrakazas, Quddus, Chen, & Deka, 2015). To plan an overtaking manoeuvre the vehicle uses perception data (position and velocity estimates of neighbouring vehicles, infrastructure limits, road geometry, headway time) and subject vehicle data (current state, lateral and longitudinal dynamics) to check feasibility of the manoeuvre and design a collision free and safe local reference trajectory for an overtaking manoeuvre (Carvalho, Lefévre, Schildbach, Kong, & Borrelli, 2015; Glaser, Vanholme, Mammar, Gruyer, & Nouvelière, 2010; Kala & Warwick, 2013; Kitazawa, 2016; Milanés et al., 2012; Saengpredeekorn & Srinonchat, 2009; Shamir, 2004).

The local trajectory generated via the planning module is used as a reference trajectory to be tracked while performing an over-

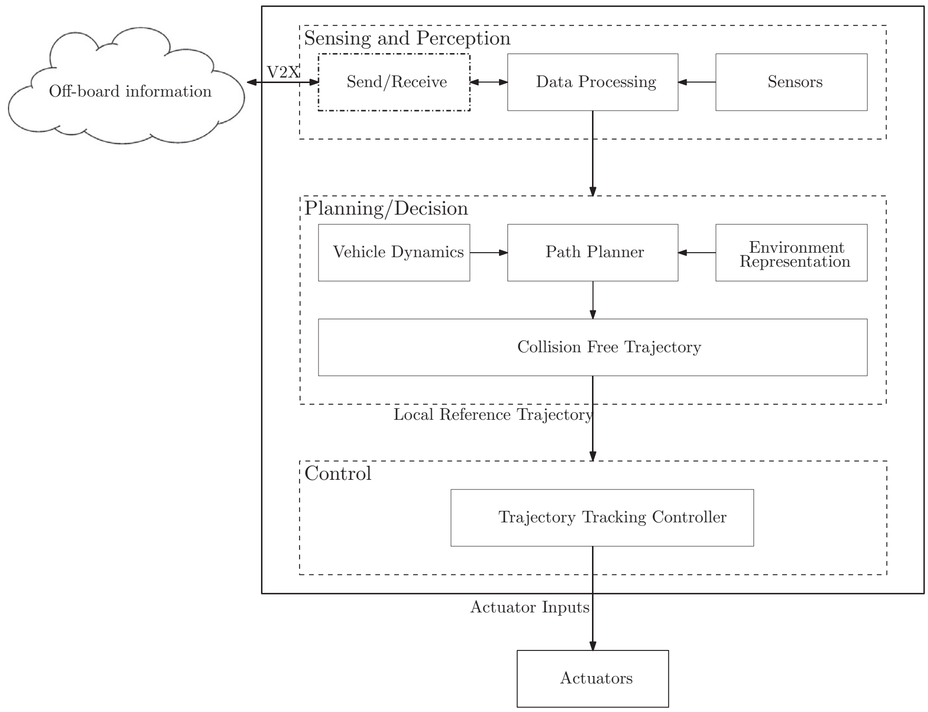


**Fig. 3.** Overview of an autonomous driving system.

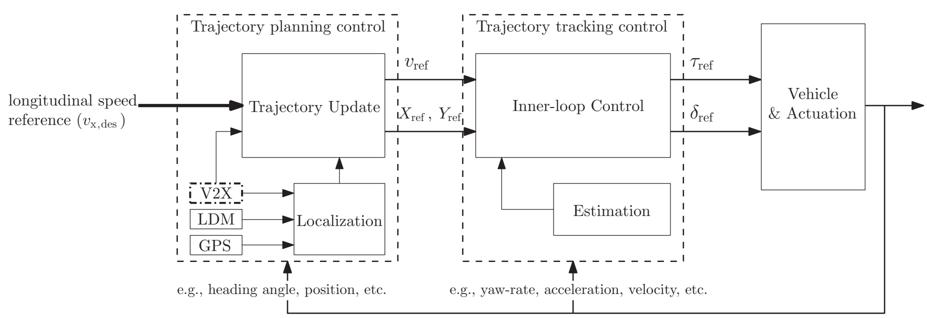


**Fig. 4.** General control architecture for an autonomous vehicle (Gao et al., 2012; Kim et al., 2016; Kitazawa, 2016; Naranjo et al., 2008; Nilsson et al., 2014). (V2X block with dot–dash boundary: optional functionality).

take (e.g., lane change, pass lead vehicle, lane-merge), and a closed-loop control system is designed to track it by controlled manipulation of steering, throttle and/or brake (Carvalho, Gao, Gray, Tseng, & Borrelli, 2013; Gao, Gray, Tseng, & Borrelli, 2014; Kala & Warwick, 2013; Kitazawa, 2016; Milanés et al., 2012; Murgovski & Sjöberg, 2015; Petrov & Nashashibi, 2014; Saengpredeekorn & Srinonchat, 2009; Schildbach & Borrelli, 2015; Shamir, 2004).

To preserve the modular nature of the architecture presented in the section above, the different driving tasks can be translated to a control architecture for an autonomous vehicle as shown in Fig. 4, i.e. trajectory planning controller and trajectory tracking controller (Gao et al., 2012; Kim et al., 2016; Kitazawa, 2016; Naranjo, González, García, & De Pedro, 2008; Nilsson, Gao, Carvalho, & Borrelli, 2014). The objective of the trajectory planning controller is to perceive the environment, monitor vehicle states (longitudinal and lateral positions, longitudinal and lateral velocities, longitudinal and lateral accelerations, and heading) and compute safe trajectories (e.g., $X_{ref}$, $Y_{ref}$, and $v_{ref}$) for the vehicle to track (Glaser et al., 2010). The trajectory tracking controller then computes, via feedback algorithms based on the tracking error, the necessary torque ($\tau_{ref}$) and steering inputs ($\delta_{ref}$) required to track the reference, despite possible measurement noise, un-modelled dynamics, parametric uncertainties which may or may not be accounted for by the trajectory planning controller.

## 3. Trajectory planning

An autonomous vehicle relies on real-time vehicle state and environment information (e.g., surrounding vehicles, road conditions) to derive a local trajectory that ensures a safe passage while minimising the deviation from the overall journey trajectory (global trajectory). Local trajectory planning can be defined as – *real-time planning of the vehicle's transition from one feasible state to the next while satisfying the vehicle's kinematic limits based on vehicle dynamics and constrained by occupant comfort, lane boundaries and traffic rules, while, at the same time, avoiding obstacles* (Katrakazas et al., 2015). Technical literature shows that the vast majority of trajectory planning methods for an overtaking application employ one of the four well known techniques i.e., potential fields, cell decomposition, interdisciplinary methods and optimal control. In this section, these techniques are reviewed to gain insight into their performance for different specifications such as computational requirements, safety, feasibility in high-speed overtaking and real-time implementation.

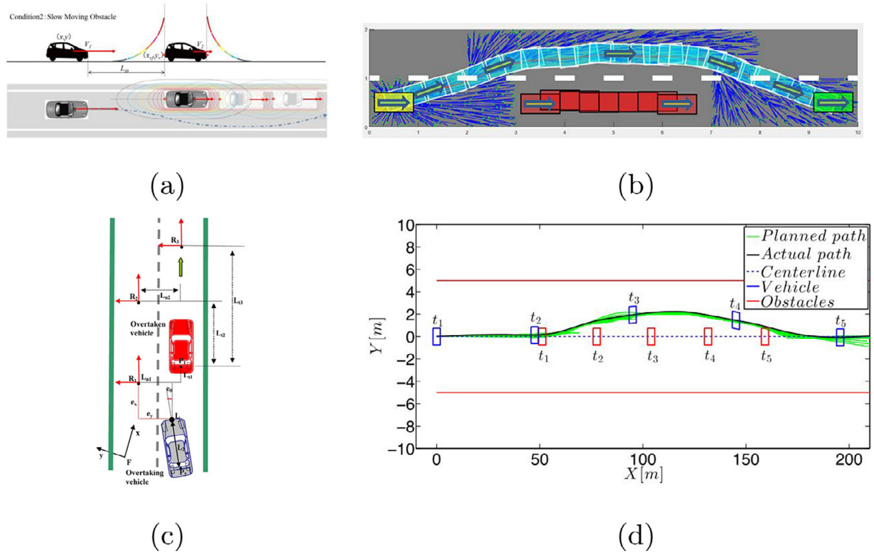


**Fig. 5.** Trajectory planning via (a) potential fields (Kitazawa, 2016); (b) RRT (Khaksar, Sahari, & Hong, 2016); (c) virtual reference tracking (Petrov & Nashashibi, 2014); (d) Model Predictive Control (Carvalho et al., 2013).

Potential field algorithms assign repulsive fields to obstacles and attractive fields to safe zones of the vehicle and then use an algorithm to compute trajectories along the steepest potential gradient in the resulting field (Glaser et al., 2010; Kitazawa, 2016), see Fig. 5(a). The computed path is guaranteed to follow the lowest potential (i.e., find collision free trajectory) in a given space but its safety and accuracy depends heavily on the accuracy of the generated potential field (i.e., definite knowledge of position of stationary and moving obstacles). However, due to the high computation costs and need for very accurate surrounding environment information, the method has only been experimentally verified for low speed (i.e., urban) manoeuvres (Kitazawa, 2016). Additionally, it is seen that the algorithm cannot handle vehicle kinematic constraints which may cause safety issues in high-speed driving scenarios (Glaser et al., 2010; Shim, Adireddy, & Yuan, 2012).

Cell decomposition algorithms such as Rapidly-exploring Random Tree (RRT) is a method used for collision free path planning (Kuwata, Fiore, Teo, Frazzoli, & How, 2008; Ma et al., 2014), see Fig. 5(b). These algorithms can be modified to incorporate the vehicle constraints but they also suffer from computational and memory costs (Glaser et al., 2010; Kuwata et al., 2008; Ma et al., 2014). The computational complexity of such algorithms increases with increasing traffic density and frequency of road curvature thus jeopardising the on-board computation of an autonomous vehicle on busy roads (Ma et al., 2014). Furthermore, the paths created by RRT's are jerky and tracking such a trajectory will have an adverse effect on the comfort of the occupants (Katrakazas et al., 2015).

Inter-disciplinary techniques inspired by robotics and missile guidance systems (Ghumman, Kunwar, & Benhabib, 2008; Petrov & Nashashibi, 2014; Usman & Kunwar, 2009) for vehicle path-planning are also reported in literature. One of the novel approaches proposed was to use motion primitives (combination of steady-state equilibrium trajectories and pre-specified manoeuvres) (Gray et al., 2012). The experimental results demonstrated that collision free and feasible trajectories can be generated in real-time using this approach (Gray et al., 2012). Ghumman et al. designed a trajectory planning method based on Rendezvous Guidance technique (passing vehicle is guided in real-time to match the position and velocity of a shadow target during an overtaking manoeuvre) inspired from missile guidance systems (Ghumman et al., 2008; Usman & Kunwar, 2009), see Fig. 5(c). Similarly, an approach for overtaking manoeuvre consisting of consecutive tracking of virtual reference points positioned a priori at known distances from the lead vehicle is proposed in Petrov and Nashashibi (2014). Simulation results of both these approaches demonstrated acceptable real-time capabilities for generating feasible trajectories but tracking performance was validated using low order models in computer simulations. Thus, in the absence of experimental validation it is difficult to form conclusions on the efficacy of such approaches.

Optimal control methods minimise a performance index (e.g., change in kinetic energy, Shamir, 2004; jerk, Chu et al., 2012; Shim et al., 2012; lateral acceleration, Shim et al., 2012) under a set of constraints (e.g., vehicle lateral and longitudinal limits, environment constraints, neighbouring vehicles) to obtain a trajectory for a safe overtaking manoeuvre. The results from literature demonstrate that the method is successful in generating collision free trajectories without high computational requirements (Chu et al., 2012; Shamir, 2004; Shim et al., 2012). The autonomous vehicle Junior developed by Stanford University has successfully demonstrated the effectiveness of optimal control based trajectory planning techniques at the DARPA Urban Challenge (Werling, Ziegler, Kammel, & Thrun, 2010). In this control framework, the researchers design two sets of trajectories, one for lateral motion and another for longitudinal motion each optimised for safety and occupant comfort. A set of combined lateral and longitudinal motion is obtained by combining these two sets. The final trajectory that is provided to the trajectory tracking controller is computed by following the steps; (i) filter out trajectories that breach safety and comfort limits to create a subset of applicable trajectories, (ii) use this subset of applicable trajectories to identify ideal trajectory that minimises deviation from the road centre. However, most of these techniques do not take into account the non-linearities in the vehicle and tire dynamics resulting in unfeasible trajectories under high-speeds and/or low road friction conditions which pose a safety risk for autonomous vehicles (Gao et al., 2012). Additionally, trajectories obtained by such open-loop single stage optimisation do not account for uncertainties in a dynamic environment and therefore these trajectory planning methods have limited potential unless used in either extremely controlled or structured environments.

Recently, Model Predictive Control (MPC) methodology has also been used by researchers for local trajectory planning, due to its ability to better handle system constraints and nonlinearities, see Fig. 5(d). The approach involves solving a constrained finite-time optimal control problem to determine a sequence of control inputs that minimise a performance index (cost function) and applying the optimal inputs (e.g., steering wheel angle, throttle, and brake) using a receding horizon principle (Carvalho et al., 2013). However, the presence of (i) nonlinear vehicle dynamics, and (ii) time-varying state and input constraints while navigating in a dynamic environment, leads to a nontrivial control problem thus presenting a computational burden to solve the optimisation problem in real-time (Carvalho et al., 2013). Researchers have attempted to reduce the computational complexity arising due to the nonlinear vehicle dynamics by using (i) point mass vehicle model (Kim et al., 2016; Murgovski & Sjöberg, 2015; Nilsson et al., 2014), (ii) linear kinematic bicycle vehicle model (Gao et al., 2012; Gao et al., 2014; Schildbach & Borrelli, 2015) and (iii) iterative linearisation of nonlinear vehicle model (Carvalho et al., 2013), in the prediction model. It is noted that the collision avoidance constraints are non-convex in nature which means that the feasibility and uniqueness of the optimisation cannot be guaranteed. Researchers have proposed different techniques (translating problem from time-dependent system to position-dependent system (Gao et al., 2012; Karlsson, Murgovski, & Sjöberg, 2016; Kim et al., 2016; Murgovski & Sjöberg, 2015), relaxing collision avoidance constraints (Nilsson et al., 2014), approximate linearisation (Carvalho et al., 2013) to guarantee uniqueness of solution and reduce the computing and memory requirements of the controller. The experimental results demonstrate the ability of these approaches to generate safe collision free trajectories around static or moving obstacles (i.e. overtaking manoeuvre) but it should be noted that these path-planner methods required exact knowledge of the states, the obstacles (stationary, moving) and/or a high performance computing platform (desktop class computer) to calculate safe collision free trajectories (Carvalho et al., 2013; Gao et al., 2012, 2014; Kim et al., 2016; Murgovski & Sjöberg, 2015; Nilsson et al., 2014; Schildbach & Borrelli, 2015). It is noteworthy that recent publications have demonstrated that computing constraints may soon become an issue of the past as highly efficient algorithms for implementing MPC controllers on real-time prototyping systems and vehicle electronic control units have been developed and a few successful implementations are discussed in Cesari, Schildbach, Carvalho, and Borrelli (2017), Kong, Pfeiffer, Schildbach, and Borrelli (2015), Schildbach and Gmbh (2016). Among the reviewed approaches, MPC provides a promising approach for trajectory planning due to its ability to: (i) include system dynamics and constraints, and (ii) perform receding horizon control which allows it to plan feasible trajectories over a larger operating range.

It is noteworthy that all methods discussed above operate under the assumption that accurate knowledge of the environment and lead vehicle states are available on-demand to the trajectory planning system. The advantages and disadvantages of the various trajectory planning methods discussed above are summarised in Table 1. However, due to limitations of on-board sensing systems, the following situations may arise. First, the measurements of the lead vehicle states (e.g., position, velocity, and heading) might have errors, missing information, low accuracy, etc. resulting in inaccurate environmental representation. Second, variations in external conditions (e.g., road legislation, road surface condition, road width, weather, etc.) which are not captured might impact the subject vehicle dynamic limits (e.g., lateral acceleration, longitudinal speed, lateral acceleration, etc.). Trajectory planning methods that are not robust to environmental variations and sensor inaccuracies might lead to unfeasible and/or unsafe reference trajectories, posing a major safety risk especially during high-speed driving. The various trajectory planning techniques discussed above propose different ways for dealing with the uncertainty in current environment perception and limited future prediction capabilities. Potential field and cell decomposition based methods assign additional buffer zones (based on headway time, instantaneous relative velocity, etc.) around each obstacle and thus the search for feasible trajectories is performed in a constrained search space (Wolf & Burdick, 2008). Similarly, the trajectory planning techniques in Petrov and Nashashibi (2014), Usman and Kunwar (2009), Ghumman et al. (2008) also compute virtual target points conservatively by expanding the margins of the virtual reference points in accordance with the relative velocities of the subject and lead vehicle. On the other hand, a type of MPC control technique known as Scenario-Based MPC (SCMPC) has been proposed in literature to mitigate the uncertainty arising due to traffic interactions in a systematic manner (Carvalho, Gao, Lefevre, & Borrelli, 2014; Cesari et al., 2017; Schildbach & Borrelli, 2015; Schildbach, Fagiano, Frei, & Morari, 2014). In this approach either an interaction-aware traffic prediction model (Schildbach & Borrelli, 2015) or manoeuvre based traffic prediction model (Cesari et al., 2017) is incorporated within the MPC framework to simulate traffic scenarios as a probability distribution and a finite horizon optimal control problem is solved to generate a trajectory that is safe, feasible, and admissible under a selected set of traffic scenarios. The efficacy of the SCMPC trajectory planning technique for generating safe lane change manoeuvres has been demonstrated numerically and its real-time capability has been experimentally validated (Carvalho et al., 2014; Cesari et al., 2017; Schildbach & Borrelli, 2015; Schildbach et al., 2014). However, the effectiveness of this method has a dependence on the accuracy of the modelled traffic scenarios which makes obtaining large quantity of actual traffic data a necessity. Recently, it has been proposed by researchers that a V2X communication system can augment a vehicles sensing and perception capabilities to potentially mitigate the issues discussed above (Damerow, Flade, & Eggert, 2016; Hegeman et al., 2005; Luo et al., 2016; Motro et al., 2016; Ohara, Slot, Monteil, Cahill, & Bouroche, 2015; Schildbach & Borrelli, 2015). Initial studies for trajectory planning using the information obtained through V2X systems, suggest that the safety and feasibility of a manoeuvre can be enhanced by incorporating off-board information (Huang, Wu, Ma, & Fan, 2015; Pérez, Milanés, Onieva, Godoy, & Alonso, 2011; You et al., 2015). Nonetheless, tangible benefits of using off-board information (e.g., lead vehicle states, road conditions, etc.) in trajectory planning methods are not very clearly understood and thus such studies are open to further research. Nonetheless, how a V2X system capable of providing accurate surrounding (e.g., lead vehicle states, road conditions, etc.) information in real-time can improve trajectory planning methods needs to be understood and is a question open to further research. Moreover, a wireless information sharing system induces additional dynamics related to communication delays, packet losses, and connection drop-outs which adds to the complexity of a control system (Wymeersch, De Campos, Falcone, Svensson, & Ström, 2015). Therefore, meticulous studies are required to ensure that the trajectory planning methods are robust and fault-tolerant against such network imperfections (Houben & Houben, 2015).

## 4. Trajectory tracking

Vehicle trajectory tracking (lateral-longitudinal control) is a mature scientific field with a plethora of control methodologies available in literature dating all the way back to the middle of the 20th century. Some useful properties for assessing tracking controllers for autonomous vehicle applications are listed below (Watzenig & Brandstätter, 2017).

**Table 1**
Summary of techniques for trajectory planning to avoid a moving obstacle.

| Control strategy | Strength(s) | Weakness |
|---|---|---|
| Potential fields | • Optimality of searched path guaranteed<br>• Collision free path guaranteed | • High computation cost<br>• Inability to handle system constraints<br>• No systematic procedure to consider environmental uncertainties |
| Cell decomposition | • Guaranteed collision free trajectories | • Computation requirements sensitive to traffic density<br>• Computed paths are jerky<br>• No systematic procedure to consider environmental uncertainties |
| Interdisciplinary techniques | • Reduced complexity of collision avoidance as trajectory planning converted to reference tracking problem<br>• Real-time capable | • Experimentally unproven<br>• No systematic design procedure<br>• Do not consider uncertainties in environment perception while generating reference points |
| Optimal control | • Generate collision free trajectories<br>• Ability to include kinematic constraints | • Unsuitable for high-speed driving manoeuvres with large angles of tire slip<br>• Inability to consider tire dynamics |
| Model Predictive Control (MPC) | • Include vehicle and tire dynamics<br>• Systematic handling of constraints and traffic uncertainties<br>• Computational requirements independent of environment | • Optimisation sensitive to number of constraints<br>• Computation complexity scales quickly with high-order system models, non-linearity, and non-convexity of constraints |

- Real-time capability: The control law needs to be implementable on a vehicles Electronic Control Unit (ECU) and function within the calculation time
- Robustness: The designed controller should be robust against system nonlinearities, model parameter variations, and external disturbances
- Operating Range: The tracking controller should ideally work across the entire range of vehicle speeds (0–120 km/h)
- Controller parameter tuning: A systematic tuning procedure for the controller parameters allows for a structured controller design procedure

The performance of closed-loop tracking controllers depends on the accuracy of the modelled system dynamics. Vehicle models used for capturing the dynamics should provide a trade-off between model accuracy and fidelity. In literature a variety of vehicle models (ranging from low dimension point mass-models to high-fidelity multi-body models) are presented. Different vehicle models that have been developed over the years to capture the longitudinal, lateral and yaw dynamics of a vehicle have been documented in Rajamani (2011). Out of the wide variety of vehicle models available in literature a kinematic bicycle model and dynamic bicycle model have been found to provide a good compromise between model complexity and accuracy for controller design related to highway driving applications (Kang, Lee, & Chung, 2014; Kong et al., 2015). A comprehensive review of trajectory tracking control on the aspects of choice of vehicle model, control strategies, and controller performance criteria has been performed in Hafizah, Hairi, Hudha, and Abdul (2016). The review demonstrated that geometric models based on Ackermann steering are not suitable for high-speed trajectory tracking due to their inability to include vehicle dynamics (e.g., acceleration and velocity). Additionally, it is highlighted that kinematic models (bicycle, four-wheel) are also unsuitable for high-speed trajectory tracking as they are inaccurate in regions of tire force saturation. Both linear and nonlinear dynamic vehicle models (full vehicle model, half vehicle model, and bicycle model) were found to mitigate these limitations and furthermore providing a more accurate representation of a vehicle during high-speed driving (Hafizah et al., 2016). However, it was also shown that a dynamic bicycle model (linear) was suitable for driving tasks (lane-change manoeuvre, overtaking manoeuvre, highway driving) with small lateral acceleration ($\leq 0.5$ g) and low vehicle side-slip angle (5°) (Hafizah et al., 2016; Kim, Kim, & Lee, 2015). Most of the papers in literature have used a single-track vehicle model (bicycle model) for developing a tracking controller for performing overtaking manoeuvres since an overtaking manoeuvre is performed well within the dynamic limits of the vehicle (i.e., lateral acceleration, vehicle side-slip, and yaw-rate) where both the vehicle as well as tire dynamics can be approximated by linear models. However, at high-speeds and/or under low road friction overtaking scenarios, it is quite possible that the system (i.e., vehicle, and tires) may exhibit significant non-linear behaviour and therefore for appropriate scenarios either nonlinear models, linear parameter varying (LPV) models or multiple models can be used to capture the relevant dynamic behaviour of the system (Filev, Lu, & Hrovat, 2013; Kim et al., 2015). For a detailed review of different vehicle models the reader is directed towards the work by Hafizah et al. (2016), Snider (2009), Sorniotti, Barber, and Pinto (2017), Rupp and Stolz (2017).

### 4.1. Tracking controllers

A comparison of different tracking controllers for autonomous vehicles was performed in Hafizah et al. (2016), Snider (2009), Sorniotti et al. (2017), Rupp and Stolz (2017). Some relevant observations of these comparisons along with other examples of tracking controllers for autonomous overtaking are discussed below.

Geometric controllers are designed using geometric vehicle models (Hafizah et al., 2016; Rupp & Stolz, 2017; Snider, 2009; Sorniotti et al., 2017). Pure-pursuit and Stanley method are two prevalent geometric controllers (Hafizah et al., 2016; Rupp & Stolz, 2017; Snider, 2009; Sorniotti et al., 2017). Pure-pursuit is a technique where the vehicle is in constant pursuit of a virtual moving point in front of the vehicle and ‘Stanley’ controller is based on non-linear geometric controller which considers heading and lateral error to compute steering angle corrections (Hafizah et al., 2016). These type of controllers (pure pursuit, Stanley, etc.) are easy to implement but are suitable only for applications that do not need to consider vehicle dynamics. Furthermore, since this approach does not follow a systematic control parameter tuning method, it is difficult to achieve a trade-off between stability and tracking performance (Rupp & Stolz, 2017; Snider, 2009; Sorniotti et al., 2017). It is observed that over-tuning of both pure-pursuit and Stanley controllers leads to poor tracking performance during cornering (Snider, 2009). Kinematic controllers are alternative control techniques for trajectory tracking. They are feedback controllers which are designed considering the vehicle kinematics (e.g., longitudinal velocity, lateral velocity, yaw-rate, etc.). Kine-

**Table 2**
Summary of control strategies for vehicle trajectory tracking (Hafizah et al., 2016; Snider, 2009; Sorniotti et al., 2017; Tagne et al., 2016; Watzenig & Brandstätter, 2017).

| Control strategy | Strength(s) | Weakness |
|---|---|---|
| Geomteric and kinematic | • Adequate performance (experimentally validated) in conditions without disturbances (e.g., wind, road banking)<br>• Good tracking performance and robustness at moderate speeds (e.g., kinematic) | • Do not consider vehicle dynamics<br>• Steady-state error increases for high-speed driving (e.g., geometric)<br>• Unsuitable for high-speed driving as dynamics are neglected (e.g., kinematic)<br>• Requires smooth and continuous reference trajectories |
| Classical | • Established method with good performance for non-linear systems<br>• Robust closed-loop performance against uncertainties and noise (e.g., SMC) | • Tuning of controller parameters is tricky (e.g., PID)<br>• Robust performance only in limited scenarios (e.g., SMC)<br>• Control law is sensitive to path curvature variations (e.g., SMC) |
| Dynamic state feedback | • Consider vehicle dynamics in calculating control law<br>• Optimisation shifted offline resulting in simple implementation of control law | • Obtaining vehicle states (e.g., wheel forces, slip angles, torques etc.) is non-trivial<br>• Control law is sensitive to path curvature variations (e.g., LQR) |
| Neural network | • Sufficient training can make the behaviour very human-like to make the automated car feel natural | • Controller tuning requires simulation with large amounts of real world (training) data<br>• No failure explanations possible |
| Fuzzy logic | • Closed-loop system acts similar to a human-driver (because of human-like rules) | • Controller tuning is not systematic with no formal stability analysis<br>• Rules can become unmanageable if number of variables is large |
| Model Predictive Control (MPC) | • Systematic design procedure<br>• Ability to include system and actuator constraints in design procedure<br>• Inclusion of vehicle and tire dynamics in control problem | • Non-linear MPCs with have high computing requirements making them unsuitable for high-speed driving environments<br>• The tracking performance is sensitive to the accuracy of prediction model<br>• Larger tuning parameter set compared to industry standard PID |

matic controllers have been shown to improve the tracking performance provided by geometric controllers but the gains over a geometric controllers are not high enough to justify the additional effort involved in designing and tuning the controller (Hafizah et al., 2016; Snider, 2009; Sorniotti et al., 2017). Moreover, since these methods ignore vehicle dynamics, their applicability in critical driving environments (e.g., high-speed driving, extreme path curvature, etc.) cannot be assured.

Examples of classical control algorithms (e.g., PID, sliding mode controller) are also found in literature. Tracking controllers using classical techniques (PID) are shown to have good tracking performance but tuning of the parameters was found to be major challenge due to the presence of vehicle and tire non-linearities. Sliding Mode Control (SMC), a well-established classical non-linear state-feedback controller has also been used to design vehicle trajectory tracking controllers and shows good tracking accuracy due to the non-linear control law (Hafizah et al., 2016; Tagne, Talj, & Charara, 2016). However, it suffers from a few drawbacks namely: (i) performance is sensitive to the sampling rate of the controller (ii) chattering problems, (iii) robustness only on the sliding surface, and (iv) needs prior knowledge of disturbance and uncertainty bounds (Hafizah et al., 2016; Rupp & Stolz, 2017; Tagne et al., 2016).

Dynamic state feedback (linear and nonlinear) based control methods demonstrate better performance that geometric and kinematic controllers as they consider the dynamics of the vehicle and tires while computing the control law. Linear Quadratic Regulator (LQR) based control law is easy to design but while tracking trajectories with varying curvature feedforward control is required to achieve error-free tracking. However, adding feedforward control makes the tracking controller sensitive to discontinuities in the reference trajectory which requires additional tuning to attenuate (Snider, 2009). On the other hand, optimal control based methods can provide accurate trajectory tracking even at high-speeds but this is achieved only when certain assumptions (e.g., velocity of the subject vehicle remains constant during the optimisation horizon) are fulfilled. Recently, nonlinear adaptive control techniques such as Inversion & Immersion (I&I) have also been used for vehicle trajectory tracking controllers. Initial studies demonstrate that this method provides robust closed-loop tracking performance but the controller is sensitive to parameter uncertainties (Tagne et al., 2016). In the same body of work, an adaptive Proportional-Integral (PI) with non-linear gains controller for trajectory tracking was also proposed (Tagne et al., 2016). Simulation results indicate that the controller provides tracking performance at par with an SMC and I&I controller with added advantage in the form of insensitivity to parameter uncertainties. However, in presence of large curvature variations or when operated in non-linear region of vehicle dynamics, the controller gains have a tendency to become high which may have a detrimental effect on the actuators.

There are also examples of advanced model based control techniques such as MPC being used for vehicle trajectory tracking (Carvalho et al., 2013; Gao et al., 2012; Gao et al., 2014; Gray et al., 2012; Kim et al., 2016; Murgovski & Sjöberg, 2015; Nilsson et al., 2014). Nonlinear MPC was found to provide very accurate tracking performance but at the same time suffer due to computational requirements of online optimisation (Besselmann & Morari, 2009). To reduce the computational burden researchers use a linear vehicle model but such controllers are applicable only in linear region of vehicle and tire behaviour (Gao et al., 2014; Schildbach & Borrelli, 2015). Designing a MPC framework based on iterative linearisation of a non-linear model has been proposed as a way to expand the working range of linear MPC controllers for trajectory tracking and has been experimentally validated (Carvalho et al., 2013). This approach helps in meeting the compromise between computational requirements and modelling errors.

Neural network and fuzzy logic based approaches have also been proposed in literature and demonstrate tracking performance similar to LQR controllers. However, in the absence of formal stability proofs and exception handling, such approaches cannot be suggested for real-world implementation (Chaib, Netto, & Mammar, 2004; Sorniotti et al., 2017). The advantages and disadvantages of the different controllers discussed above are summarised in Table 2. Since, an overtaking manoeuvre is not standardised and every researcher demonstrates their tracking controller under a unique setting, it is difficult to perform a direct comparison between the different controllers proposed in literature. However, in Rupp and Stolz (2017), five different trajectory tracking controllers (Stanley, LQR, SMC, Fuzzy, and MPC) were designed to simulate an overtaking manoeuvre performed at 120 km/h. This setup provides a basis for direct comparison of different control algorithms since they were applied on an identical system. The tracking performance was assessed by comparing lateral errors and angular errors. Additionally, the actuation effort was compared using steering angle induced during the manoeuvre. The results from this preliminary comparison (i.e., trajectory tracking, and actuation) demonstrated that MPC resulted in the smallest tracking errors (i.e., lateral position and heading angle) with smooth actuation of the steering angle.

All the controllers discussed above are validated in well controlled environments where parameter variations (e.g., vehicle mass, moment of inertia, road friction, etc.) and environmental uncertainties (e.g., headwind, tailwind, etc.) are kept to a minimum. While such practices allow researchers in benchmarking different controllers, most of the proposed controllers are operational in a narrow operating window which is not a realistic representation of real-world driving. The operating window of a controller subject to large variations in system dynamics can be increased in the following three ways: (i) control robustness against all uncertainties, (ii) design a 'bank' of controllers to cover possible different operational regimes, or (iii) update parameters in real-time to prevent performance drop-off. However, the order of a controller rises with the number robustness criteria that are incorporated and the number of controllers in a 'bank' scales exponentially with the number of varying parameters making both these approaches unviable for practical application (Hafizah et al., 2016). On the other hand using a V2X system to update required parameters based on the surrounding conditions can potentially provide a practical solution. Some attempts to use V2X to update control parameters for improving tracking performance have been presented in literature. For instance, in Jong et al. (2016), an automated emergency braking (AEB) system that exploits V2X communication to update the road friction co-efficient parameter in the control system model has been proposed. This allows for modification in real-time key constraints such as minimum braking distance and time-to-collision (TTC) making the system suitable for use under a wider range of conditions. Using a similar strategy, a communication system that updates the vehicle model parameters (e.g., road-friction, Jalalmaab, Pirani, Fidan, & Jeon, 2016, mass, etc.) and system constraints (e.g., road width, speed limit, cross-wind, traffic state and future trajectory) can enhance the usability of model based tracking controller in diverse driving conditions. Hence, V2X communication systems can update relevant parameters of a controller with accurate and real-time information thus preventing the applicability of a designed tracking controller to be limited to certain pre-set conditions and scenarios. However, the range of benefits (e.g., tracking performance, safety improvements, etc.) that can be gained by such a system needs further investigation resulting in an open research question.

## 5. Conclusion

This paper reviewed different approaches towards trajectory planning tracking for autonomous overtaking. The review of trajectory planning methods brings forth the following important aspects. First, vehicle dynamics, constraints and surrounding environment information needs to be considered while designing a trajectory for an overtaking manoeuvre and methods that incorporate these requirements within their framework are suitable candidates for real-world applications. Second, the trajectory planning techniques depend on accurate surrounding environment information, and off-board information via V2X communication can aid in expanding the accuracy and perception horizon thereby reducing safety concerns that might arise due to diverse driving conditions. For tracking controllers, the review showed that: (i) control algorithms that considered vehicle and tire dynamics over large speed ranges provided accurate tracking even at high-speeds and/or large trajectory variations, and (ii) the effectiveness of such controllers hinges on the accuracy of the modelled system dynamics which has difficulty in capturing the large variations encountered typically in daily driving with one low order system. Examples from literature showed that off-board information via V2X systems can be used to update controller parameters in real-time which can prevent drop-off in tracking performance when operated in conditions with variations in system dynamics. However, integration of off-board information into a multi-tier control architecture needs to be seamless as well as capable of graceful degradation on occasions of wireless communication failure. This added complexity in control design can pose significant challenges that will need to be addressed to develop a safe, dependable, and robust control system.

It is noteworthy that the study of potential benefits that can be achieved by leveraging off-board information via V2X communication systems for autonomous trajectory planning and tracking is in a nascent stage and marks a new chapter of study in the field of autonomous vehicles.

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