J. Indian Inst. Sci.
A Multidisciplinary Reviews Journal
ISSN: 0970-4140 Coden-JIISAD

REVIEW ARTICLE

Review of Lane-Changing Maneuvers of Connected and Automated Vehicles: Models, Algorithms and Traffic Impact Analyses

Zhen Wang[1], Xiaowei Shi[2] and Xiaopeng Li[2]*

Abstract | Connected and automated vehicle (CAV) technologies have been developed to improve traffic safety, mobility, and environmental impacts throughout the years. One of the enabling CAV technologies is the lane-changing function, which has attracted much attention from both industry and academia in recent years. This paper provides an overview of representative studies on CAV lane-changing models, algorithms, traffic impact analyses as well as testing experiments. Several crucial concepts, such as vehicle-to-vehicle (V2V) communication, lane-changing decision and planning, and vehicle control algorithms are focus of this review. Overall, despite existing successful studies on CAV lane changing, research gaps between state-of-the-art technologies and real-world CAV applications are identified in the hope of facilitating future research in this direction.

Keywords: *Connected and automated vehicle, Lane changing, Models, Algorithms, Traffic impact analysis*

1 Introduction

Developments of connected and automated vehicles (CAVs) have brought significant benefits in promoting road capacity, enhancing mobility, and reducing fuel consumption[1]. The major research efforts on CAV technologies include cooperative collision avoidance, platooning, cooperative cruise control, and lane changing[2]. Lane-changing technology is arguably the most complex one among them and critical to enabling higher levels of vehicle automation. It pertains to opportunistic or mandated transfer of a host CAV from the current lane to an adjacent lane. In general, the CAV lane-changing system consists of four key modules: vehicle-to-vehicle (V2V) communication, localization, lane-changing decision and planning, and vehicle control algorithms[3]. With the help of V2V communication, the position, speed, and acceleration of the surrounding vehicles can be acquired faster and more accurately. Often to complement V2V, localization aims to provide information on surrounding vehicles based on the on-board sensors. The provided information is used for lane-changing decision and planning when V2V communication is not stable, or CAVs operate in a mixed traffic environment, including CAVs and regular human-driven vehicles. Currently, existing studies concerning CAV localization can provide both absolute and relative positions[4]. A variety of sensors including vision, light detection and ranging (LiDAR) and radar can offer relative measurements concerning the surrounding environment[5–7]. Moreover, the absolute position can be acquired based on global navigation satellite system (GNSS) receivers. With the help of the information from V2V communication and localization, the lane-changing decision module can predict surrounding vehicles' movements and decide when and where to perform the lane-changing operation[8]. Then, the lane-changing planning model is able to generate one or more reference trajectories from the current position to the target position concerning safety and

Connected and automated vehicle: Connected and automated vehicle is a self-driving vehicle equipped with communication devices, allowing the vehicle to share information with the roadside unit and surrounding vehicles.

Platooning: Platooning is a method for driving a group of vehicles together. It is meant to increase the capacity of roads via an automated highway system and decrease associated energy consumption and emissions.

Light detection and ranging: LiDAR is a surveying method that measures the distance to a target by illuminating the target with laser light and measuring the reflected light with a sensor.

[1] School of Information Engineering, Chang'an University, Xi'an, Shaanxi 710064, People's Republic of China.
[2] Department of Civil and Environmental Engineering, University of South Florida, Tampa, FL 33620, USA.
*xiaopengli@usf.edu

Springer IISc Press

comfort. To accomplish lane changing as expected, a trajectory-tracking controller should be developed to track the predefined trajectories according to the CAV state and road information. The differences between the actual trajectory and reference trajectory in terms of errors on longitudinal and lateral locations and the CAV's heading angle will be corrected. The vehicle control algorithms then can be converted into an input to the actuators. The desired speed and yaw rate are realized by controlling the torque and the steering wheel, respectively. These four key modules cooperate continuously to complete the lane-changing task. Besides the addressed individual vehicle control technologies, cooperative lane-changing maneuvers from multiple vehicles in traffic flow have been shown to impact overall traffic flow performance significantly[9]. For example, to achieve some specific objectives of the subject vehicle (e.g., lane-changing maneuvers with the shortest duration time or the most comfortable trajectory), vehicles in the target lane will adjust their speed to cooperate with the subject vehicle, which will cause completely different trajectories from a microscopic view. This affects the characteristics of traffic flow from macroscopic view. Thus, there is an imperative need to understand the impacts of cooperative CAV lane-changing maneuvers in a traffic system.

A decent number of studies have been conducted on CAV lane changing from different disciplines (e.g., electrical engineering, computer science, transportation engineering, and mechanical engineering) with different focuses (e.g., communication, vehicle control, pattern recognition, and traffic impacts) in the last decade. Yet the existing studies are relatively segregated by disciplines or perspectives. There lacks a high-level survey that provides a unified multi-disciplinary view on the existing studies and further helps identify future research needs.

To address this need, this paper provides a review of representative studies of CAV lane changes on models, algorithms, traffic impact analyses, and testing experiments. These reviewed studies are categorized based on their modeling techniques and investigated problem focuses. Rather than merely putting relevant studies together, this paper focuses on presenting the characteristics of these categories with selected representative studies and thereby revealing connections and relationships among the related studies.

This paper is organized as follows. Section 2 summarizes the existing CAV lane-changing models that include V2V communication, localization, lane-changing decision and planning, and vehicle control. Section 3 introduces the studies that investigate the traffic impact caused by CAV lane-changing maneuvers. In Sect. 4, simulation and field experiments for CAV testing are addressed. Section 5 concludes this paper and proposes research gaps for future studies.

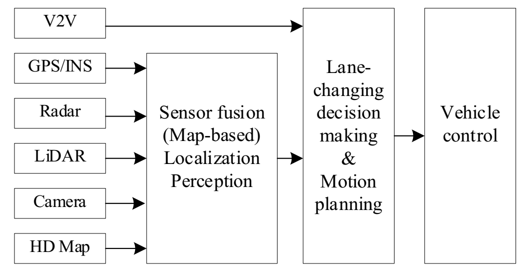

Figure 1: Architecture of CAV lane change.

2 Lane-Changing Models

Figure 1 shows the architecture of CAV lane change. The whole CAV lane-changing architecture consists of four key components: V2V communication, CAV localization, lane-changing decision and planning, and vehicle control. V2V communication enables real-time interactions among CAVs during the lane-changing process. A CAV can send and receive the lane-changing decision and vehicle states with other nearby CAVs. This may decrease the reaction time of CAVs to improve potential collision avoidance. In addition to communication, CAV localization provides absolute or relative distances and speeds with surrounding vehicles and infrastructure objects. Different kinds of sensors and classification algorithms are used for real-time detection and tracking of surround vehicles. Then, a CAV makes the lane-changing decision and plans a trajectory from its current position to target position by fusing information from V2V communication and CAV localization. The planned trajectory shall avoid potential collisions and guarantee passenger riding comfort. Vehicle control algorithms aim at tracking the planned trajectory by controlling the CAV's longitudinal and lateral movements. Studies on these four key components are summarized in the following subsections.

2.1 V2V Communication

Compared with autonomous vehicles (AVs), CAVs can get real-time information from surrounding vehicles with communication

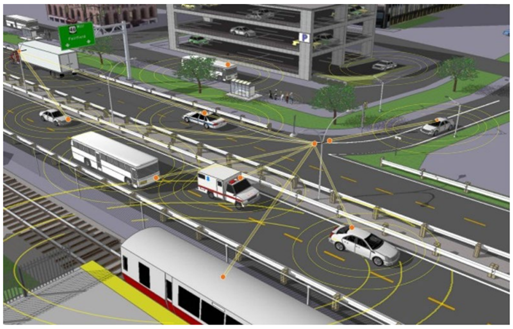

Figure 2: Visual representation of V2V communication[12].

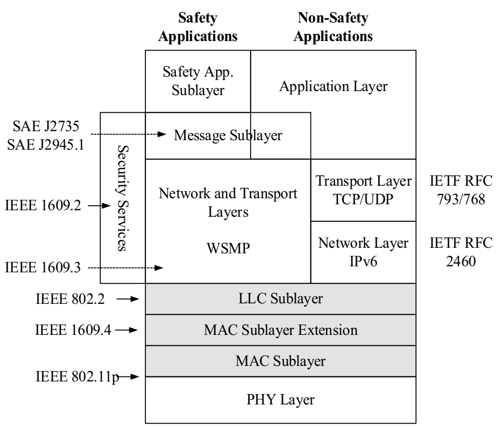

Figure 3: Standard DSRC stack[2].

capabilities[10, 11]. Figure 2 shows a schematic diagram on how CAVs exchange information with each other[12]. The exchanged information includes vehicle size, position, speed, heading, later/longitudinal acceleration, yaw rate, throttle position, brake position, steering wheel angle, wiper status, and turn signal status[12]. Based on the acquired information, CAV can make the cooperative lane-changing decision and conduct cooperative motion control[13]. V2V communication can effectively help eliminate potential collision risks and improve road traffic transportation efficiency, especially during relatively complex lane-changing maneuvers.

Dedicated short-range communications (DSRC) and cellular network are two main methods for wireless data exchange. The comparisons between DSRC and cellular network are listed in Table 1.

Among CAV lane-changing studies, most researchers adopt DSRC as the V2V communication method[2,13,14]. And also, National Highway Traffic Safety Administration has mandated that

Table 1: Comparisons between cellular network and DSRC[70].

Characteristics	Cellular network	DSRC
Coverage	Extended coverage up to 15 km	Intermittent coverage
Capacity	High	Medium
Transmission mode	Dual mode	Distributed
Standard	3 GPP 5 GAA	Different standards
Deployment cost	Low	High

V2V communication should use DSRC radios[12]. The standard DSRC stack is shown in Fig. 3. PHY layer and MAC layer use IEEE 802.11p standards. The IEEE 802.11p standards provide fast, reliable exchange of safety messages needed for vehicular environments[15,16]. The IEEE 1609 contains the basic safety message[17]. SAE J2735 standards are used for message transmit. The message layer is at the top of the stack. However, the standard DSRC stack does not provide CAV lane-changing protocols or standards, and no study has yet addressed CAV lane-changing protocols so far. Communication protocols can affect the V2V communication rate and time delay, and this can significantly affect CAV lane-changing performance. Thus, a possible future research direction is to propose dedicated protocols for CAV lane-changing applications based on the standard DSRC stack.

Many researchers have proposed CAV lane-changing models based on V2V communication[17–20]. However, these studies regard V2V communication as a real-time information exchange. Actually, the V2V communication time delay can reach up to 100 ms under a complex electromagnetic environment, and packet drops also occur in this situation. These uncertainties will have severe negative impacts on CAV lane-changing operations. Future researchers can focus on studying how the V2V robustness and time delay will affect CAV lane change, and proposing CAV lane-changing models considering these uncertainties.

2.2 Localization

Localization is responsible for providing relative distance and speed information of surrounding vehicles for CAV lane-changing decisions and planning. Although V2V communication can provide the information mentioned above, in

PHY layer: The physical layer consists of the electronic circuit transmission technologies of a network. It is a fundamental layer underlying the higher-level functions in a network and can be implemented through a great number of different hardware technologies with widely varying characteristics.

MAC layer: MAC (medium access control) layer is the layer that controls the hardware responsible for interaction with the wired, optical, or wireless transmission medium.

Dedicated short-range communications: Dedicated short-range communications are one-way or two-way short-range to medium-range wireless communication channels specifically designed for automotive use and a corresponding set of protocols and standards.

Springer IISc Press

mixed traffic or complex electromagnetic environments, CAVs still need to rely on on-board sensors.

Currently, commonly used localization technologies mainly can be classified into two categories, namely, absolute localization technology and relative localization technology[4]. GNSS is used to provide the absolute position, including latitude, longitude, and altitude information. LiDAR, radar, and vision sensors are usually used to output the relative position of the objects.

GNSS is the most popular localization system. It acquires and analyzes satellite signals to know its longitude, latitude, altitude, and speed information. Many researchers have proposed a differential global position system (DGPS) method to improve localization accuracy through optimization[21]. Based on this method, the carrier phase difference technology is further studied, which significantly enhances localization accuracy. However, due to the multi-path effect,, GNSS devices cannot provide precise position information under a complex environment, especially with high buildings around.

Multi-path effect: Multi-path effect is the propagation phenomenon that results in radio signals reaching the receiving antenna by two or more paths. Causes of multi-path include atmospheric ducting, ionospheric reflection and refraction, and reflection from water bodies and terrestrial objects such as mountains and buildings.

LiDAR has been widely used in CAV perception system to detect obstacles (pedestrians, vehicles, etc.) within a range of 80 meters[21–24]. Many researchers have combined LiDAR with deep learning techniques to identify and track other vehicles during CAV lane-changing processes. Besides, the point cloud information obtained by LiDAR sensors is also widely used in high-definition (HD) map construction[25]. An HD map contains features of the surrounding environment and can be used for high-precision localization of CAV[26],[27]. Localization with methods fusing LiDAR and HD maps will be the main trend in the future.

Radar and vision sensors are widely used in adaptive cruise control and lane departure warning systems[27–31]. Radar sensors can work in a variety of road conditions and weather conditions, with strong robustness and reliability. In lane-changing applications, vision sensors can assist in lane level localization and pre-collision avoidance.

Future research might depend not only on a single type of sensor, but also on the fusion of information from multiple sensors to compensate for the deficiencies of each sensor type[31–34]. Moreover, multiple sensors fusion can increase the robustness and accuracy of CAV localization. For example, radar and vision sensors can output precise detection result at a high frequency, but they cannot provide 360° view of CAV (shown in Fig. 4)[35]. The blind area may cause collisions

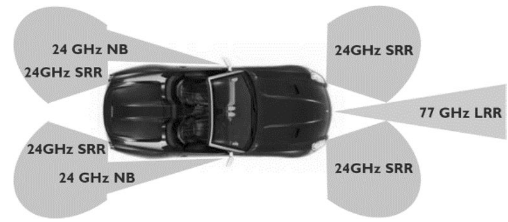

Figure 4: Illustration of radar sensors' sensing range.

during lane changing. On the contrary, it is easy for LiDAR to provide a 360° point cloud view, but its disadvantage of low frequency is also apparent. Currently, most multi-sensor data fusion methods are based on the probabilistic methods that apply Bayes' rule for combining prior and observation information. These methods are implemented in many different ways, including the Kalman filter and its variations, sequential Monte Carlo methods, and functional density estimation[36]. However, most existing studies mainly consider data fusion of two types of sensors, e.g., radar, vision, and LiDAR sensors, for CAV perception and localization.

2.3 Decision and Planning

After getting surrounding information from V2V communication and on-board sensors, CAVs are able to decide when and where to perform lane-changing maneuver based on real-time information and decision models. Single-vehicle lane-changing decision models have been studied extensively[13],[37],[38]. However, these models cannot be applied directly to tackle multi-vehicle cases. Many researchers have presented cooperative CAV lane-changing decision models[13],[38–41]. For example, Nie et al. propose a decentralized cooperative lane change decision-making framework for CAVs. The proposed framework is composed of three modules: state prediction, candidate decision generation, and coordination[13]. With the help of V2V communication technology, the state prediction module can obtain the modern system state. A cooperative car-following model is employed to predict the future state of surrounding vehicles. Based on the anticipated results, the optimal decision variables, including both desirable and undesirable situations, are determined to form a candidate decision (lane changing or lane keeping). The final lane-changing decision will be made after receiving the candidate decisions from surrounding vehicles. Cunningham et al. present a multi-policy decision-making algorithm, which exploits knowledge from the autonomous driving domain to make a decision online for CAVs[39]. The proposed lane-changing decision algorithm takes a series of candidate policies as input. Then, by conducting the forward simulation, the lane-changing decision algorithm captures the necessary interactions between vehicles to make reasonable choices. These lane-changing decision models are able to handle different sceneries. However, the above-mentioned studies consider only one CAV lane changing at one time. Namely, only one CAV can execute the lane change maneuver at one time, while the other vehicles must remain on their lanes. In real-world applications, it is possible to encounter two or more CAVs making the lane-changing decisions at the same time. Desiraju et al. present an algorithm using information (vehicles' position, speed, acceleration) to make a reasonable lane-changing decision. The proposed decision model classifies all the involved CAVs into multiple groups according to their target lanes and then sequentially executes lane changing in each group[40]. The decision model is simple, yet not ready for real-world implementation. Multi-CAV lane-changing decisions may be made "jointly" in a collaborative manner rather than merely "simultaneously." Thus, a possible research direction is to propose a multi-CAV lane-changing model considering multiple CAVs making lane-changing decisions cooperatively.

As discussed above, CAV lane-changing maneuvers inevitably affect traffic flow characteristics[42]. Researchers need to consider the impact on the traffic stream when designing lane-changing decision models. Desiraju et al. present an algorithm to minimize the disruption of the traffic flow by optimizing the number of safe lane changes[40]. The proposed decision model can alleviate lane-changing disruptive effects on traffic flow. The problem of deciding whether a CAV should change its lane instead of longitudinal control alone (e.g., speeding up or slowing down) for the best traffic performance needs further investigation.

To the best of our knowledge, current CAV lane-changing decision models assume that all operating vehicles are CAVs. Few consider the mixed traffic environment including CAVs, AVs, CVs (connected vehicles), and HVs. Therefore, a possible research direction is to propose multi-CAV lane-changing decision models in a mixed traffic environment.

After making lane-changing decisions, CAVs need to plan one or more reference trajectories appealing for a set of objectives, such as safety, driving comfort, traffic efficiency, and low fuel consumption. In addition, CAVs will update the proposed trajectories in real time to avoid potential collisions until the lane-changing process is completed. Due to the time delay in V2V communication, CAV computation, and execution, CAVs need to predict the possible behaviors of surrounding vehicles. Information about surrounding vehicles is necessary to generate the reference trajectories. Researchers have proposed a set of prediction models[13,39]. These existing studies use the same model and parameters to predict the possible behaviors of surrounding vehicles. The differences between vehicle types and vehicle kinematics are not considered yet. Besides, the offline calibrated prediction model may not always predict all vehicles' possible actions precisely. Therefore, a potential research direction is to propose prediction models that can absorb real-time information of surrounding vehicles and modify the corresponding vehicle's prediction model parameters online.

Based on acquired prediction information, researchers have proposed a series of trajectory planning algorithms[14,18,41,43,44]. Luo et al. propose a dynamic automated lane-changing maneuver based on V2V communication to accomplish lane-changing and eliminate potential collisions during the lane-changing process. The reference trajectory is calculated by establishing a proper cost function and satisfying related constraints and converting the problem into a constrained optimization problem. With a cost function that includes constraints of the comfort and the traffic efficiency and safety, the results of the constrained optimization problem satisfy the multi-objective demands on the reference trajectory[14]. However, this research does not address passenger comfort on a curved road, e.g., constraining the yaw rate. Li et al. propose a two-stage multi-vehicle motion planning framework to find high-quality online solutions[41]. This cooperative lane-changing solution is composed of two main stages. At stage 1, CAVs try to widen the inter-vehicle gaps via longitudinal control. The main objective is to guarantee enough gaps for lane-change maneuvers. Then, at stage 2, CAVs can safely implement lane-changing maneuvers without violating collision avoidance constraints. All these trajectory planning algorithms can generate smooth and continuous reference trajectories. However, the kinematic features of the CAVs are not fully exploited. Instead, they are limited by specified types of path shapes[14], simple rules[18], and specified car-following principles[40]. These specification strategies can

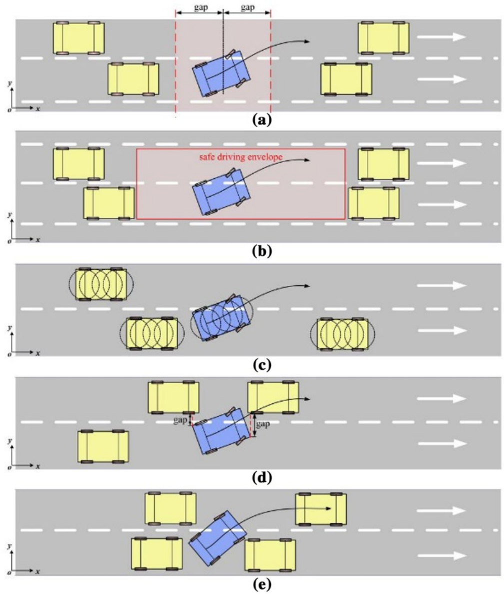

Figure 5: Various collision avoidance constraints[41].

drastically reduce the computational complexity, but the chances to find high-quality solutions are decreased as a tradeoff.

Moreover, collision avoidance constraints in the existing studies may not be formulated precisely. Some researchers use gaps to keep the lane-changing CAV from the through vehicles (Fig. 5a)[14]. Similarly, Suh et al. associate a moving box with the lane-changing CAV to define the non-entrance region (Fig. 5b)[45]. The formulations in[45–48] are less conservative (Fig. 5c and d, respectively), but none of them can achieve the delicate maneuvers as shown in Fig. 5e, wherein the vehicles are making good use of the road space. Finally, if the decentralized algorithms are not complete, then additional recovery steps are needed to ensure deadlock free and collision free in some corner cases[14,48].

Overall, the current studies on CAV lane-changing planning only focus on the planning of subject CAV. No model considers cooperative lane-changing planning. For example, when one CAV plans to perform lane-changing, adjacent vehicles on the target lane will modify their speed accordingly to minimize impacts on traffic flow.

2.4 Vehicle Control

To accomplish CAV lane-changing maneuver, a controller should be designed to track the reference trajectories according to the CAV states and road information. There are two layers of the CAV controller. The higher control layer focuses on trajectory tracking and the lower control layer concentrates on CAV drive-by-wire control. The drive-by-wire control includes the steering wheel, gear shift, brake, throttle, and turning lights control.

Drive-by-wire: Drive-by-wire technology is the use of electrical–mechanical systems for performing vehicle functions traditionally achieved by mechanical linkages. This technology replaces the traditional mechanical control systems with electronic control systems using electromechanical actuators and human–machine interfaces such as pedal and steering feel emulators.

Actually, CAV control and AV control are essentially the same. Many researchers have proposed trajectory-tracking models[14,37,38,45,46,48–57]. Bayer designs an improved proportional-integral-derivative (PID) controller for trajectory tracking, not only because of its simple structure and easy implementation but also because of its acceptable tracking performance[51]. However, the proposed controller is not satisfactory for applications that require high tracking accuracy. Luo et al. propose a trajectory-tracking controller based on sliding mode control. The tracking controller is based on the backstepping principle. It is capable of ensuring global convergence during the lane-changing process. Besides, concerning the subject vehicle's kinematic characteristics and passenger comfort, the output of the controller is limited to avoid a slip between wheels and ground[14]. However, this trajectory-tracking model only considers current tracking errors. It may not handle a high-dynamic motion environment. Suh et al. formulate a stochastic model predictive control (MPC) controller[45]. The MPC controller can predict future states and implement constraints directly into the control algorithm. The MPC controller applies the first input from the control sequence and predicts the future state based on a prediction model. With constraints, the MPC controller can minimize the errors between the target state and the predicted state of vehicle speed or acceleration and the corresponding input[58], while all these trajectory-tracking controllers consider a kinematic car-like model with nonholonomic constraints that restrict the wheels to roll with no slip. This assumption simplifies real-time calculations but decreases tracking accuracy. Therefore, a possible research direction is to propose trajectory-tracking controllers that consider the tire model and vehicle kinematic dynamics.

The lower layer controller implements CAV drive-by-wire control. The fixed gain PID controller is commonly used in the lower layer control[59]. As there are some differences in the brake systems between gasoline vehicles and electric vehicles, Lee proposed the brake system model and control laws for an electronic-vacuum booster (EVB)[60]. A nonlinear computer model for the EVB has been developed and the simulation is performed using a nonlinear vehicle model. A possible research gap is to find the longitudinal control differences between gasoline vehicles and electric vehicles.

3 Traffic Impact Analysis

Due to the recent developments in communication technologies, such as the V2V and V2I (vehicle-to-infrastructure) systems, CAVs are able to communicate with other vehicles/infrastructures that are equipped with communication units and sensors, which widely expand the perceptible environment of CAVs. For example, compared with HVs (human-driven vehicles) or AVs, CAVs have the capability to obtain the environment information out of the sensor detection range. It renders the possibilities for CAVs to achieve the optimal or near-optimum system performance rather than the individual optimum, which will impose thoroughly different traffic impacts to the transportation system. In the literature, a series of studies are conducted regarding the traffic impacts of lane-changing maneuvers[9],[42],[61],[62], while only a handful of them investigate the traffic impacts caused by the lane-changing maneuver of CAVs.

Based on the on-board sensor characteristics, Talebpour et al. propose a deterministic acceleration modeling framework for CAVs with considering lane-changing maneuver[63]. Then, the proposed model is used to analyze the stability of traffic flow under different market penetration rates of CAVs. Ding et al. learn a cooperative lane change decision-making framework for CAVs[13]. The traffic impact of the proposed framework is analyzed from traffic stability, efficiency, homogeneity, and safety. With considering the lane-changing maneuver, Ye et al. propose a two-lane model to study the impact of CAVs on the heterogeneous traffic flow and Ye et al. study the impact of setting dedicated lanes for CAVs in a three-lane heterogeneous traffic flow environment[64],[65].

4 Simulations and Field Experiments

4.1 Simulation

Due to the immaturity of CAV technologies and field test environment restrictions, it is difficult to test the proposed CAV lane-changing models, algorithms in the real world. As a result, the commonly used method for CAV experiments still is simulation in recent years.

Liu et al. use Carsim-simulink to validate the proposed lane-changing algorithms[19]. Compared with traditional lane-changing algorithms, the proposed algorithm is able to reduce the lane-changing time cost by 20%. Suh et al. also employ the Carsim-simulink simulation to study the performance of the proposed SMPC (stochastic model predictive control) algorithm[45]. The results show that the combinatorial predictor is much safer than the deterministic prediction. Liu et al. conduct the simulation on 1000 different kinds of lane-changing situations[10]. To evaluate the performance of the investigated algorithm, the real-time capability of handling dynamic safety constraints is treated as the criterion. Ye et al. propose a two-lane CA-based (Cellular Automation-based) lane-changing model with the heterogeneous traffic flow[64]. The simulation of the proposed model is conducted on a hypothetical 10 km two-lane road segment, and the studied HVs and CAVs are randomly distributed on the road segment. The simulation result indicates that the road capacity increases with an increase in the CAV penetration rate, which is not over 30%. When the CAV penetration rate exceeds 30%, the road capacity is mainly decided by the capability of the CAV. Ye et al. study a three-lane heterogeneous flow model incorporating CAV dedicated lane policy and lane-changing maneuver[65]. A fundamental approach is used to verify the advantages and disadvantages of the CAV-dedicated lane policies under various CAV penetration rates. The simulation of this paper is conducted on a 10-km three-lane road segment under the periodic boundary condition. The results indicate that the CAV penetration rate and individual CAV capability are the main factors that affect the performance of setting CAV dedicated lanes. An et al. study a cooperative lane-changing protocol considering the V2V communication delay for CAVs[66]. A highway driving simulation environment is set up to test the effectiveness of the protocol. The OBB (oriented bounding box), which is served as the representative of the vehicle, is used to study the collision. Talebpour et al. study a deterministic acceleration modeling framework for CAVs with a gap-acceptance lane-changing model[63]. They adopt Kesting and Treiber's methodology[67] to study the stability for different market penetration rates of CAVs. The results reveal that the flow rate of the fundamental diagram increases as the market penetration rate of CAVs increases from 0 to 50%. Ding et al. examine a decentralized cooperative lane change decision-making model for CAVs[13]. The simulation is designed with three lanes, two scenarios (with and without on-ramp) and heterogeneous traffic flow. As

Carsim-simulink: Carsim-simulink is a commercial software package that predicts the performance of vehicles in response to driver controls (steering, throttle, brakes, clutch, and shifting) in a given environment (road geometry, coefficients of friction, wind).

a result, it outlines that the proposed model can improve traffic stability, homogeneity, and efficiency and reduce traffic congestion. Makridis et al. conduct the simulation based on the ring road of Antwerp[68]. Considering the lane-changing maneuver of CAVs, several different scenarios are tested to account for the impact of various mixtures of HVs, AVs, and CAVs. The result reveals that low penetration rates of CAVs have a small negative effect on the traffic, but high penetration rates of CAVs are able to accept smaller gaps while cruising or maneuvering on network. This finding can effectively prevent the formation of traffic oscillations and improve the performance of the traffic system.

4.2 Field Experiments

To the best of our knowledge, there are no CAV publications that implement the proposed methods or algorithms to the field experiments so far. As a result, several latest field experiments correlated to CAV lane-changing maneuvers (e.g., CV and AV lane-changing maneuvers) are listed in this section and hope it can inspire future studies in some aspects.

Wang et al. present a dynamic lane-changing model for AV incorporating human driver behavior in mixed traffic. Field experiments are conducted on a large-scale test track with an AV and three HVs, which aim to assess and validate the proposed model.

Suh et al. conduct the AV lane-changing experiments based on a Hyundai-Kia Motors K7 vehicle at the on-ramp section of the Yeongdong expressway[45]. The results show that the proposed algorithm can effectively control the test vehicle to accomplish the lane-changing maneuver.

To test the proposed AV lane-changing method, Luo et al. implement the hardware-in-loop experiment with a driving simulator, which is based on a real vehicle. And the driver's view and perception can be simulated in reality[14]. The experimental results exhibit that the suggested lane-changing trajectory can avoid the collision.

Hardware-in-loop: Hardware-in-loop is a technique that is used in the development and test of complex real-time embedded systems. This technique provides an effective platform by adding the complexity of the plant under control to the test platform.

Milanes et al. test the proposed CV merging algorithm at an experimental driving circuit with three vehicles[69]. Each vehicle communicates with each other through the V2I communication. The experimental results reveal that the vehicles already on the major road can modify their speeds to permit the entrance of the merging vehicle.

5 Conclusions and Future Work

This paper summarizes current studies concerning CAV lane-changing models and their impacts on traffic flow. Four critical components of the CAV lane-changing model, including V2V communication, localization, lane-changing decision and planning, and vehicle control are detailed discussed.

We present the development of V2V communication and discuss the importance of standard lane-changing protocols. Then, we found that a common lane-changing protocol has not been proposed yet. As a result, further analyses and improvements in lane-changing protocols are required. In addition, on-board sensors and classification algorithms are presented in the CAV localization module, while the fusion of multiple sensors, including vision, radar, and LiDAR, which can render more accuracy capability of CAV to perceive the surrounding environment, still needs to be deeply studied. Lane-changing decision and planning are the core of CAV lane-changing maneuvers. Based on the discussions above, three kinds of factors are not well addressed in the existing studies, i.e., communication time delay, mixed traffic, and cooperation with surrounding CAVs. We address vehicle control algorithms through the trajectory-tracking layer and drive-by-wire control layer. It is found that the current trajectory-tracking models assume that the vehicles are all with nonholonomic constraints but do not fully consider detailed vehicle kinematic dynamics and associated uncertainties. This assumption simplifies the computation but decreases the tracking accuracy of CAVs. Hence, future studies need to consider these issues into the trajectory-tracking models.

While several studies have examined the possible impact of CAVs on traffic flow, most of them focus on the car-following maneuver rather than the lane-changing maneuver, which restricts the further research of CAVs. As a result, future studies can devote to fill this methodology gap.

Additionally, to the best of our knowledge, there are still no CAV lane-changing field experiments. It is meaningful to establish an experimental platform based on real vehicles to conduct field tests.

Publisher's Note

Acknowledgements

This research was supported by the National Science Foundation (No. # 1558887) and Key Research Plan in Shaanxi Province of China (Program No. 2019GY-131). Mr. Zhen gratefully acknowledges financial support from China Scholarship Council.

Received: 22 August 2019 Accepted: 21 September 2019
Published online: 9 October 2019

References

1. Rios-Torres J, Malikopoulos AA (2016) A survey on the coordination of connected and automated vehicles at intersections and merging at highway on-ramps. IEEE Trans Intell Transp Syst 18(5):1066–1077
2. Bevly D, Cao X, Gordon M, Ozbilgin G, Kari D, Nelson B, Redmill K (2016) Lane change and merge maneuvers for connected and automated vehicles: a survey. IEEE Trans Intell Veh 1(1):105–120
3. Tang J, Liu F, Zhang W, Ke R, Zou Y (2018) Lane-changes prediction based on adaptive fuzzy neural network. Expert Syst Appl 91:452–463
4. Ozguner U, Acarman T, Redmill K (2011) Autonomous ground vehicles. Artech House, Norwood
5. Meinel HH, Bösch W (2017) Radar sensors in cars. Automated driving. Springer, Cham, pp 245–261
6. Gerónimo D, Vázquez D, de la Escalera A (2017) Vision-based advanced driver assistance systems. Computer Vision in Vehicle Technology: Land, Sea and Air, pp 100–121
7. Thakur R (2016) Scanning LIDAR in advanced driver assistance systems and beyond: building a road map for next-generation LIDAR technology. IEEE Consum Electron Mag 5(3):48–54
8. Yu H, Tseng HE, Langari R (2018) A human-like game theory-based controller for automatic lane changing. Transp Res Part C Emeg Technol 88:140–158
9. Jin WL (2010) A kinematic wave theory of lane-changing traffic flow. Transp Res Part B Methodol 44(8–9):1001–1021
10. Liu K, Gong J, Kurt A, Chen H, Ozguner U (2018) Dynamic modeling and control of high-speed automated vehicles for lane change maneuver. IEEE Trans Intell Veh 3(3):329–339
11. Darbha S, Konduri S, Pagilla PR (2018) Benefits of V2 V communication for autonomous and connected vehicles. IEEE Trans Intell Transp Syst 20(5):1954–1963
12. Harding J, Powell G, Yoon R, Fikentscher J, Doyle C, Sade D, Wang J (2014) Vehicle-to-vehicle communications: readiness of V2 V technology for application (No. DOT HS 812 014). United States National Highway Traffic Safety Administration
13. Nie J, Zhang J, Ding W, Wan X, Chen X, Ran B (2016) Decentralized cooperative lane-changing decision-making for connected autonomous vehicles. IEEE Access 4:9413–9420. https://doi.org/10.1109/ACCESS.2017.2649567
14. Luo Y, Xiang Y, Cao K, Li K (2016) A dynamic automated lane change maneuver based on vehicle-to-vehicle communication. Transp Res Part C Emerg Technol 62:87–102
15. Klein Wolterink W, Heijenk G, Karagiannis G (2010) Constrained geocast to support cooperative adaptive cruise control (CACC) merging. In: IEEE vehicular networking conference, VNC 2010. IEEE Communications Society
16. Morgan YL (2010) Managing DSRC and WAVE standards operations in a V2V scenario. Int J Veh Technol 2010
17. Kenney JB (2011) Dedicated short-range communications (DSRC) standards in the United States. Proc IEEE 99(7):1162–1182
18. You F, Zhang R, Lie G, Wang H, Wen H, Xu J (2015) Trajectory planning and tracking control for autonomous lane change maneuver based on the cooperative vehicle infrastructure system. Expert Syst Appl 42(14):5932–5946
19. Liu ZQ, Zhang T, Wang YF (2019) Research on local dynamic path planning method for intelligent vehicle lane-changing. J Adv Transport 2019
20. Talebpour A, Mahmassani HS, Hamdar SH (2015) Modeling lane-changing behavior in a connected environment: a game theory approach. Transp Res Procedia 7:420–440
21. Martin S (2011) Closely coupled gps/ins relative positioning for automated vehicle convoys. Doctoral dissertation
22. Feng D, Rosenbaum L, Dietmayer K (2018) Towards safe autonomous driving: capture uncertainty in the deep neural network for lidar 3d vehicle detection. In 2018 21st International conference on intelligent transportation systems (ITSC) IEEE, pp. 3266–3273
23. Hata AY, Wolf DF (2015) Feature detection for vehicle localization in urban environments using a multilayer LIDAR. IEEE Trans Intell Transp Syst 17(2):420–429
24. Caltagirone L, Scheidegger S, Svensson L, Wahde M (2017) Fast LIDAR-based road detection using fully convolutional neural networks. In: 2017 IEEE Intelligent Vehicles Symposium (iv) IEEE, pp 1019–1024
25. Hess W, Kohler D, Rapp H, Andor D (2016) Real-time loop closure in 2D LIDAR SLAM. In: 2016 IEEE international conference on robotics and automation (ICRA), IEEE, pp 1271–1278
26. Wolcott RW, Eustice RM (2017) Robust LIDAR localization using multiresolution Gaussian mixture maps for autonomous driving. Int J Robot Res 36(3):292–319
27. Kim H, Liu B, Goh CY, Lee S, Myung H (2017) Robust vehicle localization using entropy-weighted particle filter-based data fusion of vertical and road intensity information for a large scale urban area. IEEE Robot Autom Lett 2(3):1518–1524
28. Amodio A, Panzani G, Savaresi SM (2017) Design of a lane change driver assistance system, with implementation and testing on motorbike. In: 2017 IEEE intelligent vehicles symposium (IV) IEEE, pp 947–952

29. Yi SC, Chen YC, Chang CH (2015) A lane detection approach based on intelligent vision. Comput Electr Eng 42:23–29
30. Whitney J, Hedblom T, Clear S (2018) Improved day-time detection of pavement markings with machine vision Cameras (No. 18-05478)
31. Baili J, Marzougui M, Sboui A, Lahouar S, Hergli M, Bose JSC, Besbes K (2017) Lane departure detection using image processing techniques. In: 2017 2nd international conference on anti-cyber crimes (ICACC) IEEE, pp 238–241
32. Kim J, Emeršič Ž, Han DS (2019) Vehicle path prediction based on radar and vision sensor fusion for safe lane changing. In: 2019 International conference on artificial intelligence in information and communication (ICAIIC). IEEE, pp 267–271
33. Choi J, Kong K (2017) Optimal sensor fusion and position control of a low-price self-driving vehicle in short-term operation conditions. Int J Control Autom Syst 15(6):2859–2870
34. Cho H, Seo YW, Kumar BV, Rajkumar RR (2014) A multi-sensor fusion system for moving object detection and tracking in urban driving environments. In: 2014 IEEE international conference on robotics and automation (ICRA), IEEE pp 1836–1843
35. Ju Y, Kim S, Jin Y, Lee J (2017) Design and development of the 24 GHz FMCW radar sensor for blind spot detection and lane change assistance systems. ICAS 2017: The thirteenth international conference on autonomic and autonomous systems, p 54
36. Durrant-Whyte H, Henderson TC (2008) Multisensor data fusion. Springer handbook of robotics, New York, pp 585–610
37. Nilsson J, Silvlin J, Brannstrom M, Coelingh E, Fredriksson J (2016) If, when, and how to perform lane change maneuvers on highways. IEEE Intell Transp Syst Mag 8(4):68–78
38. Paden B, Čáp M, Yong SZ, Yershov D, Frazzoli E (2016) A survey of motion planning and control techniques for self-driving urban vehicles. IEEE Trans Intell veh 1(1):33–55
39. Cunningham AG, Galceran E, Eustice RM, Olson E (2015). MPDM: Multipolicy decision-making in dynamic, uncertain environments for autonomous driving. In: 2015 IEEE International conference on robotics and automation (ICRA) IEEE, pp 1670–1677
40. Desiraju D, Chantem T, Heaslip K (2014) Minimizing the disruption of traffic flow of automated vehicles during lane changes. IEEE Trans Intell Transp Syst 16(3):1249–1258
41. Li B, Zhang Y, Feng Y, Zhang Y, Ge Y, Shao Z (2018) Balancing computation speed and quality: a decentralized motion planning method for cooperative lane changes of connected and automated vehicles. IEEE Trans Intell Veh 3(3):340–350
42. Xu R, Huang L, Yin S, Yao D, Zhang H, Peng L (2011) An analysis on traffic flow characteristics and lane changing behaviors in Beijing urban expressway bottlenecks. In: 2011 14th International IEEE conference on intelligent transportation systems (ITSC) IEEE, pp 822–827
43. Ulbrich S, Maurer M (2015) Towards tactical lane change behavior planning for automated vehicles. In: 2015 IEEE 18th international conference on intelligent transportation systems IEEE, pp 989–995
44. Kesting A, Treiber M, Helbing D (2007) General lane-changing model MOBIL for car-following models. Transp Res Rec 1999(1):86–94
45. Suh J, Chae H, Yi K (2018) Stochastic model-predictive control for lane change decision of automated driving vehicles. IEEE Trans Veh Technol 67(6):4771–4782
46. Fu X, Jiang Y, Huang D, Huang K, Wang J (2017) Trajectory planning for automated driving based on ordinal optimization. Tsinghua Sci Technol 22(01):62–72
47. Li B, Zhang Y, Ge Y, Shao Z, Li P (2017) Optimal control-based online motion planning for cooperative lane changes of connected and automated vehicles. In: 2017 IEEE/RSJ International conference on intelligent robots and systems (IROS), IEEE, pp 3689–3694
48. Samiee S, Azadi S, Kazemi R, Eichberger A, Rogic B, Semmer M (2016) Performance evaluation of a novel vehicle collision avoidance lane change algorithm. Advanced microsystems for automotive applications. Springer, Cham, pp 103–116
49. Wang D, Hu M, Wang Y, Wang J, Qin H, Bian Y (2016) Model predictive control–based cooperative lane change strategy for improving traffic flow. Adv Mechl Eng 8(2):1687814016632992
50. Wang M, Hoogendoorn SP, Daamen W, van Arem B, Happee R (2015) Game theoretic approach for predictive lane-changing and car-following control. Transp Res Part C Emerg Technol 58:73–92
51. Bayar G (2013) Long distance autonomous trajectory tracking for an orchard vehicle. Ind Robot 40(1):27–40
52. Xu G, Liu L, Ou Y, Song Z (2012) Dynamic modeling of driver control strategy of lane-change behavior and trajectory planning for collision prediction. IEEE Trans Intell Transp Syst 13(3):1138–1155
53. Franco A, Santos V (2019) Short-term path planning with multiple moving obstacle avoidance based on adaptive MPC. In: 2019 IEEE International conference on autonomous robot systems and competitions (ICARSC), IEEE, Porto, Portugal, 24−26 April 2019. https://doi.org/10.1109/ICARSC.2019.8733653
54. Dixit S, Montanaro U, Fallah S, Dianati M, Oxtoby D, Mizutani T, Mouzakitis A (2018) Trajectory Planning for autonomous high-speed overtaking using MPC with terminal set constraints. In: 2018 21st International conference on intelligent transportation systems (ITSC) IEEE, pp 1061–1068. https://doi.org/10.1109/ICARSC.2019.8733653

55. Naranjo JE, Gonzalez C, Garcia R, De Pedro T (2008) Lane-change fuzzy control in autonomous vehicles for the overtaking maneuver. IEEE Trans Intell Transp Syst 9(3):438–450
56. Hatipoglu C, Ozguner U, Redmill KA (2003) Automated lane change controller design. IEEE Trans Intell Transp Syst 4(1):13–22
57. Schubert R, Schulze K, Wanielik G (2010) Situation assessment for automatic lane-change maneuvers. IEEE Trans Intell Transp Syst 11(3):607–616
58. Kreuzen C (2012) Cooperative adaptive cruise control: using information from multiple predecessors in combination with MPC
59. Yi K, Cho Y, Lee S, Lee J, Ryoo N (2000) A throttle/brake control law for vehicle intelligent cruise control (No. 2000-05-0369). SAE Technical Paper
60. Lee C, Yi K (2002) Modeling and control of an electronic-vacuum booster for vehicle cruise control. KSME Int J 16(10):1314–1319
61. Laval JA, Daganzo CF (2006) Lane-changing in traffic streams. Transp Res Part B Methodol 40(3):251–264
62. Pan TL, Lam WH, Sumalee A, Zhong RX (2016) Modeling the impacts of mandatory and discretionary lane-changing maneuvers. Transp Res Part C Emerg Technol 68:403–424
63. Talebpour A, Mahmassani HS (2016) Influence of connected and autonomous vehicles on traffic flow stability and throughput. Transp Res Part C Emerg Technol 71:143–163
64. Ye L, Yamamoto T (2018) Modeling connected and autonomous vehicles in heterogeneous traffic flow. Physica A 490:269–277
65. Ye L, Yamamoto T (2018) Impact of dedicated lanes for connected and autonomous vehicle on traffic flow throughput. Physica A 512:588–597
66. An H, Jung JI (2018) Design of a cooperative lane change protocol for a connected and automated vehicle based on an estimation of the communication delay. Sensors 18(10):3499
67. Kesting A, Treiber M (2006) Influence of reaction times and anticipation on the stability of vehicular traffic flow. Ifac Proc Vol 39(10):205–210
68. Makridis M, Mattas K, Ciuffo B, Raposo MA, Toledo T, Thiel C (2018) Connected and automated vehicles on a freeway scenario. Effect on traffic congestion and network capacity. 7th Transport Research Arena
69. Milanes V, Shladover SE, Spring J, Nowakowski C, Kawazoe H, Nakamura M (2014) Cooperative adaptive cruise control in real traffic situations. IEEE Trans Intell Transp Syst 15:296–305
70. Muhammad M, Safdar GA (2018) Survey on existing authentication issues for cellular-assisted V2X communication. Veh Commun 12:50–65

Zhen Wang is currently a PhD student in School of Information Engineering, Chang'an University at Xi'an, Shaanxi, China. Zhen Wang obtains bachelor degree in automation and master degree in computer science and technology. His current research focuses on autonomous vehicle localization and control.

Xiaowei Shi is a PhD student in Civil and Environmental Department at the University of South Florida. He obtained his Bachelor and Master degree from Beijing Jiaotong University, Beijing, China in 2015 and 2018, respectively. His main research interests are transportation modeling, optimization and CAV-related problems.

Xiaopeng Li received the BS degree in civil engineering from Tsinghua University, Beijing, China, in 2006, and the MS degrees in civil engineering and applied mathematics, and the PhD degree in civil engineering from the University of Illinois at Urban-Champaign, Urbana, IL, USA, in 2007, 2010, and 2011, respectively. He is currently an associate professor in the Department of Civil and Environmental Engineering, University of South Florida (USF), Tampa, FL, USA. He has served as an associate editor for the Department of Transportation Systems Analysis for IIE Transactions and on the editorial boards for Transportation Research Part B and Transportation Research Part C. He received the US National Science Foundation CAREER Award. Dr. Li's recent research focuses on modeling and decision making for emerging transportation technologies and services with trajectory optimization, traffic flow analysis, network modeling, continuum approximation and machine learning methods.