A Survey of Driving Safety With Sensing, Vehicular Communications, and Artificial Intelligence-Based Collision Avoidance

Yuchuan Fu, *Member, IEEE*, Changle Li, *Senior Member, IEEE*, Fei Richard Yu, *Fellow, IEEE*, Tom H. Luan, *Senior Member, IEEE*, and Yao Zhang

***Abstract*— Accurately discovering hazards and issuing appropriate warnings to drivers in advance or performing autonomous control is the core of the Collision Avoidance (CA) system used to solve traffic safety problems. More comprehensive environmental awareness, diversified communication technologies, and autonomous control can make the CA system more accurate and effective, thereby improving driving safety. In addition, the assistance of Artificial Intelligence (AI) technology can make the CA system adapt to the environment and facilitate fast and accurate decisions. Considering the current lack of a thorough survey of driving safety with sensing, vehicular communications, and AI-based collision avoidance, in this paper, we survey existing researches for state-of-the-art data-driven CA techniques. Firstly, we discuss the major steps of CA and key research issues. For each step, we review the existing enabling techniques and research methods for CA in detail, including sensing and vehicular communication for safe driving, as well as CA algorithm design. Particularly, we present a comparison between the most common AI algorithms for different functions in the CA system. Testbeds and projects for CA are summarized next. Finally, several open challenges and future research directions are also outlined.**

***Index Terms*— Collision avoidance, edge computing, artificial intelligence, vehicle-to-everything (V2X), connected autonomous vehicle.**

I. Introduction

WHILE traffic systems have developed for decades, traffic injuries still represent the top killer globally. According to World Health Organization (WHO), on average, about 2.4 people are killed every minute on the roads [1], and the number of traffic accidents is still on the rise yearly [2], [3]. Preventing collision accidents, as an effective measure to solve driving safety problems, is the basic goal pursued in the transportation system, which motivates the technologies in *Collision Avoidance* (CA). By applying sensing technology, computing technology, and communication technology, the primary goal of the CA is to accurately detect driving hazards and warn the driver or take automatic braking measures at the appropriate time, accordingly to reduce the probability of accidents.

Existing CA solutions rely on some traffic facilities (e.g., roundabout, traffic signs, roadside units (RSUs)) and on-board sensors of vehicles. Specifically, traditional methods such as traffic rules and traffic facilities rely heavily on the driver's response, weather, and light intensity [4]. For instance, the driver's distraction, misjudgment, and misoperation while driving will increase the risk of accidents. In addition, some sensor-based methods are also trying to improve driving safety. In this method, the current economical vehicles are equipped with ultrasonic radar sensors and Global Positioning System (GPS), however, it is far from satisfying the need for collision avoidance of high-speed vehicles. For some luxury vehicles, other sensors, such as camera vision, can be installed to form the basis of safety-enhancing systems. Nevertheless, in addition to increasing vehicle costs, the performance of expensive sensors still suffers from several drawbacks: encountering bad weather, relatively short monitoring ranges, interference of radar signals, and blind angle during detection [5], [6]. Meanwhile, the effectiveness of some sensor-based systems still relies on drivers' subsequent actions.

The application of vehicular communication technology to intelligent transportation systems (ITS) is expected to reduce collisions through effective road traffic management. Vehicular communication is a low-cost and highly reliable technology that can be combined with existing sensing technologies to extend the sensing range and increase the sensing dimension, thus improving the timeliness of CA systems [7]–[9]. This in turn has inspired new use cases, ranging from services based on vehicle communication to complex systems (such as autonomous vehicles). There is no doubt that connected cars will also be needed. the development of Connected Autonomous Vehicles (CAVs) enables vehicles not only to recognize the current potential collision hazard and adopt different levels of autonomous control but also to achieve driving safety in a collaborative manner. As vehicles become increasingly intelligent, it is challenging to efficiently use vehicular sensors, communication technologies, and computing

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Yuchuan Fu, Changle Li, and Yao Zhang are with the State Key Laboratory of Integrated Services Networks, Xidian University, Xi'an 710071, China, and also with the Research Institute of Smart Transportation, Xidian University, Xi'an 710071, China (e-mail: clli@mail.xidian.edu.cn).

Fei Richard Yu is with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON K1S 5B6, Canada.

Tom H. Luan is with the School of Cyber Engineering, Xidian University, Xi'an 710071, China.

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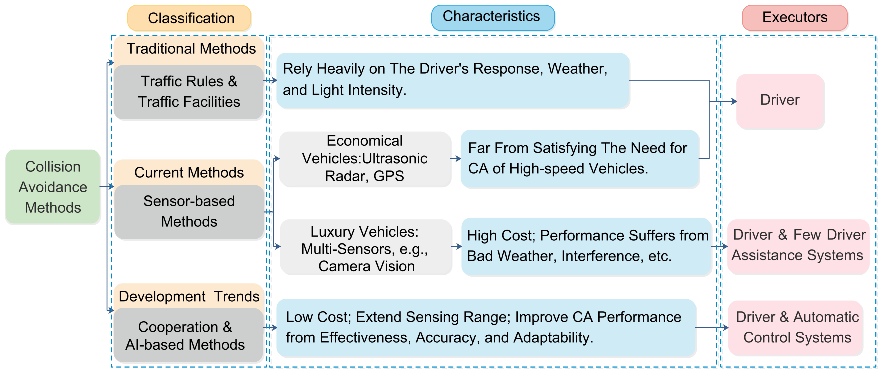

Fig. 1. Collision avoidance methods and their characteristics.

technologies to achieve effective and reliable CA [10], [11]. In the face of a large volume of data and the increasingly complex traffic environment, *artificial intelligence* (AI) technology can quickly and accurately handle a large volume of data and adapt to the environment, thus further achieving the accuracy and comfort goals of CA [12]. Fig. 1 shows the CA methods and their characteristics.

Previously, researchers have studied the work related to traffic safety from a specific perspective, such as motion prediction and risk assessment algorithms for CA [13], motion planning approaches [14], as well as vision-based vehicle detection and tracking for CA systems [15]. In [16], the authors focused on different detection techniques for vehicle safety. However, we found that sensing, vehicular communications, and AI are indispensable for the development of CA systems. Different from previous surveys, this work focuses on how to apply AI to vehicle communication and sensing technology to further improve collision avoidance systems. First, we provide a comprehensive survey on major steps, characteristics, key research issues, and Key Performance Indicator (KPI) of CA, which can provide readers with a systematic understanding and basic concepts of this direction. According to the major steps of the CA system, we will introduce in detail the sensing, vehicular communications, and AI-based algorithms related to vehicle safety. Considering that autonomous vehicle control can reduce the risk of driver misoperation, some algorithms for autonomous decision strategies are also involved. We also discuss the opportunities and challenges of the existing technology and emerging directions in the CA application scenario from the perspective of communication. Furthermore, we identify and analyze the importance of AI technology in CA and conduct an extensive survey on the implementation of some popular algorithms in different functions of CA systems. In order to bridge the gap between academic research and the actual products of the industry, we also discuss some recent popular testbeds and projects.

The remainder of this paper is organized as follows. First, background knowledge of CAVs, as well as communication and computing for CA, are introduced in Section II. In Section III, we focus on major steps of CA in terms of software architecture, KPI, and key research issues. Subsequently, a series of enabling techniques and individual methods are discussed in Section IV to Section VI, including 1) sensing for CA (Section IV), 2), communication for CA (Section V) and 3) AI algorithms for CA (Section VI). Section VII describes testbeds and projects for CA. At last, Section VIII outlines several open challenges, which need to be addressed to make the solution more adaptable to the actual traffic environment as well as satisfy efficient and reliable requirements, followed by concluding remarks in Section IX. Fig. 2 outlines the organization of the survey.

II. Background Knowledge

In this section, we briefly introduce the background knowledge of sensing, communication, and computing for CA systems, as well as autonomous vehicles.

A. Sensing, Communication and Computing for CA

Using **sensing** technology, information about the vehicle and surrounding environment can be obtained. However, sensors have limitations in line-of-sight characteristics and are susceptible to be blocked by other vehicles and buildings. By combining communication, vehicles can exchange information and the sensing range can be expanded accordingly.

From the perspective of **communication**, its function is to establish a vehicular communication network that satisfies the delay sensitivity and high reliability, thereby expanding the range and dimensions of vehicular sensing. During driving, sensing data and safety-related data require efficient and real-time transmission, which greatly depends on the timeliness and reliability of communication.

From the perspective of **computing**, it is necessary to efficiently process the data generated by the vehicle and make predictions and decisions accordingly. The integration of communication and computing can enhance the edge processing capability of the network, reduce the data processing delay, and enable the sensing data to communicate among a wider range of vehicles. In addition, the application of AI technology can form innovative prediction and decision-making algorithms to achieve active safety. Moreover, the self-learning ability and environmental adaptability of AI algorithms can make the CA system more flexible and accurate.

B. Autonomous Vehicles

An autonomous vehicle is defined as an intelligent vehicle that senses the road environment through an on-board sensor system and automatically plans driving routes as well as

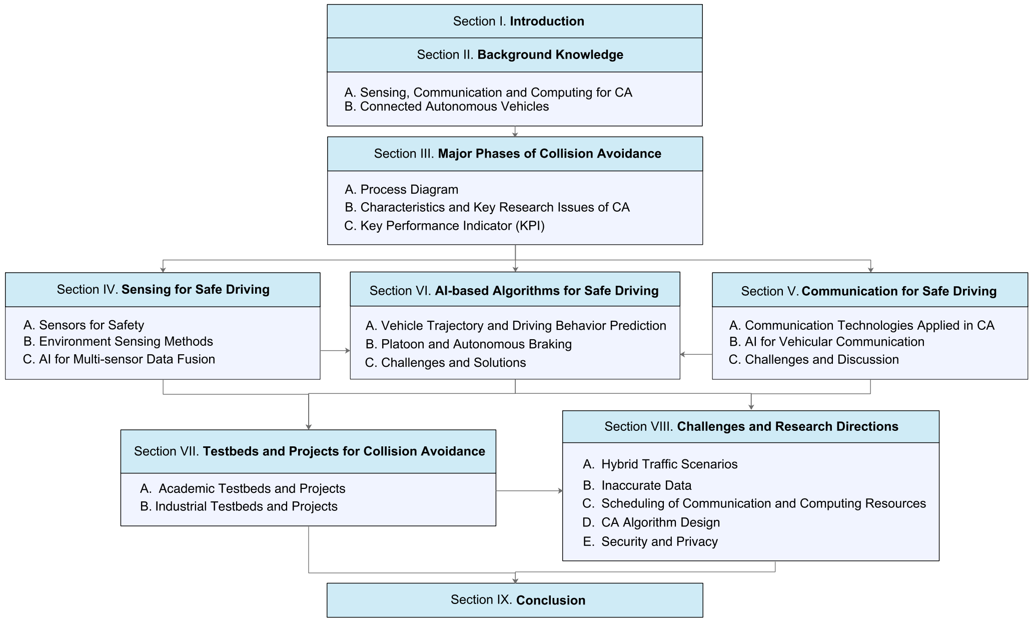

Fig. 2. Road map of the survey.

making decision [17], [18]. The Society of Automotive Engineers (SAE) divided autonomous driving into 6 levels in the SAE standard for autonomous vehicles released in 2014 and revised in 2018 [19]. From level 0 to level 3, the role of the human driver gradually shifts from driving operation to peripheral monitoring and support. At level 4 and level 5, no human operation is required. Currently, autonomous driving technology integrates a variety of technologies, relying mainly on the vehicle's sensing, decision-making, and execution to replace the driver's operation [20]. With the help of communication technology, CAVs are autonomous vehicles that maintain a continuous network connection between each other and the surrounding environment.

III. Major Phases of Collision Avoidance

In this section, we will refine the major steps of CA and investigate the KPI as well as key research issues.

A. Process Diagram

Based on the advanced sensor, communication, and computing technologies, the current CA solution has three major phases, i.e. sensing, communication, and collision avoidance, as shown in Fig. 3 and described as follows:

The phase **Sensing** collects and processes surrounding environmental and vehicle information, including traffic status and vehicle status information, through on-board sensors and corresponding sensing technology. We will describe the sensing technology from the aspects of sensor classification, existing sensing methods, and AI for multi-sensor data fusion in Section IV.

The phase **Communication** mainly relies on different communication technologies, such as dedicated short-range communications (DSRC), cellular network, and visible light to ensure the real-time and reliable transmission of sensing data both from the vehicles and from the road-side infrastructure to surrounding vehicles, road-side infrastructure, edge server and the remote clouds [18]. Vehicles are allowed to share their driving intent (e.g., emergency braking) and exchange sensing data, which can provide higher predictability. We will discuss communication technologies for safe driving will in Section V.

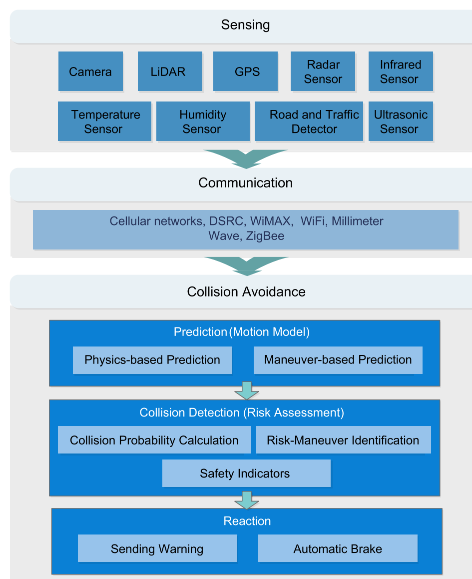

Fig. 3. Major phases for collision avoidance system.

The phase **Collision Avoidance** contains three steps, namely prediction, risk assessment, and reaction, as shown in Fig. 3, which is used to process the sensing data, detect the potential danger and make the corresponding reaction in time to avoid or mitigate it [13]. In general, CA algorithms can be run on a vehicle, on an edge server, or on a central cloud server.

1) Prediction: The prediction stage mainly uses the motion model to infer the future trajectory of the vehicle or the driver's behavior [14], [21]. According to the object being considered, there are two categories of motion models, that is, physics-based prediction and maneuver-based prediction, as the level of abstraction increases [13], [14], [22].

The physics-based prediction model is the simplest, which can guarantee the accuracy of the short-term prediction [13], [14], [22]. Berntorp employs the Rao-Blackwellized particle-filtering framework for vehicle-motion estimation by using a kinematic model [23]. Xiang *et al.* propose to use the vehicle kinematics (VK) model for vehicle trajectory prediction [5]. Ji *et al.* develop a 3-D potential field to generate a collision-free trajectory for the autonomous vehicle based on the boundary conditions of the road and the VK model in [24]. Most of the traditional VK models only consider the vehicle factors (e.g. speed and acceleration) and neglect the human factors. Because this model consideration is relatively simple, reliability and accuracy are affected in complex traffic environments and in dealing with uncertainty. There are two main approaches for predicting this type of model. One is to assume that the vehicle parameters are known with accurate data, and directly use the VK formula to derive the vehicle's subsequent state [5], [24], [25]. The second type of approach takes into account the existence of uncertainty. In order to eliminate the uncertainty of prediction, Kalman filter (KF) and its extended form, such as unscented Kalman filter (UKF) and extended Kalman filter (EKF) are often used for state estimation [13], [22], [26], [27].

The maneuver-based prediction model can be used to obtain the future state of the vehicle by identifying and predicting the driver's intention as well as combining it with the vehicle state parameters and road structure information. Therefore, this model is capable of performing longer and higher-level predictions in consideration of driver behavior and even interaction between vehicles [13], [14], [22]. However, considering the various uncertainties and the interaction between multiple moving entities, the computational complexity will increase. In general, such methods require a large database of real driving data for model training. Stochastic processes and AI techniques have spurred many algorithms for predicting driver's behavior, including but not limited to: Neural Network (NN) [26], Bayesian Network [28], [29], Dynamic Bayesian Network (DBN) [4], [30]–[32], Hidden Markov Model (HMM) [33], [37], Support Vector Machine (SVM) [33], and Recurrent Neural Network (RNN) [34]–[36].

In addition to using the above two types of methods alone, we can also combine physics-based and maneuver-based prediction methods to form a more comprehensive integrated prediction method.

2) Risk Assessment: Based on predicted results, how to apply the prediction results to assess whether a dangerous situation occurs is the work done by the risk assessment. For risk assessment, we found that the three most popular methods are collision probability calculation [26], [27], [40], risk-maneuver identification [4], [30] and other safety indicators [28], [41]–[43].

The method of collision probability calculation is generally based on driving trajectory prediction. Barrios *et al.* determine whether there is a collision by judging whether the future trajectory of the vehicle will cross at the same time [27]. Then the information could be used in a vehicle-to-vehicle/vehicle-to-infrastructure (V2V/V2I) system to warn drivers. Joerer *et al.* exchange vehicles state data, such as speed, acceleration, and distance to the intersection, through intervehicle communication to calculate the collision probability based on the predicted trajectories [40]. Chen *et al.* establish a collision probability model to evaluate driving risks with drivers' intentions and vehicular trajectories considered [26].

The risk-maneuver identification can be defined as a problem where researchers want to distinguish between what is a safe behavior and what is not. Al-Sultan *et al.* propose a probabilistic model for inferring normal and abnormal driving behavior by combining contextual information [30]. Four types of driving behavior, such as normal, drunk, reckless, and fatigue, are defined in advance. However, this method has limitations that cannot fully take into account all possible situations.

As a kind of safety indicator and a crucial point, time-to-collision (TTC) indicates the remaining time before the collision. Due to the simple calculation principle and process, it is widely used in driving behavior analysis and potential collision assessment [41]. In general, there will be no danger if the TTC is much larger than time-to-avoidance (TTA) [4]. However, since it only considers the speed and distance of the vehicles and ignores important factors such as acceleration and human factors, the accuracy will be affected. Schreier *et al.* promotes TTC as time-to-critical-collision-probability, making it valid for longer prediction horizons [28]. Another indicator, time-to-react (TTR), is the remaining time for a human driver to avoid an imminent collision by emergency braking with full deceleration, steering with maximum lateral acceleration, or a kickdown maneuver [25]. Therefore, TTR can be approximately expressed as the maximum of the time-to-brake (TTB), time-to-steer (TTS), and time-to-kickdown (TTK) [42], [43].

3) Reaction: There are two main ways to deal with an emergency. For vehicles without automatic control, a warning message is issued to the driver through the user interface (UI) or voice prompts [4], [5], [27]. After receiving the warning information, the driver can make corresponding judgments and actions according to the actual situation. This method can be adapted to the driver's own driving habits, but due to excessive dependence on the driver's operation, timeliness and reliability cannot be guaranteed. The other way is to trigger the vehicle Automatic Brake System (ABS) or Active Control System (ACS) to automatically brake to avoid the danger of collision for critical situations [4], [5], [26]. This method is time-sensitive and can reduce the uncertainty of the driver's operation, but cannot take into account the habits of different drivers and passengers, thus affecting the driving experience. In addition, the automatic control system may also go wrong.

We outline the main steps of CA and the mainstream methods used in each step are depicted in Table I.

B. Characteristics and Key Research Issues of CA

1) Multi-Source Data: High quality data is the premise and foundation of subsequent prediction, control, and management.

TABLE I

A SUMMARY OF COLLISION AVOIDANCE STEPS

Step	Category	Paper	Characteristics	Mainstream Approach
Prediction	Physics-based Motion Models	[5], [22]–[27]	Short-term motion prediction; Relatively simple approach; Cannot be altered by external influences.	VK Equation; KF and its extended form.
	Maneuver-based Motion Models	[4], [26], [28]–[30] [31]–[33], [37]	Long-term motion prediction; Consider driver factors and vehicle interactions; Need a lot of real data training models; Large computational complexity of some models.	Discriminative approaches (i.e. SVM, RVM); Infering approaches (i.e. DBN, HMM, NN).
Risk Assessment	Collision Probability Calculation	[26], [27], [40]	Intuitively capture collision information and probability; Need to predict complex driving trajectory.	Probabilistic model based on driving trajectory prediction.
	Risk-Maneuver Identification	[4], [30]	Avoid complex driving trajectory prediction; Need to define safe driving behavior in advance; May not fully consider the actual situation.	Probabilistic model based on maneuver prediction (i.e. DBN).
	Safety Indicators	[28], [41]–[43]	Concepts and calculation formulas are relatively simple; Reduced accuracy due to ignoring certain key factors.	TTA, TTC, TTR, etc.
Reaction	Sending Warning	[4], [5], [27]	Drivers can take action according to their driving habits; Overdependence on driver reaction and manipulation; Timeliness and reliability are challenging.	Display on the UI; Voice prompts.
	Automatic Control	[4], [5], [26]	No need for driver reaction time; Reduce the uncertainty of driver operation; Cannot fully consider the diverse driving habits; Automatic control systems can also go wrong.	ABS and ACS.

TABLE II

COMMUNICATION AND POSITIONING REQUIREMENTS FOR TYPICAL SAFETY-RELATED APPLICATIONS

	End-To-End Latency	Communication Type	Data rate	Positioning Accuracy
Rear-end Collision Warning	100 ms	Event-driven	<10 kb/s	<150 cm
Intersection Collision Warning	100 ms	Event-driven	<10 kb/s	<150 cm
Pedestrian Warning	100 ms	Event-driven	<10 kb/s	<150 cm
Post-crash Warning	0.5s	Event-driven	≥ 10 kb/s	<150 cm
Pre-crash Sensing	20 ms	Periodic broadcast	$20-25000$ kb/s	$50-100$ cm
Lane Change Assistance	100 ms	Periodic broadcast	$10-5000$ kb/s	30 cm
Vehicle Platooning	≤ 20 ms	Periodic broadcast	10 kb/s	30 cm

In addition, over-the-horizon information exchange will make the transportation system safer and more efficient. At the same time, however, the volume and variety of data generated by multiple sources such as sensors, roadside detectors, remote sensing, GPS, cell phone tracking, and Unmanned Aerial Vehicle (UAV) increase dramatically [27], [44], [45].

Using the communication network as the channel of sensing information gathering, the multi-source sensing data can be collected and exchanged as data support for follow-up work. However, due to the different characteristics of various sensors, the sensing data has characteristics of a wide variety, large volume, and scattered storage, etc. On one hand, the attributes of the sensor determine the attributes of the original data, including the type, period, information content, and data structure. On the other hand, based on accuracy, reliability, and other requirements, different types of data are determined in terms of importance, timeliness, and transmission reliability. To overcome the limitations of low reliability and small effective detection range of the single sensor, multi-source data fusion, as the inevitable trend of the development of ITS, is carried out to obtain more comprehensive information, which makes the vehicle make a timely evaluation and accurate decision to improve the safety [45]–[47].

2) Ultra-Low Delay Requirement: The Internet of Vehicles (IoV), especially in safety-related application scenarios, requires extremely low latency, which is demanding. On one hand, from a communications perspective, guaranteeing ultra-low latency in data transmission is an indispensable requirement. Authors in [48], [49] summarize some system performance requirements, such as communication mode, minimum transmission frequency, and critical latency. If the requirement of ultra-low latency is satisfied, the driving distance before the vehicle receives the instruction will be greatly reduced. To meet this requirement, one of the current research trends in the design of vehicle-to-everything (V2X) is to support the ultra-low latency and ultra-high reliability requirements of driving safety [50]–[52]. In addition to transmission delays, the computation time, which mainly depends on the hardware facilities and algorithm complexity, also seriously affects the effectiveness of safety-related applications.

TABLE III
KPIs FOR COLLISION AVOIDANCE SYSTEMS

Category	KPI	Description
Effectiveness [4], [53], [60]	Communication Time	Mainly refers to transmission delay; Can vary depending on the density of the traffic and the topography.
	Computing Time	Depends on the computing power of the device and the complexity of the algorithm.
Accuracy [5], [58]–[60]	False Positive	Alerts that have been sent and refer to situations of low or no danger (i.e. False Alarm).
	False Negative	Alerts that have not been sent and refer to collisions that actually occurred.
	True Positives	Alerts that have been sent and refer to collisions that actually occurred.
	True Negative	Alerts that have not been sent and refer to situations of no danger.
	True and Timely Positives	Alerts for which driver had enough time to brake before collision happened.
	True but Late Positives	Alerts for which driver did not have enough time to brake before collision happened.
	Communication Reliability	The accuracy of the transmitted information, e.g., error in received messages.
Comfort [56], [61]	Brake Deceleration	Brake deceleration after the danger is detected until the danger is eliminated.

According to [4], the computation process lasts/(does not stop) until the danger is eliminated. It is expected that one computation process does not exceed 200 ms [53].

3) Ultra-High Accuracy Requirement: Traffic accident prediction and collision avoidance require accurate data related to scene measurements. However, different sensors will affect the accuracy of the sensing data. Due to many uncertainties, driver behavior and vehicle trajectory are often difficult to accurately predict, and the consequences of inaccurate sensor data may be more serious [4], [13], [54]. The accuracy of the algorithm can also influence the results of the prediction and the decision. Therefore, advanced mathematical methods such as stochastic, nonlinear, and fuzzy theory should be considered to develop predictive models more accurately [54]. In addition, AI algorithms are used to better adapt to the driving environment, thereby further improving the accuracy of prediction and decision making.

4) Passenger Comfort Requirement: A good CA system not only ensures high accuracy and reliability but also ensures passenger comfort during collision avoidance. Passenger comfort is affected in many ways during collision avoidance. The brake deceleration is an important indicator for assessing passenger comfort [55], [56]. The existing works are mainly studied from the perspective of vehicle control. According to [49], [57], a summary of requirements for some typical safety-related applications is depicted in Table II. Among these applications, the communication type required by collision warning-related applications is event-driven, while the communication type of other applications is periodic broadcast. In addition, V2V communication technology is the most widely used. Intersection collision warning, post-crash warning, and pedestrian warning will use V2I or V2P communication. Safety-related applications have strict requirements for latency and positioning accuracy.

C. Key Performance Indicator (KPI)

A KPI is any measurable value that demonstrates the performance of CA systems and helps to improve system performance. We can analyze current and historical KPI data to predict what might happen in the future, thus understanding the performance changes of the system.

Ultimately, the performance of the CA system can be measured by the accuracy of the warning, the real-time of the warning, and the number of collisions that are successfully avoided. Depending on the characteristics and needs of the CA system, KPIs are generally divided into three categories: effectiveness, reliability, and comfort of the passengers [4], [5], [53], [58], [60]. According to the description of KPIs in the literature, we list the typical KPI categories and provides descriptions and examples for each category in Table III.

Effectiveness has always been an important indicator of safety-related applications. Specific indicators include but are not limited to communication time and computing time [4], [53], [60]. For example, the authors in [60] study the effect of the server location (i.e. on the edge and the cloud) on the effectiveness of collision avoidance.

Accuracy mainly includes the quality of the alarm and quality of communications. The indicators used by many studies and tests to evaluate the performance of alarm systems are false positive, false negative, true positive, and true negative [5], [58]–[60]. Evaluation and verification of CA systems are full of challenges. These four indicators can roughly reflect the accuracy of CA systems. After receiving the warning, the driver (automatic controller) still has the opportunity to avoid collision by steering or braking. In more recent works, the authors also consider the effectiveness in the quality of the alarm, such as true and timely positives and true but late positives [60]. Communication accuracy refers to the accuracy of the transmission of information, mainly expressed as error rate. The accuracy of the transmitted information will directly affect the prediction and decision-making effects of the CA system.

Comfort of passengers is closely related to the performance of the CA system. A highly effective system will have more time to deal with dangerous situations, thus eliminating the need for hard braking. Similarly, a highly accurate system will produce fewer false positives, which will have less impact on the passenger experience. The comfort of passengers can be measured by the brake deceleration during emergency braking [56], [61].

IV. Sensing for Safe Driving

Sensing of complex driving environment and collecting data are the necessary prerequisite for accurate decision-making and safe driving. Therefore, it is necessary to briefly introduce the sensor technology currently used in the CA system.

A. Sensors for Safety

Through sensors, the distance from the obstacle, vehicle status, and position information can be obtained. Therefore, these sensors can be classified into the following types according to their functions.

Distance Sensors: Multiple sensors, such as radar sensors, LiDARs, camera vision, and infrared sensors have been installed on vehicles. All of them are adopted as distance sensors for monitoring the area surrounding a vehicle to detect the hazard.

Vehicle State Sensors: Speed sensors and accelerometers are considered here to be the most important source of vehicle status information, and they provide the vehicle speed and acceleration information needed for early warning algorithms.

Position Systems: The positioning based on the inertial navigation system (INS) has the characteristics of fast update frequency and high short-term accuracy, but the accumulated error over time is relatively large [62]. Global Navigation Satellite System (GNSS) is the most mature global positioning technology applied today, but there are many problems in the urban canyon environment. Although differential GNSS and INS combined methods can achieve centimeter-level positioning accuracy, this method is expensive and highly dependent on GNSS base stations. Currently, it is mostly applied to algorithm testing of autonomous vehicles [63]. Multi-system and multi-frequency fusion is the development trend of GNSS positioning, and abundant observation data will bring many advantages to precision positioning technology. With the continuous development of vision technology, vision-based positioning technology has been widely used. The relative positioning technology based on vision mainly includes Visual Odometry (VO), as well as Visual simultaneous localization and mapping (V-SLAM) [64].

Since the introduction of sensors is not the focus of this survey, the detailed introduction of sensor principles and characteristics can be referred to [15], [65]–[67].

B. Environment Sensing Methods

Benefiting from these huge numbers of vehicular sensors, vehicles can be considered to be an important source of sensing data. Collecting, sensing, and computing various traffic factors around the vehicle as vehicles move is also one of the most widely used methods of data collection. However, the high dynamic of vehicles makes the sensing and processing of data have some limitations. Vehicular communication allows data generated by on-board sensors to be propagated to other vehicles or infrastructure. Specific communication technologies will be discussed in Section V.

Information fusion technology synthesizes information from different sources, different modes, different media, and different forms of expression to obtain a more accurate description of the sensed object, thus improving the knowability of information and the detectability of the target [41], [47], [68]. Fig. 4 depicts the pipeline of multi-sensor data fusion.

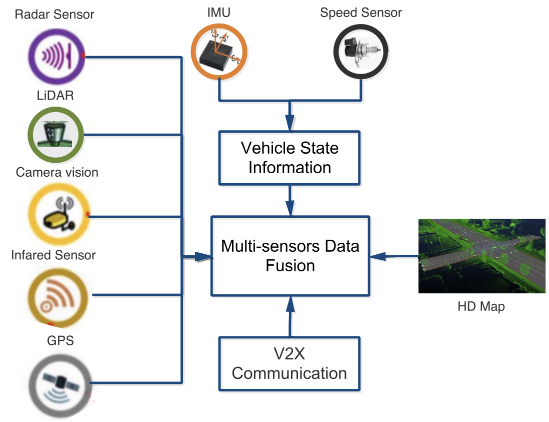

Fig. 4. Multi-sensor data fusion.

Current methods are difficult to achieve accurate and comprehensive sensing of complex conditions, and the sensing data cannot be fully mined and utilized. Therefore, we need to carry out further research on data sensing methods in the complex traffic environment, as well as to carry out data fusion and adaptive processing by leveraging AI technology.

C. AI for Multi-Sensor Data Fusion

Timely and accurate multi-source fusion data can make up for the defect of single sensor data that maximizes the safety and efficiency of the transportation system. Table IV summarizes the related up-to-date research works on data fusion. Lahat *et al.* introduce a comprehensive list of challenges in data fusion and corresponding solutions. Extensive works utilize intelligent technology to efficiently fuse multi-source data efficiently and accurately [68].

The probability-based data fusion method is the most classic and simple and has been widely used [69]. Common methods are mainly based on HMM and Bayes. Utilizing a defined joint density model over multimodal input space, the missing inputs can be filled, thus easily fusing multimodal data with noisy or missing input modalities. Finally, the target data are fused based on Bayesian Estimation [70]. Biresaw *et al.* [71] propose to use two Bayesian trackers with different formulas for visual tracking. Then various sequences are used to show the robustness of the fusion framework with challenges such as occlusion, illumination changes, and shadows. However, this type of method does not accurately represent complete information and the accuracy needs to be improved. Therefore, more works are currently done using learning-based methods, such as KF, SVM, ANN, and Boltzmann Machine.

The Kalman filter and its extended forms are some of the earliest research and widely used methods in data fusion problems [72]. Conventional state-vector fusion and measurement fusion are two kinds of methods for KF-based data fusion [72]. For example, in order to obtain complete target information and improve perceptual performance, Yu *et al.* propose the parallel KF to track the target of the camera and radar respectively [70]. Geng *et al.* present a data

TABLE IV
SUMMARY OF THE SELECTED RESEARCH LITERATURE AND CONTRIBUTIONS TO THE DATA FUSION

Method	Paper	Data Set	Design Object	Main Contribution
Bayesian Estimation	[70]	Millimeter wave radar and camera data	Estimation accuracy	Data fusion based on Bayesian Estimation; Parallel Kalman filter for reducing measurement noise.
Bayesian	[71]	Color image	Fusion performance Robustness	Two Bayesian trackers for visual tracking; Online performance measures as enabling factor.
FTKF	[73]	GPS, barometric altimeter and radar altimeter	Fusion accuracy	FTKF based sensor fault detection; Multi-sensor fusion and real-time fault tolerance.
SVM and Bayesian	[74]	Hyperspectral and LIDAR data	Effectiveness Fusion accuracy	SVM-based data fusion in decision level; Classifier fusion based on Naive Bayes.
SVM and ANN	[75]	Inertial sensors data	Effectiveness	SVM and ANN for activity recognition; Explore the impact of different parameters.
MLP	[76]	3D-LIDAR and a color camera	Fusion accuracy	Multimodal data fusion based on MLP; Evaluate 3D-LIDAR modalities for vehicle detection.
Deep Belief Networks	[77]	Image	Classification accuracy Feasibility	Multimodal data fusion based on DBN; Can effectively handle missing data modalities.
multimodal DBM	[78]	Image-text and audio-video data	Classification performance	Learn multimodal data based on DBM; Can effectively handle missing data modalities.

fusion scheme based on fault-tolerant Kalman filter (FTKF) for integrated navigation systems [73]. The scheme enables multi-height sensors data fusion, detecting faulty sensors, and performing fault tolerance in real-time.

The Bayesian-based algorithm can make a large part of the prior knowledge, which has great advantages to process small amounts of data. However, when the data dimension increases, there is a limit to the Bayesian-based algorithm, and SVM can overcome this defect and play its role. In [74], an SVM-based method for fusion hyperspectral and LiDAR data is proposed. In recent work, Zebin *et al.* [75] propose a general-purpose framework for facilitating the use of machine learning algorithms, such as SVM and ANN, for data fusion and pattern recognition. In addition, the authors explore the amount of data and data fusion such as multi-sensor locations as well as issues affecting overall performance in detail. In [76], a multisensor and multimodal vehicle detection system is proposed, which fuses the data of color camera and 3D-LiDAR. Particularly, an MLP is used to learn the nonlinear relationship between data to perform multimodal detection fusion.

Since some missing data modalities can be handled, a Deep Belief Networks model is proposed for learning a joint representation of multimodal data [77]. Similarly, the well-known Boltzmann Machine (BM) and its generalizations are suitable for data fusion. Srivastava and Salakhutdinov propose a multimodal Deep Boltzmann Machine (DBM) for learning a generative model of multimodal data [78]. A DBM [79] is a network of symmetrically coupled stochastic binary units. Because of the features of DBM, such as layer-by-layer pretraining procedure, incorporating top-down feedback for approximate inference, and optimizing jointly parameters of all layers, the DBM can better incorporate uncertainty about missing or noisy inputs, thus suitable for modeling the multimodal data for a system with multiple sensors.

According to the type of mathematical method used, the data fusion method can be divided into the probabilistic method and the learning method. From the results of the literature review of data fusion, we can conclude that most of the current works tend to be based on learning methods. In particular, SVM-based methods are suitable for processing high-dimensional data. The KF-based methods are relatively simple, and their extended form can be used to process linear or nonlinear data. The deep belief network-based and BM-based methods are good ways to handle missing data. The ANN-based methods work well with nonlinear data to explore complex data relationships. Compared with probabilistic methods, the accuracy of learning methods is higher while the complexity and requirements for computing power are higher.

V. COMMUNICATION FOR SAFE DRIVING

In addition to sensors, real-time communication of the vehicle while driving are also required. With V2X communication, a vehicle can "talk" to other vehicles, non-motor vehicles, transportation infrastructure, and pedestrians, even if they are not within the vehicle's direct line-of-sight. In this section, we will describe the communication technologies applied in CA.

A. Communication Technologies Applied in CA

As two or more V2X-enabled entities enter the communication range, they form an ad-hoc wireless network that allows them to automatically send real-time dedicated safety-critical messages. Some communication technologies such as DSRC, cellular network, ZigBee, and visible light communications (VLC), have been studied or applied to CA systems. Among them, DSRC and cellular-based V2X (C-V2X) have always been the focus of research and are being deployed. VLC is a new technology using visible light and is in the research stage. ZigBee is a low-power technology that is more used in experiments.

1) IEEE 802.11 Family Technologies:

DSRC is an efficient wireless communication technology based on the IEEE 802.11p standard that enables the identification and communication of moving targets in high-speed motion in specific small areas. The DSRC standards are not compatible with each other in the United States, Europe, and Japan. European ITS-G5 reserves 70 MHz (5855 MHz–5925 MHz) for V2X communications, of which 30 MHz (5875 MHz-5905 MHz) is reserved for traffic safety-related applications. The US Federal Communications Commission (FCC) has allocated 75 MHz (5850 MHz–5925 MHz) in the 5.9 GHz frequency band for V2X applications and has reserved 5885 MHz–5895 MHz "control channel" frequency band for traffic safety. In Japan, ARIB STD-T55 (ETC), ARIB STD-T75 (DSRC) and ARIB STD-T88 (DSRC application sublayer (ASL)) have used 80 MHz (5.770-5.850 GHz) DSRC spectrum. In 2011, ARIB STD-T109 allocated a new frequency range of 755.5–764.5 MHz for various types of ITS applications [16], [18], [80], [81]. The IEEE 802.11p / ITS-G5 protocol is mainly used in the US and Europe. On-Board Unit (OBU), RSU and related protocols are important parts of DSRC. For example, V2V and V2I communications enable real-time transmission of image, voice, and data information to organically connect vehicles and roads. DSRC-based communications offer the benefits of low end-to-end latency, self-organization, and low cost for V2X applications [80]. According to statistics, it is possible to reduce traffic accidents by 81% using V2X communication [81].

DSRC-based technology has been the focus of many researches supporting vehicle communication in the previous 20 years. Xiang *et al.* propose a DSRC-based model for rear-end collision avoidance [5]. Zhao *et al.* propose a rear-end collision warning system (ReCWS) and explicitly states the functional specifications of the DSRC technology such as transmission delay and propagation delay [82]. In [4], V2I communication is used to collaborate on intersection collision avoidance, which provides a wider range of communication. In addition, DSRC-based V2V communication is also used for vehicle cooperative positioning, improving positioning accuracy and indirectly improving traffic safety [83], [84]. In the industry, Toyota and General Motors have launched DSRC-enabled vehicles. However, the number, distance, and interference of the RSU layout remain to be resolved. Therefore, DSRC performance evaluation, protocol design is worthy of continuous research. In addition, another problem that the IEEE 802.11p-based DSRC must solve is to provide secure, verified and authenticated messaging and protect user privacy. Although DSRC/ITS-G5 had long-term plans in the US and Europe, many researchers believe that C-V2X technology will develop faster in the future. In particular, in November 2020, FCC officially decided to allocate the 5.9 GHz frequency band to Wi-Fi and C-V2X, which marked the elimination of DSRC in the US.

2) Basestation-enabled Technologies:

C-V2X is a cellular-based V2X technology, which is a term proposed by 5GAA to distinguish cellular-based V2X from DSRC. Conceptually, it includes LTE-V2X and NR-V2X. LTE-V2X mainly relies on current LTE technologies, as well as the old standards [80]. The LTE-based technology called LTE-V2X started in 2010. LTE-V2X technology includes two working modes: mode 3(LTE-V-Cell) and mode 4 (LTE-V-Direct). The difference between the two modes lies in the wireless resource allocation method. Resources are allocated by the cellular network in mode 3, and mode 4 uses distributed scheduling that does not require cellular coverage scheme. Since V2V security applications cannot rely on infrastructure-based cellular coverage, mode 4 is considered the baseline mode and an alternative to DSRC [85]. In China, the 5905-5925 MHz frequency has been officially allocated for LTE-V2X verification. Li *et al.* [86] analyze and improve the collision avoidance strategy based on LTE-V2X for an autonomous vehicle, thereby enhancing the practicality of autonomous driving on the highway. LTE-eV2X R15 introduces additional, and LTE-V2X R14 compatible, key enhancements such as 64-Quadrature Amplitude Modulation (64QAM), small-delay Cyclic Delay Diversity (CDD), and carrier aggregation, thereby further improving the performance of delay, speed and reliability [87]. Currently, C-V2X can enhance road safety and traffic efficiency, which is also an important part of achieving autonomous driving. Related standardization work is also continuing to be discussed and promoted.

C-V2X includes PC5 interface and Uu interface, supporting smooth evolution from LTE-V2X to 5G-V2X. 5G does not involve specific standards, but instead of changing the existing communication architecture (eg, LTE), the next step of demands and new technologies [18], [80]. The Recommendation ITU-R proposes to support eight key KPI improvements in peak data rate, user experienced data rate, latency, mobility, connection density, energy efficiency, spectrum efficiency, and area traffic capacity [88]. The IoV is a very important application scenario for 5G. 5G can use the existing LTE frequency range (600 MHz to 6 GHz) and the Millimeter-Wave band (24-86 GHz). Non-orthogonal multiple access (NOMA) technology is used to improve spectral efficiency. It can reach a data rate of 10 Gb/s compared to other vehicular communication technologies [18], [89]. With the development of communication technology, authors of [90] put forward a theoretical analysis of C-V2X-based basic safety-related ITS spectrum requirements, and the results indicate that at least 20MHz frequency should be allocated to support V2V/V2I basic safety applications. 3GPP announced the freezing of the R16 standard (NR-V2X), marking the completion of the first evolutionary version of 5G. The standard supports V2V and V2I direct communication. By introducing a variety of communication methods and technologies, V2X supports more abundant application scenarios such as platoon, semi-autonomous driving, and remote driving. However, from the introduction of the standard to the actual application, a strict performance and safety test process is required.

Therefore, the current application of the IoV depends more on the mature LTE-V2X-based technology.

5G Automotive Association (5GAA) compared DSRC and C-V2X in the laboratory and in the field. It can be seen from the test results that C-V2X supports longer communication distance, better non-line-of-sight performance, stronger reliability, higher capacity, and better congestion control [91]. Performance advantages in these aspects are very important for improving traffic safety. For example, in non-line-of-sight scenarios, the performance of on-board sensors is limited. In addition, cost and standardization also make C-V2X develop rapidly. C-V2X is based on a cellular network with wide network coverage, low deployment cost, and clear evolution route.C-V2X utilizes and reuses the upper-level protocols that the automotive industry has defined, including organizations such as the Society of Automotive Engineers (SAE) and the European Telecommunications Standards Institute (ETSI), as well as the entire industry's investment in the ITS-G5/DSRC upper-level protocols over the years.

3) Visible Light Technology:

Due to the limited bandwidth available, current networks cannot fully meet the growing traffic demands. Ease of use, low cost, high data rate, and large geographical distribution of VLC make it a great potential to become a wireless communication technology that complements or replaces existing radio frequency (RF)-based communications [92]. Some light sources such as headlights, taillights, traffic lights, and billboards can be used to transmit vehicle or traffic information. Compared to RF communication, VLC uses visible light (380-780 nm) as a carrier for data to provide greater bandwidth. In addition, the cost of this technology is low due to the unregulated spectrum. In addition, the huge available spectrum enables VLC to achieve very high data rates [93]. Finally, VLC technology is also fully compatible with RF communications and can be part of the future 5G technology [94]. This feature can be used to build heterogeneous systems consisting of VLC and other RF-based communication schemes to provide reliable communication systems for vehicles, as these technologies can complement each other.

The VLC has been the focus of intensive research in the past few years. Wang *et al.* [95] propose to use VLC-based ITS for accident avoidance, especially when the truck fleet is crossing an intersection. Specifically, signals related to acceleration, deceleration, and braking are sent through the VLC to RSUs that can trigger the appropriate signal. By using the directionality and impermeability of light, Ucar *et al.* [96] propose a hybrid communication hybrid protocol based on IEEE 802.11p and VLC, namely SP-VLC, for autonomous vehicle platoon, which mainly solves the security issues caused by RF-based communication technology. Uysal *et al.* [97] evaluate the performance of VLC-based V2V systems, taking into account the effects of measured headlamp beam patterns and road reflected light. The results show that according to the position of the headlights, a data rate of 50 Mbps can be achieved when the distance between the vehicles is $70m$. However, this technology is still in its infancy and needs to overcome current challenges, such as noise robustness, communication range, mobility, data rate, and heterogeneous communication networks [94].

4) Low-power Technology:

ZigBee is a short-range, low-complexity, low-power, low-data-rate, low-cost wireless network technology, which is based on the IEEE 802.15.4 standard. ZigBee relies on independent nodes, and each node has different functions. It has a communication range from 10 to 100 m, and a maximum data rate of 250 Kb/s (2.4 GHz band with Offset Quadrature Phase Shift Keying). Priyanka and Kumar [98] use Zigbee to transmit information about their speed and position between vehicles to avoid collisions. In addition, ZigBee can also be used to connect electronic components of CAVs for vehicle monitoring and status reading [18]. If ZigBee terminal equipment is distributed along streets, a GPS-like service can be provided with more precise and specific information. Although the performance of ZigBee is relatively low, its low complexity and low-cost feature make it suitable for communication simulation.

Since the scope of this survey is not vehicular communication technology, we do not introduce other technologies such as Wi-Fi, WiMAX and Bluetooth. In addition, the detailed introduction of vehicular communications can be referred to [18], [48], [80]. Communication technology is mainly used in the following aspects to improve traffic safety.

Early Warning Information Release: This is the most important application of communication technologies in CA. Safety-related applications are characterized by very stringent requirements in terms of communication delay, reliability, and packet error rate, otherwise, they will cause unimaginable serious consequences. Therefore, DSRC, VLC, and 5G are more suitable for conducting early warning information releases. It can be applied to broadcast abnormal driving behavior, vehicle overtaking, and other lane changing behaviors, so as to facilitate early understanding of driving intentions [4], [5], [26]. In addition, it can be applied to PCW systems to alert pedestrians to potential traffic accidents or minimize the impact of the accident [99], [100]. In general, the warning information consumes little bandwidth, but the vehicle status information used to evaluate the risk of accidents between vehicles needs to occupy network resources, depending on the data type and the volume of data. According to [80], the early warning information application requires a latency of 20-100ms.

Traffic Supervision: This type of application is mainly used for real-time monitoring of traffic status by traffic regulatory authorities. It can make information available for the first time after the accident, so as to take effective rescue and traffic evacuation measures to avoid secondary accidents [101]. Both V2V and V2I communication are effective methods. This type of application does not require extremely high latency for early warning information transmission. In addition, traffic regulation may rely on images and video data acquired by cameras, and take the form of remote processing events, thus requiring transmission bandwidth and network throughput.

Cooperative Driving: Some cooperative driving applications use vehicular communications, such as vehicle cooperative positioning [83], [84], cooperative platooning [102], [103], and cooperative adaptive cruise control (CACC) [104], [105], can also reduce traffic accidents. Cruz *et al.* propose to use vehicular communication (i.e. DSRC) and smartphone sensors to improve overall localization performance [83]. In [84], V2V communication is used to share motion states and physical measurements between vehicles, and the positioning accuracy is improved. And similar to safety-related applications, they also have strict requirements on communication latency and frequency. According to [80], approximately 5 Mbps throughput and latency as low as 2-10 ms for supporting cooperative driving applications.

Cooperative Collision Avoidance: Adding inter-vehicle communication to the CA system can form cooperative collision avoidance (CCA), allowing vehicles to obtain more accurate information and expand the perception range. Hafner *et al.* use V2V communication to determine whether vehicles at intersections need automatic braking for collision avoidance [106]. On the basis of considering the information sharing of neighbors, authors of [107] propose a comprehensive method for designing and analyzing the behavior of CAVs, which is used to study multi-vehicle CCA problems. In [108], authors use V2X communication to design a real-time and implementable collision avoidance algorithm and simulated different collision risks. For intersections, authors set up a supervisor, which receives status information from cars, then estimates possible collisions and sends control signals when necessary [109]. It can be concluded that vehicle communication can effectively overcome the defects of sensors and improve driving safety.

B. AI for Vehicular Communication

In recent years, some applications of AI technology in vehicular communication have shown tremendous potential to utilize multiple generated data sources and store them in the network to learn the dynamics in the environment, and then extract the appropriate features for use in many tasks for communication purpose [110]. Some learning methods are used for routing, resource allocation, channel quality estimation, etc. Together with AI, communication technologies can obtain information from different sources, expand the range of vehicle sensing, and predict to avoid potential accidents, thereby improving driving comfort, safety, and effectiveness [111]. In addition, AI technology can improve the ability to adapt to the environment in the case of high dynamic scenarios and uncertainties [110].

In terms of learning-based channel estimation, Wen *et al.* [112] utilize the propagation characteristics of massive MIMO systems and then uses the sparse Bayesian learning method for accurate channel estimation. Ye *et al.* [113] propose to use deep learning to perform channel estimation and signal detection in OFDM systems. The deep learning-based approach can resolve channel distortion and detect transmitted symbols with performance comparable to the minimum mean square error estimator, making the system more robust.

Another application of AI in vehicular communication is the design of routing protocols. In [114], a deep reinforcement learning (DRL)-based routing strategy is proposed for software-defined vehicular networks. The software-defined networking (SDN) controller acts as an agent to learn the most trusted routing path through DNN. In another work [115], a clustering-based reliable routing algorithm for vehicular communication is proposed, in which simulated annealing is used for proper clustering of nodes, and a radial basis function neural network (RBFNN) is used for cluster head selection.

For resource allocation, He *et al.* [116] present an integrated framework to dynamically allocate networking, caching, and computing resources and the DRL algorithm is used to solve highly complex joint resource optimization problems. In the scenario where the RSU has a limited-lifetime power source, a DRL-based scheme is proposed for optimizing the RSU's downlink traffic scheduling during a discharge period [117]. DRL enables RSU to learn and adapt to optimal decisions, extending battery life while meeting the maximum number of service requests. In another work [118], authors propose a decentralized DRL-based resource allocation mechanism for V2V communication. In this work, both unicast and broadcast scenarios are considered. The decentralized mechanism can tightly control the transmission overhead.

Since the vehicular network is vulnerable, authors use the artificial neural network (ANN) to design the VANET intrusion detection mechanism for Denial of Service (DoS) attacks [119]. Alheeti *et al.* [120] use fuzzy logic to detect packet loss attacks in the vehicular network. Berlin *et al.* [121] propose a Security Information and Event Management System (SIEM), which combines the deep learning algorithm and Big data algorithm to identify attacks. Authors of [122] and [123] propose AI-powered jamming DoS detection to enhance the communication security of highway vehicle platoon.

Table V summarizes the related up-to-date research works on applying AI to vehicular communication. AI technology plays an important role in channel estimation, routing, resource allocation, and network security. However, the current standards for V2X systems are not uniform enough, and the application of communication technologies still faces challenges. AI technology provides intelligent methods for codec and data transmission for different communication systems (*e.g.*, DSRC and cellular).

C. Challenges and Discussion

High Dynamics: The fast-moving speed of the vehicles makes the network have high dynamic characteristics, which will have many influences on the application of communication technologies. For example, the network topology changes frequently and the communication link life is relatively short, which affects the establishment and selection of routes. Communication between vehicle nodes in the IoV is disturbed by weather conditions, surrounding buildings, accidental obstacles, and road traffic conditions. Some emerging technologies such as mmWave communication have strong directionality but are not suitable for omnidirectional antenna communication, so there is still a need to study fast beamforming in high dynamic scenarios.

TABLE V

SUMMARY OF THE SELECTED RESEARCH LITERATURE AND CONTRIBUTIONS TO THE VEHICULAR COMMUNICATION

Method	Paper	Tasks	Design Object	Main Contribution
Bayesian	[112]	Channel estimation	Estimation accuracy Achievable rates	Model the channel component in the beam domain as a Gaussian mixture; Bayesian learning for massive MIMO channel estimation.
DNN	[113]	Channel estimation	Bit-error rate (BER) Robustness	Deep learning-based algorithm for channel estimation in OFDM system; Channel estimation without online training.
DRL	[114]	Routing	Effectiveness	DRL-based trust management scheme for vehicular networks; DNN is used to learn the most trusted routing path.
RBFNN	[115]	Routing	Route discovery rate Packet delivery rate	Clustering-based reliable routing algorithm; Use RBFNN for cluster head selection.
DRL	[116]	Resource allocation	Effectiveness	Integrated framework for dynamically allocating resources; DRL algorithm for solving complex joint resource optimization problems.
DRL	[117]	Resource allocation	Quality of experience RSU's throughput	Consider the scenario where the RSU has a limited-lifetime power source; DRL-based RSU's downlink traffic scheduling strategy.
DRL	[118]	Resource allocation	V2I Capacity V2V Latency	Decentralized DRL-based resource allocation mechanism; Can be applied to both unicast and broadcast scenarios.
ANN	[119]	Network security	Detection efficiency	ANN-based intrusion detection mechanism.
Fuzzy Logic	[120]	Network security	Detection rate	Fuzzy petri nets (FPN)-based packet dropping attacks detection mechanism.

Infrastructure Deployment Issues: For DSRC communications, the deployment of the RSU remains a challenge. From an economic perspective, the cost of installation and maintenance cannot be ignored. For C-V2X, although there are already many mobile network infrastructures in operation, it still does not provide comprehensive cellular network coverage. In order to meet the communication requirement, providing a wide coverage and high-capacity communication network, infrastructure layout still has problems.

Security and Reliability of Communications: The application of communication technology enables vehicles to provide driving safety data to surrounding vehicles in advance, so that surrounding vehicles can predict the driving behavior of other vehicles and implement active safety strategies. At the same time, the safety and reliability of communication are of paramount importance due to the connectivity between the vehicle and the environment. For example, due to network security issues, vehicles may receive wrong data or instructions, which may cause more serious traffic accidents. However, safety-related data usually has a short processing period, which makes it a big challenge to ensure the security and reliability of information transmission. In addition, it is very important to perform security authentication on the identity of the participants in the vehicle communication process. The security of vehicular communication needs to meet the following requirements, such as the integrity and privacy of information, the ability to resist external security attacks, the authenticity of received data, as well as the integrity of data. In addition, vehicular communications must provide secure, verified and authenticated messaging and protect user privacy. A detailed assessment of communication security is not within the scope of this survey. Authors of [124] have conducted a complete overview of the security vulnerabilities and solutions of vehicular networks.

VI. AI-BASED ALGORITHMS FOR SAFE DRIVING

In the collision avoidance algorithms, AI technology has been applied in multiple aspects, ranging from vehicle trajectory and driving behavior prediction [4], [31]–[39], [125]–[129], to platoon and autonomous breaking [102], [104], [105], [130]–[132].

A. Vehicle Trajectory and Driving Behavior Prediction

In a CA system, both driver behavior prediction and vehicle trajectory prediction are indispensable links. Since the previous works are mostly considered from the state of the vehicle, the vehicle trajectory prediction study is earlier than the driving behavior prediction. Recent works tend to be more predictive of driving behavior, or combined driving behavior with a driving trajectory to get more accurate predictions.

In order to improve the safety of intersections, Aoude *et al.* [33] develop an HMM-based algorithm to estimate the driver's behavior at the intersection, that is, whether it is violating. For highway scenarios, Lane Keeping Assistance Systems (LKAS) is important for driving safety and comfort. In [37], a new LKAS system is proposed, which mainly designed the driver learning model combined with HMM and Gaussian mixture regression (GMR) to predict the lane departure. Combine on-board sensor data such as machine vision and lidar, Laugier *et al.* [125] use traffic scene modeling and collision risk assessment to ensure driving safety in any traffic scenarios. In particular, the layered-HMM and Gaussian process (GP) models are built to predict behaviors in a short term, which can handle uncertainty during driving. Gadepally *et al.* [126] propose a framework for estimating driver behavior at intersections based on modeling driver behavior and vehicle dynamics as a hybrid state system (HSS), which can be flexibly applied to other scenarios. Among them, HMM is used to estimate driver behavior.

In view of the limited ability of HMM to express, more works have recently focused on a more complex graph model, i.e., DBN. Unlike the HMM, which uses a variable to represent the implicit state, the DBN uses a set of variables to represent the implicit state. Specifically, the graph model can be used to express the conditional independent relationship between variables in each unit of the data sequence and the unit. In [4], considering the influence of driver behavior on vehicle status, the authors propose a DBN-based vehicle state evolution model. Similarly, for the intersection scenario, the authors consider that the interaction between vehicles is governed by traffic rules. Based on this fact, the DBN is used to estimate the state of the vehicle [31]. Gindele *et al.* [32] build a hierarchical DBN to simulate the driver's decision-making process. In order to make the prediction more accurate, the road topology was taken into account in the modeling process.

In addition to the generation methods such as HMM, the discriminative learning algorithm is also widely used. The driver's behavior is not only related to the current state but also affected by the state of the previous moment. Therefore, it is necessary to combine the state of the previous moment to obtain a more accurate prediction result. The authors in [33] also use a discriminative approach, *i.e.*, a SVM-based algorithm, for driver behavior classification at intersections. The performance of this method is better than the traditional method. For vehicles approaching the traffic light scenario, Ortiz *et al.* [38] use a simple neural network model, that is MLP, to predict driver behavior. Due to the simplicity of the model, it can be extended to large-scale online learning. In [39], an RVM-based driver behavior prediction method is proposed, which can predict the driver's intention to change lanes a few seconds in advance. At the same time, this paper deeply analyzes the challenges from laboratory simulation to an actual road test. However, these methods are not sufficient to cope with increasingly complex traffic conditions.

Among many ANN algorithms, RNN is well suited for this type of prediction scenario because it allows neuronal connections from a layer of neurons to previous layers of neurons. In the transportation domain, it was applied for vehicle trajectory prediction and driving behavior prediction. In [128], two types of deep learning models, i.e., Long Short-Term Memory (LSTM) and the Convolutional Neural Network (CNN) model, are proposed to predict a human-driven vehicles' trajectory. In particular, CNN feeds more information to the LSTM by using images, making trajectory prediction more accurate. For the unsignalized intersections scenario, Zyner *et al.* [127] propose an RNN-based prediction algorithm for predicting driver intention. In particular, the data used for forecasting is the Lidar-based tracking system, which is in line with the future direction of autonomous vehicles. In [34], RNN is introduced to develop a car-following model to study its effectiveness in predicting the vehicles' acceleration distribution of highway. Due to the variety of shapes and forms of intersections, it is impossible to find general features and models to generalize them. Phillips *et al.* [35] use RNN to build a predictive model to predict the driver's behavior at intersections (i.e., turning or going straight), and performing performance tests at intersections of different shapes.

In addition to these single prediction models, other works take into account the advantages of different models and methods to design a combined model [36], [129]. Bahram *et al.* [36] fully consider the advantages of combinations of model-based and learning-based estimation methods in terms of scalability of expert knowledge and difficulty of reducing dimensionality hazards, and propose an online-capable driving behavior prediction framework. The spatio-temporal cost map is used to determine the vehicle interaction-aware behavior, and then the Bayesian filter (BF) is used for maneuver prediction. For the problem that a specific model cannot balance quality and scope, the authors in [129] propose a model that combines multiple classifiers, each of which is suitable for a specific scenario. In particular, the author uses the scenario model tree (SMT) to organize the scenario and scenario-specific classifiers.

Table VI summarizes the related up-to-date research works that predict vehicles' trajectory and driving behaviors. As the number of data increases, driver behavior prediction can avoid complex vehicle trajectory prediction and become the preferred choice for many CA algorithms. The probability-based methods still occupy very important positions and maintain good performance in most scenarios. However, classic machine learning methods, such as SVM and MLP, are not suitable for increasingly complex traffic conditions. Algorithms based on RNN and deep-RNN will be promising.

B. Platoon and Autonomous Braking

Although the collision warning system greatly improves driving safety, it still causes problems such as the driver's nervousness. Vehicle platoon can actively control vehicles to avoid collisions and improve traffic safety. Enabling the connectivity between vehicles and the cloud, vehicles and vehicles, vehicles and the environment, the CACC application will reduce crashes by forming a platoon with small space/time headway. Long-term research shows that the AI-based methods outperform the traditional methods in vehicle platoon. Douglass *et al.* [130] use LSTM Neural Network to predict the cut-ins in multiple trucks in leader-follower platoons, thereby improving the safety of truck platooning. Guo *et al.* [102] propose a Chebyshev neural network-based distributed adaptive approach combined with sliding mode technique for handling vehicle-following platoons with input saturation. In an earlier work [104], an RL-based method is proposed to obtain an autonomous longitudinal vehicle controller. Different from other RL methods, a policy-gradient algorithm is designed that can result in efficient behavior for CACC. More recently, a supervised reinforcement learning (SRL)-based framework for the CACC system is proposed in [105]. During the training process, the network is updated under the guidance of the supervisor and the gain dispatcher.

Autonomous braking plays an important role in the CA system. At the same time, this function is also one of the enabling technologies of CAVs. It can effectively brake when the driver reacts too late to the dangerous situation or the

TABLE VI

SUMMARY OF THE SELECTED RESEARCH LITERATURE AND CONTRIBUTIONS TO VEHICLE TRAJECTORY AND DRIVER BEHAVIOR PREDICTION

Method	Paper	Scenario	Design Object	Main Contribution
HMM	[33]	Intersection	True positive rates	HMM-based driving classification algorithm; Use naturalistic data set to verify algorithm.
HMM	[37]	Highway	Efficiency Prediction accuracy	Lane departures prediction based on HMM; Combine GMR on HMM to reduce intrusiveness.
Layered-HMM	[125]	Any traffic scenario	Recognition rate Prediction accuracy	Traffic scene modeling based on on-board sensor data; Collision risk assessment based on HMM and GP.
HSS-HMM	[126]	Intersection	Prediction accuracy	Use HMM to estimate driver behavior; Model driver behavior and vehicle dynamics as HSS.
DBN	[4]	Traffic light controlled intersection	Algorithm complexity Prediction accuracy	Analye critical influencing factors; Vehicle state evolution model based on DBN.
DBN	[31]	Intersection	Prediction accuracy Robustness	Use DBN to estimate the status of the vehicle; Study interaction between vehicles regulated by traffic rules.
DBN	[32]	Intersection	Prediction accuracy	Driver's decision-making process modelled by DBN; Modeling takes into account the road topology.
SVM-BF	[33]	Intersection	True positive rates	SVM-based driving classification algorithm; Use naturalistic data set to verify algorithm.
MLP	[38]	Inner-city environment (Approaching a traffic light)	Prediction accuracy	System-level learning focused on (semi-) autonomous agents; MLP-based behavior prediction.
RVM	[39]	Lane Change	Efficiency Prediction accuracy	Lane change prediction based on RVM; In-depth analysis of the actual road test challenges.
RNN	[127]	Unsignalized intersections	Timeliness Prediction accuracy	Information sources based on LiDAR; Driver intention estimation based on RNN.
RNN (LSTM)	[34]	Highway (Car-following)	Prediction accuracy	Acceleration distributions prediction based on LSTM; Easy to extend to more complex feature recognition.
RNN	[35]	Intersection	Prediction accuracy	Research and promotion of feature categories; Algorithm adapts to multiple intersection compositions.
LSTM CNN	[128]	Car-following platoon	Prediction accuracy	LSTM and CNN-based trajectory prediction model; Mixed traffic flow scenario.
Cost-map + BF	[36]	Highway	Timeliness Prediction accuracy	A combined intention estimation model with on-line capability; Integrate expert knowledge to simplify interaction modelling; Reduce data only for supervised learning.
SMT	[129]	Highway and inner-city	Timeliness Prediction accuracy Scope	Propose a hierarchical model combining multiple classifiers; Organize scenario-specific classifiers in a tree; Able to balance quality and scope.

brake is insufficient, thus reducing the speed of the vehicle and reducing the consequences of the accident. The DRL technology is not only widely used in systems such as ACC, but also has significant research progress on autonomous brake control. More recent works have been done in this area. In [131], an autonomous braking system based on DRL is proposed to automatically decide whether to take the brake according to the actual driving situation. According to the relative position of the obstacle and the speed of the vehicle, the DQN is used to learn the optimal braking control strategy by setting the reward and punishment function. Since one common feature in current ADAS applications is to focus on the environment of the vehicle and its surrounding vehicles, while ignoring the driver's factors, the authors in [132] propose an FCW system based on the RL algorithm to handle the driving preferences of different drivers.

Table VII summarizes the related up-to-date research works for platoon and autonomous braking. It can be seen that RL technology is widely used in vehicle automatic control. As data acquisition is more convenient, data such as images can be used for more accurate vehicle control. The method of combining deep CNN and RL is worth studying.

C. Challenges and Solutions

AI technology has been researched and applied in many aspects of CA systems, but these systems still cannot achieve

TABLE VII
SUMMARY OF THE SELECTED RESEARCH LITERATURE AND CONTRIBUTIONS TO PLATOON AND AUTONOMOUS BRAKING

Method	Paper	Scenario	Design Object	Main Contribution
LSTM	[130]	Truck platooning	Prediction accuracy	LSTM-based method to predict vehicles cut-in for platooning trucks.
Chebyshev NN	[102]	Car-following	Control accuracy	Distributed adaptive control for platoon based on Chebyshev NN; Compensation input saturation effect by adjusting a single parameter.
RL	[104]	Car-following	Control accuracy	RL-based method for CACC; A policy-gradient method is used to reduce learning parameters.
SRL	[105]	Car-following	Effectiveness Adaptability	SRL-based framework for CACC; Network is updated under the guidance of the supervisor.
DQN	[131]	Pedestrian crossing the road	Control accuracy	Autonomous braking based on DQN; Design a desirable reward function to learn the best control strategy.
RL	[132]	Forward collision	Accuracy Timeliness	FCW system based on RL; Consider the driving preferences of drivers.

100% collision avoidance, and the characteristics of AI algorithms still affect safety. The CA system has strict requirements for AI-based algorithms, and current researchers are working hard to overcome the following challenges. The first is the verifiability of neural networks. One challenge in applying neural networks to systems that are critical to safety is that it is difficult to provide formal guarantees for their behavior. Katz *et al.* [133] propose Reluplex, which combines linear programming technology with SMT (Satisfiability Module Theory) solving technology for neural network error detection. The second is poor interpretability and non-transparency. Increasing the expressiveness of ML models usually comes at the expense of transparency. Opacity is an obstacle to safety because it is more difficult for researchers to establish confidence that the model will perform as expected. In [134], authors use the influence function to determine the most relevant training node for a given prediction result. In [135], authors combine neural networks and decision trees to maintain high-level interpretability while using neural networks to make low-level decisions. The proposed NBDT has the same interpretability as decision trees and can output intermediate decisions that predict results. Gehr *et al.* [136] propose a system called AI2 to use the abstract interpretation framework to solve the scalability and precision challenges of neural networks. The third is the error rate. AI models usually do not work perfectly and have errors. The sources of errors may be training data and algorithms. Therefore, when designing an algorithm, on the one hand, it is necessary to select appropriate training data, on the other hand, it is necessary to study the propagation and amplification of deviation. The fourth point is the instability of the AI algorithm, for example, it may fall into a local optimum. As a result, even if the training set remains the same, the training process may produce different results. In order to solve the problem, a theoretical framework by Monte Carlo dropout sampling in DNN is proposed for uncertainty estimation [137]. In [138], Bayesian Deep Learning (BDL) is proposed to solve this problem and improve safety.

VII. TESTBEDS AND PROJECTS FOR COLLISION AVOIDANCE

Recently, research on CA has gradually moved from theory to practice. In order to better adapt to actual traffic scenarios and reduce product risks, many testbeds and projects have been made by academic and industrial research communities. In this section, we will briefly introduce some recent projects and tests dedicated to achieving traffic safety in actual scenarios.

A. Academic Testbeds and Projects

In 2005, Caltrans collaborated with the Metropolitan Transportation Commission (MTC) and California PATH program of UC Berkeley established the nation's first public-Connected Vehicle Test Bed on El Camino Real (State Route 82). And in 2018, they collaborated to update the equipment in the testbed to meet the latest connected vehicle standards and implementation architecture. The testbed is currently operating at El Camino Real in Palo Alto, which includes 11 signalized intersections. It provides an operating environment where intersections and vehicles can communicate with each other using DSRC, so that CACC, cooperative intersection collision avoidance, advanced traffic signal controls using connected vehicle data, and truck platooning can be implemented. More detailed information can be referred to [139]. At the same time, this team conducted research on deep automotive perception to guide autonomous driving, such as efficient pedestrian detection, pedestrian intent detection, and deep driving control policies. In Canada, the University of Alberta (UofA) and the University of British Columbia (UBC) jointly set up a connected vehicle testbed network called ACTIVE-AURORA, which provides a harsh winter climate to test the application of ITS and connected vehicles. The current focus of the project is to improve safety by using connected vehicles and DSRC V2I technology to reduce pedestrian collisions at signalized intersections. As a result, a DSRC has been used to develop a proof of concept for the upcoming pedestrian detection notice for connected vehicles. Carleton University, Transport Canada, and BlackBerry QNX have collaborated on both connected vehicle systems and autonomous vehicles to achieve safe, automatic navigation and automatic control of the autonomous driving system. The system is embedded with the AI algorithm for image recognition, as well as an on-board unit (OBU) and RSU for communication. Driving safety is improved through improved GPS positioning and communication security [140]. Using this testbed, DRL-based automatic driving control, DNN-based driving behavior prediction, CNN-based target detection, and other algorithms are proposed and tested. The European Commission proposes the Coordinated Automated Road Transport (C-ART) project, which applies scenarios that coexist with AVs and traditional vehicles, and fully affirms the effectiveness of driving safety aids such as FCW with V2I communication [141]. Cooperative ITS and V2X communication are expected to make road traffic safer. Nanyang Technological University (NTU Singapore) and M1 Limited (M1) are cooperating to build a 5G C-V2X testbed. C-V2X communication is used to enhance traffic safety by transmitting real-time traffic navigation and hazard information to users [142]. From 2011 to 2015, under the funding of the European Union, the University of Twente, SIT, AISEC, and other units launched the PRESERVE project to solve key issues such as performance, scalability, and deployability of the V2X security system. The project proposed hardware, software, and security certificate architectures that comply with V2X security standards, such as harmonized V2X security architecture, implementation of V2X security subsystem, as well as cheap and scalable security ASIC for V2X.

B. Industrial Testbeds and Projects

Generally speaking, the realization of vehicle CA system in the industry mainly relies on radar or camera. For example, Volvo's City Safety system is a combination of monocular cameras and millimeter-wave radar sensors, and BMW Driver Assistance Pro uses ultrasonic radar, millimeter-wave radar, and camera fusion. The Google Driverless Car uses the LiDAR on the roof of the vehicle to emit 64 laser beams. These vehicles have been tested in California for a long time, but how to avoid traffic accidents in the coexistence with traditional vehicles is still a problem to be solved. Tesla is also equipped with a lot of equipment, including 8 cameras, 12 ultrasonic sensors, and a radar facing forward. The Autopilot algorithm is tested on real vehicles, and the total number of vehicles is increasing rapidly, which together form an amazing test platform. It can be seen that the industry is mainly based on the combination of AI and data-driven solutions.

The implementation of the autonomous vehicle in the industry is based primarily on AI combined with data-driven solutions. On one hand, a variety of sensors make up the automatic driving perception system and large-scale user data (Tesla), which can capture a large amount of real test data and driving data. These data provide accurate, stable, and reliable input to the autopilot decision control module. On the other hand, these collected data are analyzed using deep learning AI techniques, and AI algorithms are trained to determine the driving environment and scheme of the vehicle. Core algorithms include lane detection, obstacle detection, target tracking, trajectory management, prediction algorithms, and control algorithms.

In addition, the industry has some organizations to evaluate the active safety of automobiles, such as IIHS&NHTSA in the United States, Euro-NCAP in Europe, J-NCAP in Japan, C-NCAP, and i-VISTA in China. The test content of active safety mainly includes forward collision warning (FCW), lane departure warning (LDW), ACC, etc.

In 2017, the US Federal Transportation Administration (FTA) provided Pierce Transit with a grant of US $1.66 million for research and demonstration projects on bus collision avoidance. The scope of the project includes the pedestrian avoidance safety system (PASS), which uses lidar sensors to trigger an automatic deceleration and braking system. The Alpha test stage realized the collision avoidance and automatic braking system based on light detection and ranging, and completed the verification of the system. The potential benefit of this technology is that the technology cost is low and old cars can be retrofitted [143].

In Europe, AUDI AG, Ducati, Ericsson, SWARCO, the Technical University of Kaiserslautern, and Qualcomm launched Europe's first demonstration of direct C-V2X communication between motorcycles, vehicles, and roadside infrastructure. The European C-V2X testbed uses Qualcomm's V2X chipset solution, SWARCO's V2V and V2I communications, and Ericsson's 4G/5G cellular test network. The demo demonstrates how the Audi Q7, Audi A4, and motorcycles use C-V2X technology for intersection warnings to improve road safety [144]. In addition, the H2020 5GCroCo project aims to provide cross-border cooperative, connected and automated mobility (CCAM) services. Among them, the Anticipated Cooperative Collision Avoidance (ACCA) was deployed on the Barcelona small-scale trial site, including infrastructure, vehicles, and ACCA backends deployed in MEC and public clouds [145].

In summary, academic projects and testbeds mainly start from both communication and autonomous driving, fully affirming the role of communication technologies in the CA system. The industry is more concerned with the intelligence of the vehicle itself, using the on-board sensors to sense and make decisions about the surrounding driving environment. However, from the current situation that there are still misjudgments and accidents in autonomous vehicles. We can infer that using communication technologies to connect vehicles infrastructure, pedestrians will be the most promising means to solve the problem.

VIII. Challenges and Research Directions

Through long-term efforts in various research fields, potential traffic accidents have been effectively avoided. However, the current hybrid traffic scenario, inaccurate sensing data, communication, and computing resources, as well as the design of CA algorithms pose challenges to the complexity, flexibility, accuracy, and effectiveness of CA systems. In addition, the security and privacy issues of vehicles and data will also bring traffic safety issues. Therefore, an in-depth research is needed in these aspects.

A. Hybrid Traffic Scenarios

For the foreseeable future, there will be a hybrid traffic scenario where CAVs and driver-controlled (or common) vehicles coexist. In CA systems, accurate predictions of driving behaviors and driving trajectories are important. Although algorithms such as HMM, DBN, and RNN [4], [34], [37], [127] improve the accuracy and effectiveness of predictions, there are still challenges in applying this mixed scenario. Unlike CAVs, the drivers' behavior is flexible and makes predictions more difficult. For the hybrid traffic scenario, game theory is a viable tool for analyzing the interaction between CAVs and driver-controlled vehicles [46].

B. Inaccurate Data

Inaccurate sensing data will seriously affect the accuracy of the CA system and driving safety. On one hand, as time goes on, the aging of the sensor will cause their performance degradation. On the other hand, external environmental factors such as light, rain, and snow can reduce the accuracy of sensing. In addition, the quality of the communication link determines whether the data can be transmitted accurately and timely. Many efforts in this area have made efforts to improve data accuracy to some extent, such as data fusion, and data error correction. For example, authors in [146] propose to fuse GPS and IMU information to improve the robustness and accuracy of autonomous vehicle positioning. In [147], authors fuse LiDAR, GPS, and IMU data together, and use convolutional neural networks to generate safe driving routes for vehicles. Therefore, in addition to the sensor itself, the use of AI technology to ensure that the system can make accurate judgments in a noisy data environment is still worthy of further study.

C. Scheduling of Communication and Computing Resources

In actual scenarios, vehicle users and service types are diversified, and the requirements between each other may also cross and conflict. The difference between these services and users will affect the performance of the network [148]. Authors in [148] propose a dual-importance evaluation method to study the relationship between the priority of vehicles and the priority of contents. Safety-related applications need to respond extremely quickly, or they can have serious consequences. The increase in vehicles and data poses a huge challenge to limited communication and computing resources. The allocation of communication resources in traffic scenarios will inevitably affect the allocation of computing resources and vice versa. The current communication architecture and computing resource allocation schemes cannot effectively meet the requirements of safe driving, and relying on a single resource cannot provide reliable, efficient, and low-latency information services. The lack of information transfer will not complete the calculation and processing work quickly. Conversely, communication resources will not provide safer and better quality communication services if they do not coordinate computing resources. Future research can achieve an efficient and rational allocation of two types of resources according to the delay sensitivity of the business by integrating the characteristics of different services and different users.

D. CA Algorithm Design

On one hand, the complexity of the traffic scenario makes the design of the CA algorithm need to consider more influencing factors. On the other hand, the source, type, and volume of sensing data will also increase. These characteristics have higher requirements for the adaptability, flexibility, scalability, and complexity of the CA algorithms. With deep learning techniques, data processing and analysis performance can be increased, making the CA algorithm more suitable for the environment. In addition, the adaptability of a single method in a variable scenario and the performance of extending to a new scenario can be greatly challenged. Therefore, when designing the CA algorithm, we need to consider the characteristics of different AI algorithms, so as to quickly and accurately assess the driving environment and eliminate potential hazards.

E. Security and Privacy

Another major area of concern is security and privacy issues. Current vehicle information interaction is frequent and complicated and faces threats such as information leakage and hacker attacks. As vehicles become more intelligent, the attack surface is also increasing. In addition to the sensor and vehicular communication security, it also includes operating system and control system security. How to ensure the security of additional components and external information required for safe driving, as well as the new external interface required for autonomous driving, is full of challenges. Key component system reinforcement technology, sensor abnormal data recognition technology, CAN bus authentication encryption technology, OTA data packet encryption, and digital signature technology, and vehicle IDPS technology can be used to provide security protection for cars. Communication security also needs to focus on ensuring the confidentiality, integrity, and availability of data. In addition, it is necessary to take advantage of the decentralization of emerging technologies such as blockchain to realize secure data storage and interaction. For example, authors in [149] and [150] use blockchain to safely store and share vehicle data.

IX. Conclusion

We surveyed the state-of-the-art researches for state-of-the-art data-driven CA techniques. The large volume of sensing data places higher demands on data transmission and processing, which makes it challenging to implement effective and reliable CA using vehicular sensors, communication, and computing technologies. We explored the applications of deployed or candidate sensing technologies, communication technologies, and AI-based collision avoidance algorithms in driving safety. By classifying the reviewed literature, we developed a more comprehensive foundation for the readers to understand the three basic phases of CA design and how the current popular AI algorithms are applied in different aspects of the CA system. Finally, we discussed current challenges and future research areas for researchers to refer to and carry out further studies.

The current challenges in improving traffic safety are multifaceted, so there is still much room for further research in this

TABLE VIII
LIST OF ACRONYMS

Acronym	*Explanation*	*Acronym*	*Explanation*
ABS	Automatic Brake System	ACC	Adaptive Cruise Control
ACS	Automatic Control System	ADAS	Advanced Driver Assistance System
AI	Artificial Intelligence	ANN	Artificial Neural Network
AV	Autonomous Vehicle	BF	Bayesian Filter
BM	Boltzmann Machine	BPNN	Back Propagation Neural Network
CA	Collision Avoidance	CACC	Cooperative Adaptive Cruise Control
CAV	Connected Autonomous Vehicle	CHMM	Coupled Hidden Markov Model
CICA	Cooperative Intersection Collision Avoidance	CNN	Convolutional Neural Network
C-V2X	Cellular-based V2X	DBM	Deep Boltzmann Machine
DBN	Dynamic Bayesian Network	DoS	Denial of Service
DQN	Deep Q-Network	DRL	Deep Reinforcement Learning
DSRC	Dedicated Short-Range Communications	EHF	Extremely High Frequency
EKF	Extended Kalman Filter	FCW	Forward Collision Warning
GPS	Global Positioning System	HD Maps	High Definition Maps
HMM	Hidden Markov Model	IMU	Inertial Measurement Unit
ITS	Intelligent Transportation Systems	IoV	Internet of vehicles
KF	Kalman Filter	KPI	Key Performance Indicator
LDW	Lane Departure Warning	LSTM	Long Short-Term Memory
MAC	Medium Access Control	MEC	Mobile Edge Computing
MIMO	Multiple-Input-Multiple-Output	MLP	Multi-Layer Perceptrons
mmWave	Millimeter-Wave	MOG	Mixture of Gaussians
NOMA	Non-Orthogonal Multiple Access	NN	Neural Network
OFDM	Orthogonal Frequency-Division Multiplexing	PCW	Pedestrian Collision Warning
QoS	Quality of Service	RNN	Recurrent Neural Network
RSU	RoadSide Unit	RVM	Relevance Vector Machines
SDN	Software Defined Network	SVM	Support Vector Machine
TTA	Time-to-Avoidance	TTB	Time-to-Brake
TTC	Time-to-Collision	TTK	Time-to-Kickdown
TTR	Time-to-React	TTS	Time-to-Steer
UAV	Unmanned Aerial Vehicle	UI	User Interface
UKF	Unscented Kalman Filter	V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle	V2X	Vehicle-to-Everything
VK	Vehicle Kinematics	VLC	Visible Light Communications

area. The intelligence and networking of vehicles contribute to the improvement of driving safety from different perspectives. In the future, on one hand, in the face of increasing sensor data, data fusion technology is worthy of attention. The future increase in vehicle sensing data and user service data requires an AI-based solution to process data and learn user requirements in a relatively short period of time. On the other hand, the application of communication technology realizes data sharing, which improves the efficiency and accuracy of the CA system. However, although research work and standard setting have been carried out, more practical testing is still needed. In addition, AI-based algorithms are a focus of this survey, including applications in perception data fusion, communication performance improvement, and CA algorithm design. After investigating related algorithms and progress, we summarized the corresponding challenges and unsolved problems and tried to propose preliminary solutions, which are convenient for researchers to refer to and conduct further research.

Academically, although many current algorithms can accurately identify dangerous situations and take timely and accurate warning measures in specific scenarios, it is still necessary to carefully evaluate the scalability and reliability of these algorithms. The hybrid traffic scenarios where the CAVs and the traditional driver-controlled vehicles coexist will last for a while, which will have huge impacts on the design of CA systems. Driver factors are still not negligible in algorithm design, which brings a lot of uncertainty. The AI-based algorithms need to be further explored to adapt to current traffic conditions and enhance the ability to handle uncertainty.

APPENDIX

We summarize the definitions of the acronyms that will be frequently used in this paper in Table VIII for ease of reference.

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Yuchuan Fu (Member, IEEE) received the Ph.D. degree from the School of Telecommunications Engineering, Xidian University, Xi'an, China, in 2020. From 2018 to 2019, she was a joint Ph.D. Student with Carleton University, Ottawa, ON, Canada. She is currently a Lecturer with the State Key Laboratory of ISN, School of Telecommunication Engineering, Xidian University. Her current research interests include algorithm design in vehicular networks and autonomous driving.

Changle Li (Senior Member, IEEE) received the Ph.D. degree in communication and information system from Xidian University, China, in 2005. He conducted his post-doctoral research in Canada and the National Institute of information and Communications Technology, Japan, respectively. He had been a Visiting Scholar with the University of Technology Sydney. He is currently a Professor with the State Key Laboratory of Integrated Services Networks, Xidian University. His research interests include intelligent transportation systems, vehicular networks, mobile ad hoc networks, and wireless sensor networks.

Fei Richard Yu (Fellow, IEEE) received the Ph.D. degree in electrical engineering from The University of British Columbia (UBC) in 2003.

From 2002 to 2006, he was with Ericsson, Lund, Sweden, and a start-up in California, USA. He joined Carleton University in 2007, where he is currently a Professor. His research interests include connected/autonomous vehicles, security, artificial intelligence, blockchain, and wireless cyber-physical systems. He is a fellow of IET and the Engineering Institute of Canada (EIC). He is an Elected Member of the Board of Governors of the IEEE VTS. He received the IEEE TCGCC Best Journal Paper Award in 2019, the Distinguished Service Awards in 2019 and 2016, the Outstanding Leadership Award in 2013, the Carleton Research Achievement Awards in 2012 and 2021, the Ontario Early Researcher Award (formerly Premiers Research Excellence Award) in 2011, the Excellent Contribution Award at IEEE/IFIP TrustCom'10, the Leadership Opportunity Fund Award from Canada Foundation of Innovation in 2009, and the Best Paper Awards at IEEE ICNC'18, VTC'17 Spring, ICC'14, Globecom'12, IEEE/IFIP TrustCom'09, and Int'l Conference on Networking 05. He has served as the technical program committee (TPC) co-chair of numerous conferences. He serves on the editorial boards of several journals, including the Co-Editor-in-Chief for *Ad Hoc & Sensor Wireless Networks*, a Lead Series Editor for IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE COMMUNICATIONS SURVEYS & TUTORIALS, and IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING. He is the Editor-in-Chief for *IEEE VTS Mobile World newsletter*. He has been named in the Clarivate Analytics list of Highly Cited Researchers in 2019 and 2020. He is an IEEE Distinguished Lecturer of both Vehicular Technology Society (VTS) and Communication Society. He is a registered Professional Engineer in the province of Ontario, Canada.

Tom H. Luan (Senior Member, IEEE) received the B.Eng. degree from Xi'an Jiaotong University, China, in 2004, the M.Phil. degree from the Hong Kong University of Science and Technology in 2007, and the Ph.D. degree from the University of Waterloo, Waterloo, ON, Canada, in 2012. He is currently a Professor with the School of Cyber Engineering, Xidian University, Xi'an, China. His research mainly focuses on content distribution and media streaming in vehicular ad hoc networks and peer-to-peer networking, as well as the protocol design and performance evaluation of wireless cloud computing and edge computing. He has authored/coauthored more than 40 journal articles and 30 technical papers in conference proceedings, and awarded one U.S. patent. He served as a TPC member for IEEE Globecom, ICC, and PIMRC. He served as a Technical Reviewer for multiple IEEE Transactions, including IEEE TRANSACTIONS ON MOBILE COMPUTING, IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, and IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS.

Yao Zhang received the B.Eng. degree in telecommunication engineering from the Xi'an University of Science and Technology, China, in 2015. He is currently pursuing the Ph.D. degree in telecommunication engineering with Xidian University, Xi'an, China. His current research interests include communication protocol and performance evaluation of vehicular networks, edge caching, and wireless sensor networks.