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Review

A Review of Intelligent Connected Vehicle Cooperative Driving Development

Biyao Wang [1], Yi Han [1,*], Siyu Wang [1], Di Tian [1], Mengjiao Cai [2], Ming Liu [3] and Lujia Wang [3]

1 Department of Automobile, Chang'an University, Xi'an 710064, China
2 Shaanxi Institute of Coal Science, Xi'an 710043, China
3 Department of Electronic and Computer Engineering, The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong SAR, China
* Correspondence: hany@chd.edu.cn; Tel.: +86-132-2805-5890

Abstract: With the development and progress of information technology, especially V2X technology, the research focus of intelligent vehicles gradually shifted from single-vehicle control to multi-vehicle control, and the cooperative control system of intelligent connected vehicles became an important topic of development. In order to track the research progress of intelligent connected vehicle cooperative driving systems in recent years, this paper discusses the current research of intelligent connected vehicle cooperative driving systems with vehicles, infrastructure, and test sites, and analyzes the current development status, development trend, and development limitations of each object. Based on the analysis results of relevant references of the cooperative control algorithm, this paper expounds on vehicle collaborative queue control, vehicle collaborative decision making, and vehicle collaborative positioning. In the case of taking the infrastructure as the object, this paper expounds the communication security, communication delay, and communication optimization algorithm of the vehicle terminal and the road terminal of intelligent connected vehicles. In the case of taking the test site as the object, this paper expounds the development process and research status of the real vehicle road test platform, virtual test platform, test method, and evaluation mechanism, and analyzes the problems existing in the intelligent connected vehicle test environment. Finally, the future development trend and limitations of intelligent networked vehicle collaborative control system are discussed. This paper summarizes the intelligent connected car collaborative control system, and puts forward the next problems to be solved and the direction of further exploration. The research results can provide a reference for the cooperative driving of intelligent vehicles.

Keywords: intelligent connected vehicle; cooperative driving system; V2X; communication technology

JEL Classification: 68T01

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Citation: Wang, B.; Han, Y.; Wang, S.; Tian, D.; Cai, M.; Liu, M.; Wang, L. A Review of Intelligent Connected Vehicle Cooperative Driving Development. *Mathematics* **2022**, *10*, 3635. https://doi.org/10.3390/math10193635

Academic Editor: Aydin Azizi

Received: 8 August 2022
Accepted: 29 September 2022
Published: 4 October 2022

1. Introduction

Conducting research on intelligent connected vehicle systems will introduce a new stage of development in China's automotive industry and intelligent transportation industry [1]. In recent decades, single-vehicle-based intelligent driving technology made great progress. With sensors and processors loaded on the vehicles, some sample vehicles were implemented for demonstration operations on the road. However, there are still many problems to be solved [2], such as (1) inaccurate individual sensor readings; (2) the limited detection distance of on-board sensors; (3) the existence of blind areas for on-board sensor detection; (4) high costs of on-board computational processors; and (5) a lack of predictive mechanisms for other vehicle behaviors.

Specifically, the direction of automobile development is intelligent and networked. Intelligence includes the perception, decision making, and control of intelligent cars. Car intelligence is usually through the radar system (laser radar, millimeter wave radar, and ultrasonic radar) and visual system (camera) to collect the surrounding environment, and then through the vehicle computer and algorithm for data processing, it makes the optimal decision, the decision signal goes to the vehicle chassis control system, and the intelligent control is realized [3]. Networking refers to the function of communication and real-time information between the network environment and real-time information interaction, which can be divided into vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N), and vehicle-to-pedestrian (V2P). An intelligent connected vehicle generally refers to a single vehicle to achieve intelligence through sensor technology. At present, in order to improve the safety and comfort of intelligent vehicles, intelligent connected vehicles, in addition to directly perceiving the environment to make decisions, also need to have the ability to cooperate and act, and reflect the advantages of multi-vehicle intelligence through the cooperation and coordination of vehicle to vehicle [4].

In the development and advancement in vehicle-to-everything (V2X) technologies, including vehicle-to-vehicle communication technologies and vehicle and roadside infrastructure communication technologies, collaborative vehicle infrastructure systems (CVIS) and information factors play an increasingly important role in transportation systems [5–7]. Intelligent collaborative vehicle control based on vehicle–road cooperation will enable all-round information sensing and compensate for the lack of on-board computing power, which is a future direction in this field. Under the conditions of intelligent networks, vehicles on the road are no longer isolated individuals but multi-vehicle systems formed by wireless communication networks. In the vehicle network environment, intelligent vehicles can obtain information about other vehicles and roads within the communication range based on workshop communication and vehicle–road communication, and they use this information for distributed decision making and control in order to realize the collaborative control of the whole system. At present, the development of technologies, such as vehicle–road cooperation and vehicle–vehicle communication became a breakthrough in the development of single-vehicle agents in the intelligent network environment [8]. The European SAFESPOT project [9], the U.S. path project [10], and the Japanese Smartway project [11], etc., researched and explored the field of vehicle–road cooperation from various aspects by establishing an experimental platform to verify the technical problems in the process of vehicle–road cooperation in an effort to achieve intelligent information sharing between vehicles and road facilities, and ultimately ensure traffic safety and improve traffic efficiency. Among them, the intelligent connected vehicle formation, as a kind of both traffic efficiency and traffic safety mode, through the real-time communication and coordination between vehicles, makes full use of road infrastructure, simplifies the complexity of traffic control and management, improves road capacity, eases traffic congestion, reduces environmental pollution, has great potential, and is the new way of road vehicle traffic in the future. Intelligent connected vehicle formation is mainly for more intelligent snatched vehicles in a complex traffic environment. By adjusting their driving speed and steering, it makes itself and nearby intelligent connected vehicles keep relatively stable geometric posture and the same movement, and meets the task requirements and constraints (such as obstacle avoidance), so as to realize more intelligent connected vehicles between wireless communication collaborative driving behavior. The main technologies involved in the autonomous vehicle formation include: vehicle combination positioning and multi-sensor and multi-source information fusion technology, collaborative formation control technology, and cooperative perception and communication technology. In this context, this paper focuses on the intelligent vehicle cooperative control system in the vehicle networking environment.

In the 1980s, some scholars put forward the concept of formation system control. After the 1990s, the problem of multi-vehicle formation gradually attracted more and more researchers. At present, the formation control of multi-vehicle cooperative system mainly includes following the pilot method, virtual structure method, artificial potential energy field method, virtual pilot method, and behavior-based method. Benefits of a vehicle–road collaborative intelligent system are as follows: firstly, from the perspective of safety, many bicycle intelligent scenarios can be easily solved through intelligent roads and powerful cloud network facilities. Secondly, through the intensive construction of intelligent roads and the intelligent cloud network, intelligent capabilities can be shared by all the cars on the road to reduce the amount of cars, reduce the cost of the car, thus reducing the cost of the whole automatic system. From the perspective of the three parts of autonomous driving perception, decision making and control, the perception of bicycle intelligence is only based on its own sensors, with blind spots and dead corners. The vehicle-road collaborative "intelligent look" can be based on the sensor network on the road, namely based on the 5G "car-road-side-edge-cloud" level 4 fusion data processing system network, covering vehicle perception data, roadside perception data, edge, area, central cloud access of traffic/road data, environment/public service data, and other basic service platform data, no dead angle, and long distance, also called "god perspective". The intelligent decision of a bicycle vehicle can only be made based on its own incomplete information, which cannot be taken into account by other vehicles, so the decision result is locally optimal. Vehicle–road collaborative intelligence can comprehensively take into account the next movement trend of all cars, so as to make a comprehensive and optimal decision result. Based on such advantages, vehicle-to-road collaborative intelligence can achieve very good driving safety and economy.

In this context, the research of this paper focuses on intelligent connected vehicle cooperative driving development. The overall framework of the article is shown in Figure 1. The intelligent vehicle cooperative driving system is discussed, and the latest developments in vehicle network cooperative driving are introduced.

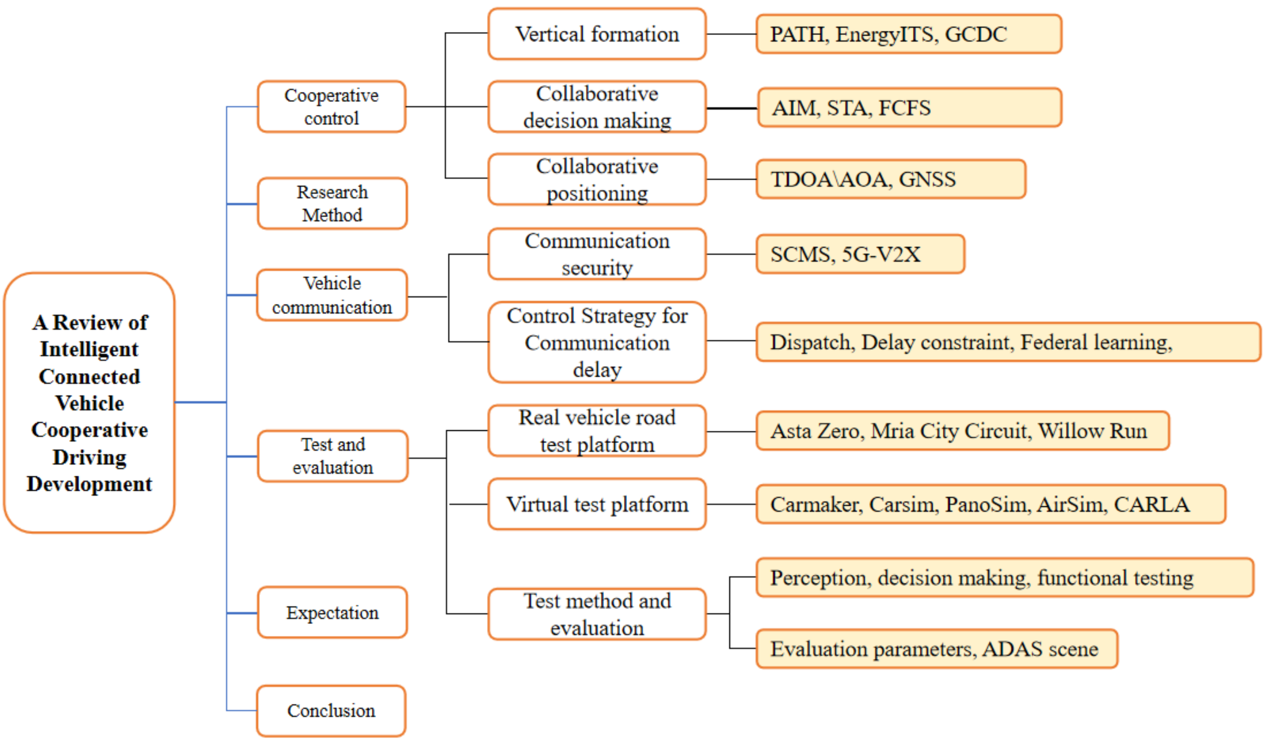


Figure 1. Structural framework.

The remainder of this paper is organized as follows: Section 2 presents the selection methods of the references and details the literature screening process for the systematic review and the preferred reporting guidelines for the meta-analysis. Section 3 describes the details and problems of the collaborative control algorithms for intelligent vehicles. Section 4 describes current situation and problems of the exit vehicle and internet communication. Section 5 explains the test platform and evaluation system of the intelligent vehicle collaborative control system. Section 6 summarizes the current status of the study and suggests directions for future research. Finally, the article is summarized in Section 7.

2. Research Method

In this paper, preferred reporting items for systematic reviews and meta-analysis (PRISMA) are used to analyze the literature to review the cooperative development of intelligent and connected vehicles [12,13].

2.1. Literature Search

Relevant Chinese and English literature of eight databases, including Google Academic, Web of Science Core Collection, Inspec, KCI-Korean Journal Database, SciELO Citation Index, IEEE Xplore, and China Knowledge Network of China and Baidu Academic, were searched. The following search keywords will include the following four categories:

(1) intelligent vehicle cooperative development, intelligent connected vehicles;
(2) vehicle queue, collaborative positioning, collaborative control and decision, multi-vehicle, CACC;
(3) communication security, communication delay, and internet of vehicles;
(4) intelligent connected vehicle test platform, test software, experimental method and evaluation system.

The selection of keywords can be divided into three levels: layer 1 is the Chinese and English keywords related to intelligent vehicle cooperative development; layer 2 is a general name, generic name or nickname, such as "vehicle collaborative control technology", "Intelligent connected vehicle communication", "Intelligent connected test platform, evaluation system" and its corresponding English name; layer 3 is the specific classification name, such as the vehicle queue, communication security, vehicle road collaborative positioning, and selects their respective names as the search keywords. The above three layers of keyword search and classification provide a complete summary of the collaborative control system from the aspects of concept, general classification and classification, so a comprehensive and detailed research literature can be obtained accordingly. Some of the search keywords were not listed because there was no relevant literature under the entry, or the retrieved literature was repeatedly recorded by other keywords.

2.2. Literature Screening

The literature screening process used in this paper and the literature screening situation at each stage are shown in Figure 2, and the n is the number of documents. First, the relevant literature of eight databases was searched according to the keywords mentioned above. Secondly, the repeated literature between databases was eliminated and the subject and content were screened. Finally, the evaluation indicators of these literature were scored for quality, and the literature finally included in the review was determined according to the scoring results.

In terms of literature quality scoring standards [14–16], this paper constructs the literature quality evaluation indicators required by the research of the intelligent connected vehicle cooperative control system, as shown in Table 1. Specifically, score 2 if the indicator answers "Yes", 1 if it answers "Not exactly Yes", and 0 if the indicator answers "No". Among them, the literature quality score of 17 or above is excellent, while 12–17 is classified as qualified, and that of 12 or below 12 points is unqualified. Only qualified and above documents are retained, and unqualified documents are excluded. The whole literature was scored by two authors, respectively, and the literature with a difference of less than three and the final score was decided by two people through discussion. If the scoring results of either literature are quite different (the score difference is greater than 3), the remaining two authors will make a decision on the scoring results.

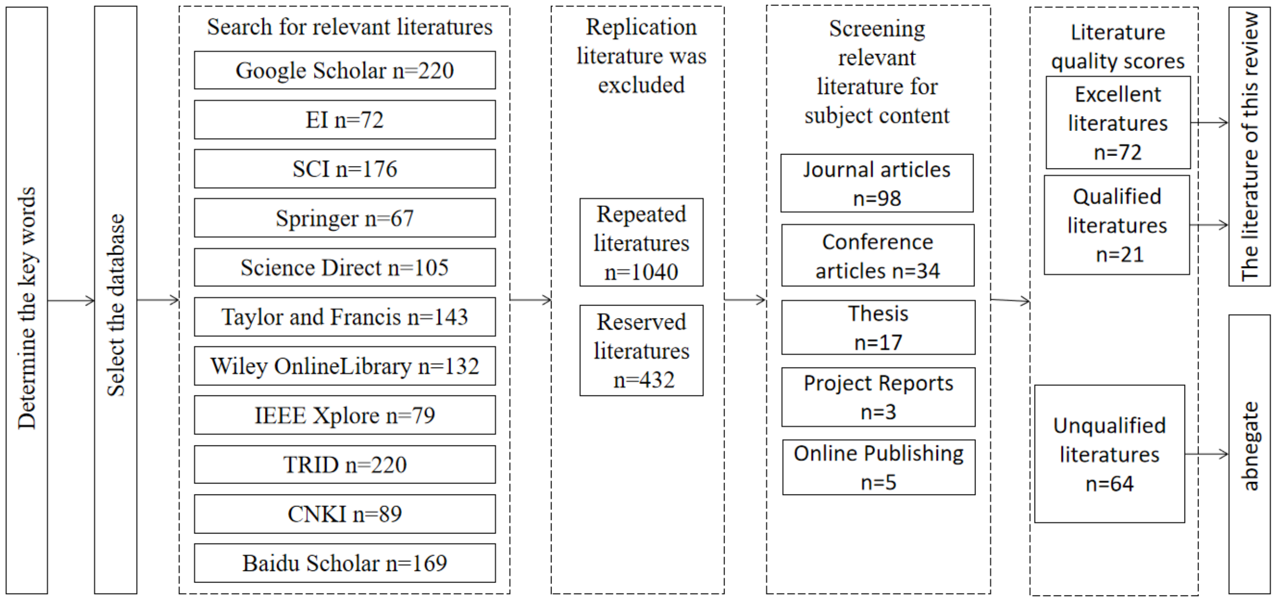


Figure 2. Literature screening process.

Table 1. Measurement Indexs of Literature Quality.

Number	Literature Quality Assessment Index	Marking
1	Is the motivation clear?	Yes is 2, Not exactly 1, No is 0
2	Are the hypotheses/questions under study clearly and adequately stated?	Yes is 2, Not exactly 1, No is 0
3	Is the study design suitable for the study purposes?	Yes is 2, Not exactly 1, No is 0
4	Does the study clearly describe the type or characteristics of collaborative control clearly?	Yes is 2, Not exactly 1, No is 0
5	Is the test environment clearly described?	Yes is 2, Not exactly 1, No is 0
6	Is the way of data collection is clear and reasonable?	Yes is 2, Not exactly 1, No is 0
7	Are all the influencing factors strictly restricted in the experimental studies?	Yes is 2, Not exactly 1, No is 0
8	Are the data fully analyzed?	Yes is 2, Not exactly 1, No is 0
9	Are the investigation or test results clearly stated?	Yes is 2, Not exactly 1, No is 0
10	Are the study conclusions fully discussed?	Yes is 2, Not exactly 1, No is 0
11	Is there any lack of research and prospects?	Yes is 2, Not exactly 1, No is 0

2.3. Information Extraction

After eliminating the unqualified literature of all the literature included in the review of standardized information extraction, the following data are extracted from the literature: ① author and publication year, ② country and region, ③ research object, ④ sample size, ⑤ research length, ⑥ research method, ⑦ research index, ⑧ influence factors, and ⑨ literature conclusion. In order to ensure the accuracy of literature information extraction, two authors were, respectively, responsible for the relevant literature information extraction, and two other authors randomly selected 10 documents from each part for information verification to ensure reliability.

2.4. Comprehensive Analysis of the Literature Results

Quantitative analysis cannot be performed directly due to the heterogeneity of the different studies. Therefore, the results of the screened literature were systematically summarized and reported by narrative comprehensive analysis. Specifically, the steps of this analysis include determining the review problem, sorting out and comparing the data, and drawing conclusions.

3. Cooperative Control

3.1. Vertical Formation

The development of intelligent transportation technology has advantages in solving the problems of low traffic efficiency, poor safety, and high energy consumption. V2X-based traffic environment information sensing and interaction technology enables vehicles in the road network to obtain real-time status information about other vehicles within communication range, identify vehicle driving intentions through model predictive reasoning, adjust driving strategies, and ensure vehicle driving safety [17]. V2X technology lays the foundation for the development of vehicle group operation. Vehicle group operation is an important means to improve road traffic efficiency; when vehicle group driving, on the one hand, with the increase in the number of vehicles in line, the driving resistance coefficient of each vehicle decreases, so the driving mode of the vehicle group can reduce the vehicle driving resistance and reduce energy consumption. On the other hand, vehicle group driving can reduce traffic stress by integrating vehicle driving states, reducing the vehicle following distance, and improving road occupancy [18]. Therefore, the team operation mode will be a future development trend in self-driving vehicles.

The vehicle platoon driving system is also called the cooperative adaptive cruise system, and its structure is shown in Figure 3. Through the introduction of inter-vehicle communication, the vehicle platoon driving system realizes the information transmission and sharing between connected vehicles, and can achieve continuous tracking control of multiple vehicles, ensure vehicle safety, and improve the performance of the entire vehicle plat. The research on vehicle platoons began in the early 1990s with the Partnership for Advanced Transportation Technology (PATH) project in the United States [19,20], as shown in Figure 4a. Japan and Europe also launched related projects on vehicle platoons, such as Japan's Energy ITS project [21], the Grand Cooperative Driving Challenge (GCDC) in Europe as shown in Figure 4b [22,23], etc. In recent years, there were many studies related to vehicle queues in China. For example, the vehicle platoon of Chang'an Automobile CS55 is shown in Figure 4c, and the Baidu 6-vehicle mixed fleet is shown in Figure 4d shown [24,25].

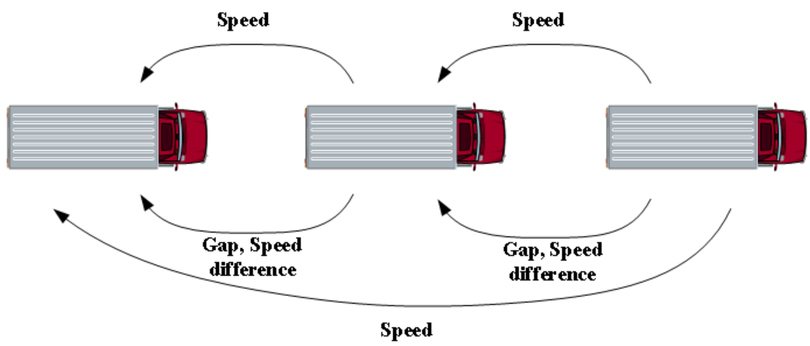
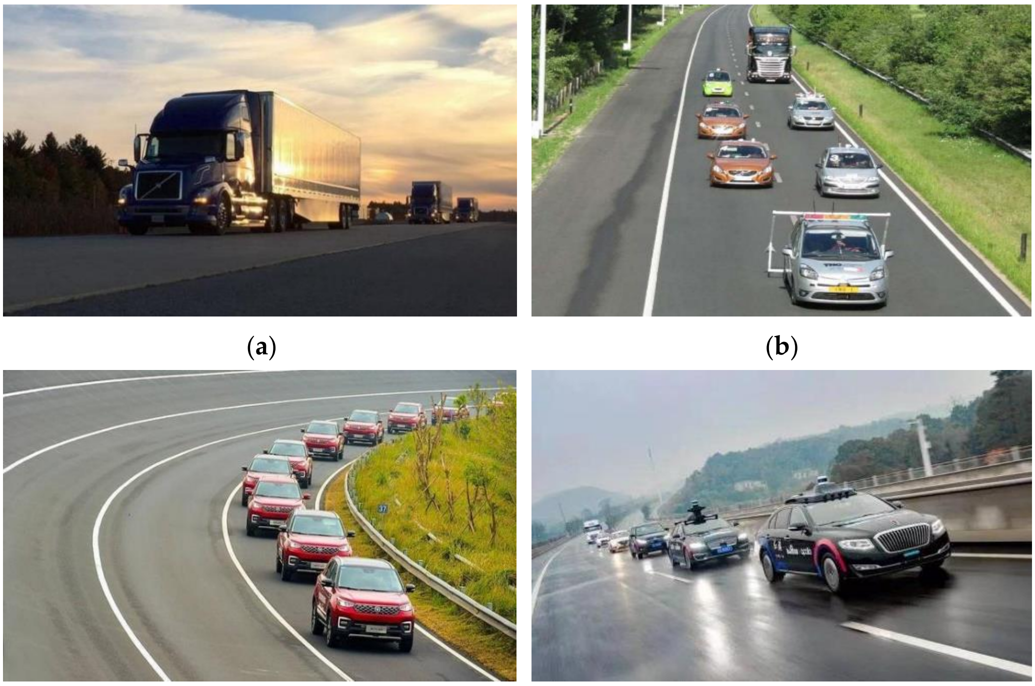


Figure 3. Vehicle platoon structure.

The ideal distance between vehicles is also referred to as the geometric configuration. It is used to describe the relative position or attitude between the controlled vehicle and the driver's vehicle in a steady state. Different spacing control strategies can affect the safety and stability of the vehicle queue. By maintaining a reasonable distance, aerodynamics can effectively use the traction effect to improve fuel economy. In the 1890s, scholars such as Loannou P.A. and Swaroop D. proposed a fixed forward constant time headway (CTH) strategy to maintain a distance between front and rear vehicles. In 1997, Yanakiev [26] also considered the vehicle speed and acceleration when developing a headway control strategy. In 2004, Fred Browand [27], a scholar at the University of Southern California, considered the situation of two trucks tailing each other. The model predictive control (MPC) approach has three typical features: model prediction, rolling optimization, and feedback correction. It allows for better advanced control and online roll optimization calculations. It is suitable for complex systems where it is difficult to build accurate numerical models. Memon [28] developed a continuous time-domain vehicle model based on MPC techniques that can capture the steady state and transient states of the vehicle in real time. It focuses on the critical state characteristics of the vehicle response of adaptive cruise control (ACC). Through simulation, it was verified that the ACC model controlled by MPC has high sensitivity and can truly reflect the behavior of the actual vehicle.



(**a**) (**b**)

(**c**) (**d**)

Figure 4. Vehicle queue display [25]: (**a**) US path truck queue; (**b**) European GCDC mixed queue driving competition; (**c**) driving demonstration of 55 Chang'an Cs55; and (**d**) Baidu 6-car mixed queue driving display.

In recent years, with the gradual maturity of the ACC system, its cost reduced, and ACC technology fell to the 100,000 range. For example, Nissan's Sylphy and Versa are equipped with an ACC system. Pan Chaofeng et al. [29] detailed the components, design methods, and research hotspots of the ACC, and reviewed future research directions and development trends. In addition, CACC can realize collaboration with traffic signals, and alvert Simeon C et al. [30] realized the interaction with intelligent traffic signals by queuing suburban trunk lines in real traffic. In addition, YuanHeng Zhu et al. [31] proposed a new control structure for the vehicle queue with multiple front vehicles, transforming the heterogeneous CACC problem into the adjustment problem of each error dynamic, and ensuring the stability of the minimum front time distance of the vehicle queue through the sum of square planning. Shuaidong Zhao et al. [32] proposed a model predictive control method based on distributed robust stochastic optimization for collaborative adaptive cruise control under uncertain traffic conditions, which then improves the stability, robustness, and safety of longitudinal collaborative autonomous driving with multiple CAVs. In the process of car following, CACC's coordination ability and adaptability of various goals are a very important part in the complex and changeable driving environment. Yang, Ld et al. [33] adjusts the weighted value according to the deceleration duration and the deceleration change, and increases the relative distance between the two cars under a deceleration condition. In addition, Chen JZ et al. [34] proposed an improved variable front time distance strategy for the collaborative cruise control system, which redesigned the second-layer controller on the basis of existing technologies, and verified the effectiveness of the strategy through the simulation of two traffic scenarios. Liang H et al. [35] proposed a new consensus-based input saturation and variable workshop time–distance control method, considering the communication delay in the algorithm. At present, some researchers carried out the study of applying the communication between the multiple front vehicles to the collaborative adaptive cruise system, so that the communication between the target vehicles and the multiple front vehicles is made. The current research on the CACC technology control method is mainly divided into classical control method, optimal control method, synovial control method, and machine learning-based method, which is the latest development trend.

3.2. Vehicle Collaborative Decision-Making and Control Strategy

Traffic congestion in signal road intersections became a central problem in both developed and developing countries. Collaborative decision making of vehicle control can solve this problem very well and reduce the traffic congestion problem at highway and road intersections [36]. Based on vehicle–road communication technology, vehicle–road cooperative decision making became a research hotspot within intelligent traffic organization systems. Vehicle–road collaborative decision making needs to realize active vehicle safety control and road collaborative management. Vehicle active safety control is divided into three directions, namely no signal intersection, road section between the adjacent intersection and road network. Seeking effective ways to maximize traffic at intersections, maximizing traffic flow, while considering various factors, the rapid development of truth–time strategy, signal timing limit, traffic system, speed, and other actual implementation are our goals [37]. First, for non-signalized crossing, autonomous intersection management (AIM) is more effective than signal timing assignment (STA) [38]. Research on the spatial dispersion of road intersections is mostly based on the first-come-first-served (FCFS) traffic principle [39–41], which is more prone to delays than STA. Based on the analysis of intersection conflict points, one can overcome the shortage of reserved space for an intelligent driving vehicle at the whole intersection [42–46]. Some researchers study methods that are different from FCFS by optimizing the departure sequences of intelligent vehicles at intersections, such as optimizing the departure sequence of conflict traffic flow [47–51], sharing control based on the real-time traffic state at intersections [52], adaptive traffic decision making based on insertion [53], distributed conflict resolution mechanisms [54], etc. Secondly, for the adjacent intersection link, the trajectory can be optimized by speed coordination. Hamilton and Euler–Lagrange equations are constructed to obtain the analytical expressions of vehicle motion parameters [55]. On this basis, the vehicle trajectories between two intersections are optimized [56], the trajectory solving process is extended [57], and the existence of feasible solutions is proven. Bichiou et al. [58] estimated the arrival time of vehicles at intersections and solved the convex programming problem of the vehicle movement process according to the minimum principle. Finally, for the road network, the road network traffic organization method for intelligent driving vehicles is still in the initial stage of research. Guo et al. [59] focused on the road network scenario with multiple intersections, and Huasknecht et al. [60] introduced the internet of vehicles to study the performance of aim. Huang et al. [61] studied the design and evaluation of vehicle trajectory planning methods in a multi-intersection traffic network using an integrated simulator, and Chu et al. [62] studied vehicle trajectory optimization in road networks based on dynamic variable lanes. Milanes et al. [63] used vehicle-to-vehicle (V2V) communication technology to determine the vehicle speed and location at a signalized intersection, estimated the intersection location through these data, designed a fuzzy logic decision algorithm according to vehicle speed, and predicted the optimal vehicle speed trajectory by using short-range radar and traffic signal information. Liu et al. [64] regarded drivers and signalized intersections as automatic agents in a multi-agent system, and elaborated new mechanisms to imitate traffic signals and stop signs in the system. Since the factors influencing the collaborative control of vehicles exhibit complex interactions, these factors must be identified to propose solutions that can address this complexity and still need to be implemented.

In terms of road collaborative management, the accurate and effective prediction of vehicle traffic flow plays an important role in the construction and planning of signal intersections. The application of the AI prediction model in traffic flow performance prediction achieves positive results. However, there is still great uncertainty in determining which AI approach can effectively solve traffic congestion problems. Isaac Oyeyemi Olayode [36] et al. compared an artificial neural network trained by a particle swarm optimization model (ANN-PSO) and a heuristic artificial neural network model (ANN) for vehicle traffic flow prediction, using the South Africa transportation system as a case study. Results show that the ANN-PSO model is more efficient than the neural network model in predicting vehicle traffic flow at four-way signal intersections, and is robust enough to predict traffic flow. This research idea provides traffic flow information and guidance for the collaborative control system to optimize its travel time decision.

In the multi-vehicle queue forming control system, the system needs to be specially designed when individual vehicles need to leave or join the fleet. Ying ZB et al. [65] added a dynamic AVP management protocol to the control system for how to effectively manage the addition of vehicles and the leaving of vehicles in the vehicle queue. Vehicles joining and leaving the queue will need to communicate with the queue leader, and all the messages will be related to the corresponding transactions specified by the smart contract. Cai MC et al., for the real-time collaborative lane change and queue switching problems, [66] proposed a dynamic staggered hierarchical queue generation method, which introduces the lane change function of all vehicles, establishes the optimal problem model, and develops the on-board local controller of vehicles to ensure a safe distance between vehicles. Gao W et al. [67] proposed a spectrum-aware scheduling scheme for queue communication resource management for the problems of communication between queues when vehicles join queues, and shown through simulation results that the scheme achieves a smaller queue error when vehicles join multi-vehicle queues. Won M [68] proposed the concept of L-Platooning for especially long heavy trucks, the first queuing protocol that can seamlessly, reliably, and quickly form a long platoon, introducing a new concept—the virtual leader, a vehicle that acts as a platoon leader, to support the addition and departure of the long platoon. Fina NA [69] proposes an improved multi-mobility management protocol (IMMP) for queue, join, leave, and disrupt scheduling operations, where IMMP manages multiple connections and leave operations through vehicle-to-vehicle infrastructure and vehicle-to-vehicle communication, simultaneously. By verifying the design features of various systems using PROMELA and SPIN validation tools, the logical flow of IMMP is proposed, and the simulation results and analysis verify the behavior of the connection and departure process without affecting the safety of the entire system, this study shows that IMMP works successfully within an acceptable duration of mobility. Santini S et al. [70] proposed a longitudinal controller based on distributed consensus, while maintaining the stability and performance of the formation topology and control gain, showing the dynamic characteristics of the system and the addition, leaving performance in the middle of a typical set of queue maneuvers, and finally the simulation confirmed the feasibility of the strategy. Liu B et al. [71], for multi-vehicle queue forming control problem, proposed a distributed reinforcement learning method based on the deep Q-network and consensus algorithm; the queue problem is decomposed into multiple bicycle tasks, each car by interacting with the front and rear car accumulated experience data samples, and then uses the consensus algorithm to make all the vehicles in the scattered queue close to each other, which only needs to directly connect the communication between vehicles. Li LH et al. [72] combined graph theory and safety potential field (G-SPF) theory and proposed a new model of networked automatic vehicle (cav) under different vehicle distribution, which compared with previous studies, innovatively introduced the concept of safety potential field, better described the actual driving risk, ensured the absolute safety of the vehicle, put forward the four-step team optimization strategy, realized the optimization control of team pre-formation and team drive, and finally verified the effectiveness of the vehicle queue forming method based on G-SPF theory through simulation results. Dai SL et al. [73] uses the prescribed performance control methods, neural network approximation, interference observer, dynamic surface control technology, and Lyapunov method to comprehensively propose an adaptive formation control strategy to ensure the internal stability of the closed-loop system while guaranteeing the specified performance. In the vehicle collaborative decision making and control, the researchers gradually study the indicators, such as ride comfort and fuel economy, on the premise of ensuring the vehicle safety. Multi-objective optimization is now the future development trend.

3.3. Collaborative Positioning

The vehicle–road collaboration technology in the automotive internet integrates modern communication technology and network platforms. Through information sharing among vehicles, roads, and people, it realizes complex environmental sensing, collaborative decision making, and intelligent control functions to build a safe, comfortable, and energy-efficient automotive internet platform. Vehicle GPS technology is usually used to achieve positioning. Due to signal blockage and the multiplex effect, GPS positioning technology often suffers from missing signals or insufficient accuracy to achieve lane-level positioning accuracy and cannot meet the requirements of vehicle–road collaboration applications [74]. Cooperative positioning (CP) technology is another method to improve the positioning accuracy of vehicle–road collaboration networks [75].

Currently, using various methods to obtain more and more meters or even centimeter-level high precision position information research, based on the global navigation satellite system positioning technology, based on computer vision sensor positioning technology, based on the laser radar sensor positioning technology, and based on super broadband signal positioning technology, the four methods are the mainstream of the high-precision positioning technology route.

The global navigation satellite system is the existing and widely used positioning technology in the field of road traffic, and the GPS, Beidou, and other systems are integrated to improve the positioning accuracy and reliability of the positioning system. Zeng Qinghua and others of Nanjing University of Aeronautics and Astronautics proposed that the positioning method of multi-constellation-combined navigation can improve the accuracy of users. [76]. Robert Odolinski and others of Otago University also did relevant research in order to reduce the cost of RTK and improve the positioning accuracy, and proposed that [77] uses the measurement antenna to improve the positioning accuracy of the receiver. However, the impact on the interference of streamers and tall buildings on satellite signals is [78], and satellite signals are vulnerable to road conditions and weather, which will cause signal drift and signal loss, affect normal driving, and even cause safety accidents, which cannot meet the conditions of the high reliability requirements of the positioning system.

Computer visual positioning can be divided into: monocular visual positioning navigation, binocular visual positioning navigation, and multiocular visual positioning navigation [79–82]. These positioning and navigation technologies achieved good results in the research of visual positioning. However, bad weather can lead to poor work normally, and existing technology can only well solve the identification of specific targets. The complex scene of the social road cannot well identify any problems, nor can it meet the requirements of real-time and the reliability of the positioning system.

Lidar positioning technology uses adjacent point cloud data to derive the rigid body transformation [83] between two adjacent frames through feature extraction and a registration algorithm. Compared with other sensors, lidar has incomparable advantages in the unmanned positioning system, and the positioning algorithm, based on lidar sensors, plays an important role in the intelligent driving positioning module of [84,85].

Ultra wiband technology is a new wireless communication technology. Its positioning technology has low system complexity, low power consumption, good anti-interference ability, high multi-path resolution, and high positioning accuracy [86,87]. Kegen et al. [88]

proposed that in order to locate and track the target, we applied the Kalman filtering algorithm in an ultra-wideband positioning system.

Car–car and car–road information collaborative interaction drives multiple collaborative positioning applications, for example, car–car collaborative positioning [89], based on roadside positioning enhancement [90], car–car collaborative integrity monitoring [91], and beyond visual distance detection perception [92]; at the same time, it also greatly expands the traditional bicycle autonomous positioning weight calculation based on the perceptual range in the weight distribution and actual satellite observation quality level to establish closer correlations. Liu [93] et al. established the overall framework of vehicle satellite positioning and collaborative positioning enhancement based on vehicle–road information interaction for the tracking and adaptation of navigation satellite positioning and weight allocation in a complex dynamic operating environment. Based on high-precision mapping and multi-sensor fusion positioning technology, Yao [94] and others complement the advantages of various sensing and positioning methods, such as the global navigation satellite system and roadside multi-sensor sensing, and realize the continuous tracking and high-precision positioning of vehicles in urban ground and underground garage scenes. In view of the problem of large positioning errors of unmanned vehicles in unstructured scenarios, combined with on-board lidar and a roadside binocular camera, the dual-layer fusion collaborative positioning algorithm is adopted to achieve high-precision positioning.

Figure 5 [95] shows a typical cooperative localization system in which the participating nodes include vehicles and roadside infrastructure. The location of the roadside infrastructure is known and can receive GPS signals. The vehicle with a brighter color knows its GPS location, while the vehicle with a darker color does not obtain sufficient GPS signals to obtain its location information. However, it can estimate its own position data from the position information of neighboring nodes, i.e., it calculates its own position information from the position information of neighboring nodes received from neighboring nodes and the estimated distance between neighboring nodes. Positioning observation data are limited, and the evaluation of a collaborative localization system based on GPS/RSS/CFO can effectively improve the localization accuracy.

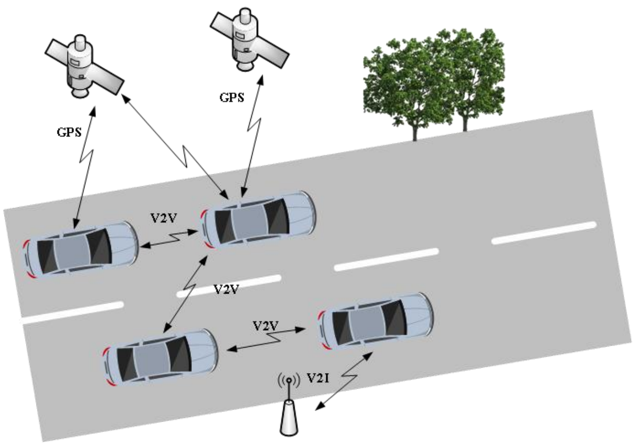


Figure 5. Collaborative positioning system in urban scene showing the block diagram of the system, consisting of four parts: RSS filter, GPS filter, decision center, and integrated Kalman filter.

In 2006, Europe achieved a breakthrough in the information exchange between vehicles and roadside units. In the preset platform, researchers initially achieved a mutual balance between the traffic infrastructure and vehicles, and freely used the information of various vehicles [96]. A weighted least squares algorithm based on the maximum likelihood estimation of the distance between the sensor and the target was proposed [97]. A simple filtering algorithm based on least squares was proposed, but the positioning accuracy was not high [98]. A total least squares target location algorithm based on the time difference of arrival (TDOA) and the angle of arrival (AOA) was proposed [99], but it had low accuracy and complex steps. The iterative constrained weighted least squares localization algorithm based on TDOA and frequency difference of arrival (FDOA) measurement was adopted in reference [100], which has high accuracy but complex implementation. Sensor-based location is a common method of vehicle location. However, the high cost, sensitivity to the environment, and the mapping and updating of maps also limit the rapid diffusion and spread of sensor-based positioning. No single technology, such as global navigation satellite systems (GNSS) or sensors, can guarantee high-accuracy positioning performance for vehicles in any environment, so a combination of inertial navigation, high-accuracy maps, and other complementary methods, such as cellular networks, is used to improve the positioning accuracy and stability. Among them, cellular networks are very important for improving positioning performance, such as real-time kinematic (RTK) data and sensor data transmission and high-precision map downloads. In addition, the positioning capability of 5G also provides strong support for the high-accuracy positioning of vehicles.

Due to the high technical difficulty and rich application scenarios of vehicle–road collaboration, the positioning research and application of vehicle–road collaboration in China is still in the stage of exploration and attempting, with more design schemes, less implementation, and no unified standard formed. Pilot application is in the Beijing–Hong Kong–Macao expressway Zhuozhou service section of the vehicle–road collaborative demonstration area construction. Four millimeter-wave radars will be installed in the pilot demonstration area, which are fixed to the surveillance lever or gantry by the back-to-back installation mode, and the installation position is close to the surveillance camera and millimeter-wave radar. China Mobile built 65G base stations in the vehicle–road collaborative demonstration area, realizing the full coverage of 5G signals. A total of 3 V2X roadside units were installed, with a single coverage radius of 800 m and a coverage range of 3 km. According to the application scenario of the expressway, the Zhuozhou service section of the G4 Beijing–Hong Kong–Macao expressway conducted the pilot application of the expressway collaborative positioning construction mode based on "5G + Beidou high-precision positioning", and the system functions of the typical application scenario are verified.

The development direction of the collaborative orientation for road cloud integration control, 5G + fusion high-precision positioning is based on AI multi-source heterogeneous data fusion, holographic simulation and consistency test public service platforms, and other key technologies, such as the formation of "car-road-road-edge-cloud" level 4 fusion of data processing, 5G + beidou dynamic cm/static millimeter-level high-precision positioning, real-time interaction, and all-round decision management of collaborative system.

4. Vehicle Communication

As one of the key technologies in this field, vehicle communication refers to the use of wireless communication, physical terminals, and intelligent sensors to realize V2V, vehicle–road communication (V2I), to enhance traffic efficiency, improve traffic safety and travel experiences, and construct the vehicle network (IOV) or vehicle self-organization network (VANET).

The frequency band of on-board communication is mainly divided into low frequency, intermediate frequency, and high frequency, and the name and scope are shown in Table 2. The application representative of low-frequency technology mainly includes automobile anti-theft and keyless systems. The product application of this technology mainly includes vehicle remote control keys; high-frequency communication mainly includes Bluetooth communication, mobile communication, dedicated short-range communication (DSRC), ultra-wideband (UWB) communication, etc.

Table 2. Name and range of frequency bands [101].

Classification/ Characteristics	Frequency Band	Band Range	Frequency Range
Ultra-long-wave	VLF	105~104 m	3~30 kHz
Long-wave	Low frequency	104~103 m	30~300 kHz
Medium-wave	Intermediate frequency	103~102 m	300~3000 kHz
Short-wave	High frequency	102~10 m	3~30 MHz
Ultra-short-wave	VHF	10~1 m	30~300 MHz
Microwave	Extra-high frequency UHF Very high frequency Ultra-high frequency	100~10 cm 10~1 cm 10~1 mm <1 mm	300~3000 MHz 3~30 GHz 30~300 GHz >300 GHz

The beginning of the development of vehicle communication systems can be traced back to a patent introduced in the United States in 1922 on the use of peer-to-peer (P2P) wireless communication vehicle alarm systems [102]. In recent years, with the development of wireless communication technology, on-board communication technology attracted increasing attention from a number of fields. The United States (CAMP/VSC-2) [103], Japan [104], and the European Union (SAFESPOT) successively carried out relevant research projects, taking place around 2010. As early as the 10th five-year plan, China began to strengthen its focus on and planning of intelligent transportation-related fields. Since 2010, a number of "863" projects and National Nature Science Foundation of China (NSFC) projects related to vehicle communication were launched. Collaborative data processing and security privacy are key issues in wireless sensor networks. We focus on network delays, external interference, impulsive behavior, and structural instability.

4.1. Communication Security

With the rapid development of wireless communication technology, intelligent vehicle communication is becoming more vulnerable to potential security attacks [105]. Due to the openness of wireless channels, the signal exposed in the open environment is likely to be stolen, interfered with, or even modified by the attacker [106]. If the attacker maliciously impersonates the vehicle to release false information and mislead other vehicles to form incorrect judgments, serious consequences may result. In 2018, the U.S. Department of transportation took the lead in proposing the security credential management system (SCMS), exploring the security process of V2X certificate management through a small-scale pilot. Vijayakumar et al. [107,108] proposed a dual group key management scheme, which distributes the group key to each vehicle and ensures the update of the group key when the vehicle joins or leaves the VANET. Combined with fingerprint authentication technology and hash codes, it improves the security of the vehicle terminal in the VANET environment and effectively prevents malicious vehicles from participating in communication. Ma et al. [109] proposed an energy-saving cooperative communication model for wireless sensor networks based on the genetic algorithm. In 2018, Kang et al. [110], drawing upon fog computing, constructed a privacy protection pseudonym scheme, which used the resources at the edge of the network for effective pseudonym management, in order to prevent the occurrence of overly centralized pseudonym management, resulting in large communication delays and high costs. Yang et al. designed a security architecture for the internet of vehicles based on digital signatures. Through in-depth study of the internal mechanism of the security framework, and the detailed design of the architecture, the whole life cycle's security mechanism is integrated into the design, and the identity authentication service in the whole life cycle of multiple scenarios is realized. Hubaux et al. [111] focused on the privacy protection and GPS positioning of vehicles, analyzed the main security problems in the internet of vehicles from different perspectives, and highlighted the relationship between the message accountability mechanism and the message anonymity mechanism.

Data privacy and scheme efficiency are the basic requirements for the application of the internet of vehicles system. In this section, various security and privacy threats are discussed from three aspects: the signature stage of the internet of vehicles, the data collection and transmission stage of the internet of vehicles users, and the data processing stage of the cloud platform. The characteristics and major security threats at the various stages of the internet of vehicles are shown in Table 3.

At present, the homomorphic aggregation scheme [112], elliptic curve encryption algorithm [113], and Chinese residual theorem [114] are often used to achieve data aggregation. The homomorphic encryption algorithm is the most commonly used technical method of data aggregation [115] because it satisfies the cipheric homomorphism operation properties. Homomorphic encryption (HE) refers to the specific calculation of the ciphertext after homomorphic encryption, and the ciphertext calculation results are equivalent to the same calculation [116] after the corresponding homomorphic data. Although the scheme in literature [117,118] can meet the basic privacy protection requirements and efficiency requirements in the internet of vehicles, it still has some deficiencies. The homomorphic encryption algorithm used in the scheme includes the elliptic curve-based encryption algorithm and the Paillier homomorphic encryption algorithm. The scheme based on the Paillier homomorphic encryption algorithm is not based on an elliptical curve.

Scheme [119] also adopts a homomorphic encryption algorithm and a data aggregation scheme based on heterogeneous fog layer nodes. The scheme uses resource-rich buses as dynamic fog nodes, and the roadside units are static fog nodes. At the same time, the scheme still does not support anti-collusion attack, and there is no reasonable and efficient method in the selection of dynamic fog nodes. In order to solve the above problems, Liu et al. [120] proposed the selection problem of dynamic fog nodes. The scheme adopted a heuristic algorithm to optimize the selection of core vehicles, and proposed a vehicle mobility measure based on relative average speed and a Convolutional Neural Networks (CNN)-based destination prediction method. Unfortunately, the programme also does not support anti-collusion attacks and has a high demand for resources. The current commonly used data aggregation schemes are limited by the computing performance of homomorphic encryption algorithms. Although the aggregation schemes basically meet the needs of data privacy protection, they still need to be optimized in terms of computational efficiency. At the same time, the related privacy and security issues caused by the highly centralized internet of vehicles also deserve the attention of researchers.

To protect the privacy of the internet of vehicles, there should be the following points: First, ensure that all the vehicles received by the nodes in the vehicle ad hoc network send and receive messages can be verified. The authentication is a method to determine whether the information received is true when the receiving vehicle successfully receives the information sent to it, as well as a method to determine whether the vehicle sending the message is a registered vehicle in the network. Second, ensure the integrity of the messages in the vehicle self-group network. Integrity refers to the message, from sending to receiving, not being tampered with by unauthorized vehicle nodes, add, delete, or packaging. However, a message integrity defect is not necessarily caused by an attacker, but also may be caused by the roadside units, relay vehicle node, routing, and other network line hardware or software equipment failure leading to timeout, packet loss, and other phenomena. Third, ensure that the communication of vehicles in the ad hoc network is confidential. Communication confidentiality means that only the parties sending and receiving the information can correctly interpret the information content, and other vehicle nodes or devices that relay the message cannot obtain the true content of the message. Fourth, ensure the traceability of messages in the vehicle ad hoc network. Traceability means that any message sent, received, relayed, or forwarded by the sender, relay, or receiver of the information will be recorded and retained. The vehicle cannot change or delete the sending, receiving, or relay records, nor can it deny the message sent, received, or relay by itself. Traceability plays an important role in investigating traffic crimes and confirming vehicle tracks. Fifth, it must be ensured that the spatiotemporal correlation of the vehicle's location is cut off for the attacker in the network. The spatial and temporal correlation of the location is cut off, which means that the attacker cannot know the name, position, and corresponding time of the vehicle at the same time. Once the attacker knows the three points, the location information of the owner or the vehicle can be judged according to the spatial and temporal correlation of the vehicle. There are two kinds of types of privacy protection for in-car ad hoc networks, namely the protection of information privacy and location privacy.

Table 3. Characteristics of each stage and major security threats [121].

Classification	Frequency Band	Data Security and Privacy Threats	Security Research Methods Addressed
The internet of vehicles signature phase	Calculation consumes large resources, dynamic changes of user attributes, diverse data types, etc.	Fake attack, witch attack, location attack, mission related attack	Homomorphism encryption, fuzzy generalization
Data collection and transmission stage of internet of vehicles users	Network topology changes frequently, data rights and user permissions are complex	Middle node attack, witch attack, position attack, background knowledge attack	Secure multi-party computing, homomorphic encryption
Cloud platform processing data stage	Easy to be vulnerable to malicious attacks, the security and benefit game between users, the vehicle parties to seek benefit maximization, highly centralized	Plot attack, time association attack	Game theory method, blockchain technology

With the development of 5G technology, information sharing among the complete internet of vehicles system is promoted. After the information is collected, it is processed and analyzed in a timely manner to recommend the best route for drivers to bypass congested roads. Boban et al. [122] analyzed the use cases and requirements of 5G-V2X, highlighted the gaps in existing communication technology, and provided guidance on how to overcome these gaps. Hameed et al. [123] used machine learning to enhance fog computing-related applications and services, effectively reduced the latency and energy consumption, improved the security, and provided more efficient resource management.

4.2. Control Strategy for Communication Delay

At present, the limited computing resources of vehicles are unable to meet the computing resource requirements of many delay-sensitive messages [124]. In order to cope with the expanding computing requirements of this vehicle terminal, the existing cloud computing technology can process a large amount of data information, which effectively reduces the local computing burden to a certain extent. However, when the security message is sent to the cloud server for processing through the core network, the processing delay of the message may be greatly affected. At the same time, the transmission of security messages often displays the phenomenon of redundant propagation, which causes a broadcast storm during message transmission and leads to the poor performance of message transmission. Generally, the transmission of emergency messages involves directional propagation, and the emergency messages are broadcast to the farthest receiving vehicles within the communication range [125].

The existence of communication delay will affect the following performance of the vehicle, and even threaten the driving safety. Therefore, it is necessary to design [126] for CACC control strategy for communication delay. On the one hand, the internal performance of the network can be studied from the perspective of communication, and the communication efficiency and quality can be improved by designing a reasonable network scheduling algorithm and communication protocol, so as to reduce its adverse impact on the control system. On the other hand, the optimization design of the control strategy under limited communication restriction gradually became a research hotspot, and a variety of solutions [127–130] were formed.

From the perspective of communication, Yin et al. designed a PID controller with a Smith estimation compensator to effectively control the [131] for the delay system. Xing et al. used the Smith estimator to effectively estimate the vehicle dynamics time delay and communication time delay, thus achieving the vehicle formation control [132] with a smaller following time distance. However, the delay estimation compensation control has some disadvantages, that is, it needs a more accurate prior cognition of the estimation system, and requires a high degree of accuracy and invariance.

Sun et al. [133] proposed a new multi-objective coverage optimization complex alliance strategy (CASMOC) algorithm, which can effectively improve the coverage of nodes. Wang et al. [134] proposed a dynamic clustering and cooperative scheduling algorithm based on SINR analysis of the signal-to-noise ratio in V2V communication for a two-way road data service. This algorithm can enable vehicles to dynamically join or leave a cluster according to the actual time and place. Yang et al. [135] proposed a system that can relax the communication attributes of the vehicle–road system by considering the time dependence. If the vehicle generates multiple signatures in the same time period, it indicates that the vehicle can be connected. Guo et al. [136] established delay constraints by introducing a delay index, and redistributed and controlled resources and power by using the method of distribution solution, so as to realize the high demand of the security mechanism of the vehicle network on the delay.

According to the relevant team of Intel [137], in the future, each intelligent vehicle will generate 4000 GB of data per day, which is equivalent to the amount of data consumed by around 3000 mobile users. Such prediction studies show that the future development of transportation systems will face severe challenges, and efficient sensor data processing needs reliable and efficient underlying technology to support the system. Therefore, in the face of this challenge, the vehicle edge information system (VEIS), which integrates vehicle communication technology and edge technology architecture, is proposed [138]. This vehicular edge information system is a new application that imposes strict requirements for communication and computing resources in the future intelligent transportation system by enhancing the communication, storage, and computing capabilities at the edge of the vehicular network and realizing the corresponding vehicular communication, edge cache, edge computing, and other technologies.

From the control point of view, due to the inevitable existence of wireless communication delay, the string stability of the cooperative adaptive cruise control queue system may not be guaranteed if the controller gain is not adjusted in time. Zhang Yuqin et al. [139] considered a dynamic gain regulation algorithm based on local traffic characteristics in collaborative adaptive cruise control considering wireless communication delay. The stability of CACC string is guaranteed by a dynamic C gain setting algorithm, which outperforms traditional methods and can significantly suppress interference along the upstream direction of the fleet. Vite Leopoldo et al. [140] proposed an adaptive cruise control based on dynamic predictors for input delay compensation, a filtered version of the standard finite spectrum allocation method, which overcomes the robustness problem, especially caused by the approximation of the distributed delay term, and finally, demonstrates the effectiveness of the study by performing simulations on five vehicles. Wang CJ et al. [141]

proposed ideas to dynamically optimize the IFT for CACC to optimize the string stability of the queue under environmental traffic conditions. When the CACC system is operating, the communication failure should be prepared at any time, because the CACC is too dependent on the communication quality, and is very sensitive to the communication failure. The safety impact of cooperative adaptive cruise control vehicle degradation under disruption of spatial continuous communication is described in paper [142] by Yu Weijie et al. Liu Yi et al. [143] proposed a safety-enhanced collaborative adaptive cruise control strategy for dynamic vehicle–vehicle communication failure, in which the safety-enhanced platoon control system is embedded with a dual-branch control strategy. When a fatal wireless communication failure is detected and confirmed, the SR-CACC system will automatically activate an alternative sensor-based adaptive cruise control strategy, which can significantly improve the safety performance of organized vehicle rows in extremely harsh communication environments. In order to reduce the impact of security vulnerabilities and network attacks possible when wireless communication networks work, Petrillo A et al. [144] handles and solves the network security tracking problem of a queue, embedding a distributed malicious information mitigation mechanism. Fiengo G et al. [145] investigated the leader tracking problem of connected autonomous vehicle queues in the presence of both uniform time variable parameter uncertainty and vehicle workshop time-varying communication delay.

Literature [146] proposes a strategy to mitigate communication delays between vehicle queues by using expected information from the lead and following vehicles. Literature [147] devised a strategy to mitigate communication latency in various traffic situations by providing flexible ad hoc links. Some researchers proposed a consensus strategy to alleviate the vehicle queue stability problem by designing more effective queue controllers or follower control strategies, such as the literature [148], as a dynamic network affected by time-varying heterogeneous communication delays. In addition, the distributed control protocol is derived based on graph theory. For example, literature [149] proposes a vehicle tracking control strategy based on considering the time-varying communication delay, and deduces and proves the sufficient conditions for local stability and serial stability in the frequency domain. Furthermore, the literature [150–152], to handle communication and parasitic delays, models the vehicle queue as multiple delay linear systems under various time-varying network topologies, investigating internal and serial stability, proposing an adaptive control method and a consensus method designed to mitigate the impact of communication delays.

Asadi and Muller [153] used an online machine learning algorithm to solve the problem of beam selection in vehicle millimeter-wave communication, which reduced the complexity of directional millimeter-wave communication and allowed a better application effect to be achieved in vehicle communication scenarios. Samarakoon and Bennis et al. [154] set up a distributed federated learning algorithm for the delay and reliability requirements of the edge side, especially in the vehicle dynamic scene, to ensure the stability of the queue by estimating the tail distribution of the length of the communication queue. Gyawali and Qian et al. [155] improved the reliability, safety, and stability of on-board communication by establishing an abnormal behavior detection mechanism based on machine learning. Hasselt et al. [156] evaluated the temporal and spatial patterns of traffic network flow using a multi-task learning architecture. Zhao et al. [157] combined a CNN with a deep Q-learning network (DQN) based on LSTM to identify surrounding vehicles by extracting features from input images to help vehicles identify the positions of adjacent vehicles and detect lane changes, and then to feed these features into the DQN based on LSTM, which can learn the optimal driving sequence of vehicles through input features after training. It can be seen that the application of artificial intelligence in vehicle edge information systems mainly focuses on distributed algorithms, online algorithms, and other intelligent learning algorithms, which require lower data training costs. At the same time, it also meets the requirements of data processing efficiency and response time in vehicle scenes. However, there are still many challenges in future research. Deep learning technology needs a large number of accurately labeled data for training, and the efficiency of processing largely depends on the training algorithm. On the other hand, due to the randomness of driver behavior and environmental impacts, the system may encounter many emergencies, which may lead to a system response delay. Therefore, the core deep learning method must ensure the robustness of the system through a large amount of learning so that the system can effectively deal with emergencies and be rapidly adjusted to account for them.

5. Test Method and Evaluation

5.1. Real Vehicle Road Test Platform

The real vehicle road test of an intelligent network includes three test scenarios: a closed scene test, a semi-open road test, and an open road test. Firstly, the representative closed test sites in foreign countries include the following: the Asta Zero test site in Sweden, which contains complete experimental facilities and has the capacity to test vehicle dynamics, driver behavior, and V2X technology; the Mria City Circuit test site in the UK, whose main features are simulated signal masking and various V2X communication facilities, with the flexible design of traffic lights and transmitting towers, and is oriented towards the testing of intelligent transportation systems and intelligent networked vehicles [158]; the Willow Run test site in Michigan, U.S., which is suitable for the extreme testing of V2X technology and autonomous driving technology, etc. [159]. The closed test sites also occupy a large proportion of the domestic real-world test sites. On July 30, 2021, the Ministry of Industry and Information Technology, the Ministry of Public Security, and the Ministry of Communications jointly issued the "Management Specification for Road Testing and Demonstration Application of Intelligent Connected Vehicles (Trial)" [160], adding the demonstration application of manned vehicles and special operating vehicles, and opening some expressway tests. At present, there are around 50 test sites in a state of completion or under construction, 30 of which are equipped with testing capability for intelligent networked vehicles. The intelligent driving test base of the Ministry of Transport in Beijing contains traffic scenes of various road shapes and surfaces, such as urban and rural roads, high-speed roads, and their ramps, and is equipped with street lights, traffic lights, weather simulation equipment, and other facilities, which can be used for intelligent driving, intelligent road networks, and other tests. Changsha, Wuhan, and other cities within intelligent network pilot demonstration areas can simulate a variety of road conditions, including wet roads, mountain roads, woodlands, high-speed roads, masonry, bridges, etc.; equipped with intelligent sensors and other monitoring equipment, they can be used for intelligent networked vehicle testing. Secondly, the domestic open test sites mainly include the following: the Shanxi (Yangquan) autonomous driving vehicle–road cooperation demonstration area, where roadside sensing, collection, and transmission systems are being built, and the deployment of the vehicle–road cooperation cloud control platform and autonomous driving vehicle supervision platform based on Baidu's public cloud was completed, so as to realize object detection technology based on environmental sensing and V2X communication technology to support L4-level autonomous driving vehicle over the horizon, etc. The Yongchuan Baidu Western Autonomous Driving Open Test Base is an open test and demonstration operation base for L4-level autonomous driving. The base deploys 5G communication in the road network environment in all aspects and includes more than 30 typical open road test scenarios in the mountain city, such as interchanges, tunnels, and bridges, with the unique traffic terrain of Chongqing, and it can accommodate 200 intelligent driving vehicles for testing at the same time. The efficient data transmission based on 5G technology and intelligent data processing based on artificial intelligence technology are of great significance for the application of intelligent connected vehicles. The Changsha test demonstration area has a wealth of intelligent connected vehicle test scenarios, and 5G widely covers the intelligent connected vehicle test area. It is the first [161] demonstration area to carry out high-speed tests and manned tests in China.

Domestic test areas are constructed in the following ways: 1. leading by application scenarios; 2. leading testing and demonstration application by standard formulation; 3. promoting the integrated development of intelligent connected vehicles and intelligent transportation with 5G commercialization; 4. policy exploration and demonstration operation promoting each other; and 4. national intelligent transportation comprehensive test base.

5.2. Virtual Test Platform

The simulation test experiments of intelligent network connected systems seek to establish a real static scene and carry out dynamic scene modeling according to the actual situation through computer simulation technology, so as to realize the model and algorithm of the network-connected vehicle. The system can carry out a variety of test verification experiments in the simulated traffic scene, reducing the dependence on real vehicle experiments to a certain extent, such as the current mainstream of intelligent driving vehicle sensor physical model simulation authenticity, intelligent transportation system V2X model construction, and the construction of dynamic traffic flow in the simulation scene. At present, a new generation of intelligent driving simulation systems integrating physical characteristic information is being gradually developed, which cannot only verify and iterate intelligent driving algorithms more effectively, but also meet the overall test requirements of intelligent driving simulation platforms for physical information systems more comprehensively. With the rapid development of advanced driver assistance systems (ADAS) and intelligent driving, the development of simulation software underwent the following stages: The early simulation test software mainly used dynamic simulation. The Simulink module of control design simulation software MATLAB was used to build the vehicle dynamics model and carry out real-time simulation, such as Carmaker [162], CarSim, Panosim [163], and other simulation software. With the further development of the ADAS function, simulation and test software to assist this function began to appear, such as Prescan [164]. In recent years, the ability of unreal engines to restore the virtual environment became stronger, and more researchers paid attention to the open-source simulators, such as AirSim [165], CARLA [166], and Unity. However, due to the diversity and functional complexity of the current mainstream intelligent driving simulation tools, most of them cannot support multi-agent co-simulation or simulation in large-scale scenarios, so the test verification of the off-vehicle networking system in large-scale complex traffic environments is not yet realized. At present, the optimization control of urban traffic in intelligent vehicle network systems is mainly concentrated within single-point traffic control, lacking real-time linkage control. However, the simulation of intelligent driving in large-scale open scenes shifted from macro-centralized control to meso-edge-side coordination control, and then to micro-single-car intelligent control. Therefore, it is necessary to develop simulation tools that can support this hierarchical control model. A microscopic traffic flow simulation model takes vehicles as the description unit, which can describe in detail the car-following and lane-changing behavior between vehicles. At present, the more common ones include SUMO [167] and PTV-Vissim [168], both of which have corresponding interfaces for secondary development. An intelligent driving simulation simulator based on SUMO and Unity3D [169] was proposed through the TraCI protocol. It can be seen that the use of intelligent driving simulation tools to provide single-vehicle intelligent decision making, traffic flow simulation models to provide specific traffic scene modeling and design, and the combination of the two through an interface, can support intelligent networked vehicle collaborative simulation in large-scale open scenes.

Elrofai et al. [170] believes that the scene is the dynamic interaction of various elements over a continuous period of time, and divides the scene into three main elements, namely, the tested vehicle, passive environment (such as road topology, traffic signs, etc.) and active environment (such as traffic lights, weather, etc.); De Gelder et al. [171] further defines the scene as a collection of internal movement, static environment, and actions related to the environment and autonomous vehicles. It can be seen that the above literature emphasizes that the test scenario is time-varying, and includes driving tasks, dynamic environment, and other elements of the environment. On this basis, this paper defines the test scenario as the dynamic description and abstraction of the behavior and operating environment of autonomous vehicles in certain times and airspace, with the characteristics of inexhaustible, extremely complex, infinite and rich, and difficult to predict [172]. The scale size of time and airspace needs to be formulated according to the specific test requirements. For example, the time domain of the lane change scene generally lasts from tens of seconds to several minutes; the space domain of the follow scene is a road network composed of several roads. Further decomposed from the elements, the scene generally includes the input flow of the road, weather, traffic rules and traffic popularity, as well as the output flow of the autonomous driving car to the environment.

In the construction of virtual scenes, the influence of the complexity of public transportation should be considered. Researchers will generally set up various traffic simulation scenarios, among which, rain and fog weather is an important environmental scenario in the traffic simulation scenarios. In the extreme environment test area of the project, there is an extreme environment warehouse and a signal-shielding warehouse, combined with augmented reality (AR) technology. The extreme environmental warehouse will simulate extreme weather conditions, such as "wind, rain, thunder and electricity", allowing vehicles to be tested under extreme weather conditions. When the intelligent car passes by from the warehouse, the warehouse can accurately adjust the rain and fog visibility that the vehicle can feel, observe the operation of the car when "being in it", so as to accelerate the research and development efficiency of intelligent vehicles, and provide effective support for improving the performance of intelligent vehicles. The signal-shielding warehouse will simulate the car communication environment after the tunnel, intelligent connected car into the tunnel, tunnel traffic internally and out of the tunnel, and the communication signal strength will present "strong-weak-no signal-weak-strong" change, thus the intelligent connected car in the case of weak signal control and operation status of the research and evaluation work.

In order to fully expose the design defects of autonomous vehicles, it is necessary to build a workflow, including a simulation test, closed site test, and open road test based on the scene, and solve the technical problems in scene definition, classification, data mining and analysis, scene generation, and other aspects. Table 4 shows the performance of virtual test, closed site test and real car road test under test specification.

Table 4. Virtual test, closed site test, real car road test comparison [173].

Test Specification	Virtual Test	Closed Site Test	Real Car Road Test
Test the truth	Depending on the authenticity of the model, the authenticity is relatively low in comparison.	More real, but not the real dynamic elements of other traffic participants.	Real, consistent with the actual driving environment of autonomous cars on the road.
Test cost	Low, the cost of the software systems is relatively low.	The construction cost of the test site is relatively high.	High, it requires too many people and over a long time to drive.
Testing efficiency	High, multi-core parallel testing can greatly improve the simulation speed.	High, can be targeted to strengthen the test for key scenarios.	Low, road mileage-based test methods require long driving times with multiple people and multiple cars.

Table 4. *Cont.*

Test Specification	Virtual Test	Closed Site Test	Real Car Road Test
Repeatability	Strong, you can build the same test scenario according to the defined data.	Strong, the scene elements can be reconstructed through the scene configuration requirements.	Poor, not a reproducible test on the public road.
Number of test scenarios	Many, any number of test scenarios can be generated given the logical scenario parameter space.	Less often, although as many scenarios can be built as possible according to scene element changes, the number of virtual test and open road test scenarios is still low.	Many, as many required test scenarios can be encountered long enough.
Test purpose	Embedded in each link of the system development, massive scene testing, to verify the boundaries of the autonomous driving function.	At the same time, the scene type that is not encountered or with low probability in reality can be built by configuring the field and the scene elements to verify the operation of the system under the boundary situations.	Clarify the statistical laws of related events, verify the system boundaries in practical situations, detect the interaction between autonomous vehicles and traditional vehicles, and find new scenarios that were not considered.

5.3. Test Method and Evaluation

The test and evaluation of intelligent connected vehicles is an important stage in the development of its vehicle functions. Similar to human drivers, the test method can be divided into three parts: the perception function test, the decision function test based on perception information, and the action function test. Vargas et al. [174] proposed a conceptual sensor testing framework for automatic driving vehicles, which is oriented towards different types of sensors and communication mechanisms, and provides a means of performing test scenarios similar to those occurring in the physical world. Wei et al. [175] implemented a parallel computing framework and system for intelligent driving tests and verification. It constructs a set of intelligent test models, which enables the system to develop a cognitive mechanism of automatic self-upgrading under the guidance of human experts, and further improves the ability of intelligent driving vehicles to adapt to complex environments. In order to speed up the scene testing, virtual environment simulation can be used. The mainstream virtual environment simulation software includes Prescan, Carmaker, dSpace, etc. At present, most of the tests only cover intelligent driving, and the test methods for intelligent driving vehicles in static, dynamic, and uncertain environments are not perfect. The vehicle decision-making ability test and V2X-based traffic integration test also need to be improved.

The evaluation mechanism design of intelligent driving vehicles is an important link in the research field. The evaluation of intelligent driving vehicles is affected by the interaction between the intelligent driving system, static traffic environment, and dynamic traffic environment, which is a more complex type of system engineering. At present, the main test and evaluation mechanisms are mostly for auxiliary intelligent driving. For example, the American Highway Safety Insurance Association issued the test procedures for automatic emergency braking systems in 2013, with the reduction in collision speed as the evaluation parameter. EU evaluation regulations for new cars cover most ADAS functions. In the process of continuously enriching the functional test scenarios, a rich and complete ADAS test and evaluation method system was gradually formed. In China, the 2021 evaluation regulations for new cars cover the ADAS test and evaluation system with automatic emergency braking, lane departure alarms, speed assist systems, and blind spot detection as the main content, and communication evaluation systems are rarely involved.

Domestic and foreign scholars and institutions carried out a lot of basic research work in simulation test methods, test scenarios, simulation modeling, tool chain reliability, and other aspects of [176–179]. For the different stages of the product, different types of simulation and simulation test methods are not only applied to the development process of intelligent and connected vehicles, but also gradually play an important role in the product verification, confirmation, and evaluation. The UN is in the automatic lane keeping system for L3 automated lane keeping systems (ALKS)-type approval regulations for test verification, and put forward the relevant requirements for the simulation tools and models [180,181]. Japan explicitly introduced the software in the rings in its software-in-the-loop (SIL) and hardware-in-the-loop (HIL) to test the [182]. The new test assessment method proposed by the United Nations Informal Working Group on Autonomous Driving Verification Methods requires the use of a proven simulation tool chain to conduct simulation tests to evaluate the safety of autonomous driving systems, and proposes SIL testing for driving safety and critical safety scenario assessment [183]. In the draft regulation on the type approval requirements of autonomous driving systems, the EU made it clear that simulation, closed sites, and practical law can be adopted, and roads introduced the United Nations study of [184] on the credibility of simulation tests. The vehicle dynamics simulation model and test methods developed by ISO provide the basic [185,186] for the vehicle dynamics simulation test and verification. The research of SCHONER et al. [187] proposed that SIL testing is an effective means to solve the verification of control algorithms, behavior, and rule compliance verification in complex and difficult scenarios. Domestic relevant institutions propose a set of intelligent connected vehicle safety tests and evaluation methods from the perspective of a third party, and clearly states that the simulation test is used to evaluate the function and performance verification of intelligent connected vehicles in diversified scenarios and complex conditions. Ahamed et al. [188] designed a framework for freely constructing vehicle models, and developed the SIL simulation platform in Gazebo using a robot operating system. Bachuwar et al. [189] proposed a software-in-loop simulation framework based on the open source autonomous driving software Autoware [190], which uses Simulink to communicate with the robot operating system (ROS). The above research shows that, with the maturity of technology and simulation tests for intelligent connected car safety test evaluation, among them, SIL test with its low cost, low risk, high advantages, high efficiency, and high coverage, become intelligent car safety, especially the lack of function and important means of algorithm defects. Hardware-in-loop simulation is a semi-physical test method where some components or systems of autonomous vehicles adopt real physical equipment, and the scene and charged objects are digital models. Hardware in loop simulation combines mathematical model and physical hardware equipment, and introduces the nonlinear physical characteristics, such as time delay, saturation, and friction, which significantly improves the confidence of the test results and overcomes the shortcomings of the model and data in MIL/SIL test to some extent.

At present, about 30 closed test sites for autonomous vehicles were built in China, basically covering typical traffic environments, such as rural areas and urban roads. Some of the closed sites also established a heterogeneous network of the internet of vehicles, [191]. However, the existing closed site has an inconsistent service level, high operating costs, mutual recognition, and other test results are very prominent. The main reason behind this is the lack of standard specifications. The specific performance, in two aspects, is as follows: The first is the lack of standard site construction. Construction levels are uneven, some site scenes have single scenes, are unable to support IoV testing, and fell behind the technological development level of self-driving cars. Secondly, the test passing standards are not uniform. For example, test preparation, vehicle technical status, scene setting, vehicle end, and roadside data collection and processing methods are inconsistent. This directly leads to the differences in the evaluation results among the closed sites. It restricts the development of test mutual recognition work.

Considering the complexity of the actual working conditions, the evaluation results of the simulation and the closed site may deviate from the real situation. Therefore, self-driving vehicles must be continuously tested on open roads before mass production. It is a necessary part for self-driving vehicles to accumulate test data, improve their technology, and ultimately commercialize it. However, there is still a lack of norms for testing autonomous driving vehicles on most open roads, especially highways.

Compared with simulation and site testing, the actual road test method is still in the preliminary exploration stage. The actual road test of autonomous driving can use the randomization characteristics of various targets and events on the actual road to verify the autonomous vehicles: (1) the safety impact of the vehicle and the surrounding traffic environment when running on the actual road; (2) whether the response to various typical goals and random dynamic events meets the expectations; and (3) the impact on the overall road traffic efficiency. Therefore, the actual road test is an indispensable link in the testing and evaluation process of autonomous vehicles. Since 2017, the major auto industry countries launched the exploration of the actual road testing of autonomous driving. In 2018–2019, 36 companies in California completed 5.635 million km of public road autonomous driving tests. Auto companies in Germany, Britain, Finland, Japan, and other countries also carried out a large number of practical road tests under the framework of their own autonomous driving-related laws and regulations. By October 2021, more than 3200 km of test roads were opened, more than 700 test licenses were issued, and the total length of road testing exceeded 5.3 million km. Shanghai and Beijing carried out demonstration applications of manned cargo loads. However, the current international actual, general road testing to improve the single model technology scheme for the purpose, due to the diversity of autonomous driving research and development technology, leads to strong research and development test scheme pertinence, test index, and research and development technology scheme correlation; such a test evaluation scheme does not have typical universality standardization characteristics.

6. Expectations

After decades of development, the vehicle collaborative driving system made great progress in all aspects. Facing the future intelligent vehicle collaboration technology under the network environment, it is suggested to carry out further work from the following three aspects:

(1) Multi-vehicle intelligence, instead of bicycle intelligence. became a current development trend, in addition to realizing comprehensive perception driving decision and control execution function, it is suggested to further enhance the intelligent road infrastructure, realize comprehensive intelligent cooperation between vehicles, namely vehicle–road collaborative perception, vehicle–road collaborative prediction decision and vehicle–road collaborative control system integration function, improve the commercial landing, thus forming the comprehensive development of car and road, and jointly promote the realization of automatic driving.

(2) Wireless communication delay inevitably exists in the internet of vehicles system. The collaborative system can consider the communication delay, the middle section, and other factors in the policy planning of the control system. The application of AI algorithms in vehicle communication became a new research hotspot. It is suggested that, to improve the quality of the data set, reduce the interference caused by emergencies, improve and optimize the control algorithm, and improve the ride comfort of the road.

(3) Scene-based test theories and methods became the mainstream technical route to deal with this challenge, but the research in this field is in its initial stage and is yet to receive enough attention from the academic community, which still needs to be further studied and explored. At present, the high-level automatic driving car test evaluation index,

evaluation model, and evaluation system of research is still in its infancy; in the future, there is a need to test scene classification, test task classification, improve the test system, and speed up the unified evaluation standards to further strengthen the comprehensive evaluation system of the integration of subjective and objective research.

7. Conclusions

This paper analyzes the collaborative control system of intelligent connected vehicles from three aspects of the collaborative control of intelligent vehicles, communication technology in vehicle networking environment, connected vehicle test platform, and evaluation system. At present, the future development of the collaborative control of intelligent connected vehicles has limitations, which are as follows: First, price restriction; the related hardware and software facilities, such as the internet of vehicles system and intelligent connected vehicles, are expensive, which poses great obstacles to the test of the intelligent networked collaborative control system. At present, most tests are still based on simulation. Second, laws and regulations limit it. At present, only a very small part of the intelligent connected vehicle testing sites are open in China, and the real vehicle testing sites and the testing process are greatly limited. Third, there is no uniform test standard. This paper puts forward the next urgent problems and the direction of in-depth exploration, and its related research can provide a reference for the intelligent vehicle–road collaboration technology.

Author Contributions: Conceptualization, B.W. and D.T.; methodology, B.W.; formal analysis, S.W.; investigation, M.L.; resources, B.W.; data curation, B.W. and L.W.; writing—original draft preparation, B.W. and M.C.; writing—review and editing, Y.H.; supervision, B.W.; project administration, Y.H.; funding acquisition, Y.H and B.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key Research and Development Program of China under Grant 2021YFE0203600 and in part by the Fundamental Research Funds for the Central Universities-Research on the cultivation of Excellent Doctoral Dissertations in Chang'an University under Grant 300203211221.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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