SCIENCE CHINA
Technological Sciences

Special Topic: Technology Progress of US-China Collaboration on Clean Energy Vehicles
•Review•

October 2018 Vol.61 No.10: 1446–1471
https://doi.org/10.1007/s11431-017-9338-1

Intelligent and connected vehicles: Current status and future perspectives

YANG DianGe[1*], JIANG Kun[1*], ZHAO Ding[2*], YU ChunLei[1], CAO Zhong[1], XIE ShiChao[1], XIAO ZhongYang[1], JIAO XinYu[1], WANG SiJia[1] & ZHANG Kai[1]

[1] State Key Laboratory of Automotive Safety and Energy, Department of Automotive Engineering, Collaborative Innovation Center of Intelligent New Energy Vehicle, Tsinghua University, Beijing 100084, China;
[2] University of Michigan Transportation Research Institute, Ann Arbor, MI 48109, USA

Received October 9, 2017; accepted August 2, 2018; published online September 19, 2018

Intelligent connected vehicles (ICVs) are believed to change people's life in the near future by making the transportation safer, cleaner and more comfortable. Although many prototypes of ICVs have been developed to prove the concept of autonomous driving and the feasibility of improving traffic efficiency, there still exists a significant gap before achieving mass production of high-level ICVs. The objective of this study is to present an overview of both the state of the art and future perspectives of key technologies that are needed for future ICVs. It is a challenging task to review all related works and predict their future perspectives, especially for such a complex and interdisciplinary area of research. This article is organized to overview the ICV key technologies by answering three questions: what are the milestones in the history of ICVs; what are the electronic components needed for building an ICV platform; and what are the essential algorithms to enable intelligent driving? To answer the first question, the article has reviewed the history and the development milestones of ICVs. For the second question, the recent technology advances in electrical/electronic architecture, sensors, and actuators are presented. For the third question, the article focuses on the algorithms in decision making, as the perception and control algorithm are covered in the development of sensors and actuators. To achieve correct decision-making, there exist two different approaches: the principle-based approach and data-driven approach. The advantages and limitations of both approaches are explained and analyzed. Currently automotive engineers are concerned more with the vehicle platform technology, whereas the academic researchers prefer to focus on theoretical algorithms. However, only by incorporating elements from both worlds can we accelerate the production of high-level ICVs.

intelligent connected vehicle (ICV), autonomous driving, artificial intelligence, advanced driver assistance systems (ADAS), electrical/electronic architecture (EEA), environmental perception, decision-making, ICV computation platform

Citation: Yang D G, Jiang K, Zhao D, et al. Intelligent and connected vehicles: Current status and future perspectives. Sci China Tech Sci, 2018, 61: 1446–1471, https://doi.org/10.1007/s11431-017-9338-1

1 Introduction

In the early stage of the automotive industry, the pursuit of speed was the initial driving force to develop new technologies. In the late 20th century, the consumer's concerns about safety, comfort and fuel efficiency became the major motivation and direction to improve vehicle performance. In the early 21st century, the intelligent connected vehicle (ICV) was widely accepted as a promising technology to eliminate traffic accidents and improve traffic efficiency. A vehicle that can drive itself is fascinating enough just be-

*Corresponding authors (email: ydg@tsinghua.edu.cn; jiangkun@tsinghua.edu.cn; zhaoding@umich.edu)

cause of its surprising intelligence; moreover, the safety, comfort, convenience, and efficiency that ICVs promise provide even more benefits to passengers and society. Therefore, research institutes, car manufacturers and even IT companies are keeping investing in this new technology trend. Many universities and research labs have already successfully built demonstration vehicles with high-level intelligent abilities to prove the feasibility of ICV concepts. However, transposing these intelligent systems from a developmental context to mass production requires breakthroughs in both hardware and software technologies. An interesting aspect of the development of ICV technologies is that the automotive manufacturers and academic researchers understand the ICV from quite different angles of view. The manufacturers tend to focus on developing industrially standardized equipment, which is to regard the perception, decision, and control algorithms as part of some subsystem or equipment. On the contrary, the academic researchers are more interested in developing the intelligent algorithms, regarding the sensors, controllers, and actuators as black boxes that are always functional and available. The lack of understanding of each other's work results in a gap between the two worlds. For the purpose of accelerating the development of autonomous driving, the industrial and academic sides should work together to truly integrate the development of automotive hardware and software.

This study provides an overview of the history of ICVs and analyzes the key technologies for mass production of autonomous driving. The paper is organized as follows: Section 1 reviews the history and current status of ICV. Section 2 introduces the architecture of ICV, explaining why and how the electric and electronic architecture (E/E architecture, EEA) should be changed to be more adapted to the requirements of autonomous driving. Sections 3 and 4 discuss the advantages and drawbacks of different sensors and actuators that would be installed in future ICVs. Section 5 provides an overview of recent advances in decision making technology. Section 6 draws conclusions on current ICV research. The relationship between E/E Architecture, sensors and actuators is illustrated in Figure 1.

1.1 Worldwide classification standards of ICV levels

An ICV can be defined as a next-generation vehicle that is equipped with advanced sensors, controllers, and actuators, and is designed with the intelligent and cooperative driving capacity to ensure safety, comfort, energy-efficiency, and relief of human drivers. In the following paragraphs, we will present a general overview of ICVs by comparing different classification standards of ICV levels in the world and reviewing the important events or breakthroughs in the history of ICV development.

Generally, ICVs can be classified according to the level of driving intelligence. Different standards of ICV level classification have been published in Europe, the U.S. and China. In 2014, Society of Automotive Engineers (SAE) published a standard of intelligent vehicle levels [1]. Many companies around the world use this standard to guide their research and development, such as Toyota, Nissan, Tesla and Audi. There are six levels in the SAE standard:

Level 0, no automation, needs the driver to perform all the dynamic driving tasks;

Level 1, driver assistance, achieves either longitudinal or lateral control when activated;

Level 2, partial automation, achieves both longitudinal and lateral control when activated;

Level 3, conditional automation, can provide a part-time or driving mode-dependent performance to execute all the dynamic driving tasks;

Level 4, high automation, can perform all the dynamic driving tasks even if the driver does not respond to system's request to intervene in certain driving modes or geographical areas;

Level 5, full automation, can finish all the dynamic driving tasks once programmed with a destination in at least all the environments manageable by a human driver.

In Table 1, we classify some representative ICVs based on SAE intelligent levels.

In September 2017, National Highway Traffic Safety Administration (NHTSA) released Automated Driving systems 2.0 Voluntary Guidance, offering further explanation of SAE levels[1).

Apart from the SAE level, the BASt levels[2) released by German Federal Highway Research Institute in 2012 and NHTSA levels[3) proposed in 2013 are also important standards of ICV classification with global influences.

Figure 2 illustrates the similarities and differences of these standards in an intuitive way. The description of Level 0 to Level 2 in NHTSA standard are functionally the same as that of SAE standard. BASt standard has similar description of Level 0 to Level 4 as that of SAE standard. NHTSA standards and SAE standards are different in the definition of high-level ICV.

China has also released its intelligent vehicle level standard based on the SAE standard, adding specific traffic mode explanations to consider the complexity of traffic in China:

1) National Highway Traffic Safety Administration. Automated Driving Systems 2.0 Voluntary Guidance. 2017.

2) Gasser TM, Westhoff D. BASt-study: Definitions of automation and legal issues in Germany. In: Proceedings of the 2012 Road Vehicle Automation Workshop. Bergisch Gladbach: German Federal Highway Research Institute, 2012. 1–20.

3) National Highway Traffic Safety Administration. Preliminary statement of policy concerning automated vehicles. Washington, DC, 2013. 1–14.

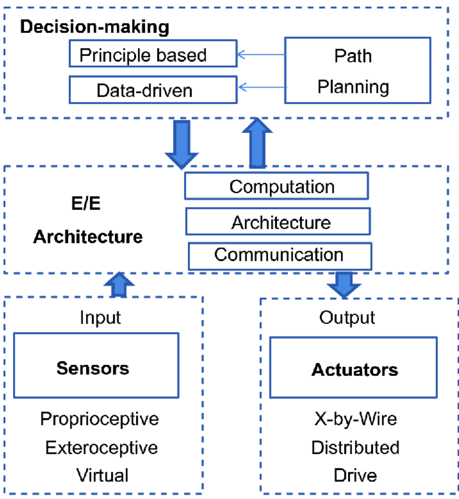

Figure 1 (Color online) Key ICV technologies and structure of this article.

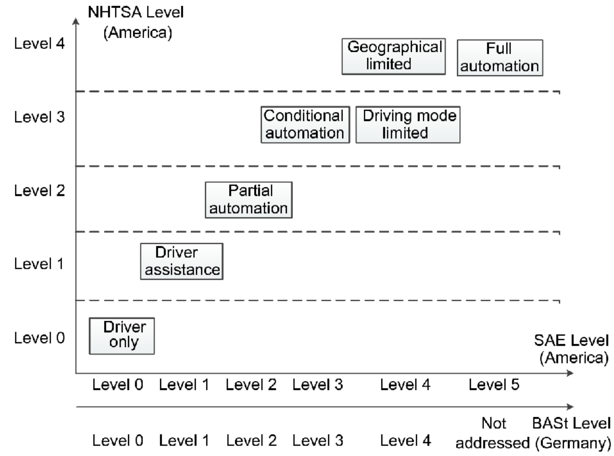

Figure 2 Comparison of SAE, NHTSA and BASt levels.

Level 1 (DA) vehicles provide accelerating/decelerating or steering assistance to the driver, relieving the driver's hands or feet from the driving tasks;

Level 2 (PA) vehicles provide multiple assistance of accelerating/decelerating and steering to the driver, relieving both the driver's hands and feet from the driving tasks;

Level 3 (CA) vehicles can perform all driving tasks in certain conditions, the driver should properly intervene according to system request;

Level 4 (HA) has one more requirement than Level 3, that the system should be able to deal with the situation in which the driver does not intervene upon the system's request;

Level 5 (FA) vehicles can accomplish all driving operations in all the road environments manageable by a human driver, completely relieving the driver from the dynamic driving tasks.

1.2 History and milestones of ICV development

This subsection analyzes the significant events during the development of ICVs and the key technologies behind them. The brief history is shown in Figure 3. The lower part of figure shows the important events that are pushed forward by these technologies. The upper part shows the occurrence time of revolutionary technologies in autonomous driving. In 1925, the Houdina Radio Control demonstrated the radio-controlled "American Wonder" on New York City streets [12], which was based on the invention of electron tube radio transmitters in 1920s [13]. This can be called the prototype of the driverless car. During the 1950s through the 1960s, General Motors showcased the Firebirds, a series of experimental cars that were guided by detector circuits buried in the pavement and controlled by radio[4),5),6)]. Thereafter, to enhance the autonomy of vehicles, radar was introduced to avoid collision in the 1970s [14]. In 1977, the Mechanical

Table 1 SAE levels of representative ICVs [a)]

Level 1-2	Production Vehicles: 2015 Infiniti Q50S; 2016 Lexus RX; 2016 Volvo XC90; BMW 750i xDrive; Ford (High end production); Mercedes-Benz E and S-Class [2]; Otto Semi-Trucks; Renault GT Nav Research Vehicles:
Level 3	Production Vehicles: Audi's A8; Tesla Model S Research Vehicles: AutoNOMOS's MadeIn-Germany; LIVIC's CARLLA [3]; Delphi's Research Vehicle; Bosch's Research Vehicle; tuSimple's Research Vehicle; ZhiXingZhe's Research Vehicle; Nvidia's Research Vehicle; SAIC Motor MG iGS; General Motors Cadillac CTS; Nissan's Research Vehicle; VisLab's BRAiVE [4]; PSA's Research Vehicle; Nagoya and Nagasaki University's Open ZMP Robocar HV [5]
Level 4-5	Production Vehicles: Research Vehicles: Ford's Hybrid Fusion Research Vehicle; KIT and Ohio State University's AnnieWAY [6]; Carnegie Mellon's Boss[3)] [4,7]; Googles Research Vehicle; Baidu's Research Vehicle; Uber's Research Vehicle; Drive.ai Research Vehicle; Pony.ai Research Vehicle; MIT's Talos [8]; Stanford's Junior [9,10]; Virginia Tech's Odin [11]; Apple's Research Vehicle

a) We classify production vehicles and research vehicles based on published data and descriptions. The classification may have some errors due to the limited available information. But we can see from the Table 1 that most production vehicles belong to Level 1-2.

4) Motors G. The Future is our Assignment-Book 4 in a Series of Visits behind the Scenes at the GM Research Laboratories: Flight the Firebird. Detroit, USA: General Motors, 1959.
5) Temple D W. GM's Motorama: The Glamorous Show Cars of a Cultural Phenomenon. Minneapolis, MN: Motorbooks, 2006.
6) West K L. Convertible top conversion 1970–1981 GM Firebird and Camaro. 1986. https://opus.ipfw.edu/etcs_seniorproj_mcetid/13.

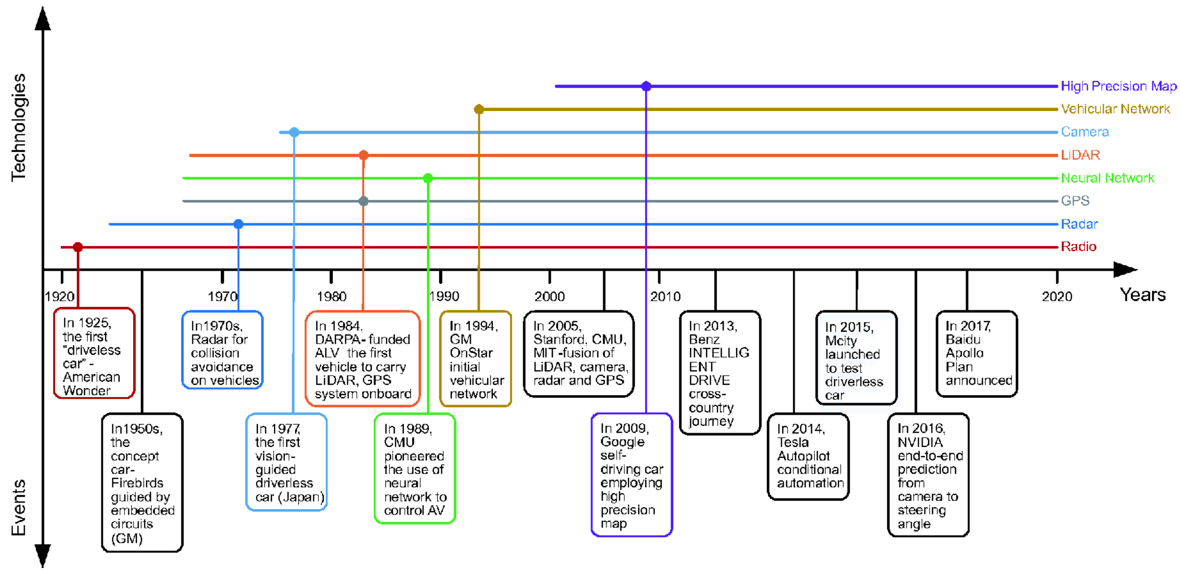

Figure 3 (Color online) Technology Roadmap of ICV.

Engineering Laboratory of Tsukuba in Japan developed the first camera-based driverless car that can detect obstacles in real time [15], the application of which benefitted from the appearance of digital camera in 1975 and the improvement of real-time image processing technology. In the 1980s, a vision-guided driverless Mercedes-Benz robotic van achieved a speed of 63 km/h on streets without traffic [16].

In the same decade, from 1984 to 1989, the DARPA-funded Autonomous Land Vehicle (ALV) project in the United States achieved the first road-following demonstration by using light detection and ranging (LiDAR), computer vision, and autonomous robotic control technologies to direct a robotic vehicle [17]. Even though LiDAR originated in the early 1960s, this event marked the first use of LiDAR in autonomous car [18]. Nevertheless, the LiDAR at that time was a five-channel multispectral laser range scanner, the output of which was a planar digital image [19]. Besides, the ALV vehicle employed global positioning system (GPS) to help navigation [20], which entered service in 1984. Based on the ALV project, in 1989, Carnegie Mellon University (CMU) pioneered the use of neural networks to steer and otherwise control autonomous vehicles[7)], forming the basis of contemporary control strategies, the key control algorithm of which was based on the purpose of perceptron in 1958.

Beginning in 1994, GM developed the OnStar telematics business to realize communication between vehicle and system, which pioneered the application of the vehicular network [21]. The vehicular network was later extended to V2X (e.g., vehicle, road, pedestrian, cloud). The dedicated short-range communications (DSRC) and WAVE [22] became the core of vehicular network.

Stanford [10,23], CMU [7,24] and MIT [8] applied the sensor layout of LiDAR, radar, camera and GPS/IMU on their intelligent vehicles in 2005 and 2007, which is an important milestone of multi-sensor fusion.

In 2009, Google self-driving car was introduced as breaking news. High-precision map growth in the past decade [25–27] had contributed to this success. In 2016, NVIDIA realized end-to-end prediction from camera to steering angle with deep learning, which performed well in road tests [28], leading a new trend of deep learning applications in autonomous driving [29,30]. Deep learning proposed by Hinton et al. [31] is a milestone of neural network development, which is based on increasing performance and lower costs of computational hardware (e.g., the emergence of graphics processing unit (GPU) in 1999) [32].

With the development of autonomous driving technology, many companies joined this fast-growing trend. For example, the Mercedes Benz's S-Class S500 INTELLIGENT DRIVE recreated the first cross-country automobile journey in 2013 [33]. The Tesla Autopilot for Model S realized conditional automation in 2014. Many other automotive companies and research institutes such as Audi, Ford, Chana, Baidu and University of Michigan are also developing their own intelligent vehicles. This is surely an era for the prosperity of the intelligent vehicle.

2 E/E architecture of ICV

In this section, we focus on one question: what are the differences between the EEA of a traditional vehicle and an

7) Pomerleau D A. Alvinn: An autonomous land vehicle in a neural network. Technical report. Pittsburgh: Carnegie Mellon University, 1989.

ICV? In order to answer this question, it is necessary to understand the requirements of an ICV's platform. The intelligence of an ICV actually comes from the capacity of acquiring and processing different sensor data. It is a fact that the traditional EEA is not designed to support the implementation of autonomous driving functionalities. The main drawback of the traditional EEA is its limited capacity in communication and computation. A practical and temporary method that is often used when building a demonstration ICV is to add additional cables and industrial computers to the vehicle. Nevertheless, this is not a standard solution for mass production vehicle in either quality, robustness, or cost. Therefore, the EEA has to be updated or even revolutionized to meet the requirements of communication and computation capacity. In the author's opinion, the major differences between the EEA of the next generation and a traditional one can be expressed in three aspects: the overall structure of EEA, the in-vehicle communication network and the computation platform.

2.1 The change in overall E/E architecture

The traditional EEA is designed for the situation in which human drivers have control, where most of the information is acquired and processed by human drivers [34]. Most of the modern vehicles were designed according to the gateway-based EEA. The central gateway works as the information transfer center to enable communication between multiple different clusters and provide diagnostic application. With the development of automotive technologies, especially the development of autonomous driving, the connected components need to transmit and receive much more data. The central gateway tends to be a bottleneck for data transfer, furthermore, it cannot provide support in processing data.

Therefore, the EEA of the vehicle has to evolve to have the ability to acquire large amounts of environment information in real time, and process these data simultaneously.

One feasible approach is to divide the controllers into several domains according to their function, which is called domain-based architecture and is recently applied in production vehicles. The so-called central domain electronic control units (ECUs) [35], are assigned to different domains, supporting the needs of both communication and computation. With the domain controller, the needed number of ECUs can be reduced, as their functions and computation can be integrated into domain controllers. Furthermore, the communication within the domain will not occupy the bandwidth of the backbone and gateway, which results in better performance and scalability. A typical domain-based EEA is illustrated in Figure 4.

Another type of EEA for future high-level ICVs is the centralized architecture. Different from a domain architecture, components in the centralized architecture are grouped according to their physical placement or their communication properties, rather than a functional domain. Each group has a controller in charge of the subnetwork, which is called a zone controller[8)]. The characteristic of this architecture is that most of the data processing is done in a central entity, illustrated as the driving brain in Figure 5, but not in the zone controller.

The centralized architecture has many significant advantages. First, as most algorithms are implemented in the central server, it is very convenient for diagnostics, debugging, and testing of the algorithms. Moreover, it provides a central control platform making it possible to consider all information together, such as situation inside and outside the vehicle, and information from local and cloud-based approaches, to optimize the overall safety and performance. Last but not least, the centralized architecture is flexible and easy to extend[9)]. The architecture can work as a "plug and play" system, if only the software drivers could be installed in the central computation unit. Research from Bosch also predicted that centralized architecture will be the future trend [35]. Many demonstration ICVs are developed by using centralized architecture, mainly because of its feasibility in implementation for non-automotive background researchers. However, for mass production, the application of this structure requires more powerful and more automotive-industry-adapted communication methods and computation platform.

2.2 The change of in-vehicle communication network

One of the most challenging tasks during the development of ICV is handling the communication among on-board electronic components, which are continuously increasing in both quantity and complexity. For the automotive industry, the task is even more difficult as the cost is very sensitive. The controller area network (CAN) protocol has been the dominant standard for vehicle hardware communication since it was firstly published by Bosch in the 1986 SAE congress with a paper titled "Automotive Serial Controller Area Network" [36]. Compared to other network technologies, CAN has been much more successful and will continue to be so mainly for two reasons: cost efficiency and flexibility. CAN with flexible data-rate (CAN-FD) is a variant of

8) Brunner S, Roder J, Kucera M, et al. Automotive E/E-architecture enhancements by usage of ethernet TSN. In: 13th Workshop on Intelligent Solutions in Embedded Systems (WISES). Hamburg: IEEE, 2017. 9–13.

9) Weiss G, Schleiss P, Drabek C. Towards flexible and dependable E/E-architectures for future vehicles. In: 4th International Workshop on Critical Automotive Applications-Robustness & Safety. Göteborg, 2016.

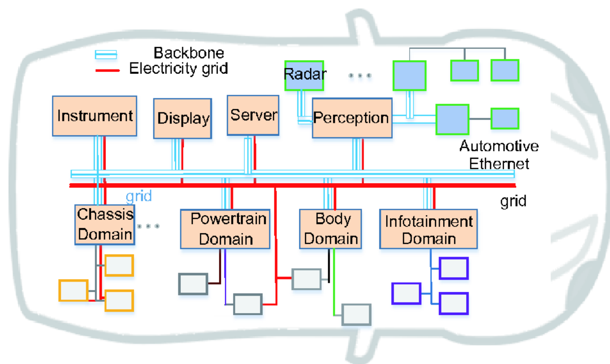

Figure 4 (Color online) Domain-based E/E architecture.

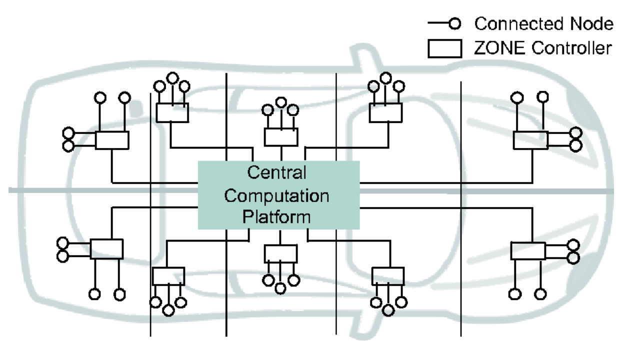

Figure 5 (Color online) Centralized E/E architecture.

CAN [37,38], it uses different data rate during one cycle of message transmission, with normal data-rate when sending arbitration bits, and faster data-rate when sending actual data bits. The bandwidth of CAN-FD is up to 8 Mb/s [39].

Apart from CAN, local interconnect network (LIN) is also widely applied in the automotive network [36]. Compared with CAN, LIN permits more low cost and flexible wire harness, as it is a single wire network. LIN can be easily implemented on various kinds of controllers, even the 8-bit microcontroller, without special support requirements, but its maximum transmission speed can only reach 20 kb/s. FlexRay and media oriented serial transport (MOST) are created to meet some specific requirements that are unique and critical in automotive environment [40]. FlexRay was created to support safety critical "X-by-wire" applications [41]. MOST was designed to obtain a higher data rate to support infotainment applications [42–44].

The recent advances in in-vehicle communication networks mainly concentrate upon automotive Ethernet (AE)[10] [40,45]. AE is an "old but new" technology, as Ethernet has been the most common technology for local area networks (LANs) in the computer world for nearly 45 years, whereas it has to be greatly modified to be adapted to the automotive industry. The first application of AE in production passenger vehicle could be found in the BMW X5 for connecting the onboard cameras, in 2013. The comparison of different networks is shown in Table 2.

AE is a promising option of in-vehicle network for the following reasons: (1) Larger bandwidth. The current AE bandwidth capacity can reach 100 Mbps, and soon will be updated to 1 Gbps. (2) Improved security. In the design of CAN and LIN, security was not considered thoroughly [46,47]. This kind of problem can be solved in the AE owing to its nature, as the Ethernet employs an IP-based routing method, stopping one hi-jacked ECU from getting full access to the whole Ethernet. Furthermore, the switches in Ethernet are capable to prevent the situation in which one ECU floods too much unwanted information into the network, causing an overload. (3) Low latency. The time sensitive network (TSN) can be applied to implement low-latency communication[8]. (4) Fewer ECUs and cables. With higher communication bandwidth, the AE can be used as a high-speed backbone to simplify the network, and reduce ECUs and cables. (5) Available standards. Many mature Ethernet standards would be applied in the automotive industry directly or with some minor modification.

Table 2 Characteristics of different in-vehicle networks

	AE	CAN	FlexRay	MOST	LIN
Bandwidth (Mb/s)	1000 (developing)	1 or 10 (CANFD)	20	150	0.02
Maximum number of nodes	Number of switch ports	30	22	64	16
Network length	15 m per link	40 m	24 m	1280 m	40 m
Messaging	IP based	Multi-master	Multi-master	Cyclic frames/streams	Master-slave
Cost	High	Low	Low	High	Very low
Safety-critical functionality	Proven outside of automotive applications	Yes	Yes	Yes	No
Availability	Growing	Many	Few	One	Many
Cabling	UTP	UTP	UTP	Optical, UTP	1-wire
Main applications	Infotainment, Backbone (future)	General bus	Safety-critical, X-by-wire	Infotainment	Switches, doors, seats

10) ABIresearch. Ethernet in-vehicle networking to feature in 40% of vehicles ship-ping globally by 2020. 2014. Available at: https://www.abiresearch.com/press/ethernet-in-vehiclenetworking-to-feature-in-40-of.

Owing to these advantages, more and more companies are planning to use Ethernet in cars. However, in the author's opinion, the traditional networks such as CAN will not be replaced completely. The cohabitation of heterogeneous networks in the vehicles will last for many years.

2.3 The change of V2X communication network

The vehicle to X (vehicle, roadside and people) communication network is a dynamic network which combines the inter-vehicle network and the mobile network. The V2X communication is fundamental to realize the intelligent traffic control, the vehicle intelligent control. According to the communication protocol and the data exchange standard, the wireless communication and information exchange are carried out from vehicle to vehicle, roadside and people, so as to realize the intelligent traffic management control, the vehicle intelligent control and the intelligent dynamic information service.

In 1990s, the development of vehicle networking was focusing on the telematics vehicle information service based on wide area mobile communication. For instance, Toyota Corporation launched G-Book intelligent vehicle communication system to provide emergency rescue, anti-theft tracking, and safe driving reminder for vehicles.

In the late 1990s, the short-range communication technology was gradually rising, people began to study the communication through the point to point mode. Among them, dedicated short-range communication (DSRC) technology is widely used in vehicle networking communication [48], which has optimized the reliability of data transmission and delay performance. At present, various countries have formulated different technical standards for DSRC. For Europe, the DSRC carrier frequency band is 5.795–5.815 GHz, while it is 5.850–5.925 GHz for North America, Japan uses the 5.770–5.850 GHz band, and the 5.8 GHz band is adopted in China. The high cost of DSRC communication module is a significant drawback of this system. In addition, because of its use of CSMA access mechanism, when vehicle density is large, packet loss and network congestion of DSRC will appear.

The development of ICV results in the increasing demand for bandwidth, connection reliability and transmission delay of the wireless network. 4GLTE technology has great advantages in this regard, and the technology can support a large number of terminal access at the same time. It has been applied in some vehicle networking projects, such as the European CoCar project. The feasibility of applying the cellular mobile communication technology including UMTS and LTE to the V2V and V2I scenarios is studied. In some applications, mobile communication networks have more advantages. DhilipKumar et al. [49] applies 4GLTE technology to the internet of cars. By analyzing data throughput, time delay, power consumption and other indicators, it confirms that 4GLTE can indeed improve the performance of the network. However, 4GLTE technology requires base station to establish communication. At present, the point to point communication of car cannot be realized in the area without the base station covering.

In 2012, the United States Department of transport led the Connected Vehicle Safety Pilot project, which mainly studied the influence of V2X system based on DSRC technology on vehicle driving safety. The project installed V2V equipment on more than 2800 vehicles, and established a regional connected transportation system to improve the actual traffic efficiency [50]. In Japan, the AHS project research vehicle synergy technology impact on traffic safety. In Europe, vehicle road coordination system (CVIS) project [51] and DRIVE C2X [52] project realize vehicle and vehicle communication, and verifies the driving safety and transportation efficiency in collaborative environment.

2.4 The change of computation platform

After a mass of information being collected in the ICV, huge amounts of computation are expected to be performed swiftly, precisely and robustly, as well as at low power consumption. In traditional vehicles, the computation platforms mainly refer to the ECUs. The traditional ECU can no longer meet the stringent requirements of high-level ICVs, and thus more elaborate hardware and more powerful software are urgently needed.

In the early stage, some simple controllers were widely used in traditional vehicles, such as microcontroller units (MCUs) (8-bit, 16-bit and 32-bit) and digital signal processing (DSPs). Relatively simple control, including taillights on and off [53], air-conditioning [54], powertrain [55], etc., can be realized through classic MCUs. DSPs, featuring high integration and great processing capacity, are more proper for onboard multimedia systems [56], also commonly applicable in driver assistance functions [57,58].

Recently, with emergence of computation demands for artificial intelligence (AI), such as image processing and deep learning, the in-vehicle computation hardware revolution has been underway. Graphics processing units (GPUs) are designed to perform massive parallel computation, especially good at image processing [59]. It can be equipped not only for the entertainment system, but also for automated driving functions like obstacle detection and collision avoidance. Field-programmable gate arrays (FPGAs) are also characterized with parallel computation, but it is realized based on hardware, whereas GPUs depend more on algorithms. GPUs have the advantage of being programmed much more easily and applying to more unexpected situations, but they may consume more power [60]. Recently, Google developed a new processor for machine learning, called a tensor processing unit (TPU). TPU is a kind of application specific integrated circuit (ASIC), while central processing unit (CPU) is a typical general-purpose processor (GPP), DSP and GPU are classified into application-specific processors (ASPs), and FPGA is a kind of configurable hardware. The TPU has been regarded to possess the highest computation efficiency so far [61], considering the performance and power consumed. A new concept called a neuromorphic chip [62], which can work like human brain, also emerges, hoping to further reduce the delay and power consumption when performing deep learning. The performance of different chips are compared in Figure 6.

A popular scheme for ICV central control is CPU+GPU [63], represented by NVIDIA Drive PX 2, which is announced to be able to support high-level automated driving. Intel applies another hardware approach for AI, which is the CPU+FPGA scheme[11]. It can handle deep learning with lower power consumption, less time delay and greater acceleration performance, but it is not able to execute instructions not programmed, which means it is less flexible. The multi-core heterogeneous architecture is believed to be the solution of computation hardware design for future ICVs.

Software of computation platforms also has to evolve alongside with hardware, in order to make the best use of the updated hardware. By the mid-1990s, OSEK/VDX, a specification for open system and the corresponding interfaces for automotive electronics and vehicle-distributed executive, had been developed by the European automotive industry [64]. In addition to Europe, Japan also established JASPAR (Japan Automotive Software Platform and ARchitecture) in 2004, whose main members included Toyota, Nissan, Honda and Denso.

However, as the automotive electronic systems are becoming far more complicated, OSEK/VDX or JASPAR is not qualified enough to meet the requirements of reusability and transferability. The standard AUTOSAR (AUTOmotive Open System ARchitecture) was designed by an organization which is now made up of almost all the main OEMs, Tier1 parts suppliers, semiconductor suppliers and software developers. The most prominent contribution of AUTOSAR is separating application software from the associated hardware, which can obviously improve the reusability and transferability, and save a lot of development costs [65].

The classic AUTOSAR is designed to support control and runtime functionality in ECUs, but infotainment and user application functions, which are increasingly important to automated driving, remain unaddressed. Conversely, Linux, Android, and other general operating system can perfectly

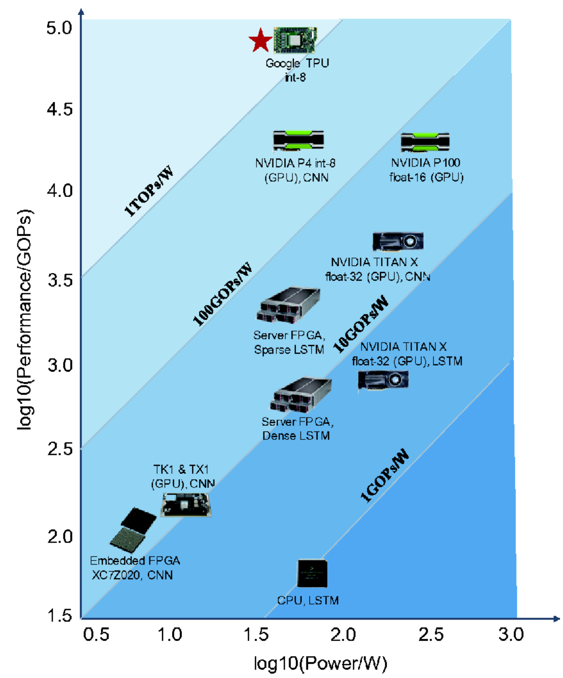

Figure 6 (Color online) Computation capacity and power consumption of different computing elements.

meet the requirements for connectivity and infotainment, but fail to be utilized in ECUs. To implement more possible functions for the future automated vehicles, the gap between these two kinds of software platforms has to be eliminated [66]. One solution to this problem is improving the automotive software, such as the development of AUTOSAR adaptive platform[12], which is designed to meet the POSIX standard and is thus compatible with other operating systems. Another solution is changing the general operating systems to be adapted to the automotive industry. Robot operating system (ROS) is a typical software platform for ICV based on Linux, and has been widely used by ICV developers [65].

With the unified and integrated platform and open source, manufacturers will be able to produce more types of application software and realize more automated functions in the future [67]. As is roughly illustrated in Figure 7, the consumer electronics and automotive electronics are converging into the revolutionized computation platform for future ICVs [68].

Besides the intelligent functionality, software updates and security are two other critical elements in software development. As the ICV is under a continuous modification process, the “over the air” update of software applications is quite necessary to ensure the ICV running with most recent

11) Zhang C, Chen R, Prasanna V. High throughput large scale sorting on a CPU-FPGA heterogeneous platform. In: 2016 IEEE International Parallel and Distributed Processing Symposium Workshops. Chicago, IL: IEEE, 2016. 148–155.

12) Fürst S, Bechter M. AUTOSAR for connected and autonomous vehicles: The AUTOSAR adaptive platform. In: 46th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshop. Toulouse: IEEE, 2016. 215–217.

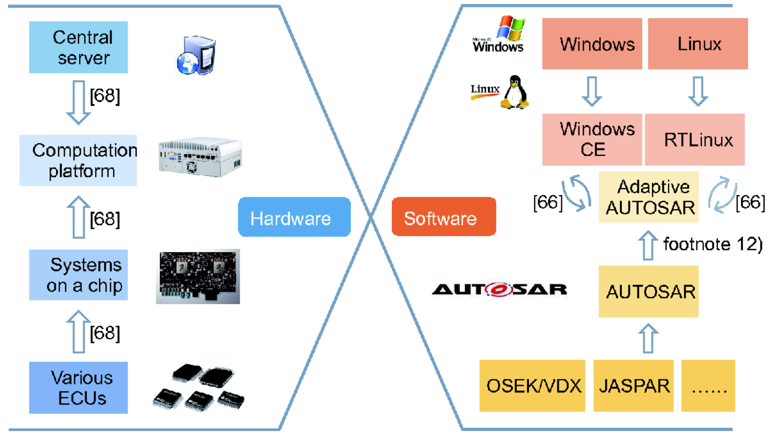

Figure 7 (Color online) Relationship between hardware computation platform and software operation system.

technology. Distributing update is a possible method[13)], which can evidently reduce the update time. Moreover, current formal methods for verifying correctness of transition systems may be extended to vehicle system by specifying correct behavior [69], which can further improve the security.

3 Sensors in ICV

In order to achieve intelligent driving capacity, it is essential for ICVs to have full observations of both their own state, surrounding environment and even the situation beyond the visual range. The self-state is the basis of decision making, and the perception of self -state is mainly based on proprioceptive sensors. In order to ensure the driving safety of the car, it needs to be aware of the surrounding vehicles, obstacles, road conditions, and so on. These perception tasks are mainly completed by exteroceptive sensors. However, in the high-speed driving condition, in order to ensure the driving safety, comfort and economy, it is necessary to sense the long-distance environment. In addition, blind-spots also need to be sensed in order to ensure traffic safety, as shown in Figure 8. Some typical technologies are listed in Table 3.

From Table 3, we can draw the conclusion that if we want ICVs to achieve high/full autonomous driving, proprioceptive, exteroceptive, and virtual sensors are all necessary.

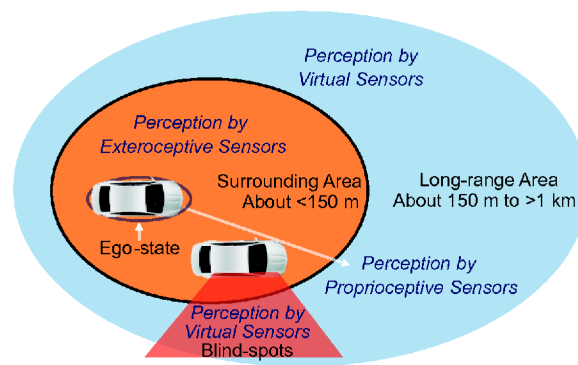

Figure 8 (Color online) ICV perception requirement area.

3.1 Proprioceptive sensors

Proprioceptive sensors usually refer to sensors such as pressure sensors, engine temperature sensors, gas concentration sensors, flow sensors, wheel speed sensors, and knock sensors, which are mainly used to guarantee the basic driving functions. For better driver comfort and driving convenience, more sensors have been used on the car such as

Table 3 Typical technologies perception requirement

	Ego state	Surro-unding	Long range	Blind spot
Lane-keeping [70]	++	++		
ACC/CACC [71]	++	++	+	
Collision Warning [72,73]	++	++	+	++
Auto Parking [74]	+	++		+
Path-Planning [7,75]	++	++	++	++
Stop & Go [76]	++	++		

13) Onuma Y, Terashima Y, Kiyohara R. Ecu software updating in future vehicle networks. In: 31st International Conference on Advanced Information Networking and Applications Workshops. Taipei, China: IEEE, 2017.

vehicle speed sensors and pedal position sensors for ACC, air temperature sensors and humidity sensors for the air conditioning system, localization sensors and inertial sensors for the navigation system [77,78].

The localization sensor mainly refers to the GPS sensor. The localization accuracy of the traditional GPS is usually approximately 10 m. However, with the development of driverless vehicles, the requirement of the ICV's position accuracy becomes higher, and the traditional navigation GPS cannot meet this demand. In order to improve the positioning accuracy, the real-time kinematic (RTK) technique is presented. It uses measurements of the phase of the signal's carrier wave, rather than the information content of the signal, and relies on a single reference station or interpolated virtual station to provide real-time corrections, providing up to centimeter-level accuracy. The current RTK method are virtual reference station (VRS) [79], master-auxiliary concept (MAC) [80], Flaechen-Korrektur parameter (FKP) [60], combined bias interpolation (CBI) [81] and so on. Currently, the methods of reference station establishment are the ground-based augmentation system (GBAS), also called local area augmentation system, and satellite-based augmentation system (SBAS), also called wide area augmentation system. GBAS is mainly applied in ICVs, as the ground reference stations' accuracy can be guaranteed. And SBAS are normally used in ships and planes, where the ground reference stations cannot be established.

3.2 Exteroceptive sensors

The exteroceptive sensors are mainly used to sense a vehicle's driving environment. The characteristics of typical exteroceptive sensors employed in ICV[14),15)] [6,82–88] are shown in Figure 9.

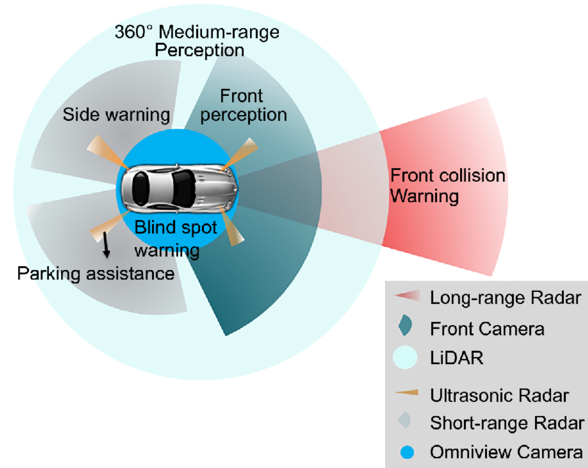

Figure 9 Typical exteroceptive sensors characteristics.

Ultrasonic radar data processing is simple and fast, the ultrasonic wave energy will be greatly attenuated as it propagates through the air, and it is difficult to obtain accurate distance information. Therefore, it is usually used as reversing detection radar in the traditional manned vehicle.

Millimeter wave radar has the capability of penetrating fog, smoke, and dust. It has the characteristics of handling all-weather, small size, low cost, and long detection distance. It is widely used in ICV to detect long-range targets. However, the millimeter-wave radar horizon resolution is not high [89]. Millimeter wave radar usually cooperates with other sensors. The most common solution is to incorporate vision sensor for target detection and tracking [90].

The visual sensors used in ICV are monocular vision system, stereo vision system, Omniview system, and infrared vision system. Monocular vision systems are mainly employed in the semantic segmentation of driving environment [89], target detection and tracking [91], ranging [73,92], driver behavior analysis [93] and so on [82,94]. At present, monocular vision systems are widely used and have been equipped on some production vehicles.

The Israeli company Mobileye's monocular vision products have been provided road semantic feature descriptions, and pedestrian and vehicle identification and ranging. By the end of 2015, it had been installed in more than 10 million vehicles, covering more than 20 automotive enterprises.

The stereo vision systems consist of several visual sensors. The distance of feature points is directly measured by the parallax principle. Currently, stereo vision system is mainly used in ranging and target recognition and tracking based on depth image [95]. The latest trends in the stereo vision field mainly pursue real-time execution speeds, as well as decent accuracy, whereas these two properties are always in opposition [96,97]. In the applications towards intelligent vehicles, Mercedes Benz uses a stereo vision system, called SMPC, to achieve three-dimensional human/vehicle testing, BOSCH and Continental have binocular camera products.

Omniview system is also composed of several cameras, designed to make the system reach 360° visual field. In a common Omniview system, there are four wide-field cameras, covering the whole area around vehicle. The system synthesizes a bird's-eye view image in front of the vehicle by distortion correction, projection transformation, and image fusion. Omniview technology first became available in vehicle electronic products in 2007, as a vehicle parking assistant technology.

Infrared night vision systems are developed to make the

14) No Hands Across America Official Press Release. http://www.cs.cmu.edu/~tjochem/nhaa/official_press_release.html.
15) Gehrig S, Reznitskii M, Schneider N, et al. Priors for stereo vision under adverse weather conditions. In: Proceedings of the IEEE International Conference on Computer Vision Workshops. Sydney, NSW: IEEE, 2013.

environment perceptible by the ICV at low light conditions. Visible light ranges from 400 nm (violet/blue) to 700 nm (red); wavelengths above 700 nm and up to about 30 mm (=30000 nm) are known as infrared. Sensors working in the near-infrared (NIR) radiation region are based on the detection of NIR photons reflected from objects, whereas the mid-wave infrared (MWIR) and long-wave infrared (LWIR) detectors detect thermal photons which are emitted by an object originating from its heat, which can be used for ranging and detection at night [98].

The relationships between different kinds of vision sensors are shown in Figure 10.

LiDAR is used to measure 3D-representations of a target by illuminating the target with a pulsed laser light and measuring the reflected pulses and reflected laser intensity. The current applications and algorithm for LiDAR are mainly obstacle detection (segmentation) [99,100], target tracking [101,102], 3D mapping (SLAM) [103,104], and fusion with image [105–107]. The LiDAR used in ICV can be divided into high- and low-definition LiDAR according to the number of laser channels. High-definition LiDAR has a view of 360° with more than 16-layer laser. Low-definition LiDAR has a view approximately 100° to 200° with usually four or one layer laser. According to the method of changing laser scanning angle, LiDAR can be also divided into mechanical LiDAR, semisolid-state LiDAR and solid-state LiDAR. Mechanical LiDAR and semisolid-state LiDAR achieve the rotation of scanning through the way of hardware rotation. Without special indication, mechanical LiDAR means mechanical and semi-solid state in the following paper. Solid-state LiDAR fulfills horizon scanning without mechanical rotation. Current research on solid-state LiDAR

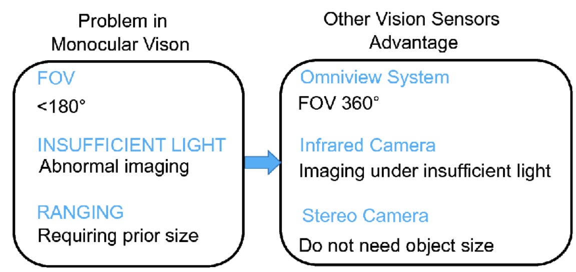

Figure 10 (Color online) Comparison of monocular with other vision sensors.

based on a micro electro mechanical system (MEMS) mirror [108,109] or optic phased array (OPA) [110,111]. The properties of these LiDARs are compared in Table 4, and the principles are shown in Figure 11.

3.3 Multi-sensors fusion and virtual sensors

3.3.1 Multi-sensors fusion

It is important to fuse multiple sensors information, such as camera-radar [112], camera-LiDAR [107], and visual odometry-GPS-IMU [113]. The mainstream fusion algorithms are the filter method (e.g., Kalman filter, particle filter) and the optimization method (e.g., graph optimization). The information fusion technology improves the accuracy and reliability of the data [114,115]. With the development of the intelligent driving system, there is also perception demand for blind spots and targets outside the field of view (FoV). In order to solve this problem, fusing other information sources, such as other vehicles or infrastructure facilities, can be applied. Figure 12 shows that for high-level ICVs, the V2X and HD map are the essential sources of information. V2X

Table 4 Comparison between mechanical, MEMS mirror and OPA LiDAR

	Scanning frequency	Resolution	Directional controllability	Sidelobe	FoV	Price
Mechanical	<100 Hz	0.08° (Horizon) 0.4° (Vertical)	Spinning direction controllable	None	Up to 360°	5000~70000$
MEMS Mirror	>1 kHz	μrad level	Direction controllable	None	~200°	<100$
OPA	>1 MHz	μrad level	Direction controllable	Have	~150°	<100$

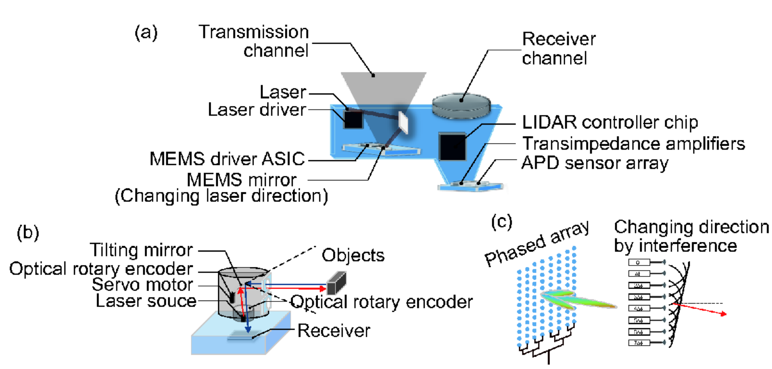

Figure 11 (Color online) Mechanical and solid-state LiDAR. (a) MEMS mirror; (b) mechanical; (c) OPA LiDAR.

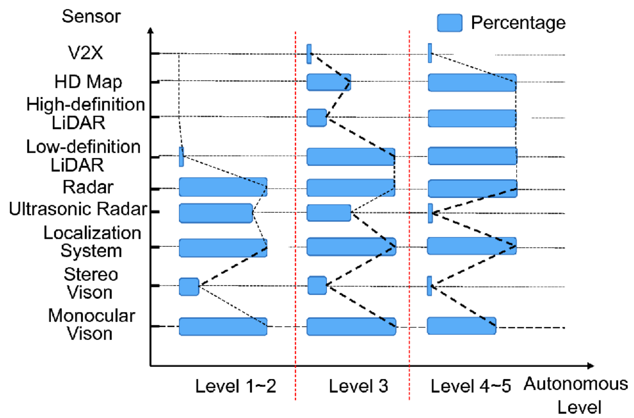

Figure 12 (Color online) Sensors used in different autonomous level (concluded from Table 1).

and HD map are called virtual sensors in this study, as they are not the normal sensors, but provide useful information.

3.3.2 V2X

The concept of V2X communication emerged in the late 20th century. With the rapid development of networking, a variety of wireless communication technologies appeared: the development of 4G LTE and 5G remote communication technologies, and the breakthrough of DSRC. Cooperative intelligent transportation systems (ITS) based on vehicular communication are the next important steps to the vision of accident-free driving [116].

At present, the V2X communication is employed to enhance two kinds of intelligent driving. The first one is the onboard-based intelligent driving, where the V2X is employed as an additional sensor to provide supplementary information besides the on-board sensors. Typical usage of V2X is to realize cooperative localization and cooperative perception. The other kind of intelligent driving is the could-based intelligent driving. The information of connected vehicles will be collected and analyzed by the cloud servers to manage the overall traffic efficiency. The cloud-based intelligent driving is more a topic of intelligent transportation system, which is out of the scope of this article. The V2X is very helpful to localization. Although the fusion of IMU, visual odometry or filtering algorithms [117,118] can improve the positioning accuracy in this situation, the errors will accumulate with time. However, the accurate localization can be fulfilled through V2X communication, as the infrastructure could correct the position errors [119,120].

Furthermore, cooperative perception based on V2X is an effective way to solve the problem of limited perception range and blind-spots. Cooperative perception based V2X can not only be used to improve the reliability of target recognition and tracking in FoV [121], but also achieve perception of the area out of the FoV or in occlusion [72,122,123], and realize the fusion of free space [74,124].

As Figure 13 shows, there has already been some research

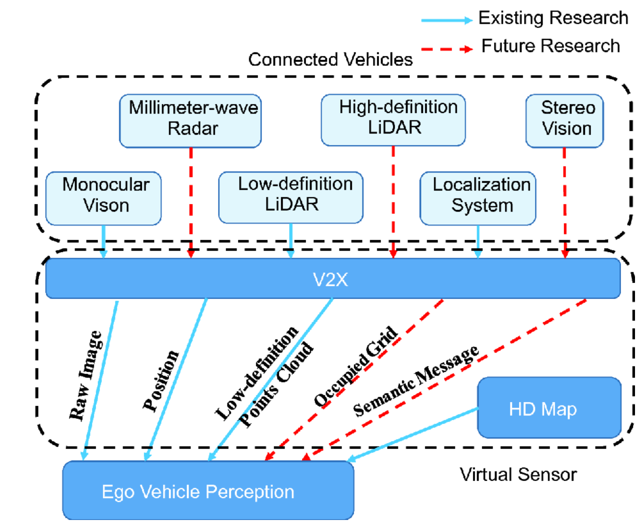

Figure 13 (Color online) Majority message exchange in V2X currently and the future research topic.

on exchange monocular vision [72], low-definition LiDAR [72,122,123] and localization systems [121]. However, the amount of information communicated is limited. The future trends in V2X include the perception results such as the occupied grid and semantic messages, rather than enormous raw data.

3.3.3 HD map

HD map can provide accurate and reliable surrounding environment information for ICVs. The prototype high-precision map was generated from the Urban Challenge. Organizers provide the road network description file (RNDF) for each vehicle.

The storage format and expression form of HD map [125–127] the acquisition devices, and the feature exaction-association problem [107,128,129] are still the focus of the research. Different research institutions have different expressions of HD map. In order to carry out a common layered structure to classify HD maps of different forms in future research, we propose a seven-layers HD map structure, as shown in Figure 14.

Layer 1: Road-level network layer. Providing road-level message, which can be used in global route planning (mission planning) [130].

Layer 2: Global dynamic layer. Providing global dynamic message, such as traffic jam and road works, which can be used in congestion avoidance and dynamic global path planning.

Layer 3: Inter layer. Providing lane-level road network data, mainly the lane data.

Layer 4: Lane-level detail layer. Providing roadside information of the road, such as point of interest (POI), building and guidepost. Layer 3 and Layer 4 can be used in behavior planning [10] or lane-level global route planning

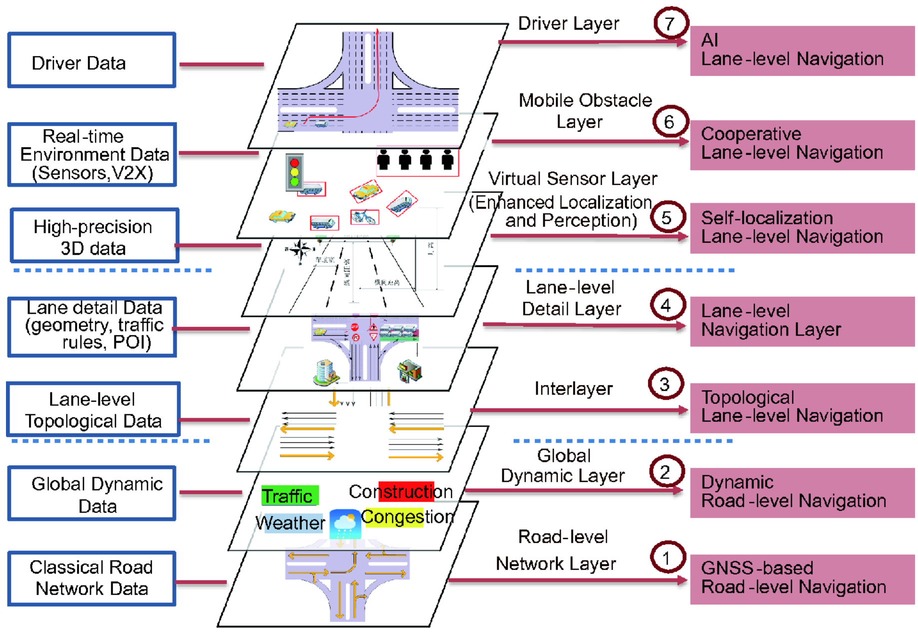

Figure 14 (Color online) Seven layers HD map structure.

[131].

Layer 5: Virtual sensor layer. Providing high-precision 3D data, which can be used in HD map based localization or perception [132–134].

Layer 6: Mobile obstacle layer. Providing standardized interfaces for fusing the information from multisensors (LiDAR, camera, V2X and etc.), which can be used in motion planning [7] and dynamic local route planning.

Layer 7: Driver layer. Characteristic driving date layer, which learn driver's habits or provide different driving modes.

One significant benefit of using the seven-layers HD map is that it provides a unified information fusion platform with standardized data exchange structures, which are able to exchange data from static maps and real-time sensors.

4 Actuators in ICV

4.1 Current vehicle platform for ICV

Vehicle platform technology is a key technology in developing ICV. The vehicle platform mainly refers to the actuators of vehicle, which are responsible for executing the driving behaviors, such as the turning, braking. In the traditional vehicles, the actuators are designed to be controlled by human drivers, thus cannot support the autonomous driving. To enable the autonomous driving functions in prototype ICVs, the actuators of vehicle should be customized to react to the orders of controller. In the early state, the automated control of steering, brakes, and throttles are realized by mounting additional motors. For example, Sandstorm [24,135] of CMU in 2005 DARPA Grand Challenge controls the steering angle by a gear attached to a dc motor. Similarly, for longitudinal dynamics control, the throttles and brakes are also controlled by additional motors with analog position feedback. With the development of automotive electronics, the electronic control systems have been widely employed in the production vehicles. The steering, brakes and throttles are controlled by the ECU through CAN bus. In this way, the control of vehicle behavior can be realized by sending CAN signal according to the protocol. For instance, Tsinghua University has realized the autonomous driving from Chongqing to Beijing together with an automotive manufacturer. The vehicle platform in this activity is provided by the manufacturer with full access to the CAN bus.

4.2 Future vehicle platform for ICV

Electric actuators are becoming very common in passenger cars, especially in electric vehicles, executing almost all tasks during driving, including steering, braking, suspending and even accelerating. The characteristics of actuators are deeply coupled with the design of control algorithms. Thus, it is necessary to acknowledge the recent advances in actuators. This section will review two kinds of technologies related to actuators: X-by-wire and distributed drive, which are changing or are going to change the control algorithms of ICVs.

X-by-wire technology was originally used on airplanes. In 1972, the first digital fly-by-wire fixed-wing aircraft without a mechanical backup was developed by NASA [136]. After approximately 40 years development, the X-by-wire system has quickly become an standard equipment for luxury cars [137,138], as shown in Figure 15.

One large benefit introduced by X-by-wire technology is the standard digitalized control platform, where internal or external controllers can have full control of brake pressures and wheel angles through the CAN or FlexRay bus. X-by-wire enables the development of active safety technology by controlling the longitudinal and lateral dynamics together, further improving the vehicle's stability in critical situation [139–143]. In addition, compared with the traditional cars, a car equipped with X-by-wire could be transformed into a high level ICV with less modification. For example, Junior by Stanford in 2008 utilized "drive-by-wire interface" to pass controls on throttle, brake, steering, gear shifting, turn and emergency brake [10]. P1 by Seoul University was equipped with throttle and two front steering wheels by wire [144].

Distributed drive technology has garnered great attention from ICV researcher worldwide, as it offers higher energy efficiency and motion control performance [145,146]. The first application of distributed drive technology was proposed by Ferdinand Porsche as early as in 1898, when he designed the world's first electric vehicle using hub motors. Nearly a century later, the distributed drive technology enters into a rapid development stage along with the popularity of electric vehicle, as shown in Figure 16. In 2012, Tesla released Model S, of which the front and rear axles are respectively arranged with motors to realize all-wheel drive.

In the author's opinion, the distributed drive electric vehicle (DDEV) is the most promising chassis platform for ICV for the following reasons: (1) More space. The chassis of DDEV has much more space for flexible arrangement [147]. (2) Better controllability. The individual torque of each wheel can be distributed according to dynamic configuration. (3) More power. The Tesla Model S uses a dis-

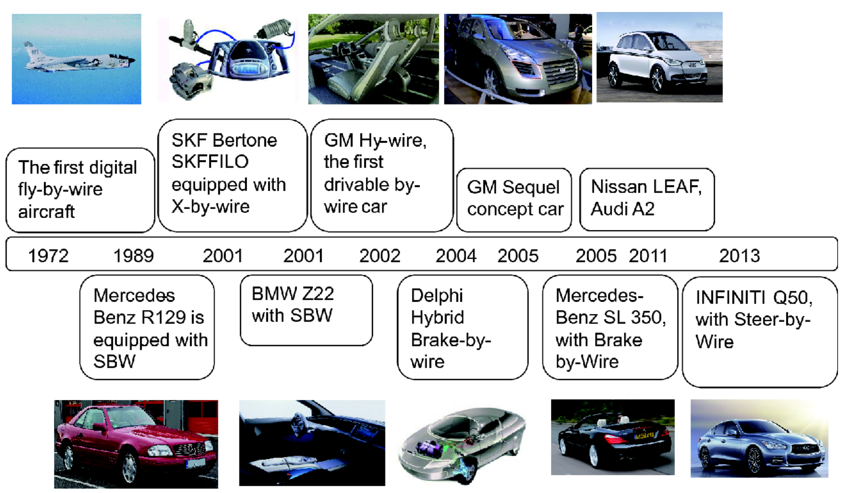

Figure 15 (Color online) Development of X-by-wire.

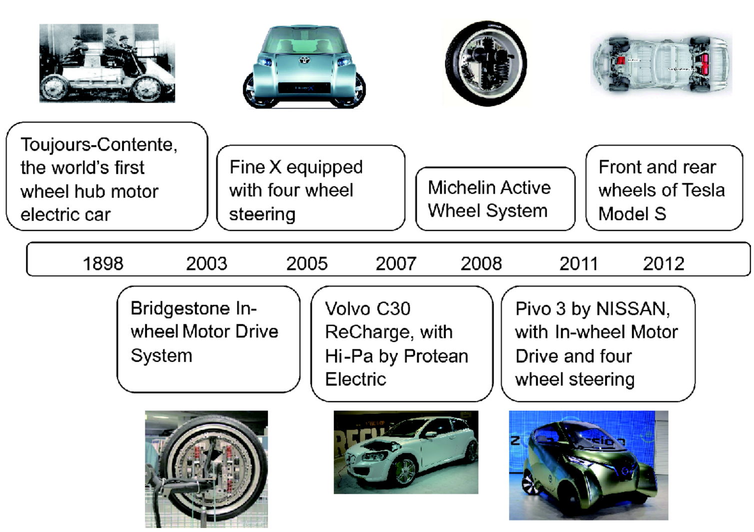

Figure 16 (Color online) Development of distributed drive and independent steering technology.

tributed front and rear drive mode to achieve higher acceleration performance. (4) Higher energy efficiency. It reduces vehicle weight and simplifies the transmission system. (5) More flexibility. Fully distributed drive can be combined with independent steering technology, enabling much flexible motion, such as oblique and lateral movement.

Although these new actuators have many advantages and some of them have already been used in ICVs, the mentioned new actuators can still be improved in the following aspects: (1) Reliability of system. The improvement of reliability is essential to the vehicle safety. It can be achieved by redundancy design [148]. (2) Multi-goal optimized control algorithms. The new electrical actuators provide a new platform with much flexibility and different dynamics characteristics, resulting in significant changes in the vehicle control model. Thus, new dynamics models and new control algorithms need to be redesigned to realize multi-goal optimization. Some initial research have already been published [149–151], but further research is needed.

5 Decision algorithms

In general, the main intelligent vehicle algorithm framework is divided into three elements: environment perception, decision making and vehicle dynamic control. Environment perception is the principal focus for modeling the environment and providing information about surrounding objects to the intelligent vehicle. Excellent research and reviews, such as refs. [152–154], have been published. Vehicle dynamic control, including lateral and longitudinal control, is related to the structure and model of the controlled vehicle [155]. In this section, we focus on the review of decision-making algorithms, especially motion planning.

An essential task for ICVs is to "decide" how to plan a feasible path towards the destination against obstacles and dynamic limitations. Some reviews for motion planning already exist and made great contributions. To generate the trajectory directly, Souissi et al. [156] summarized the path planning approaches. The methods in that study could generate a trajectory between two points on the roads, but did not consider much about the vehicles' features. Furthermore, Katrakazas et al. [157] mainly focused on the vehicles. They described the main approaches for systematically planning maneuvers and trajectories, and covered some of the most important ideas concerning intelligent vehicle motion planning. González et al. [158] found that the generated trajectories were not always suitable to all conditions. They compared the benefits and limitations of these methods such as computing efficiency, required hypothesis and applied scenarios. In addition, some reviews focus on the specific requirements of motion planning. Veres et al. [159] described how to model the environment and form data abstractions for symbolic processing and logic-based reasoning. Eskandarian [77] summarized motion planning in terms of safety issues, focusing on risk estimation. Motion planning needs to be able to predict surrounding objects and some approaches are summarized in ref. [160]. Bila et al. [161] reviewed the safety issues related to motion planning.

Most of these articles focus on specific approaches, and are not so much written for the autonomous vehicle decision framework itself. Therefore, this study will focus on how the vehicle makes a decision and then generates a trajectory. We will provide the big picture for researchers and developers embarking on future work.

5.1 How humans learn to drive

"Learning" is an important ability for human beings. Drivers need to take professional training courses to learn how to drive. Similarly, the autonomous vehicle decision framework needs to deal with information in the environment through a perception system and then calculate the control signals for controllers. Thus, the decision framework also needs to "learn" to drive similar to how human beings do. It is therefore meaningful for researchers to understand how humans learn to drive.

The two main processes by which humans learn are through "procedural memory" and "declarative memory". "Procedural memory" is created through procedural learning or repeating a complex activity over and over again until all of the relevant neural systems work together to automatically produce the activity [162]. The "procedural knowledge" needs to be mastered by practicing. "Declarative memory" is the conscious, intentional recollection of factual information, previous experiences and concepts [163]. People usually recall "declarative knowledge" to finish a task or make a decision. Both memory processes are important for human beings and are often used together.

Inspired by the human learning process, researchers have recourse to two ideas for developing a framework for autonomous vehicle decision-making. Some researchers hope to "practice" the system and "develop" it based on driving data. Weng [164] proposed an autonomous mental development robot, which is the application of "procedural memory" on the robot. Other researchers try to summarize the models that can describe the environment and vehicles and present them as "declarative knowledge". In this study, we try to summarize the autonomous vehicle decision approaches and applications in terms of these two points of view. In order to explain the relationship and differences between the approaches more clearly, we define the "principles-based methods" and "data-based methods" as follows. There are two stages in the process of the autonomous vehicles learning to drive for the unfamiliar situations, which are explained in Figure 17: (1) the vehicles "search" the

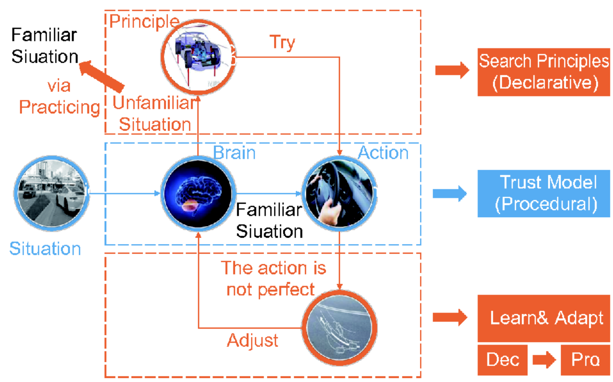

Figure 17 (Color online) How the autonomous vehicles learn to drive compared with human drivers.

principles and "choose" a suitable one to generate the action; (2) after this action, the vehicles "observe" the results and adjust the action for the next time. If the autonomous vehicle just uses principles and does not adjust, this approach is considered as a total "principles-based method". By contraries, if the vehicle generates the action only by adjusting without any principles, this is a "data-based method". Most approaches are based on both principles and data. In Figure 18, we summarize the main approaches and applications in terms of these two methods and the details will be introduced in the following paragraphs.

5.2 Data-driven motion planning

5.2.1 Why the data-based method gets attention

Data-based methods want to learn the rules from database which means the methods should find the relationship from the input and output data. Machine learning [165] is just an important technology for establishing a relationship between the input and output based on real data, which is also a key method among data based methods. In fact, the development of machine learning can be traced back to the 1950s. Samuel [166] developed the famous Checker programs to beat humans, which turned people's focus to machine learning. Connectionism based on neural networks developed rapidly soon thereafter. One of the representative results was the "Perceptron" proposed by Rosenblatt [167]. Michalski et al. summarized the developing process of machine learning up to 1983[16]. In 1985, Ackley et al. [168] made an important breakthrough in this area, proposing an approach where the neural network can adjust itself according to the error of the output data. That means that neural networks can learn from the dataset, without prior experience and knowledge. The neural network has much deeper layers and need more benchmark data. Deep learning [169] grows up and is gradually applied in many fields, including computer vision and chess. In 2012, Krizhevsky et al. [170] achieved much greater accuracy than before based on deep learning. The record from the image detection challenge race in PASCAL VOC [171] shows that the results via deep learning are more accurate than the results from model-based methods. The famous competition in which AlphaGo beat the best player in the world [172] also showed the great potential of the learning method.

From all the above, we can see that data-based methods (deep learning) provide the possibility to break through the limitations of human cognition. For the autonomous vehicle system, particularly motion planning, there are many non-measurable parameters [173] and errors [174] need to be

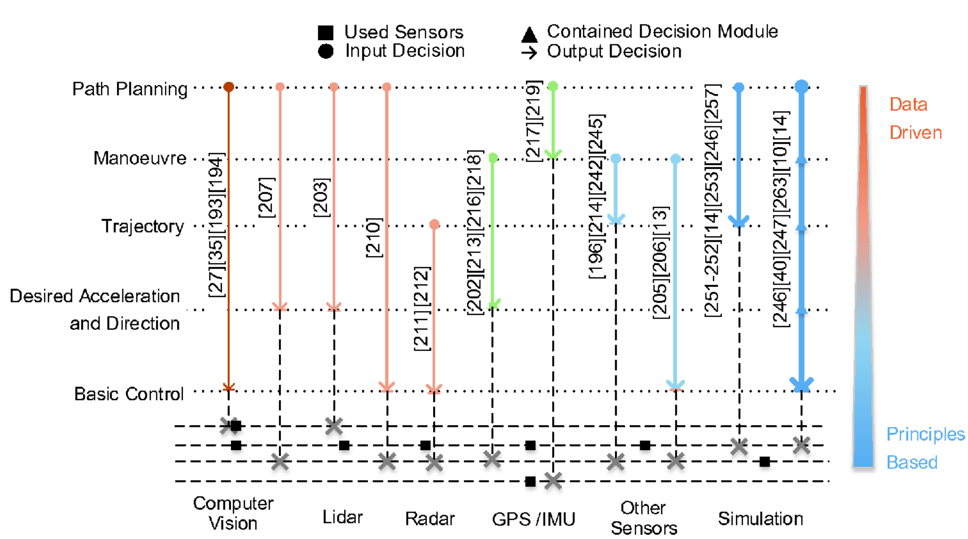

Figure 18 (Color online) Factors which the references trust and the control level they apply.

16) Michalski S R, Carbonell G J, Mitchell M T. Machine Learning an Artificial Intelligence Approach Volume II. Berlin, Heidelberg: Springer, 1984.

considered. These factors are difficult to be modeled and measured accurately, and should be addressed with learning methods. On the other hand, control signals data are much easier to collect [175] in intelligent vehicles, providing the conditions for the learning process. Because of these considerations, some researchers have focused on this area which will be described in details in the next part.

5.2.2 How deep learning is used on autonomous vehicles

Data-based methods in intelligent vehicles date back to the 1990s. Alex Waibel et al. at Carnegie Mellon made an autonomous land vehicle in a neural network called ALVINN[7)]. Limited by the sensors, computing ability and neural network structure, ALVINN can only drive on some simple roads in some specific situations. This vehicle is not yet “autonomous” but demonstrates the concept.

Similar to this idea, Bojarski et al. [28] developed the “end-to-end” autonomous vehicle that can learn to drive from the front camera to the control signal by deep learning. Compared with ALVINN, the scale of images are more than 40 times greater (39600 pixels) and the neural network structure has ten layers (27 million connections and 250 thousand parameters). The DRIVE™ PX[17)] is loaded on the test vehicle for learning and driving. With these updates, this autonomous vehicle can achieve autonomy in approximately 98% of the driving from the NVidia office in Holmdel to Atlantic Highlands. Santana and Hotz [176] establish a similar system, and Bojarski et al. [177] explain why this system works.

Some researchers also suggested an improved method for the supervised learning system. Zhang and Cho [30] proposed “SafeDAgger” to solve the problem where the training process suffered from unexpected behaviors from expert drivers. Chen et al. [178] proposed a direct perception approach for autonomous vehicles. This method pre-treats the images and detects a small number of key perception indicators. In this way, the efficiency has significantly improved. Xu et al. [29] found that the main approaches for supervised-learning-based autonomous vehicles are suitable only for the vehicle which the training data taken from. Thus, their approach can be used by different sourced video data. Liu et al. [179] combined the classical trajectory planning and the supervised learning to park the vehicle like human beings. Yang et al. [180] analyzed the influence of the features in the images and selected the more influential features to improve efficiency. Some research presented at international conferences have discussed basic technology in deep learning [181,182] that is meaningful for those who wish to know more. We will not discuss it further here.

As can be seen in the review above, neural networks are important tools in deep learning. A typical neural network[7)] is shown in Figure 19(a), in which the hidden units do not have a distinct physical meaning, which is problematic for being able to adjust the system. In Bayesian network classifiers [183], on the other hand, the units’ meaning can be described and understood by developers, allowing us to observe and adjust intermediate variables during the training. Nevertheless, the weights between the units in Bayesian dynamic network should also learn from dataset [184]. Therefore, the decision process based on a Bayesian dynamic network is also the data-based process. One Bayesian network is shown in Figure 19(b). This approach has been implemented in the autonomous vehicle decision framework.

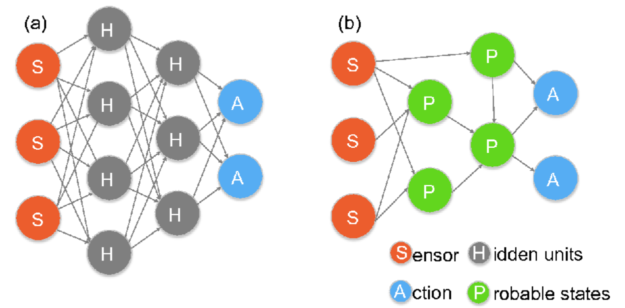

Figure 19 (Color online) Network instances. (a) Neural network; (b) Bayesian network.

In 1995, Forbes et al. [185] established a decision framework based on a Bayesian network considering sensor noise, sensor failure, and uncertainty about the behavior of other vehicles. They verified the framework in a simulation system and the vehicles were able to make reasonable decisions under various conditions. In order to understand the environment more accurately, Van Dan and Kameyama [186] mainly estimated the motion of the intelligent vehicle, which is developed for high safety, via a Bayesian network. Collisions are also a significant factor while making decision. Hamlet and Crane [187] developed a prediction system for collision avoidance that can help autonomous vehicles travel through intersections. The Bayesian network can also be applied to control the vehicles. For examples, Eilers and Möbus [188,189] built a Bayesian autonomous driver mixture-of-behaviors model that can control a simulated autonomous vehicle in real time. Based on this model, they built a longitudinal support system for driver assistance strategies [190].

For both machine learning and Bayesian network learning, the primary issue is to be able to adjust the network parameters to make the output closer to real output data. In another words, the success of this approach is determined by the quality and consistency of the training data, as already

17) NVIDIA Announces World’s First AI Computer to Make Robotaxis a Reality. 2017. http://www.marketwired.com/press-release/nvidia-announces-worlds-first-ai-computer-to-make-robotaxis-a-reality-nasdaq-nvda-2236493.htm.

mentioned in several papers[7] [28,30]. Different from supervised learning, reinforcement learning [191] does not only rely on real data. When generating an action, the reinforcement learning system will observe the effect according to a value function which is built according to the final target. If the effect does not meet requirement, the system will adjust the policy and generate another action next time. This adjustment process will repeat until we find the best policy which is different from the policy based on the collected dataset. Kaelbling et al. [192] summarized the strategies for solving reinforcement-learning problems. AlphaGo [172] also used deep reinforcement learning to beat the world champion.

In order to achieve the driving target in the optimized way, some data-based autonomous vehicles use reinforcement learning as their learning structure. Koutník et al. [193] developed the racing vehicle system based on deep reinforcement learning. In the racing video game, the controlled vehicle can always win the game based on the image shown on the screen. Xia et al. [194] combined the reinforcement learning with data from the experience of professional driver, which improved the learning efficiency and reduced the learning time by 71.2%. Xiong et al. [195] took safety-based control as their goal and built the system to be suitable on unfamiliar roads based on deep reinforcement learning. Chae et al. [196] implemented reinforcement learning on the braking system to make the vehicle much safer for the environment. Isele et al. [197] generated policy for intersections, where many factors cannot be predicted.

Apart from the above methods, there is also a data-based method called the partially observable Markov decision process (POMDP) which is developed from Markov decision process (MDP). The MDP is a discrete time stochastic control process. At each time step, the process is in some state, and the decision maker may choose any action that is available in this state. The process responds at the next time step by randomly moving into a new state, and giving the decision maker a corresponding reward. If we consider the driving process as a discrete time process, the autonomous vehicle will make the action just according to the current state, and this process is similar with MDP. However, the state cannot always be observed clearly in the autonomous vehicle decision process because of the uncertainty of the sensors. As result, it must maintain a probability distribution over the set of possible states, based on a set of observations and observation probabilities, and the underlying MDP. The policy of POMDP should also be adjusted according to the real data collected by sensors, and so POMDP is also a data-based method and is applied in the autonomous vehicle decision process. A typical application is to navigation, which takes the position and direction as the states to drive to the destination. Koenig and Simmons [198] developed the robot navigation architecture on the robot "Xavier" just based on POMDP to guide the robot in the measured map. This approach has also been applied in some autonomous vehicle frameworks. Liu et al. [199] developed a situation-aware decision-making framework for autonomous driving via an online POMDP. The proposed algorithm has been applied in various urban road scenarios and performed well. Agussurja and Lau [200] helped a taxi make cruising decisions in a congested urban city via POMDP using the data from a Singaporean taxi company. Brechtel et al. [201] presented a generic approach for tactical decision-making under uncertainty in the context of driving and this method did not use a symbolic representation or discretize the state space a priori. The generated actions in the approaches above are the control signals that are "low-level actions". Some decision frameworks also try to generate the "high-level actions" such as some maneuvers with POMDP. Amato et al. [202] developed the POMDP system facing to "macro-actions," which were high-level temporally extended actions.

In the end of this part, we provide the main relationship and differences between these data-driven methods in Figure 20 and Table 5 in order to make them clear. These differences have been mentioned in this review.

5.2.3 *Relative dataset for data-based methods*

The dataset is one of the most important factors for data-based systems. The training data must be large enough and contain rich information. Here, we summarize some public datasets for autonomous vehicle developers. It should be mentioned that some famous datasets, such as ImageNet [203] and Pascal VOC [171], which contain objects [204,205] unrelated to autonomous vehicles, will not be included.

The dataset for "end-to-end" learning [28] is easy to collect, because the dataset just need the front video and the control signals. Some companies have published their "end-to-end" dataset. Riccardo Biasini et al. published the driving dataset lasting more than 7 h[18]. Similar to this type, Baidu published a much bigger dataset[19]. Udacity developed a simulation system for developers to build "end to end" dataset[20]. Some data-based methods also published the dataset they used. For example, the dataset mentioned in ref. [178] is published [206].

The datasets mentioned above are collected by normal vehicles with some simple sensors such as cameras. In fact, the autonomous vehicle decision process usually needs more

18) Commaai, 7 and a quarter hours of largely highway driving dataset . 2016. https://archive.org/details/comma-dataset.
19) Baidu, Roadhackers dataset. 2017. http://roadhackers.baidu.com
20) Udacity, Behaviorial Cloning Project. https://github.com/udacity/CarND-Behavioral-Cloning-P3.

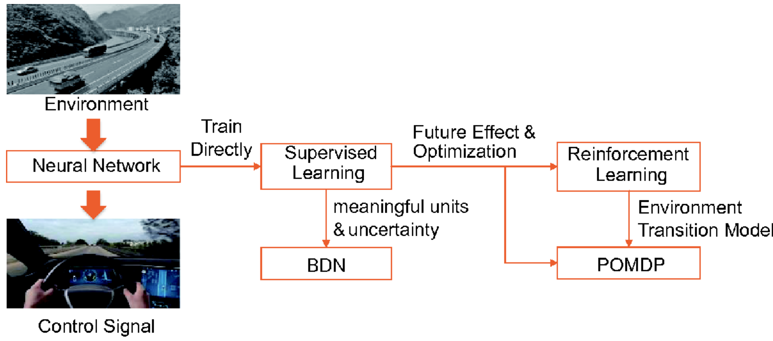

Figure 20 (Color online) Data-driven approach for autonomous driving.

Table 5 Main idea behind data-based methods

Approaches	Main idea
Supervised learning	Imitate directly from real-driving data.
Bayesian network	Build a network with meaningful units. Adjust the parameters of the network according to real-driving data.
Reinforcement learning	Consider future effects of the actions and make optimized decisions.
POMDP	Considering sensor and data uncertainties.

information that cannot be collected just by cameras. Some approaches also need the dataset taken by professional vehicles integrating various sensors such as Lidar and GPS. Some datasets are built for this purpose. Oxford RobotCar projects published over 1000 km dataset and lasting one year[21]. The dataset is collected from the Oxford RobotCar platform [207], and contains all sensors' data on this platform. Similarly, Koschorrek et al.[22] published the dataset taken by the autonomous platform[23]. KITTI is also the dataset taken by the professional autonomous vehicle. However, KITTI mainly services for environmental perception which kindly different from the other datasets above. The dataset can be downloaded from ref. [208].

Some datasets are not only collected from a car but also built for the autonomous vehicles. Usually, these datasets make contribution to environment perception. For example, Cityscape is an image segmentation dataset containing some common traffic conditions [209]. Some traffic signs detection dataset[24] [210], lane detection [209], vehicle detection[25] [171,203] or pedestrian detection [211,212] dataset are also collected for environment perception. We will not completely summarize them in this work.

Datasets are valuable sources for data-based methods. We summarize some important datasets for autonomous vehicle decision framework in Table 6.

5.3 Principles-based motion planning

In some conditions, we can drive the vehicle even though we have never seen a similar scene. This is because we have some principles to guide us make suitable decisions. Some autonomous vehicle decision frameworks are also mainly based on principles. In other words, researchers summarize certain principles based on experience and knowledge. The autonomous vehicles just drive according to these principles. Compared with the data-based approaches, it is much clearer to know how the system generates the control signals. The control orders can also be adjusted easily. In this part, we will summarize principle based methods for autonomous vehicle decision.

5.3.1 Classical framework for principles-based methods

Usually, the decision frameworks are divided into three main parts, which are global planning, maneuver decision and trajectory planning suggested [213]. Certain frameworks also have some slight differences. For example, Wei et al. [214] added the "reference planner" in the framework to combine the global planning with the maneuver planning. Noh and An [215] further divided the maneuver planner into two parts. Global planning provides the driving target for the decision process. Some approaches have been described in

21) Oxford Robotcar Dataset. 2014. http://robotcar-dataset.robots.ox.ac.uk.
22) Koschorrek P, Piccini T, Öberg P, et al. A multi-sensor traffic scene dataset with omnidirectional video. In: IEEE Conference on Computer Vision and Pattern Recognition Workshops. Portland, OR, 2013, 727–734.
23) The automotive multi-sensor (AMUSE) dataset. 213. http://www.cvl.isy.liu.se/research/datasets/amuse.
24) Timofte R. BelgiumTSC Dataset. http://btsd.ethz.ch/shareddata.
25) Udacity, Self-Driving Car. Annotated Driving Dataset. https://github.com/udacity/self-driving-car/tree/master/annotations.

Table 6 Some dataset attributes

Dataset	Attribute
Commaai [18)]	Seven and a quarter hours driving data
Roadhackers [19)]	10000 km driving data in China
Udacity [20),24)]	The platform generating driving data
Princeton [206]	The dataset for "Direct Perception" in ref. [178]
Oxford RobotCar [16)]	One year collection in complex environment
AMUSE [18)]	Muti-sensors collection
KITTI [208]	Dataset for environment perception
Cityscape [209]	Dataset for image segmentation

refs. [154,216]. Global planning is an independent module related to the navigation and HD map, so that we will not introduce this part in detail.

Principles-based methods have recently been developing rapidly. Some researchers have summarized these approaches from different directions. These reviews are mentioned in Section 5.1. In this study, we hope to introduce the main framework of principles-based approaches.

5.3.2 *Principles-based methods*

How to generate a trajectory that vehicles can follow is the key point of principles-based decision-making. Traffic rules, driver comfort and other requirements provide the principles to choose a suitable trajectory from the available curves.

In order to make the planning process simple, some researchers choose a certain geometric curve as the generated trajectory. Common curves include lines and circles [217], clothoid curves [218], polynomial curves [219], Bezier curves [220] and spline curves [152]. Sometimes, these types of curves may be used combined with each other, in order to make the trajectory more suitable for the planned condition and the controlled vehicle. Some details about how to build and adjust the fixed curve have been summarized [158]. The fixed curves are the principles for the autonomous vehicles. They are usually in some fixed road conditions. However, there are also some unpredicted conditions the vehicle may meet. The trajectory should be optimized according to the speed, steering speed, rollover constraints, and jerk etc. of the controlled vehicle. Therefore, some articles generate the trajectory via optimizing the trajectory. In [221–223], the trajectory estimation methods are described constrained by road conditions, vehicle dynamic models and traffic rules. The trajectory optimization approach is one of the main methods in DARPA Urban Challenge [224,225].

We can also "search" a trajectory on the real road map in real time, because we cannot consider all road conditions the trajectory optimizations can apply. Another way to generate the trajectory is searching on the lattice map. This approach has two main steps: (1) build the dynamic lattice map; (2) search a trajectory on the map. Some classical approaches for searching is Dijkstra's Algorithm [226,227], A* [11], D* [228] Algorithm and state lattices [229,230]. Every algorithm mentioned before is a masterpiece. However, we could not introduce them in details in this paper.

In the approaches above, the systems need to generate a whole perfect trajectory and then drive the vehicle to follow it. In this way, the trajectory needs to finish the entire planning. However, this process may cost too many computing re-sources, and it may not always be able to search a trajectory to follow. In order to solve this problem, rapidly exploring rand trees have been proposed. This method constructs a tree data structure which is expanded stochastically by adding new configurations (vertices) in each iteration that are randomly sampled from the configuration space until the goal configuration is reached [231]. Some researchers have also improved the performance of this method. For example, Dolgov et al. [221] guaranteed the kinematic feasibility; Kuwata et al. [232] handled general dynamical models in real-time.

The autonomous vehicle decision framework should also be verified in the design process, because different modules should cooperate with each other without error. The approaches above cannot be verified by themselves and this may cause risk. The formal method can be a tool which is a particular kind of mathematically based technique for the specification, development and verification [233]. Linear temporal logic (LTL), one of the approaches in formal method, was proposed [234]. It has been used in some autonomous control framework [235]. Some details are described in the mentioned references [236,237], which we cannot introduce exhaustively in this article. Because this method can achieve the design and verification at the same time, researchers try to apply this method to the autonomous vehicle. Wongpiromsarn [238] changed the Alice (the autonomous vehicle in DUC) framework based on LTL. Finally, Alice finished the tasks designed by DUC. Sadigh et al. [239] proved it was possible to apply LTL on the autonomous vehicles in theory, and provided the direction for future work.

6 Conclusions and the future policy of ICV

The objective of this paper is to present an overview of both the state of the art and the future trends of key technologies in ICVs, including EEA, sensor technology, actuator technology, and decision-making algorithms. Even though many demonstration ICVs have been developed to prove the concept of autonomous driving and the possibility of improving traffic efficiency based on ICVs, there still exists a big gap that must be closed before the mass production of high-level ICVs can be achieved. The causes of this gap, which indicate the key technologies to eliminate this gap, seem to be different from different perspectives. From the automotive industry perspective, the key technologies needed to be developed are the high-quality electronic components, like sensors, controllers, actuators. From the academic research perspective, the problems are mainly the lack of reliable algorithms to perform driving tasks like perception, decision and control. Both perspectives can provide a unique point of view of the current ICV development state. This study combined the two perspectives aiming at helping researchers from industry and robotics to better understand each other's work and cooperate more efficiently.

As a conclusion, to realize mass production of ICVs, technological breakthroughs are needed in both vehicle platform and intelligent algorithms. In the aspect of developing vehicle platform, the domain-based architecture and centralized architecture are the promising solution for the EEA of the next generation to provide much better capacity in communication and computation. AE and multicore heterogeneous computation platforms are expected to be introduced into the vehicle very quickly. Apart from the powerful architecture, the future vehicle platform should also be equipped with high-tech sensors, which are able to acquire information and output recognition results by integrating perception algorithms. Electric actuation, such as X-by-wire and distributed drive, are widely considered as the best platform for ICV for their outstanding performance in dynamics control and energy saving. From the aspect of algorithm design, perception, decision, and control are all essential processes in autonomous driving, however perception and control algorithms could be covered by the development of sensors and actuators. Many companies and universities are already working together to integrate the sensor hardware and perception algorithms. A successful example is the Mobileye, which has transferred the vision algorithms into a sensor product. The decision algorithms should be given more attention. As introduced in this study, data-driven decision processes and principle-based decision processes should be combined in the future to provide more intelligent driving instructions in complex driving environment.

This work was supported by the International Science and Technology Cooperation Program of China (Grant No. 2016YFE0102200), the National Natural Science Foundation of China (Grant No. 61773234), the National Key R&D Program of China(Grant No. 2108YFB0105004), and Beijing Municipal Science and Technology Commission (Grant Nos. D171100005117001 & D171100005117002).

1 SAE On-Road Automated Vehicle Standards Committee. Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. *SAE Standard J*, 2014, 3016: 1–16
2 Ulrich L. Top Ten Tech Cars. IEEE Spectr, 2014, 51: 38–47
3 Vanholme B, Gruyer D, Lusetti B, et al. Highly automated driving on highways based on legal safety. IEEE Trans Intell Transp Syst, 2013, 14: 333–347
4 Grisleri P, Fedriga I. The braive autonomous ground vehicle platform. IFAC Proc Volumes, 2010, 43: 497–502
5 Kato S, Takeuchi E, Ishiguro Y, et al. An open approach to autonomous vehicles. IEEE Micro, 2015, 35: 60–68
6 Geiger A, Lauer M, Moosmann F, et al. Team AnnieWAY's entry to the 2011 grand cooperative driving challenge. IEEE Trans Intell Transp Syst, 2012, 13: 1008–1017
7 Urmson C, Anhalt J, Bagnell D, et al. Autonomous driving in urban environments: Boss and the urban challenge. J Field Robotics, 2008, 25: 425–466
8 Leonard J, How J, Teller S, et al. A perception-driven autonomous urban vehicle. J Field Robotics, 2008, 25: 727–774
9 Levinson J, Askeland J, Becker J, et al. Towards fully autonomous driving: Systems and algorithms. In: 2011 IEEE Intelligent Vehicles Symposium (IV). Baden-Baden: IEEE, 2011. 163–168
10 Montemerlo M, Becker J, Bhat S, et al. Junior: The stanford entry in the urban challenge. J Field Robotics, 2008, 25: 569–597
11 Bacha A, Bauman C, Faruque R, et al. Odin: Team VictorTango's entry in the DARPA urban challenge. J Field Robotics, 2008, 25: 467–492
12 Merrill G P. The First One Hundred Years of American Geology. New York: Hafner Publishing Company, 1924
13 Kurzweil R, Richter R, Kurzweil R, et al. The Age of Intelligent Machines. Cambridge, MA: MIT Press, 1990
14 Grimes D M, Jones T O. Automotive radar: A brief review. Proc IEEE, 1974, 62: 804–822
15 Tsugawa S. Vision-based vehicles in Japan: Machine vision systems and driving control systems. IEEE Trans Ind Electron, 1994, 41: 398–405
16 Dickmanns E D, Graefe V. Dynamic monocular machine vision. Machine Vis Apps, 1988, 1: 223–240
17 Leighty R D. DARPA ALV (autonomous land vehicle) summary. Report No. ETL-R-085. Army Engineer Topographic Labs Fort Belvoir VA, 1986
18 Schwarz B. Mapping the world in 3D. Nat Photon, 2010, 4: 429–430
19 Turk M A, Morgenthaler D G, Gremban K D, et al. VITS-A vision system for autonomous land vehicle navigation. IEEE Trans Pattern Anal Machine Intell, 1988, 10: 342–361
20 Lowrie J W, Thomas M, Gremban K, et al. The autonomous land vehicle (ALV) preliminary road-following demonstration. In: Intelligent Robots and Computer Vision IV. Cambridge, 1985. 336–351:
21 Barabba V, Huber C, Cooke F, et al. A multimethod approach for creating new business models: The General Motors OnStar project. Interfaces, 2002, 32: 20–34
22 IEEE 802.11 Working Group. Part 11-Wireless LAN medium access control (MAC) and physical layer (PHY) specifications: Higher-speed physical layer extension in the 2.4 GHz band. ANSI/IEEE Std 802.11, 1999
23 Montemerlo M, Thrun S, Dahlkamp H, et al. Winning the DARPA grand challenge with an AI robot. In: The National Conference on Artificial Intelligence. Boston, 2006. 982–987
24 Urmson C, Ragusa C, Ray D, et al. A robust approach to high-speed navigation for unrehearsed desert terrain. J Field Robotics, 2006, 23: 467–508
25 Jung I K, Lacroix S. High resolution terrain mapping using low altitude aerial stereo imagery. In: Proceeding of the Ninth IEEE International Conference on Computer Vision. Nice, 2003. 946
26 Chen M, Liu Y. Recognition and extraction high precision digital road map. In: International Conference on Information Technology: Coding and Computing (ITCC'05)-Volume II. Las Vegas, NV: IEEE, 2005. 129–134
27 Noyer U, Schomerus J, Mosebach H H, et al. Generating high precision maps for advanced guidance support. In: 2008 IEEE Intelligent Vehicles Symposium. Eindhoven: IEEE, 2008. 871–876
28 Bojarski M, Del Testa D, Dworakowshi D, et al. End to end learning for self-driving cars. arXiv:1604.07316, 2016
29 Xu H, Gao Y, Yu F, et al. End-to-end learning of driving models from large-scale video datasets. arXiv:preprint, 2017, http://openaccess.

thecvf.com/content_cvpr_2017/papers/Xu_End-To-End_-Learning_of_CVPR_2017_paper.pdf
30 Zhang J, Cho K. Query-efficient imitation learning for end-to-end autonomous driving. ArXiv:1605.06450, 2016
31 Hinton G E, Osindero S, Teh Y W. A fast learning algorithm for deep belief nets. Neural Computation, 2006, 18: 1527–1554
32 Deng L. A tutorial survey of architectures, algorithms, and applications for deep learning. APSIPA Trans Signal Inf Process, 2014, 3: e2
33 Ziegler J, Bender P, Schreiber M, et al. Making bertha drive—An autonomous journey on a historic route. IEEE Intell Transport Syst Mag, 2014, 6: 8–20
34 Yang D, Kong W, Li B, et al. Intelligent vehicle electrical power supply system with central coordinated protection. Chin J Mech Eng, 2016, 29: 781–791
35 Haas W, Langjahr P. Cross-domain vehicle control units in modern E/E architectures. In: Bargende M, Reuss H C, Wiedemann J, Eds. Proceedings of Internationales Stuttgarter Symposium. Fachmedien Wiesbaden: Springer, 2016. 1619–1627
36 Zeng W, Khalid M A S, Chowdhury S. In-vehicle networks outlook: Achievements and challenges. In: IEEE Communications Surveys & Tutorials. IEEE, 2017. 1552–1571
37 Afsin M E, Schmidt K W, Schmidt E G. C^3: Configurable CAN FD controller: Architecture, design and hardware implementation. In: 12th IEEE International Symposium on Industrial Embedded Systems. Toulouse: IEEE, 2017. 1–9
38 Hartwich F. CAN with flexible data-rate. In: IEEE International Conference on Communications. Gerlingen, 2012. 1–9
39 BOSCH. CAN With Flexible Data-Rate Specification. Version 1.0. Gerlingen: BOSCH, 2012
40 Matheus K, Königseder T. Automotive Ethernet. Cambridge: Cambridge University Press, 2015
41 FlexRay Consortium. FlexRay Communication System Protocol Specification. Version 3.0.1. 2010
42 Engelmann B. MOST150-development and production launch from an OEM's per-stective. In: 11th MOST Interconnectivity Conference. Seoul, 2010. 1–23
43 Grzemba A. MOST: The Automotive Multimedia Network, from MOST25 to MOST150. Poing: Franzis Verlag GmbH, 2011
44 Zeeb E. Optical data bus systems in cars: Current status and future challenges. In: Proceedings 27th European Conference on Optical Communication. Amsterdam, 2001. 70–71
45 Hank P, Suermann T, Müller S. Automotive ethernet, a holistic approach for a next generation in-vehicle networking standard. In: Meyer G, Ed. Advanced Microsystems for Automotive Applications. Berlin, Heidelberg: Springer, 2012. 79–89
46 Patsakis C, Dellios K. Securing in-vehicle communication and redefining the role of automotive immobilizer. In: International Conference on Security and Cryptography. Rome, 2012. 221–226
47 Patsakis C, Dellios K, Bouroche M. Towards a distributed secure in-vehicle communication architecture for modern vehicles. Comput Security, 2014, 40: 60–74
48 Misener J A, Biswas S, Larson G. Development of V-to-X systems in North America: The promise, the pitfalls and the prognosis. Comput Networks, 2011, 55: 3120–3133
49 DhilipKumar V, Kandar D, Sarkar C K. Enhancement of inter-vehicular communication to optimize the performance of 3G/4G-VANET. In: International Conference on Optical Imaging Sensor and Security. Coimbatore, 2013. 1–5
50 Smith S, Razo M. Using traffic microsimulation to assess deployment strategies for the connected vehicle safety pilot. J Intelligent Transpation Syst, 2016, 20: 66–74
51 Toulminet G, Boussuge J, Laurgeau C. Comparative synthesis of the 3 main European projects dealing with Cooperative Systems (CVIS, SAFESPOT and COOPERS) and description of COOPERS Demonstration Site 4. In: 11th International IEEE Conference on Intelligent Transportation Systems. Beijing, 2008. 809–814
52 Stahlmann R, Festag A, Tomatis A, et al. Starting European field tests for Car-2-X communication: The DRIVE C2X framework. In: 18th ITS World Congress and Exhibition. Orlando, FL, 2011. 1–9
53 Shenjiang L D W. The design of the controller on automobile taillight based on AT89S52 (in Chinese). Foreign Electronic Meas Technol, 2010: 60–63
54 Jin X U, Zhong F M. Automotive air conditioning control system based on STC12C5A60S2 singlechip (in Chinese). Auto Electric Parts, 2014, 6: 14–16
55 Gan H, Zhang J, Lu Q. Study on operating mode control of hybrid electric vehicle based on the high performance32-Bit SCM MPC555. Automob Technol, 2004, 11: 9–12
56 Yu X, Chen B, Ji T. DSP software design for EQ effect of car multimedia system. Microcompute Its Applications, 2011, 30: 47–50
57 Yu Y, Fu Z, Rao L, et al. DSP-based advance collision warning system. Process Automat Instrum, 2009, 30: 11–13
58 Yu J Q, Chen Z Z, Liang P. The design and implementation signal processing system of the automotive collision avoidance based on TMS320vc5402 (in Chinese). Microcomp Inf, 2007: 266–267
59 Lindholm E, Nickolls J, Oberman S, et al. NVIDIA Tesla: A unified graphics and computing architecture. IEEE Micro, 2008, 28: 39–55
60 Wübbena G, Bagge A. GNSS multi-station adjustment for permanent deformation analysis networks. In: Symposlum on Geodesy for Geotechnical & Structural Engineering of the IAG Special Commission. Eisenstadt, 1998. 139–144
61 Jouppi N P, Young C, Patil N, et al. In-datacenter performance analysis of a tensor processing unit. In: 2017 ACM/IEEE 44th Annual International Symposium on Computer Architecture. Toronto, ON: IEEE, 2017. 1–12
62 Chevitarese D S, Dos Santos M N. Real-time face tracking and recognition on IBM neuromorphic chip. In: 2016 IEEE International Symposium on Multimedia. San Jose, CA: IEEE, 2016. 667–672
63 Rethinagiri S K, Palomar O, Moreno J A, et al. System-level power & energy estimation methodology and optimization techniques for CPU-GPU based mobile platforms. In: 2014 IEEE 12th Symposium on Embedded Systems for Real-time Multimedia. Greater Noida, 2014. 118–127
64 Liu B L, Sun Y B. OSEK/VDX: An open-architectured platform of vehicle electronics system. Acta Armamentarll the Volume of Tank, Armored Vehicle Engine, 2002, 2: 61–64
65 Guettier C, Bradai B, Hochart F, et al. Standardization of generic architecture for autonomous driving: A reality check. In: Langheim J, Ed. Energy Consumption and Autonomous Driving. Lecture Notes in Mobility. Cham: Springer, 2016. 57–68
66 Aly S. Consolidating AUTOSAR with complex operating systems (AUTOSAR on Linux). SAE Technical Paper 2017-01-1617, 2017
67 Leitner A, Ochs T, Bulwahn L, et al. Open dependable power computing platform for automated driving. In: Watzenig D, Horn M, Eds. Automated Driving. Cham: Springer, 2017. 353–367
68 Traub M, Maier A, Barbehon K L. Future automotive architecture and the impact of IT trends. IEEE Softw, 2017, 34: 27–32
69 Sagstetter F, Lukasiewycz M, Steinhorst S, et al. Security challenges in automotive hardware/software architecture design. In: Proceedings of the Conference on Design, Automation and Test in Europe. Grenoble, 2013. 458–463
70 Risack R, Mohler N, Enkelmann W. A video-based lane keeping assistant. In: Proceedings of the IEEE Intelligent Vehicles Symposium. Dearborn, MI: IEEE, 2000
71 Kesting A, Treiber M, Schönhof M, et al. Adaptive cruise control design for active congestion avoidance. Transpat Res Part C-Emerg Technol, 2008, 16: 668–683
72 Kim S W, Qin B, Chong Z J, et al. Multivehicle cooperative driving using cooperative perception: Design and experimental validation. IEEE Trans Intell Transp Syst, 2015, 16: 663–680
73 Dagan E, Mano O, Stein G P, et al. Forward collision warning with a single camera. In: IEEE Intelligent Vehicles Symposium. Parma: IEEE, 2004. 37–42
74 Leung K Y K, Barfoot T D, Liu H H T. Decentralized cooperative

slam for sparsely-communicating robot networks: A centralized-equivalent approach. J Intell Robot Syst, 2012, 66: 321–342
75 Perumal D G, Saravanakumar G, Subathra B, et al. Nonlinear state estimation based predictive path planning algorithm using infrastructure-to-vehicle (I2V) communication for intelligent vehicle. In: Proceedings of the Second International Conference on Emerging Research in Computing, Information, Communication and Applications (ERCICA 2014). NMIT, Yelahanka, Bangalore, 2014. 243–248
76 Sawant N R. Longitudinal vehicle speed controller for autonomous driving in urban stop-and-go traffic situations. Dissertation of Masteral Degree. Columbus, OH: The Ohio State University, 2010
77 Eskandarian A. Handbook of Intelligent Vehicles. London: Springer, 2012
78 Marek J, Trah H P, Suzuki Y, et al. Sensors for Automotive Technology. Weinheim: Wiley-VCH, 2003
79 Landau H, Vollath U, Chen X. Virtual reference station systems. J GPS, 2002, 1: 137–143
80 Brown N, Geisler I, Troyer L. RTK rover performance using the master-auxiliary concept. Positioning, 2006, 5: 135–144
81 Wanninger L. Improved ambiguity resolution by regional differential modelling of the ionosphere. In: Proceedings of the ION GPS 95. Palm Springs, 1995. 55–62
82 Bertozzi M, Broggi A, Fascioli A. Vision-based intelligent vehicles: State of the art and perspectives. Robotics Autonomous Syst, 2000, 32: 1–16
83 Maurer M, Behringer R, Furst S, et al. A compact vision system for road vehicle guidance. In: Proceedings of 13th International Conference on Pattern Recognition. Vienna: IEEE, 1996. 313–317
84 Bertozzi M, Broggi A, Conte G, et al. Vision-based automated vehicle guidance: The experience of the ARGO vehicle. Tecniche di Intelligenza Artificiale e Pattern Recognition per la Visione Artificiale, 1998: 35–40
85 Broggi A, Bertozzi M, Fascioli A. Architectural issues on vision-based automatic vehicle guidance: The experience of the ARGO project. Real-Time Imag, 2000, 6: 313–324
86 Campbell M, Egerstedt M, How J P, et al. Autonomous driving in urban environments: Approaches, lessons and challenges. Philos Trans R Soc A-Math Phys Eng Sci, 2010, 368: 4649–4672
87 Göhring D, Latotzky D, Wang M, et al. Semi-autonomous car control using brain computer interfaces. In: Lee S, Cho H, Yoon KJ, Eds. Intelligent Autonomous Systems 12. Advances in Intelligent Systems and Computing. Berlin, Heidelberg: Springer, 393–408
88 van Nunen E, Koch R, Elshof L, et al. Sensor safety for the european truck platooning challenge. In: 23rd World Congress on Intelligent Transport Systems. Melbourne, 2016. 306–311
89 Johnson D G. Development of a high resolution MMW radar employing an antenna with combined frequency and mechanical scanning. In: 2008 IEEE Radar Conference. Rome: IEEE, 2008. 1–5
90 Han S, Wang X, Xu L, et al. Frontal object perception for Intelligent Vehicles based on radar and camera fusion. In: 35th Chinese Control Conference. Chengdu, China: IEEE, 2016
91 Song S, Chandraker M. Robust scale estimation in real-time monocular SFM for autonomous driving. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Columbus, OH: IEEE, 2014. 1566–1573
92 Park K Y, Hwang S Y. Robust range estimation with a monocular camera for vision-based forward collision warning system. Sci World J, 2014, 2014: 1–9
93 Dong Y, Hu Z, Uchimura K, et al. Driver inattention monitoring system for intelligent vehicles: A review. IEEE Trans Intell Transp Syst, 2011, 12: 596–614
94 Tawari A, Sivaraman S, Trivedi M M, et al. Looking-in and looking-out vision for urban intelligent assistance: Estimation of driver attentive state and dynamic surround for safe merging and braking. In: 2014 IEEE Intelligent Vehicles Symposium Proceedings. Dearborn, MI: IEEE, 2014. 115–120
95 Klette R, Kruger N, Vaudrey T, et al. Performance of correspondence algorithms in vision-based driver assistance using an online image sequence database. IEEE Trans Veh Technol, 2011, 60: 2012–2026
96 Lazaros N, Sirakoulis G C, Gasteratos A. Review of stereo vision algorithms: From software to hardware. Int J Optomechatron, 2008, 2: 435–462
97 Tippetts B, Lee D J, Lillywhite K, et al. Review of stereo vision algorithms and their suitability for resource-limited systems. J Real-Time Image Proc, 2016, 11: 5–25
98 Benet G, Blanes F, Simó J E, et al. Using infrared sensors for distance measurement in mobile robots. Robotics Autonomous Syst, 2002, 40: 255–266
99 Takagi K, Morikawa K, Ogawa T, et al. Road environment recognition using on-vehicle LIDAR. In: 2006 IEEE Intelligent Vehicles Symposium. Tokyo: IEEE, 2006. 120–125
100 Himmelsbach M, Hundelshausen F V, Wuensche H J. Fast segmentation of 3d point clouds for ground vehicles. In: 2010 IEEE Intelligent Vehicles Symposium (IV). San Diego, CA: IEEE, 2010. 560–565
101 Lee J H, Tsubouchi T, Yamamoto K, et al. People tracking using a robot in motion with laser range finder. In: 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems. Beijing, China: IEEE, 2006. 2936–2942
102 Brscic D, Kanda T, Ikeda T, et al. Person tracking in large public spaces using 3-D range sensors. IEEE Trans Human-Mach Syst, 2013, 43: 522–534
103 Pathak K, Birk A, Vaskevicius N, et al. Online three-dimensional SLAM by registration of large planar surface segments and closed-form pose-graph relaxation. J Field Robotics, 2010, 27: 52–84
104 Zhang J, Singh S. LOAM: Lidar odometry and mapping in real-time. In: Robotics: Science and Systems. Berkeley, CA: 2014. 9
105 Park J, Kim H, Tai Y W, et al. High quality depth map upsampling for 3D-TOF cameras. In: 2011 International Conference on Computer Vision. Barcelona: IEEE, 2011. 1623–1630
106 Hwang S, Kim N, Choi Y, et al. Fast multiple objects detection and tracking fusing color camera and 3D LIDAR for intelligent vehicles. In: 2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI). Xi'an, China: IEEE, 2016. 234–239
107 Zhong Y, Wang S, Xie S, et al. 3D scene reconstruction with sparse LiDAR data and monocular image in single frame. SAE Int J Passeng Cars-Electron Electr Syst, 2017, 11: 48–56
108 Hofmann U, Senger F, Soerensen F, et al. Biaxial resonant 7mm-MEMS mirror for automotive LIDAR application. In: 2012 International Conference on Optical MEMS and Nanophotonics. Banff, AB: IEEE, 2012. 150–151
109 Ye L, Zhang G, You Z. 5 V compatible two-axis PZT driven MEMS scanning mirror with mechanical leverage structure for miniature LiDAR application. Sensors, 2017, 17: 521
110 McManamon P F, Bos P J, Escuti M J, et al. A review of phased array steering for narrow-band electrooptical systems. Proc IEEE, 2009, 97: 1078–1096
111 Yoo B W, Megens M, Chan T, et al. Optical phased array using high contrast gratings for two dimensional beamforming and beamsteering. Opt Express, 2013, 21: 12238–12248
112 Sugimoto S, Tateda H, Takahashi H, et al. Obstacle detection using millimeter-wave radar and its visualization on image sequence. In: Proceedings of the 17th International Conference on Pattern Recognition, 2004. Cambridge, UK: IEEE, 2004. 342–345
113 Song Y, Nuske S, Scherer S. A multi-sensor fusion MAV state estimation from long-range stereo, IMU, GPS and barometric sensors. Sensors, 2016, 17: 11
114 Chen Z. Bayesian filtering: From Kalman filters to particle filters, and beyond. Statistics, 2003, 182: 1–69
115 Zhang Z, Li Y, Wang F, et al. A novel multi-sensor environmental perception method using low-rank representation and a particle filter for vehicle reversing safety. Sensors, 2016, 16: 848
116 Weiß C. V2X communication in Europe—From research projects towards standardization and field testing of vehicle communication

technology. Comput Networks, 2011, 55: 3103–3119
117 Kalman R E. A new approach to linear filtering and prediction problems. J Basic Eng, 1960, 82: 35–45
118 Arulampalam M S, Maskell S, Gordon N, et al. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. IEEE Trans Signal Process, 2002, 50: 174–188
119 Ghods A, Severi S, Abreu G. Localization in V2X communication networks. In: 2016 IEEE Intelligent Vehicles Symposium (IV). Gothenburg: IEEE, 2016. 5–9
120 Rohani M, Gingras D, Vigneron V, et al. A new decentralized Bayesian approach for cooperative vehicle localization based on fusion of GPS and VANET based inter-vehicle distance measurement. IEEE Intell Transp Syst Mag, 2015, 7: 85–95
121 Obst M, Hobert L, Reisdorf P. Multi-sensor data fusion for checking plausibility of V2V communications by vision-based multiple-object tracking. In: 2014 IEEE Vehicular Networking Conference (VNC). Paderborn: IEEE, 2014. 143–150
122 Liu W, Kim S W, Marczuk K, et al. Vehicle motion intention reasoning using cooperative perception on urban road. In: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC). Qingdao, China: IEEE, 2014, 424-430:
123 Kim S W, Liu W, Ang M H, et al. The impact of cooperative perception on decision making and planning of autonomous vehicles. IEEE Intell Transp Syst Mag, 2015, 7: 39–50
124 Luthardt S, Han C, Willert V, et al. Efficient graph-based V2V free space fusion. In: Intelligent Vehicles Symposium (IV). Los Angeles, CA: IEEE
125 Bétaille D, Toledo-Moreo R. Creating enhanced maps for lane-level vehicle navigation. IEEE Trans Intell Transp Syst, 2010, 11: 786–798
126 Jo K, Sunwoo M. Generation of a precise roadway map for autonomous cars. IEEE Trans Intell Transp Syst, 2014, 15: 925–937
127 Joshi A, James M R. Generation of accurate lane-level maps from coarse prior maps and lidar. IEEE Intell Transp Syst Mag, 2015, 7: 19–29
128 Billah M, Maskooki A, Rahman F, et al. Roadway feature mapping from point cloud data: A graph-based clustering approach. In: 2017 IEEE Intelligent Vehicles Symposium (IV). Los Angeles, CA: IEEE, 2017
129 Guan H, Li J, Yu Y, et al. Using mobile laser scanning data for automated extraction of road markings. ISPRS J Photogramm Remote Sens, 2014, 87: 93–107
130 Zeng W, Church R L. Finding shortest paths on real road networks: The case for A*. Int J Geogr Inf Sci, 2009, 23: 531–543
131 Vu A, Ramanandan A, Chen A, et al. Real-time computer vision/DGPS-aided inertial navigation system for lane-level vehicle navigation. IEEE Trans Intell Transp Syst, 2012, 13: 899–913
132 Levinson J, Montemerlo M, Thrun S. Map-based precision vehicle localization in urban environments. In: Robotics: Science and Systems. Georgia, 2007. 1
133 Wolcott R W, Eustice R M. Visual localization within LIDAR maps for automated urban driving. In: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems. Chicago, IL: IEEE, 2014. 176–183
134 Xu Y, John V, Mita S, et al. 3D point cloud map based vehicle localization using stereo camera. In: 2017 IEEE Intelligent Vehicles Symposium (IV). Los Angeles, CA: IEEE, 2017. 487–492
135 Crane C D. The 2005 DARPA grand challenge. In: International Symposium on Computational Intelligence in Robotics and Automation. Jacksonville, 2007. 1
136 Hodge K E, Kellogg Y. Proceedings of the F-8 digital fly-by-wire and supercritical wing first flight's 20th anniversary celebration. Volume 1. Technical Report NASA-CP-3256-Vol-1. Edwards, CA: National Aeronautics and Space Administration, Dryden Flight Research Center, 1996
137 Stjärne K, Werner P. Brake by wire system for construction vehicles. Dissertation of Masteral Degree. Göteborg: Chalmers University of Technology, 2014
138 He L, Ma B, Zong C. Fault-tolerance control strategy for the steering wheel angle sensor of a steer-by-wire vehicle. Automot Eng, 2015, 37: 327–330, 345
139 Fahimi F. Full drive-by-wire dynamic control for four-wheel-steer all-wheel-drive vehicles. Vehicle Syst Dyn, 2013, 51: 360–376
140 Janbakhsh A A, Bayani Khaknejad M, Kazemi R. Simultaneous vehicle-handling and path-tracking improvement using adaptive dynamic surface control via a steer-by-wire system. Proc Instit Mech Eng Part D-J Automobile Eng, 2013, 227: 345–360
141 Abeysiriwardhana W S P, Abeykoon A H S. Simulation of brake by wire system with dynamic force control. In: 7th International Conference on Information and Automation for Sustainability. Colombo: IEEE, 2014. 1–6
142 Pisu P, Serrani A, You S, et al. Adaptive threshold based diagnostics for steer-by-wire systems. J Dyn Sys Meas Control, 2006, 128: 428–435
143 Cetin A E, Adli M A, Barkana D E, et al. Compliant control of steer-by-wire systems. In: 2009 IEEE/ASME International Conference on Advanced Intelligent Mechatronics. Singapore: IEEE, 2009. 636–643
144 Kang J, Hindiyeh R Y, Moon S W, et al. Design and testing of a controller for autonomous vehicle path tracking using GPS/INS sensors. In: Proceedings of the 17th IFAC World Congress. Seoul, 2008. 6–11
145 Xiong L, Teng G W, Yu Z P, et al. Novel stability control strategy for distributed drive electric vehicle based on driver operation intention. Int J Automot Technol, 2016, 17: 651–663
146 Yin G D, Jin X J, Zhang Y. Overview for chassis vehicle dynamics control of distributed drive electric vehicle. J Chongqing Univ Technol, 2016: 13–19
147 Liu H, Chen X, Wang X. Overview and prospects on distributed drive electric vehicles and its energy saving strategy. Prz Elektrotechniczn, 2012, 88: 122–125
148 Wilwert C, Song Y Q, Simonot-Lion F, et al. Evaluating quality of service and behavioral reliability of steer-by-wire systems. In: 9th IEEE International Conference on Emerging Technologies and Factory Automation-EFTA'2003. Lisbonne: IEEE, 2003. 193–200
149 He L, Xiang H O, Chen D X, et al. Emergency obstacle avoidance control method based on driver steering intention recognition for steer-by-wire vehicle. In: Liu X H, Zhang K F, Li M Z, Eds. Manufacturing Process and Equipment. Volumes 694-697. Advanced Materials Research. Switzerland: Trans Tech Publications, 2013. 2738–2741
150 Hirano Y. Integrated vehicle control of an in-wheel-motor vehicle to optimize vehicle dynamics and energy consumption. In: 2012 10th World Congress on Intelligent Control and Automation. Beijing, China: IEEE, 2012. 2335–2339
151 Pei X, Zhou Y, Sheng Z. Torque ripple suppression of a new in-wheel motor based on quantum genetic algorithm. In: 23rd International Conference on Mechatronics and Machine Vision in Practice. Nanjing, China: IEEE, 2016. 1–6
152 Thrun S, Montemerlo M, Dahlkamp H, et al. Stanley: The robot that won the DARPA grand challenge. J Field Robotics, 2006, 23: 661–692
153 Sivaraman S, Trivedi M M. Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis. IEEE Trans Intell Transp Syst, 2013, 14: 1773–1795
154 Gwon G P, Hur W S, Kim S W, et al. Generation of a precise and efficient lane-level road map for intelligent vehicle systems. IEEE Trans Veh Technol, 2017, 66: 4517–4533
155 Khodayari A, Ghaffari A, Ameli S, et al. A historical review on lateral and longitudinal control of autonomous vehicle motions. In: 2nd International Conference on Mechanical and Electrical Technology. Singapore: IEEE, 2010. 421–429
156 Souissi O, Benatitallah R, Duvivier D, et al. Path planning: A 2013 survey. In: Proceedings of 2013 International Conference on Industrial Engineering and Systems Management. Rabat: IEEE, 2013.

1–8
157 Katrakazas C, Quddus M, Chen W H, et al. Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. Transpat Res Part C-Emerg Technol, 2015, 60: 416–442
158 Gonzalez D, Perez J, Milanes V, et al. A review of motion planning techniques for automated vehicles. IEEE Trans Intell Transp Syst, 2016, 17: 1135–1145
159 Veres S M, Molnar L, Lincoln N K, et al. Autonomous vehicle control systems: A review of decision making. Proc Inst Mech Eng Part I-J Syst Control Eng, 2011, 225: 155–195
160 Lefèvre S, Vasquez D, Laugier C. A survey on motion prediction and risk assessment for intelligent vehicles. Robomech J, 2014, 1: 1
161 Bila C, Sivrikaya F, Khan M A, et al. Vehicles of the future: A survey of research on safety issues. IEEE Trans Intell Transp Syst, 2017, 18: 1046–1065
162 Eichenbaum H. A cortical-hippocampal system for declarative memory. *Nat Rev Neurosci*, 2000, 1: 41
163 Cohen M D, Bacdayan P. Organizational routines are stored as procedural memory: Evidence from a laboratory study. Organ Sci, 1994, 5: 554–568
164 Weng J. Artificial intelligence: Autonomous mental development by robots and animals. Science, 2001, 291: 599–600
165 Mitchell T M. Machine Learning. Burr Ridge, IL: McGraw Hill, 1997. 870–877
166 Samuel A L. Some studies in machine learning using the game of checkers. IBM J Res Dev, 1959, 3: 210–229
167 Rosenblatt F. The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Rev, 1958, 65: 386–408
168 Ackley D, Hinton G, Sejnowski T. A learning algorithm for Boltzmann machines. Cogn Sci, 1985, 9: 147–169
169 Lecun Y, Bengio Y, Hinton G. Deep learning. Nature, 2015, 521: 436–444
170 Krizhevsky A, Sutskever I, Hinton G E. ImageNet classification with deep convolutional neural networks. In: PereIra F, Burges C J C, Bottou L, et al, Eds. Advances in Neural Information Processing Systems 25. Cambridge, MA: MIT Press, 2012. 1097–1105
171 Everingham M, Eslami S M A, Van Gool L, et al. The pascal visual object classes challenge: A retrospective. Int J Comput Vis, 2015, 111: 98–136
172 Silver D, Huang A, Maddison C J, et al. Mastering the game of Go with deep neural networks and tree search. Nature, 2016, 529: 484–489
173 Pacejka H. Tire and Vehicle Dynamics. 3rd Ed. Amsterdam: Elsevier, 2012
174 Moravec H. Sensor Fusion in Certainty Grids for Mobile Robots. Berlin Heidelberg: Springer, 1989. 61–74
175 Hoskins S R, Tefend M F. Steering angle sensor. USA Patent, US8164327, 2012
176 Santana E, Hotz G. Learning a driving simulator. arXiv:1608.01230, 2016
177 Bojarski M, Yeres P, Choromanska A, et al. Explaining how a deep neural network trained with end-to-end learning steers a car. arXiv:1704.07911, 2017
178 Chen C, Seff A, Kornhauser A, et al. Deep driving: Learning affordance for direct perception in autonomous driving. In: IEEE International Conference on Computer Vision. Santiago, 2015. 2722–2730
179 Liu W, Li Z, Li L, et al. Parking like a human: A direct trajectory planning solution. IEEE Trans Intell Transp Syst, 2017, 99: 1–10
180 Yang S, Wang W, Liu C, et al. Feature analysis and selection for training an end-to-end autonomous vehicle controller using the deep learning approach. In: 2017 IEEE Intelligent Vehicles Symposium (IV). Los Angeles, CA: 2017. 1033–1038
181 Kisacanin B. Deep learning for autonomous vehicles. In: IEEE International Symposium on Multiple-Valued Logic. San Francisco, 2017. 142
182 Shapiro D. Accelerating the race to autonomous cars. In: ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. Novi Sad, 2016. 415
183 Friedman N, Geiger D, Goldszmidt M. Goldszmidt. Bayesian network classifiers. Mach Learn, 1997, 29: 131–163
184 Ontañón S, Montaña J L, Gonzalez A J. A dynamic bayesian network framework for learning from observation. In: Bielza C, Eds. Advances in Artificial Intelligence. CAEPIA 2013. Lecture Notes in Computer Science, Vol 8109. Berlin Heidelberg: Springer, 2013. 373–382
185 Forbes J, Huang T, Kanazawa K, et al. The Batmobile: Towards a Bayesian automated taxi. In: International Joint Conference on Artificial Intelligence. Montreal, 1995. 1878–1885
186 Dan N V, Kameyama M. Bayesian-networks-based motion estimation for a highly-safe intelligent vehicle. In: 2006 SICE-ICASE International Joint Conference. Busan, 2007. 6023–6026
187 Hamlet A J, Crane C D. Joint belief and intent prediction for collision avoidance in autonomous vehicles. arXiv:1504.00060, 2015
188 Eilers M, Möbus C. Learning of a bayesian autonomous driver mixture-of-behaviors (BAD MoB) model. In: International Conference on Applied Human Factors and Ergonomics. Boca Raton, 2011. 436–445
189 Möbus C, Eilers M. Further steps towards driver modeling according to the bayesian programming approach. In: Duffy V G, Ed. Digital Human Modeling. ICDHM 2009. Lecture Notes in Computer Science, Vol 5620. Berlin Heidelberg: Springer, 2009. 413–422
190 Eilers M, Möbus C, Tango F, et al. The learning of longitudinal human driving behavior and driver assistance strategies. Transpation Res Part F-Traffic Psychology Behaviour, 2013, 21: 295–314
191 Sutton R S, Barto A G. Reinforcement Learning: An Introduction. Cambridge, MA: MIT Press, 2005
192 Kaelbling L P, Littman M L, Moore A W. Reinforcement learning: A survey. J Artif Intell Res, 1996, 4: 237–285
193 Koutník J, Schmidhuber J, Gomez F. Online evolution of deep convolutional network for vision-based reinforcement learning. In: International Conference on Simulation of Adaptive Behavior. Castellón, 2014. 260–269
194 Xia W, Li H, Li B. A control strategy of autonomous vehicles based on deep reinforcement learning. In: International Symposium on Computational Intelligence and Design. Zhejiang, China, 2017. 198–201
195 Xiong X, Wang J, Zhang F, et al. Combining deep reinforcement learning and safety based control for autonomous driving. arXiv:1612.00147, 2016
196 Chae H, Kang C M, Kim B D, et al. Autonomous braking system via deep reinforcement learning. In: IEEE International Conference on Intelligent Transportation Systems. Yokohama, 2017. 1–6
197 Isele D, Rahimi R, Cosgun A, et al. Navigating occluded intersections with autonomous vehicles using deep reinforcement learning. arXiv:1705.01196, 2018
198 Koenig S, Simmons R G. Xavier: A robot navigation architecture based on partially observable Markov decision process models. In: Artificial Intelligence Based Mobile Robotics: Case Studies of Successful Robot Systems. Cambridge, MA: MIT Press, 1998. 91–122
199 Liu W, Kim S W, Pendleton S, et al. Situation-aware decision making for autonomous driving on urban road using online POMDP. In: Intelligent Vehicles Symposium. Seoul, 2015. 1126–1133
200 Agussurja L, Lau H C. A POMDP model for guiding taxi cruising in a congested urban city. In: Batyrshin I, Sidorov G, Eds. Advances in Artificial Intelligence. MICAI 2011. Lecture Notes in Computer Science, vol 7094. Berlin, Heidelberg: Springer, 2011, 7094. 415–428
201 Brechtel S, Gindele T, Dillmann R. Probabilistic decision-making under uncertainty for autonomous driving using continuous POMDPs. In: IEEE International Conference on Intelligent Trans-

portation Systems. Qingdao, China, 2014. 392–399

202 Amato C, Konidaris G D, Kaelbling L P. Planning with macro-actions in decentralized POMDPs. In: International Conference on Autonomous Agents and Multi-Agent Systems. Paris, 2014. 331–333

203 Deng J, Dong W, Socher R, et al. ImageNet: A large-scale hierarchical image database. In: IEEE Conference on Computer Vision and Pattern Recognition. Miami, 2009. 248–255

204 Griffin G, Holub A, Perona P. Caltech-256 object category dataset. Technical Report 7694. Caltrch: California Institute of Technology, 2007

205 Lin TY, Maire M, Belongie S, et al. Microsoft COCO: Common objects in context. In: Fleet D, Pajdla T, Schiele B, et al, Eds. Computer Vision—ECCV 2014. Lecture Notes in Computer Science, Vol. 8693. Cham: Springer, 2014. 740–755

206 Chen C, Self A, Kornhauser A, et al. Deepdriving: Learning affordance for direct perception in autonomous driving. In: IEEE International Conference on Computer Vision. Santiago: IEEE, 2015. 2722–2730

207 Maddern W, Pascoe G, Linegar C, et al. 1 year, 1000 km: The Oxford RobotCar dataset. Int J Robotics Res, 2017, 36: 3–15

208 Geiger A, Lenz P, Urtasun R. Are we ready for autonomous driving? The KITTI vision benchmark suite. In: IEEE Conference on Computer Vision and Pattern Recognition. Providence, RI, 2012. 3354–3361

209 Cordts M, Mohamed O, Sebastian R, et al. The cityscapes dataset for semantic urban scene understanding. In: IEEE Conference on Computer Vision and Pattern Recognition. Las Vegas, NV: IEEE, 2016. 3213–3223

210 de Charette R, Nashashibi F. Real time visual traffic lights recognition based on Spot Light Detection and adaptive traffic lights templates. In: 2009 IEEE Intelligent Vehicles Symposium. Xi'an, China: IEEE, 2009. 358–363

211 Wu B, Nevatia R. Cluster boosted tree classifier for multi-view, multi-pose object detection. In: IEEE 11th International Conference on 2007 ICCV. Rio de Janeiro: IEEE, 2007. 1–8

212 Ess A, Leibe B, Schindler K, et al. A mobile vision system for robust multi-person tracking. In: Computer Vision and Pattern Recognition, 2008. Anchorage: IEEE, 2008. 1–8

213 Varaiya P. Smart cars on smart roads: problems of control. IEEE Trans Automat Contr, 1993, 38: 195–207

214 Wei J, Snider J M, Gu T, et al. A behavioral planning framework for autonomous driving. In: Intelligent Vehicles Symposium Proceedings. Dearborn, MI: IEEE, 2014. 458–464

215 Noh S, An K. Decision-making framework for automated driving in highway environments. IEEE Trans Intell Transp Syst, 2017, 19: 58–71

216 Buehler M, Iagnemma K, Singh S. The DARPA Urban Challenge. Tracts in Advanced Robotics. Berlin: Springer, 2010

217 Reeds J, Shepp L. Optimal paths for a car that goes both forwards and backwards. Pac J Math, 1990, 145: 367–393

218 Fraichard T, Scheuer A. From reeds and shepp's to continuous-curvature paths. IEEE Trans Robot, 2004, 20: 1025–1035

219 Petrov P, Nashashibi F. Modeling and nonlinear adaptive control for autonomous vehicle overtaking. IEEE Trans Intell Transp Syst, 2014, 15: 1643–1656

220 Rastelli J P, Lattarulo R, Nashashibi F. Dynamic trajectory generation using continuous-curvature algorithms for door to door assistance vehicles. In: Intelligent Vehicles Symposium Proceedings. Dearborn, MI: IEEE, 2014. 510–515

221 Dolgov D, Thrun S, Montemerlo M, et al. Path planning for autonomous vehicles in unknown semi-structured environments. Int J Robotics Res, 2010, 29: 485–501

222 Gu T, Dolan J M. On-road motion planning for autonomous vehicles. In: International Conference on Intelligent Robotics and Applications. Montreal, Quebec: Springer, 2012. 588–597

223 Ziegler J, Bender P, Schreiber M, et al. Making bertha drive-an autonomous journey on a historic route. IEEE Intell Transport Syst Mag, 2014, 6: 8–20

224 Cremean L B, Foote T B, Gillula J H, et al. Alice: An information-rich autonomous vehicle for high-speed desert navigation. In: Buehler M, Iagnemma K, Singh S, Eds. The 2005 DARPA Grand Challenge. Springer Tracts in Advanced Robotics, Vol 36. Berlin, Heidelberg: Springer, 2007. 777–810

225 Kogan D, Murray R M. Optimization-based navigation for the DARPA Grand Challenge. In: Conference on Decision & Control. San Diego, CA: IEEE, 2006. 1–6

226 Bohren J, Foote T, Keller J, et al. Little ben: The ben franklin racing team's entry in the 2007 DARPA urban challenge. In: Buehler M, Iagnemma K, Singh S, Eds. The DARPA Urban Challenge. Springer Tracts in Advanced Robotics, Vol 56. Berlin, Heidelberg: Springer, 2008. 231–255

227 Chen Y L, Sundareswaran V, Anderson C, et al. TerraMax™: Team Oshkosh urban robot. J Field Robotics, 2008, 25: 841–860

228 Kammel S, Ziegler J, Pitzer B, et al. Team AnnieWAY's autonomous system for the 2007 DARPA Urban Challenge. In: Buehler M, Iagnemma K, Singh S, Eds. The DARPA Urban Challenge. Springer Tracts in Advanced Robotics, Vol 56. Berlin, Heidelberg: Springer, 2010. 359–391

229 Ferguson D, Howard T M, Likhachev M. Motion planning in urban environments. J Field Robotics, 2010, 25: 939–960

230 Mcnaughton M, Urmson C, Dolan J M, et al. Motion planning for autonomous driving with a conformal spatiotemporal lattice. In: IEEE International Conference on Robotics and Automation. Shanghai, China: IEEE, 2011. 4889–4895

231 Lavalle S. Rapidly-exploring random trees: A new tool for path planning. Research Report. Ames, IA: Computer Science Department, Iowa State University, 1998

232 Kuwata Y, Fiore G A, Teo J, et al. Motion planning for urban driving using RRT. In: 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems. Nice: IEEE, 2008. 1681–1686

233 Thurston D L. A formal method for subjective design evaluation with multiple attributes. Res Eng Des, 1991, 3: 105–122

234 Emerson E A. Temporal and modal logic. In: Handbook of Theoretical Computer Science (vol. B). Cambridge, MA: MIT Press, 1990. 995–1072

235 Kloetzer M, Belta C. A fully automated framework for control of linear systems from temporal logic specifications. IEEE Trans Automat Contr, 2008, 53: 287–297

236 Artale A, Kontchakov R, Wolter F, et al. Temporal description logic for ontology-based data access. In: International Joint Conference on Artificial Intelligence. Beijing, China, 2013. 711–717

237 Liu J, Ozay N. Abstraction, discretization, and robustness in temporal logic control of dynamical systems. In: International Conference on Hybrid Systems: Computation and Control. Berlin, 2014. 293–302

238 Wongpiromsarn T. Formal methods for design and verification of embedded control systems: Application to an autonomous vehicle. Dissertation of Doctrol Degree. Caltrch: California Institute of Technology. 2010

239 Sadigh D, Kim E S, Coogan S, et al. A learning based approach to control synthesis of Markov decision processes for linear temporal logic specifications. In: 53rd IEEE Conference on Decision and Control. Los Angeles, CA: IEEE, 2014. 1091–1096