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A Survey on Hybrid Human-Artificial Intelligence for Autonomous Driving

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***Abstract*— With the continuous development of Artificial Intelligence (AI), autonomous driving has become a popular research area. AI enables the autonomous driving system to make a judgment, which makes studies on autonomous driving reaches a period of booming development. However, due to the defects of AI, it is not easy to realize a general intelligence, which also limits the research on autonomous driving. In this paper, we summarize the existing architectures of autonomous driving and make a taxonomy. Then we introduce the concept of hybrid human-artificial intelligence (H-AI) into a semi-autonomous driving system. For making better use of H-AI, we propose a theoretical architecture based on it. Given our architecture, we classify and overview the possible technologies and illustrate H-AI's improvements, which provides a new perspective for the future development. Finally, we have identified several open research challenges to attract the researchers for presenting reliable solutions in this area of research.**

***Index Terms*— Artificial intelligence, hybrid human-artificial intelligence, autonomous driving, theoretical architecture.**

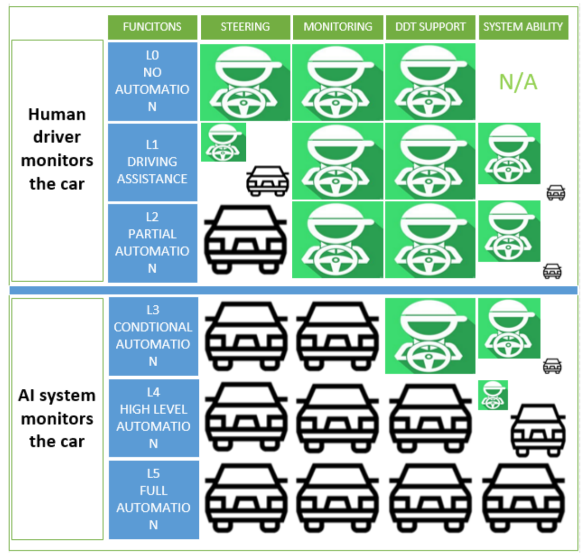

Fig. 1. The classification of SAE.

I. Introduction

AUTONOMOUS driving was first proposed in the 1950s, and the related research has continued for many years. Due to the development of Artificial Intelligence (AI), the advance of autonomous driving is in a booming stage. In 2014, the International Society of Automated Engineers (SAE) released the J3016 automated driving classification standard, and the latest version was released in 2018, as shown in Fig 1. However, according to this standard, most manufacturers still stay in level two and level three. Although high-level Autonomous Vehicles (AVs) will be commercially available in some jurisdictions, their usage and application will be limited [1]. Based on experience with previous technologies, it is hard to achieve fully autonomous driving comprehensively [2], [3].

Autonomous driving has inadequate capabilities to handle dynamically changing conditions due to sudden and complex accidents [4]. Intelligent Transportation System (ITS) play a vital role in managing transportation and related constraints. ITS can be modified to handle the shortcomings of autonomous driving by providing real-time data about road conditions, traffic jams, and weather predictions in the region of driving. Due to mobile phones and computers, AV is a wheeled robot involved in many functionalities and characterized by a high degree of coupling with other features.

AI has powerfully prompted the core technologies related to autonomous driving. For example, Computer Vision (CV) allows AVs to get more environmental information than humans [5]–[9]. Using the decision AI model trained from a large amount of driving data, AVs can perform driving tasks well in certain situations. Nowadays, the new wave of AI emerges with the era of big data [2], [10], [11].

Although the last several decades have witnessed numerous achievements of AI, its shortages are also evident. As we all know that Deep Learning (DL) relies too much on labeling. Meanwhile, it is a challenge for AI to realize the causality between different things. In short, it is impossible to simulate human intelligence by data merely [2]. Current AI algorithms, such as Machine Learning (ML) and DL, pay so much attention to the probability generated by data, which lead to data spoofing and an inability to cope with unknown situations [12]. Besides, it is limited by certain conditions, namely deterministic information, complete information,

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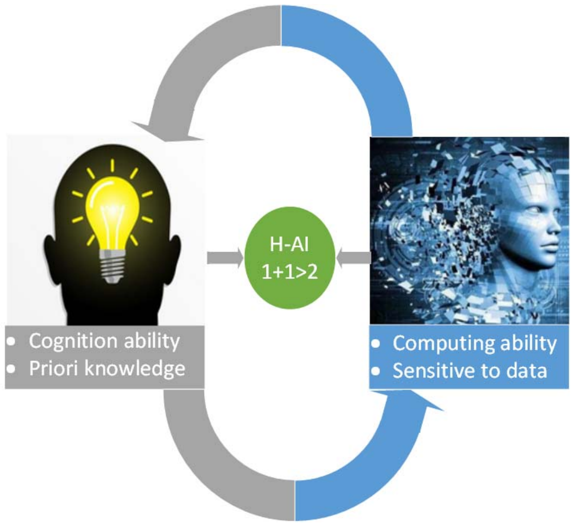

Fig. 2. Hybrid Human-Artificial Intelligence.

static data, single task, and limited field [13]. The limitation of AI also incurs the shortages of autonomous driving systems [14].

The research on brain science has lasted for many years. In the 1990s, some scholars analyzed the mechanism of human brain waves in terms of cells and neural networks [15], [16]. At present, a new type of control system called brain control is developing rapidly [17]. It can capture the weak brain wave signals by susceptible acquisition equipment, amplify the signals, then process and analyze it. It has been applied in healthcare and achieved remarkable effects. The cognitive science, proposed in the middle of the last century, has also done much to shed light on the workings of the human brain [18]. A wonderful prospect is that brain can be linked with autonomous driving to control the vehicle as per brain conditions automatically. It can be sufficient to auto-drive the vehicle to a nearby hospital when a driver suffers a heart attack, paralysis, or other severe medical conditions.

Given the problems and technologies we mentioned above, we introduced a hybrid AI. In the last few years, many scholars introduced human participation into the AI system to complete tasks that AI cannot fulfill independently [10], [19], which formed the human-in-the-loop augmented AI [12]. Therefore, we introduce Hybrid Human-Artificial Intelligence (H-AI), a promising interaction paradigm, into autonomous driving to solve the problems that traditional AI systems cannot solve. There is a high coupling between the human and AI systems, making the whole system perform much better than the two single systems, as shown in Fig 2.

H-AI aims at solving the disharmony of human-machine relationships in the hybrid system and finally realize human-machine integration. Several similar concepts have been proposed already, like Cyborg. Based on H-AI, we hope to propose a semi-autonomous driving architecture emphasizing high human-machine coupling. Through effective interaction media, the human agent and machine agent achieve the driving task cooperatively.

In this paper, we summarized the autonomous driving and AI from development and existing problems. The main contributions of this paper are as follows:

1) Current limitations of AI are concluded. We point out that introducing H-AI into an autonomous driving system may make up for the deficiency of current AI.
2) After retrospecting the development of autonomous driving, we present a theoretical autonomous driving architecture based on H-AI and give a detailed review of related technologies involved.
3) Some open challenges worthy of studying are also put forward. Given those challenges, we summarize some existing schemes and provide ideas to solve them.

This paper's remaining structure is as follows: In section II, we mainly talk about the background of policies of different countries and milestones in industrial development. In section III, the definition of Human-Machine Conflict (HMC) and some existing problems are presented. Based on it, we propose an autonomous driving architecture based on H-AI, which may solve the problems. In section IV, the details of our architecture will be discussed, and we reviewed the technologies which may be used. In section V, we discuss a simple scenario to illustrate the advantage of H-AI-based architecture. In section VI, we present several open challenges for H-AI-based autonomous driving. In section VII, we conclude and put forward a prospect.

II. Background

The recent craze for AVs began with the Defense Advanced Research Projects Agency (DARPA) Grand Challenge held by the US department of defense [20].Nowadays, most countries and companies are also attaching great importance on it. In this section, we will summarize the development of AVs in national policies and industry.

A. National Policies

Nowadays, each government is actively formulating related policies and acts to promote its development of autonomous driving [14]. AV can reduce traffic stress and transport costs and improve productivity, and mobility [1], which has caught policymakers' eyes. At present, most countries are mainly paving the way for AV testing, including expanding the testing area and deregulating AV testing gradually. Moreover, several measures have been taken to increase the generalization of Electric Vehicles (EVs) in the domestic market which have laid the foundation for the promotion of AVs at home [1], [22], [38]. In the autonomous vehicle readiness index (AVRI) [38], based on the level of policy and legislation, technology and innovation, infrastructure, and consumer acceptance, they summarized the development of autonomous driving across 30 countries and jurisdictions and ranked them. We are going to introduce seven nations' levels of preparedness for autonomous driving. Table I shows some related policies of them.

a) Singapore: In western area, AV testing is legitimate on all public roads. In 2019, VOLVO had collaborated with NANYANG Technologies University to test autonomous buses

TABLE I
POLICIES ABOUT SERVAL COUNTRIES

Countries	Year	Policies	Main contents
Singapore	2017	*Road Traffic Act*	Allowed the testing of AV [21].
	2019	*Technical Reference 68*	Regulated the testing and deploy of AV [22].
European Union	2016	*Amsterdam Declaration*	Set the strategy of Intelligent Connected Vehicle(ICV) [22].
	2018	*On the road to automated mobility: An EU strategy for mobility of the future*	Defined the development direction of ICV [23].
	2019	*Guidelines on the exemption procedure for the EU approval of automated vehicles*	Improved the safety assessment of ICV [24].
The Netherlands	2015	*the Decree on Exemption of Exceptional Transport*	The testing of ICV was allowed [22].
	2018	*Autonomous vehicle experimentation*	Allowed the remote testing of ICV [25].
Norway	2017	*Act Relating to Testing of Self-Driving*	The testing of AV was allowed [22].
	2020	*National Strategy for Artificial Intelligence*	Took AV as an important field of AI [26].
United States	2016	*Federal Automated Vehicles Policy*	Laid the foundational regulations [27].
	2017	*Automated Driving Systems 2.0: A Vision for Safety*	Described the production and testing [28].
	2018	*Automated Vehicles 3.0*	Liberalized AV in terms of Policy [29].
Finland	2016	*Public Road Automated Vehicle Testing in Finland*	Allowed AV testing on public roads [30].
	2020	*Road Traffic Act*	Promoted digital raffic [31].
British	2015	*The Pathway to Driverless Car: A detailed review of regulations for automated*	Clarified the details about testing [32].
	2017	*Key Cybersecurity Principles for Connected and Automated Vehicles*	Clarified relevant issues of AV [33].
	2018	*Automated and Electric Vehicles Bill*	Classified the insurance and liability issues [34].
Japan	2016	*Road Test Guide for Automated Vehicles*	Clarified safety requirements of AV test [35].
	2018	*Safety Technical Guide for Automated Vehicles*	Stipulated a series of safety conditions [36].
	2019	*Public-Private ITS Initiative/Roadmaps 2019*	Promoted the development of AV and ITS [37].

in several sites. The government's active promotion and appropriate road conditions make Singapore an excellent choice for the manufacture and testing of autonomous vehicles [38].

b) The Netherlands: It did well on policy and legislation. Also, government investment and numerous AV testing sites enable the Netherlands to keep the leading position in AVRI [38]. Although the government is actively developing AV related policies, technical bottlenecks have slowed the spread of autonomous driving on public roads. Thus they may use AVs in closed areas or considering dedicated roads or lanes. Even so, the Netherlands still has the most sophisticated and developed self-driving related infrastructure in the world.

c) Norway: This country has high coverage of EVs and a considerable market for it. The government has also legislated to ensure every citizen has equal access to AVs [38]. In 2017, AV testing had been allowed in some sites. In 2019, Ruter, the Oslo metropolitan area's mass-transit company, had tested autonomous buses in the Norwegian capital, where three driverless bus routes are available now.

d) United States: American technology companies and carmakers dominate AV development worldwide [38]. Waymo offers the most advanced self-driving solutions. Furthermore, General Motors, as an established carmaker, after merging with Cruise, has become leaders in making self-driving cars and, in 2020, unveiled the Origin, a self-driving car designed for ride-sharing. The government has built a series of laws on autonomous driving since 2011, and most states have passed legislation to make AVs legal. However, there is little concern in the US about road infrastructure and self-driving public transport [38].

e) Finland: The strong performance of its government enables Finland prepared for autonomous driving excellently [38]. It has comprehensive AV regulations and the efficiency of the legal system. In 2019, GACHA Autonomous Shuttle Bus, a self-driving bus that works under all-weather conditions, had operated in Espoo. The leading research on 5G also boosts the popularity of AVs in Finland [38].

f) United Kingdom: The British government has made many efforts to develop AV in recent years, including legislation, regulation, and unstinting investment. In 2014, the government had invested nearly iê200m to fund the research on AVs. In 2017, the British Ministry of Transport and the center for the protection of national infrastructure (CPNI) enacted a set of principles to ensure the design process's reliability and security for AVs. Thanks to the appropriate ecosystem [38], many trials are held in the UK, including a public service test of a full-length 1.5-meter AV bus by three companies.

g) Japan: In 2014, Japan formulated the innovation of automated driving for universal services plan and launched the research and application project of autonomous driving officially. In 2018, Japan's national police agency held its first research meeting to discuss related details and revised traffic regulations. In 2019, the latest rule about AV testing had been released. Japan has the largest number of AV-related patents, and its excellent road quality is also an advantage to generalize AV usage.

B. Industry

a) Waymo: As a technology company, Waymo aims to provide the most advanced solutions for autonomous driving. Because Waymo is the sub-company of Google, it is well-funded and technologically advanced. Thanks to its early start in AV testing on the public road, Waymo has now amassed more than 20 million kilometers of road data [39]. Waymo has collaborated with several large companies. In 2020, it announced a partnership with VOLVO, becoming the exclusive global partner of VOLVO for the research on level 4 automated driving.

b) Baidu: Apollo is Baidu's autonomous driving project, which includes an open-source platform and solutions for enterprises. In February 2020, the California authority released the 2019 California Autopilot Disengagement Report, which showed that Apollo's AVs performed excellent in annual MPI (the average mileage traveled between every two human

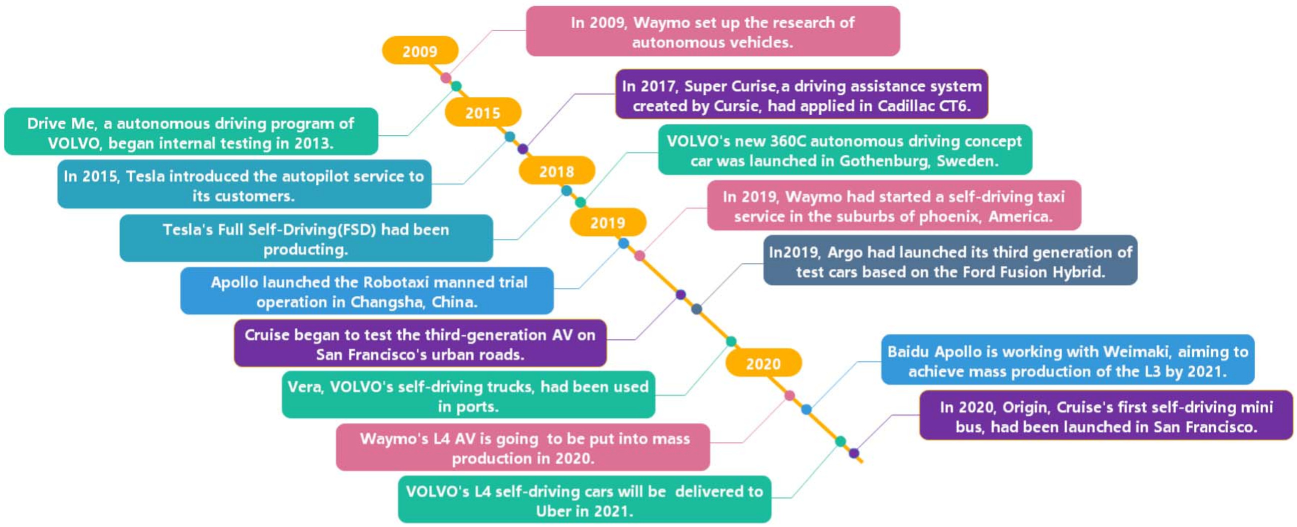

Fig. 3. The timeline of six companies.

interventions). Based on the Apollo project, Baidu is branching out into ICV and smart transportation.

c) Argo AI: It is a self-driving technology platform company funded by Ford and Volkswagen Group jointly. In 2018, Argo began vehicle testing in Miami, Florida. In 2019, it had announced a $15 million investment over five years to create research center with Carnegie Mellon University. In 2020, Volkswagen Group had invested $ 2.6 billion in capital and assets in Argo AI to expand their global alliance to include the electric vehicles business.

d) VOLVO: It is trying to move from a car manufacturer to an IT technology company. VOLVO is a few companies to have a clear technical path and a long-term plan for autonomous driving and test and apply it on the road. It also attaches great importance to the safety of AV and is working on a vision of zero casualties. Sunfleet, VOLVO's sub-company responsible for the car-sharing service, launched a new mobile travel brand in 2018, integrating all the current travel businesses. VOLVO is likely to introduce autonomous driving solutions in the future that retain the option for humans to drive cars.

e) General Motors Cruise: In 2016, GM acquired Cruise, and now it has become an independent company. Headquartered in San Francisco, its subsidiaries include Cruise Automation and Strobe, responsible for the self-driving development and autonomous driving sensor development. Although Cruise was a late starter, the former company's experience in self-driving research and GM's ability to manufacture vehicles have made it proliferate. According to the latest California Autopilot Disengagement Report, Cruise's MPI had climbed from around 300 miles to 4600 miles.

f) Tesla: Tesla introduced an autopilot service to its customers in 2015 firstly. The company collects the most driving data used to train its AI models, which is a powerful strength. It has never been stingy with its research on autonomous driving. With the launch of a fully self-developed chip in 2019, Tesla already has a complete industry chain.

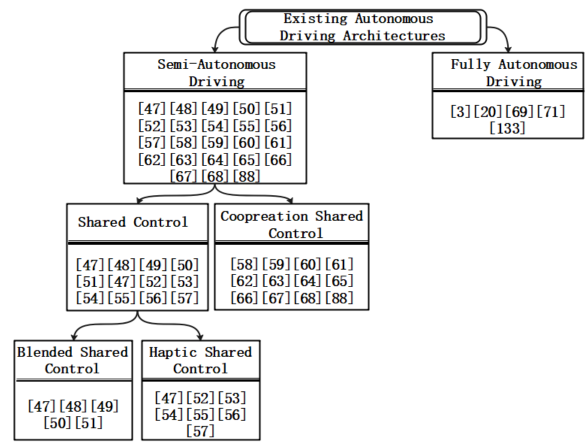

Fig. 4. The taxonomy of autonomous driving architectures.

Its research on autonomous driving advocates using computer vision and millimeter-wave instead of the lidar used by most manufacturers, which costs a lot and performance poorly.

III. Literature on General Autonomous Driving Based Architectures With H-AI

In this section, we intend to summarize and discuss the existing architecture of autonomous driving as shown in Fig 4. We present a taxonomy of existing architectures, as shown in Fig 5. At present, autonomous driving architecture can be classified as semi-autonomous driving characterized by humans in the loop and fully autonomous driving without human participation. Then, we propose a theoretical architecture based on H-AI. Note that the HMC is so crucial for a hybrid human-machine system that we decide to discuss it first.

A. Definition of Human-Machine Conflict

The HMC is a scene that can be defined as the operations of the human and system is contrary [40]. It is an inherent topic

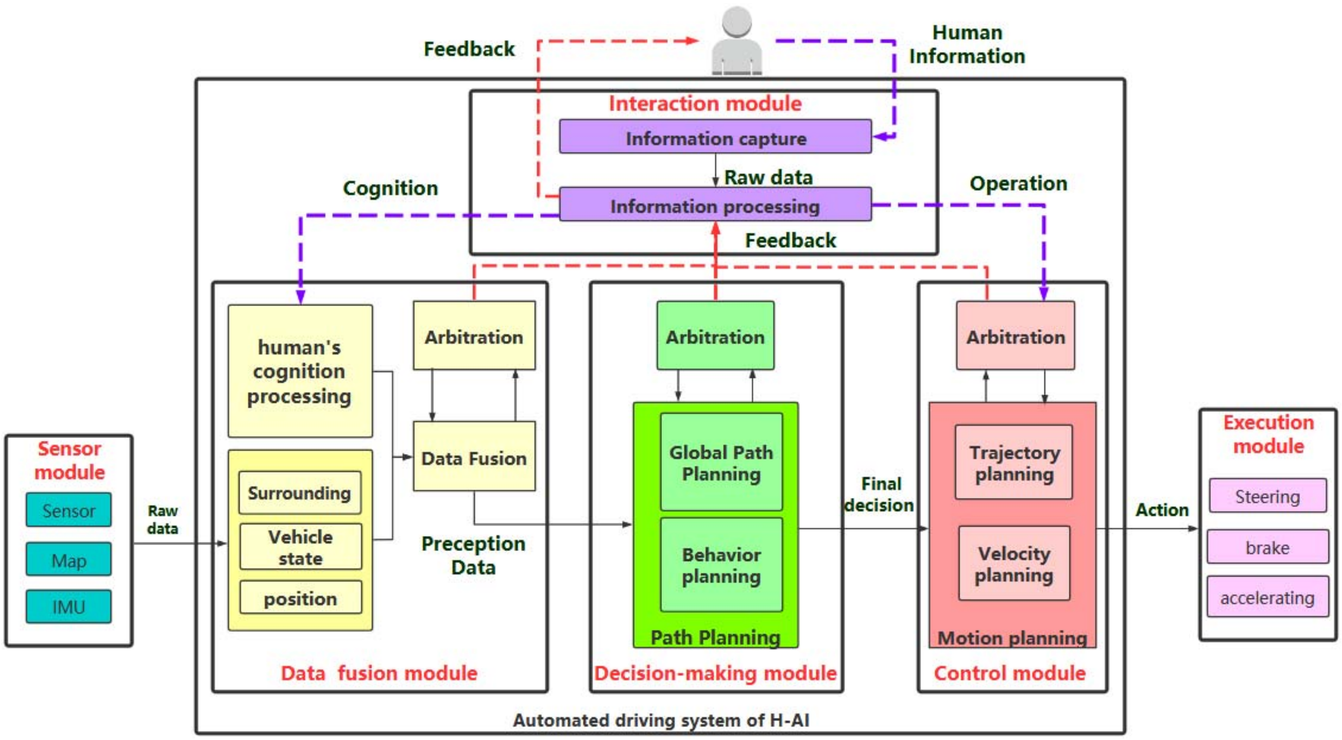

Fig. 5. A general autonomous driving system architecture of H-AI.

in a hybrid system [41]. When the deviation of two actions exceeds a threshold, the task may fail, or one of them is forced to give up its operations [42], [43].

Frank O. Flemisch *et al.* discussed the origin of conflict in the technosphere and biosphere perspective, and they indicated that solving conflict was the key to a successful cooperation [44]. In terms of semi-autonomous driving, the human agent and system agent usually have the same driving goal. However, they may make operations based on discrepant information they collected. HMetaphor or the AiAIDo-Metaphor could help us understand the conflict and provide us with ideas [44].

At present, the research on HMC focuses on the design of decision-making and arbitration module [44], [45] and the transition between assisted and non-assisted control [41], which relieves the conflict but ignores the nature of the HMC. Essentially, it is different understanding of surrounding information that incurs conflicts of human and system and the ineffective of human-machine interaction can weaken a hybrid driving system [46]. Thus, the best solution is enhancing the interaction of two agents, which is in line with H-AI's idea. Such a highly coupled human-machine interaction paradigm enables them to share information, eliminate divergences of judgment, and make operations collaboratively.

B. Shared Control

The definition of shared control is humans and the driving system drives the vehicle concurrently. Based on the control interface, shared control has two contributions: blended shared control and haptic shared control [47].

The operation of the driver and the system generate the final information of the control system. When the driver's operation conflicts with the system's judgments, the control system can fix the car's behaviors by the steer-by-wire system and Erlien *et al.* proposed a shared control framework for obstacle avoidance and stability control [48]. Blended shared control can complete the task more efficiently compared with the way without the shared controller [49]. Under the condition of operator input delay and distance drift, a hybrid human-machine shared control structure also performed well in some situations [50].

The research on shared control architecture is still necessary. It can be applied in Advanced Driver Assistance Systems (ADAS) [39], like lane-keeping assistance system (LKAS) is an example of applied shared control [51], [52]. For blended shared control, the system's operation is sightless for the human, which hinders human-machine interaction. Given the problem, haptic shared control was raised. Such an interaction paradigm enables the human to be aware of the decisions of the automated system, which could generate short-term performance promotion and performed better than blended shared control [53].

The design of a shared control driving system is affected by several factors. The media may be the prime factor and steering wheel is a popular solution [47], [52], [54], [55]. Based on the media, the guideline of the automated system should be defined. Li, Mingjun and Cao *et al.* adopted feedback torque on the steering wheel to achieve haptic shared control, which is possible to infer the driver [52]. Neuromuscular Analysis can also be a resultful guideline to haptic shared control [47]. Different guidelines apply to various assistance systems, but the main goal of shared control can be concluded to enhance the comfort and safety of the human-in-the-loop driving.

According to the haptic shared control architectures, the conflict between driver and automated systems seems obvious. The Model Prediction Control (MPC) is used to strike a balance between stability and avoidance, but the collide is always existing [48]. The constricted shared control algorithm is a source that incurs the conflict, which can be reduced by adopting individualized guidance torques [56]. However, the method could not eliminate the conflict because both lateral and timing errors were not solved. Besides, the level of haptic shared control is also a key factor. In terms of various degrees of haptic shared control, Franck Mars *et al.* summarized the shared control system and concluded that the control system with a low level of haptic authority might be more beneficial for drivers [41]. Based on the cooperative status between the driver and automated system, Ryota Nishimura *et al.* proposed a methodology that achieved smooth driver-initiated lane changes and improved lane-keeping performance excellently [57].

C. Cooperation Shared Control

Cooperation driving emphasizes dynamic task distribution, interface design, and keeping a shared model [58]. Compared with haptic shared control, such an interaction paradigm enables humans and the system to handle what they are adept at and decreases the possibility of HMC. In [59], they graded the autonomy mode and discussed the human-machine cooperation under various degrees of autonomy mode. They pointed out that a human operator can decrease the perturbation of an autonomous system and designed a system, based on autonomy mode and cooperation control, to adapt to various environmental constraints. However, the system is not able to learn from the driver's decisions, which is significicate for the robustness of autonomous driving system [60], [61].

A system is not always reliable during driving and the driver need to monitor it [62]. Meanwhile, the human driver needs to consider some irregular conventions while driving, making the system confused. The transition process is determined by driving state that refers to the driving task performed by the driver or automated system at a particular moment [63]. The control transfer initiator can be the driver or automation, and human factors can be the key to the transition of control. In recent years, the research on human factors focuses on the driver's behavior and cognition [63]. In 2001, a theoretical framework about human-machine cooperation in dynamic situations had been proposed [64], and it had been developed in 2009 [46]. Arbitration module can be used to reduce conflicts. Baltzer *et al.* designed a cooperation driving system based on dynamic task division, which was applied in automated vehicles successfully [65]. Shortly, the current studies are mainly about choosing different transfer strategies. van Wyk *et al.* raised an optimal driving-entity switching policy based on an MDP model and extended the model by using approximate solution strategies [66].

In terms of the semi-autonomous driving system, the driver and the automated system complete the driving tasks cooperatively. Therefore the design of Human-Machine Interfaces (HMI) is quite curial. HMI is the medium of human-computer interaction, and human-machine coopreation [67]. Guo, Chunshi *et al.* proposed a cooperative driving system in the case of highway merging, and they adopt the haptic shared control to enhance the feedback of HMI [58]. The user trust for the system is also a key factor of HMI design. An HMI focusing on user trust was developed, and they indicated that user trust is dynamic and sustains long after the interaction occurring [68]. Thus, when we intend to introduce the user trust factor into HMI, a holistic perspective on trust should be considered.

D. Fully Autonomous Driving

Although the interference of human factors is negligible for a fully autonomous driving system, it needs to complete all driving tasks such as the perception of the surrounding environment, the avoidance of obstacles, and decision-making in complex environments.

Fully autonomous driving is also a hot spot and lots of related architectures have been proposed. After summarizing the existing architectures, Ta *et al.* proposed a fully automated driving architecture for the future [69]. In 2011, a team for DARPA Urban Challenge presented a safety-oriented, fully autonomous driving vehicle, and they discussed the details about the design of their car and related algorithms [3]. The challenge is how to ensure the system's robustness and the safety of driving without human monitoring [3]. Moreover, the fully autonomous driving scheme's cost remains too high to be commercially available immediately [1].

Even if fully autonomous driving has realized in some situations now and may be widely applied in the future, it cannot replace semi-autonomous driving and manual driving because some people will enjoy driving. So in our opinion, those schemes for autonomous driving should not be shockable but complement each other to meet different user needs.

E. General Autonomous Driving Architecture With H-AI

Semi-autonomous driving remains a focus for autonomous driving [1] because fully autonomous driving will probably not affect situations comprehensively and encounter a set of technical and ethical obstacles [63], [66]. Also, the architecture we proposed is a kind of semi-autonomous driving.

HMC is always a pressing challenge of semi-autonomous driving. In our opinion, it is insufficient human-machine coupling that triggers conflicts. Some similar opinions were also proposed in [44], [62], [70]. Thus, a theoretical architecture based on H-AI is derived, as shown in Fig 5. The function of general autonomous driving systems includes sensing, decision-making, and control [69], [71]. Note that the human-machine interaction is so critical in the whole system that we separately extract human-machine interaction as a separate part. Such a mediator module is the key to this architecture to manage and resolve the conflict timely. Therefore, our architecture contains six parts: sensors module, action module, data fusion module, decision-making module, interaction module, and control module.

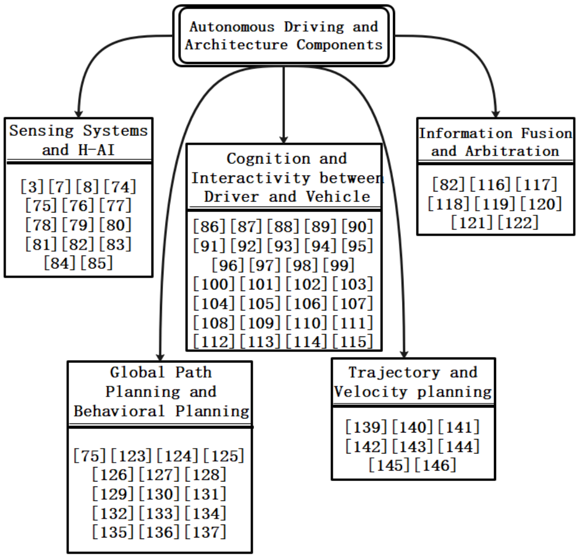

Fig. 6. The taxonomy of technologies related to autonomous driving.

F. Discussion About the Arbitration

We introduced the arbitration sub-modules into each module. Morignot *et al.* [72] introduced the conception of ITS [70] into semi-autonomous driving, which indicated that the arbitration module generated the unique motion from several sources, including the reliability of the automatic system, the output of the autonomous driving module, and humans' operation. The arbitration is characterized by dynamic and real-time. It also determines the control priority of the vehicle. When one party is authorized as the master, the other party's operation and a decision will be regarded as a modification and supplement. Introducing arbitration into semi-autonomous driving can never be a new idea [46], [58], [72], [73]. The fuzzy logic approach may be an effective solution to integer multi-source information [72]. The human's performance and reactions to the road conditions are different each time they drive. Based on historical data, such as the average driving ability of drivers, the automatic system's performance score, probability prediction can dynamically adjust the weight of human agents and machine agents in the system. We can also design the second-level probability prediction function based on some scenarios to improve the arbitration module's accuracy further. Because the design of an arbitration system is always complicated and H-AI is still in its infancy and full of potential, we would discuss the possibilities rather than provide a solution specifically.

IV. Detailed Overview and Future Development Involved in the Architecture

In this section, we summarize the related technologies and schemes that may be helpful for the implementation of H-AI architecture. We also indicate the problems of them and explain how H-AI may solve them. About the technologies related to autonomous driving, we also make a taxonomy, as shown in Fig 6.

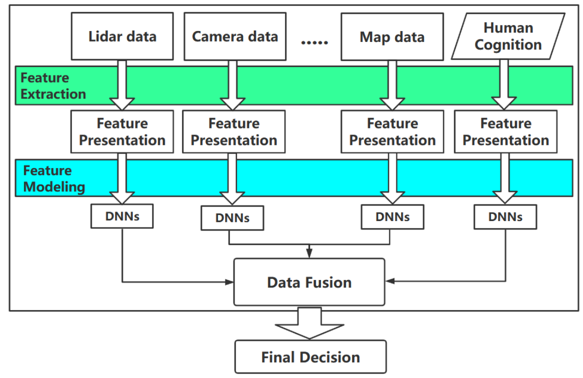

Fig. 7. The hierarchical data fusion process of H-AI-based architecture.

A. Sensing Systems and H-AI

This section is related to the sensor module in Fig 5. The main task is to collect information about the state of the vehicle, location, and surrounding by a set of sensor devices.

The vehicle's state includes speed, energy-consuming, and press of wheels. Those states are usually detected by the odometer, Inertial Measurement Unit (IMU), gyroscope, and other equipment. At present, the technologies are mature and widely applied in vehicles [7]. It is an popular choice to adopt high-precise maps and IMU or radar to get position information. High-precision maps provide a large amount of driving assistance information with the accuracy of centimeters [74]. The IMU can get the current vehicle's position in the coordinate system by calculating the relative position of the rotating axis and the external balance ring, then obtains the real-time information. However, the error of the IMU will be accumulated all the time until the result is wrong. At this time, device compensation is usually used to eliminate such error [3].

The sensing technologies include visual perception, radar perception [75], and microwave perception. With the development of AI, applying CV to AVs becomes a hotspot [76], [77]. Using DNNs can significantly improve the accuracy of perception [78], [79]. The CV-based autonomous driving systems mainly have two paradigms: mediated perception approaches making a driving decision based on complete surrounding information, and behavior reflex approaches through matching an input image to a driving action [80]. The visual perception scheme is expensive and does not perform well at the moment. Compared with it, radar perception technology is relatively mature and performs well in many scenes. By combining various sensing technologies, each technology's defects can be eliminated to the greatest extent, and the robustness of the whole perception system can be improved [8], [81], [82]. At present, the popular scheme is to use cameras to obtain the object information and radars to detect the relative distance between the object and the vehicle [83].

There are still several challenges. Sensors may break down when the weather condition is quite terrible [8]. Laser scanner technology has been a reasonable way to improve the visibility range in foggy weather. The dependencies between light fog transmission and wavelengths are the key factors [4]. In the computation of visual semantics, it is not easy to balance the trade-off between accuracy and computational cost. An offline-online strategy was proposed to settle it [84]. In [85], an object recognition system through classifying the tracks of all the objects was presented. However, in the case of a complex environment, the system still have difficult to understand the surroundings precisely [7], [8]. In short, a combination of a series of technologies seems not to enable the system to handle the open-ended environment completely.

B. Cognition and Interactivity Between Driver and Vehicle

This section is related to the interaction module in Fig 5. The interaction module is the interface for information exchange. Most of the operations of the system should be shown to the driver through it. Also, and it collects the driver's information.

The feedback information mainly comes from each module's arbitration system and is shown through HMI. Based on the idea of cooperation shared control, the information should be informed to the user in various forms, such as text, image, and voice. Results given by the arbitration system and information collected by the sensor module are required to be shown in the interaction interface [86]. Also, Bach-y-Rita *et al.* proposed an HMI based on brain science research, which conforms to the idea of H-AI [87].

The conflict between humans and machines is an inherent challenge of semi-autonomous driving. An approach to resolve conflict is driver behavior modeling [88]. In [89], dynamic Markov models recognized and predicted human behaviors through the data collected by a series of sensors. In a cognitive architecture, computational modeling has developed as a powerful tool for analyzing the complex task of driving. In the context of ordinary user abilities and constraints, a model understanding driver behavior was presented in [90], which served as a basis for predicting and recognizing driver behavior. If the driver's driving behavior as a servo performance is optimal, control theory could be used to model the driver behavior effective method. In the work of MacAdam and Charles C, they proposed a model that reproduces the driving process by minimizing or maximizing the objective function in the context of interference and constraint [91]. The fuzzy logic is also proved to be a mature method, which can accurately determine the minimum longitudinal safety distance during driving so that the possibility of collision will be decreased [92]. Also, the decision maker's weight might be necessary to resolve the conflict [93].

At present, driving behavior modeling is the popular solution to build an intelligent controller [88]. Nevertheless, those methods use driver information incompletely. As we mentioned in III-A, the HMC is that the human agent and the system make decisions based on incomplete environmental information concurrently when they communicate with each other inadequately. The high coupling degree of humans and the automatic system can make up for the conflicts caused by such insufficient interaction and fundamentally avoid conflicts. Thus, we must introduce the driver's information into the architecture comprehensively.

The driver's information includes appearance, eye movement, iris, behaviors. We can collect them to adjust the driver agent's relationships and the automated system [94]. In 1991, a testing report about monitoring drivers' physiological signals during the driving process was released [95]. Also, the related research is summarized in [96], [97]. Eye movements can be used to analyze whether the driver is distracted in real time [98]. Besides, a fatigue degree is a vital factor in evaluating the reliability of the driver. In [99], based on the CV, they monitored and traced the face information and eye movement to calculate fatigue. However, fatigue should be reflected in more indicators. In [100], a fatigue detection method based on multiple visual cues was presented, which performed more reliably and precisely than single or fewer indicator methods.

Humans have a much better understanding of the open-ended environment than machines [12], and utilizing human cognition is the most challenging step. For a semi-autonomous driving, people and systems dynamically perform driving tasks. They share information to make driving decisions efficiently. Based on the same driving goal, the driver and system can make the final decision convergence through negotiation, which improves user experience.

Although those methods collect and analyze the psychological information effectively, human cognition, the most significant information source for a human, is always invisible. In 2008, Anup Doshi and Mohan Trivedi adopted sparse Bayesian learning to predict the driver's intent of lane change by analyzing the driver's eye gaze and head motion [101]. Similar works were presented in [102], [103]. The general design scheme uses human physiological data to train a classification or probability model to predict the driver's intent of some operations. However, such predictions are often limited to specific scenarios and driving intentions are only a part of driving cognition.

As we discussed in III-B, the current interaction model uses the driver's physiological data to train the AI model. In essence, it is a mapping between physiological signal and driving intention [88], which is not reliable, because the physiological signal itself is an indirect representation of human thinking. During information transmission, the indirect transformation of information will produce random noise which is hard to eliminate. With the accumulation of errors caused by noise, errors will be produced eventually.

Human brain waves are a more straightforward representation of human cognition. Thus, utilizing brain waves is a tremendous advantage, and an efficient way of man-machine information exchange is required. Using BCI to collect and analyze human intention is a typical solution and widely applied in health care [104]. Compared with other interaction paradigms, like haptic interaction, using BCI to analyze driving intention has the following advantages:

1) Delay. Typically, the time cost of predicting a driver's intention includes the time it takes to generate physiological signals from the reaction of the human brain and the time it takes to analyze physiological signals. The length of the former depends on the characteristics of the individual and cannot be changed by technology, while the latter can be shortened by technology. Since BCI

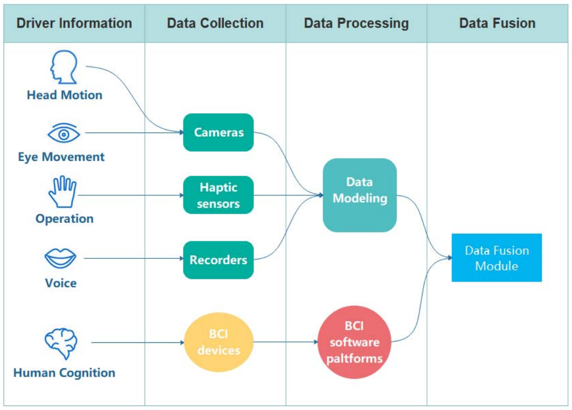

Fig. 8. The collecting and processing the driver information of H-AI-based architecture.

direct analysis of brain waves, the cost of time mainly lies in the processing of brain signals. The H-AI requires rapid information exchange, to share information and negotiate decision-making in a short time.

2) Accuracy. Human intention is characterize by indeterminacy. During each driving process, the driver may be in a different state, establishing an accurate and universal model to predict driving intention is complex [88]. Compared with using other physiological signals, brain waves are much more direct for prediction and reflects the driver's intention more precisely.
3) Robustness. In the process of driving, people may have a state of mismatch between their behavior and intention, such as delayed response or misoperation. This abnormality will lead to the failure of the system to understand. The direct analysis of driving intention using BCI can fundamentally avoid the potential risks brought by such anomalies, making H-AI-based system more stable.
4) Realizability. Neuroimaging has shown that decode a person's consciousness is likely, which makes understanding human cognition possible [105]. BCI is now gaining popularity. The rapid advance of applied science and AI makes BCI move from theory to application. Both invasive and non-invasive BCI have achieved breakthroughs, making it reasonable to imagine BCI as a potential human-computer interaction medium in H-AI systems.

At present, BCI research mainly involves improving accuracy, reducing delay and cost, and designing for generalization [104], [106], [107]. Inspired by that, we hope to apply BCI to the system to meet the requirement of H-AI. For a H-AI-based architecture, the acquisition of driver's information is shown in Fig 8.

The current BCI technology includes hardware technologies and software platforms. The electrode is an integral part of BCI devices. In [108], using dry EEG electrodes, they designed a visual-evoked-potentials-based BCI system that performed stable and high-speed. BCI has a wide variety of software platforms including BCI2000 [17], BCILAB [109], openVIBE [110], openBCI [111], BCI++ [112]. According to the way the BCI is placed, it can be divided into invasive BCI and non-invasive BCI. The invasive BCI surgically places electrodes in the human brain and captures high-quality signals. The non-invasive BCI, on the contrary, collects brain signals through in-vitro devices, but the signal quality is relatively lower. In [113], through a slow but reliable BCI called P300, the user completed a scheduled walk in the wheelchair. It is a young and cross-cutting field. The functional framework of BCI had been proposed in [107], which come up with an idea for later BCI design.

A set of progress lays the foundation for BCI to be applied in more fields. For the no-invasive BCI, in 2019, a laboratory of the University of San Francisco(USF) extracted the deep semantics from human brain activity and translated them into words first. Its lowest wrong word rate is 5 percent [114]. Neuralink, a BCI technology company, revealed its latest invasive BCI device and surgery robot on 28 August 2020 [115]. Their invasive BCI collected the animals' brain activity explicitly and continuously and their BCI implantation was minimally invasive and addressed the impact of chip fever for an organism. Facing the challenges of inadequate long-term reliability and time-consuming recalibration for BCI, Daniel B. Silversmith *et al.* provided a plug-and-play BCI that performed stable [106].

Although BCI has been widely applied in health care, it still faces a set of challenges [104]. Firstly, there is no uniform standard and entirely appropriate electrode (the perception module of BCI) of BCI [104]. The ethical issues are quite considerable. BCI is still in its infancy, and at present, invasive BCI cannot be used commonly because the cost of wearing such a device might be unacceptable for a healthy person. However, as these technologies continue to evolve, there will surely be a future in which machines become part of the human body (Cyborg) to improve body abilities rather than solve physical obstacles. Then H-AI will be a familiar concept, where humans and machines communicate and collaborate in language, behavior, and thinking.

C. Data Fusion and Arbitration

This section is related to the data fusion module in Fig 5. In this part, Multisensor Data Fusion (MDF) and human-machine data fusion are the main tasks. The raw data comes from the sensing module is integrated and processed so that the decision-making module can use them.

The data collected by the sensing module often comes from multiple sensors, which need to be processed and integrated. The fundamental process of MDF is transforming raw data to decisions, and inference [82]. However, the transformation was a complex and composite process. The scheme of data fusion is hierarchical [116]. Early MDF schemes extracted features from the raw data, integrated those features and finally built the model by machine learning or some statistical methods. With the rise of DL, later schemes, after feature extraction, undergo neural network training, and carry out multi-model features. Then, those features are integrated according to a distinct weight [117].

Current MDF can be achieved at the data layer, the feature layer, and the decision layer [82]. Nevertheless, the multisensor data are usually heterogeneous, and it is hard to complete the fusion on the data layer. In recent years, many data fusion systems have been proposed, like JDL data fusion framework [118]. Many other frameworks were presented in [119], which provided ideas for the data fusion system design.

The fundamental requirements of fusion algorithms are high robustness and parallel computation. Kalman filtering has always been an excellent algorithm for processing redundant data of low-level real-time dynamic multisensor. It determines the optimal fusion and data estimation statistically by recursing the statistical characteristics of the target model [120]. Dynamic Bayesian Networks (DBNs) are probabilistic graphical models representing random variables with conditional dependencies. DBNs perform excellently in handling time-series data, and multimedia analysis tasks [117]. Note that DNNs have been widely used in data fusion in recent years [6], [9]. DNNs have strong fault tolerance, self-learning, and self-adaptation ability and can simulate complex nonlinear mapping, which meets the multisensor data fusion [121].

However, there are few techniques for combining human cognition with information gathered by machines. We believe that the idea of MDF can be an excellent reference. The process is shown as Fig 7. According to our architecture, human cognition is fused with multisensor data. Those data are standardized and extracted to generate multi-model features which should be processed by DNNs [118]. Finally, data fusion algorithms integrate those data to draw the decision. The state vectors can be used for data fusion and then make a joint inference to obtain the final result. Note that fuzzy logic [122] may perform better than binary logic because the information generated by human intention is often vague and uncertain.

At present, there is no general model and algorithm for MDF. In the application of automatic driving, data inconsistency caused by multiple sensors has always been an obstacle. The robustness and real-time requirements of the information fusion framework will increase significantly. Furthermore, the introduction of human cognition will bring new challenges to information fusion, including data uncertainty, system design, and other system interaction interface design.

D. Global Path Planning and Behavior Planning

This section is related to the decision-making module in Fig 5. This module will generate the vehicle's global path planning and behavior planning by utilizing the information fusion module.

The global path planning is built on a topological map, and its implementation relies on a high-precision map. It refers to find an available and collisionless path that can safely reach the target point from the starting point based on the environmental model [123].

In terms of environment modeling, grid methods may be a common choice for map segmentation, which has performed quite outstanding. The grid methods divide the workspace into regular and uniform grids with binary information. Binary information indicates whether there are obstacles at the grid. A grid without obstacles is called a free grid. Otherwise, it is an obstacle grid [124].

The path search of AVs is a 3D path planning for wheeled robots. In [123], they summarized and classified 3D path planning algorithms that have been applied in aerial robots, ground robots, and underwater robots. Dijkstra algorithm [125] and A* [126] have been common optimal search algorithms. Some random-exploring algorithms like probabilistic roadmaps [127] and rapidly exploring random tree [128] perform well in spares graph. Inspired by metaheuristic technique, Mazzeo, Silvia, and Loiseau, Irene used the ant colony algorithm that performs better than most of the other algorithms [9], [129]. After the path search is complete, we need to set appropriate route costs to generate the final results. DL is a way to use path selection as a recommendation system, emphasizing human choice. A system utilizing a fuzzy neural networks to calculate the selection possibility of each route was presented in [130].

The behavior planning makes final action decisions based on all the external information collected by the information fusion module, interaction module, and path planning path. Compared with global path planning, behavior planning is a process of local decision. The behavior mainly includes lane change, obstacle avoidance, and traffic sign recognition. It is difficult to use a single model to achieve behavior planning. At present, the most widely used approach is based on the deterministic behavior decision-making rules, including MDP [131] and partially observable MDP [132]. BOSS, the autonomous vehicle of MCU, won the championship in DARPA, adopted the rule-oriented decision-making method to calculate the distance between lanes to complete lane transformation [133]. In [134], a real-time path planning algorithm was presented, which provided an optimistic plan for avoiding static obstacles. In their approach, each candidate route was transformed to a Cartesian coordinate system, which would be evaluated by obstacle data. In terms of obstacle avoidance of mobile robots, Wu *et al.* proposed an integrated algorithm based on lidar, which made use of the nearest point around the obstacle to draw the shortest route to avoid obstacles [75]. Li *et al.* proposed a mobile robot collision avoidance method based on HyperOmni Vision and their approach combined the improved dynamic window approach with an artificial potential field [135].

The decision-making module needs to compensate for the error accumulation of each sub-module. Some scholars proposed to use a Bayesian probabilistic model to model behavioral decisions instead of relying on deterministic rules [132], [136]. The advantage is accessible to modularization, and the whole process is transparent so that the driver can correct the decision-making process, which is in line with H-AI and considers the role of the human in the system. By analyzing the preception data or direct interference, errors will be compensated. Also, in an open-ended environment, emergencies are difficult to avoid. In extreme cases, when the system judges that it cannot understand the situation, it will deliver the driver the right to drive. However, with H-AI development, the transfer of driving right needs more research and consideration according to a specific scenario. Besides, in recent years, with the proposition of reinforcement learning

(RL) [137], scholars deem that RL may be an appropriate way to decide driving priority [138].

E. Trajectory and Velocity Planning

This section is related to the motion planning module in Fig 5. The control module is responsible for generating the motion planning that includes trajectory planning and velocity planning [139]. This process can be thought of as solving the optimal path problem in a given range under a certain constraint [140]. According to the final action decisions, motion planning is to make a time-related track route passed to the execution module. Note that the driver's operation in the H-AI-based interaction paradigm also affects the system, impacting the final vehicle's movement. Once the motion planning is achieved, the result will be delivered to the execution module.

Trajectory planning was developed to solve the mechanical arm movement problem initially [141]. Trajectory planning, based on the existing planned route, considers vehicle dynamics to correct the actions that cannot be completed by vehicles generated by path planning [4]. In term s of autonomous driving, vehicle dynamics and traffic regulations, and interior comfort should be taken into consideration [142]. When the trajectory planning is completed, speed planning will assign velocity and acceleration information to each track point [143]. In [144] a motion planning approach based on a rapidly-exploring random tree was presented, which can still work in an open-ended urban environment. In [145], they proposed a hierarchical motion planning framework to deal with navigation problems. The mobile robot's control plan is described in detail [142], [146].

Motion planning is quite sensitive to calculating delays, and how to cooperate and coordinate the various parts is an unavoidable challenge. Fortunately, the research on motion planning is relatively mature [146]. At present, the main idea is to decompose a complex problem and use multiple modules to solve each sub-problem. There are also several options available, most of which work well. Similarly, we hope to introduce human operation to make the vehicle's actions more reasonable. By analyzing people's states and manipulations, the arbitration system will decide what to do with people's input information and adjust the weight of people and machines dynamically.

V. A Simple Maneuver of H-AI-Based Autonomous Driving System

This section illustrates our proposition's advantage through a simple maneuver, as depicted in Fig 9. We will also discuss how H-AI-based architecture solves the HMC that is unavoidable for existing semi-autonomous driving.

A. Illustration of the Scenario

As Fig 9 depicts, the driver makes a maneuver while his vision is blocked and the sensors detect the oncoming motorcycle. The automatic system must want to prevent the driver from changing lanes because it is likely to send a collision. In such a scenario, the driver makes a different maneuver from the system entirely, which raises HMC.

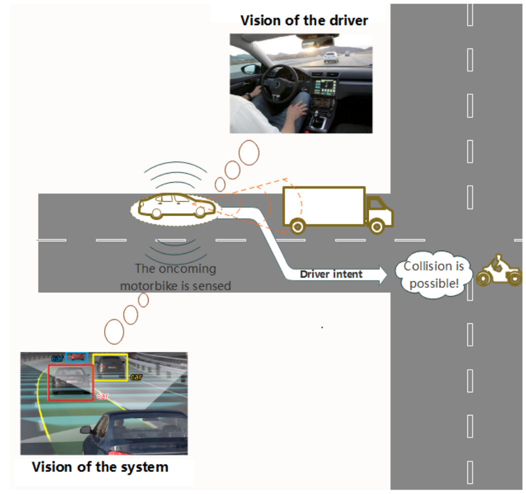

Fig. 9. A simple scenario about overtaking.

B. Discussion About the H-AI-Based Architecture

In this scenario, as we discussed in IV-B, HMC incurs due to the operation of two agents based on different information. As shown in Fig 9, there is a difference in the world perceived by humans and autonomous driving systems. Current sensors, information fusion, and high-precision mapping enable the system to collect more abundant information than the human. However, the human excels at judging and predicting the things around them. Therefore, it is inevitable for human agents and system agents to collide with each other. For the traditional ADAS, without a strong message, users can not know why the system rejected its operations. Then, the traditional interaction approaches incur the delay that the driver processes the sensory information. In the case of an emergency, it may lead to severe consequences. Thus it is hard to strike a balance between user experience and security [147]. We should strengthen the communication between the driver and the system.

H-AI-based architecture emphasizes the high coupling between the human agent and machine. The conflict is the friction of their operations. As we all know, humans intent guides their operations while instructions control the machines' actions. Since all of those processes happen before the two agents making the operations, the machine and human are not in conflict with each other but communicate about decision-making, which improves the user experience of semi-autonomous driving while also improving the safety of driving.

There is uncertainty in predicting the driver's intention through movement and physiological signals. Driving behavior is controlled by the driver's thinking. A behavior may correspond to a set of various intentions, and the probabilities of these intentions are different in some scenes, which requires the establishment of complex models to find the optimal solution. However, unknown intentions lead to a failure of prediction. BCI is used to translate the prediction of driving intention into direct communication decreasing the HMC.

Under the scenario shown in Fig 9, BCI will capture and analyze the driver's lane change intention before the driver makes the lane change action. When the system senses an oncoming motorcycle, it analyzes road conditions and vehicle speed to make a judgment of a high-risk collision. The system will inform the driver of this judgment through the BCI immediately and make the final arbitration according to rules. Once verify the danger, the driver can choose to give up the lane change operation or change the timing of the change. The whole negotiation is rapid because it builds on the human brain's thinking.

VI. Open Challenges

In this section, we are going to discuss several open challenges. Meanwhile, in the perspective of H-AI, we hope to provide some promising solutions.

a) The integration of complicated systems: Since AVs are regularly composed of multiple subsystems, how to reduce the conflicts among various parts and make each module cooperate efficiently is the difficulty of the overall design [148]. Also, how to achieve fault tolerance is a complicated problem. The integration of algorithms designed for each part also needs to consider many factors, including screening of information, noise, and error accumulation. In [3], [133], they provided ideas about enhancing the autonomous driving system's integration and robustness.

b) The ability of prediction: In an open environment, the current prediction algorithms are likely to make wrong judgments. Thus, the idea of using the Bayesian probability model to make decisions was proposed. The idea of Bayesian is in line with the real world because events happen with a certain probability rather than a fixed model [149]. Decision-making based on Bayesian probability may be an effective way to handle the uncertainty of driving [150]. The enhancement of the predictive capability is related to AI development, which enables autonomous vehicles to complete driving tasks in complex scenes and achieve higher levels of autonomous driving.

c) Ensure robustness and interaction problems during driving: Current technologies used in autonomous driving often struggle to maintain reliability in the face of complex scenarios and extreme weather conditions. In [151] based on the driving experience of Tesla Model S, they analyzed the problems in human-computer interaction, especially the Situational Awareness (SA), and provided relevant solutions. In terms of drivers' attention in human-computer interaction, in [152], they compared different systems and concluded that frequent handover would increase drivers' burden, which provided a basis for analyzing and solving drivers' distraction and retention in human-computer interaction. The research concerned will make semi-automatic driving more efficient, which is also the key to introduce H-AI into the automatic driving system.

d) Better usage of human cognition: Understanding human cognition and making use of it is not an easy thing for a machine. Human cognition can be manifested in many ways. Fortunately, today's perceptual technology is quite advanced and can capture most of the information. With cognitive science development, the research on the human brain and thinking has been deepened continuously. In [18], the author discussed the possible problems based on specific cases and points out the key to understanding the thought and reason of humans is understanding the complex relationships and interactions between different types of strategies and resources. In [153], a wheeled robot with a simple structure directly controlled by the human brain was proposed. The related research will further enhance the judgment ability to drive systems in complex environments and reduce accidents, making H-AI possible.

e) Data privacy protection: The H-AI based architecture involves the cognition data that is extremely privy. The cognition data collected by experiments are limited now. However, in the future, with the advance of research on brain science and BCI, many systems will get interfaces to process cognitive data and its protection will be quite significant. In terms of autonomous driving, it must be known which data are relevant to driving, which data are expected to be obtained by the autonomous driving system, and how to specify the degree of acquisition of cognition data. These challenges may be overcome with the development of brain science, cognitive science, and BCI. In [154], they discussed data sharing in cognitive science, which may insight us. Generally, data privacy protection is significantly complicated and considerable.

f) Some ethical challenges: Autonomous driving raises ethical questions, such as accountability for accidents. Also, the trust between the driver and the system should not be ignored. How to express trust and integrate the trust into the carrier's perception and planning are factors to be considered. Introducing H-AI can address some of these issues, such as accountability in accidents and increased acceptance of autonomous driving. But it will take time for such a high degree of human-computer coupling to be widely adopted.

VII. Conclusion and Outlook

We reviewed and categorized the existing schemes of autonomous driving and present a taxonomy of autonomous driving architectures. Then, we proposed a theoretical architecture based on H-AI. The overview and future development involved in autonomous driving architecture were also summarized. In a similar vein, we presented a taxonomy of technologies related to autonomous driving. For H-AI-based architecture, we emphasized human information integrity and man-machine integration rather than machine replace drivers merely. Such a people-oriented driving scheme can promote autonomous driving and maybe a part of ITS in the future. We put forward several open research challenges of autonomous driving architectures that may focus on future research. In the future, humans and machines will cooperate and exchange thinking in contact or non-contact ways. With the development of brain science, BCI, and other related technologies, such human-machine relationships will appear shortly. In the future work, we shall evaluate the real-time autonomous driving scenarios where enormous bridging is incorporated for data exchange across different emerging networks and various input support using H-AI.

References

[1] T. Litman, "Autonomous vehicle implementation predictions," Victoria Transp. Policy Inst. Victoria, Victoria, BC, Canada, Tech. Rep. TRID 01727624, 2020. [Online]. Available: https://www.vtpi.org/avip.pdf

[2] Y. Pan, "Heading toward artificial intelligence 2.0," *Engineering*, vol. 2, no. 4, pp. 409–413, Dec. 2016.

[3] J. Levinson *et al.*, "Towards fully autonomous driving: Systems and algorithms," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011, pp. 163–168.

[4] M. Kutila, P. Pyykönen, W. Ritter, O. Sawade, and B. Schäufele, "Automotive LIDAR sensor development scenarios for harsh weather conditions," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 265–270.

[5] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep learning for computer vision: A brief review," *Comput. Intell. Neurosci.*, vol. 2018, pp. 1–13, Feb. 2018.

[6] S. Grigorescu, B. Trasnea, T. Cocias, and G. Macesanu, "A survey of deep learning techniques for autonomous driving," *J. Field Robot.*, vol. 37, no. 3, pp. 362–386, Apr. 2020.

[7] G. Bresson, Z. Alsayed, L. Yu, and S. Glaser, "Simultaneous localization and mapping: A survey of current trends in autonomous driving," *IEEE Trans. Intell. Vehicles*, vol. 2, no. 3, pp. 194–220, Sep. 2017.

[8] Y. Ma, Z. Wang, H. Yang, and L. Yang, "Artificial intelligence applications in the development of autonomous vehicles: A survey," *IEEE/CAA J. Autom. Sinica*, vol. 7, no. 2, pp. 315–329, Mar. 2020.

[9] G. Meiring and H. Myburgh, "A review of intelligent driving style analysis systems and related artificial intelligence algorithms," *Sensors*, vol. 15, no. 12, pp. 30653–30682, Dec. 2015.

[10] E. Kamar, "Directions in hybrid intelligence: Complementing AI systems with human intelligence," in *Proc. 25th Int. Joint Conf. Artif. Intell.*, 2016, pp. 4070–4073.

[11] M.-H. Huang and R. T. Rust, "Artificial intelligence in service," *J. Service Res.*, vol. 1, no. 2, p. 18, 2018.

[12] N.-N. Zheng *et al.*, "Hybrid-augmented intelligence: Collaboration and cognition," *Frontiers Inf. Technol. Electron. Eng.*, vol. 18, no. 2, pp. 153–179, Feb. 2017.

[13] A. Bundy, "Preparing for the future of artificial intelligence," *AI Soc.*, vol. 32, no. 2, p. 285, 2017.

[14] M. Martínez-Díaz and F. Soriguera, "Autonomous vehicles: Theoretical and practical challenges," *Transp. Res. Procedia*, vol. 33, pp. 275–282, Jan. 2018.

[15] F. L. da Silva, "Neural mechanisms underlying brain waves: From neural membranes to networks," *Electroencephalogr. Clin. Neurophysiol.*, vol. 79, no. 2, pp. 81–93, Aug. 1991.

[16] K. Amunts, C. Ebell, J. Muller, M. Telefont, A. Knoll, and T. Lippert, "The human brain project: Creating a European research infrastructure to decode the human brain," *Neuron*, vol. 92, no. 3, pp. 574–581, Nov. 2016.

[17] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.

[18] A. Clark, "An embodied cognitive science?" *Trends Cognit. Sci.*, vol. 3, no. 9, pp. 345–351, 1999.

[19] Z.-M. Zhang, F.-F. Shi, Y.-L. Wan, Y. Xu, F. Zhang, and H.-S. Ning, "Application progress of artificial intelligence in military confrontation," *Chin. J. Eng.*, vol. 42, no. 9, pp. 1106–1118, 2020.

[20] S. Thrun *et al.*, "Stanley: The robot that won the DARPA grand challenge," *J. Field Robot.*, vol. 23, no. 9, pp. 661–692, 2006.

[21] Ministry of Transport. *Road Traffic Act*. Accessed: Dec. 21, 2020. [Online]. Available: http://image.ccidnet.com/ccidgroup/2019zhinengwanglianqichefalv.pdf

[22] TSI Policy and Regulation. *2019 Intelligent Connected Vehicle Policy and Legal Research Report*. Accessed: Dec. 21, 2020. [Online]. Available: http://image.ccidnet.com/ccidgroup/2019zhinengwanglianqichefalv.pdf

[23] European Commission. *On the Road to Automated Mobility: An EU Strategy for Mobility of the Future*. Accessed: Dec. 21, 2020. [Online]. Available: https://ec.europa.eu/transport/sites/transport/files/3rd-mobility-pack/com20180283_en.pdf

[24] European Commission. *Guidelines on the Exemption Procedure for the EU Approval of Automated Vehicles*. Accessed: Dec. 21, 2020. [Online]. Available: https://ec.europa.eu/growth/content/guidelines-exemption-procedure-eu-approval-automated-vehicles_en

[25] E. Kamer. *Autonomous Vehicle Experimentation*. Accessed: Sep. 3, 2020. [Online]. Available: https://www.eerstekamer.nl/wetsvoorstel/34838_experimenteerwet

[26] Norwegian Ministry of Local Government and Modernisation. *National Strategy for Artificial Intelligence*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.regjeringen.no/contentassets/1febbbb2c4fd4b7d92c67ddd353b6ae8/en-gb/pdfs/ki-strategi_en.pdf

[27] U.S. Department of Transportation. *Federal Automated Vehicles Policy*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.transportation.gov/AV/federal-automated-vehicles-policy-september-2016/

[28] National Highway Traffic Safety Administration. *USDOT Automated Vehicles 2.0 Activities*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.nhtsa.gov/press-releases/us-dot-releases-new-automated-driving-systems-guidance

[29] U.S. Department of Transportation. *Preparing for the Future of Preparing for the Future of Artificial Intelligenceransportation: Automated Vehicles 3.0*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.transportation.gov/av/3

[30] Finnish Transport Agency. *Public Road Automated Vehicle Testing in Finland*. Accessed: Dec. 21, 2020. [Online]. Available: https://connectedautomateddriving.eu/wp-content/uploads/2017/02/FI-Presentation-Workshop-16.12.2016.pdf

[31] Finnish Transport and Communications Agency. *What are the AIMS of the New Road Traffic Act?* Accessed: Dec. 21, 2020. [Online]. Available: https://www.traficom.fi/en/transport/road/what-are-aims-new-road-traffic-act

[32] J. Du. *Overview of UK Driverless Policy*. Accessed: Dec. 21, 2020. [Online]. Available: http://www.istis.sh.cn/list/list.aspx?id=11636

[33] Department for Transport and Energy, Industrial Strategy Department for Business. *Centre for Connected and Autonomous Vehicles*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.gov.uk/government/organisations/centre-for-connected-and-autonomous-vehicles

[34] Department for Transport. *Vehicle Technology and Aviation Bill*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.gov.uk/government/collections/vehicle-technology-and-aviation-bill

[35] C Automotive Technical Information. *Road Test Specifications for Autonomous Vehicles in Japan*. Accessed: Dec. 21, 2020. [Online]. Available: http://www.sohu.com/a/216452949_372601

[36] Gasgoo. *Japan has Issued a Safety Guide for Self-Driving Cars, Making 10 Rules for the L3 and L4*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.d1ev.com/news/jishu/76896

[37] JM Transport. *Public-Private Its Initiative/Roadmaps 2019*. Accessed: Dec. 21, 2020. [Online]. Available: https://japan.kantei.go.jp/policy/it/2019/2019_roadmaps.pdf

[38] R. Threlfall. *2020 Autonomous Vehicles Readiness Index*. Accessed: Dec. 21, 2020. [Online]. Available: https://home.kpmg/uk/en/home/insights/2020/07/2020-autonomous-vehicles-readiness-index.html

[39] Automotive Business Review. *The World's 16 Autonomous Driving Companies are Competing With Each Other*. Accessed: Dec. 21, 2020. [Online]. Available: https://www.iyiou.com/p/128321.html

[40] C. Tessier and F. Dehais, "Authority management and conflict solving in human-machine systems," *AerospaceLab-J.*, vol. 4, p. p-1, May 2012.

[41] F. Mars, M. Deroo, and J.-M. Hoc, "Analysis of human-machine cooperation when driving with different degrees of haptic shared control," *IEEE Trans. Haptics*, vol. 7, no. 3, pp. 324–333, Jul. 2014.

[42] R. Parasuraman and C. D. Wickens, "Humans: Still vital after all these years of automation," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 50, no. 3, pp. 511–520, Jun. 2008.

[43] M. Klein, "Supporting conflict resolution in cooperative design systems," *IEEE Trans. Syst., Man, Cybern.*, vol. 21, no. 6, pp. 1379–1390, Nov. 1991.

[44] F. O. Flemisch *et al.*, "Conflicts in human-machine systems as an intersection of bio- and technosphere: Cooperation and interaction patterns for human and machine interference and conflict resolution," in *Proc. IEEE Int. Conf. Hum.-Mach. Syst. (ICHMS)*, Sep. 2020, pp. 1–6.

[45] E. Altendorf, M. Baltzer, M. Heesen, M. Kienle, T. Weißgerber, and F. Flemisch, "H-mode, a haptic-multimodal interaction concept for cooperative guidance and control of partially and highly automated vehicles," in *Handbook of Driver Assistance Systems*. Cham, Switzerland: Springer, 2015.

[46] J.-M. Hoc, M. S. Young, and J.-M. Blosseville, "Cooperation between drivers and automation: Implications for safety," *Theor. Issues Ergonom. Sci.*, vol. 10, no. 2, pp. 135–160, Mar. 2009.

[47] D. A. Abbink and M. Mulder, "Neuromuscular analysis as a guideline in designing shared control," in *Advances in Haptics*. London, U.K.: IntechOpen, 2010.

[48] S. M. Erlien, S. Fujita, and J. C. Gerdes, "Shared steering control using safe envelopes for obstacle avoidance and vehicle stability," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 2, pp. 441–451, Feb. 2016.

[49] A. Enes and W. Book, "Blended shared control of Zermelo's navigation problem," in *Proc. Amer. Control Conf.*, Jun. 2010, pp. 4307–4312.

[50] A. A. Allaban, V. Dimitrov, and T. Padır, "A blended human-robot shared control framework to handle drift and latency," in *Proc. IEEE Int. Symp. Saf., Secur., Rescue Robot. (SSRR)*, Sep. 2019, pp. 81–87.

[51] O. Törő, T. Bécsi, and S. Aradi, "Design of lane keeping algorithm of autonomous vehicle," *Periodica Polytechnica Transp. Eng.*, vol. 44, no. 1, pp. 60–68, 2016.

[52] M. Li, H. Cao, X. Song, Y. Huang, J. Wang, and Z. Huang, "Shared control driver assistance system based on driving intention and situation assessment," *IEEE Trans. Ind. Informat.*, vol. 14, no. 11, pp. 4982–4994, Nov. 2018.

[53] D. A. Abbink, M. Mulder, and E. R. Boer, "Haptic shared control: Smoothly shifting control authority?" *Cognition, Technol. Work*, vol. 14, no. 1, pp. 19–28, Mar. 2012.

[54] S. K. Sim, "Lane keeping assistance system and method thereof," U.S. Patent 9 545 922, Jan. 17, 2017.

[55] K. Okamoto and P. Tsiotras, "Data-driven human driver lateral control models for developing haptic-shared control advanced driver assist systems," *Robot. Auton. Syst.*, vol. 114, pp. 155–171, Apr. 2019.

[56] R. Boink, M. M. van Paassen, M. Mulder, and D. A. Abbink, "Understanding and reducing conflicts between driver and haptic shared control," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2014, pp. 1510–1515.

[57] R. Nishimura, T. Wada, and S. Sugiyama, "Haptic shared control in steering operation based on cooperative status between a driver and a driver assistance system," *J. Hum.-Robot Interact.*, vol. 4, no. 3, pp. 19–37, 2015.

[58] C. Guo, C. Sentouh, J.-B. Haué, and J.-C. Popieul, "Driver–vehicle cooperation: A hierarchical cooperative control architecture for automated driving systems," *Cognition, Technol. Work*, vol. 21, no. 4, pp. 657–670, Nov. 2019, doi: 10.1007/s10111-019-00559-2.

[59] S. Zieba, P. Polet, and F. Vanderhaegen, "Using adjustable autonomy and human–machine cooperation to make a human–machine system resilient—Application to a ground robotic system," *Inf. Sci.*, vol. 181, no. 3, pp. 379–397, Feb. 2011.

[60] J. L. Kolodneer, "Improving human decision making through case-based decision aiding," *AI Mag.*, vol. 12, no. 2, p. 52, 1991.

[61] A. Rosenfeld and S. Kraus, "Predicting human decision-making: From prediction to action," *Synth. Lectures Artif. Intell. Mach. Learn.*, vol. 12, no. 1, pp. 1–150, Jan. 2018.

[62] N. J. Goodall, "Vehicle automation and the duty to act," in *Proc. 21st world Congr. Intell. Transp. Syst.*, 2014, pp. 7–11.

[63] Z. Lu, R. Happee, C. D. D. Cabrall, M. Kyriakidis, and J. C. F. de Winter, "Human factors of transitions in automated driving: A general framework and literature survey," *Transp. Res. F, Traffic Psychol. Behaviour*, vol. 43, pp. 183–198, Nov. 2016.

[64] J.-M. Hoc, "Towards a cognitive approach to human–machine cooperation in dynamic situations," *Int. J. Hum.-Comput. Stud.*, vol. 54, no. 4, pp. 509–540, Apr. 2001.

[65] M. Baltzer, F. Flemisch, E. Altendorf, and S. Meier, "Mediating the interaction between human and automation during the arbitration processes in cooperative guidance and control of highly automated vehicles," in *Proc. 5th Int. Conf. Appl. Hum. Factors Ergonom. (AHFE)*, 2014, pp. 2107–2118.

[66] F. van Wyk, A. Khojandi, and N. Masoud, "Optimal switching policy between driving entities in semi-autonomous vehicles," *Transp. Res. C, Emerg. Technol.*, vol. 114, pp. 517–531, May 2020.

[67] J.-M. Hoc, "From human–machine interaction to human–machine cooperation," *Ergonomics*, vol. 43, no. 7, pp. 833–843, Jul. 2000.

[68] F. Ekman, M. Johansson, and J. Sochor, "Creating appropriate trust in automated vehicle systems: A framework for HMI design," *IEEE Trans. Human-Machine Syst.*, vol. 48, no. 1, pp. 95–101, Feb. 2018.

[69] O. C. S. Taş, F. Kuhnt, J. M. Zöllner, and C. Stiller, "Functional system architectures towards fully automated driving," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2016, pp. 304–309.

[70] F. Flemisch, M. Heesen, T. Hesse, J. Kelsch, A. Schieben, and J. Beller, "Towards a dynamic balance between humans and automation: Authority, ability, responsibility and control in shared and cooperative control situations," *Cognition, Technol. Work*, vol. 14, no. 1, pp. 3–18, Mar. 2012.

[71] S. Behere and M. Törngren, "A functional architecture for autonomous driving," in *Proc. 1st Int. Workshop Automot. Softw. Archit. (WASA)*, May 2015, pp. 3–10.

[72] P. Morignot, J. P. Rastelli, and F. Nashashibi, "Arbitration for balancing control between the driver and ADAS systems in an automated vehicle: Survey and approach," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2014, pp. 575–580.

[73] B. Trăsnea, C. Pozna, and S. M. Grigorescu, "AIBA: An AI model for behavior arbitration in autonomous driving," in *Proc. Int. Conf. Multi-Disciplinary Trends Artif. Intell.* Cham, Switzerland: Springer, 2019, pp. 191–203.

[74] J. Levinson, M. Montemerlo, and S. Thrun, "Map-based precision vehicle localization in urban environments," in *Robotics: Science and Systems*, vol. 4. Cambridge, MA, USA: MIT Press, Jun. 2007, p. 1, doi: 10.15607/RSS.2007.III.016.

[75] P. Wu, S. Xie, H. Liu, J. Luo, and Q. Li, "A novel algorithm of autonomous obstacle-avoidance for mobile robot based on LIDAR data," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2015, pp. 2377–2382.

[76] W. Yi-Fan, "Overview on key technology of perceptual system on self-driving vehicles," *Autoelectr. Parts*, vol. 57, no. 12, pp. 12–16, 2016.

[77] A. Geiger, P. Lenz, and R. Urtasun, "Are we ready for autonomous driving? The KITTI vision benchmark suite," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2012, pp. 3354–3361.

[78] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017.

[79] L. Zhang, L. Lin, X. Liang, and K. He, "Is faster R-CNN doing well for pedestrian detection?" in *Proc. Eur. Conf. Comput. Vis.* Cham, Switzerland: Springer, 2016, pp. 443–457.

[80] C. Chen, A. Seff, A. Kornhauser, and J. Xiao, "DeepDriving: Learning affordance for direct perception in autonomous driving," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2015, pp. 2722–2730.

[81] H. Cho, Y.-W. Seo, B. V. K. V. Kumar, and R. R. Rajkumar, "A multi-sensor fusion system for moving object detection and tracking in urban driving environments," in *Proc. IEEE Int. Conf. Robot. Automat. (ICRA)*, May 2014, pp. 1836–1843.

[82] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. IEEE*, vol. 85, no. 1, pp. 6–23, Jan. 1997.

[83] J. Kocić, N. Jovičić, and V. Drndarević, "Sensors and sensor fusion in autonomous vehicles," in *Proc. 26th Telecommun. Forum (TELFOR)*, Nov. 2018, pp. 420–425.

[84] G. Ros, S. Ramos, M. Granados, A. Bakhtiary, D. Vazquez, and A. M. Lopez, "Vision-based offline-online perception paradigm for autonomous driving," in *Proc. IEEE Winter Conf. Appl. Comput. Vis.*, Jan. 2015, pp. 231–238.

[85] A. Teichman, J. Levinson, and S. Thrun, "Towards 3D object recognition via classification of arbitrary object tracks," in *Proc. IEEE Int. Conf. Robot. Automat.*, May 2011, pp. 4034–4041.

[86] D. J. Tulbert, "Human-machine interface," U.S. Patent 7 859 519, Dec. 28, 2010.

[87] P. Bach-y-Rita and S. W. Kercel, "Sensory substitution and the human–machine interface," *Trends Cognit. Sci.*, vol. 7, no. 12, pp. 541–546, Dec. 2003.

[88] Y. Hu *et al.*, "Human-machine cooperative control of intelligent vehicle: Recent developments and future perspectives," *Acta Automatica Sinica*, vol. 45, no. 7, pp. 1261–1280, 2019.

[89] A. Pentland and A. Liu, "Modeling and prediction of human behavior," *Neural Comput.*, vol. 11, no. 1, pp. 229–242, Jan. 1999.

[90] D. D. Salvucci, "Modeling driver behavior in a cognitive architecture," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 48, no. 2, pp. 362–380, Jun. 2006.

[91] C. C. MacAdam, "Application of an optimal preview control for simulation of closed-loop automobile driving," *IEEE Trans. Syst., Man, Cybern.*, vol. 11, no. 6, pp. 393–399, 1981.

[92] H. Wu, Y. Li, C. Wu, Z. Ma, and H. Zhou, "A longitudinal minimum safety distance model based on driving intention and fuzzy reasoning," in *Proc. 4th Int. Conf. Transp. Inf. Saf. (ICTIS)*, Aug. 2017, pp. 158–162.

[93] C. Tessier and F. Dehais, "Authority management and conflict solving in human-machine systems," *AerospaceLab-J.*, vol. 4, p. p-1, May 2012.

[94] H. Singh, J. S. Bhatia, and J. Kaur, "Eye tracking based driver fatigue monitoring and warning system," in *Proc. India Int. Conf. Power Electron. (IICPE)*, Jan. 2011, pp. 1–6.

[95] D. de Waard and K. A. Brookhuis, "Assessing driver status: A demonstration experiment on the road," *Accident Anal. Prevention*, vol. 23, no. 4, pp. 297–307, Aug. 1991.

[96] D. F. Dinges *et al.*, "Evaluation of techniques for ocular measurement as an index of fatigue and as the basis for alertness management," United States Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep. DOT HS 808 762, 1998.

[97] H.-B. Kang, "Various approaches for driver and driving behavior monitoring: A review," in *Proc. IEEE Int. Conf. Comput. Vis. Workshops*, Dec. 2013, pp. 616–623.

[98] Y. Liang, M. L. Reyes, and J. D. Lee, "Real-time detection of driver cognitive distraction using support vector machines," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 2, pp. 340–350, Jun. 2007.

[99] J. He, S. Roberson, B. Fields, J. Peng, S. Cielocha, and J. Coltea, "Fatigue detection using smartphones," *J. Ergonom.*, vol. 3, no. 3, pp. 1–7, 2013.

[100] Y. Qiao, K. Zeng, L. Xu, and X. Yin, "A smartphone-based driver fatigue detection using fusion of multiple real-time facial features," in *Proc. 13th IEEE Annu. Consum. Commun. Netw. Conf. (CCNC)*, Jan. 2016, pp. 230–235.

[101] A. Doshi and M. M. Trivedi, "On the roles of eye gaze and head dynamics in predicting Driver's intent to change lanes," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 3, pp. 453–462, Sep. 2009.

[102] C. L. R. McGhan, A. Nasir, and E. M. Atkins, "Human intent prediction using Markov decision processes," *J. Aerosp. Inf. Syst.*, vol. 12, no. 5, pp. 393–397, May 2015.

[103] B. Morris, A. Doshi, and M. Trivedi, "Lane change intent prediction for driver assistance: On-road design and evaluation," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011, pp. 895–901.

[104] R. A. Ramadan and A. V. Vasilakos, "Brain computer interface: Control signals review," *Neurocomputing*, vol. 223, pp. 26–44, Feb. 2017.

[105] J.-D. Haynes and G. Rees, "Neuroimaging: Decoding mental states from brain activity in humans," *Nature Rev. Neurosci.*, vol. 7, no. 7, p. 523, 2006.

[106] D. B. Silversmith *et al.*, "Plug-and-play control of a brain–computer interface through neural map stabilization," *Nature Biotechnol.*, vol. 39, pp. 1–10, Sep. 2020.

[107] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 1, pp. 70–85, Mar. 2003.

[108] M. Nakanishi, Y. Wang, Y.-T. Wang, Y. Mitsukura, and T.-P. Jung, "A high-speed brain speller using steady-state visual evoked potentials," *Int. J. Neural Syst.*, vol. 24, no. 6, Sep. 2014, Art. no. 1450019.

[109] C. A. Kothe and S. Makeig, "BCILAB: A platform for brain–computer interface development," *J. Neural Eng.*, vol. 10, no. 5, Oct. 2013, Art. no. 056014.

[110] Y. Renard *et al.*, "OpenViBE: An open-source software platform to design, test, and use brain–computer interfaces in real and virtual environments," *Presence, Teleoperators Virtual Environ.*, vol. 19, no. 1, pp. 35–53, Feb. 2010.

[111] H. Suryotrisongko and F. Samopa, "Evaluating OpenBCI spiderclaw v1 headwear's electrodes placements for brain-computer interface (BCI) motor imagery application," *Procedia Comput. Sci.*, vol. 72, pp. 398–405, Jan. 2015.

[112] P. Perego, L. Maggi, S. Parini, and G. Andreoni, "BCI++: A new framework for brain computer interface application," in *Proc. SEDE*, 2009, pp. 37–41.

[113] B. Rebsamen *et al.*, "A brain controlled wheelchair to navigate in familiar environments," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 590–598, Dec. 2010.

[114] J. Makin, D. Moses, and E. Chang, "Machine translation of cortical activity to text with an encoder-decoder framework," *Nature Neurosci.*, vol. 23, no. 4, p. 575, 2020.

[115] E. Musk and Neuralink, "An integrated brain-machine interface platform with thousands of channels," *J. Med. Internet Res.*, vol. 21, no. 10, Oct. 2019, Art. no. e16194.

[116] G. Ye, D. Liu, I.-H. Jhuo, and S.-F. Chang, "Robust late fusion with rank minimization," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2012, pp. 3021–3028.

[117] A. K. Katsaggelos, S. Bahaadini, and R. Molina, "Audiovisual fusion: Challenges and new approaches," *Proc. IEEE*, vol. 103, no. 9, pp. 1635–1653, Sep. 2015.

[118] M. W. Roth, "Survey of neural network technology for automatic target recognition," *IEEE Trans. Neural Netw.*, vol. 1, no. 1, pp. 28–43, Mar. 1990.

[119] J. Esteban, A. Starr, R. Willetts, P. Hannah, and P. Bryanston-Cross, "A review of data fusion models and architectures: Towards engineering guidelines," *Neural Comput. Appl.*, vol. 14, no. 4, pp. 273–281, Dec. 2005.

[120] H. Zhao and Z. Wang, "Motion measurement using inertial sensors, ultrasonic sensors, and magnetometers with extended Kalman filter for data fusion," *IEEE Sensors J.*, vol. 12, no. 5, pp. 943–953, May 2012.

[121] L. Deng and D. Yu, "Deep learning: Methods and applications," *Found. Trends Signal Process.*, vol. 7, nos. 3–4, pp. 197–387, Jun. 2014.

[122] H. Tahani and J. M. Keller, "Information fusion in computer vision using the fuzzy integral," *IEEE Trans. Syst., Man, Cybern.*, vol. 20, no. 3, pp. 733–741, May 1990.

[123] L. Yang, J. Qi, D. Song, J. Xiao, J. Han, and Y. Xia, "Survey of robot 3D path planning algorithms," *J. Control Sci. Eng.*, vol. 2016, pp. 1–22, Mar. 2016.

[124] W. Hackbusch, *Multi-Grid Methods and Applications*, vol. 4. New York, NY, USA: Springer, 2013.

[125] S. Broumi, A. Bakal, M. Talea, F. Smarandache, and L. Vladareanu, "Applying dijkstra algorithm for solving neutrosophic shortest path problem," in *Proc. Int. Conf. Adv. Mech. Syst. (ICAMechS)*, Nov. 2016, pp. 412–416.

[126] P. Hart, N. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Trans. Syst. Sci. Cybern.*, vol. SSC-4, no. 2, pp. 100–107, Jul. 1968.

[127] L. E. Kavraki, P. Svestka, J.-C. Latombe, and M. H. Overmars, "Probabilistic roadmaps for path planning in high-dimensional configuration spaces," *IEEE Trans. Robot. Autom.*, vol. 12, no. 4, pp. 566–580, Aug. 1996.

[128] S. M. LaValle *et al.*, "Rapidly-exploring random trees: Progress and prospects," in *Algorithmic and Computational Robotics: New Directions*, vol. 5. Boca Raton, FL, USA: CRC Press, 2001, pp. 293–308.

[129] S. Mazzeo and I. Loiseau, "An ant colony algorithm for the capacitated vehicle routing," *Electron. Notes Discrete Math.*, vol. 18, pp. 181–186, Dec. 2004.

[130] G. K. H. Pang, K. Takabashi, T. Yokota, and H. Takenaga, "Adaptive route selection for dynamic route guidance system based on fuzzy-neural approaches," *IEEE Trans. Veh. Technol.*, vol. 48, no. 6, pp. 2028–2041, Nov. 1999.

[131] C. H. Papadimitriou and J. N. Tsitsiklis, "The complexity of Markov decision processes," *Math. Oper. Res.*, vol. 12, no. 3, pp. 441–450, 1987.

[132] H. Bai, S. Cai, N. Ye, D. Hsu, and W. S. Lee, "Intention-aware online POMDP planning for autonomous driving in a crowd," in *Proc. IEEE Int. Conf. Robot. Automat. (ICRA)*, May 2015, pp. 454–460.

[133] C. Urmson *et al.*, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 425–466, 2008.

[134] K. Chu, M. Lee, and M. Sunwoo, "Local path planning for off-road autonomous driving with avoidance of static obstacles," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 4, pp. 1599–1616, Dec. 2012.

[135] S.-A. Li, L.-H. Chou, T.-H. Chang, C.-H. Yang, and Y.-C. Chang, "Obstacle avoidance of mobile robot based on hyperomni vision," *Sensors Mater.*, vol. 31, no. 3, pp. 1021–1036, 2019.

[136] T. Kumagai, Y. Sakaguchi, M. Okuwa, and M. Akamatsu, "Prediction of driving behavior through probabilistic inference," in *Proc. 8th Int. Conf. Eng. Appl. Neural Netw.*, 2003, pp. 1–7.

[137] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement learning: A survey," *J. Artif. Intell. Res.*, vol. 4, no. 1, pp. 237–285, Jan. 1996.

[138] V. Mnih *et al.*, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, p. 529, 2015.

[139] K. Kant and S. W. Zucker, "Toward efficient trajectory planning: The path-velocity decomposition," *Int. J. Robot. Res.*, vol. 5, no. 3, pp. 72–89, Sep. 1986.

[140] M. Matthew, "Parallel algorithms for real-time motion planning," Ph.D. dissertation, Carnegie Mellon Univ., Pittsburgh, PA, USA, 2011.

[141] F. Pfeiffer and R. Johanni, "A concept for manipulator trajectory planning," *IEEE J. Robot. Autom.*, vol. RA-3, no. 2, pp. 115–123, Apr. 1987.

[142] B. Paden, M. Čá, S. Z. Yong, D. Yershov, and E. Frazzoli, "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Trans. Intell. Vehicles*, vol. 1, no. 1, pp. 33–55, Mar. 2016.

[143] M. H. Hebert, C. E. Thorpe, and A. Stentz, *Intelligent Unmanned Ground Vehicles: Autonomous Navigation Research at Carnegie Mellon*, vol. 388. New York, NY, USA: Springer, 2012.

[144] S. M. Lavalle, "Rapidly-exploring random trees: A new tool for path planning," Dept. Comput. Sci., Iowa State Univ., Tech. Rep. TR 98-11, 1998.

[145] X. Li, Z. Sun, D. Cao, Z. He, and Q. Zhu, "Real-time trajectory planning for autonomous urban driving: Framework, algorithms, and verifications," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 2, pp. 740–753, Apr. 2016.
[146] J.-C. Latombe, *Robot Motion Planning*, vol. 124. New York, NY, USA: Springer, 2012.
[147] K. A. Brookhuis, D. De Waard, and W. H. Janssen, "Behavioural impacts of advanced driver assistance systems—An overview," *Eur. J. Transp. Infrastruct. Res.*, vol. 1, no. 3, pp. 1–9, 2019.
[148] M. Campbell, M. Egerstedt, J. P. How, and R. M. Murray, "Autonomous driving in urban environments: Approaches, lessons and challenges," *Phil. Trans. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 368, no. 1928, pp. 4649–4672, Oct. 2010.
[149] A. M. Ellison, "An introduction to Bayesian inference for ecological research and environmental decision-making," *Ecol. Appl.*, vol. 6, no. 4, pp. 1036–1046, Nov. 1996.
[150] T. C. Terwilliger *et al.*, "Decision-making in structure solution using Bayesian estimates of map quality: The phenix autosol wizard," *Acta Crystallograph. D, Biol. Crystallogr.*, vol. 65, no. 6, pp. 582–601, 2009.
[151] M. R. Endsley, "Autonomous driving systems: A preliminary naturalistic study of the tesla model s," *J. Cognit. Eng. Decis. Making*, vol. 11, no. 3, pp. 225–238, Sep. 2017.
[152] R. E. Llaneras, J. Salinger, and C. A. Green, "Human factors issues associated with limited ability autonomous driving systems: Driver'allocation of visual attention to the forward roadway," *Accident Reconstruction J.*, vol. 25, no. 3, pp. 1–8, 2015.
[153] G. Vanacker *et al.*, "Context-based filtering for assisted brain-actuated wheelchair driving," *Comput. Intell. Neurosci.*, vol. 2007, p. 25130, Jan. 2007.
[154] M. A. Pitt and Y. Tang, "What should be the data sharing policy of cognitive science?" *Topics Cognit. Sci.*, vol. 5, no. 1, pp. 214–221, Jan. 2013.

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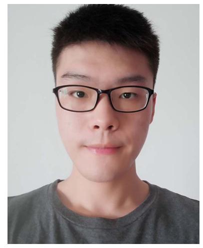

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