Visual Human-Computer Interactions for Intelligent Vehicles and Intelligent Transportation Systems: The State of the Art and Future Directions

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***Abstract*—Research on intelligent vehicles has been popular in the past decade. To fill the gap between automatic approaches and man-machine control systems, it is indispensable to integrate visual human-computer interactions (VHCI) into intelligent vehicles systems. In this paper, we review existing studies on VHCI in intelligent vehicles from three aspects: visual intelligence, decision-making, and macro deployment. We discuss how VHCI evolves in intelligent vehicles and how it enhances the capability of intelligent vehicles. We present several simulated scenarios and cases for future ITS.**

***Index Terms*—Intelligent vehicles, visual human-computer interactions, visualization, federated learning, augmented reality.**

I. Introduction

In recent decades, an increasing number of researchers are dedicated to developing intelligent vehicles. Intelligent vehicles refer to self-driving vehicles that perform driving missions independently or vehicles that assist drivers to achieve a safer and more efficient driving experience. Self-driving vehicles can replace humans to perform dangerous tasks, such as lunar expeditions, search and rescue tasks under natural disasters, etc. With safe, comfortable, and efficient self-driving service, disabilities are allowed to ride vehicles. The environment and economy can also be benefited from appropriate driving behaviors advised by intelligent assistance through avoiding traffic accidents and decreasing fuel consumption [1].

The application of intelligent vehicles need supports from multiple aspects, including traffic signs identification, pedestrian avoidance, collision avoidance [2], vehicle deployment, etc. Brooks et al. [3] describe the degree of human participation and the autonomy of intelligent vehicles as a set of antonyms. The state-of-art in various fields, like computer vision [4], artificial intelligence [5], block chain [6], etc., has been leveraged to improve related technologies and raise the automation level of intelligent vehicles. As shown in Table I, the role of people is gradually replaced with the increasing of automation. However, the high level of autonomy may make drivers and other passengers relax their vigilance, and lead to concerns of safety [3], [7].

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TABLE I
Descriptions of increasing levels of autonomy proposed by Brooks et al. [3]

Levels of Autonomy	Descriptions
0	Human driver controls all: steering, brakes, throttle, power.
1	Most functions are still controlled by the driver, but a specific function (like steering or accelerating) can be done automatically by the car.
2	At least one driver assistance system is automated. Driver is disengaged from physically operating the vehicle (hands off the steering wheel AND foot off the pedal at the same time).
3	Driver shifts "safety critical functions" to the vehicle under certain traffic or environmental conditions.
4	Fully autonomous vehicles perform all safety-critical driving functions in certain areas and under defined weather conditions.
5	Fully autonomous system is equal to that of a human driver, in every driving scenario.

To address safety issues, Shneiderman [8] introduced human participations and computer autonomy as a two-dimensional framework. A reliable, safe, and trustworthy artificial intelligence needs the combination of a high level of human control and a high level of automation [8], as shown in Figure 1. Humans and computers have different strengths and weaknesses. For example, Radar measures the distance from obstacles to the vehicle more accurately than human eyes, while humans can understand the intention of other humans, like warning for dangers or asking for sharing a ride. Thus, the guidance of humans should be considered when designing automatic features.

Intelligent vehicles can implement driving tasks based on humans' requirements. The detailed level of instructions corresponds to different development stages of intelligent vehicles. For current vehicles used for daily drive, human drivers still have to make specific instructions, such as turning the steering wheel and stepping on the brakes. After comprehending humans' driving behavior, intelligent vehicles may able to arrange the travel independently according to human-defined stops and destinations. Therefore, the development of intelligent vehicles can be reflected from streamlined instructions and highly intelligent guidance. In addition, humans can monitor the operations of intelligent vehicles and deploy them. It is necessary to notify humans of the upcoming driving plans

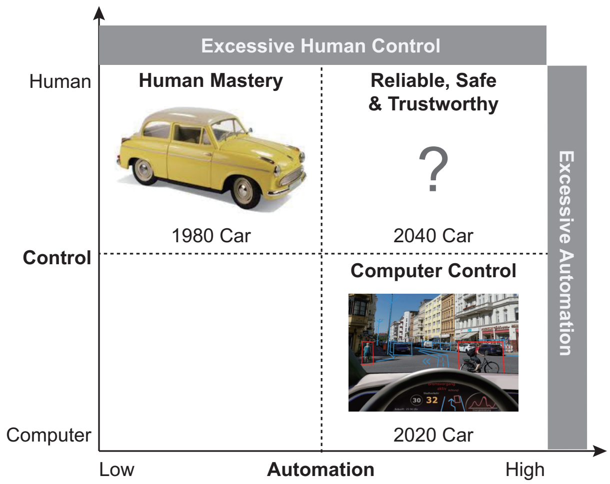

Fig. 1. The two-dimensional framework proposed by Shneiderman [8].

and allow humans to timely correct the inappropriate decisions of intelligent vehicles. For instance, when the passenger has a medical emergency, the intelligent vehicle need to bypass the relevant areas to avoid congestion.

As mentioned in Norman's principles of interaction designs, intelligent vehicles should provide visual functions and respond to humans interactions. In this paper, we elaborate how VHCI penetrates into various aspects of intelligent vehicle technologies, including environment perception, visual analytics and cloud monitoring. The rest of paper is organized as following: Existing technologies and applications on visual human-computer interaction related to intelligent vehicles are explained in Section II and Section III respectively. We introduce the prospective of intelligent vehicles in Section IV. The prospective of intelligent transportation system is described in S nection V. Finally, this paper is concluded in Section VI.

II. VHCI for Intelligent Vehicles

A. Environment Perception

For safety issues [9], intelligent vehicles must keep learning about the surroundings to make timely and reasonable decisions [10], [11], [12], [13], [14]. Considering normal driving scenarios, it is necessary to perceive both internal environments and external environments by multiple sensors [15], [16], [17], [18], [19].

1) Internal environments: Internal environments include the status of the ego-vehicle (e.g., fuel remaining) and the humans in the vehicle (e.g., the drowsiness of the driver [20], [21]). Intelligent vehicles need to determine whether the itinerary can be assured by self-examination.

2) External environments: External environments are complex and diverse, which include static information (e.g., road network, lanes, and traffic signs) and dynamic objects (e.g., self positions, other vehicles, and pedestrians).

As required by traffic regulations, vehicles must respond to the former, which is mainly collected by vision sensors. As the vehicle moves, the camera on the vehicles can turn the surrounding scene into pictures or a video. Image recognition and video recognition can be applied to detect traffic signs and traffic markings and determine their position relative to the vehicle [4], [22], [23]. Distinct artificial intelligence (AI) approaches, including machine learning approaches [24], [25], [26], [27] and deep learning approaches [28] are leveraged to construct classifiers for different traffic signs. Existing studies proposed assumptions, like road texture consistency and correct placements for road marking, to reduce the difficulty of the problems to be solved [29].

To navigate routes, Global Positioning System (GPS) and Inertial Navigation System (INF) are applied to learn about the absolute position of the vehicle. Other dynamic objects, like other vehicles and pedestrians, are regarded as obstacles. Unlike static information, understanding other dynamic objects requires not only consideration of the objects' current position, but also the prediction of possible behaviors afterward [30]. Descriptions, like speed and directions are significant to understand their behaviors and assess risks of their aims, like changing lanes or making turns [31], [5]. Multiple sensors, consisting of visual sensors, Radar (radio detection and ranging) and LiDAR (light detection and ranging), infrared vision, etc., are fused to capture the comprehensive description of obstacles [32], [33], [34].

In addition, the vehicular communication of Connected and Autonomous Vehicles (CAVs) is of great significance to traffic control [35], [36], [37]. With the development of communication technologies (e.g., blockchain [38], [39], [40], [41]), intelligent vehicles can learn about the dynamics of surrounding intelligent vehicles by wireless communication technologies [42]. Reliable communication can assist intelligent vehicles in receiving the messages from each other. For example, when a vehicle comes to an all-way stop intersection, it can negotiate with the other vehicles that arrive at the intersection automatically and implement the principle of "first-come-first-go."

However, full autonomy of intelligent vehicles would be achieved in a about decade [43]. It would take longer to enable the technologies to participate in daily life. Thus, there will be intelligent vehicles with different automation levels simultaneously in a long-term period. Researchers should pay attention to the compatibility of their studies under this premise. Vehicle perception can be enhanced by communication technologies but can not rely on it completely, because not all vehicles can communicate automatically or have the same level of communication capability. Thus, it is necessary to leverage probabilistic models, like Gaussian mixture models [44], Gaussian process regression [45], Bayesian approach [46], and Markov decision process [47] to learn about the uncertainty of other vehicles' movements.

B. Visualization and Visual Analytics

Intelligent vehicles collect various information and feedback it to humans. Besides, humans need to express their requirements through interactions to guide intelligent vehicles. Considering that vision is the most efficient way for humans to receive information, the communications between humans and intelligent vehicles should be supported by visualization and visual analytics [48], [49], [50].

1) Real-time Feedback from Vehicle End: Real-time communications between humans and intelligent vehicles is necessary to deal with the dynamic traffic scenarios. To support different levels of human control, intelligent vehicles need to provide various levels of details.

In fact, visual elements have long been used in the interior design of vehicles. As shown in Figure 2 (a), the meters for speed, accelerate speed, etc. encode numbers by angles. Because the magnitude of the changes can be better reflected by angles instead of numbers. Similarly, compared with numbers, color encodings have better warning effects [51], [52], [53]. Thus, color is applied to display the distance between the car and the obstacles, as shown in Figure 2 (b) and (c).

(a) The dashboard

(b) The reversing image

(c) The parking control

Fig. 2. Visual elements in vehicles, including (a) the dashboard showing speed, fuel remaining, etc., (b) the reversing image where fixed distance is labeled, and (c) the parking control displaying the distance to surrounding obstacles measured by radar.

Visual encodings can also be found in navigation applications. For instance, the level of congestion on the road is always encoded by color [54], [55], [56], [57]. Drivers have a chance to get ready for the upcoming situation in advance, like bypassing congested areas. Also, navigation applications notify drivers of the next step based on recommended routes. To avoid distractions, notifications are generally communicated to drivers in two ways simultaneously: image and sound. Drivers can follow the instruction of sounds when they keep their eyes on roads. If instruction details or other information (e.g., speed limits) are needed, they can check the image.

2) Human-Guided Driving: Driving vehicles has to face various decisions from four hierarchies: route planning [58], behavioral layer, motion planning [59], and vehicle control [60], [61]. As mentioned in Section II-B1, humans need to provide different detailed levels of guidance for intelligent vehicles at different stages of development.

As in low level of automation, humans need to make driving-related decisions from all the four hierarchies. Vehicles need precise manual control, like stepping on the accelerator pedals to increase the speed, turning the steering wheel to adjust directions. However, the commands are not always correct, especially in emergencies. Besides, humans may not have sufficient knowledge of maps, traffic rules, etc.

With the increased safety requirements, assistant services are added to enhance driving operations [62]. For instance, steering functions are applied to ensure vehicles stay in the lanes. Current vehicles can identify lane markings automatically. When vehicles are passing lanes without the use of turn signals, the driving behavior will be judged as an erroneous lane departure. To ensure the safety of drivers, vehicles will alert drivers by hinder steering wheels from turning.

However, immature detection techniques may lead to other issues. Assume that a driver forgot to use the turn signal when changing lanes in an emergency. Locking the steering wheel will put the driver in greater danger. To avoid conflicts between humans and vehicles, researchers attempt to figure out ego-vehicle driver intention accurately [5], [63], [64], [65], [66], [67]. Detailed driving operations, including steering angle, steering force, and velocity are collected [68]. In addition to driving operations and traffic contexts, drivers' behaviors (e.g., eye movements [69], [70], foot dynamics [71]) are also monitored to infer the intention. Based on various input, intention simulator is built by generative models [72], [73], discriminative models [74] and deep learning approaches [63].

Besides, partial vehicles can respond to simple voice commands [75], [76], [77], [78]. On the one hand, humans are used to communicate through natural language. On the other hand, it is cumbersome to call a specific functions from a control panel which embeds multiple functions.

Semantic communications, like voice queries [79], is applied to provide convenience with humans [80], [81]. In addition to natural language, humans may used to express by body language. For example, requirements, like selecting, turning pages, zooming in, etc., can be expressed by gesture interactions [82], [83], [84], [85], [85]. For humans, certain actions are made unconsciously in the process of thinking. Responding to those details can contribute to better user experiences. For instance, capturing humans' eye movements [86], [87], [88], [89] can understand what humans are focusing on and show them the information they may need in the next step.

C. Cloud Monitoring

To develop intelligent vehicles, it is significant to regard them as a community. On the one hand, massive training data is indispensable for the above-mentioned technologies, like deep learning. On the other hand, community contacts can not only enhance security by improving the accuracy of environment perception, but also contribute to the construction of intelligent traffic system.

The idea of constructing intelligent transportation systems (ITSs) has been developed for several decades. In recent years, various senors all over the cities can collect massive traffic data, which allows ITS to develop rapidly [90], [91], [92], [93], [94], [56], [95], [96], [97], [98], [99], [100], which raises humans' expectation and requirements for ITS. After the intelligent vehicles with high-level automation are widely-applied, more data will be generated and recorded.

Based on cloud monitoring, humans can deploy intelligent vehicles from the macro level. Considering the huge amount of information, the cloud monitoring system is always rendered in large screens. Conventional interaction devices, like keyboards and mouses, can hardly support flexible interactions on large screens. Because humans can hardly browse and interact with the entire screen without moving. Portable devices, like smart watches, can better support related interactions [101]. Besides, body language [102] is also an effective way to express human intentions.

III. Existing Applications

Fig. 3. The interface of Autonomous Visualization System.

A. Log Analysis

Autonomous Visualization System (AVS)[1] is developed to analyze autonomous vehicle data (e.g., the calculative experimental data from parallel driving). After converting the log data into a specific format, researchers can review the performance of the intelligent vehicles in AVS in 3D scenes. As shown in Figure 3, the results of environment perception, real scenes, and real-time parameters, consisting of acceleration, velocity, and wheel, are listed. Hence, the effectiveness of different configurations can, be evaluated and compared.

B. Driver Assistance

1) Navigation: To narrow the gap between the map representations and the real vision, 3D artMatp[2] improves navigation service by rendering artistic 3D maps. Compared with photorealistic navigation systems, 3D artMap omits unnecessary details to avoid distracting drivers.

2) Safety Warnings: SenseDrive[3] can issue warnings, like lane departure warning and collision warning, to drivers. Considering that different humans may prefer different warning threshold—receiving warning at different risk levels, SenseDrive allows drivers to adjust related parameters.

[1]Autonomous Visualization System: https://avs.auto/

[2]3D artMap developed by Bosch: https://www.bosch.com/research/know-how/success-stories/3d-artmap-easy-and-personalized-automotive-navigation/

[3]SenseDrive: https://www.sensetime.com/en/Service/Drive_SenseDrive.html

C. Self-Driving Vehicles

1) Environment Perception: Tesla[4] integrates eight devices (i.e., ultrasonics, radar, and six cameras for different directions) to perceive environmental dynamics and meet the safety requirements of autopilot. As shown in Figure 4, omnidirectional vision is provided by sensor fusion, based on which, various targets can be identified and categorized accurately. Combined with advanced functionalities of autopilot, Tesla can be summoned to pick up drivers at reservation locations.

Fig. 4. Environment perception technology developed by Tesla.

2) Safety Rules: Mobileye prompts intelligent vehicles and humans to reach consensus on driving safety by proposing Responsibility-Sensitive Safety (RSS)[5]. Based on common senses, RSS summarizes dangerous situations (e.g., unsafe cut-ins) by quantification models and provides feasible reactions. The intelligent vehicles that follow related guidelines will be agreed upon by humans easily.

D. City Management

Based on cloud monitoring, urban traffic state can be actively perceived. As Ye and Wen [103] proposed a compressed sensing method which adaptively detects the urban traffic situation, the cloud monitoring will provide a further micro data source for inference. Also it is feasible to dispatch emergency vehicles such as police cars, fire trucks, and ambulances to the scenes and solve problems as soon as possible. For example, City Brain[6] (see Figure 5) can identify the emergency vehicles that can arrive at the scenes rapidly and dispatch them. City brains can also remotely correlate traffic lights to ensure that emergency vehicles are unobstructed when carrying out tasks.

Besides, private intelligent vehicles can take on responsibilities other than transporting passengers or goods. For example, polices can post descriptions of the suspects at large. When any feature matching the description are identified, intelligent vehicles can submit reports (e.g., photos, videos, etc.) to facilitate the sharing of information in tracking suspects.

[4]Autopilot provided by Tesla: https://www.tesla.com/autopilot

[5]Responsibility-Sensitive Safety: https://www.mobileye.com/responsibility-sensitive-safety/

[6]City Brain: https://www.alibabacloud.com/solutions/intelligence-brain/city

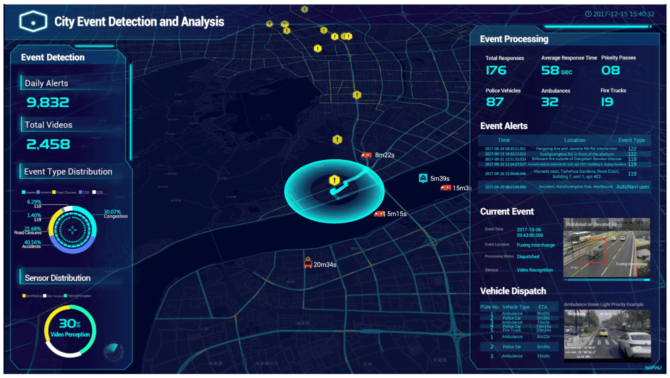

Fig. 5. Intelligent vehicle dispatching supported by Hangzhou City Brain.

IV. The Prospective of VHCI for Intelligent Vehicles

Combined with application, the development of intelligent vehicles should be iteratively improved through five stages, consisting of analysis and development, vehicle manufacture, preference loading, vehicles usage and driving log collection (see Figure 6). Humans play indispensable roles in each stage.

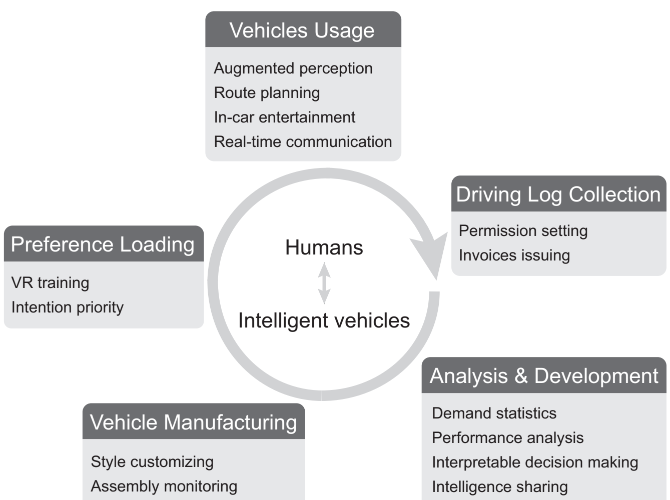

Fig. 6. Human-computer interactions in the life cycles of intelligent vehicles.

A. Analysis and Development

The experiment data and driving logs can be analyzed to perfect existing technologies. Related tasks can be facilitated by visualization.

1) Demand statistics: The priority of research and development can be set based on user demands. Functions that are frequently called need to be valued. Developers should also reflect on whether infrequently called functions are inconvenient to use. It is necessary to figure out if users' requirements are satisfied by intelligent vehicles. Simultaneously, the unnecessary functions should be removed to reduce learning costs.

2) Performance analysis: Intelligent vehicles can understand themselves by performance data. Different driving tasks will lead to different levels of loss to intelligent vehicles. Intelligent vehicles need to assess the urgency of maintenance and go to a garage in their free time.

After integrating massive performance data, the pros and cons of various technologies can be evaluated to guide further improvements. Based on sufficient descriptive data, the driving behaviors of intelligent vehicles can be simulated by models [104]. The simulation results can be used for alternative experiments and user test drives [105].

3) Interpretable decision making: Norman's principles emphasize the importance of mapping, which means that humans need to understand the potential effect before making a decision. Nowadays, AI is widely applied in intelligent vehicle development. Because of the black-box manner, it is challenging to understand how a decision is made by AI approaches and what results the decision may lead to, which lead difficulties to make improvements, like setting appropriate parameters or modifying models, etc. Related researches can be facilitated by VHCI. Visualization can not only explain the internal mechanisms, but also assess the results [106], [107], [108], [109], [110]. For example, the TensorFlow Graph Visualizer [111] provides a platform for users to design and understand the complex architectures of neural networks interactively. The intuitive expressions can be used to communicate ideas with others, which is of great importance in collaborative studies. For the result assessments, Squares [112] can compare the effects of multi-class classification models. Different models may have different strengths and weaknesses in identifying different classes. Squares can demonstrate the detailed performances of models in identifying each specific class.

Cognitive computing is another way to interpret the decision-making process. Recent representative work comes from Ye et al. [113], [114], [115]. In their work, a two-layered cognitive architecture called TiDEC is proposed which takes advantages of both logic reasoning and neural network based deep learning. Such architecture can model the semantic reasoning of human's deliberation and thus, may provide a interpretable decision-making process. More recently, adaptive driving style learning is studied in detail for the vehicle control [116].

4) Intelligence sharing: Intelligent vehicles meet different scenarios, in which the objects and environments could both be unknown. Sharing relevant information, coping strategies and corresponding results can rich collective experience.

B. Vehicle Manufacture

While the vehicles become intelligent, the corresponding manufacturing industry needs to upgrade synchronously.

1) Style customizing: The diversity of existing vehicle styles are far from satisfying user needs. The specific needs are affected by many factors. For examples, users have different preferences on appearances. More importantly, the number and identity of potential passengers affect the user's requirements for space and layout in the vehicles. Certain passengers (e.g., humans with reduced mobility, children, pets, etc.) may require special designs for seats. There are also needs for devices, like refrigerators, desks, screens, etc. However, some requirements may conflict with features or fuel efficiency–large size vehicles or non-aerodynamic body types will increase fuel consumption. There should be automatic systems to receive users' requirements and assist them to seek the appropriate solutions.

2) Assembly monitoring: Considering that intelligent vehicles are customized, the traditional production lines need to be adjusted to meet the new demand. Each assembly link will be dynamically connected together. Seeking high efficiency, hundreds of orders should be allowed to implement simultaneously. Humans need to schedule production tasks and monitor the assembly progress [117].

C. Preference Loading

1) VR training: Intelligent vehicles need to choose schemes or set default selections when specific instructions are omitted. To be user-friendly, intelligent vehicles should respect users' preferences by accepting related settings or learning the humans' assessments based on the interaction provenance—when the automation level is low, intelligent vehicles have the chances to learn driving style from experienced drivers [118]. To customize personal services for those who can not drive alone, the preference need to be collected through simulated scenarios supported by technologies, like virtual reality (VR) [119], [120], [121], [122], [123], [124]. After inputting performance parameters, the riding experience in different scenes (e.g., mountains, snow) can be reproduced indoors. Compared with the textual descriptions in questionnaires, simulated scenarios can better provide authentic experiences and capture corresponding preferences.

2) Intention priority: If passengers have a slight motion sickness reaction or panic about high speed, intelligent vehicles need to adjust the driving plan to provide stable services. When passengers rush to the destination, such as a hospital, intelligent vehicles will accelerate within the safe allowable range. If necessary, intelligent vehicles can negotiate the use of lanes with surrounding vehicles. To better understand such intentions, intelligent vehicles should not only respond to active interactions, but also observe passengers' status and implicitly expressions, including emotions and behaviors and state of health. For example, Vögel et al. [125] construct cognitive model to infer passengers' emotion based on their voice tonality, language sentiment, facial expression, etc. To monitor health status, Dineshkumar et al. [126] leverage sensors, like pulse rate sensors and temperature sensors.

D. Vehicles Usage

1) Augmented perception: In the early development of intelligent vehicles, humans still need to pay attention to their surroundings due to the low level of automation. It is not user-friendly enough to show auxiliary information in the small screen next to the steering wheel (see Figure 2) or other devices, like smartphones. Drivers sometimes have to keep switching views from the front view of the vehicles, to the small screens, or smartphones. Such behaviors may hinder drivers from dealing with unexpected situations and lead to accidents. Augmented reality (AR) techniques can superimpose computer-generated annotations in real vision through wearable devices, such as smart glasses [127], [128], [129], [130].

Note that the superimposed annotations have to be concise. Because excessive information may distract drivers' attention and obscure the original vision. AR can mainly convey two categories of significant feedbacks: safety warnings and direction navigation. To ensure safety, intelligent vehicles should augment drivers' vision by the results of environment perception. Manual driving can benefit from augmented operations, like highlighting identified traffic signs, labeling the distance to obstacles when changing lanes or parking, etc. In addition, drivers need clear descriptions when following the instructions involving roundabouts and ramps. Using navigation applications supported by smartphones, drivers need to compare real road networks with the maps on the screens. It will be much more convenient to label the correct directions on the "roads" by AR.

2) Route planning: To assist humans make travel plans, intelligent vehicles should be able to list all feasible schemes and corresponding assessment comprehensively. Especially, the potential risks, like traffic congestion risks, collision risks, etc., should be highlighted. The real-time information may affect existing decisions. Intelligent vehicles should re-evaluate related schemes and report necessary changes (e.g., recommend new schemes) to humans. To understand the reasons of temporary changes, humans need to compare the new schemes and the previous ones. Taking advantages of visual analytics, the schemes comparison processes will be easier [116], [131], [132], [133], [134], [135].

3) In-car entertainment: Display and touch technology is widely-applied by entertainment services and complicated instruction input, such as spacecraft-related controls [136], [137]. To provide convenience, intelligent vehicles should also be able to understand complex semantic expressions. Low hierarchy driving problems can be solved when high level of automation is realized, which means that intelligent vehicles are able to deal with high-hierarchy instructions, e.g., "go home." When human hands are freed—without holding the steering wheel—more rich functions, like watching movies, searching for nearby restaurants, can be supported.

4) Real-time communication: When the high level of automation is achieved, humans will pay more attention to surrounding news and travel plans, instead of specific driving operations. With the support of advanced communication techniques, intelligent vehicles will receive various messages from multiple devices in real time. Those messages could involve the intents of the vehicles on the same roads, news about surrounding activities, traffic flows, etc. To assist humans to learn about those messages sequentially, intelligent vehicles should group the messages and set priorities to groups according to urgency and interests.

In addition, intelligent vehicles can provide a contact platform for humans in nearby vehicles. Humans on the same roads may have similar destinations, which is a good chance to start a conversation and maybe even form a social group. Also, restaurants, theaters and other places can send advertisements to the humans in the nearby vehicles. Whether to receive those notifications can be decided by humans.

E. Driving Log Collection

Collecting data from intelligent vehicles can contribute to improvement of service quality, but may leak of personal privacy. As the awareness of privacy protection increases, a series of regulations (e.g., the General Data Protection Regulation) are in force in recent years, which ensure more rights for data subjects and limit the usage of personal data, like driving styles and trajectories. To solve this conflict, intelligent vehicles need not only privacy preserving approaches, but also the permission of data subjects.

1) Permission setting: As a state-of-the-art solution to privacy issues, federated learning [138], [139], [140], [141] requires a server to initialize the training tasks. Then, data subjects can train their own models locally and update local model parameters to the server. The server aggregates local models and sends updated global parameters back to data subjects to complete an iteration. Hence, there is no real data exchange happened in the entire federated learning process.

However, there exists a chance that data is decrypted according to transmitted parameters. Encryption technologies and classic privacy preservation approaches can be applied to parameter transmission to provide more comprehensive protection. Data subjects should be allowed to set the privacy preserving approaches. Note that they can apply the default options, that is, they do not need to check every detail of the settings.

In addition, the data subjects may deny access to certain data by specific individuals or organizations. For example, passengers may request temporary vehicles such as taxis to delete their contact information and personal settings after their rides.

2) Invoices Issuing: To get more permissions, intelligent vehicles should provide data subjects with "invoices" that describe data collection and potential usages (e.g., the mechanics of Federated Learning). Long text always makes humans lose interest in reading. Visualization can be applied to avoid such situation. An extra bonus of visualization is that data subjects can customize privacy preserving schemes interactively according to their own demands [142], [143]. There exist multiple privacy preserving approaches and all of them have pros and cons. Data subjects should be allowed to select the best match ones.

V. The Prospective of VHCI for Intelligent Transport Systems

The development of intelligent vehicles will exert radiating effects to the transport system, which contributes to high efficiency and convenience.

A. Digital Twin

The popularity of intelligent vehicles will generate massive data, which provides a chance to construct the transport system as a digital twin [144], [145], [146], [147]. According to the uploaded data, digital twin can reproduce the objects (i.e., people, relationships, processes, etc.) and their behaviors in the physical space into the digital models in the information space. Tasks, like prediction, hypothesis verification, can be implemented by running the digital models.

B. Parallel World

The theory of parallel world [148], [149] extends digital twins to adapt to applications of intelligent vehicles and intelligent transport systems.

1) Parallel Driving: To further develop intelligent vehicle researches, Wang et al. [150] introduced the concept of parallel driving. Parallel driving theory introduces three coexisting worlds: physical world (i.e., the physical attributes of both vehicles and humans), mental world (i.e., the cognitive attributes of human drivers) and artificial world (i.e., driving-related control and information) [150].

In this ternary world, a real dynamic system and parallel artificial system are executed simultaneously to generate big data for parallel learning and deep reinforcement learning [151]. Artificial Drivers and Artificial Vehicles (ADAV) interact with humans to collect the data from their cognitive behaviors (i.e., environment perception and understanding in the mental world) and physical behaviors (i.e., driving operations in the physical world). To solve the issue of insufficient data, a parallel level is constructed to execute calculative experiments in the artificial world, which can generate massive experimental data. Both the data from human drivers and experiments can help enhance the ADAV modules. Therefore, ADAV modules can control the intelligent vehicles to provide better services to humans.

2) Parallel Transportation: A similar framework, called Parallel transportation Management Systems (PtMS), is designed to manage transport systems [152]. With such a framework, Ye et al. proposed a large-scale artificial population [153], [154], [155], which is the basis of artificial transportation systems (ATS). Then, the actual transportation systems and the artificial transportation systems (ATS) are executed in a parallel manner. Operator Training Systems for transportation (OTSt) learn mode operations from the actual transportation systems. Then, OTSt train related models for the ATS. Dynamic network assignment based on Complex Adaptive Systems (DynaCAS) is employed to be responsible for evaluation experiments, whose tasks include experiments design, traffic simulation, performance evaluation, data support centers and decision generation. Note that, for specific applications, not only the traffic data is used, data from the aspects of social, economic, ecologic, etc. may also be involved in the experiments. The management operations are provided by agent-based Distributed and Adaptive Platforms for Transportation Systems (aDAPTS), which connect to traffic-control centers and various traffic devices (e.g., traffic signals).

C. The Framework of ITS with VHCI

According to the above studies, we propose a framework of ITS with VHCI, which integrates potential tasks and available techniques. As shown in Figure 7, the physical transport system and the artificial transport system interact through three modules: abstraction, simulation and management.

1) Abstraction: Based on the Internet of Things (IoT) [33], [156], [157], [158], [159], [160], intelligent vehicles can construct the internet of vehicles, through which the real-time monitoring data can be collected. Besides of sensors,

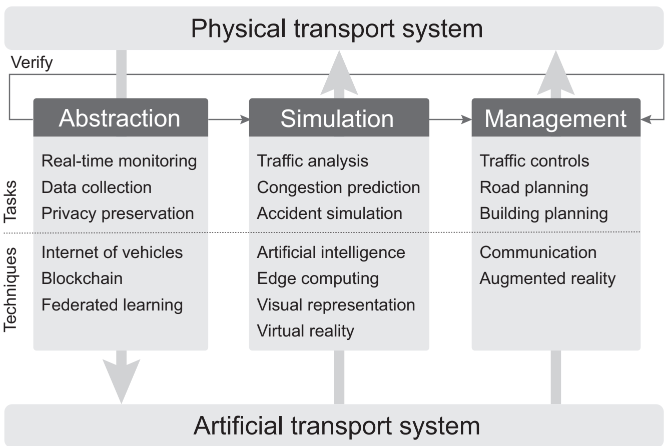

Fig. 7. The framework of intelligent transport systems based on digital twins.

intelligent vehicles can monitor the transport systems through environment perception. Information on different areas from intelligent vehicles can be anonymously submitted to different blocks in a blockchain. The history can be reviewed by the public. However, identity anonymity is not able to provide full privacy preservation. Adversaries can infer identities by behaviors or descriptions when adversaries have certain background knowledge. Privacy preserving approaches, like federated learning is necessary.

2) Simulation: The simulation of physical transport system requires a series of parameter optimization and model architecture selection. To accomplish this goal, automatic approaches and human intelligence can be combined. In order to speed up the understanding process of human beings, visual techniques can be leveraged to summarize data, explain models and display the simulation results, i.e., map the controls to corresponding effects. To deal with the massive data, edge computing [161], [162] can be take into consideration. Tasks, like traffic analysis, congestion prediction, etc., can be implemented in the artificial transport system.

3) Management: The physical transport system includes vehicle flows, roads, etc. According to the simulation results, humans can manage not only the objects in the physical transport system but also related environments (e.g., building planning) efficiently and comprehensively. Management schemes can first test in the artificial transport system and then issue to the physical transport system. The effects of adopted schemes will generate new abstraction and verify the simulated results in the artificial transport system.

D. Potential Impacts

The maturity of the intelligent transport system will bring changes to the existing transport system.

1) Adjustment for Traffic Regulations: In the future, there should be a method similar to the driving license test to verify the intelligent level of intelligent vehicles [105]. When the intelligent vehicles can understand and perform tasks strictly, traffic regulations can be modified to seek high efficiency of traffic systems. For example, the speed limit can be relaxed appropriately on roads without interference from other participants (e.g., pedestrians, bikers, etc.).

The communication among vehicles such as turn signals and emergency lights may be gradually replaced by wireless communication. In addition to notifications from vehicles, the notifications in traffic signs can also be conveyed in the same way, which means that vehicles can respond to dynamic deployment of signs.

2) Adjustment for Traffic Facilities: Given self-driving technologies, parking lots can distribute intensively and become smaller. Intelligent vehicles can drop passengers off in an open and safe area and drive into crowded parking spaces. Because there is no need to open and close the door, the distance between parked vehicles can be decreased. Similarly, gas station and auto repair shops can provide self-service for intelligent vehicles to further reduce the time consumption of maintenance.

E. Potential Cases

We introduce the intelligent transport systems in the future by several cases (see Figure 8).

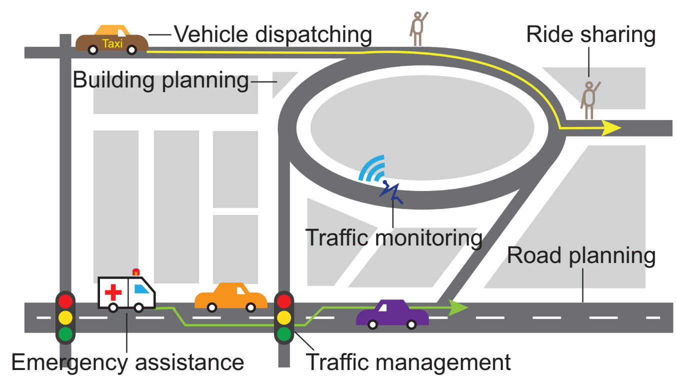

Fig. 8. The city scene after the popularization of intelligent vehicles.

1) Emergency Assistance: In emergencies, vehicles need to reach their destinations as soon as possible. There is a greater probability of traffic accidents in hurry rides. In order to avoid this situation, intelligent vehicles will evaluate the emergency of the driving tasks they perform. The intelligent vehicles with low emergencies will provide assistance (e.g., giving ways) to those with high emergencies.

2) Ride Sharing: Based on the simulated vehicle demands, unmanned taxis and unmanned buses can be dispatched on different functions. During idle periods, such as at night and in the early morning, vehicles can switch to part-time cargo transportation after switching modes.

3) Traffic Management: Dynamic traffic planning can be supported by real-time information, which is collected by intelligent vehicles and sensors on the roads. The density of vehicles varies according to time segments and areas. Crowded traffic always appears near tourist attractions on holidays or company gathering area in commuting hours. Besides, traffic is affected by occasional activities (e.g., carnivals) and traffic accidents. Thus, it is significant to flexibly take measures, like adjusting the waiting time of traffic signals, setting tidal drives, adjusting speed limits, etc.

However, frequent changes may disrupt others' travel plans. There should be supervisors to monitor the traffic flows and make decisions (i.e., judge if the changes are necessary and set specific changing schemes). Visual systems can facilitate humans to review history records and build up related experiences. For example, population mobility patterns can be reflected from populations flow visualizations [163], [164], [165], [166], [167], [168].

If necessary, additional devices can be implemented to assist in the management process. Smart wearable devices, like smartwatches and smart glasses can provide personal services [169], [170], [171], [172], which is significant to collaborative analysis. Independent analysis logs can be maintained for each humans.

Also, different users may have different access rights and deployment rights. Intelligent vehicle operators should make sure that there is no identity theft.

VI. Conclusion

Constantly interactions between intelligent vehicles and humans (i.e., researchers, developers, drivers, and users) are indispensable to the development of intelligent vehicles. In this paper, we explore the future of vehicles human computer interaction in a prospective fashion based on existing studies. We hope related researchers can be inspired from this paper.

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