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Parallel Internet of Vehicles: ACP-based System Architecture and Behavioral Modeling

Xiao Wang, Shuangshuang Han, Linyao Yang, Tingting Yao, and Lingxi Li

***Abstract*—Vehicles in Internet of Vehicles (IoV) exchange information about location, environment, infotainment, as well as social information with other units via vehicular communication networks. This makes IoV with key social entities in the human-vehicle-infrastructure-roadside units (RSU) as integrated intelligent transportation systems. Therefore, by identifying the cyber-physical-social features of IoV and presenting its complexity issues of both engineering and social dimensions, this paper proposes and introduces the concept, architecture, and applications of Parallel Internet of Vehicles (PIoV). Three main components of PIoV are demonstrated, which are artificial IoV to learn and describe the physical IoV, computation experiments to evaluate and predict the consequences and values of driving strategies, and parallel execution to prescribe the operation of the physical IoV. PIoV makes it possible to achieve safe, smart, effective, and efficient transportation management and control. The final objective of PIoV is to equip IoV with descriptive, predictive, and prescriptive intelligence based on the parallel intelligence approach.**

***Index Terms*—Parallel Internet of Vehicles; Cyber-Physical-Social System (CPSS); Parallel Intelligence.**

I. Introduction

Internet of Vehicles (IoV) is the extended application of Internet of Things (IoT) technology in intelligent transportation systems (ITS) [1]–[4]. In recent years, the self-perception, planning, and decision capabilities of vehicles have been significantly improved with the development of artificial intelligence and self-driving technologies [5]–[10]. Information including news, signals, and orders are exchanged among vehicles, people, and roadside-units (RSU), which inspired novel scientific ideas and technical means considering social signals to be the key means of management and control of ITS [11]–[13].

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The operation of IoV systems involves multiple processes including information transmission, interaction, reorganization, analysis, and scenarios-oriented decision making in real-time traffic situations. On one hand, the driver's psychological and behavioral mutability, uncertainty, and instability introduce new complexities for the cooperation of drivers, vehicles, and RSU. On the other hand, the synthesis of in-vehicle networks, inter-vehicle networks, and on-board mobile networks inevitably makes human-in-car become an indispensable link of more than one social networks, making IoV a typical cyber-physical-social system (CPSS) [14]–[19].

CPSS augments the ability of cyber-physical systems (CPS) by integrating additional human and social dimensions. CPSS intends to integrate the advantages of human, machine, and open-source intelligence, and achieve more efficient and effective CPS operations [5]. IoV is a typical CPSS, it is hard to accurately predict and control a physical IoV system due to the comprehensive complexity of human, machine, and environment. Besides, current IoV technologies cannot guarantee accuracy and robustness under complex real scenarios, making it difficult to put IoV in practical use. Previous research mostly focuses on the improvement of certain technologies under some assumptions. However, there still lacks a new scheme for the evolution of IoV systems.

The artificial societies, computational experiments, and parallel execution (ACP) approach developed by Fei-Yue Wang and his group in the State Key Laboratory for Management and Control of Complex Systems provides a paradigm for CPSS research. It integrates artificial systems (A), computational experiments (C) and parallel execution (P) to describe, predict, and prescribe system behaviors in a parallel framework. The ACP-based parallel intelligence [20] has been continuously verified and improved through industrial practice in the last decade, and has facilitated corresponding theories and methods of parallel perception [21], [22], parallel vision [23]–[25], parallel learning [26], [27] and parallel testing [28], [29]. The wide use of those new theories and methods in transportation, logistics, robots, and autonomous driving has achieved remarkable results. Therefore, in order to improve the accuracy and robustness of IoV systems, this paper introduces parallel intelligence into IoV systems and develops the ACP-based

Parallel IoV (PIoV).

To summarize, the main contributions of this paper are as follows.

1) In this paper, PIoV, an evolutional IoV scheme based on the ACP approach, is firstly presented. Through the modeling and prediction of the artificial IoV systems as well as the co-optimization of the artificial IoV and the physical IoV, a more optimized and robust IoV system can be obtained.
2) The modeling of artificial IoV in the proposed PIoV framework is discussed, which is achieved by using the bottom-up multi-agent method. An example of multi-agent modeling method is given for overtaking behavior in IoV systems.
3) Computational experiment and parallel execution process for the proposed PIoV are also demonstrated and discussed in detail. Based on computational experiment, all kinds of experimental scenarios are designed for providing suitable choices for different real traffic scenes. Through parallel execution, two-way feedback for physical IoV and artificial IoV is obtained in a highly-efficient way.
4) The implementation system design for PIoV is presented, which includes PIoV management and control center, intelligent vehicle platform, and dispatching platform. Besides, one of its application cases is also introduced.

The remainder of this paper is organized as follows. Section II outlines the concept and framework of PIoV. Section III describes the artificial IoV based on multi-agent modeling methods, the computational experiments that enables predictive intelligence of PIoV, and the parallel execution that enables prescriptive intelligence of PIoV. Besides, the implementation details of PIoV are also described in Section III. Finally, some conclusions and prospect are given in Section IV.

II. IoV and CPSS

IoV is the implementation of IoT in transportation area, which possesses common IoT characteristics and is a typical complex network system [30]. Traditionally, IoV architecture has similar features as IoT, and is commonly divided into three layers, i.e., on-board vehicle layer, communication layer, and cloud layer. The on-board vehicle layer collects perception information and provides application services. Communication layer transmits information. Cloud layer is not only responsible for data analysis, calculation, and modeling based on different social and economic needs, but also provides support for vehicular application services. Each layer provides data needed for decisions in its next layer, as shown in Fig. 1.

On one hand, the perception and service layer collect information of vehicles, road, environment, as well as vehicle's location. On the other hand, it also provides entertainment, traffic safety, and traffic environment identification services, which are the foundation of IoV services, such as self-driving decision-making, intelligent traffic control, and vehicular information services. Recent advances on high-precision sensors as well as sensor fusion technologies have improved the environmental awareness of vehicles. In particular, computer vision technologies based on deep neural networks give vehicles the ability to clearly identify surrounding objects. Advanced sensors such as Radar and lidar also compensate for the lack of accuracy of GPS to some extent [31]. However, current perception and localization technologies for IoV still lack robustness, which makes it not safe enough to be used. For example, insufficient diversity of manually collected and annotated sample data leads to mis-judgement in some complex traffic situations.

Communication layer realizes connected vehicles by using the network transmission and data communication technologies. At the same time, according to the network load condition and the access resource limitation, stable, safe, and high-quality information transmission channels are built. There are several solutions for different kinds of IoV communications, such as dedicated short-range communication (DSRC) technology, cellular network technologies, and other wireless communication technologies. However, in spite of their good performance on coverage, latency, and data rate, there still lacks a candidate suitable for all IoV scenarios like vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) [32]. Besides, routing and security issues are still open problems in IoV communications. Commonly investigated routing protocols such as topology-based routing protocols and location-based routing protocols still cannot guarantee the packet loss rate requirements. Researches have also revealed that current vehicular communication networks are vulnerable to cyber attacks [33].

Inspired by the idea of "Local simple, cloud complex" [34] and with the help of edge computing, cloud computing, social computing, and pervasive computing, cloud layer makes full use of the transmitted information in IoT, Internet, social networks, and Internet of mind to enable key functions and applications such as intelligent planning and decision making. Usually, RSUs serve as a central node which provides the content-centric information for different kinds of IoV services. Emerging technologies such as named data networking (NDN) and software-defined networks (SDN) promoted the development of cloud layer services [35].

The concept of CPSS [36], which is defined as a complex system constituted by a physical system, a social system including human beings [37], and a cyber system that connects both [38], was firstly proposed in 2010 [5]. CPSS integrates physical world and social world by intelligent human-machine interaction in cyber world, achieving intelligent management and control of such socio-technical complex systems. The introduction of social system poses new challenges to the management and control of the CPSS. These challenges mainly include cyber networks in the information domain, mental elements in the cognitive domain, and social networks in the social domain.

Clearly, IoV is a typical CPSS system with "human in the loop". Each pedestrian, vehicle, roadside facility, and mobile base station can be considered as a network node in IoV. They are connected by social networks, the Internet, and the IoT, and then construct the interactive communities that provide support for IoV services. As a special complex network, IoV system elements are time-varying and structurally distribut-

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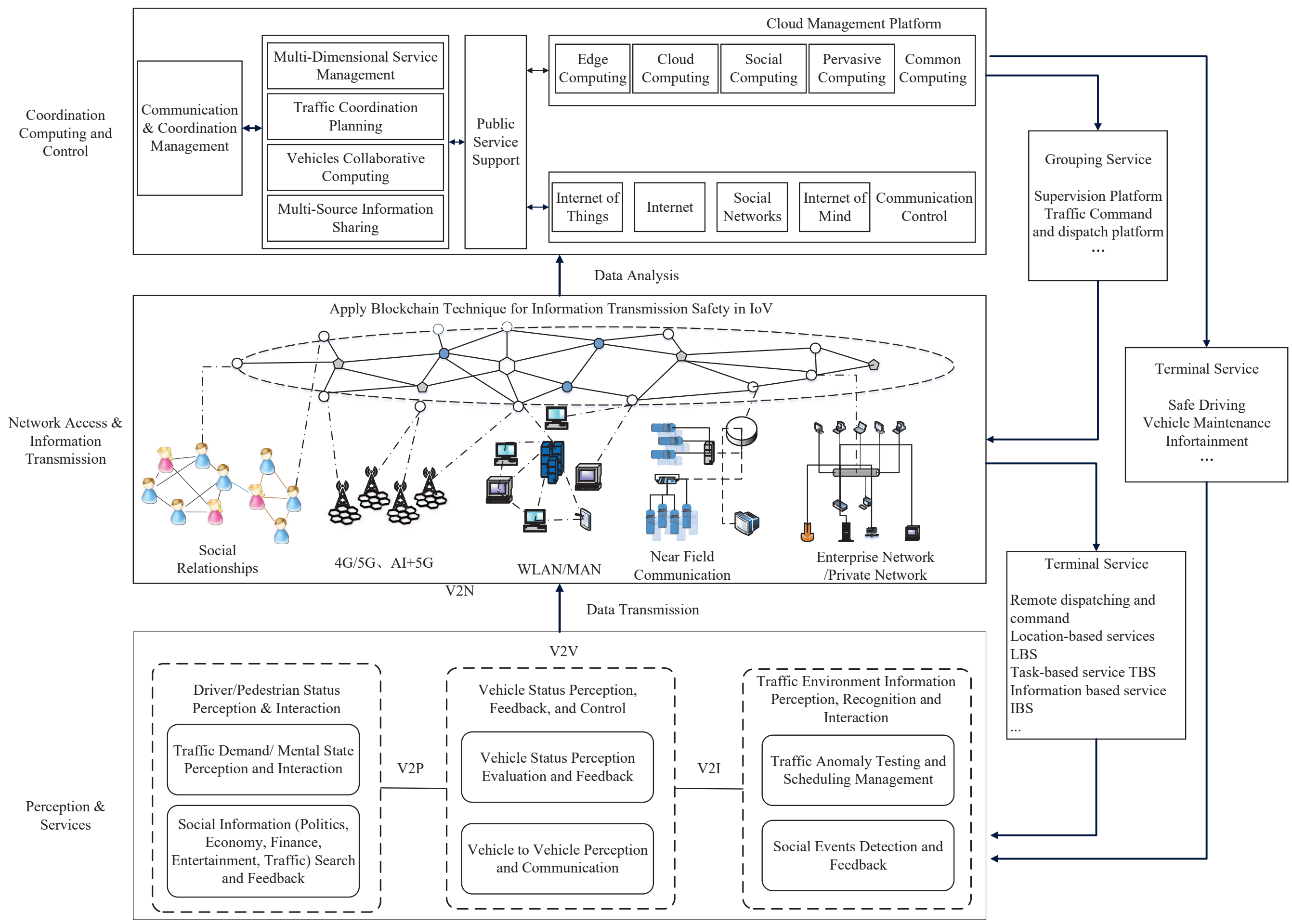

Fig. 1. General infrastructure of IoV systems.

ed, and the participating individual's behaviors also present uncertainty, complexity, and diversity. All of these make the internal dynamic mechanism of IoV difficult to understand. Meantime, "human-vehicle" collaborated driving style driven by intelligent driving technology will exist for a long time in the future. This typical phenomenon not only needs to consider the complicated factors such as fast mutability, uncertainty, and dynamics of the driver's behaviors, but also requires to think about the difficulty of understanding the intention and habits. In addition, a variety of social signals introduced by the coupling of in-vehicle networks, inter-vehicle networks, and onboard mobile networks have brought new challenges to the management of complex transportation [39].

Two fundamental characteristics are essential to CPSS. The first is inseparability, i.e., a CPSS is a complete and integrated system and cannot be explained via independent analysis of its components [40]. The second characteristic is unpredictability, which means that the global behaviors of a CPSS cannot be explained or determined in advance at a large scope. In IoV, due to the deep integration of people, vehicles, processes, and systems, and the dynamic, self-organizing, abrupt, and highly complex nature of human behaviors, the accuracy and effectiveness of the system's "behavior model" are highly dependent, making it impossible to be directly controlled.

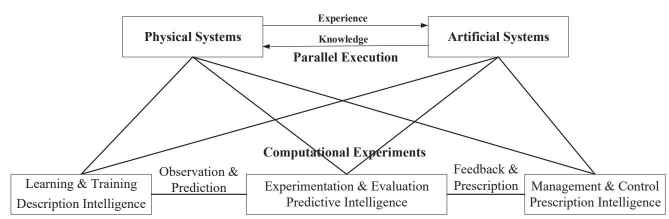

Fig. 2. Framework of the ACP-based parallel intelligence approach.

Therefore, the behaviors of IoV cannot be accurately predicted even given current status and control conditions.

III. The ACP-based Parallel Internet of Vehicles

At the beginning of this century, Parallel intelligence was proposed as an original research paradigm. It mainly focused on CPSS systems with high sociality and engineering complexity, which are enabled by the ubiquitous mobile intelligent devices and social signals. The framework of ACP-based parallel intelligence approach is shown in Fig. 2. Through data-driven descriptive intelligence, experiment-driven predictive intelligence, and interactive prescriptive intelligence, parallel intelligence provides agile, focused, and convergent solutions for indefinite, diverse, and complex issues. It augments technologies including wireless communication, multi-agent modeling, computer graphics, machine learning, social media networks, etc., and is driven by physical, cyber, and social signals.

A. Parallel IoV

The basic idea of PIoV is to introduce ACP-based parallel intelligence into IoV. The framework of PIoV is illustrated in Fig. 3. It is composed of "three stages", namely, artificial IoV systems, computational experiments, and parallel execution. With the help of software-defined objects (SDO), software-defined relationships (SDR), and software-defined processes (SDP), etc., artificial elements and the relationship among them in IoV, such as V2V, V2I, and vehicle-to-pedestrian, are described and designed. Then, the computable and programmable artificial system is formed for the physical IoV system. Social and economic policies that cannot be tested and evaluated in the physical system, such as oil price rising and highway toll free of charge, now can be easily tested and evaluated in artificial IoV systems. Based on the operating data of both physical IoV system and the artificial IoV system, optimized policies on the operations of IoV can be gained. By delivering the validated policies into the physical IoV, the physical IoV "rehearsals" the policy operating process under the guidance of the artificial IoV, ensuring that these pairs jointly run along our expected directions and goals.

1) Artificial IoV: With the aid of knowledge representation and knowledge engineering, the artificial IoV takes advantage of the theories and methods of artificial society [41]. For various elements and problems in IoV, it constructs software-defined objects (SDO), software-defined processes (SDP), and software-defined scenes (SDS). After that, it constructs and cultivates "software-defined IoV" through integrating thousands of traffic scenes. Therefore, the intelligent transportation "computational lab" is established, which studies computational experiments of complex problems and decisions in IoV systems. An artificial IoV system mainly includes several components as shown in Fig. 4.

System modeling is achieved by using the bottom-up multi-agent method. There are at least eight types of intelligent agent objects, including artificial human, artificial vehicle, artificial road, artificial roadside unit, artificial base stations, artificial buildings, artificial weather, artificial time, etc. Each agent is capable of simple calculation and interaction. Weather and time factors are considered as special agents. In view of the combinations among time, light conditions, rain, snow, wind, fog, and so on, specific artificial IoV subsystems for different real traffic scenes are built by defining the interaction, organization, and coordination rules among agents. Through the redefinition of the actions and interaction rules of the agents, various traffic scenarios can be simulated and assessed, and the knowledge of different situations can be acquired.

For example, overtaking behavior in traffic systems is complex where accidents usually happen due to driver's inaccurate judgements. Through the multi-agent modeling of overtaking in the artificial IoV system, the knowledge of overtaking under various scenarios can be obtained and intelligent assistance can be provided to drivers. In the artificial IoV system, the vehicle agent is modeled with the ability of perception, motion, and cognition [42]. Through the interactions of the agents, the velocity of the overtaking vehicle (V_o), the velocity of the vehicle in front (V_f), the velocity of the vehicle in the neighbouring lane (V_n) as well as the the distance to the front vehicle (S_f), and the distance to the backward vehicle in the adjacent lane (S_b) can be acquired. In order to avoid collisions, the feasibility of the lane changing maneuver must be calculated. For instance, if the adjacent lane is in the same direction as shown in Fig. 5, and assuming that $V_o < V_f$. While $V_o < V_n$, the lane changing can happen only when [14]:

$$S_f > D. \tag{1}$$

$$S_b > \frac{V_n^2 - V_o^2}{2d_{cc}} + \tau V_n + D. \tag{2}$$

and if $V_o > V_n$, the overtaking vehicle must calculate the feasibility based on the formula (3), (4) to avoid collisions.

$$S_b > D. \tag{3}$$

$$S_f > \frac{V_o^2 - V_n^2}{2d_{cc}} + \tau V_o + D. \tag{4}$$

where D is the minimum safe distance to avoid collision, d_{cc} is the maximum deceleration of the backward vehicle, and τ stands for the driver's reaction time which is influenced by the road agent and weather agent.

The judgement of the feasibility is more complicated if the opposite lane needs to be occupied while overtaking. If the velocity of the front car C_r in the opposite lane is V_r, the overtaking vehicle must calculate the time needed for overtaking (T_o) as well as the time before the collision with C_r happens, which is given by equation (5).

$$T_c = \frac{L}{V_o + V_r}. \tag{5}$$

$T_o < T_c$ must be satisfied [15] before the operation.

In the artificial IoV system, the vehicle density, speed, and reaction time under different roads and weather conditions can be changed, thus various models with different parameters can be created. Based on the data generated by these models, the feasibility of overtaking under different scenarios can be automatically calculated and simulated in advance, making the overtaking behavior much more intelligent and safer.

By building digitized artificial vehicles, artificial population, artificial scene of complex traffic systems, some works have been completed for dynamic mechanism based on analysis and experiment. In 2003, Fei-Yue Wang et al. [16] proposed to apply digital vehicle/highway techniques in intelligent transportation system, aiming to improve the driving safety and guide the safe driving behavior through reminding drivers about the potential threats. Subsequently, the basic idea and framework of Artificial Transportation Systems (ATS) [17] and ACP-based management and control method for complex transportation system [18] were proposed in 2004. Fenghua Zhu et al. [19] took the whole transportation system as a

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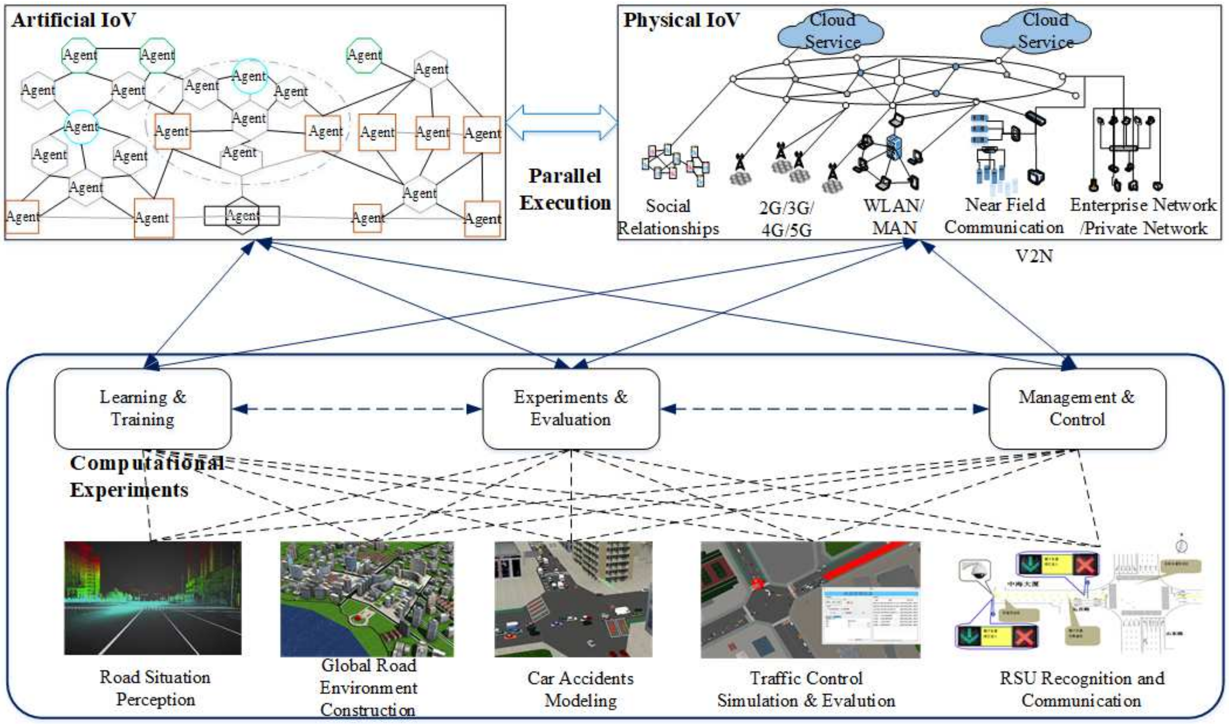

Fig. 3. Infrastructure and analysis of PIoV.

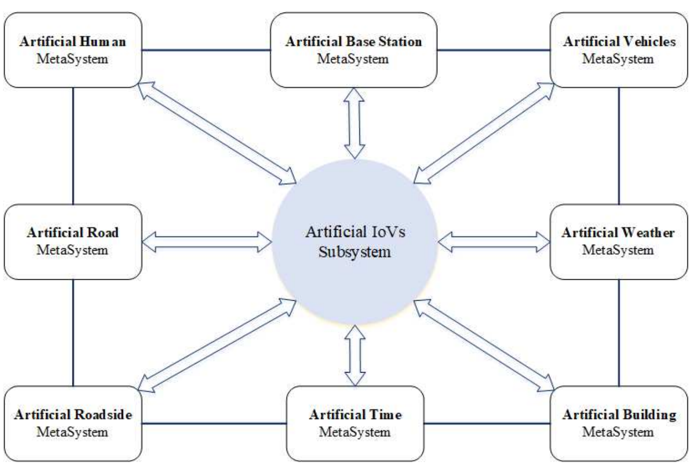

Fig. 4. Composition of artificial IoV (AIoV) subsystem.

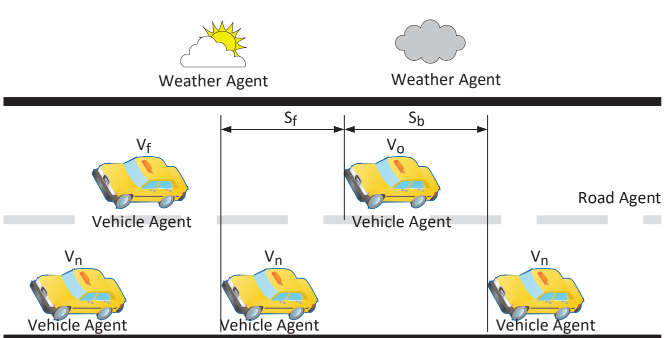

Fig. 5. Lane changing process of overtaking.

temporal communication system, adopted the method of Petri nets to model ATS interactions and processes, simulated the interaction behavior of complex traffic system, and then provided scientific control strategy for physical transportation systems. With the help of JXTA computing platform, Qinghai Miu et al. [43] designed an ATS based on peer-to-peer computing, which built ATS by P2P communication mechanism and verified the feasibility by the simulation experiments. It provided the fundamental method for the construction of digital intelligent transportation computational laboratory. Jinyuan Li et al. designed a growth model of ATS based on the iterative evolution of rules by introducing the multi-agent modeling method [44]. Fengzhong Qu et al. [45] proposed the concept of intelligent transportation space, and clearly demonstrated the CPSS characteristic of transportation systems, and emphasized the need to fully consider the interaction among the pedestrian, vehicle, road unit, mobile base stations, and satellite traffic factors. By building the virtual intelligent transportation space corresponding to the physical space, control strategy for physical space transportation system is found with the help of virtual space strategy of calculation, experiment, and evaluation. Miao et al. [46] designed an agent-oriented modularized and distributed simulation platform for the modeling and calculation of the artificial transportation systems. By using artificial population for game design, 3D simulation environment and the management for mobile roles (including vehicles and pedestrians, etc.) is achieved by using Delta3D game engines and dynamic role mechanism of Delta3D. In [21], Sewall et al. reconstructed and visualized the continuous traffic flow based on the discrete data of time and space, which enables users to watch virtual traffic events in the virtual world.

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This method is able to reconstruct the traffic flow and realize the immersive visualization of virtual city.

Corresponding to physical IoV system, generation, interaction and evolution processes of the vehicle behavior in artificial IoV system are complete. On one hand, it greatly alleviates the data deficiencies in the physical IoV system (especially the extreme environment data and the abnormal situation data); On the other hand, with the help of statistical machine learning, data mining, and deep learning methods, initial state parameters of artificial IoV system are set up based on the parameters of the physical IoV data. At the same time, combining with rule learning method, agent behavior rules are automatically extracted, and then the interaction between objects in artificial IoV is modelled by the bottom-up multi-agent method. Such artificial IoV system, cultivated by mainframe computers and multi-agent technology, can model and show static and dynamic characteristics of actual traffic system. For example, the behavior characteristics of drivers are simulated by the interaction between driver agent and vehicle agent; traffic environmental awareness is achieved through the Interactions between vehicle agent and road agent. This design of the large-scale artificial scene could "visually" and " parametrically" explain "complex macro phenomenon originated from micro". It further explains the structure, function, and dynamic characteristics of different levels in the complex network system, as shown in Fig. 6.

2) Computational Experiments: The main purpose of the computational experiments is to design the quantitative grouping strategy and sequential interaction rules for all kinds of intelligent objects with the help of the "computing lab" of the artificial IoV. Then, it produces all kinds of complex traffic scenes, and makes vehicles running and learning by means of experiments. Furthermore, the application of the "knowledge" is also reversely analyzed and evaluated; Thus, the driving strategies suitable for different real traffic scenes could be obtained through the artificial vehicle running in the artificial traffic laboratory. Fig. 7 illustrates the experiment design methods in the "computational lab".

The main process includes three steps. Firstly, with the help of data mining, machine learning, and statistical analysis techniques, features and rules are extracted for the operation of physical IoV, and a physical IoV data support center is built. Secondly, based on operations and interaction rules of the extracted people-vehicle, vehicle-vehicle, vehicle-roadside unit, artificial IoV and its traffic scenes are built to realize the simulation of physical IoV operation. Finally, experiments are designed for different targets around specific scenarios, the management and control of specific strategies are also tested and evaluated. If a strategy meets the predefined target, it can be applied into the physical IoV and guide its operations. The experimental architecture is shown in Fig. 8. By building a dynamic network allocation method based on complex adaptive system, the computational experiments could be designed, implemented, evaluated, and validated. Consequently, it is possible to learn the existing traffic patterns and to predict potential traffic patterns, and can provide effective prevention before some severe traffic patterns happen.

In the computational architecture, there are two main operating modes: learning and training, experiment and evaluation. There are plenty of work about intelligent driving, such as virtual learning, training, testing, and evaluation. By "driving vehicle" in the artificial traffic environment integrated with a lot of artificial scenes, the ability of complex environment perception and complex scene cognition is significantly improved before the vehicle going on road. It offers valuable experience for the experimental experiment in PIoV. In 2003, Fei-Yue Wang et al. [22] proposed the concept of "Digital-Vehicle Proving Ground (DVPG)". The DVPG can generate testing tasks in an active or passive manner, satisfy at least two types of services: standard testing and specific testing, and provide training and assessment for self-driving vehicles. Li Li et al., proposed work about parallel testing of vehicle intelligence via virtual-real interaction in Science Robotics in 2019 [47], [23], which integrated scenario-based test and functionality-based tests method and proposed a new framework of Intelligent test. Then, "Parallel Learning" [24] was proposed, which uses state transition to depict system change, makes the vehicle obtaining driving experience from virtual traffic scenes. The method could identify specific "traffic/driving mode". Once perceiving certain "local characteristics", the overall traffic or driving conditions could be predicted; Thus, the driving decision-making and path planning could be adjusted. The Carcraft and Carcastle project about self-driving of Alphabet, Google, and Waymo, construct a virtual city and virtual space to provide driving learning environment for intelligent vehicles. This method makes the vehicle "decision" in the real world rather than "look like decision" in the real world [25]. Kunfeng Wang et al. [26], recently proposed to use "virtual image" to train and test the object detection method. This method not only solves the lack of real data sets, but also provides a new data set for detection visual identification algorithm. Different with Waymo method, Kunfeng Wang et al. have also established open-source parallel visual research platform (http://openpv.cn) to promote the research of parallel visual [27]. Eric P. Xing et al., proposed "unified unsupervised method from reality into the virtual domains" [28], which exploits Conditional Generative Adversarial Networks to map the physical driving image into virtual space and predict vehicle control commands to improve the performance of prediction task for vehicles instruction.

Computational experiment is one of the most important components in PIoV. In complex physical IoV, it is hard to collect complete data for object state, organizational behavior, and the evolution process. However, artificial IoV could simulate the whole network system, and automatically acquire or generate accurate annotation information in "learning and training" mode. Thus, complex experiments could be finished, while conventional methods could not be executed because of a huge economic cost. Meanwhile, through computational experiments, specific training for artificial IoV can be carried out from the perspective of global optimization to satisfy the needs of specific applications, such as specific traffic scene, driving function, and traffic tasks. Further, under the operating mode of "experiment and evaluation", the results of the artificial IoV are used to comprehensively evaluate the performance and the degree of danger in complex situations.

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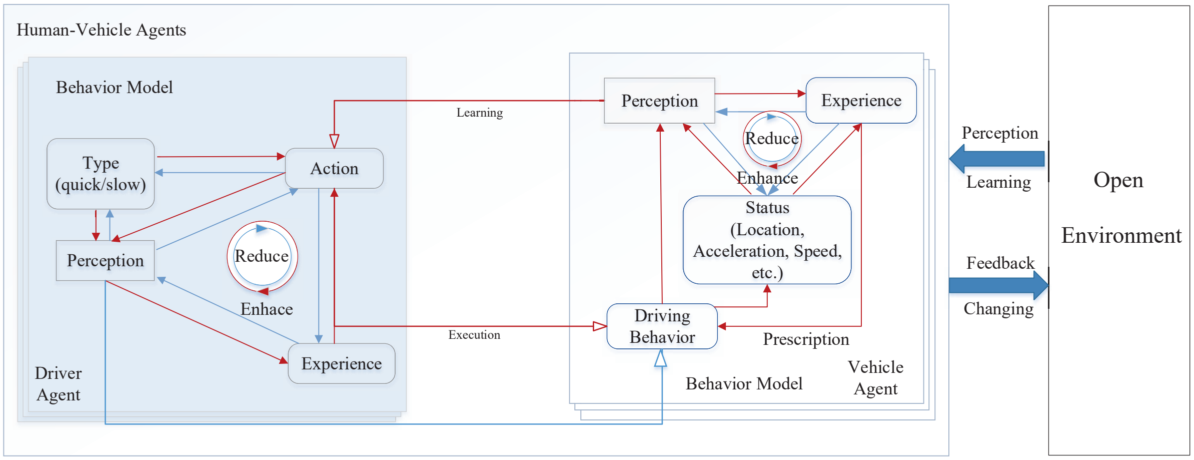

Fig. 6. Illustration of the human-vehicle-road interaction in AIoV based on multi-agent modeling.

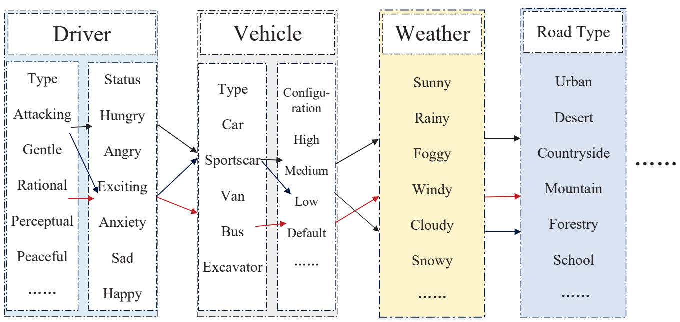

Fig. 7. Experiment design in computational experiment laboratory.

3) Parallel Execution: PIoV jointly considers in-vehicle networks, inter-vehicle networks, onboard mobile networks, and social networks, as shown in Fig. 9. By building virtual artificial IoV corresponding to physical IoV and with the help of computational experiments, IoV management and control experiment can be designed to be repeatable, configurable, computable, and guidable. For effective evaluation, computational experiments forecast and guide the operation state of physical IoV. The computational experiment results become a possible outcome in the running state of the system, but are no longer just "simulation" of the physical operation status. The physical IoV provides the real data information to the PIoV, and provides the state parameters for the establishment, adjustment, and optimization of the artificial IoV mode. Computational experiments use the real data for model training, generate a large number of "artificial data", and carry out a large number of learning based on the "mixed huge amounts of data" from both real "small data" and artificial "big data". Therefore, the system scenario learning and cognitive ability can be improved and optimized. On the other hand, by parallel execution, computational experiment results are fed back to the physical IoV for real-time and online reference, prediction, and prescription.

Parallel vehicles, human-vehicle coordinated individuals that connect network infrastructure and human social network in the CPSS space, is the key to address the problem of human-vehicle and vehicle group coordination. The human-vehicle coordination unit realizes collaborative perception, planning, and decision-making. Through the direct&indirect interaction between vehicle and environment, the control and feedback of information perception among the elements of IoV environment can be realized. Through the life service interaction provided by social networks, it is possible to implement the extension of social demand and relationship in IoV. These social relationships of the owners of those vehicles are either based on sociological relations such as colleagues, roommates, and classmates, or based on the geographical location. For example, if someone is a frequent traveler for work and needs the network to connect to his colleagues, customers, and family. His vehicle becomes a member of vehicular network and is able to get information about the routes that are frequently used between home to company and his companies to the locations of customers, as well as the places in his surroundings that are covered by a stronger signal, less congested cells and its operator base stations. In this way, if a new colleague firstly joins the vehicular network, he/she can automatically obtain various knowledge such as the routes to the customer's companies, test sites, and other interested places. Moreover, the artificial vehicles in virtual transportation space are not restricted by the position and energy in physical space and are not restrained by data communication bottleneck. Based on the interactions with other artificial vehicles, several important tasks are completed by crowdsourcing, including environment information collection, cooperative path planning, complex scene perception and situational cognition, etc.

Based on the parallel perception, parallel learning, parallel driving, parallel planning, and parallel testing methods in PIoV, the artificial vehicles guarantee the information interaction, strategies feedback, and two-way optimization between physical and artificial IoVs. Besides, it improves performance of perception, decision-making, planning and control, and realizes the overall optimization of network resources and traffic resources for different demands. Therefore, the increasing control and management requirements in IoV system can be satisfied, and intelligent and collaborative solutions

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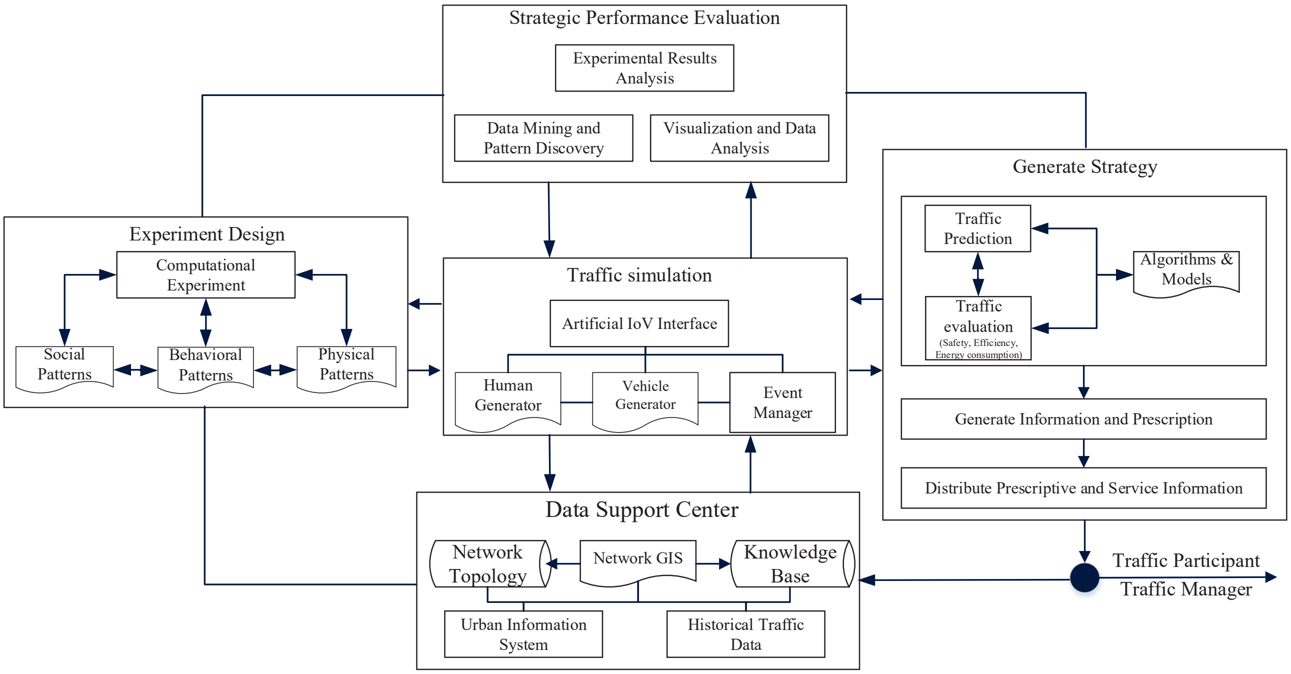

Fig. 8. Framework of dynamic network assignment based on complex adaptive systems.

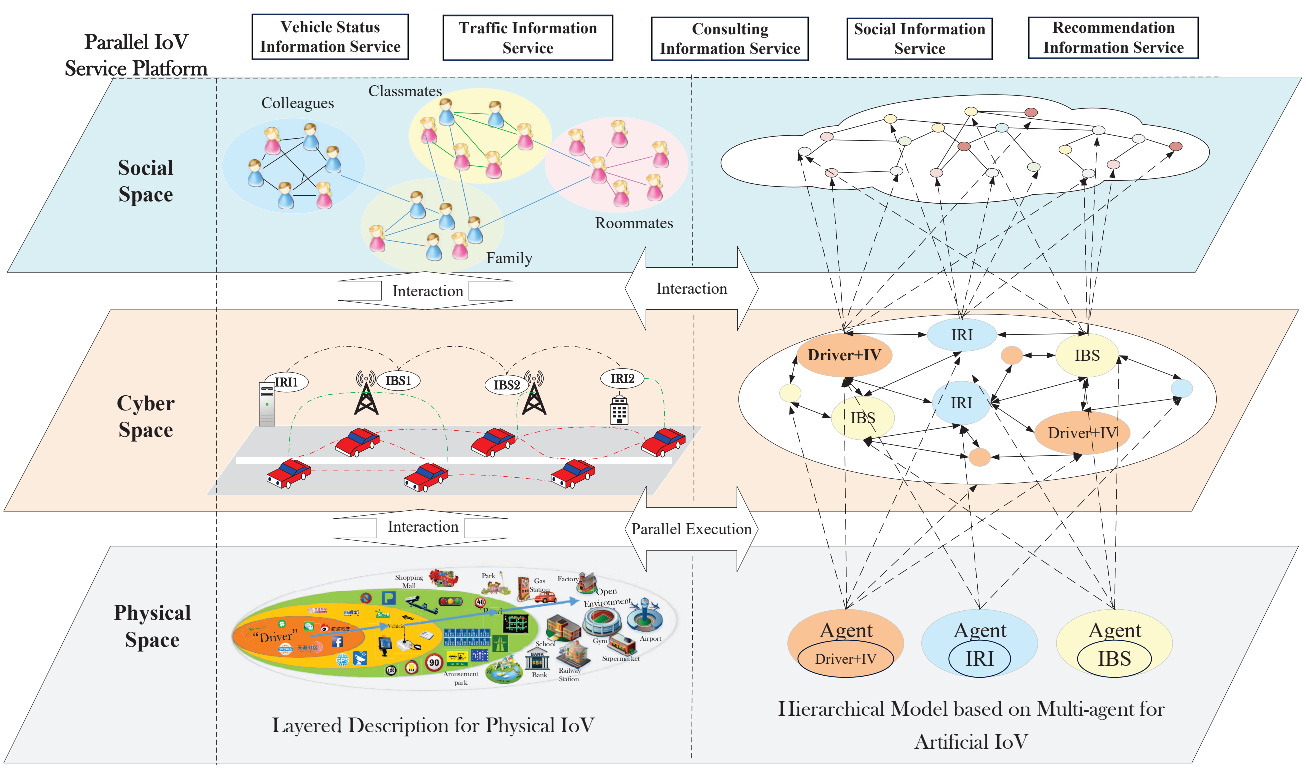

Fig. 9. Architecture of PIoV.

and framework are provided for intelligent vehicle system in different automation levels and for the future intelligent transportation systems.

AlphaGo, appeared in recent years, can be taken as the best example of parallel learning, parallel assessment, and parallel decision-making. Taking the historical "small" data of human chess players as input, self-gaming, self-adaption, and self-evolution is carried out by the experiments, and then "mixed big data" is generated by a great number of real and virtual chess games. After that, the potential result is evaluated, and the "knowledge" about the efficiency value and their behavior strategies is concluded. Besides, parallel evolution

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is achieved by the gaming with human player. In this paper, the artificial vehicle and the physical vehicle also follow this process. Through the interaction and parallel execution, two-way feedback mechanism is achieved, which is highly-efficient and in real-time. Therefore, it guarantees monitoring early warning and feedback for the physical IoV systems.

To conclude, PIoV makes up for the lack of accuracy and robustness of traditional IoV through the above mentioned three steps, including the aspects of perception, communication, and service, etc. The augmented virtual data from artificial IoV systems enhances vehicles perception and localization abilities in dynamically changing environments. Routing and security issues faced in the communications of IoV can be properly solved by strategies rehearsal via computational experiments. For example, various cyber attacks in IoV can be experimented in artificial IoV harmlessly. Thus, corresponding protection strategies can be tested and prepared. Due to the limitations of IoV communication technologies, robust routing performance is hard to achieve in the case of high speed movements, which limits the mobility of traditional IoV system. In PIoV, various vehicles movement scenarios can be configured at the same time, then an optimized routing choice can be gained and the limitation on mobility is reduced. What's more, a globally optimal IoV system can be achieved based on the comprehensive consideration and modeling of human, vehicles, roads, and so on.

B. System design and implementation

IoV system is a typical system engineering, the implementation difficulty lies in resource integration, which requires the cooperation of government, commercial companies, and the public. It is difficult to deploy and implement IoV systems, which needs to be promoted by many parties.

However, the proposed PIoV system involves the Cyber space, physical space, and social space both in the real and virtual world. By setting up the artificial PIoV module, it can perform 3D simulation on the actual PIoV. The computational experiment module conducts a variety of experiments to explore different possibilities in the artificial system, thereby breaking through the limitations of reality and realizing the management and control of multiple intelligent vehicles via the combination of virtual and real methods.

Based on the existing equipment and Parallel Driving 3.1 system [29], a PIoV application case (Fig. 10) for multi-intelligent vehicles management and control is proposed.

Corresponding to those three stages of PIoV, the system is constructed with three-parts: PIoV management and control center, Intelligent vehicle platform, and PIoV dispatching platform. Each module is described in detail below.

1) PIoV management and control center: PIoV management and control center is the key to the PIoV system. It provides all-weather and all-round monitoring and management of the PIoV, and realizes the optimization of various services, resource scheduling, equipment monitoring and maintenance.

PIoV management and control center consists of simulation equipment, industrial personal computer (IPC), server, video monitoring platform, image splicer, switch (telecommunications) and remote networking equipment. It contains two

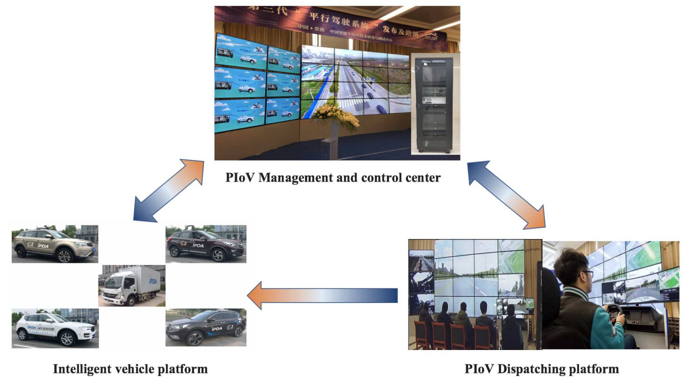

Fig. 10. PIoV application case for multi-vehicle management and control.

major functional modules: the artificial PIoV module and the computational experiment module. The artificial PIoV module performs dynamic real-time data acquisition and 3D visual simulation on the actual PIoV, and includes various artificial intelligent agents as shown in Fig 4. The computational experiment module includes data management and analysis section, learning and training section, and experiment and evaluation section. The data management and analysis section captures, stores, and analyzes data from both actual and virtual PIoV systems. The learning and training section applies corresponding algorithms from the algorithm library to optimize the various PIoV services. The experiment and evaluation section performs verification and optimization based on the actual PIoV system, so as to guide the real-time vehicle operations. In particular, if an abnormal situation is detected, it can be displayed in real time on the large screen, and emergency command and control will be conducted.

2) Intelligent vehicle platform: Intelligent vehicle platform contains several automated vehicles with different levels. All vehicles are connected to the PIoV management and control center and PIoV dispatching platform. Radar, lidar, camera, industrial personal computer (IPC), human-machine interaction device (HMI), emergency stopping equipment, wireless transmission equipment, differential GPS and inertial navigation IMU are installed on the vehicles.

Lidars and cameras are used to sense the environment. Positioning information is obtained by inertial navigation and GPS combined navigation. The control system makes decision based on the environment perception and positioning information. The mode switching module simultaneously receives vehicle vertical and horizontal control signals from the control system, PIoV Management and control center, and PIoV dispatching platform. Finally, the mode switching module executes a certain type of control signal according to a real-time mode selection command of the PIoV Management and control center.

3) PIoV dispatching platform: The dispatching platform includes a driving simulator and a dispatching system. The driving simulator includes a display screen, a steering wheel, a throttle, and a brake pedal. The screen displays the environmental and status information of the intelligent vehicle platform in real time, the driving state of the artificial vehicle

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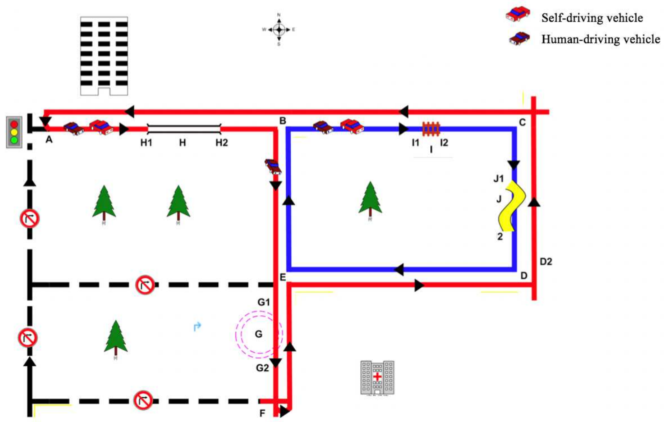

Fig. 11. Driving route map [48].

in the artificial PIoV, and the real-time trajectory on the map, on which the location of all vehicles can be viewed in real time.

The dispatching system performs reasonable takeover of the multi-mode vehicle, rational dispatching, and traffic command and diversion, thus realizing the communication cooperative management and improving public service support capability of the PIoV system.

C. Application Case

In March 2018, an application case for monitoring and takeover of multi-mode vehicles is performed in China Intelligent Vehicle Integrated Technology Research and Development and Test Center, Changshu, Jiangsu [48]. As shown in Fig. 11, two self-driving vehicles (A and B) and two human-driving vehicles are operated at the test site at the same time. The self-driving vehicle A and B travel along the red and blue trajectories respectively. In the course of driving, when the vehicles encounter perception limitations and internal faults, the self-driving vehicles will either initiate takeover, or be taken over passively by PIoV management and control center when exceptions are detected.

Starting from point A, self-driving vehicle A is interfered by GPS interferometer when arriving at the point G. Vehicle A initiates to request takeover from the PIoV management and control center after detecting the abnormal GPS data. At this time, the PIoV management and control center feeds back the request to the PIoV dispatching platform, synchronizes the current state information of the vehicle to the driving simulator, and then the dispatch driver takes over the vehicle by remote control with the driving simulator. When the dispatch driver drives vehicle A out of the GPS jammer interference range, the driver clicks the exit remote control button on the driving simulator, and PIoV management and control center sends the command to the mode switching module of vehicle A, which switches back to automatic driving mode.

Starting from point B, self-driving vehicle B successfully avoids obstacle from the vicinity of I1-I2 and automatically drives to the J1 point along the route. The PIoV management and control center monitors the trajectory with a jagged abnormality, and actively sends a takeover request to the driving simulator, i.e. vehicle B is taken over passively. After the driver has discharged the fault, the PIoV management and control center sends command to vehicle B. The mode switching module switches back to automatic driving mode.

During the process, PIoV dispatching platform performs rational dispatching for the other two human driven vehicles in order to avoid congestion and interference. At the same time, the status information, the location, and trajectory of the vehicles are displayed on the screen of the PIoV dispatching platform in real time, thus realizes the communication cooperative management and improves public service support capability of the PIoV system.

IV. Conclusion and Discussions

In this paper, based on the systematic analysis of IoV in the view of CPSS, a novel PIoV framework was proposed and thoroughly discussed by applying parallel intelligence theory and ACP approach in the IoV area. PIoV integrates data mining, machine learning, artificial intelligence, virtual reality, knowledge of automation, etc., and comprehensively considers the fusion of information, psychology, simulation, and decision-making. Further, this paper analyzed the structure and functional characteristics of different levels for the complex IoV system, and provided new ideas and methods for the intelligent management and control of the future transportation systems.

IoV is a complex system that involves many individual behaviors. The efficiency of prescription strategy is largely related to whether the driver and the administrator completely execute the plan. In physical IoV systems, due to the subjective and/or objective factors, users might not carry out the optimized plan. Therefore, how to compute, flexibly adjust, and allocate available resources according to social acceptance is one of the most challenging and important problems that need to be solved.

Currently, the research about parallel driving, parallel learning, and parallel testing has gained significant attention among international counterparts. PIoV shows a bright future for promoting the applications of IoV. However, there are some challenges on the realization of a complete PIoV system. Firstly, there are no unified paradigms for the agent-based modeling of objects in IoV, in particular, the description and modeling of the communication process. Besides, there also lacks effective modeling and analysis methods of humans. Secondly, IoV consists of large volume of sensor data and communication data with different forms, it is hard and time-consuming for accurate analysis and prediction of these data, where an efficient data mining approach of multi-modal data that fully meets the real-time needs of IoV is needed. Thirdly, a well-performed standardized interface is needed for the parallel execution, which is also challenging due to the diversity of interfaces of different kinds of devices.

With further development of related technologies, as an integrated authentication platform, the proposed PIoV will become one of the most important directions in the future research of intelligent transportation systems. Considering the continuously developed self-driving technology and the increasing business requirements, the research and application of PIoV would receive great attention. In addition to further development of fundamental technologies such as communication and computing, more efforts should be paid to refined artificial IoV system modeling, as well as application-oriented services. Therefore, our future work will focus on agent-based modeling, multi-modal data process methods, standardized interface for parallel execution, among others.

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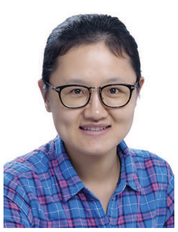

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