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Cognitive Internet of Vehicles

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ABSTRACT

To fully realize future autonomous driving scenarios, Internet of Vehicles (IoV) has attracted wide attention from both academia and industry. However, suitable cost and stable connectivity cannot be strongly guaranteed by existing architectures such as cellular networks, vehicular ad hoc networks, etc. With the prosperous development of artificial intelligence, cloud/edge computing and 5G network slicing, a more intelligent vehicular network is under deliberation. In this paper, an innovative paradigm called Cognitive Internet of Vehicles (CIoV) is proposed to help address the aforementioned challenge. Different from existing works, which mainly focus on communication technologies, CIoV enhances transportation safety and network security by mining effective information from both physical and network data space. We first present an overview of CIoV including its evolution, related technologies, and architecture. Then we highlight crucial cognitive design issues from three perspectives, namely, intra-vehicle network, inter-vehicle network and beyond-vehicle network. Simulations are then conducted to prove the effect of CIoV and finally some open issues will be further discussed. Our study explores this novel architecture of CIoV, as well as research opportunities in vehicular network.

1. Introduction

Since 1970s, the world has witnessed a rapid growth of vehicles, which have indeed become the most important transportation tool for people's daily travelling. However, due to blocked line of sight, fatigue driving, overspeeding, etc., traffic car incidents could not be effectively reduced from beginning to the end. According to research statistics [1], 90% of traffic accidents are caused by human driving errors or misjudgments. Oppositely, an investigation report published by Eno Center for Transportation reveals that, if autonomous driving technology and vehicular communication cooperation could be adopted, traffic accidents caused by driving errors would be significantly reduced and urban traffic jam would be greatly relieved [2].

Currently, the vehicle industry is going through a huge technological revolution in order to deal with challenges mentioned above. Since 2012, with rapid development of big data technology and Internet of Things (IoT) [3], the first generation of Internet of Vehicles (IoV) has become the key enabling technology to realize future autonomous driving scenarios. Cognition and autonomicity are enabling paradigm for peculiar features of every IoT systems [4,5], and hence also for IoV. According to a report by McKinsey & Company in 2016 [6], the autonomous vehicles in future should be equipped with both intelligence and connectivity, and the sales volume of fully autonomous vehicles will take up 15% of the world's vehicle market in 2030. The new business model in autonomous vehicle market may enlarge the total revenue by about 30%.

Some research has discussed a few problems on IoV at present. Insights on layered architecture, protocol stack and network model of IoV have been put forth in [7]. As to vehicle-to-anything (V2X) communication problems, a joint communication scheme with dedicated short range communication (DSRC) and cellular network has been investigated and evaluated in [8]. Intuitively, IoV can be regarded as a powerful wireless sensor network (WSN) moving without human intervention. However, compared with traditional WSN, many problems remain to be solved due to the extremely strict application requirements for IoV:

(1) **High speed mobility**: the key element in IoV is autonomous vehicles moving at high speed. Due to the complexity and variety of traffic conditions, it is important to guarantee the accuracy in autonomous vehicles.
(2) **Delay sensitivity**: in IoV, communication delay need to be

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measured by millisecond. Once a network congestion or long delay happens, due to slow computation or limited band width, a series of life-threatening traffic accidents would take place.

(3) **Seamless connectivity**: in the future, user's requirements on network quality and service continuity would be much higher. Specifically, many computation-intense tasks need to be processed in real time. Therefore, QoS of many vehicular application can be satisfied only if a stable and uninterrupted network connection is guaranteed.

(4) **Data privacy**: large amounts of private information on vehicle owners are involved in vehicular networks, and it cannot be protected by traditional network protection mechanism. Additionally, the urban traffic system needs a secure and robust network environment to guarantee the orderly conduct of autonomous driving.

(5) **Resource constraints**: though self-organizing networks of vehicles may provide real-time communication, the computing resources and network resources possessed by a single vehicle is still limited, especially during a transition period of a semi-autonomous driving scenario. Resources need to be precisely scheduled in real time, based on actual driving course of massive vehicular networks.

In order to solve those problems, the intelligence of IoV need be strengthened in comprehensive directions. Therefore, Cognitive Internet of Vehicles (CIoV) is proposed in this paper to realize intelligent cognition, control and decision-making for future autonomous driving scenarios. In contrast to existing works on IoV, the human-centric CIoV utilizes hierarchical cognitive engines and conduct joint analysis in both physical and network data space. To grasp a concrete idea, we divided main participants in CIoV into intra-vehicle network, inter-vehicle network and beyond-vehicle network in Fig. 1, different scaled networks also focus on different cognitive functions. Main advantages of CIoV are listed below:

(1) **Cognitive Intelligence**: CIoV enables IoV to bear more accurate perceptive ability, through cognition in intra-vehicle network (driver, passengers, smart devices, etc.), inter-vehicle network (adjacent intelligent vehicles) and beyond-vehicle network (road environment, cellular network, edge nodes, remote cloud, etc), it can also provide macrocosmic information and scheduling strategies to the whole transportation system.

(2) **Reliable decision-making**: by introducing cognitive computing into autonomous driving systems, learning ability of autonomous vehicles can be effectively improved. Moreover, the decision-making process of autonomous vehicles will be more thorough and reliable through the cognitive cycle of perception, training, learning and feedback.

(3) **Efficient utilization of resources**: with perception of network traffic status and real-time road circumstance, the decisions derived by analytic technologies such as machine learning and deep learning, can help resource cognitive engine to conduct more effective control over vehicles, and to enhance information sharing efficiency within vehicular networks.

(4) **Rich market potentiality**: in terms of market opportunities, the benefits brought by CIoV are not limited to vehicle market, they are also closely linked to many other aspects in people's life, such as entertainment, healthcare, agenda and so on. Such a feature will also drive many traditional application devices to be transformed into intelligence embedded application devices.

The remainder of this paper is organized as follows. We first present the evolution of CIoV and review its related technologies in Section 2. Then in Section 3, the five-layered CIoV architecture is presented, with a particular emphasis of interaction between data cognitive engine and resource cognitive engine under cloud/edge framework. In Section 4 we explore critical cognitive design issues from three perspectives (intra-vehicle network, inter-vehicle network and beyond-vehicle network), aiming to enhance user experience and performance of traffic system. In Section 5, we simulate a vehicular edge scenario in CIoV to prove the effectiveness of our proposed architecture. Finally, we discuss some open issues related with the implementation of CIoV in Section 6 and draw our conclusions in Section 7.

2. Background and related work

CIoV is proposed as the advanced solution to strengthen cognitive intelligence of IoV. In order to better understand the development of vehicular networks, this section will explain the differences between CIoV and three related concepts, i.e., ITS, VANET and IoV. Fig. 2 illustrates the evolution process of CIoV. Furthermore, key technologies that enables CIoV, including self-driving technology, cloud/edge hybrid framework and 5G network slicing, is further presented.

2.1. ITS, VANET, IoV and CIoV

Intelligent transportation system (ITS) is an extensive conception, put forth before 2000. ITS involves a series of application systems:

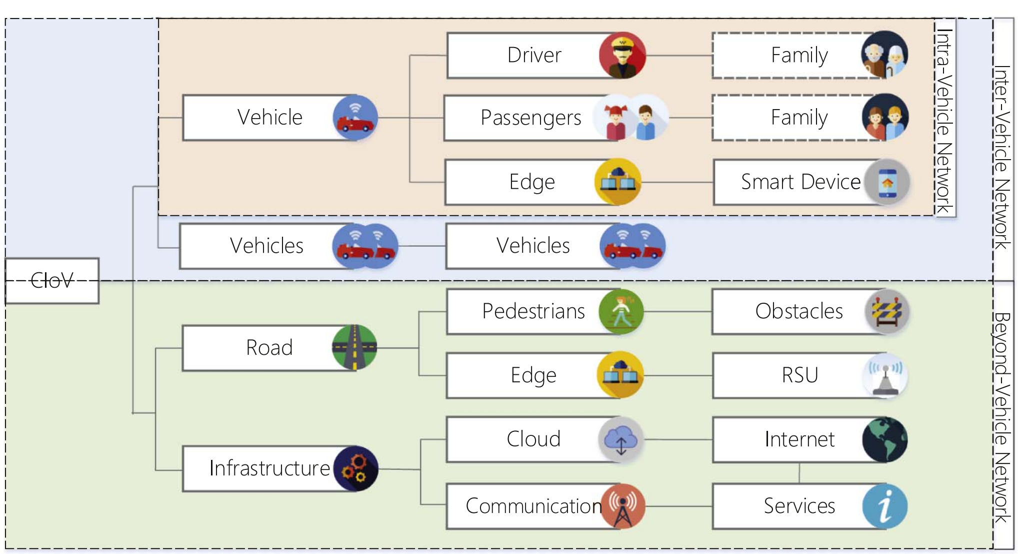


Fig. 1. Participants in CIoV.

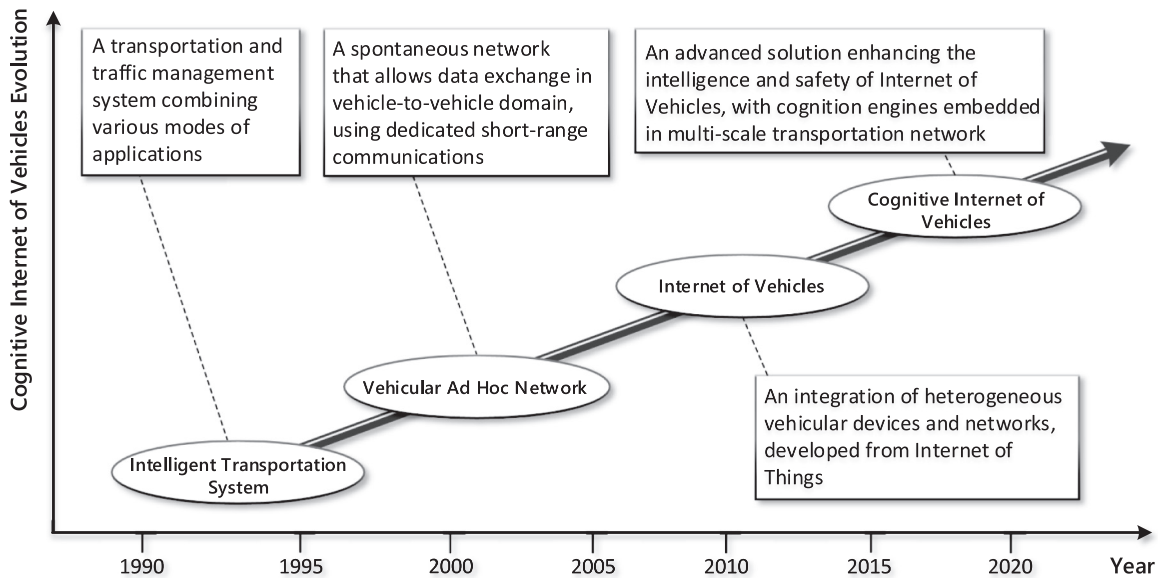


Fig. 2. Evolution of CIoV.

vehicle management system, automatic license plate recognizing system, traffic signal control system. A typical example is that, in order to realize extraction and utilization of static and dynamic information of vehicles on information network platform, electronic tags carried on vehicles can be recognized by technologies such as wireless radio-frequency identification (RFID).

The rapid development of wireless mobile communication technology attracts researchers' attention to communication between vehicles as a way to enhance road safety and improve transportation efficiency. For a long time, vehicular ad hoc network (VANET) has been under the spotlight. VANET mainly utilizes DSRC communication technology [9]. Yet a few problems remain unsolved: due to the high speed mobility of vehicles and currently incomplete infrastructure, the reliability of service connection in VANET is vulnerable.

As a result, VANET alone could not meet requirements for future autonomous driving scenarios. The emergence of big data and IoT leads to the concept of IoV. Under agreed communication protocol and data interaction standard, wireless communication and information exchange may be conducted on IoV between vehicle-to-anything (V2X), such as other vehicles, road, pedestrian, etc.

In the macro-framework of IoV, CIoV aims to solve the top-level problem of IoV, i.e., enhancing intelligence of IoV comprehensively. To be specific, how to fully mine information of all participants (Fig. 1) to reach the following objectives based on joint cognition of physical data space and network data space: (1) enhancing user experience as per private demand; (2) improving driving safety in traffic system; (3) strengthening data safety in network environment; (4) comprehensively optimizing network resource allocation. The cognitive design issues will be explored in detail in Section 4. In order to present a complete and clear understanding of CIoV, the architecture of CIoV will be provided in next section.

2.2. Self-driving technology

In recent years, artificial intelligence (AI) technology is again in the ascendant, and deep learning gradually becomes the most important part in AI technology. As a vertical application of AI, self-driving/autonomous driving technology attracts much attention in vehicle industry. The investigation report published by Eno Center for Transportation reveals that self-driving technology may significantly reduce the quantity of traffic accidents caused by driving errors [2].

AI-based self-driving technology and IoV can complement each other. On one hand, large amounts of data generated during driving process of vehicles can provide sufficient learning and training basis to AI. On the other hand, with rapid development of electronic circuits such as GPU, TPU, FPGA, ASIC etc., the performance of deep learning algorithm in aspect of real-time processing has been improved significantly, ensuring real-time business guarantee to environment perception, decision-making and control on CIoV. At present, great progress has been made in research on self-driving with introduction of algorithms such as AI-based path optimization algorithm [10] and obstacle and road identification algorithm [11].

In CIoV, information cognition and interaction of intelligent autonomous vehicles, which are able to obtain more information with adjacent vehicles, road and infrastructure, are brought into consideration. Thus, the perceptive ability of CIoV is greatly increased in contrast to a single autonomous vehicle.

2.3. Cloud/edge hybrid framework

Characterized by powerful computing and storage capacity, cloud computing platform can reduce the deployment cost of software services [44]. However, with more and more accessed mobile devices and high-quality local processing requirements, edge computing, as a framework much closer to the user end, supplements the functions of cloud computing effectively. Authors in [12] present the advantages of edge computing pattern in background of IoT, from angles such as delay constraint, bandwidth constraint and limited resources constraint. In [13], a comparison is made between feature of Cloud Radio Access Network (C-RAN) and that of Mobile Edge Computing (MEC), and the importance of mutual collaboration of MEC in 5G network is elaborated.

Cloud/edge hybrid framework is a rational solution for CIoV. Specifically, intelligent application services may be provided in the neighbourhood through collaboration of edge nodes, thus to meet demands of many delay-sensitive vehicular applications that require local processing, such as real-time road condition analysis and real-time behavior analysis for driver. However, with limited storage and computing capacity, edge computing could not meet the requirements for long-term cognition of users and environment. In this case, it is necessary to unload tasks to cloud for further analysis in idle time of non-driving condition. In addition, communication between vehicular edge and cloud is also important, especially in emergent situations.

2.4. 5G network slicing

With the evolution of mobile communication industry, 5G network service is booming recently with special features such as closer to user requirements, enhanced customization capability, deep integration between network and business, and more friendly services. Due to its elasticity and expandability, 5G network slicing becomes the research focus in network communication field. Network slicing may explore and release the potentiality of telecommunication technology, enhance efficiency and reduce cost. On the other hand, there is potential market demand for network slicing in fields such as vehicles, smart city and industrial manufacturing.

5G network slicing can meet IoV requirements on ultra-low delay and high reliability and other specific applications [15]. In nature, it divides the physical network of operators into multiple virtual networks, each virtual network corresponds to one of service requirements such as delay, bandwidth, security and reliability, thus it can cope with different network application scenarios flexibly. Moreover, with introduction of network slice broker [14], 5G network slicing technology may realize network resources sharing, and integration & allocation will be conducted to network resources that were mutually independent originally, thus to realize real-time and dynamical scheduling of network resources corresponding to special requirements.

At present, attempts have been made in some research projects to introduce network slicing technology into IoV. In [16], a network computing resource allocation algorithm on IoV with cluster as unit is put forth, but the part of core network including road-side unit is not involved. In [17], the network resources in the space and in air segments are provided to vehicles in ground segments for shared use, but the delay indicator, which is most important in service quality of 5G network slicing, has not yet been taken into consideration. In CIoV, double cognitive engines are introduced to conduct cognition, control and scheduling to network resources, and the cognitive design issue on resource allocation of 5G network slicing will be discussed in Section 4.

3. Architecture of cognitive internet of vehicles

When compared with traditional sensor network, there are higher requirements on perception accuracy, stability in data transmission, real-time analysis, intelligent decisions and network reliability for CIoV, demanding for more complex architectures. In this section, an architecture that meets requirements of CIoV is put forth, as shown in Fig. 3, comprising the sensing layer, communication layer, cognition layer, control layer and application layer.

3.1. Sensing layer

The sensing layer of CIoV is in charge of collecting and pre-processing for multi-source heterogeneous big data [45]. These data come from multidimensional space-time data in physical space on one hand, and from network traffic and resource distribution data in network space on the other hand.

Compared with big data set in traditional fields, big data in physical space are often unstructured. To be specific, driver related information should be described through driving video, facial expression data and etc. Route related information such as accurate position and environment should be described through multiple sensors collecting real-time data from ambient pedestrians, vehicles and environment, and it should be transformed into multidimensional space-time data.

The data that are current in network space are mainly operator data, for example, RSU, information on resource occupation by base station etc., and service request information of users, basic data information of user, etc. Generally speaking, the original data set collected may be unclean, redundant and inconsistent. Therefore, in order to enhance effective usage rate of resources in edge devices, appropriate data analysis algorithms should be adopted in perception layer to conduct cleaning, formatting and normalization for data, thus to extract useful information preliminarily.

3.2. Communication layer

In order to be adapted to requirements of applications with different timeliness, cloud/edge hybrid architecture is mainly adopted in communication layer of CIoV. Related radio technologies in communication layer (such as Wi-Fi, DSRC, LTE etc.) are shown in Table 1. At the scale of intra-vehicle network, most of the driving data need timely local processing and computing, exploiting the real-time communication between intelligent devices on intra-vehicle network and edge cloud. On premise of meeting connectivity demand, the main objective of inter-vehicle network is resource optimization. On one hand, real-time information interaction can be realized through self-organizing network between vehicles or star network between vehicles and RSUs. On the other hand, when there is no inter-operable units near a demand, cellular network may be adopted for communication. At large scale, the cloud needs to conduct centralized control over the whole traffic information, and to establish the feature model for network topology, road condition information and space-time service of group autonomous moving objects of the whole IoV. Furthermore, the communication between one vehicle and another vehicle is necessary, e.g., those in-vehicle services that are not delay-sensitive can be gradually unloaded to cloud for computing and analysis.

3.3. Cognition layer

In order to combine specific service demands, and to enhance intelligence of CIoV, cognitive engines are arranged at cloud/edge, divided into data cognitive engine at cognition layer and resource cognitive engine at control layer. Physical data space and network data space provide the data to data cognitive engine.

As for cognition in physical data space, the data cognitive engine processes and analyzes heterogeneous data flows through cognitive analysis methods (machine learning, deep learning, data mining, patten recognition etc.). In detail, data cognitive engine is able to conduct cognition of user tasks by use of data collected, e.g., driving behavior model analysis, emotion analysis, road condition investigation and etc. Based on cognition of user tasks, these can be divided into real-time vehicle area network services and non-real-time vehicle area network services. Generally speaking, real-time vehicle area network services are generally deployed on edge closer to user terminals, and non-real-time vehicle area network services can be deployed on the cloud, even far away from user.

In network data space, the data cognitive engine can realize dynamic cognition of data such as computing, storage and network resources, based on the resource allocation feedback on cloud/edge network, provide network optimization methods & real-time resource allocation strategies, and send analysis results to resources cognitive engine to guide network resource allocation. To be specific, when there is a delay-sensitive task, the edge will firstly check whether it has sufficient resources to complete this task, if no, those tasks not sensitive to delay may be transferred to cloud to realize reallocation of resources, thus to meet the delay demand of the delay-sensitive task. On this basis, different engines may be deployed as per different business types and application scenarios, e.g., engine oriented to collection and storage of mass data, engine oriented to driving behavior analysis and engine oriented to network security, and etc.

3.4. Control layer

As the scale of IoV constantly extends, exponentially increased data need to be processed and corresponding strategies need to be provided. Thus, control layer is the key factor determining system performance. Since the traditional method of centralized control in data center

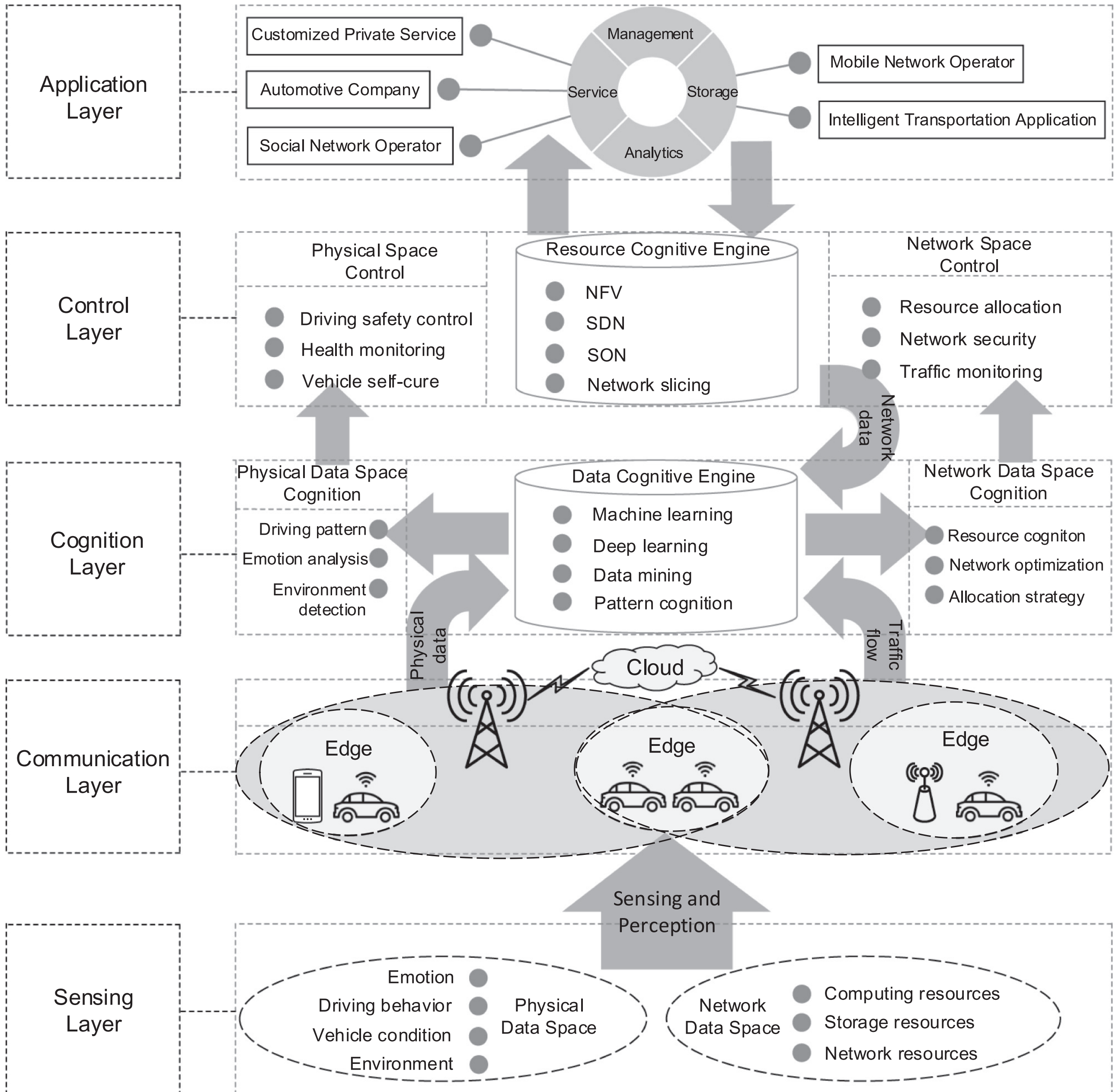


Fig. 3. Architecture of CIoV.

Table 1
Related radio technologies in communication layer.

Communication scale	Radio technology	Main functionality	Requirement		
			Delay sensitivity	Transmission capacity	Stable connectivity
Intra-vehicle network	Wi-Fi, WLAN	Data collection	Medium	Large	Medium
Inter-vehicle network	DSRC	Message exchange	High	Small	High
Beyond-vehicle network	LTE, WiMAX	Connection to cloud	Medium	Large	Medium

cannot guarantee low delay constraint of interactions between autonomous moving objects, it is not suitable for delay sensitive applications on the edge of IoV. Enabled by technologies like NFV, SDN, SON and network slicing, the main function of resource cognitive engines are to manage and dispatch network resources.

Resource cognitive engines are deployed at different locations of cloud/edge in order to strengthen stability and reliability of the network where different business requirements need to be satisfied. Resource cognitive engines deployed on edge support delay sensitive data management. Although the storage, processing and bandwidth resources available for edge are limited, distributed decision-making can be realized to process data from bottom layer. To meet QoS requirements of intra-vehicle cognitive applications, the resource cognitive engine on intra-vehicle edge are responsible for real-time

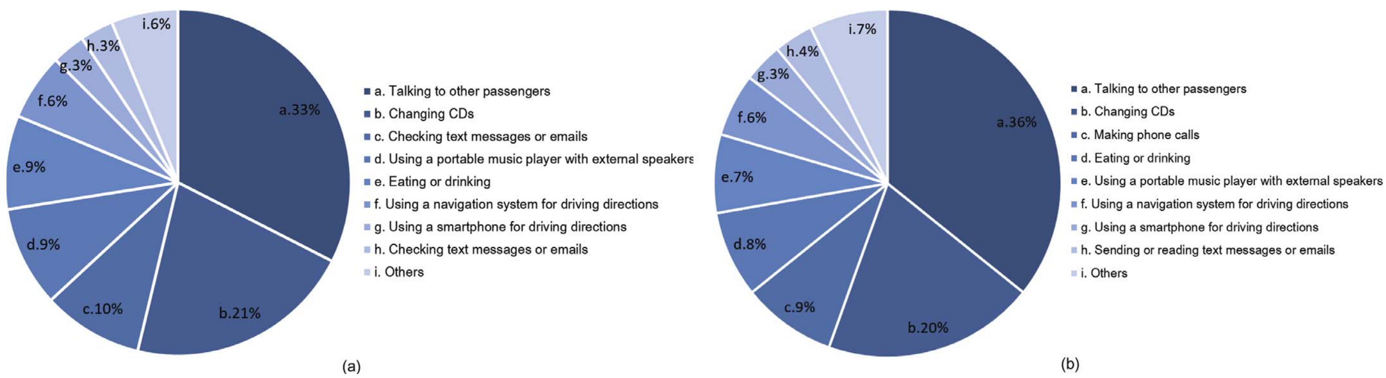


Fig. 4. (a) Distracted driving activities distribution in 2010 and (b) distracted driving activities distribution in 2012.

processing of driving data. In this way, the fastest decision-making can be guaranteed. Resource cognitive engines deployed on cloud conduct network optimization in a centralized way through effective utilization of the global information of IoV. Execution on cloud is at the cost of large centralized data storage, processing and bandwidth resources. Specifically, the most important work of cloud is to monitor resource utilization on edge network and to conduct dynamic scheduling for resources in real time. In addition, cloud receives emergent messages sent by edge and conducts a series of emergency treatment through high-performance computing. With cooperative control of resource cognitive engines at different levels, safety of the whole traffic system can be improved.

3.5. Application layer

At the operation level, CIoV involves coordination and cooperation among multiple parties, including manufacturer of automatic driving vehicles, mobile communication operator, social networking services provider, manufacturer of intelligent devices, software services provider and etc. Among plenty of applications provided by CIoV, two main categories are customized application services and intelligent transportation applications, it is noted that such services can be defined as Opportunistic since they are markedly dynamic, context-aware and co-located [18].

– Customized application services are aimed to reduce safety risks during driving; typical examples are driver fatigue detection, driving guidance, driver emotion monitoring and etc. Since many intelligent devices have access to CIoV, cognitive applications (such as mobile health monitoring) can be customized based on the different features of users. Cognitive applications will be elaborated in next section.
– Intelligent transportation applications include intelligent driving, intelligent transportation management, etc. To be specific, (1) intelligent driving helps drivers with accurate judgment on road conditions through communication between one vehicle and another vehicle/road, in combination with cognition of personal driving behavior. (2) intelligent transportation management means helping traffic management department to analyze service condition of road and vehicles by the use of information analyzed in cognition layer, thus to relieve traffic jam and improve road condition.

4. Cognitive design issues in multi-scale networks

The key issues of CIoV lies in how to excavate the information of all participants (Fig. 1) and enhance safety of physical space and security of network space; in other words, CIoV aims to (1) promote user experience based on personal demands, (2) improve driving safety of traffic system, (3) strengthen data security of network environment, (4) optimize the distribution of network resources. Due to the heterogeneity and complexity of CIoV network, we divide CIoV into intra-vehicle network, inter-vehicle network, and beyond-vehicle network from the perspective of scale and main functions. This section will focus on the cognitive design issues of these three networks. Three networks own their independent characteristics respectively. However, we also lay emphasis on the interaction and cooperation of these three networks to optimize the overall performance.

4.1. Cognition in intra-vehicle network

The edge cognitive computing (ECC) of 5G cognitive network enables the communication between wearable and vehicular embedded computing devices to be faster, more intelligent and more stable. In the scale of intra-vehicle space, safety and comfortableness of driver and passenger become the main concern. Furthermore, through cognition of intra-vehicle network, we can promote the safety of the whole traffic system, which will be discussed in detail in the interaction with beyond-vehicle network.

4.1.1. Driving guidance based on long-term behavioral cognition

Among the existing methods of driving guidance, many articles consider reducing the traffic accidents by the real-time driver monitoring from two aspects. The first method is through detecting the driving behavior of drivers. According to the survey of National Highway Traffic Safety Administration in 2012 [19], several typical distracted driving activities are shown in Fig. 4. By supervising and controlling these driving behaviors [20], proper warning beforehand can be provided and the response time of drivers can be increased to reduce the occurrence of traffic accidents. The second method is through monitoring the fatigue state and negative emotion of drivers in real time, vigilant measures will be taken for the tired drivers [21]. A novel method of detecting cardiac defense response using ECG signal [22] is promising since it can be well combined with wearable computing, effectively monitoring drivers without giving rise to their uncomfortableness.

These two monitoring methods are feasible, however, both focus on intervention on the driver. Besides, information of intra-vehicle network is not excavated fully. In fact, intra-vehicle network is a relatively private environment, and the behavior and mental state of the driver in the intra-vehicle network can reflect his recent living status. American Time Use Survey (ATUS) reports the average time of American people in the vehicle [23] and the result indicates that vehicle has become the essential part in people's life. Thus, the long-term cognitive analysis of intra-vehicle network data is a significant work. In addition, Pope et al. [24] discusses the influence of basic information (age, gender and executive capability) of the owner. Zhang et al. [25] discusses the influence of the living status of the owner such as stress disorder on driving. Chen et al. [26] discusses machine learning methods on disease prediction problems. These works show that the long-term data collection, processing and cognition of personal information can further guide the driving behaviors of the driver to avoid the occurrence of traffic accidents, and also can improve the user experience in all aspects with customized service. In short, cognitive intra-vehicle network can help to adjust the living status of the user and provide guidance in many aspects (such as driving, health, work, amusement and diet) to the user.

Specifically, the vehicular embedded sensors (such as camera, navigator, and speedometer) collect the intra-vehicle network data mainly involving picture, voice, video, physical health data, and driving related data. Then the vehicular edge cloud carries out data processing and real-time data analysis. The vehicular terminal can finish the real-time computing of most tasks locally. However, the storage space of local device is limited, so the vehicular edge need to upload the local data to user's private cloud for processing and storage in the time when user leaves the vehicle. The cloud carries out the analysis training of the private data involving basic information, driving behavior, emotion, health condition, then converts original data to personalized rules by cognitive computing. These rules reflect past and current living status records of the owner (involving driving habits, health history and travel period). In other words, the cooperation of vehicular edge and remote cloud maps the history record and real-time information of the user into an iterative living habit document for the purpose of further guiding specific user. Particularly in the case of emergence, for example, if the driver is detected of fatigue driving, the vehicular edge will send the abnormal message to the cloud. Due to small data size but high real-time performance of such message, communication mode of mobile network will be adopted. The cloud will make the emergency treatment in view of different message types, involving taking measures such as playing the prompt voice or music to stimulate the emotion and fatigue state of the driver, and adjusting the vehicular device into the safe autonomous driving mode forcibly. The safety driving can be guaranteed by the cooperative effect of long-term behavioral cognition and real-time behavioral detection.

4.1.2. Mobile cognitive application based on interactions among multiple smart devices

In recent years, due to rapid development of artificial intelligence and chip design, the quantity of mobile intelligent device is increased. For example, it is estimated that 325 million devices in 2016 will be significantly increased to about 929 million devices in 2021 globally [27]. The mobile intelligent devices include smart phone, augmented reality helmet, smart clothing, and smart watch, etc. These enhanced devices have been commonly defined as Smart Objects (SOs) [28,29] and represent fundamental building block for all IoT scenarios, including IoV.

Under the environment of vehicle-mounted edge cloud, the strict requirements on latency and reliability of the majority of mobile intelligent devices can be met. NB-IoT technology can also enhance the seamless connection among numerous devices [30]. Meanwhile the mobile intelligent device can enhance the user experience of vehicle-mounted environment, provide the convenient channel of information, and facilitate other aspects of people's life based on different applications. We explain the mobile cognitive application based on multi-intelligent device interaction with the example of mobile health surveillance (Fig. 5).

The health status of the driver not only influences his/her own safety, but also influences the safety of passenger in the vehicle, safety of other drivers, and even the traffic system security. In the case of poor health or fatigue driving of the driver, the attention of the drive will be significantly reduced, and the response time will be increased, which often results in the occurrence of traffic accidents. Therefore, it is very important to monitor the physical health of the driver during the driving process.

Under the traditional driving environment, the passenger and driver fail to understand the mutual healthy conditions before. Due to weakened state of consciousness, the tired driver even fails to know his/her own status but selects to drive continuously, which greatly threatens the safety of personnel in the vehicle. To improve such situation, the cognitive intra-vehicle network carries out the emotion analysis, driving behavior surveillance, and physical health surveillance. The camera of the intra-vehicle network can entrust the facial expression data of the driver to the vehicle-mounted edge device for analysis. As for the driving behavior detection, the camera detects the eyelid state and micro-nod of the driver, to discover the micro-sleep behavior effectively, analyze in combination with the data collected by the devices such as steering wheel and intelligent odometer embedding in the sensor, remind and give an early warning to the driver, and prevent the occurrence of traffic accidents. In addition, the healthy and physiological index data of each passenger and driver can be collected by the smart clothing and other wearable device, and uploaded to the vehicle-mounted edge for real-time analysis. D2D can be applied in this situation [31]. The vehicle-mounted edge assesses the health grade of each user by the data cognitive engine, and reports the analysis result to user's smart phone. Users in the same intra-vehicle network can select the visible window sharing the health status. If the driver suddenly feels unwell (such as burst of acute disease) during the driving activity, the vehicle-mounted edge will perceive the critically ill condition of the driver timely from the data collected by the smart clothing, adopt the safety automatic driving mode timely, and give an alarm to the nearby vehicles and cloud. The cloud will dispatch more resources (communication resources of cellular mobile network, and computing resources of remote data center, nearby vehicles and RSU) to carry out deeper and more comprehensive condition analysis for the ill driver. At the same time, the cloud rapidly contacts the ambulance, doctor and driver's home [32]; and delivers the analysis result to the doctor, so as to make the diagnostic analysis for patients by the time of the ambulance is on the way and enhance the survival rate of the ill driver.

4.2. Cognition in inter-vehicle network

Inter-vehicle network is composed of all vehicles that can communicate and share flexible resources. There are various communication modes of inter-vehicle network, involving the road edge communication, V2V communication, and mobile network communication. The intelligent autonomous moving object is the most important element in CIoV. Therefore, we take the inter-vehicle network into consideration, and solve the issues of data instability collected by the vehicle and 5G network resource optimization distribution by the cooperation cognition of inter-vehicle network.

4.2.1. IoV stable service modeling based on group cognition

Due to diversity of real road environment, the environmental data reported by the vehicle has the definite error. At the same time, the high-speed mobility characteristic of vehicle and the lower stability of wireless channel result in the vehicle data failing to reach timely and the larger data delay variation. Excavating the useful information from the data with the definite error and delay variation becomes the key issue of realizing the IoV landing. Next, the density of vehicle data service is characterized by the non-uniformity of spatial and time domains. In the spatial domain, the service volume of vehicles in the rural area is very large, while the vehicle data service volume in rural area and expressway is relatively low. In the time domain, the change in data traffic is drastic. The data traffic is large in the traffic peak period, while it is opposite in the work and rest time. The dynamic change of vehicle data traffic in the spatial and time domains is very large, thus it is very urgent to meet the flexibility and intelligent demand of IoV in the issues of site deployment, hotspot coverage, and resource distribution. In a word, the data instability and the high requirements on latency and reliability of communication link are two challenges of IoV service modeling.

The cooperation cognition of inter-vehicle network can enhance the stability of IoV service modeling. The theoretical model of vehicle data service built by CIoV includes three aspects of space, time and mobility.

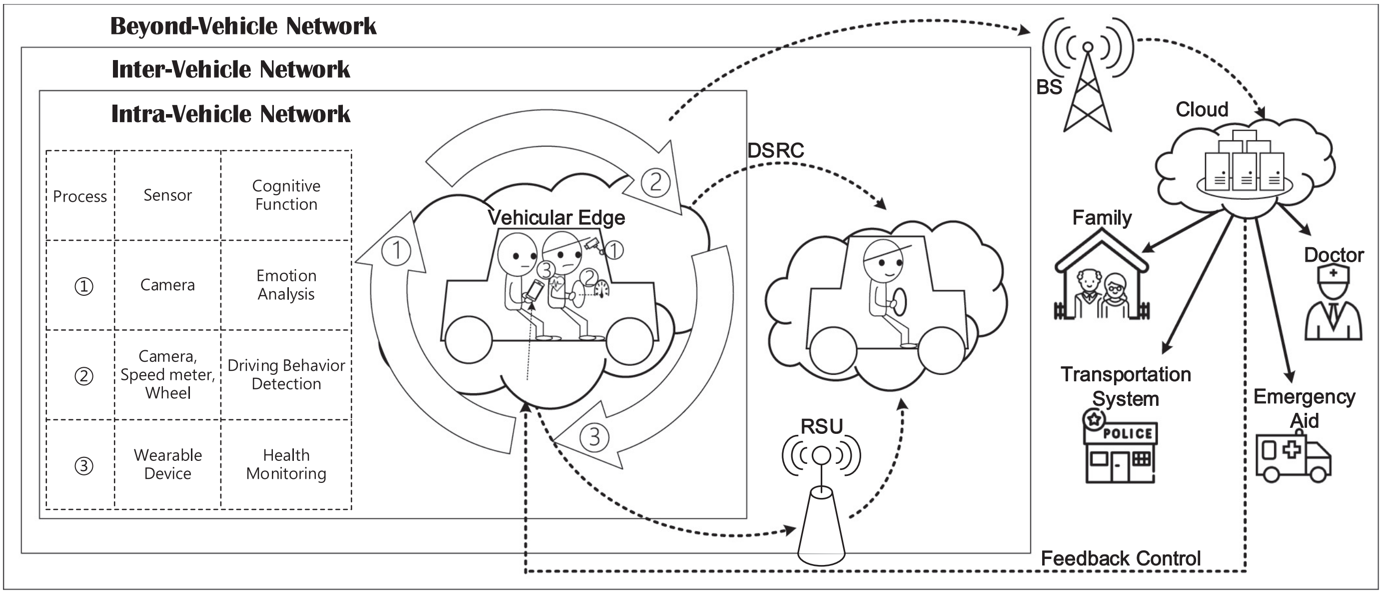


Fig. 5. A vehicular cognitive application: mobile healthcare scenario.

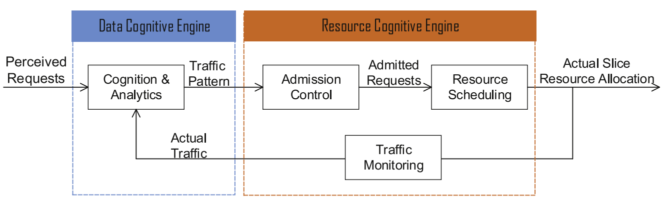


Fig. 6. 5G network slicing resource cognition.

The space model depicts the spatial position of the service data flow. The time model depicts the dynamic change of each data flow with the time. The mobility model depicts the change of service spatial position. When the cognitive IoV bears the data service, the space-time distribution of data service and the IoV transport service are closely coupled. By utilizing cognitive computing to tackle waving error and delay variation problems of vehicle data, useful information is extracted, the generalization ability of theoretical model is improved and the generalization error is under control. From the perspective of group cooperation of inter-vehicle network, the mutual cognition between the intelligent moving objects in the group can greatly enhance the pure vision-based environmental perception. Next, the sharing map modeling information by the group cooperation is more reliable. Finally by cognition of vehicle behavior in the time and space, the transport mechanism of vehicle data service with space-time random characteristics in IoV is established, and prediction accuracy of IoV service is enhanced, to enable the limited resources to provide an outstanding service.

4.2.2. Optimization of 5G network slicing resources distribution based on dynamic demand

There are different vehicle types on the traffic roads, such as private car, public car, freight wagon, ambulance, and police car. The vehicle-mounted device abilities (ratio of computing resource and flexible resource) and actual service demands (driving speed and passenger carrying capacity, whether being the special service) in different vehicle types are different. There are many different intelligent application demands inside CIoV, such as personal customizing information service, safety unmanned system, and real-time health surveillance system. In addition, the resource demand in driving is often changed dynamically. Thus, the traditional fixed resource distribution mode fails to satisfy the future driving environment.

5G network slice can create the special slice for the service with different requirements in CIoV. Specifically, it places the virtual network function in different positions (i.e., edge cloud or core cloud) in accordance with different service characteristics. The operator can customize different network slices (such as billing and strategy control) in the way as needed by the service to meet the user demands, and also it is the most cost-effective mode. Chen et al. [33] addresses green and mobility-aware caching issues in 5G networks. However, more research is required to discuss 5G resource allocation problems under the framework of Artificial Intelligence. In CIoV, we set forth the design idea of solving and realizing the closed loop optimization by double cognitive engine (Fig. 6).

Based on different demands (latency, reliability and flexibility) for different cognitive applications [40,41], the network slice service request types of IoV are also different. The data cognitive engine will combine the current resource distribution and real-time request of lessee, and carry out the fusion cognitive analysis of isomerous data in the methods of machine learning and deep learning. Then, the data cognitive engine reports the dynamic flow pattern analyzed to the resource cognitive engine. Resource cognitive engine jointly optimizes the comprehensive benefits and resource efficiency. Firstly, resource cognitive engine controls and screens the access request, then conducts the dynamic scheduling distribution of resources based on cognition to network resources, and feeds back the scheduling result to the data cognitive engine, to realize the closed loop optimization. By utilizing double cognitive engines for the dynamic scheduling of 5G network slice technology, different service qualities in IoV can be satisfied, total costs can be saved and the operation efficiency of network resources can be enhanced. Besides that, in order to further improve QoE of 5G network slicing, a delay announcement method is a new research direction [34].

4.3. Cognition in beyond-vehicle network

From the large scale, CIoV can collect and analyze the physical space data, involving data of intra-vehicle network driver, driving data of adjacent vehicles, and beyond-vehicle road environmental data. We provide the scheme of strengthening the cooperation of beyond-vehicle network, intra-vehicle network, and inter-vehicle network to achieve the total improvement of road traffic safety in CIoV in Fig. 7. On the other hand, due to its complexity, IoV has very strict requirements for the reliability of network safety. For the avoidance of events such as

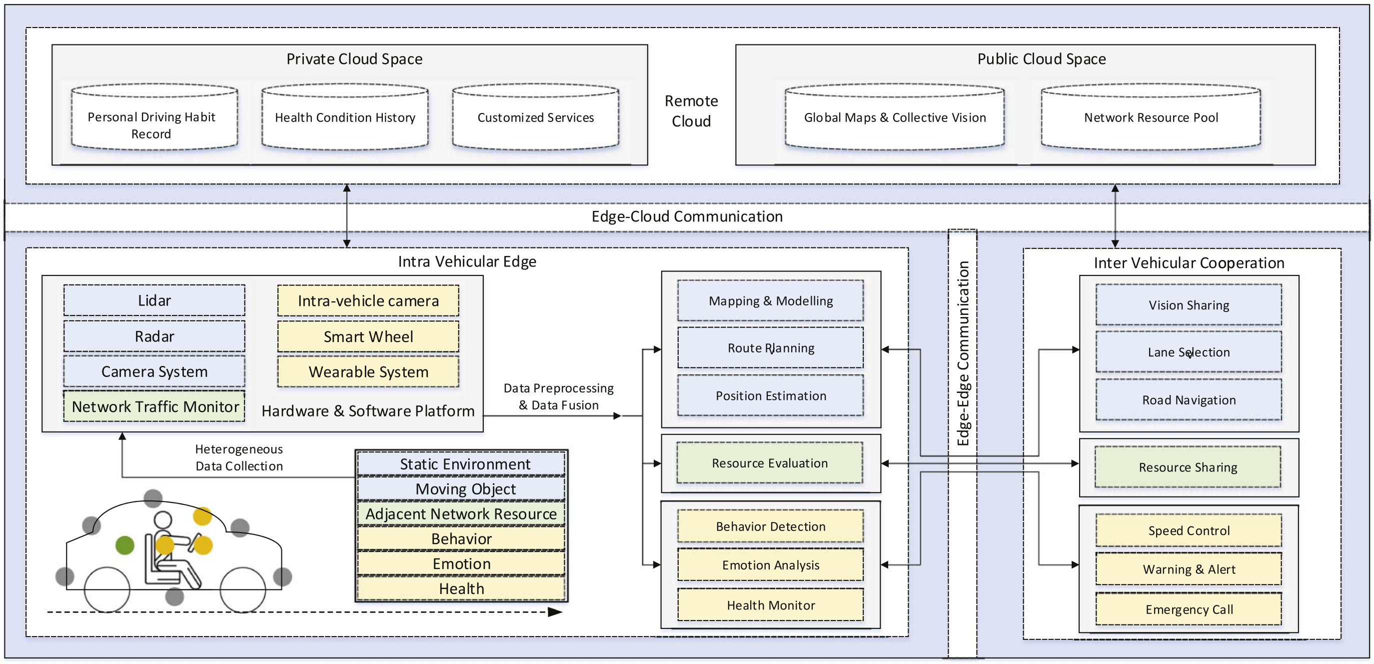


Fig. 7. Road traffic safety cognitive mechanisms.

personal information disclosure, traffic accident and breakdown of road system, CIoV realizes the network safety protection by the joint cognition of physical space and network space.

4.3.1. Road traffic safety enhancement mechanism based on cooperation of intra-vehicle network, inter-vehicle network, and beyond-vehicle network

As the most important element in CIoV, the intelligent autonomous moving object (represented by autonomous vehicle) has the correct perception and comprehension ability for the surroundings, and also has the automatic decision-making ability. The unmanned vehicle should recognize the driving behavior of the driver within the scope of intra-vehicle network. If the autonomous vehicle production, the people and the unmanned vehicle will coexist for a long term in the future, and the driving behavior of the people should be understood by the unmanned vehicle, so it is very important to research the cooperation driving mechanism between the unmanned vehicle and the driver. The driving state of each driver is the factor to be considered in the cognitive IoV. Through the cognition of intra-vehicle network to the driver state, the nearby inter-vehicle network shares the information, and gives an early warning to the driver in the fatigue state. The cloud will also distribute more resources to the driver in the fatigue state, and promote the ability of traffic system in dealing with the emergency situation.

For the cognition of beyond-vehicle environment, the intelligent autonomous moving object perceives the environment and collects the data by a series of self-equipped sensors such as radar, camera, navigator, and intelligent speedometer, and then finishes the environment modeling and builds the real-time 2D/3D map in accordance with the observed data and existing map, and automatically decides how to control the action of moving object by the motion trajectory planning modeling. At present, MODAT (Moving Object Detection and Tracking) technology of the intelligent autonomous object can solve the detection and trajectory tracking of (multiple) dynamic objects, and meanwhile predict their future trajectory, and accordingly provide the necessary information for the real-time obstacle avoidance planning. In addition, in the beyond-vehicle network environment, predicting the behavior of pedestrians is the most important category in the obstacle behavior prediction. The pedestrian detection and behavior prediction are aimed at detecting the nearby pedestrian target in the complex road conditions, classifying in accordance with the characteristics such as gray level, edge, texture, color and gradient histogram of target in the follow-up cognition process, identifying the pedestrian target, analyzing the height, age and other information of pedestrian, and predicting the dangerous acts of target. Started in the 1990s [35], the research of pedestrian behavior identification had been extensively applied to the aspects of medical rehabilitation and virtual reality, and had mainly analyzed and inferred the object behavior by monitoring the activist behavior or surroundings. The behavior identification is cored by behavior classification. There are many researches focusing on the performance of classification algorithm, such as [36] combining the decision tree and discrete hidden markov model (DHMM) for distinguishing the behavior.

The mutually adjacent intelligent autonomous moving objects can share the environmental map in real time based on the group cognition, to obtain more detailed and comprehensive perception. In addition, each intelligent autonomous moving object sends the collected traffic route information to the cloud, and the cloud gives the report of traffic road conditions based on the vehicle route. The traditional graph theory method (such as Dijkstra algorithm) and mathematical programming method have large computing amount, to result in long computing time. Moreover, according to the geometrical distance and road quality, it computes the optimal route and fails to describe the time variation of real-time traffic network objectively. CIoV makes the real-time description of traffic network possible, and also has the function of traffic flow prediction, to enable the large-scale topological network modeling to be more exquisite. The dynamic route planning optimization based on real-time traffic update of CIoV and the mechanism and algorithm of exploring the distributed solution of group intelligent moving object will be an important research direction of IoV.

4.3.2. Network data security strengthening mechanism based on joint analysis of physical space and network space

The network environment of IoV is different from the traditional network environment. Once the attacker invades, the remote control is conducted for the autonomous vehicle, to result in inestimable harms and threaten the life and property of the driver, and the massive network attack even affects the breakdown of overall traffic system. Therefore, the network security of IoV is very important. However, the safety automatic drive is confronted with great challenges. Firstly, due to complex yet diversified IoV service terminal, different service flow characteristics can not be extracted simply depending on the traditional intrusion detection model. Secondly, due to numerous devices carried in IoV, the corresponding bugs are various, and the platform difference is larger. The network security cognition should solve the issue of how to fix bugs rapidly without influencing the traffic safety. The traditional bug scanning mode has very high degree of dependence on the device and platform, and should put into lots of human and financial resources in the case of fixing the bug rapidly.

The network security protection of CIoV mainly involves two parts. Firstly, in view of characteristics of privatization and diversity of intra-vehicle network, it utilizes the semi-supervised learning algorithm, generates the large-scale accurate labeled data set based on a small amount of labeled data, to guarantee the validity of model training, and introduces the private feature encryption mode of the owner (such as basic biological feature and habitual driving behavior of the owner) on this basis, to realize the exact identification of attack on the intra-vehicle network. At the same time, in combination with the joint analysis of physical and network space, it realizes the prediction of threatening route. In the network space, the resource cognitive engine carries out the implementation monitoring for the network flow. The data cognitive engine makes the cognitive analysis on the network flow fed back from the resource cognitive engine, and provides the real-time feedback for automatic drive in combination with joint analysis of perception data of vehicle to peripheral road conditions, driving data of adjacent vehicles, and data collected from the intelligent traffic system (traffic network density and vehicle moving state) in the physical space. Once an abnormal driving tendency of a vehicle is discovered, the sensitivity of network data security will be enhanced rapidly, and the network space bug will be detected and repaired promptly. We will provide several possible solutions in the next section of Open Issue about more network security issues involved.

5. Simulation and evaluation

In order to evaluate the performance of the proposed CIoV, we simulate a network resource allocation strategy based on cognition of fatigue driving. In the simulation, we will focus on a vehicular edge system called component, which consists of RSU, BS and a range of vehicle ad hoc networks. We use MATLAB R2014a to conduct our simulation and the CPU type is AMD FX-8150 8-core. The result shows that CIoV can improve network resource utilization while ensuring QoE. In future work, a more complex experimental scenario will be considered.

5.1. Simulation setting

In our simulation scenario (Fig. 8), the resource cognitive engine on edge is responsible for the analysis and management of network resource within the component. The vehicles in the same component reports the driver's real-time fatigue state to the resource cognitive engine, and the cognitive engine allocates network resource based on the fatigue level. Specifically, we set our simulation setting as follows:

(1) *Definition of component*: we use the concept of component proposed in [37]. In a component, each vehicle can reach to one another and resource cognitive engine manage the entire network resource. The size of the component, denoted as S, is defined as the number of vehicles within it. In our simulation, considering the actual vehicular communication range, component size is chosen from 1 to 30. For each size of the component, the average of 20 groups of data are used for result analysis.

(2) *Definition of average network resources obtained per person*: for simplicity, we combine communication, computing and storage resource as network resource. Due to the component size is S, the user number is $i \in \{1, 2, 3, ..., S\}$. Based on continuous driving time, we classify the users into three levels of fatigue levels, namely, low, medium and high as shown in Table 2.
Users who drive for a long time are inclined to be more tired, correspondingly, CIoV should allocate more network resource to monitor and analyze these users' real-time status. In our simulation setting, we will quantify the network resources required by users of low, medium and high fatigue levels as 0.5, 1, 1.5, respectively. In other words, network resources required by user i should be $r(i) \in \{0.5, 1, 1.5\}$, and the average network resource obtained per person $\overline{R}$ can be derived by formula (1).

$$\overline{R} = \frac{1}{S}\sum_{i=1}^{S} r_i \tag{1}$$

According to formula (1), the average network resource obtained per person $\overline{R}$ can well quantify the utilization efficiency of network resources in the car network. As for the requirement of QoE, since the network resource allocated to tired drivers are more, this strategy can well reflect the feasibility of the resource allocation.

(3) *Concept of QoE*: we make the following assumptions on the concept of QoE: 1. If the resource obtained by the user is equal to or more than the resource required, then QoE of the user achieves its highest; 2. If the resource obtained by the user is less than required, then QoE of the user declines. It is worth noticing that extra resource will not improve the user's QoE. In this specific scenario, fatigued users require more network resource, on the contrary, users who have just started their journey would not require intensive computing resource since they are very energetic and less inclined to make driving misjudgments.

(4) *Concept of cognition*: in the absence of cognition, each driver is allocated with equal amount of network resource, where $r(i) = 1$ and $i \in \{1, 2, 3, ..., S\}$. Since in the actual situation, the allocation of resources is not uniform due to delay constraint and stability constraint, we set a up to 2% random error fluctuation in the resource obtained. In contrast, with the cognition of fatigue driving within the component, the resource cognitive engine is aware of each driver's condition and allocate corresponding network resource to meet different users QoE. The system flow is shown in Fig. 9.

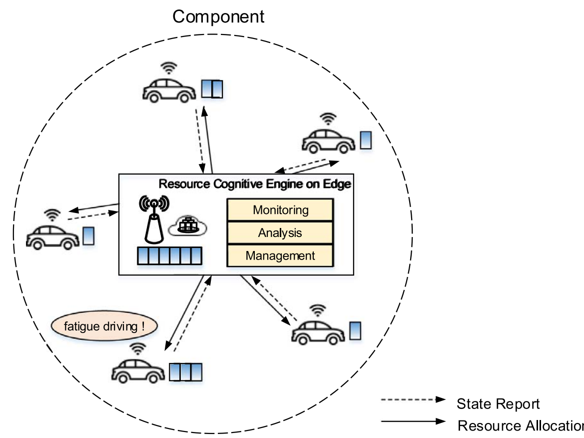


Fig. 8. Illustration of simulation scenario.

Table 2
Simulation parameter setting.

Driving time (h)	Fatigue driving level	Network resources required
< 1	Low	0.5
1–2	Medium	1
> 2	High	1.5

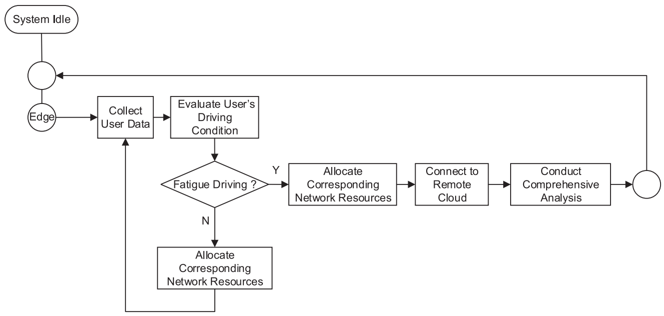


Fig. 9. Flow diagram of fatigue driving recognition and follow-up measures.

5.2. Result and analysis

The simulation result are revealed in Fig. 10. Fig. 10(a) shows the driving time for users normally follows an exponential distribution. It is noted around 90% of the users actually drive less than 1 h, which leaves great space for optimizing network resources. Taking into account the fact that network resource on edge is relatively limited, if drivers who travel more than 2 h are allocated the same amount of network resource as those who travel less than 1 h, it not only causes the abuse of limited network resource, but also greatly ignores the actual needs of drivers in the state of fatigue driving due to the invalid resource distribution. Therefore, optimization of the network resource based on cognition of fatigue driving is necessary.

As mentioned in simulation setting, network resource allocation is conducted with the guarantee of best satisfying the QoE of all users within the component. In other words, resource allocation with cognition of fatigue driving should naturally outperform the one without cognition in meeting the requirement of QoE. The simulation result of Fig. 10(b) shows that, the average network resource obtained per person with cognition of fatigue driving is around 0.6, which is far less compared to the one without cognition of fatigue driving. Therefore, with cognition of fatigue driving, less network resource is needed within a component while ensuring the QoE, in other words, the efficiency of utilization of network resource is greatly improved.

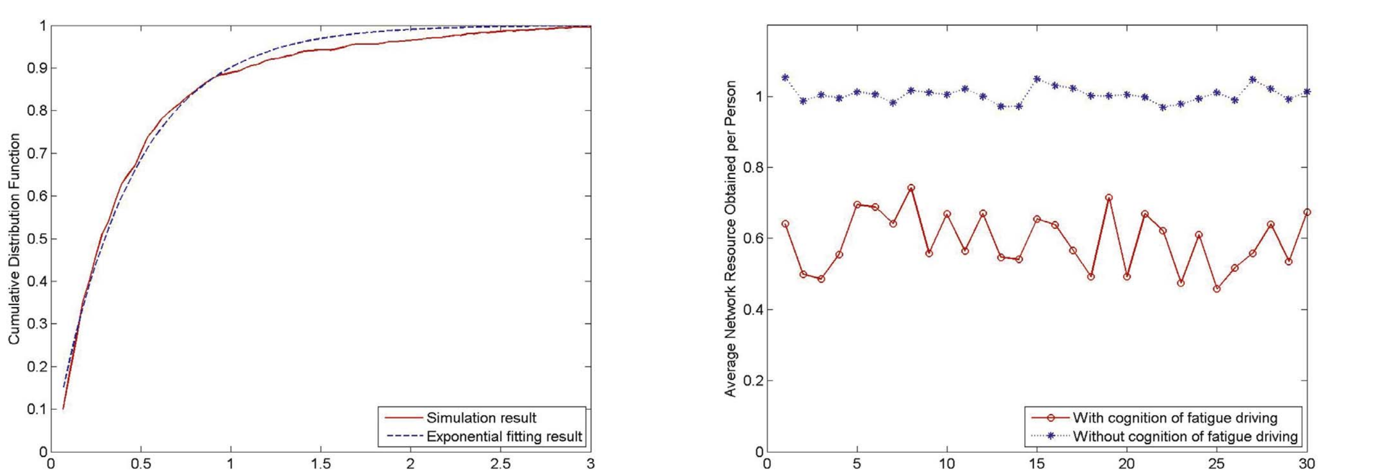
6. Open issues

6.1. Orchestration and automation

CIoV has large amount of heterogeneous access devices, e.g., an intelligent vehicle has multiple sensors, driver and passengers carry diversified intelligent devices. The structure of beyond-vehicle network is also quite complex, and high-performance computing should be considered in highly mobile network environment, otherwise, the access ways of devices are different at different scales. Therefore, how to realize automatic coordination and management among networks of different types is a quite challenging problem. Take mobile health monitoring scenario as an example. Through collecting and analyzing physiological indices, the smart clothes on cognitive intra-vehicle network has detected a driver with acute symptoms. After the hospital cloud receives alarm sent by smart clothes, it is necessary to feed back the true situation to mobile network operator, and urge mobile network operator to allocate more communication and computing resources to the specific vehicle. In this case, automatic orchestration problem of network slice resources is involved. Otherwise, if a driver is in fatigue driving, how could intelligent vehicles, pedestrians, nearby vehicles and road traffic system in the framework of CIoV automatically and rapidly make correct response in extremely short time, thus to avoid occurrence of traffic accidents. With development of 5G technology, under specific application requirements of CIoV, plenty of research work is needed to consider problems of task orchestration and automation. A feasible solution through opportunistic smartphone-based mobile gateways is proposed in [38] to address this issue.

6.2. System performance

There are a lot of limitations for control decisions of autonomous moving objects based on independent sensors, for example, in case of severe weather conditions (such as being late at night, rainstorm, fog and haze), or in case of complicated road condition scenarios (such as crossroads and turnings), the observation accuracy of radar or cameras of intra-vehicle sensors may decrease. If sensors with ultra high accuracy and stronger performance are to be developed in allusion to these special scenarios, consumers could not bear corresponding cost. AI technology provides possible solution ways to us, but the problem of system performance could not be completely solved at present. For



(a) Cumulative Distribution Function of Driving Time

(b) Comparison of Average Network Resources Obtained per Person With or Without Cognition of Fatigue Driving

Fig. 10. Simulation result.

instance, in aspect of image recognition, certain research progress has been made in DCNN (Deep Convolutional Neural Network) and the potential is also proved in intelligent driving field. However, there are still some defects for DCNN: on one hand, deep learning technology needs large amount of manually annotated training data, on the other hand, though recognition performance may be enhanced by adding hidden layer in hierachical framework [39], but the complexity of model would increase greatly. Finally, the training problem of model would become harder and harder. How to combine environment collaborative perception technology in physical space and flow data mining and prediction technology in network space on basis of AI technology will be the direction in future research on IoV.

6.3. Privacy and security

As a human-centered ecological system, CIoV will be faced with various challenges concerning privacy and security. Intra-vehicle network stores large amount of private information of the vehicle owners: the sensors on intra-vehicle network include driving videos and voices of vehicle owner in the vehicle; pictures, locations, activities and etc. may be shared on vehicular social platform; mobile healthcare application would also collect physiological health data of vehicle owner. Therefore, the information on cognitive intra-vehicle network is quite sensitive and needs extra protection. A possible solution is to conduct information encryption with biometric information, e.g., device access may be protected with iris and face recognition, otherwise, data sharing may be conducted through identifying heart rate and etc. Some data need to be shared to remote server for analysis, cooperation with network architecture and transmission protocol should be conducted in encryption [42].

Deploying machine learning capacity on vehicular edge cloud and establishing a strong distributed peer-to-peer network among edge devices is one of research trends in protection of privacy-sensitive cognitive applications. However, in the evolution course toward CIoV, there would necessarily be many vehicular devices with low intelligence and limited computing resources, and it is easier for these devices to be attacked by cyber attackers; these devices not only could not sufficiently protect their own resources, but they may also do harm to security in the whole road system. Consumers are often unwilling to upgrade vehicular devices with long service life. Therefore, with the reliability of large amount of distributed devices and system being taken into consideration, it is quite crucial to create a safe semi-automatic future driving scenario.

6.4. Power supply

With rapid development of smart grid technology, battery would probably become the chief energy storing device for automatic driving vehicles in the future. Since IoV is constantly evolving, the requirements on battery would be higher and higher. Intelligent vehicular devices contains many high-power consumption parts, such as network chips, GPS and continuous high precision sensors; furthermore, with comfort degree in driving experience being taken into consideration, it is also quite important to keep them concealed to passengers. Currently, the cruising duration of self-driving vehicles is limited, because the technological level of lithium ion batteries adopted is limited. If the energy efficiency problem is to be solved, advanced energy acquisition technology should be developed, thus to enable intelligent vehicles to acquire energy from ambient environment for direct use or storage in vehicular batteries. On the other hand, researchers are making great efforts to seek new materials, to improve energy density of batteries, and to reduce charging time, thus to enhance battery performance and to provide better user experience. Battery Management System (BMS) [43] is a possible solution which is safe, reliable and with acceptable cost.

7. Conclusion

In this paper, after overviewing the special demand brought out by future autonomous driving scenarios, a novel human-centric architecture called CIoV has been proposed, aiming to strengthen intelligence of IoV comprehensively. Embedded with cognitive intelligence, CIoV extracts and utilizes data from both physical and network space. To meet the rigorous application requirements, this novel architecture also brings abundant research challenges and opportunities. We have discussed cognitive design issues from three perspectives referred as intra-vehicle network, inter-vehicle network and beyond-vehicle network, respectively. To be specific, with the cooperation of three networks, safety of the transportation system can be guaranteed, efficiency of the network resource can be achieved and security of the cyberspace can be enhanced. Most importantly, CIoV is strongly connected with individual characteristic, therefore it can improve QoE of the driver and passengers. In our future work, we will implement the emotion communication technology in CIoV and also experiment on network slicing for more authentic driving scenarios. Though CIoV is still in its early stage, this architecture shows great potentiality in enabling future autonomous driving scenarios. enddocument

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