SENSING FUSION IN VEHICULAR NETWORK DIGITAL TWINS FOR 6G SMART CITY

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Abstract *– The aims demonstrated in this article are to effectively monitor the complex road environment in smart city transportation using the sixth generation mobile communication technology (6G) Digital Twins (DTs), to perceive the complex road environment of smart city traffic. Vehicular Networks (VN) in the smart transportation system have been selected as the research object, and the multi-sensor collaboration and fusion technology in the network is explored, so as to meet the active control requirements of intelligent vehicles. A lidar and camera fusion-based segmentation network C-LNet is proposed. The structure of a C-LNet multi-sensing data fusion segmentation network is double encoder-single decoder. Two encoders are used to extract image features and lidar features respectively. The same heterogeneous data is realized through the synchronization of lidar point cloud data and image data in sensor space. For multimodal information, a multiscale feature fusion-based vehicle collaboration method is designed. In the simulation experiment part, the C-LNet multi-sensing data fusion segmentation network is verified on the KITTI data set. The accuracy, F1 value, and MIoU of C-LNet are 98.4%, 96.7%, and 94.51%, respectively, which are better than those of an RGB network and lidar network. In summary, the smart transportation system supported by DTs in a 6G environment is explored. The proposed VN sensing fusion method can effectively realize the collaborative positioning perception of multiple vehicles, which lays the foundation for the realization of complex collaborative decision-making and control in smart transportation.*

Keywords – 6G, digital twins (DTs), sensing fusion, smart city, vehicular network (VN)

1. INTRODUCTION

The ability of mobile communications have evolved from focusing on person-to-person connection to fully utilizing object-to-object connection and further to comprehensively address object-to-object connection [1-3]. Since the rise of mobile communications, a new generation of mobile communications will begin large-scale commercial deployment to provide users with more powerful connectivity and new functions every ten years. 6G will adopt the latest technology to meet application needs from 2030 to 2040 or for even longer, and adapt and rely on each other with social and economic development. 6G adds a wide coverage and high delay communication scenario based on the three existing services of 5G to build a unified network with full coverage and connection [4]. The development of mobile communications is considered from the application demand of future intelligent urban agglomeration. Lv et al. (2018) [5] raised that the most important vision of communication technology is to enable smart urban agglomeration. 6G means faster speed, lower latency, and a lot of bandwidth. 6G goes beyond the “wired” network and uses equipment as an antenna, adopting a decentralized network that is not controlled by a single network operator. If all connections are 6G, the connected devices will be more free. The main reason is that faster data transmission speed and less delay make the instant connection from device to device possible. As one of the infrastructures of the urban agglomeration, 6G will adopt a unified network architecture and introduce new business scenarios to build a more efficient and complete network [6, 7]. In the future, 6G networks can be invested in by multiple operators to separate physical and logical networks through network virtualization technology, software-defined networks, and network slicing technology.

The smart city 3D visualization management platform realizes the scene display of various objects and data under the jurisdiction of government departments via 3D geographic information fusion technology [8]. Digital Twin (DT) technology is utilized to build a smart city digital space, supported by vivid visual effects, comprehensive data integration, and scene business display, effectively improving the monitoring and management efficiency of smart city Intelligent Operations Center (IOC) managers on urban operation, public security, transportation, government affairs, and other businesses, and support the auxiliary decision-making of a smart city and smart parks [9-11]. The spatial distribution and density of each facility component is displayed in the urban three-dimensional scene, and the status data and operational data of equipment and facilities are intelligently monitored, analyzed, and mined in combination with big data, so as to realize intelligent perception and decision support. The Internet of Things (IoT) perception channels are comprehensively integrated to construct a network logic structure of the IoT system, scene, event-based Unicom IoT perception status and business indicators. The logical relationship between the physical devices of each node and the operation of the service system is established to monitor the whole process of service operation, analyze the impact scope of events, and locate and remove obstacles for the root cause [12]. It realizes urban event convergence perception, monitors the whole process state of the event, integrates alarm, work order, personnel, vehicles, and other event monitoring and processing elements, completes early warning monitoring and event analysis via business scenarios and workflow, and helps to realize urban life cycle management.

With the acceleration of the vehicles towards intelligent, networking, and other directions, on the one hand, for urban buildings, roads, facilities, intelligent requirements are also getting higher and higher, vehicles need more support and protection of new urban infrastructure. On the other hand, the construction and development of smart cities also need to take the development of a smart Vehicular Network (VN) as the starting point and driving force, improving travel services and operational efficiency of cities through rational planning and optimization of urban infrastructure. The development of smart VNs requires smart cities as the foundation, and the development of smart cities requires smart VNs to provide an entry point. The two complement each other, so the coordinated development of smart city and smart VN needs to be accelerated. The development of a smart city is inseparable from the optimization and development of an intelligent transportation system [13, 14]. A VN is a local communication network composed of an Electronic Control Unit (ECU). On the whole, in the VN, the vehicle sensor is the input device of the vehicle computer system. It converts the various working conditions of the vehicle, such as the vehicle speed, the temperature of various media, and the operating conditions of the engine, into electrical signals to the computer so that the engine is in a good working state. It is obvious that the wheel rotation speed sensors are used to measure the speed [15-17]. At present, most of the speed meters on electric vehicles in China are converted into vehicle speed by the rotational speed of the automobile tire. Among vehicle sensors, ultrasonic radar is a common variety. For the short-distance measurement, an ultrasonic distance measurement sensor has great advantages and is often applied in reversing radar [18]. Ultrasonic radar is usually classified into two types, the first is installed on the front and rear bumper of the vehicle, which is the reversing radar used to measure obstacles. The other is an ultrasonic radar installed on the side of the vehicle to measure the distance of the obstacle on the side.

In the DTs-based smart city, the development of smart transportation should not only perceive the complex road environment, but also perceive the accurate and reliable location information of vehicles. The VN in the intelligent transportation system is selected as the research object to discuss the multi-sensor collaboration and fusion technology in the network, so as to meet the requirements of active control of intelligent vehicles. The innovation lies in the analysis of the smart city system supported by DTs technology in the 6G environment, especially the design principle of the existing VN mobile model. In addition, the vehicle-vehicle communication-based multi-vehicle cooperative positioning sensing method is improved and verified, which lays a foundation for the realization of complex cooperative decision-making and control in VNs.

2. RECENT RESEARCH DEVELOPMENT

2.1 Construction of smart city supported by 6G technology

6G has become one of the focuses of science and technology strategy competition among countries. However, there are many scattered technical points that need to be paid attention to in 6G, which is still at the level of academic research, and the concept of 6G has not yet formed a clear and consistent definition. 6G will utilize connected low earth orbit satellites and other non-ground network nodes and platforms to build a space-ground integration network, so as to achieve seamless coverage of sea, land, and air, including the sea, desert, mountainous areas, remote villages, and mobile platforms such as ships, aircrafts, and spacecrafts [19]. Moreover, it has intelligent decision-making and adaptive networking, deep integration of International Conference on Display Technology (ICDT), credible endogeneity, and the network performance is higher than that of 5G.

However, it is obvious that 6G technology, with its characteristics of high speed, low delay, and large capacity, meets the requirements of real-time, high efficiency, and stability of smart city system. Zheng et al. (2021) [20] pointed out that 6G expanded the reachable range of advanced medical technology, making telemedicine possible. Combining miniaturization and precision wearable devices with 6G technology provides a new idea for the management of chronic diseases. In addition, remote health data monitoring can monitor vital signs and capture various physiological parameters of the human body. Liu et al. (2020) [21] can realize the scientific and technological and refined management of agriculture and carry out all-round control from the aspects of crop production, distribution, and sales using the advantages of real-time, shared, remote, and fast 6G technology. High-precision soil moisture and temperature sensors are like small crop weather stations. Through 6G technology, information such as soil moisture, pH, nutrients, and meteorology are collected online, and functions such as automatic drought prediction and intelligent decisions of irrigation water consumption are realized. Therefore, 6G technology plays an important role in all aspects of a smart city, but its application in smart VN has not been reported yet. Thus, the intelligent VN in a smart city is discussed.

2.2 Intelligent perception of urban traffic

With the implementation of intelligent transportation system construction, continuous upgrading of travel services, and continuous development of intelligent computing technology, digital brings the means of innovation and technical upgrading of traffic planning. Urban traffic cognitive ability from road facilities to personal travel experience has been unprecedented improvement [22]. Zhang et al. (2021) [23] mentioned in their research that traffic sensor networks can select different sensing models and structures for different sensing objects such as fixed facilities and mobile devices, and adopt a fixed structure system to fuse all information. An intelligent sensing system has a strong adaptive ability, and the specific sensing process can be adjusted appropriately according to the changes of the environment. Kasture and Nishimura (2021) [24] realized the simulation of an ant transportation system model to analyze the cooperative perception and communication in the system. The intelligent sensing system conveys the traffic situation to a single ant, which uses this information for self-organization, so as to avoid traffic congestion. Due to the complex characteristics of an urban intelligent transportation system, a large amount of useless information in a sensing system and sensor network consumes limited computing and communication resources, resulting in the ineffective use of valuable information. Therefore, it is necessary to adopt a practical intelligent sensing method to obtain accurate traffic information in different cities.

2.3 Vehicular sensor network (VSN)

A VSN is a mobile self-organizing network formed by a large number of wireless sensor nodes loaded on the vehicle, which involves communication, computer, and wireless sensing. To meet people's requirements for vehicle safety, handling, and comfort, more and more electronic systems are integrated on the vehicle. The life cycle of vehicle sensor nodes consists of active and dormant periods. The node completes data collection in the active period, sends data to the gateway, receives and executes gateway commands; it turns off the radio frequency module during the dormant period to save energy until the next active period comes [25]. Zhang et al. (2021) [26] reported a lightweight, high sensitivity, low cost, and self powered 3D acceleration sensor based on liquid metal friction nano-generator, which retains the minimum size, minimum weight, and maximum integration. The sensor can find the collision position and collision force of the vehicle. Li and Liu (2021) [27] pointed out that the network coverage is limited by the movement of nodes, which will lead to frequent changes in network topology, and the movement of nodes is affected by many factors such as complexity, fuzziness, and randomness. The traditional sensor senses the specified physical quantity, converts it into an available input signal according to a certain law, and converts a non-electric quantity into an electric quantity. The collected information is processed by an electronic control unit to form execution instructions and complete the electronic control.

Considering that an intelligent vehicle is based on vehicle sensors, they are of great significance for the construction of intelligent transportation systems. However, the analysis on multi-sensor fusion in VN has not been reported. Therefore, a more in-depth discussion will be carried out.

2.4 Research review

Vehicle-mounted sensors have their own advantages and are difficult to replace each other, but there is a lack of overall consideration in the selection of sensor types and the number of sensors. The optimization of a fusion algorithm and the selection of fusion level lacks matching with the actual application, resulting in poor redundancy and fault tolerance of the system, and ultimately resulting in low accuracy of environment perception. Since the intelligent vehicles are based on on-board sensors, it is of great significance to the construction of intelligent transportation systems. However, the research on multi-sensor fusion in vehicle networks has not been reported. Therefore, further research should be carried out to address this research gap. The construction of multi-source information fusion-based intelligent vehicle environment perception systems aims to solve the problems of low precision and poor efficiency of traditional vehicle environment perception.

3. SENSING FUSION SCHEME FOR VN IN 6G SMART CITIES

3.1 Intelligent transportation system based on DT city

A smart city is the extension and upgrading of traditional cities. It makes full use of communication and information technology means such as IoT, cloud computing, optical networks, mobile communications and mobile Internet to comprehensively perceive, transmit, integrate, and analyze various key information among people, things, enterprises, and products, so as to make an intelligent response to citizens' various needs such as "medicine, food, housing, and transportation", It builds a new form of efficient urban management and intelligent urban development. In the context of a smart city, DTs are created to support the determination of smart city parameters and scene testing. With a land mobile communication network as the core, 6G deeply integrates a space-based network dominated by geosynchronous orbit and medium and low orbit satellite communications, a space-based network dominated by aircraft and UAV communications, a sea-based network dominated by underwater acoustic communications, and cable access dominated by optical fiber, twisted-pair, and coaxial lines. 6G connects wireless and wired media in a unified manner, enabling user data to be exchanged at the bottom as much as possible, thereby greatly shortening the time required for route selection and exchange, and thus reducing end-to-end delay for users of different access networks. As one of the infrastructures of urban agglomeration, 6G networks can be invested in and co-built by multiple operators. It separates a physical network from an operational network by network virtualization technology, software-defined networks, and network slicing technology. Artificial intelligence is deeply integrated into 6G systems, which will be applied in many aspects such as efficient transmission, seamless networking, endogenous security, large-scale deployment, and automatic maintenance.

Through 3D simulation technology + IoT access, it builds a platform for remote control and equipment linkage, which will reproduce the urban architectural geographical structure as it is, including the height, coordinates, and other geographical data of important facilities such as roads and buildings [28-30]. In addition, object-oriented facility information such as the internal structure, room layout, and pipe laying of important buildings such as committees and subway stations will be included. The DTs platform can sense the urban population heat map in real time, monitor the urban operation situation in real time through traffic flow, parking garage status, and video, or automatically collect the data returned to the center for image automatic identification and analysis, so as to intelligently find and identify abnormal problems such as garbage dumping, illegal buildings, and high-density traffic flows. It can deduce and predict future development. The key technologies in the construction of DT cities are shown in Fig. 1.

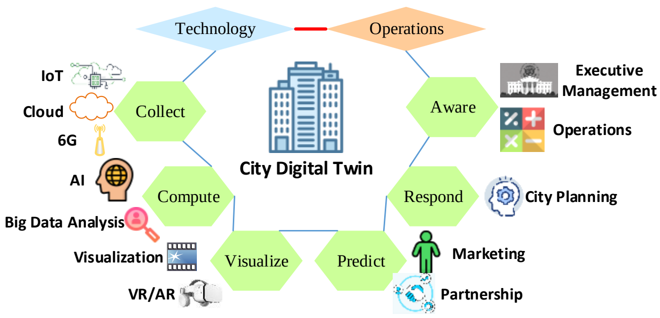

Fig. 1 – Key technologies of DT city construction

To build smart cities, useful data services will rely on data in the real environment, especially real-time data. The sensor or gateway product will send the selected data points from the building automation system to the open data platform. The smart city platform must utilize all available sensors in the building automation system instead of building overlapping sensor networks [31]. Most information in a smart city environment is location-related. This information is direct location information or reference information to location. Therefore, it requires sensors and automation Application Programming Interfaces (APIs) to associate location with data. For existing buildings, due to demolition or abandonment, the comprehensive living area will decrease linearly every year with the passage of time. For new buildings, it is assumed that the number of each specific building type increases linearly over time until it is replaced by newer buildings.

Traditional smart cities tend to pay more attention to the intellectualization of a certain industry or field such as construction, transportation, water affairs, and gardens, while DT cities are the intellectualization of the whole city based on the urban information model [32, 33]. On this platform, the professional data of the city can be integrated, so as to achieve a new pattern of planning a map, building a network of supervision, and urban governance. Taking the high-speed railway station in the DT city as an example, the biggest difference is that DT stations replace the traditional naked eye observation with scientific and technological means. For example, staff can easily access and enter equipment data through communication technology, panoramic images, and other technologies in daily operation and maintenance.

3.2 Intelligent perception and sensing network of urban traffic

A traffic intelligent environment mainly includes environment perception technology, modern communication technology, etc. Among them, environment perception technology mainly contains two solutions: independent vehicle perception (bicycle intelligence) and network collaborative perception (collaborative intelligence). Traffic information perception is a multilevel data conversion process including material, data, and feature layers. The material layer contains the sensitive phenomena and processes of the perceived traffic object; the data layer contains the conversion results of different sensors to the corresponding sensitive information; the feature layer is responsible for transmission, feature extraction, and fusion of data collected by the sensor, and finally obtains the perception information and transmits it to the perception subject [34]. Different from traditional perception, urban traffic intelligence can be adjusted to adapt to environmental changes while actively responding to changes in the surrounding environment [35, 36]. Moreover, the knowledge accumulation and reasoning rules of the perceived object can also be obtained through intelligent perception. The hierarchical relationship of urban traffic information intelligent perception is given in Fig. 2.

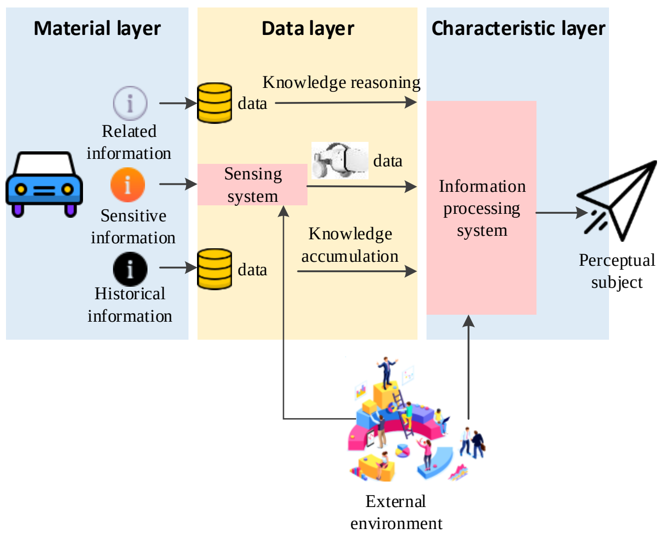

Fig. 2 – Hierarchical relationship of urban traffic information intelligent perception

In the simulation of intelligent transportation, if the collision avoidance between vehicles is considered, the exploration range of sensing equipment and the communication distance of communication technology are very important. Lidar is a kind of optical remote sensing technology to obtain target related information by detecting the scattered light characteristics of long-distance targets. The maximum detection distance of the existing lidar used in intelligent transportation is 300 m. Millimeter wave radar refers to a radar operating in the frequency band of 30 ~ 300 GHz with a wavelength of 1 ~ 10 mm. The mainstream available frequency bands are 24 GHz and 77 GHz. 24 GHz is applied for medium and short-range detection, and 77 GHz can realize long-range detection [37]. Since it is difficult for a single sensor to provide a comprehensive description of road conditions and environment under various weather conditions, multi-sensor fusion technologies such as radar-vision fusion have been gradually developed. The radar-vision integration refers to the integration of camera, millimeter wave radar, and high-performance processor to realize integrated perception and accurate prediction. Intelligent vehicles can obtain different information of the surrounding environment by configuring different sensing means and sensing the driving environment through multi-information fusion, so that intelligent vehicles have good environmental adaptability and provide safe, fast, and a reliable guarantee for autonomous navigation.

Autonomous vehicle environment perception technology in intelligent traffic environment is mainly realized through general vehicle sensors, perception sensors, high-precision maps, and other technical means [38]. General on-board sensor general vehicle sensor refers to the sensor installed on the vehicle in the vehicle manufacturing stage, which is classified into engine control sensor, chassis control sensor, and body control sensor. The basic structure of a traffic perception sensor network is illustrated in Fig. 3. The basic function is to perceive information, and then transmit the perception results to the information processing center through appropriate transmission methods.

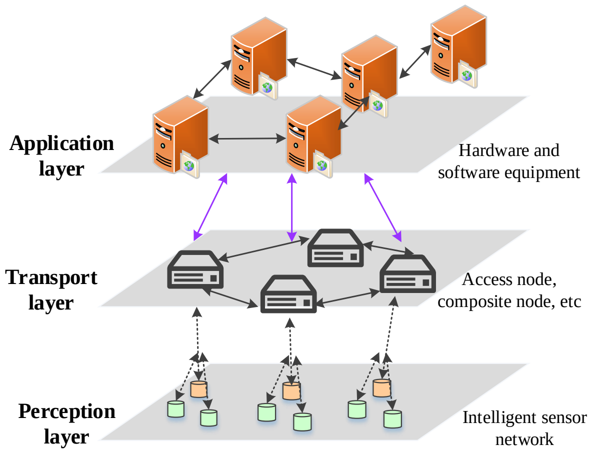

Fig. 3 – Basic structure of traffic perception sensor network

All nodes are connected wirelessly in wireless sensor networks and adopt different communication protocols. Since an electromagnetic wave is exposed in the air, it is more susceptible to interference and attack in wireless communication mode than wired communication mode, which affects the stability of communication connection. In terms of bandwidth, because the communication connection of nodes is relatively static, the complexity of system design can be reduced based on Wireless Local Area Network (WLAN) standards. As a hierarchical network, a hybrid traffic perception sensor network plays different roles at different levels. Usually, the underlying traffic detection sensor is responsible for converting the basic physical traffic information into electrical signals and sending them to the upper transmission network. At the transport layer, the access node is responsible for collecting the transmission information of the underlying sensors and managing different sensors uniformly. The composite node integrates the related functions of the network relay equipment in the communication system. Generally, an access node accesses and manages several sensors, while a composite node is mainly responsible for the link between multiple access nodes.

3.3 Mobile model of VSN

Internet of Things is the most core application in many scenarios of 6G mobile communications. The future Internet of Things will put more emphasis on the intelligence of connected devices based on its connectivity, which will realize the evolution from the traditional Internet of Things to the intelligent Internet of

Things, and greatly expand the application range of the Internet of Things. The Internet of Things-based intelligent vehicle-mounted system, combined with RFID, GPS positioning, GPRS communications, and image acquisition technologies, enables the logistics vehicles to communicate with the monitoring terminal in real time without manual operation, realizing the real-time monitoring of the whole process of the logistics vehicles. The VSN has a wide distribution range and complex and changeable network topology. Its main characteristics include fast node movement speed and vehicle movement will affect network coverage, which puts forward higher requirements for the routing protocol of VSN [39, 40]. Therefore, the analysis on network routing and data transmission can be realized by establishing an accurate node mobility model based on simulation. For a self-driving car to truly navigate autonomously, the vehicle must know its location, its surroundings, and nearby vehicles. In addition, these vehicles may be very close to each other and drive autonomously at higher speeds.

There are two main methods of Vehicle to Everything (V2X) communication: Dedicated Short-Range Communication (DSRC) and Cellular Vehicle-to-Everything (C-V2X). DSRC is supported by a series of standards, including IEEE 802.11p amendment for wireless access in vehicle environment and IEEE 1609.1-4 standard for resource management, security, network service, and multichannel operation [41, 42]. In addition, the carrier sense multiple access with collision avoidance used in IEEE 802.11p is not suitable for key communication scenarios, that is, QoS in VN applications can't guarantee security critical messages and other real-time transmission. On the other hand, 3rd Generation Partnership Project (3GPP) has been developing cellular vehicle communication to operate on cellular networks, which can provide high data rate services and wide coverage. The overview of VSN is shown in Fig. 4. Both V2X technologies have their own advantages and limitations.

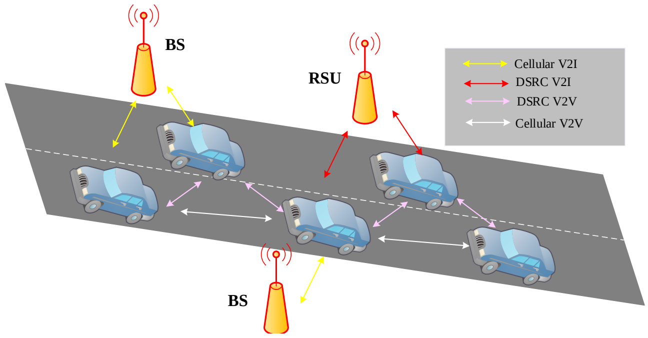

Fig. 4 – Overview of VSNs

In mobility management, Random Waypoint Model (RWP) is a random model that simulates the movement of mobile users and how their position, speed, and acceleration change with time. In the random mobility simulation model, mobile nodes move randomly and freely without restrictions. More specifically, the destination, speed, and direction are randomly selected and independent of other nodes. Mobility models are used for simulation purposes when evaluating new network protocols. Because of its simplicity and wide availability, it is one of the most popular mobile models for evaluating mobile ad hoc network routing protocols [43, 44].

Road simulation is based on the open source software Simulation of Urban Mobility (SUMO). The SUMO road network can be generated using its own program or by importing a digital road map. The road network importer allows it to read the network from other traffic simulators such as Vissim or MATsim. SUMO is a purely microscopic traffic simulation, and Fig. 4 is a map of its GUI. Each vehicle is given an identifier, departure time, and the route the vehicle takes in the road network. A macro-traffic simulator treats the entire traffic flow as a unit. SUMO can also define departure and arrival properties, such as lanes, speed, or location. Each vehicle is assigned a type that describes the physical characteristics of the vehicle and the variables of the motion model. The simulation is both time-discrete and spatially continuous, and internally describes the position of each vehicle, i.e. the lane it is in and the distance from the starting point. When the vehicle is moving, the following model is employed to calculate the speed. In addition to traditional transportation measures, SUMO has expanded to include noise emission and pollutant emission/fuel consumption models. SUMO traffic modeling defines the total number of traffic groups in a given area and calculates the mobility desires of that group as input to a traffic simulator. Some software can also take into account environmental features, such as weather conditions. The module SUMO-ROUTER reads the departure time, starting point, and destination of a group of virtual groups to be simulated, and then calculates the route in the traffic network using the Dijkstra routing algorithm.

In general, cellular-based telematics is a paid service based on subscriber subscription. It is believed that vehicle communication will be built on a hybrid architecture in the near future. In this hybrid architecture, long-distance communication technologies, such as cellular networks and WiMAX, can provide instant Internet access. However, short-range communication technologies, such as Dedicated Short-Range Communication (DSRC) and Wi-Fi (802.11a/b/g), can provide a real-time response guarantee for security systems and provide effective support for location-based information services.

In RWP, in the initial state, the nodes are uniformly distributed in the whole simulation area. Firstly, the nodes randomly select a node from the two-dimensional simulation area as the destination, and then randomly select a speed from [Vmin, Vmax], and the nodes move to the destination at this speed. After reaching the destination, the node randomly selects a residence time T in [0, Pmax], and then selects the next destination. The vehicle trajectory and speed change of the RWP motion model are given in Fig. 5.

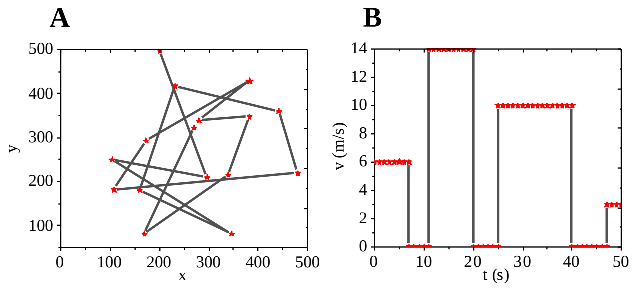

Fig. 5 – Vehicle trajectory and speed change of RWP motion model (A. Vehicle trajectory; B. Vehicle speed)

The RWP model defines a mobile station moving in a finite region *A*. Usually, *A* is a rectangle or a circle. The mobile platform moves from one "road point" M_n to the next point M_{n+1} according to the following rules. The phenomenon of density wave exists in RWP, that is, the nodes will show non-uniform distribution over time, reaching the maximum at the center of the simulation region, while the density tends to be 0 at the boundary.

In the Fluid Traffic Model (FTM), speed *v*, traffic density *k*, and traffic flow *q* are used as parameters to describe the overall characteristics of traffic flow. When the traffic flow *q* is constant, the relationship between the speed and density of the mobile node is as follows.

$$\frac{dv}{dt} = -c^2 k^n \frac{\partial k}{\partial x} \tag{1}$$

c represents the non-negative constant coefficient, *n* is a variable parameter, and Equation (2) can be obtained.

$$v = \begin{cases} \dfrac{ck_{jam}^{(n+1)/2}}{n+1}\left(1-\left(\dfrac{k}{k_{jam}}\right)^{(n+1)/2}\right) \ldots n \neq -1 \\ c\log\dfrac{k_{jam}}{k} \ldots n = -1 \end{cases} \tag{2}$$

k_{jam} means blocking density. Since the vehicle speed is a monotonically decreasing function of density, the vehicle speed will reach a critical state when blocking.

$$v = \max\left[v_{\min}, v_{\max} 1 - \left(\frac{k}{k_{jam}}\right)\right] \tag{3}$$

$v_{\min}$ and $v_{\max}$ represent the minimum speed and maximum speed, respectively. The average speed of the vehicle will increase with the increase of k_{jam}.

The Intelligent Driver Model (IDM) in VSNs is a stimulus response model, and environmental changes will stimulate drivers to make appropriate responses. The current instantaneous acceleration of the vehicle can be expressed as Equation (4).

$$a(t) = a\left[1-\left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*(v,\Delta v)}{s}\right)^2\right] \tag{4}$$

a represents the maximum acceleration of the vehicle, v_0 represents the expected speed of the vehicle under free flow, *v* means the current speed of the vehicle, Δv means the speed difference between the front and rear vehicles, and $s^*(v,\Delta v)$ is the safety distance between the rear and the front vehicles. The role of δ is to adjust acceleration behavior.

The calculation of acceleration is mainly divided into two parts based on the driving state, namely the free acceleration of the vehicle when it is not affected by other vehicles, and the acceleration of the vehicle when it is affected by the front vehicle. The expected safety spacing of nodes can be expressed as below.

$$s^*(v,\Delta v)=s_0+v\cdot T+\frac{v\cdot\Delta v}{2\sqrt{ab}} \tag{5}$$

s_0 denotes the minimum distance between the front and rear vehicles in the state of traffic congestion; T represents the safe time headway; a and b mean the maximum driving acceleration and maximum driving deceleration of the vehicle.

To further simulate the continuous speed and position changes of nodes, it sets the simulation time interval Δt of the model. The new speed, new position, and new inter-vehicle distance of the vehicle are expressed as follows.

$$v(t+\Delta t)=v(t)+\left(\frac{dv}{dt}\right)\cdot\Delta t \tag{6}$$

$$x(t+\Delta t)=x(t)+v(t)\cdot\Delta t+\frac{1}{2}\left(\frac{dv}{dt}\right)\cdot(\Delta t)^2 \tag{7}$$

$$s(t+\Delta t)=x_1(t+\Delta t)-x(t+\Delta t)-L_1 \tag{8}$$

x_1 and x are the positions of the leading vehicle and the current vehicle, respectively; L_1 indicates the body length of the leading vehicle.

In the IDM model, the following state of the two vehicles is not judged. Therefore, when the distance between the two vehicles increases to a certain value, the vehicle may not be in the following state. Therefore, based on the judgment of the following state in IDM, the optimized acceleration equation is expressed as below.

$$a(t)=\begin{cases} a\left[1-\left(\frac{v}{v_0}\right)^{\delta}\right], s^*<0 \ and \ s>s_T \\ a\left[1-\left(\frac{v}{v_0}\right)^{\delta}-\left(\frac{s^*(v,\Delta t)}{s}\right)^2\right], s^*>0 \ or \ s\le s_T \end{cases} \tag{9}$$

s_T represents the threshold for judging the following behavior.

Furthermore, a cloud model is introduced into IDM to correct relevant parameters, and then the differences reflected by different drivers in different situations are described, so that the movement model is more consistent with the actual movement law of the vehicle. The corrected acceleration and expected spacing are shown in Equations (10) and (11).

$$a(t)=a\left[1-\left(\frac{v}{v_0}\right)^{\delta}-\left(\frac{s^*(v,\Delta t)}{s}\right)^2\right] \tag{10}$$

$$s^*(v,\Delta t)=s_0+v\cdot T+\frac{v\cdot\Delta v}{2\sqrt{ab}} \tag{11}$$

Time dependence τ is introduced into the intelligent driver model, which is corrected by the cloud model, reflecting the correction of acceleration value.

$$a(t+\tau)=a\left[1-\left(\frac{v}{v_0}\right)^{\delta}-\left(\frac{s^*(v,\Delta t)}{\Delta s}\right)^2\right] \tag{12}$$

The spatial dependence k is introduced in the process of correcting the expected speed of the vehicle, and the road dependence l is introduced in the process of correcting the safety following vehicle headway.

$$v_k=k\cdot v_0 \tag{13}$$

$$T_l=T/l \tag{14}$$

For the reliability problem of the communication network, it is assumed that the reliability of nodes and links is random and independent, intelligent sensor network $G=(N,L,A)$ is a network without isolated points and parallel links. Under the constraint of cost, the reliability optimization problem of intelligent sensor networks can be expressed as follows.

$$\max R(x)=\left\{\sum_{\Omega}\left[\prod_{l\in L}P(l_j)\right]\cdot\left[\prod_{l_j\in(L/L')}\left(1-P(l_j)\right)\right]\right\}\cdot\left[\prod_{i=1}^{N}P(n_i)\right]$$

$$s.t.\sum_{j=1}^{N}c(l_j)d_ju_j+\sum_{i=1}^{N}c(n_i)\le C(x) \tag{15}$$

$$P(l_{ij})=F\left[c(l_{ij})\right] \tag{16}$$

$$P(n_j)=G\left[c(n_j)\right] \tag{17}$$

$R(x)$ represents the overall reliability of the network. $P(l_j)$ and $P(n_i)$ denote the reliability of link l_j and node n_i; Ω means the set of all available states of the network. d_j represents the link length, L is the number of links, and N is the number of nodes. $C(x)$ is the maximum usable cost, and $c(l_j)$ is cost of link j at each unit distance, $c(n_i)$ is the node cost. F denotes the functional relationship between link reliability and unit price, and G means the functional relationship between node reliability and cost.

3.4 Multi-source information fusion and multi-sensor cooperative perception method

In a smart city traffic system, multi-source information fusion intends to combine and optimize the perception results of each single signal source, so as to output more effective road safety information. Common signal sources are: millimeter wave radar, ultrasonic, camera, laser, Global Positioning System (GPS), odometer, and inertial navigation. These sensors can perceive the safety information around the body and the environmental information of the driving road, and can also be used for positioning [45, 46]. The hardware architecture of the multi-information fusion system includes two modules, namely millimeter wave radar and camera. The camera module first detects the target, and then transmits the information to the radar. The radar module completes the information fusion.

The multi-sensor fusion strategy can be divided into different levels according to different classification conditions. Under the definition of the classification index of information abstraction level, the strategy is divided into data level, feature level, and decision level. The three types of sensor information are presented in different ways, and the processing methods selected for them are also differentiated. Data-level fusion is at the lowest level of fusion, directly targeting data sensed by sensors. It retains the amount of information contained in the original data to the greatest extent, and the fusion accuracy is high. However, the calculation amount is huge, the real-time performance is poor, and the requirements for the algorithm are relatively high, and a fault-tolerant mechanism for sensor errors and noise is required. Feature-level sensor information fusion acts on the representative feature values extracted from sensor data, and the feature information is input into the fusion center for fusion. Its characteristics in all aspects are relatively balanced. Decision-level fusion is located at the highest level of fusion. Each sensor detects independently, performs feature extraction, and outputs certain detection results. The fusion process is the judgment, association, and processing of the detection results.

The world coordinate system is a three-dimensional space coordinate, and the image captured by the camera is a two-dimensional pixel coordinate. The *Z* axis in the camera coordinate system means the optical axis, and *M* is a point in the world coordinate system. The imaging position on the optical prototype is *m* point by visual sensing equipment. The relationship between *M* and its projection point *m* is as below.

$$s\tilde{m} = A\left[Rt\right]\tilde{M} \tag{18}$$

s is size scaling factor, $\left[Rt\right]$ is external parameter of camera, *A* is internal parameter matrix.

$$A = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \tag{19}$$

u_0 and v_0 are the projection center; α and β are the size scaling factor of the *u* axis and the *v* axis on the image, respectively; γ describes the skewness of the two coordinate axes.

It is assumed that the *Z* axis is always 0, and Equation (18) can be expanded to obtain Equation (20).

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = A\left[r_1\ r_2\ r_3\right]\begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \tag{20}$$

The pinhole model can be represented as below.

$$\begin{cases} s\tilde{m} = H\tilde{M} \\ H = A\left[r_1\ r_2\ r_3\right] \end{cases} \tag{21}$$

H is a 3 × 3 matrix.

It is supposed M_i and m_i are points on world coordinate and image coordinate. If m_i exists, the covariance matrix is C_i. The maximum likelihood estimation of the *H* matrix can be obtained by the following objective function.

$$\sum_i \left(m_i - \hat{m}_i\right)^T C_i^{-1}\left(m_i - \hat{m}_i\right) \tag{22}$$

The parameters in the above are defined as follows.

$$\hat{m}_i = \frac{1}{\bar{h}_3^T M_i}\begin{bmatrix} \bar{h}_1^T M_i \\ \bar{h}_2^T M_i \end{bmatrix} \tag{23}$$

The camera calibration problem can be transformed into a non-linear quadratic programming problem.

$$\min \sum_i \left\| m_i - \hat{m}_i \right\|^2 \tag{24}$$

For the sensing fusion of forward-field millimeter wave radar and camera in a VN environment, it is realized based on Kalman filtering theory and a global nearest neighbor data association algorithm.

Firstly, the multi-target tracker and the state of the target at the previous time are established based on the Kalman filter to predict the current position of the target. Next, through the global nearest neighbor algorithm, the cost matrix is applied to assign the observed values detected by radar and camera to the tracked target. Through the above fusion calculation, the current target position is finally obtained and the state update is completed.

The Kalman filter is suitable for estimating the optimal state of a dynamic system composed of random variables. Even if the observed system state parameters contain noise and the observed values are inaccurate, the Kalman filter can complete the optimal estimation of the true state values. For an object moving along the X axis with constant acceleration, based on Newton's law of motion and taking into account the noise term of uncertainty in the process of motion, Equation (25) can be obtained.

$$\frac{d}{dt}\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} a + \begin{pmatrix} 0 \\ 1 \end{pmatrix} v_k \tag{25}$$

v_k refers to the disturbance of noise, which is Gaussian white noise with mean as zero.
Equation (25) is extended to two dimensions.

$$\frac{d}{dt}\begin{pmatrix} x_1 \\ x_2 \\ y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}\begin{pmatrix} x_1 \\ x_2 \\ y_1 \\ y_2 \end{pmatrix} + \begin{pmatrix} 0 \\ a_x \\ 1 \\ a_y \end{pmatrix} + \begin{pmatrix} 0 \\ v_y \\ 0 \\ v_y \end{pmatrix} \tag{26}$$

After discretization of Equation (26), the motion equation is integrated within any time interval T to obtain Equation (27).

$$\begin{pmatrix} x_{1,k+1} \\ x_{2,k+1} \end{pmatrix} = \begin{pmatrix} 0 & T \\ 0 & 1 \end{pmatrix}\begin{pmatrix} x_{1,k} \\ x_{2,k} \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix}\tilde{v} \tag{27}$$

$\tilde{v}$ refers to the integral of noise in the sampling time domain. Equation (27) can be further converted.

$$x_{k+1} = F_k x_k + G_k u_k + v_k \tag{28}$$

F_k represents the state transition matrix, G_k is the control matrix, and v_k is the random disturbance of noise in the model. The measurement model is set as the actual measurement value associated with the current state at any time.

$$z_k = H_k x_k + w_k \tag{29}$$

w_k means the noise generated by the measurement process at the current time step.

When the object follows the nonlinear equation, the linear Kalman can be expanded to obtain the extended Kalman filter. The state Jacobian matrix is adopted to replace the state transition matrix.

$$x_{k+1} = f\left(x_k, u_k, w_k, t\right), F^{(x)} = \frac{\partial f}{\partial x}, F^{(w)} = \frac{\partial f}{\partial w_i} \tag{30}$$

$$z_k = h\left(x_k, v_k, t\right), H^{(x)} = \frac{\partial h}{\partial x}, H^{(v)} = \frac{\partial h}{\partial v} \tag{31}$$

w_k and v_k respectively refer to the noise factors in the prediction model and the measurement model.

Common development tools for multi-sensor fusion mainly include the Automated Driving System Toolbox (ADST) in a MATLAB environment. Firstly, the data collected by each sensor and the corresponding configuration parameters are loaded, and the image coordinate system is drawn after the video frame to be detected is specified. The vehicle coordinate system is drawn in the aerial view, and the lane detection results are created and updated in the aerial view and the image to display the results of visual detection and radar detection.

4. EXPERIMENTAL DESIGN AND SIMULATION RESULTS

4.1 Experimental design

Visual sensors can sense the color and texture information of the surrounding environment and complete a series of environmental perception tasks. However, when the light is insufficient, the performance of visual sensors is poor. Because lidar can provide accurate distance and speed information, in the field of automatic driving, the combination of two-dimensional image data and the lidar point cloud can realize the accurate estimation of vehicle position and direction. Simulation of Urban Mobility (SUMO) is used in MATLAB to realize the simulation of micro-traffic in the experimental part of this study. A road network file, routing file and configuration file are required. After extracting SUMO, four folders (bin, data, docs, and tools) are obtained. Most of the files under the bin folder are executable. The difference is that some executable files are not encapsulated, so it needs to open them with the command line. The docs folder mainly contains examples and help documents such as Java and Python. Tools are mostly written in Python.

During the experiment, the radar sensor is installed 15 cm to the left of the middle of the vehicle's front bumper. Firstly, data fusion and status update of existing targets are carried out. Secondly, the parameters of the fused target are integrated to obtain the target information provided by radar and camera. The final experimental data includes the original video data and the read radar signal. In the network encoder module, multiscale feature fusion is carried out for the two sensors. Learning from Full Convolutional Networks' (FCNs) network structure is to make full use of the information characteristics obtained by sensors. Only three down-sampling layers are used, and 3 × 3 convolution kernel is used in each layer, and then it is connected to the Relu non-linear activation unit. At the end of the network, the results are convoluted to Tensor with the same dimension as the label and sent to the softmax layer. After the secondary classification, the classification probability that each pixel belongs to the road is obtained. The structure of a C-LNet multi-sensing data fusion and segmentation network is double encoder-single decoder. Two encoders are used to extract image features and lidar features. The network structure of C-LNet is shown in Fig. 6.

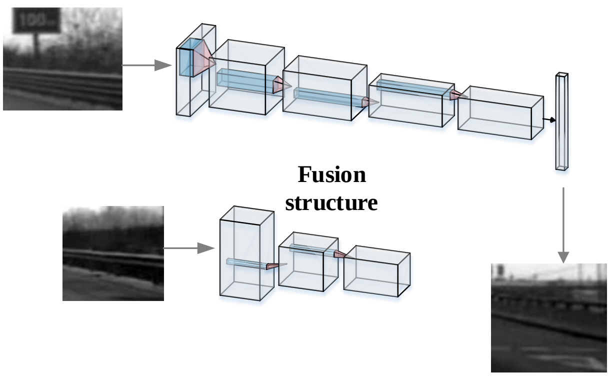

Fig. 6 – Network structure of C-LNet

The automatic driving KITTI data set is selected to test the performance of a C-LNet multi-sensing data fusion segmentation network. 50 images from the 289 images in training are used as the validation set, the training data pictures are expanded to 863 by random turning and random rotation. All KITTI image data is normalize to a size of 1248 × 384. The initial learning rate is set to 0.0001 and the Adam optimizer is adopted. Accuracy (ACC), F value, and MIoU are used to comprehensively evaluate the performance of data fusion networks.

4.2 Multi-sensor data fusion results

To verify the effect of the multi-sensing data fusion method, a target vehicle (target 1) that appears in the field of vision for about 10 seconds at the beginning of the video is selected, and the lateral and longitudinal distance tracking results of the vehicle are obtained (Fig. 7). Another target vehicle (target 2) that appears in the field of vision for about 15 seconds near the end of the video is selected, and the corresponding lateral and longitudinal distance tracking results are obtained (Fig. 8). The longitudinal distance of the target provided by the radar is relatively stable compared with the longitudinal distance observed by the camera. The lateral distance of the target provided by the camera is relatively stable, and the fluctuation of the radar is particularly intense in the initial stage. From the final fusion results, the estimation of longitudinal distance is mainly dominated by radar, while the estimation of transverse distance is mainly dominated by camera.

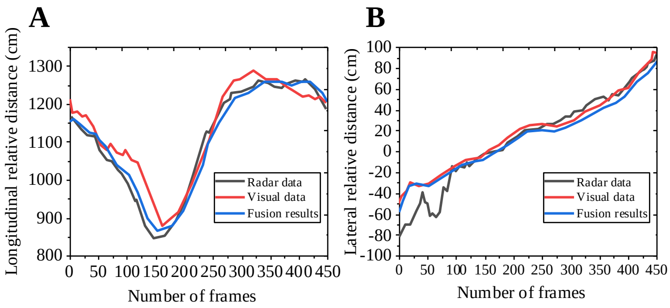

Fig. 7 – Tracking results of lateral and longitudinal distances to target 1 (A. longitudinal; B. lateral)

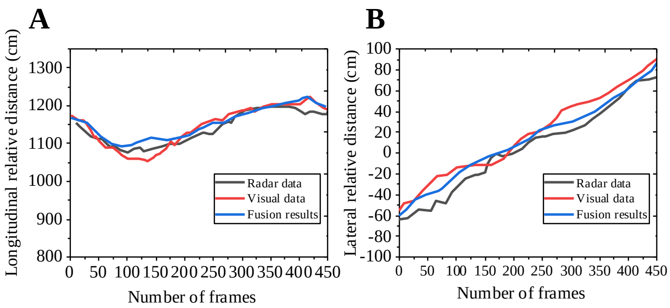

Fig. 8 – Tracking results of lateral and longitudinal distances to target 2 (A. longitudinal; B. lateral)

The C-LNet multi-sensing data fusion segmentation network is verified on the KITTI data set, and the specific results are shown in Fig. 9. The Acc, F1, and MIoU of C-LNet are 98.4%, 96.7%, and 94.51%, respectively. An RGB network and lidar network are selected for comparison. The Acc, F1, and MIoU of the RGB network are 97.2%, 95.9%, and 92.5%, respectively; the Acc, F1, and MIoU of the lidar network are 95.4%, 89.5%, and 81.6%, respectively. In conclusion, C-LNet is superior to the RGB network and lidar network in all aspects. The first mock exam is that the combination of optical radar with multiscale image can effectively extract features from different sensors, and the utilization rate of features is higher. The fault tolerance of multi-sensor fusion networks is much higher than that of single mode sensors.

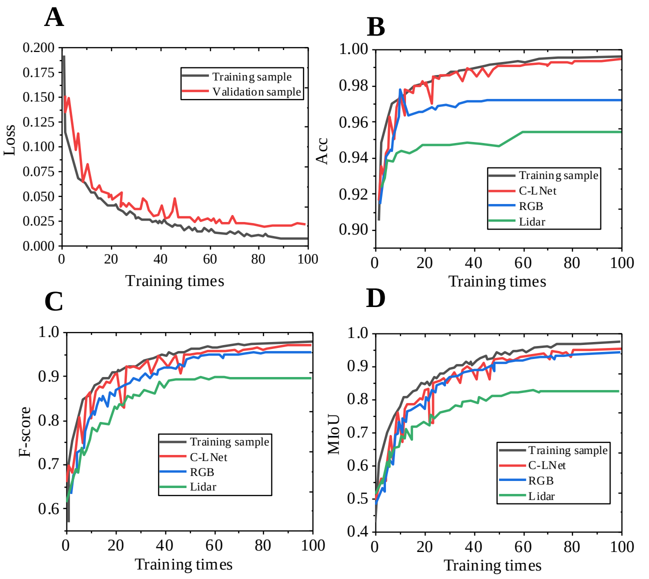

Fig. 9 – C-LNet performance evaluation results (A. loss; B. Acc; C. F1; D. MIoU)

4.3 Multi-vehicle cooperative positioning effect of multi-sensing fusion network

To further verify the effectiveness of a multi-sensing fusion network for multi-vehicle cooperative positioning in an actual situation, two multi-vehicle motion scenes of straight line and lane change are established in MATLAB. The problem of multi-vehicle cooperative localization in three cases in multi-sensing fusion networks is explored. The average value of 100 simulation results is used for comprehensive analysis, obtaining the expansion results of root mean square positioning error in a time domain under different conditions (Figures 10-12). Regarding the historical information, the multi-vehicle cooperative positioning method has little difference in error level compared with the cooperative positioning method based on single frame data. However, when the communication fails, the error of the cooperative positioning method based on single frame data will directly rise to the error level of single vehicle positioning. The error fluctuation of fusion positioning of historical information is smaller than that of single frame optimal fusion positioning, and the error level of the two multi-vehicle cooperative positioning methods is better than that of a single vehicle positioning method.

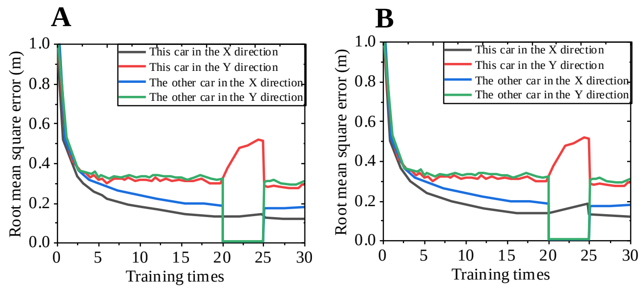

Fig. 10 – Multi-vehicle cooperative positioning method based on historical information (A. Lane changing scene; B. Straight driving scene)

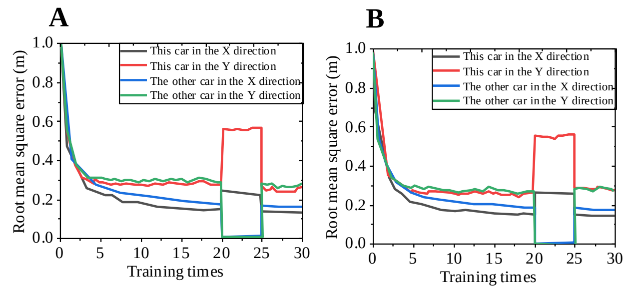

Fig. 11 – Multi-vehicle cooperative positioning method based on single frame optimal fusion

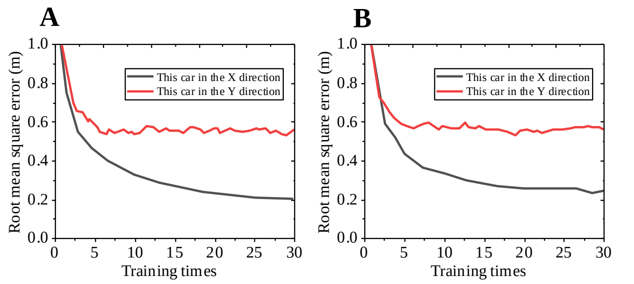

Fig. 12 – Multi-vehicle collaborative positioning method based on single vehicle positioning

5. CONCLUSION

With the continuous development of 6G communication systems, a V2X network aims to combine ground and non-ground communication networks. This will significantly improve the reliability and safety of the intelligent transportation system in a real smart city. Moreover, in the intelligent transportation system based on DTs, the transmission rate of traffic data is improved, so that three-dimensional communications can assist the local control of vehicles.

Urban traffic information intelligent perception technology provides source data for the coordinated development of vehicles and roads, and is the basis of realizing intelligent network transportation. At present, in the application field of intelligent vehicle engineering, single sensors cannot effectively identify the vehicle ahead. Therefore, in terms of the performance and other characteristic information of common vehicle surrounding environment perception sensors, a multimodal data fusion network based on sensors is proposed. In the VN, it cannot only make good use of the color and texture information of the image, but also combine with the three-dimensional distance information of the lidar data to enhance the robustness of traffic information recognition. Moreover, the application effect of the fusion network is verified on a KITTI road data set. It confirms that the multiscale combination of optical radar and image can effectively extract features from different sensors, and the utilization rate of features is higher. The fault tolerance of multi-sensing fusion networks is much higher than that of single modal sensors. However, there are still some deficiencies. For example, human error will be generated when synchronizing the two sensor data. In the future, the accuracy loss caused by lidar projection to two-dimensional space can be reduced by changing the projection mode.

ACKNOWLEDGEMENT

The research leading to these results has received funding from the Horizon2020 projects MATES (funded under grant 591889-EPP-1-2017-1-ES-EPPKA2-SSA-B) and EDISON (funded under grant n. 675419).

REFERENCES

[1] M. Z. Chowdhury, M. Shahjalal, M. Hasan, et al. "The role of optical wireless communication technologies in 5G/6G and IoT solutions: Prospects, directions, and challenges." In: *Applied Sciences* 9.20 (2019), pp. 4367.

[2] M. H. Alsharif, A. H. Kelechi, M. A. Albreem, et al. "Sixth generation (6G) wireless networks: Vision, research activities, challenges and potential solutions." In: *Symmetry* 12.4 (2020), pp. 676.

[3] S. Chen, Y. C. Liang, S. Sun, et al. "Vision, requirements, and technology trend of 6G: How to tackle the challenges of system coverage, capacity, user data-rate and movement speed." In: *IEEE Wireless Communications* 27.2 (2020), pp. 218-228.

[4] S. Zhang, J. Liu, H. Guo, et al. "Envisioning device-to-device communications in 6G." In: *IEEE Network* 34.3 (2020), pp. 86-91.

[5] Z. Lv, X. Li, W. Wang, et al. "Government affairs service platform for smart city." In: *Future Generation Computer Systems* 81 (2018), pp. 443-451.

[6] Q. Qi, X. Chen, C. Zhong, et al. "Integration of energy, computation and communication in 6G cellular internet of things." In: *IEEE Communications Letters* 24.6 (2020), pp. 1333-1337.

[7] S. Verma, S. Kaur, M. A. Khan, et al. "Toward Green Communication in 6G-Enabled Massive Internet of Things." In: *IEEE Internet of Things Journal* 8.7 (2020), pp. 5408-5415.

[8] P. Major, G. Li, H. P. Hildre, et al. "The Use of a Data-Driven Digital Twin of a Smart City: A Case Study of Ålesund, Norway." In: *IEEE Instrumentation & Measurement Magazine* 24.7 (2021), pp. 39-49.

[9] D. Wang, Z. Zhang, M. Zhang, et al. "The Role of Digital Twin in Optical Communication: Fault Management, Hardware Configuration, and Transmission Simulation." In: *IEEE Communications Magazine* 59.1 (2021), pp. 133-139.

[10] F. Jiang, L. Ma, T. Broyd, et al. "Digital twin and its implementations in the civil engineering sector." In: *Automation in Construction* 130 (2021), pp. 103838.

[11] C. Fan, C. Zhang, A. Yahja, et al. "Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management." In: *International Journal of Information Management* 56 (2021), pp. 102049.

[12] M. Liu, S. Fang, H. Dong, et al. "Review of digital twin about concepts, technologies, and industrial applications." In: *Journal of Manufacturing Systems* 58 (2021), pp. 346-361.

[13] X. Gao, J. Cai, Y. Long, et al. "Study on traffic organization for primary roads with super small spacing." In: Advances in Transportation Studies 2 (2017), pp. 3-12.

[14] J. Wang, S. Zhao, W. Zhang, et al. "Why people adopt smart transportation services: An integrated model of TAM, trust and perceived risk." In: *Transportation Planning and Technology* 44.6 (2021), pp. 629-646.

[15] E. Aliwa, O. Rana, C. Perera, et al. "Cyberattacks and countermeasures for in-vehicle networks." In: *ACM Computing Surveys (CSUR)* 54.1 (2021), pp. 1-37.

[16] J. Zhang, B. Zhang, N. Zhang, et al. "A novel robust event-triggered fault tolerant automatic steering control approach of autonomous land vehicles under in-vehicle network delay." In: *International Journal of Robust and Nonlinear Control* 31.7 (2021), pp. 2436-2464.

[17] D. Y. Kim, M. Jung, S. Kim. "An internet of vehicles (IoV) access gateway design considering the efficiency of the in-vehicle ethernet backbone." In: *Sensors* 21.1 (2021), pp. 98.

[18] C. Li, G. Cui, W. Zhang, et al. "Defect detection in vehicle mirror nonplanar surfaces with multi-scale atrous single-shot detect mechanism." In: *AIP Advances* 11.7 (2021), pp. 075202.

[19] M. Giordani, M. Zorzi. "Non-terrestrial networks in the 6G era: Challenges and opportunities." In: *IEEE Network* 35.2 (2020), pp. 244-251.

[20] Z. Zheng, L. Wang, F, Zhu, et al. "Potential technologies and ap plications based on deep learning in the 6G networks." In: *Computers & Electrical Engineering* 95 (2021), pp. 107373.

[21] G. Liu, Y. Huang, N. Li, et al. "Vision, requirements and network architecture of 6G mobile network beyond 2030." In: *China Communications* 17.9 (2020), pp. 92-104.

[22] C. Englund, E. E. Aksoy, Alonso-Fernandez F, et al. "AI perspectives in Smart Cities and Communities to enable road vehicle automation and smart traffic control." In: *Smart Cities* 4.2 (2021), pp. 783-802.

[23] J. Zhang, Z. Sun, H. Yu, et al. "Modeling and Simulation of Traffic Flow Considering Driver Perception Error Effect." In: *Journal of Transportation Engineering, Part A: Systems* 147.4 (2021), pp. 04021009.

[24] P. Kasture, H. Nishimura. "Analysis of Cooperative Perception in Ant Traffic and Its Effects on Transportation System by Using a Congestion-Free Ant-Trail Model." In: *Sensors* 21.7 (2021), pp. 2393.

[25] G. Charkoftakis, P. Liosatos, Tatlas N A, et al. "An E-Maintenance IoT Sensor Node Designed for Fleets of Diverse Heavy-Duty Vehicles." In: *International Journal of Mechanical and Industrial Engineering* 15.9 (2021), pp. 409-415.

[26] B. Zhang, Z. Wu, Z. Lin, et al. "All-in-one 3D acceleration sensor based on coded liquid–metal triboelectric nanogenerator for vehicle restraint system." In: *Materials Today* 43 (2021), pp. 37-44.

[27] Q. Li, N. Liu. "Nodes deployment algorithm based on data fusion and evidence theory in wireless sensor networks." In: *Wireless Personal Communications* 116.2 (2021), pp. 1481-1492.

[28] D. Helena, A. Ramos, T. Varum, et al. "The Use of 3D Printing Technology for Manufacturing Metal Antennas in the 5G/IoT Context." In: *Sensors* 21.10 (2021), pp. 3321.

[29] W. Zeng, Y. He, B. Li, et al. "3D Multiple-Antenna Channel Modeling and Propagation Characteristics Analysis for Mobile Internet of Things." In: *Sensors* 21.3 (2021), pp. 989.

[30] B. Mataloto, D. Calé, K. Carimo, et al. "3D IoT System for Environmental and Energy Consumption Monitoring System." In: *Sustainability* 13.3 (2021), pp. 1495.

[31] R. Kim, Y. Hong, Y. Choi, et al. "System-level fouling detection of district heating substations using virtual-sensor-assisted building automation system." In: *Energy* 227 (2021), pp. 120515.

[32] S. M. E. Sepasgozar. "Differentiating digital twin from digital shadow: Elucidating a paradigm shift to expedite a smart, sustainable built environment." In: *Buildings* 11.4 (2021), pp. 151.

[33] S. Agostinelli, F. Cumo, G. Guidi, et al. "Cyber-Physical Systems Improving Building Energy Management: Digital Twin and Artificial Intelligence." In: *Energies* 14.8 (2021), pp. 2338.

[34] J Guerrero-Ibañez, J. Contreras-Castillo, S. Zeadally. "Deep learning support for intelligent transportation systems." In: *Transactions on Emerging Telecommunications Technologies* 32.3 (2021), pp. e4169.

[35] B. Woodward, T. Kliestik. "Intelligent Transportation Applications, Autonomous Vehicle Perception Sensor Data, and Decision-Making Self-Driving Car Control Algorithms in Smart Sustainable Urban Mobility Systems." In: *Contemporary Readings in Law and Social Justice* 13.2 (2021), pp. 51-64.

[36] F. Qiao, T. Liu, H. Sun, et al. "Modelling and simulation of urban traffic systems: present and future." In: *International Journal of Cybernetics and Cyber-Physical Systems* 1.1 (2021), pp. 1-32.

[37] C. Wen, A. F. Habib, J. Li, et al. "Special Issue on 3D Sensing in Intelligent Transportation." In: *IEEE Transactions on Intelligent Transportation Systems* 22.4 (2021), pp. 1947-1949.

[38] J. Godoy, V. Jiménez, A. Artuñedo, et al. "A grid-based framework for collective perception in autonomous vehicles." In: *Sensors* 21.3 (2021), pp. 744.

[39] M. A. Akhloufi, A. Couturier, N A. Castro. "Unmanned aerial vehicles for wildland fires: Sensing, perception, cooperation and assistance." In: *Drones* 5.1 (2021), pp. 15.

[40] J. Bravo-Arrabal, J. J. Fernandez-Lozano, J. Serón, et al. "Development and Implementation of a Hybrid Wireless Sensor Network of Low Power and Long Range for Urban Environments." In: *Sensors* 21.2 (2021), pp. 567.

[41] P. Santana, A. Almeida, P. Mariano, et al. "Air quality mapping and visualisation: An affordable solution based on a vehicle-mounted sensor network." In: *Journal of Cleaner Production* 315 (2021), pp. 128194.

[42] T. Petrov, L. Sevcik, P. Pocta, et al. "A Performance Benchmark for Dedicated Short-Range Communications and LTE-Based Cellular-V2X in the Context of Vehicle-to-Infrastructure Communication and Urban Scenarios." In: *Sensors* 21.15 (2021), pp. 5095.

[43] A. Kumar, V. Varadarajan, A. Kumar, et al. "Black hole attack detection in vehicular ad-hoc network using secure AODV routing algorithm." In: *Microprocessors and Microsystems* 80 (2021), pp. 103352.

[44] J. H. Majeed, N. A. Habeeb, W. K. Al-Azzawi. "Performance investigations of internet protocol versions for mobile Ad-hoc network based on quaint simulator." In: *Indonesian Journal of Electrical Engineering and Computer Science* 21.1 (2021), pp. 497-504.

[45] Y. Guo, X. Fang, Z. Dong, et al."Research on multi-sensor information fusion and intelligent optimization algorithm and related topics of mobile robots." In: *EURASIP Journal on Advances in Signal Processing* 2021.1 (2021), pp. 1-17.

[46] S. Qiu, H. Zhao, N. Jiang, et al. "Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges." In: *Information Fusion* 80 (2022), pp. 241-265.

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