Research Problem

The vehicular ad hoc networks (VANETs) have been researched for over twenty years. Although being a fundamental communication approach for vehicles, the conventional VANETs are challenged by the newly emerged autonomous vehicles (AVs) which introduce new features and challenges on communications. In the meantime, with the recent advances of artificial intelligence and 5G cellular networks, how should the fundamental framework of VANET evolve to utilize the new technologies? In this article, we reconsider the problem of vehicle-to-vehicle communications when the network is composed of AVs. We discuss the features and specific demands of AVs and how the conventional VANETs should adapt to fit them.

I. INTRODUCTION

It is no longer doubt that the autonomous vehicles are coming soon. Nowadays, nearly all car manufactures like BMW, Volvo, Ford, have deployed the semi-autonomous driving (a.k.a advanced driver-assistance system) on their new models, which can provide the lane centering, adaptive cruise control, autonomous emergency braking, etc. As reported, all Tesla vehicles shipped since 2019 have the full autonomous driving hardware, and Tesla starts to offer the Full Self Driving 2.0 software package on their new cars which enables autosteer in city streets. In December 2018, Waymo launched the Waymo One self-driving taxi service, which allow users in the Phoenix metropolitan area to request a pick-up service on their phones for a fully autonomous driving minivan.

While the autonomous driving has gained substantial success world-wide, the large-scale deployment of full autonomous driving on the city street is still fraught with fundamental challenges. Notably, the current autonomous vehicles mainly rely on the single-car intelligence, i.e., to sense the environment and make driving decisions by the car itself. With the complex and fast changing road environments, as well as the very limited sensing and computing capability on board, the single-car intelligence not only incurs expensive hardware to enable real-time sensing and artificial intelligence (AI) processing, but also is prone to errors which may lead to severe road accidents.

Fig. 1(a) illustrates a fatal Tesla car crash reported in May, 2016. The accident was caused by the failure of multiple sensors at the same time. Specifically, a Tesla Model S driving with Autopilot crashed into the truck when the truck was turning at an intersection on the divided highway. The body of the truck was white which made the camera and vision system regarded the truck as a cloud. The radar signals traversed through the gap between the tires, making the sensors considered the front to be the entry of a tunnel. As a result, the car crashed into the hole of the track without reducing speed.

The accident can be entirely avoided when vehicular communications and collaborative driving come into play. As the example illustrated in Fig. 1(b), if there are any other vehicles on the neighboring lane and can communicate with the accident car, they can detect the truck and warn the accident car to avoid the fatal crash.

The collaborative driving, by sharing the information among vehicles using the inter-vehicular or vehicle-to-vehicle (V2V) communications, can extend the single-car intelligence to multi-car intelligence. The multi-car intelligence can significantly reduce the computation load and cost on hardware compared with its single-car counterpart, but also significantly improve the safety and performance of driving. The multi-car intelligence can be achieved with the following three aspects:

- **Collaborative Sensing**: the neighboring vehicles can share the sensing information among each other to not only extend the sensing range but also enhance the sensing accuracy. The extended information achieved by each vehicle can be crucial to make accurate driving decisions.

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1We consider VANETs as a general vehicle-to-vehicle communication framework with the IEEE 802.11p or 5G CV2X wireless radio and Ad Hoc routing suite.

2In this paper, we only consider the V2V communication mode. The vehicle-to-infrastructure (V2I) communications however can also leverage the technology discussed in the paper.
• **Collaborative Perception**: with real-time connections among each other, the neighboring vehicles can perform the distributed machine learning, *e.g.*, meta-learning and federated learning, to collaboratively learn the environment. The collaborative perception can significantly reduce the computing burden of single vehicles and make more reliable driving decisions.

• **Collaborative Error Correction**: the neighboring vehicles can directly share the driving decisions of individuals to each other and help others fix their error. As the example in Fig. 1(b), the vehicle on the left lane can broadcast its break decision and notify the danger to the vehicle on the right lane to avoid the accident.

To enable the collaborative driving relies on the vehicular ad hoc networks (VANETs) among AVs. Although been researched for decades, the conventional VANETs mainly focus on delivering conventional status update or infotainment messages, which have not considered much on the features of AVs and their demand on collaborative computing and driving [2]. In conventional VANETs, vehicles are pure mechanical systems without much intelligence; the communications in VANETs thus do not consider any software and computing advantages of vehicles. With the complete autonomous driving and omni-AI capability on board, a new paradigm of autonomous vehicular ad hoc networks (AVNETs), which can fully explore the features of AV and target to enable the collaborative driving, needs to be structured.

In this article, we discuss the paradigm of AVNET and its key design factors. We first describe the software architecture of an AV, which is important to the design of the communication systems. After that, we compare the autonomous vehicular networks with the conventional vehicular ad hoc networks and identify the new features of AVNET. We then showcase an example by applying the mmWave V2V communications in AVNET and evaluate the performance using simulations. Lastly, we conclude the article with the discussion on open research issues.

**II. SOFTWARE ARCHITECTURE OF AV**

Fig. 2 shows the software architecture of an AV, which can be divided into three parts: sensing, perception and motion control.

**A. Sensing**

An AV is typically equipped with rich sensors for localization and environment sensing, including the LiDAR, ultrasonic radar, mmWave radar, camera, GPS, GNSS, etc. Fig. 2 shows the primary sensors used in the AV and their key features. For example, Waymo has 29 cameras integrated around the body of the car, a LiDAR providing higher resolution across a 360 degree field of view with over 300-meter range, and radars to enhance the accuracy of sensing in extreme weather conditions, *e.g.*, rain, fog and snow. The Tesla cars deploy eight surround cameras, twelve ultrasonic sensors and a forward-facing mmWave radar without the LiDAR to reduce the hardware cost. A high resolution camera typically produces data at the rate of $500 - 11,500$ Mbit/s whereas a LiDAR produces data streams ranging from $20 - 100$ Mbit/s. As reported, a typical test vehicle equipped with $3 - 4$ cameras, $3 - 4$ LiDAR sensors, and other sensors create up to $10 - 20$ TB per hour.
B. Perception

Perception is the data processing module of AVs, which is used to understand the driving environments and output important perception information.

While there exists many kinds of perception systems, the core pipeline typically includes object detection, feature extraction, motion estimation, object tracking, mapping and localization. We roughly divide the current advances of computer vision technologies in perception systems into two types, i.e., object-aware methods and feature-aware methods. For the first one, two methods are popular and have potential in vehicular perception, i.e., labelling each bounding box at frames (such YOLO [3]) and labelling each pixel at frames (semantic segmentation, such as Mask RCNN [3]).

Different from object-aware CV technologies, Simultaneous Localization and Mapping (SLAM) systems focus on feature-level data processing, in order to support the real-time mapping and localization of vehicles [4]. SLAM provides a suite of cost-effective logics to collect data from camera or LiDAR and then output HD map and localization results. Therefore, combining the advantages of object detection (or semantic segmentation) and SLAM, i.e., using SLAM pipelines with the transferred object detection neural network, is a new way to build vehicular perception system.

Using the inter-vehicle collaboration over the existing perception system, not only the CV related performance metrics, such as detection accuracy, motion estimation error, could be raised, but also resources of computing and communication will be saved. The insight behind the resource saving is the adaptation of system configurations such as sensing views, frames per second, frame resolution selection, etc. Thus the configuration adaptation leaves space for the exploitation of collaborative perception (sharing sensing information) and collaborative perception (sharing AI networks).

C. Motion Control and Actuation

The ultimate goal of sensing and perception is to determine the optimal behavior and motion control of AVs. As in Fig. 2 the motion control relies on not only the fusion of sensing and perception, but also the information shared by neighboring vehicles using the collaborative error correction [5]. The collective information is processed by machine learning algorithms towards the optimal maneuver control of vehicles.

III. VEHICULAR COMMUNICATION TECHNOLOGY

Multi-car intelligence relies on real-time wireless communications among vehicles. The vehicular communications have been standardized by IEEE and Third Generation Partnership Project (3GPP), respectively.

A. Dedicated Short-Range Communication Technology (DSRC)

In 1999, the US Federal Communications Commission (FCC) has allocated a spectrum of 75 MHz at the frequency band of 5.9 Hz for the dedicated short range communication (DSRC) for vehicles. The DSRC adopts the IEEE 802.11p Wireless Access in Vehicular Environments (WAVE) standard which reuses the IEEE 802.11g OFDM physical layer and IEEE 802.11e Enhanced Distributed Channel Access (EDCA) MAC layer. The EDCA MAC is contention-based which provides differentiated priorities to safety and infotainment traffics. While being extensively researched for over twenty years, the DSRC has not been widely deployed. This is because that while the IEEE 802.11 protocol achieves great success for static indoor applications, the short-range contention-based scheme does not fit the usage in a highly dynamic and possibly populated outdoor vehicular environment for applications related to public safety [6].

B. Cellular-based Vehicular Network (C-V2X)

C-V2X is defined by 3GPP Release 14 in 2017 which adopts the cellular technology for vehicular communications [7]. The C-V2X exploits the LTE uplink and utilizes Single Carrier Frequency Division Multiple Access (SC-FDMA) at the physical and MAC layers. The vehicle-to-vehicle communications in C-V2X adopt the LTE sidelink technology which operates in a distributed manner without the need of cellular infrastructure. As compared to DSRC, the C-V2X uses the cellular time and frequency division based MAC with reserved resource blocks for each transmission which is more reliable.

C. mmWave Communications

To meet the futuristic application needs of vehicular communications, both IEEE and 3GPP have made new amendments on their V2V standards. The 802.11 standard group has defined IEEE 802.11bd protocol to replace IEEE 802.11p, and 3GPP defines the next generation of C-V2X with New Radio V2X (NR-V2X) in Release 16 in June 2019.

Both IEEE 802.11bd and 5G NR V2X standards will support operations at mmWave frequencies, i.e., in the 57-71 GHz and 24.25-52.6 GHz ranges, respectively. The large spectrum availability at these frequencies promotes high-capacity low-latency communication. More importantly, since mmWave is directional in nature, it is desirable for vehicular communications where vehicles are constrained by roads.

IV. PLATFORM BRIDGING THE COMPUTATION AND COMMUNICATIONS

Orchestrating the complicated task processing in vehicular perception systems and real-time communications of vehicles needs a platform. The Robot Operating System (ROS) gives an important insight.

Many successful AV operating systems, e.g., Baidu Apollo, autoware.ai, root from ROS, an open-source software suite for robotics application development. ROS provides the necessary operating system application services to manage a robotic system, such as robot models, perception, location and mapping, path planning, navigation, simulation tools, etc.

It is important to note that in order to support the real-time data communications between the sensing and computing units, ROS has defined its communication system based on the publish/subscribe (short as pub/sub) scheme. Specifically, as
The pub/sub scheme builds a bridge between the task processing of the publisher (the current vehicle) and active perception pulling from the participants (nearby vehicles). The bridge shifts the conventional VANET pattern to active pull-based information sharing. Particularly, the pub/sub scheme has following three features, making it very suitable to data sharing in collaborative driving.

- **Pull-based approach**: In the pub/sub scheme, the components select to pull the data from the interested topics based on their own requirements, whereas the data publishers do not worry about where to send the data. This is reasonable as in an AV, the publishers which are typically sensors have limited processing power and cannot perform complicated operations to determine where to send their data. On the other hand, in a dynamic environment, a participant may need to dynamically change topics of data to download. The pull-based approach is more reliable for a dynamic autonomous system.

- **Fully distributed system**: The pub/sub scheme has been used for both intra-vehicular and inter-vehicular communications. As plotted in Fig. 3(b), all the components of a vehicle are distributed and peer participants. The components of other vehicles, e.g., car B, are also participants which can subscribe to the topics. As a result, the GPU of car B can subscribe to the car A’s camera topic, and download the data when car A’s camera publishes new data. In this manner, collaborative perception is enabled.

- **Multicast**: The pub/sub scheme is a multicast system by nature. A topic can be subscribed by multiple subscribers intra a vehicle or inter vehicles at the same time. The update data of the topic will be accordingly multicast to all subscribers. Therefore, the AVNETs are mainly composed of multicast traffic flows managed by the topics which could be on sensing, computing model or computing results.

V. AUTONOMOUS VEHICULAR NETWORKS V.S. CONVENTIONAL VEHICULAR AD HOC NETWORKS

In this section, we present three key features of the AVNETs distinguished from the conventional VANETs.

A. Link: Blind v.s. Sighted Communications

The conventional vehicles in VANET is a mechanism system without the capability of environment perception. As a result, the vehicles in VANET are almost “blind” and send the information using omni-directional antenna. Nevertheless, the AVs are of full capability to “perceive” the environment using various sensors, LiDAR and cameras. Therefore, AVs can gauge their communication beams towards the best physical layer performance. [9] develops a federated learning framework which use the LiDAR system to assist mmWave beamforming for vehicle-to-infrastructure communications.

Fig. 3(a)-(b) show the processed sensor data viewed by the current vehicle. With the capability to "see" the targets for communications, the AVs can set up an optimized mmWave beam for communications and adapts to the vehicle’s mobility with the assistance of onboard perception devices.

B. Topology: Self-Controlled v.s. Human Controlled Topology

The topology among nodes plays an important role in the communication performance; the distance and relative velocity among vehicles determine the physical layer transmission capacity and the MAC contentions. Traditional vehicles in VANETs are controlled by human beings, and the communications among vehicles mainly serves to deliver the road information, e.g., safety messages [10], to assist driving. However, in AVNETs, the nodes are self-driving vehicles, which can fully control their own driving velocity and relative locations to each other, as long as their passengers can reach their transportation goals safely and comfortably. As a result, to benefit the collaborative sensing and computing, it is entirely possible for vehicles to collaboratively adapt their topology to achieve better transportation, sensing and communication performance.

Notably, there is a golden rule in VANETs that the communications cannot directly change the driving of drivers. This is no longer a restriction in AVNET. The new dimension would significantly benefit the communications.
TABLE I: Comparisons between VANET and AVNET

|               | Communication                    | Routing              | Mobility |
|---------------|----------------------------------|----------------------|----------|
| VANET         | IEEE 802.11p (omni-directional transmission) | Ad Hoc (e.g., OLSR, AODV) | Human    |
| AVNET         | IEEE 802.11bd, 5G NR V2X (directional transmission) | Publish/Subscribe, Ad Hoc | AI       |

C. Routing: Explicit IP Routing v.s. Implicit Published/Subscribe Routing

The VANET typically adopts the Ad Hoc approaches for traffic routing, which rely on the Internet layer 2 or layer 3 addressing approach to route the traffic. The routing methods are based on explicit addressing, where the traffic are routed to receivers with explicit IP or MAC addresses.

Unlike the explicit addressing, as discussed in Section IV, AVNETs are prone to use the implicit addressing approach such as the pub/sub mechanism for routing traffic, as specified in ROS; the implicit addressing uses "topics" for routing, instead of the explicit address. This is because that AVNET is mainly used to route collaborative sensing and computing information. The pub/sub mechanism is a multicast protocol in nature and a pull-based approach which is more suitable to transmit commonly interested sensing and computation traffic among vehicles.

TABLE I summarizes the comparison between AVNETs and VANETs from the perspectively of radio links, traffic routing and network topology.

3Another example of the implicit routing is the named data networking (NDN) which uses "interests" to route data traffic.

VI. USE CASE OF AVNET

In this section, we provide a simulation study on the collaborative AVNET.

A. Framework

The interaction between V2V mmWave communications and vehicular sensing is depicted. Specifically, two vehicles are assumed to form a simple platoon. They collect perception information from environments and communicate with each other using mmWave links. Our purpose is to evaluate the V2V mmWave performance with different bandwidth so that reflect the advantage of mmWave technologies in vehicular scenarios. To utilize the high-throughput mmWave links, reliable beam alignment is necessary, especially for two moving vehicles. To do that, we develop a system to speedup the beam alignment process using some helpful information extracted from vehicular sensing components. Therefore, there are two components in our performance evaluation system, vehicular sensing and beam alignment. In our system, the frequent feedback used for beam realignment between two transceivers can be eliminated. On the other hand, the high throughput of V2V mmWave links can also help the perception sharing between vehicles, which further help vehicles understand driving environments efficiently.

B. Performance Evaluation

Fig. 4 shows a pipeline of the performance evaluation system that combines the sensing and inter-vehicle communications, which showcases the positive effect of sensing on V2V communications. The sensor data processing components are achieved by the basic SLAM system with object detection.
capability [12]. The detected objects and extracted object features are shown in Fig. 4 (a). Using the temporal frame dynamics, the motion information of adjacent vehicles can be estimated so that the velocity and relative angle could be acquired by the current vehicle, as shown in Fig. 4 (b). The motion estimation results are then used to guide the beam-forming of inter-vehicle mmWave link as shown in Fig. 4 (c). In Fig. 4 (d), we then present the SNR performance impacted by the beamwidth. Fig. 4 gives an important insight that how to develop inter-vehicle mmWave links more efficiently using sensing information rather than the traditional beamforming methods.

To show the communication performance of mmWave empowered platooning, two metrics are further discussed, i.e., directional mmWave link performance and cooperative sensing range, as well as their potential trade-off with the changing V2V distance. All results are shown in Fig. 5. The first metric is SNR (Signal-to-Noise-Ratio), showing the impact of V2V distance on beamwidth. We set the relative beamwidth between transmitter and receiver as four different values. For simplicity, the receiver SNR only includes the directive gains in the main lobe of mmWave V2V links by resorting to the channel model and antenna pattern in [13]. We also depict the sensing range impacted by V2V distance in Fig. 5. According to [14], the sensing range is an important metric in existing commercial on-board perception devices. For example, a 64-bead LiDAR can collect 2.2 million points each second and achieve real-time sensing of 360° view [14]. Assuming that each vehicle achieves a full-view sensing, the sensing range of vehicles in a platoon thus may overlay each other. The platoon provides a new cooperative sensing paradigm where two nearby vehicles can collaborate with each other and extend their individual sensing range. Considering two vehicles with full-view sensing sensors, the aggregated sensing range that reflects the cooperative perception capability of two platoon vehicles is evaluated in Fig. 5.

We select those two metrics to show that the platoon based AVNET can combine the advantages of mmWave vehicular communications and on-board sensing, which can enhance the performance of platoon based autonomous driving. From Fig. 5 we can also see that, by combining mmWave and sensing in AVNET, many specific technical problems will motivate researchers to develop new algorithms, models or architectures to balance the performance of vehicular sensing and V2V transmissions.

VII. OPEN RESEARCH ISSUES

AI Enabled Communications and Networking: with the AVs of strong software and hardware computing and communication capabilities as the main entities of communications, how to fully explore the omni-AI of AVs towards the optimal application performance deserve in-depth study. In this article, we have demonstrated three dimensions for exploration. However, how to fully explore the new dimensions and apply the advanced AI algorithms to optimize the performance from the shoe of the entire system remain open for research.

AVs Empowered Intelligent Transportation System (ITS): the ITS relies on advanced information system and wireless communication technologies to connect the traffic control units with the transportation units. As a result, the traffic can be intelligently coordinated towards the best transportation performance from the perspective of traffic efficiency, environment and social utility. The traditional ITS is based on VANETs in which the vehicles are operated by human beings. With AVs widely adopted in the future, the ITS can significantly benefit from the controllable driving of AVs towards a global optimal transportation performance. How to manage the city-wide AV in ITS is open for research [15].

Security: different from the traditional vehicles controlled by human, the AVs require the timely processing of a titanic amount of data for driving decision making. As a result, collaborative driving with collaborative sensing, perception and error correction becomes important in AVNETs. The collaborations among AVs however impose significant security challenges. With the features of sighted communications, pub/sub and collaborative topology control mechanisms demonstrated, new security threatens to each feature may raise and deserve further study.

VIII. CONCLUSION

The research of VANETs has been carried out for more than 20 years, and a large number of outstanding research results have been derived. However, legacy VANETs only consider traditional mechanical vehicles as the main communication subjects, and have not considered the intelligence of vehicles. Emerging AVs have comprehensive environmental awareness capabilities, as well as strong intelligence and control on driving and wireless transmission strategies. The adoption of AVs therefore requires a revisit on the design of VANETs to not only accommodate the new service requirements of AVs, but also fully explores the AI features of AVs. In this article, we have discussed the software structure and operating system of an AV, and demonstrated the three features of AVNETs from the perspective of wireless transmission, traffic routing and topology control. Through simulation research, we
demonstrated the performance of collaborative driving using AVNET.

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