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# On the Integration of Enabling Wireless Technologies and Sensor Fusion for Next-Generation Connected and Autonomous Vehicles

FARAN AWAIS BUTT<sup>1</sup>, JAWWAD NASAR CHATTHA<sup>1</sup>, JAMEEL AHMAD<sup>2</sup>,  
MUHAMMAD UMER ZIA<sup>3</sup>, MUHAMMAD RIZWAN<sup>2</sup>,  
AND IJAZ HAIDER NAQVI<sup>3</sup>, (Member, IEEE)

<sup>1</sup>Department of Electrical Engineering, School of Engineering, University of Management and Technology, Lahore 54770, Pakistan

<sup>2</sup>Department of Computer Science, School of Systems and Technology, University of Management and Technology, Lahore 54770, Pakistan

<sup>3</sup>School of Science and Engineering, Lahore University of Management Sciences, Lahore 54792, Pakistan

Corresponding author: Jawwad Nasar Chattha (jawwad.chattha@umt.edu.pk)

**ABSTRACT** The automotive industry is transitioning towards intelligent, connected, and autonomous vehicles to avoid traffic congestion, conflicts, and collisions with increased driver safety. Connected and autonomous vehicles (CAV) must be aware of their surroundings and act as per their environment. Communication infrastructure can be vital in transmitting necessary information to peers and receiving critical information for timely decisions. This article provides a comprehensive review of the topic, covering the aspects of enabling wireless technologies and sensor fusion. The article reviews data acquisition using various sensing devices such as RADAR (Radio Detection and Ranging), LiDAR (Light Detection and Ranging), cameras, and multi-modal sensor fusion of the acquired data after signal processing. Thereafter, it reviews the communication and networking infrastructure for intra- and inter-vehicle communication and related technologies. For each of these themes, research challenges and future directions have been identified.

**INDEX TERMS** Sensor fusion, inter-vehicle communication, intra-vehicle communication, environment sensing, road safety, Internet of Vehicles, connected and autonomous vehicles, 5G networks.

## I. INTRODUCTION

The field of vehicular communication and intelligent transportation systems (ITS) has been progressing fast since the last decade. The rapid growth in ITS revolves around the manufacturing of autonomous and semi-autonomous vehicles with the capability of passenger safety, elimination of roadside accidents, optimal path planning, user comfort with enhanced travel experience, and use of information technology to connect with media and social networks. The 5G communication infrastructure enables ITS multiple communication paradigms, namely vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), infrastructure-to-vehicle (I2V), vehicle-to-road (V2R), vehicle-to-personal (V2P), and vehicle-to-sensors (V2S). With increased intelligence, control, and communication-enabled navigation, environment

sensing and run-time decision-making capabilities, the traditional vehicles transform into autonomous vehicles (AV) or *self-driving vehicles*. The AVs have less energy consumption, reduced carbon emissions, and optimized routing resulting in greener urban mobility. In recent years, advancements in communications, controls, and embedded systems have changed the perception of a typical conventional car. The AVs are sensory platforms capable of absorbing information from the environment (and from other cars in its vicinity) and disbursing this information to drivers and infrastructure to assist safe navigation, environment-friendly commute, and overall traffic management. The next step in this evolution is in the offing: the Internet of Connected and autonomous vehicles (CAV) or internet of vehicles (IoVs) [1]–[3]. IoV is a framework that emphasizes layered architecture, protocol stack, network model, challenges, and future aspects. Due to increased demand for higher data rates and lower latency, the computation for CAV is brought closer to these vehicles in

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the so-called vehicular fogs [4] which serves as an instantaneous internet cloud for vehicles. The concept of the IoV is pioneered by Google that used communications, storage, intelligence, and learning capabilities of CAV to anticipate the customers' intentions.

A complete CAV system is a complex combination of different technologies, sensors, actuators, algorithms, and high-performance computer systems [5]. The hardware system of a typical autonomous car includes Radio Detection and Ranging (RADAR), Light Detection and Ranging (LiDAR), cameras, a digital signal processor, an application-specific integrated circuit (ASIC), or a field-programmable gate array (FPGA) chip for computational tasks and other complementary sensors. The main idea behind the working of CAV is straightforward; CAV uses different sensors that can detect and can track all the objects in the surroundings; the vehicle then reacts according to the received input. These tasks, i.e., environment sensing and actuation based on the sensed information, are quite complex and encapsulate many diverse domains.

A RADAR in an autonomous car detects other objects' distance, direction, and speed through radio waves. A RADAR continuously emits radio waves which are reflected back to the source after hitting objects. RADAR is inexpensive, and it is also capable of performing well in extreme weather conditions. LiDAR is a laser sensor that emits laser beams that are reflected back to the photo-detector after hitting the objects in the environment. These sensors provide highly detailed geographical data in a three-dimensional (3D) map of the surroundings and have a higher resolution than RADAR because they use light instead of radio waves. However, LiDAR is much more expensive than RADAR sensors and cannot perform accurately in extreme weather conditions. Detailed information of the car's surroundings is determined through the data processed by cameras and computer vision software. Cameras are helpful in training machine learning (ML) models. Tesla's autopilot cars have eight cameras for object detection in 360 degrees. Like LiDAR, cameras cannot perform well in extreme weather, such as storms or dense fog. CAVs also have ultrasonic sensors which emit high-frequency sound waves. The receiver calculates the distance by estimating the round trip time [5].

Ultrasonic sensors have been used as parking sensors for a very long time in automobiles. They have a smaller range but are ideal for detecting objects at low speeds. CAVs also have inertial measurement unit (IMU) sensors capable of measuring the car's velocity. Moreover, microphone sensors in an autonomous vehicle help the autonomous car listen to nearby audio, such as emergency sirens. A global positioning system (GPS) is also included in an autonomous vehicle for navigation purposes. The primary function of this sensor is to track the vehicle's movement and find out its global position. A high-performance computer is also included in the hardware system of CAV to interface hardware components and sensors with software and process all the sensory data in real-time.

According to the transportation department of the United States, CAV cooperates with each other and their surroundings in three different ways, namely vehicle to vehicle interaction, vehicle to infrastructure interaction (V2I), and vehicle to pedestrian (V2P) interaction. V2V interaction allows CAVs to exchange valuable information like their current positions, route congestion, obstacles, and hazards on roads. Vehicle to infrastructure interaction (V2I) is how autonomous vehicles communicate with the infrastructure, such as an intelligent parking system to arrange parking space before even reaching there. Vehicle to pedestrian interaction (V2P) is how CAV knows the position of pedestrians on the side of the road. This communication actually happens between an autonomous car and a smart device such as a smartphone or a smartwatch of the pedestrian. Through GPS, these devices know their positions and can exchange information on position with CAV. In this way, the safety of the passengers and vehicles can improve significantly. Various types of autonomous vehicles that may hit the road in the near future are shown in Fig. 1.

#### A. BRIEF HISTORY OF CAV

CAV are also called driver-less vehicles. Researchers have been working on this concept since 1920s. General Motor organized an exhibition in 1939 named as New York world's fair to show the world its vision of how the world in the future will look like with CAVs on the road. They showed the concept of an automated intelligent highway system with connected vehicles. This was the first time that a vision of autonomous vehicles was showcased by Norman Bel Geddes [6]. The first autonomous car hit the road few years later where it guided by radio-controlled electromagnetic fields generated with magnetized metal spikes embedded in the roadway. There was slow and gradual progress in this area since then. In the year 2004, DARPA USA started to organize yearly competitions for the development of CAVs known as DARPA grand challenge. In DARPA challenge, students from well known universities were encouraged to develop CAV for a safer and environment-friendly future. DARPA challenge received great response from students and automobile industry. In another round of the Grand Challenge held on October 8, 2005 in California/Nevada state line the winner developed a robot that was developed for high-speed desert driving without manual intervention. The state of the art artificial intelligence and machine learning technology was used in the vehicular robot's software system [7]. The focus of this challenge was for military applications of autonomous vehicles. However, it created huge interest in big companies like Tesla, Google, General Motors, Ford and others who made huge investments in developing CAVs. In 2014, Tesla showed the world its first ever autopilot car. The Tesla autopilot had features like it could accelerate, steer or brake automatically within its lane, auto park, cruise control, auto lane change.

In 2015, Google tested its autonomous car, Firefly on public roads. This car did not use a steering wheel or pedals and was designed to work under 25 miles per hour and was

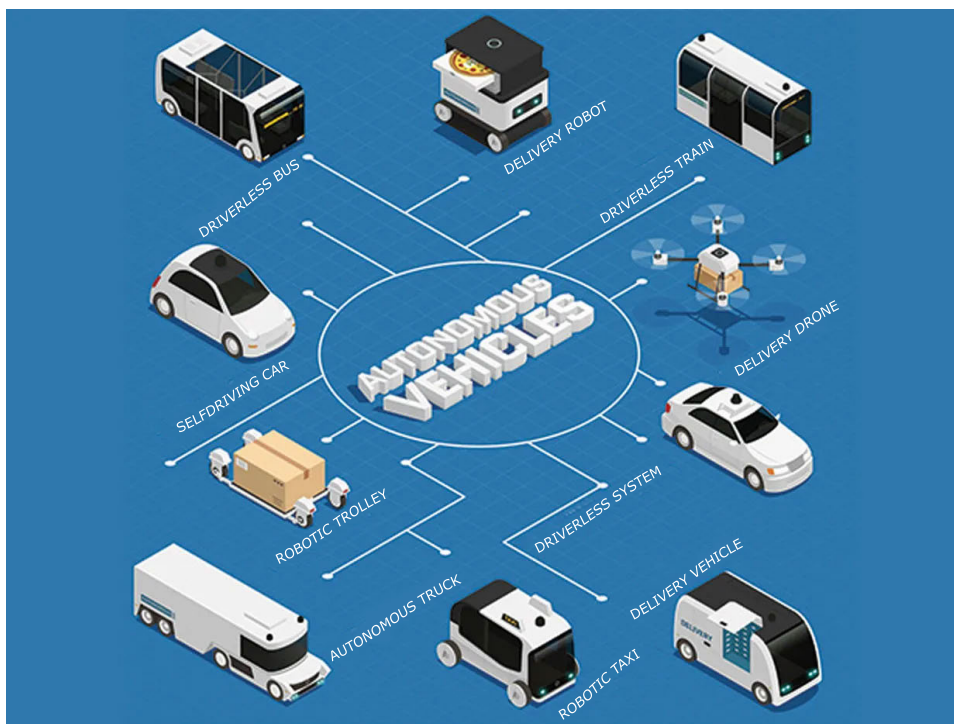


FIGURE 1. Autonomous vehicles.

discontinued shortly after its introduction. In 2016, Google introduced Waymo which launched Chrysler Pacifica hybrid minivans in 2017. This vehicle was built with fully integrated hardware design. In the same year, many other giants in the autonomous vehicle industry introduced their autonomous flagship vehicles in the market. For example Audi introduced their A8 sedan, General Motor introduced super cruise and Volvo launched their drive-me autonomous vehicle. In 2018, Nvidia collaborated with Volkswagen for CAV of next generation. They introduced a smart chip named as “Xavier” which had artificial intelligence capabilities for CAV. A lot of progress has been made since then over traditional vehicles on the road and companies like Tesla and Google are working really hard to bring CAV on the public road with advanced technological features in the near future.

Accidents on the roads mostly occur due to common human mistakes such as mobile phone or other distractions, driver drowsiness and tiredness [8]. Machines don’t feel fatigue and don’t get distracted by things like mobile phone while driving and hence these cars don’t make careless mistakes while driving. Traffic congestion can be reduced using cooperative communication by sharing position, speed and information about routes. More importantly, CAVs can help increase human productivity by converting time on the road to useful time. CAVs can play a vital role in the mobility of children, elderly and disabled people. Almost all of the autonomous vehicles are hybrid or electric vehicles and they consume less fuel compared to traditional cars because of optimal route planning. CAVs can also communicate with

parking lots to find empty slot and can self-park to save precious human time.

**B. LEVELS OF AUTOMATION IN AN AUTONOMOUS VEHICLE**

According to society of automotive engineers (SAE), there are a total of six levels of automation [9], [10]. First level, L0, is the baseline case with no automation in the car. A Human driver performs all the tasks like steering, accelerating, braking etc. Second level, L1, is the lowest level of automation. Although most of the tasks are still performed by a human but some automation features are present like adaptive cruise control where the car can be kept at a safe distance from the car in front and in the same lane. This level of automation is also known as driver assistance level. Third level of automation, L2, is known as hands off automation. At this level the driver has the main control and performs most of the driving tasks but there are some features like cruise control, advance driver assistance system, automatic accelerating/decelerating in some circumstances etc. The human driver must pay attention to the environment and take the control from the vehicle any time. This level of automation is also known as partial driving automation and Tesla’s autopilot car qualify as L2. Fourth level of automation according to SAE is L3 automation (eyes off automation). Levels of automation according to SAE J3016 standard are shown in Fig. 2. Vehicles in this level are able to do some tasks automatically in some circumstances that otherwise a human driver would perform. At this level, vehicles have the capability to detect

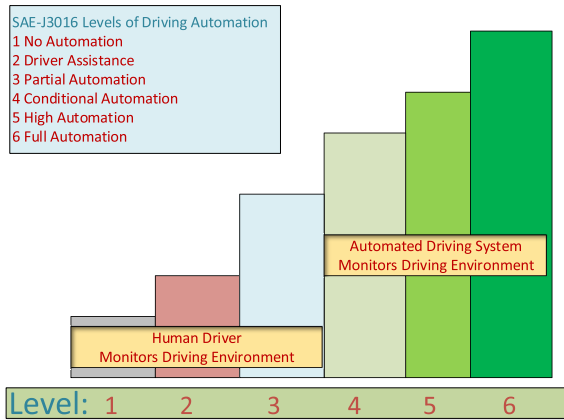


FIGURE 2. Levels of Automation according to SAE J3016.

the environment or surroundings and can perform informed tasks. However, a human assistance is still required at this level of automation. This level of automation is also known as conditional automation. Fifth level of automation according to SAE is L4 also called mind off automation. At this level, a vehicle is capable of performing all the driving tasks and monitor the environment. The cars still have a steering wheel, gear shift and brake pedal but the vehicles at this level are able to do most of the driving tasks by themselves. But, a human driver still has the option to take control of the driving tasks at this level. This level of automation is also known as high automation. The sixth level of automation is L5 or body off automation. The vehicles can perform all the driving tasks by themselves without any human assistance. The vehicles are fully automated and prepared to handle all the scenarios that can arise in the drive. These cars don't have steering wheel, gear shifts and brake pedals. These cars require zero human assistance to perform all the driving tasks. This level of automation is also known as full automation.

### C. ARCHITECTURE OF CAV

These levels of automation in CAVs are made possible through a robust and ever evolving architecture. The fundamental component for this architecture is an Electronic Control Unit (ECU) which integrates computing power with sensor and/or actuators to enable various functionalities. These functionalities include vehicles kinematics (Steering control, throttle and braking), power-train (Engine and battery), user electronics (Air Conditioning, Power windows and mirrors), infotainment (Radio, Navigation), autonomous driving system (Camera, radar, Lidar) and vehicle connectivity (V2X) as shown in the Fig. 3.

The ECUs for any particular functionality get connected using connectivity cables and protocols to a central gateway, acting as backbone of entire communication network. Autonomous driving functionality is dependant upon Perception, Localization, Fusion, Driving Policy.

### D. SCOPE OF THIS PAPER

This survey aims to provide a comprehensive view of state-of-the-art technology, practices, and future trends of the CAV

in the area of enabling wireless technologies and sensor fusion. Our main scope remains the CAVs in V2V and V2X domain, radars and sensor fusion. We believe that this multi-dimensional study of CAVs in this domain will provide industry researchers and stakeholders a better insight into the recent and emerging trends leading to optimal design and deployment strategies.

The remaining sections are organized as follows. Section II presents an in-depth treatment of state-of-the-art wireless communication and networking technologies that are shaping and realizing the cooperation and coordination among CAVs, vehicular cloud computing, and making the internet of vehicles a reality. Section III provides a comprehensive review on sensors used in CAV for data acquisition, signal processing for advanced driver assistance systems, and various sensor fusion techniques. Section IV provides some of the futures challenges and research directions related to enabling 5G and 6G wireless technologies and sensor data fusion. Finally, Section V concludes the paper.

## II. COMMUNICATION AND NETWORKING IN CAV

At this point, we have developed a basic understanding of CAV and how these vehicles work. This section will focus on the various networking and communication protocols deployed in these vehicles. The networking and communication protocols within the vehicle can be divided into two categories, namely intra-vehicle and inter-vehicle communication as mentioned in [11]. We will discuss intra-vehicle communication briefly before discussing inter-vehicle communication since it is the foundation for IoV.

### A. INTRA-VEHICLE COMMUNICATION AND NETWORKING

Intra-vehicle networking and communication is the backbone of autonomous vehicular operation since it realizes the gathering of information from the sensor. This sensor information is used in controlling various actuators within the vehicle. Intra-vehicle networking and communication can be realized using both wired as well as wireless technology. We first describe the intra-vehicle networking protocols before focusing on the communication protocols deployed to support communication within a vehicle.

Both wired and wireless interconnections are present in today's autonomous cars to exchange information and respond to control various electronic components. Both point-to-point, as well as data buses, are employed for these interconnections. Data buses substantially reduce the amount of cabling needed for point-to-point communication. The common communication technologies deployed in CAV are Controller Area Network (CAN) [12], [13], Local Interconnect Network (LIN) [14], FlexRay [15], Media Oriented System Transport (MOST) [16] and Ethernet [17]. A brief comparison of these technologies is presented in Table 3.

In addition to the wired technologies, several wireless interconnections are also used to reduce the complexity associated with wired interconnections. The wireless

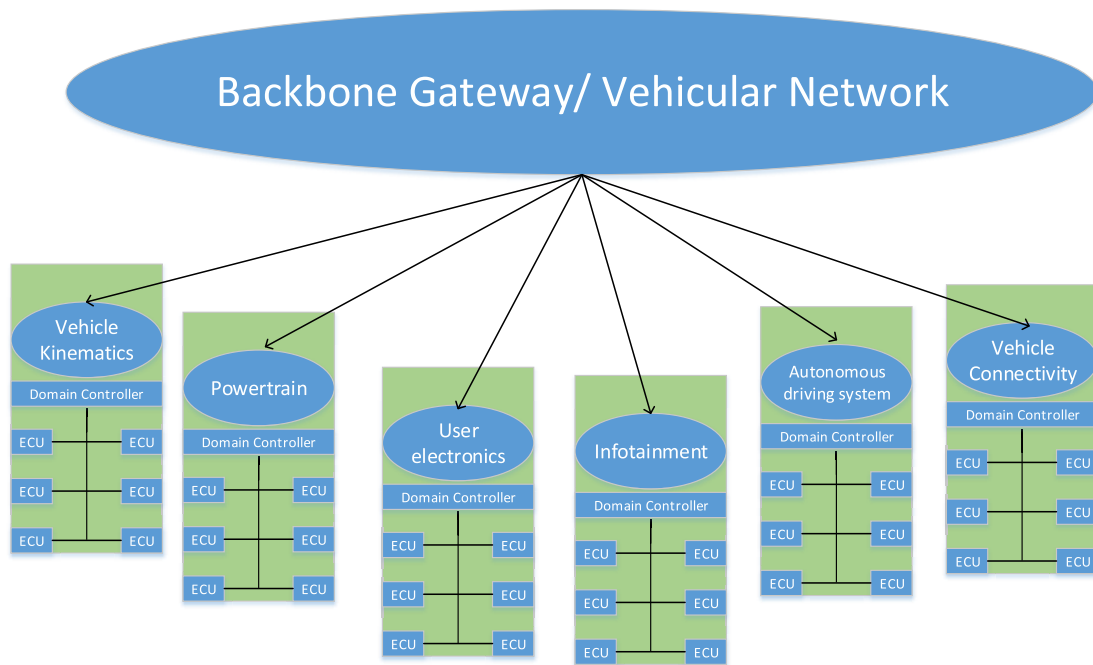


FIGURE 3. CAV Architecture.

communication standards adopted in CAV include; Bluetooth, Zigbee, Ultra WideBand (UWB), and WiFi.

Both academia and industry are simultaneously leading efforts for sustainable communication within an autonomous vehicle. Although the industry prefers already developed standards including CAN, LIN, FlexRay, and MOST, the academia favors Ethernet, mainly based on its ability to connect with the internet. The industry is led by “Tesla Model S/X/3” and “Audi A-8 D5” whereas academia-based efforts are being led by “Talos” and “Little Ben” from Cambridge and Pennsylvania teams respectively [11].

### B. INTER-VEHICLE COMMUNICATION AND NETWORKING

Inter-vehicle networking and communication techniques like intra-vehicle networking and communication constitute an important part of the perception, planning, and interaction of CAV. The communication between multiple vehicles can be achieved using vehicular ad-hoc networks (VANETs), which is the application of traditional MANET (mobile ad-hoc network) [11], [18], [19]. The ad-hoc mesh network is formed in a manner where nodes are not only vehicles but also infrastructure entities. Moreover, these mobile devices are equipped with wireless modules. The key differences include road dependent distribution of vehicle nodes and their high computing/storage capability [20], [21].

#### 1) VANETS

The communication between the entities of VANETs can be broadly categorized into V2V, V2I and V2X (Vehicle-to-Everything) [22], [23]. The term V2X encompasses all types of communications involving vehicles, which either fall

in V2V and V2I categories or involve communication with other entities like V2P. The interaction between the multiple connected entities consists of information exchange through the adoption of suitable communication protocols [24]. The aim of the communication between entities is to assist in solving the core transport problems like traffic congestion and accidents [25], [26]. In the following, we discuss these categories briefly.

**Vehicle-To-Vehicle** or inter-vehicle communication deals with wireless data transmissions between motor vehicles. The primary purpose of this communication is to exchange necessary information about positioning, traffic congestion, accidents, and speed limits [27], [28]. The vehicles which take part in communication can either form a fully connected mesh topology or a partially connected mesh topology [29]. In the fully connected mesh network, nodes can exchange messages and information with neighboring nodes to which they are directly connected, whereas a partially connected mesh network utilizes one of the different paths available to reach the destination [30]. Timely communication regarding scenarios like accident risk warning, driver’s sleep detection, an obstacle in the lane, or vehicle malfunction can lead to preventive actions such as emergency braking as well as warning through further communication with other vehicles in the vicinity.

**Vehicle-To-Infrastructure** is the communication between vehicle to infrastructure, which allows the vehicles to interact with the road infrastructure. The roadside infrastructure includes traffic lights and cameras, lane markers, street signage as well as parking meters [31], [32]. Similar to V2V, the V2I wireless communication is ad-hoc in nature which

TABLE 1. Intra-Vehicle technologies.

Network	CAN	LIN	FlexRay	MOST	Ethernet
Data Rate	1 Mb/s	19.2 Kb/s	20 Mb/s	150 Mb/s	100 Mb/s
Medium	Twisted Pair	Single wire	Twisted Pair/ Optical Fiber	Optical Fiber	Twisted Pair
Topology	Bus Star, Ring	Bus	Bus, Star Hybrid	Ring	Bus, Star
Cost	Medium	Low	High	High	Medium

enables nodes to send and receive messages regarding traffic supervision, and its safety management [33]. The Vehicle-To-Infrastructure system can be divided into the sparse roadside-to-vehicle communication system, also known as hotspots only service e.g. at parking or gas stations, and the ubiquitous roadside-to-vehicle communication system that ensures coverage throughout the road to all mobile vehicles [19]. The use cases of V2I include the exchange of information regarding road conditions, weather conditions, roadside construction, traffic lights malfunction, sharp curves, accidents, road congestion, and availability of parking spaces [1]. The use of all the traffic information enables the system to set different speed limits allowing the vehicles to maximize fuel efficiency as well as control the traffic flow. V2I technology can be utilized to manage the traffic lights for emergency vehicles like ambulances, fire brigades, and police cars. V2I also enables the vehicle to cloud (V2C) communication which encompasses cloud services of all varieties for the vehicles. A connected and autonomous vehicular network covering a broader spectrum is shown in Fig. 4. V2V and V2I are also referred to as cooperative ITS (C-ITS).

**Vehicle-To-Everything (V2X)** communication allows the vehicle to communicate with other entities for driving smoothly and safely with minimum power consumption [34], [35]. The (V2X) entities include pedestrians (V2P) [36], communication network (V2N) [37], devices (V2D) [38] and the Grid (V2G) [39]. The basic aim of V2P communication is to protect Vulnerable Road Users (VRU) [40]. VRUs includes pedestrians, cyclists, and motorcyclists. The development of a warning system is necessary due to the unavailability of separate lanes for VRUs at most places. A pedestrian warning system is also inevitable due to pedestrians distraction caused by earphones and smartphones usage. Recently, to support the possible and efficient communication mechanisms between vehicles and pedestrians, a Pedestrian Collision Warning (PCW) has been developed [41]. The PCW system can use wireless modules included in mobile phones, such as Wi-Fi, Bluetooth, and Near Field Communication (NFC).

V2V, V2I, and V2X have varying requirements from a communication perspective. Thus various wireless communication standards are utilized depending upon requirement based upon range, data rate, power and ease of deployment. Bluetooth, BLE, UWB, and Zigbee standards are deployed due to their low power requirements and short-range communication. Wi-Fi-based on IEEE 802.11 family of standards along with Dedicated Short Range Communication (DSRC)

are deployed for V2I based scenarios. These given vehicular networks access to the internet. Lastly, WiMAX and LTE-V are deployed for long-range connectivity, especially in the V2I scenario.

### C. VANET TECHNOLOGIES

In VANET, vehicles use numerous wireless access technologies to communicate with other vehicles, infrastructure, and conventional networks. The autonomous vehicle can transmit and receive real-time data (Audio/Video) as well as warnings and situation-related information. The selection of a wireless technology being deployed depends upon several factors, including range, sensor type, communication model, and topology, as well as the use case. The wireless technologies used in autonomous vehicles can be conveniently grouped into three categories based on their range i.e., short, medium- and long-range technologies. The Table 2, Table 3 and Table 4 summarize the main design principles, technical features, and protocols of some key technologies that fall into short, medium- and long-range categories respectively.

### D. RESEARCH THRUSTS IN COMMUNICATION DOMAIN FOR CAV

A subset of the most relevant research thrusts in the communication domain regarding CAV are listed below.

#### 1) ROUTING PROTOCOLS

In order to realize a sustainable and scalable growth of CAV a lot of research effort is being conducted in routing data traffic to address the dynamic needs of the CAV network. A comprehensive study of the available protocol and their various classification is done in [42]. CAV routing is faced with multiple challenges, including dynamic topology, link disruption, scalability, and security. Based on the various use cases of CAV networks, the routing protocols can be classified based on position, topology, cluster, geocast, and broadcast-based routing [11].

Position-based routing protocols utilize vehicle's location information estimated from the regularly transmitted beacons. Position-based routing does not require global routing from source to destination. Examples of this routing include Greedy Perimeter Stateless Routing (GPSR) [43], Anchor-based Street and Traffic-Aware Routing (A-STAR) [44] and Vehicle-Assisted Data Delivery (VADD) [45]. However, topology-based routing is classified into preactive, reactive, or hybrid. Preactive routing stores the routing information for

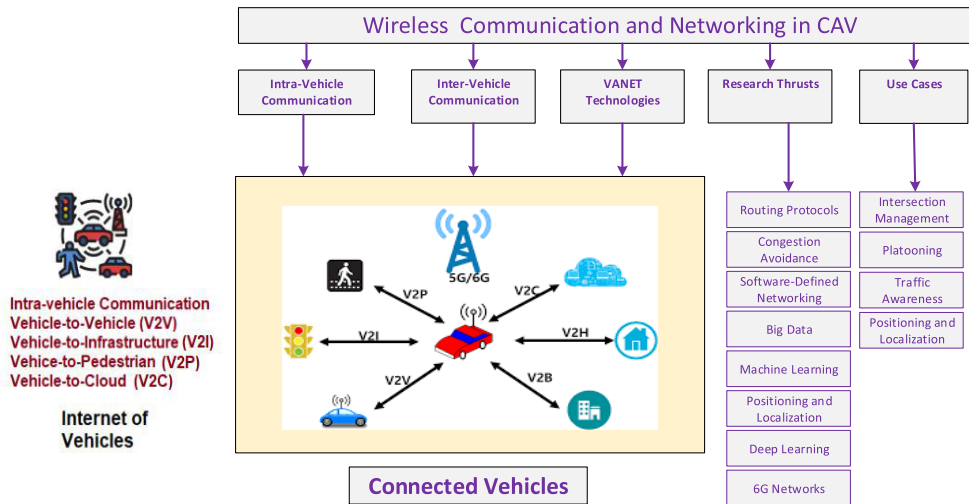


FIGURE 4. Wireless Communication and Networking for CAV.

all the connected AVs, which requires high network bandwidth [46]. In comparison, reactive routing protocols only initiate route discovery when it is required resulting in larger latency associated with route finding. Hybrid routing involves both proactive and reactive routing methods to achieve a trade-off between latency and bandwidth requirements. Some example of topology-based routing are Dynamic destination Sequenced Distance Vector (DSDV) [47], Dynamic Source Routing (DSR) [48] and Ad-hoc On-demand Distance Vector (AODV) [49].

Cluster-based routing groups together AV that have similar characteristics such as speed and direction. Within a cluster, cluster heads are responsible for routing hence making this routing strategy very scalable both in terms of bandwidth requirement and routing latency. Examples of these include Cluster-Based Vehicular Ad-hoc NETWORK (CBVANET) [50], and Adhoc On-demand Distance Vector for Clustering maintenance in VANETs (AODV-CV) [51].

Geocast based routing is a multicast routing protocol that forwards a message only to a subset of AVs based on their geographical location. Lastly, the broadcast-based routing protocol can be considered brute force routing approaches where messages are broadcasted to every other AVs and for larger network message collisions and eventually broadcast storms are created.

This section highlighted the routing protocols being adapted and devised for CAVs.

## 2) CONGESTION AVOIDANCE

The exchange of safety messages among vehicles can result in reducing the number of road traffic accidents and increasing traffic efficiency. These safety messages are both periodic or based on emergency beacons, but in both these cases, they must adhere to reliability and scalability constraints. As the vehicular network grows, the frequency of safety messages increases substantially, and hence these safety messages are

controlled through a congestion control protocol. One such protocol is presented in IEEE DSRC wireless access system, which supports efficient congestion control for vehicular safety communication. Congestion control protocols help in the effective delivery of time-critical safety messages in vehicular networks. Many studies have been carried out to validate and evaluate the performance of congestion control techniques.

## 3) SOFTWARE DEFINED NETWORKING

Software Defined Networks (SDN) is a virtualization architecture and design framework, reducing management complexity for CAV networks. It is usually based on OpenFlow, a flexible network traffic controller which separates the control plane from the data plane, thus making the network more intelligent. SDN, with its ability to deploy independent centralized controllers, processing entities, traffic forwarding, and programmability, makes the network more flexible. A great deal of research has been done on SDN for CAV deployment. Firstly, [52] propose a new architecture integrating Edge Computing with SDN, yielding flexible and effective resource management and utilization, improving the performance communication among autonomous vehicles. Another SDN for vehicular network architecture is proposed in [53], reducing traffic aggregation and delays. Similarly, [54] presents a centralized SDN network controller for autonomous vehicles that can create clusters dynamically depending upon the real-time road conditions.

## 4) BIG DATA IN VEHICULAR NETWORKING

CAV naturally depends on cellular networks to provide wide area coverage. Additionally, in small dense cells, communication cost and vehicle connectivity are made economically viable using cellular networks. Also, with increasing sensors being equipped on modern vehicles, massive data is generated. This massive data traffic in vehicular networks

**TABLE 2.** Short range inter-vehicle technologies.

Technology	Standard	Bandwidth	Rate	Range	Latency	Modulation
Bluetooth	IEEE 802.15.1	1 MHz	1–3 Mbps	10 m	100 ms	GFSK
BLE	IEEE 802.15.1	2 MHz	1–Mbps	50 m	6 ms	GFSK
ZigBee	IEEE 802.15.4	0.3/0.6/2 MHz	20–250 kbps	75–100 m	30 ms	BPSK,O-QPSK
UWB	IEEE 802.15.3	0.5/7.5 GHz	480 Mbps	75 m	0.1 ms	BPSK-QPSK

**TABLE 3.** Medium range inter-vehicle technologies.

Technology	Standard	Multiplexing	Data Rate (Mbps)	Modulation	Symbol Time	Range (m)
Wi-Fi	IEEE 802.11a	OFDM	upto 54	upto 64 QAM	4 $\mu$ s	100
DSRC	IEEE 802.11p	OFDM	upto 27	upto 64 QAM	8 $\mu$ s	300

**TABLE 4.** Long range inter-vehicle technologies.

Technology	Modulation	Channel Coding	Waveform	Multiplexing	Range	Position accuracy	Channel Bandwidth
C-V2X	16/64 QAM	Turbo	SC-FDMA	FDM	100 m-5 Km	> 1m	20 (MHz)
5G-NR V2X	256 QAM	LDPC/Polar	OFDM	TDM	50 m-5 Km	0.1m	40 (MHz)

has ushered Big Data in VANETs. With Big Data, vehicles are now being equipped with even more powerful processing units and large storage devices, evolving the VANETs into IoV since each vehicle can now be considered a computer and storage center with connectivity with other vehicles. [55] classifies such an IoV capable of big data support into four distinct phases, namely Acquisition (both inter-vehicle and intra-vehicle), Transmission, Storage and lastly, Computing.

##### 5) MACHINE LEARNING IN CAV

Machine learning, a data-driven intelligence tool, is being widely employed to solve complex and dynamic problems associated with communication and connectivity in CAV. ML has been a focus of various research thrusts in CAV. We try to highlight some of the key areas where AI has been deployed to enhance performance for CAV. [56] presents edge computing enhanced through the use of deep learning. The presented results highlight that an edge analytics architecture with deep learning algorithms can make the intelligent transport system reliable and safer. Another dimension employing deep learning is at the network traffic controller. [57] summarize architectures and algorithms designed for network traffic controllers using deep learning. Deep learning also has the potential to address message routing for autonomous vehicles networks. [58] present the deep learning scenario for packet processing and transfer. Authors in another work [59], present machine learning at the physical layer to address handover between sub-6 GHz and mm-Wave integrated CAVs.

A very recent and comprehensive survey [60] presents the machine learning application in vehicular networks. Authors have highlighted works starting from channel estimation for

orthogonal frequency multiplexing OFDM-based transmission. Works involving supervised learning for both OFDM equalization are presented. In addition to this, machine learning-based beamforming, advances in cognitive radios through machine learning, and application of machine learning in non-orthogonal multiple access are also discussed. In addition to physical layer applications, [60] also summarizes works involving reinforcement learning-based prediction and intelligent decision in resource allocation. On the networking side, vehicle mobility prediction to improve mobile routing and network traffic flow prediction-based routing are also discussed through the application of machine learning.

##### E. USE CASES ENABLED THROUGH COMMUNICATION

Communication in AV plays an integral part in various applications. The following list of applications/use cases are enabled by utilizing the communication and networking protocols that are discussed in the previous section.

###### 1) INTERSECTION MANAGEMENT

CAV has the ability to improve traffic flow through collision avoidance and intelligent management of intersections. [61] provides a survey of various centralized and decentralized approaches that have been proposed in the literature to address the coordination of vehicles. Centralized approaches include schemes that require global reservation or optimization of one parameter, whereas decentralized approaches create a vehicle control policy on the information received from the other vehicles. One centralized work is mentioned in [62], where V2X-enabled CAV scheduling is carried out



at unsignaled intersections. This work creates a collision-free model by dividing the intersection area into basic scheduling units. A distributed intersection management protocol is discussed in [63]. In this work, the authors present a Distributed Intersection Management Protocol (DIMP) for VANETs. DIMP enables vehicles to exchange messages to decide the order for crossing intersections based on real-time traffic conditions. Traffic coming from a different direction is grouped together, and a group leader is elected who is involved in negotiating a safe and timely passage through the intersection.

## 2) PLATOONING

Platooning, which is also referred to as cooperative adaptive cruise control (CACC), is an integral part of the futuristic, intelligent transportation system. Platooning is a method for increasing road efficiency by grouping vehicles together, where the distance between vehicles is decreased. Vehicles within a platoon accelerate or brake simultaneously. Platooning is enabled in modern vehicles by sharing information or a warning to the driver of a hazardous road situation using either a decentralized or cooperative approach. The Decentralized approach involves decentralized environmental notification message (DENM), whereas the cooperative approach involves sharing the kinematic state of other vehicles using cooperative awareness message (CAM) as mentioned in [64]. Multiple works highlighting different platooning aspects have been conducted to enhance knowledge and move closer to practical implementations of CACC/platooning. Although platooning/CACC are used interchangeably, some subtle differences exist between CACC and platooning, which are summarized as follows.

CACC is an inbuilt function of the vehicle that is built on top of the adaptive cruise control (ACC) function. CACC is based on kinematic data directly transmitted between consecutive vehicles, which can be either the preceding or following vehicle. In CACC, multiple vehicles equipped with CACC align together to form a caravan/platoon; however, each vehicle within such a platoon is solely responsible for its own maneuvering.

In contrast, in platooning, multiple vehicles sharing a common destination form a platoon, led by a platoon leader. Unlike CACC, in this platooning, the platoon leader is given the mandate to coordinate with platoon members for platoon maneuvering, which can include platoon joining/leaving/speed. Platoon leaders can also make a decision for individual members in certain situations. The platoon leader is also responsible for observing the driving environment not only for itself but for the whole platoon. CACC is considered as the enabling technology for platooning.

Various studies have been conducted to model the behavior of platoons. [65] uses control theory (spring mass damper system) to depict the behavior of vehicles within platoons. In another work [66], model predictive control is used for enhancing traffic performance by enabling cooperation among vehicles in the platoon. Also, within a platoon, various

scenarios are researched like in [67] authors target the catch-up strategy (i.e., the upstream vehicles accelerate to catch up with the leading vehicles) and a slow-down strategy (i.e., the leading vehicle decelerate so that the upstream vehicle can catch up and platoon with them). [68] studies the behavior of platoon in the presence of speed limit fluctuations. Lastly, we mention work [69] where various communication protocols are compared for platooning.

## 3) TRAFFIC AWARENESS (Right OF WAY)

Among the various messages mentioned in CAV, Cooperative Awareness Messages (CAMs) are one of the key messages required for traffic awareness. CAM is a high-frequency periodic message which is broadcasted by every vehicle to its neighbors. CAM includes information regarding vehicle kinematic (position, time, direction, and acceleration), vehicle attributes (like length, width, type, and role in the platoon), vehicle movement data (like historical path and predicted path), vehicle type (e.g., emergency, bus, maintenance vehicle).

CAM message related work include [70] and [71]. In [70], authors present a real-time multi-vehicle motion planning (MVMP) algorithm for the emergency vehicle clearance task. They have broken down this task into two phases. The first phase involves the emergency vehicle joining a platoon of CAV. In the second phase, the emergency vehicle is made the platoon leader by all other vehicles in the platoon by acting cooperatively. However, in [71], the proposed scheme involves both the roadside unit (RSU) and the intelligent traffic management system (ITMS) to communicate and devise a smooth transit path for the emergency vehicle.

[72] deploys cooperative rating and machine learning to detect reckless driving behaviors in CAVs. This machine learning is carried out through a cooperative driving performance rating (CDPR) mechanism by integrating the computation capabilities of neighbor vehicles and a cloud server. The system is able to detect and alert users regarding reckless driving hence providing traffic awareness and preventing collisions.

## 4) POSITIONING AND LOCALIZATION

Vehicle positioning and localization are essential for various location-based services, including the safety of the vehicle. This is also an essential part of CAV, where the vehicle is expected to be able to sense the environment and navigate the surroundings without any sort of human input. Localization for CAV can either be achieved through real-time kinematic (RTK) technology. It is based on GPS, which provides centimeter-level accuracy. But this accuracy drops significantly in the presence of structures, hence blocking GPS satellite transmission. In such localization scenarios, dead reckoning is used, where GPS signal is fused with onboard Inertial Measurement Unit which gives the centimeter-level accuracy when GPS signal is lost for a short duration. [73] covers some possible localization techniques being considered in the perspective of CAV. These include GPS, Map

matching, Cellular based, Dead reckoning, and even Fingerprinting methods. Work presented in [74] reduces the errors associated infused (dead reckoning) localization scenarios. Another technique presented in [75] achieves accuracy in localization using Cooperative Localization (CL) technique, which is used to improve GPS accuracy. CL is made possible due to V2X communication, allowing the vehicles to share location information among themselves. Typically, GPS information is used along with relative distance or angle to neighboring vehicles from LiDAR.

### III. MULTI-MODAL SENSOR DATA FUSION

An autonomous vehicle can sense its surroundings, and it can also navigate without any human assistance. Typically, an autonomous vehicle has five essential components: computer vision, sensor fusion, localization, path planning, and control. Through computer vision using camera images, CAVs figure out the surrounding environment. Sensor fusion allows the vehicle to process and incorporate data from other sensors like RADAR and laser to understand the environment better. Furthermore, CAVs use localization and path planning algorithms to determine their position and the most suitable path towards the destination. The final step is the actuation based on the decisions, i.e., turning the steering wheel, acceleration, and application of brakes automatically to follow the trajectory [76].

A connected vehicle with various onboard sensors needs to have an accurate and reliable self-localization. RADAR is the most robust sensing device against changing light and weather conditions. Werber *et al.* [77] proposed self-localization by RADAR landmarks. The landmarks are the known prominent parts of the road recognizable by the global pose. This approach is better than the conventional satellite-based approach [78] which is prone to changing weather conditions. However, the resolution is a challenge for such systems.

Several performance parameters are expected in an automotive RADAR apart from the detected range for example, range/velocity precision, range/angular resolution, and the angular width [79]. It should have several features that can make an overall system robust and operative. These features include automatic cruise control, collision warning, emergency braking, parking slot measurement, pre-crash sensing, blind-spot detection, and lane change assistance [80], [81]. All of these features demand an interference-free environment which is also an area with a lot of research potential [82].

A robust automotive system is safe, environment-friendly, and economical [83]. There are extremely stringent requirements for reliability and reaction time for a connected vehicle with collision avoidance and automated driving mechanisms [84]. These requirements are not as harsh for vehicles having conventional automatic cruise control systems [85]. Typically, such vehicles have a maximum range of 200 meters with a range resolution of less than 1-meter and can maintain a velocity resolution of 2500 meters per hour [86]. The advantage of continuous waveform lies

in its low computation time and ability to achieve higher bandwidth [86], [87] [88], [89].

The applicability of modern automotive vehicles in the desired form is most dependent on the development of robust and intelligent sensors that are well-integrated [90]. The integration of sensors holds a key as different kinds of sensors are mounted on the same platform. The sensor's accuracy and speed in an integrated system according to varying environmental conditions are of great significance to the future development of the automotive industry. The gradual deployment of 5G mobile networks has also aided the development of such platforms. The data collected by each sensor installed on the vehicle are processed in a perception block that converts this collected raw data into an understandable information [91].

RADAR sensors have low precision than cameras in the human interpretation of the measured data [92]. Moreover, cameras need training data and a machine learning model to predict and classify the target of interest [93]. Artificial Intelligence (AI)-based algorithms can convert the RADAR sensor data to valuable images, which require fusion of information collected by all sensors mounted on the vehicular platform [94]. In [95], investigators proposed a Conditional Multi-Generator Generative Adversarial Network that produces sensors fusion-based high-quality images of detected targets.

In order to cater to various types of autonomous functions in vehicles, mapping and tracking of stationary and moving objects is required. Therefore, tracking and mapping estimates from sensor measurements from RADAR, laser, and camera are used together with the standard proprioceptive sensors present in a car [96]. The accuracy and robustness of the estimates increase by fusing information from different types of sensors. [97].

Multi-modal sensor fusion assists drivers by providing timely precautions in a way that the overall experience of driving gets improved and the probability of accident gets lower [98]. Also, such a system gives a sense of autonomy to the electronic system of the vehicle to reduce the accidents caused by human errors and hence overcoming the associated hazards [99], [100].

Simultaneous localization and mapping (SLAM) algorithms use fused information to update target maps and keeps track of object's location [101], [102]. Over the last few years, SLAM algorithms are increasingly being used in a variety of RADAR-based automotive vehicles [103], [104] [105].

Fig. 5 shows different categories of sensor fusion found applied to autonomous and connected vehicles. These include classic, centralized, decentralized, hybrid, deep learning-based, and Kalman filter-based approaches [106]. The probability-based methods, like Bayesian analysis, statistics, recursive operators, fall into classical sensor fusion approaches. In the centralized fusion process, raw data is fused from each sensor and processes the joint information by centralized processing. In contrast, decentralized fusion is more suitable for non-orthogonal sensors, but it has high

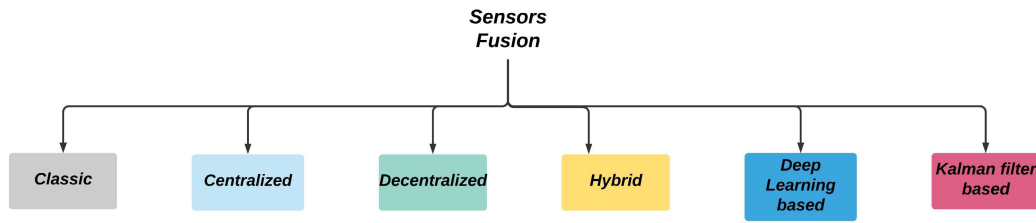


FIGURE 5. Categories of Sensor Fusion.

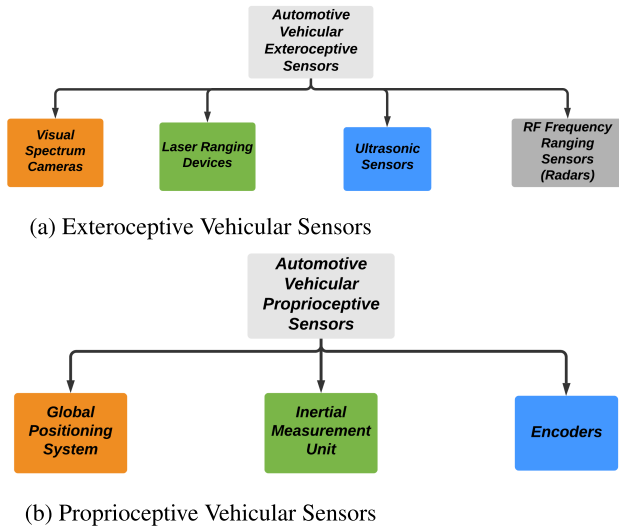


FIGURE 6. Vehicular Sensors.

data volume [107]. The hybrid fusion technique is a mixture of these two techniques. The deep learning-based category involves convolution, or recurrent neural network-based approaches [108]. Kalman filter-based approaches are used for fine tracking of identified objects [109].

**A. SENSOR FUSION**

The automation industry is striving to deploy fully equipped automated vehicles within the next few years. These vehicles will significantly rely on sensor data for safe navigation on the roads. In recent times, sensors such as vision, RADAR, LiDAR, and ultrasonic are most popular. Unlike the assisted driving case, fully automated driving vehicles have to stay functional in any situation that demands a lot from the integration of sensors which constitute an overall system [110]. An autonomous vehicle finds out about its environment is through its sensors. Sensors must have the option to make both a cognitive and locational perspective of the surroundings so that the vehicle can make choices in real-time.

There are two kinds of sensors utilized in an autonomous vehicle: exteroceptive and proprioceptive. Exteroceptive sensors are utilized for environment sensing and for separation of objects, while Proprioceptive sensors are utilized for various measurement purposes [111]. Fig. 6a and Fig. 6b show the sensors that fall into each category.

1) INFORMATION FUSION FRAME-WORKS

Sensor uncertainties are created not only by the imprecision and noise in measurements, but also by ambiguities and inconsistencies in the environment, as well as the inability to discern between them. To mitigate these impacts, data fusion algorithms should be able to take advantage of duplicate data. Sensor fusion algorithms and methodologies have been widely researched in recent years and are now well-established in the literature. However, due to the trans-disciplinary and diverse nature of algorithms, it is a difficult and time-consuming task. The algorithms are usually divided into two categories: traditional sensor fusion algorithms and deep learning sensor fusion algorithms. The traditional algorithms use statistical methods, probabilistic methods, and hence rely on ideas of probability.

Data fusion is a heterogeneous field that spans several disciplines, making it difficult to classify it clearly and precisely. The following factors can be used to categorise the approaches and techniques used:

- 1) Paying attention to the relationships between the data sources used for input.
- 2) Based on the categories of input/output data and their nature.
- 3) Using the data’s abstraction level as a guide.
- 4) Based on the various stages of data fusion
- 5) The architecture type: (a) centralised, (b) decentralised, or (c) distributed, depending on the architecture type

Information fusion typically addresses three levels of abstraction: (1) measurements, (2) characteristics, and (3) decisions. Other possible classifications of data fusion based on the abstraction levels and for combining sensory input from distinct sensing modalities are high-level fusion (HLF), low-level fusion (LLF), and mid-level fusion (MLF) [112]. In low-level fusion, the raw data are directly provided as an input to the data fusion process, which provide more accurate data (a lower signal-to-noise ratio) than the individual sources. In mid-level fusion, the qualities or features (shape, texture, and position) are combined to produce features that can be used for other purposes. Because the HLF techniques are less difficult than the LLF and MLF approaches, they are frequently used. HLF, on the other hand, provides insufficient information because classifications with a lower confidence value are disregarded if there are multiple overlapping obstacles [113].

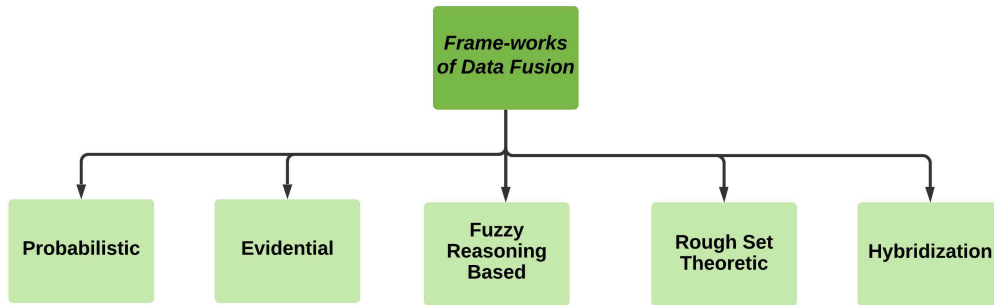


FIGURE 7. Information Fusion Frameworks.

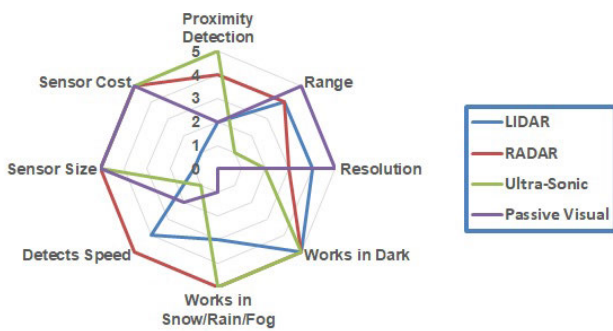


FIGURE 8. RADAR Chart for comparison of various sensors.

There are a variety of different frame-works of data fusion having its own characteristics, capabilities and limitations. The block diagram in Fig. 7 shows each of those frame-works as used in connected vehicles.

*a: PROBABILISTIC FRAMEWORK*

The probability density function is used in probabilistic fusion approaches to express sensor data uncertainty. We can arrive at a posterior probability by combining prior and observational data for the problem of decision-making or estimation. In probabilistic framework, usually Bayesian approach is used [114]. This is however considered incapable of addressing other data imperfections.

*b: EVIDENTIAL FRAMEWORK*

In evidential framework, the probability mass is used to further characterize data using belief and plausibility, and the Dempsters’ combination rule is used to fuse the data. Although it allows for the fusion of ambiguous and uncertain data, it does not address other aspects of data imprecision, therefore is ineffective when combining significantly contradicting data [115].

*c: FUZZY BASED FRAMEWORK*

Another theoretical reasoning technique for dealing with imperfect data is fuzzy set theory. It introduces a new concept

called partial set membership, which allows for imperfect reasoning. In fuzzy reasoning based framework, intuitive approach is used to deal with ambiguous data. It allows for the processing of partial data, which is typical in under-informed environments and therefore in the fusion community, it is not widely used or well understood [116].

*d: ROUGH SET THEORETIC BASED FRAMEWORK*

In rough set theoretic based approach, exact approximation is used with bounds adjusted with classical set theory operators to deal with ambiguous data. It does not necessitate any preliminary or supplementary information; nevertheless, it does necessitate an adequate level of data granularity [117]. Rough set theory has been infrequently applied to data fusion challenges since it is a relatively new theory that is not widely known within the fusion community.

*e: HYBRIDIZATION BASED FRAMEWORK*

The primary principle behind hybrid fusion algorithms is that distinct fusion methods, such as fuzzy reasoning, evidential, and probabilistic fusion should not compete because they approach data fusion from separate (but potentially complementary) perspectives. The hybridization based framework aims to provide a more complete treatment of faulty data and is deployed in a complementary rather than competitive manner. This comes with an extra computational cost due to ad hoc generalization of one fusion framework to encompass another [118].

Sensor Fusion includes the fusion of different sensors information to enhance vehicles perception, thereby creating a dependable system [119]. The vehicle is commonly furnished with a suite of sensors that give explicit data about its environmental factors. One thing common to all these sensors is their involvement in perceiving the same scenario. Hence, by combining the acquired information from these sensors, an accurate output is attained.

Multiple sensors having different technologies must be combined in order to add diversity and reliability to an overall system [120]. Individual sensors have their limitations for providing necessary information about the vehicle surroundings for performing safety functions. Fig. 8 shows



FIGURE 9. Sensor Fusion and Tracking Snapshot-A.

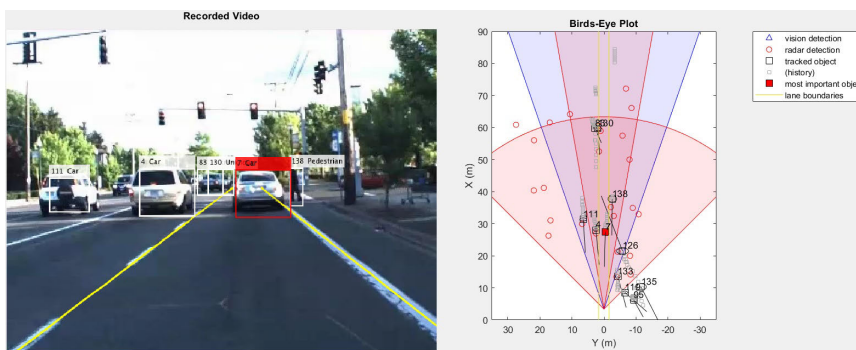


FIGURE 10. Sensor Fusion and Tracking Snapshot-B.

a RADAR-chart (also known as spider chart) for various onboard sensors that are used in connected vehicles [121]. The performance metric of each sensor is rated from one to five, where five shows the best capability corresponding to each performance metric.

A complete model of the environment can be generated with adequate confidence by combining the input from various sensors for enabling Advance driver assistance system(ADAS) features or automated driving functions. It also overcomes the weaknesses of the individual sensors and outputs a robust system [122].

Forward collision warning (FCW) is a mechanism that provides accurate and reliable information as warnings to the driver before an expected collision. For this, vision and RADAR sensors are installed in the vehicles. In order to increase the probability of accurate warnings and minimize the probability of false warnings, sensor fusion is required [123]. The outputs of the various sensors present in the CAVs are recorded. The essential sensors in CAV are a) Vision sensors: which provide lists of observed objects with their classification and information about lane boundaries, b) RADAR sensor: which operates in medium and long-range modes; and provided lists of unclassified observed objects, c) Inertial Measurement Unit sensor, that reports the speed and turn-rate of the vehicle and d) video camera, which records a video clip of the scene in front of the car.

To provide a forward-collision warning, multi-modal sensor fusion gets a list of tracks, i.e., estimated positions and velocities of the objects in front of the car, issuing warnings based on the tracks and FCW criteria. With the emerging interest in autonomous vehicles, several software algorithms have been developed for performance investigations. For engineers and scientists working in academia, MATLAB provides the most convenient solution. Fig. 9 and Fig. 10 show two snapshots of sensor fusion based collision warning system using MATLAB application. These MATLAB tools record the video and identify the corresponding type of vehicle and pedestrians in its vicinity. It uses a phased array, computer vision, and navigation toolboxes of MATLAB.

### B. FREQUENCY-MODULATED CONTINUOUS WAVE (FMCW) RADARs IN ADAS

Advanced driver assistance system (ADAS) is defined as a combination of intelligent components such as object detection and tracking systems used to protect drivers and road users. The significance of ADAS is to measure the distance between the vehicle and the detected object. It helps predict object location in the lane, avoid accidents, and improves road safety. Traditionally, the automotive industry used infrared ranging and LiDAR. In the modern-day world, a wide range of RADARs are used in cars that assist a driver for a high-quality driving experience. Research and development for

fully autonomous vehicles are on the rise in the automotive sector.

Most of the sensors can perform well under normal weather conditions [124], however when it comes to hostile weather conditions, it is the RADAR that provides a robust solution for detection [125]. RADAR sensors also have some limitations regarding the classification process as an automotive RADAR cannot identify and classify a signboard. However, LiDARs are good at mapping its vicinity [126], though this solution also has drawbacks that primarily include LiDAR performance under low contrasts and difficult angles [127]. For such cases, AI-based features turn out to be most useful [128], [129] [130].

Owing to cheap FMCW RADARs available in the market and the competition between various vendors, the cost of automotive RADARs has considerably reduced over the last few years [131]. A typical FMCW RADAR costs around 50-220 US dollars depending upon the application in terms of range as it also dictates power and hence the involved electronic circuitry [132] [133]. On the other hand, LiDAR sensors are a little expensive than RADAR sensors. However, their price is also on the fall owing to the growing interest of the automotive industry [134].

The FMCW RADARs have gained huge attention over the last decade in the automotive sector. They are not only very cheap but also offer much better resolution as compared to other RADARs. Moreover, the modulation is simpler, and it offers high average power [135]. FMCW RADARs can be operated at much higher frequencies without having the related tradeoffs that are encountered in traditional Doppler RADARs [136]. Therefore, research and development in this sector are in high demand throughout the globe. The ease of designing has also caught the attention of researchers in academia that can make use of software-defined systems to prototype for the industry [137]. In [138], a low-cost 24 GHz FMCW RADAR is designed with a single transmitter and receiver antenna array. A Gunn Voltage Controlled Oscillator (VCO) and the MMIC (a driver amplifier) are combined to act as a transmitter for the FMCW RADAR. The Rat race, which is the hybrid mixer acts as a receiver for the FMCW RADAR. Another FMCW RADAR system with an operating frequency of 24GHz is designed and implemented by using FPGA and the Digital Signal Processing (DSP) unit [139]. A different method is proposed by [140], in which Multiple Input and Multiple Output (MIMO) FMCW RADAR is developed by using the combined frequency-shift keying linear FMCW (FSK-LFMCW) waveforms. This RADAR system is very suitable for providing the high angular resolution and for detecting multiple targets with the low sampling rate of the FMCW RADAR [141]. The proposed method for FMCW RADAR has some limitations with regards to MIMO systems as each signal acts as a noise for all others transmitted and received signals which caused the low signal to noise ratio (SNR), and that is a fundamental issue in these FMCW RADAR systems [142].

### C. CHALLENGES AND ISSUES IN SENSOR FUSION

Multisensory data fusion is a technology that allows you to combine data from multiple sources to create a cohesive image. Data fusion systems are currently commonly employed in a variety of fields, including sensor networks, robotics, video and image processing, and connected vehicular systems [143]. As low-level fusion becomes increasingly well-established and mature, research on high-level fusion tasks is becoming more prominent. As connected vehicles are equipped with a lot of sensors of different types, a sensor fusion based approach is of immense importance. The data collected by sensors is always subject to some degree of imprecision and uncertainty in the measurements. Data fusion techniques should be able to properly articulate such flaws and leverage data redundancy to mitigate their impact. There are a variety of challenges that make data fusion difficult. The majority of these challenges are caused by the data to be fused, the imperfection and diversity of sensor technologies, and the nature of the application environment. While several of these issues have been identified and extensively researched, no single data fusion technique is capable of addressing all of them. The literature's various methodologies focus on a subset of these challenges to tackle, which is dictated by the application at hand [92].

There are several challenges for vehicle navigation systems, such as the uncertainties posed by the system and measurements models. Recent developments in vehicular sensors and their fusion involving artificial intelligence provide a new potential to tackle these challenges. By using AI and big data processing, vehicle navigation provides more accurate positioning results and helps the researchers resolve the problem of performance enhancement in several scenarios.

- **Data Anomaly and Perception Challenge:**

In order to achieve high angular resolution, multiple receivers are employed in modern-day RADARs. This is also required for accurate tracking and mapping of the vehicles in close proximity. This also requires careful calibration of various sensors. In extrinsic calibration, the camera location in a three-dimensional scene is specified, which maps the object's coordinates to the camera coordinates. In intrinsic calibration, for accurate range, velocity, and angle of arrival, the parameters (focal length and the optical center of the lens) are specified. RADAR systems play a vital role in sensing for autonomous vehicles and help in target detection, velocity precision, tracking precision, and parameter estimation. In Linear FCMW RADAR, signal linearity is the most critical parameter. Four individual sensors are mounted behind the front bumper instead of a single RADAR. The azimuth angle should be significant, and there should be a small range to avoid collision and pre-crash warning. Time synchronization between individual sensors is needed to avoid interference situations between RADAR sensors. Four individual chirps provide sufficient redundancy in multi-target and extended

target control to suppress the ghost target [144]. Different sensors in an autonomous car are shown in Fig. 11.

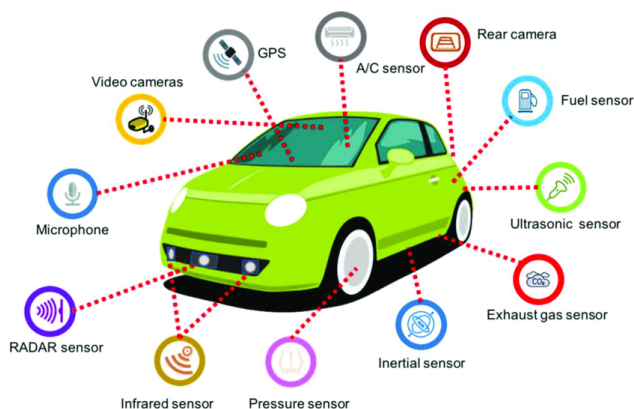


FIGURE 11. Different sensors in a autonomous Car [145].

- Interference and Security Issues:

Estimating the amplitude and frequency of the interference signal to recover the original signal as well as the interference elimination with high computational complexity is very important. In [146], a target is detected without defining an adaptive threshold. The recurrent neural network is implied with the gated recurrent unit for processing sequence data to remove the interference. Most RADARs operate in the same frequency band in the case of multiple RADAR sensors, thereby reducing the risk of interference which can become very problematic. [147] analyses automotive RADAR interference and propose counter-interference techniques.

RADAR systems are considered as key components for today's ADAS for features like adaptive cruise control and emergency brake assistance. It has been shown in [148] that interference between different FMCW RADAR systems leads to an increased noise floor. This can lead to poor detection efficiency, especially those with a small RADAR cross-section (RCS) like pedestrians. In [149], a novel concept is proposed to mitigate interference in FMCW RADAR transceivers using digital signal processing. Multiple sequences of FMCW chirps in the frequency domain are taken into account to cancel the interference effect. The object information in the RADAR image is retained by suppressing the noise and the associated interference. In [150], a prototype of the close vehicle warning system (CVWS) for bicyclists is introduced. For cost-effectiveness, a cell phone is used as a Human User Interface (HUI). Bluetooth protocol is used for communication between a RADAR system and a mobile phone. The RADAR works at a frequency of 24.1 GHz with 180 MHz bandwidth, and it is intended to detect cars behind a bicyclist.

- Signal-to-Image Encoding and internet of things (IoT) based Sensor Fusion:

Most of the sensors can perform well under normal weather conditions [124], however in hostile weather

conditions; it is the RADAR that provides a robust solution concerning detection [125]. RADAR sensors also have some limitations when regarding the classification process as it is difficult for an automotive RADAR to identify and classify small objects like signboards. For such tasks, other sensors and AI-based features processing turn out to be most useful [128], [129] [130].

Applications of IoT as a whole can be seen everywhere in the modern-day world. It relies on a range of IoT devices that gives out a massive amount of digital information. It also helps the system make agile, perceptive, and reliable decisions quickly and efficiently. There are also hazards associated with deploying so many IoT devices that make an overall system vulnerable to cyber and other attacks. Hackers are developing various IoT-focused malware that can inject false or compromised information. Blockchain is used to facilitate secure sharing of Internet of Energy (IoE) datasets; however it has associated disadvantages of complexity and energy consumption [151]. Various signal to image encoding approaches are being developed e.g. in [152]–[155]. The neural network's edge in image and data processing has paved the way towards adaption to additional sensor and sensor fusion. By including multi-modal sensor data in the sensor fusion, the research community aims to obtain more reliable results for the various tasks involved in environmental perception for CAVs [152].

Several open problems are challenging to scientists and researchers working in the area of connected vehicles. The investigations regarding the robustness of neural fusion techniques against spatial and temporal miscalibration of the sensors needs to be gauged. The application of fusion to 3D object detection is another direction that needs further in-depth analysis. In addition to this, removal of clutter from the fused data is an area that would require multi-dimensional research and development hence enabling an increase in the performance of connected autonomous vehicles.

The increase in the complexity is one of the most critical issues that is faced during the fusion process of a large number of sensors as it compromises the smooth integration of multiple data sets into a consistent, accurate, and useful representation – that is, to perform data fusion [156]. Fig. 12 shows the block diagram for a connected advanced driver-assisted sensor fusion system where data from sensors can be seen as fused in the sensor fusion block, which also takes input via digital maps and communication protocols. Machine learning-based algorithms are applied to this fused data, which eventually gives control to an autonomous system.

#### D. DIGITAL SIGNAL PROCESSING OF SENSOR DATA

Over the last two decades, many standards with regards to frequency allocation have been developed by the regulatory bodies dealing with the automotive sector [157].

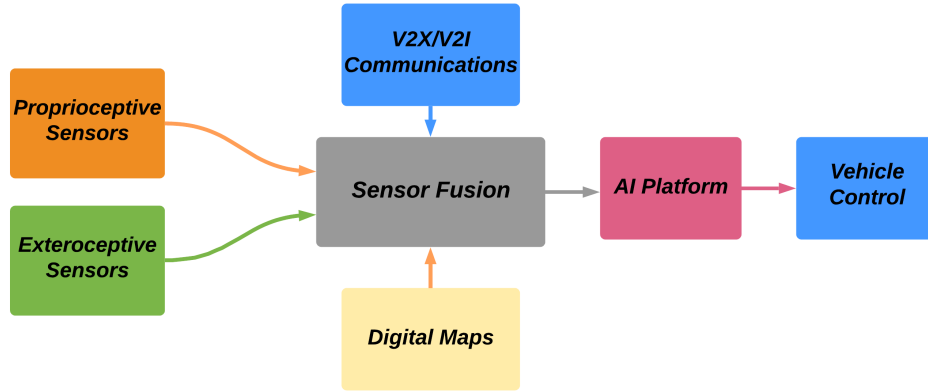


FIGURE 12. Connected ADAS Sensor Fusion.

TABLE 5. Automotive RADARs frequency band.

RADAR Type	Frequency Range [GHz]	RADAR Frequency Band
24 GHz ISM	24.05 - 25.25	K
24 GHz UWB	21.65 - 26.65	K
77 GHz LRR	76 - 77	mm-wave
79 GHz SRR	77 - 81	mm-wave

The frequency range of 76-77 GHz is regulated for the automotive RADARs, whereas 24 GHz is dedicated for short-range ultra-wideband RADARs [158]. In the last few years, cars with short-range sensors typically operated in the frequency range of 77-81 GHz. Moreover, in the last few years, dual-use of this frequency band has been considered for joint communication and RADAR purposes [159]. Research and development in the area of AI-aided communication-based automotive RADARs have been on a high over the last few years for different target ranges [160]. Table 5 shows the RADAR types and the corresponding frequency ranges, and the band. Fig. 13 shows different car sensors at different positions in a connected vehicle.

1) RADAR SIGNAL PROCESSING

In terms of waveforms, typically a pulsed RADAR is used for a wide range of applications. Most high-powered military RADARs are operated with different pulse repetition frequencies which are dependent on various other factors. A continuous-wave Doppler RADAR is used mostly on highways for speed detection, but such a RADAR cannot find the range as it does not have a reference to which a distance can be calculated. However, with the emergence of FMCW RADARs that can measure speed and range at a much lower cost, frequency modulated continuous wave RADARs are being employed in different applications, including military and commercial ones [161].

Short-range RADARs are best suited for assisted car parking and edge detections where typically the RADAR target is at a distance of less than 2 meters [162]. Mid-range RADARs are typically employed for ranges of less than 30 meters,

TABLE 6. Approximate Coverage of different automotive RADAR sensors.

RADAR Sensor	Range [meters]	Angle coverage in <sup>o</sup>
Ultra-Short Range	20	150
Short Range	80	120
Mid Range	120	90
Long Range	250	10

whereas long-range RADARs usually operate in the domain of 30-150 meters [80]. Fig. 14 shows the classification of mm-Wave automotive RADARs in terms of range and applications. Table 6 shows the approximate coverage of these sensors in terms of range and azimuth angle. Following are a few of the RADAR-related parameters that are specifically considered for connected vehicles.

- Frequency Estimation: High frequency resolution estimation in automotive RADARs have been described in [163] - [164]. Conventional automotive RADAR processing has been shown and pointed out using cases in which it is bound to fail. A flexible framework is presented for computationally efficient high-resolution frequency estimation as an enhancement to conventional RADAR processing. Real data from a series production automotive RADAR sensor have been presented to show the effectiveness of the presented approaches.
- Direction of Arrival and CFAR (Constant False Alarm Rate): Parameter estimation strategy has been proposed in [136] for various information MIMO vehicle RADARs that comprises of two phases. The primary stage is a three-dimensional CFAR discovery method followed by a subsequent stage is an ESPRIT (Estimation of Signal Parameters via Rational Invariance)-based direction of arrival (DOA) estimation strategy that embraces time-recurrence and performs DOA estimation. It offers better performance than traditional MIMO RADARs [136]. Normally CFAR and Neyman-Pearson are compared in literature for various reasons [165]. In the



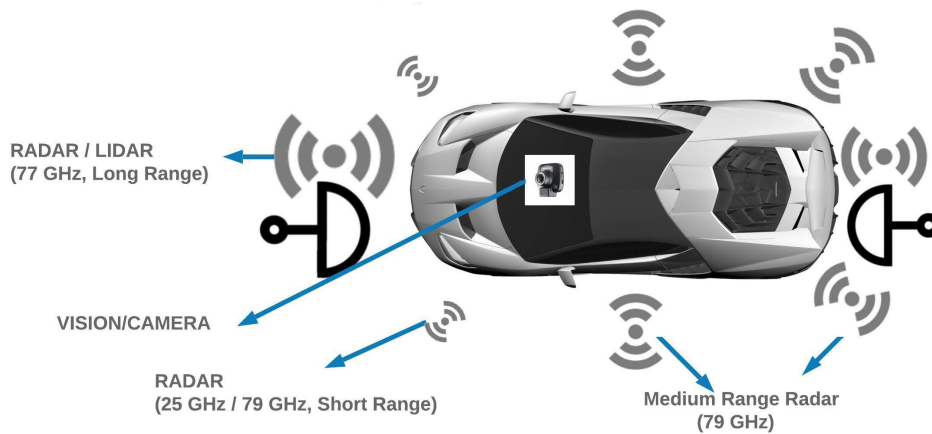


FIGURE 13. Range of different sensors connected to a vehicle.

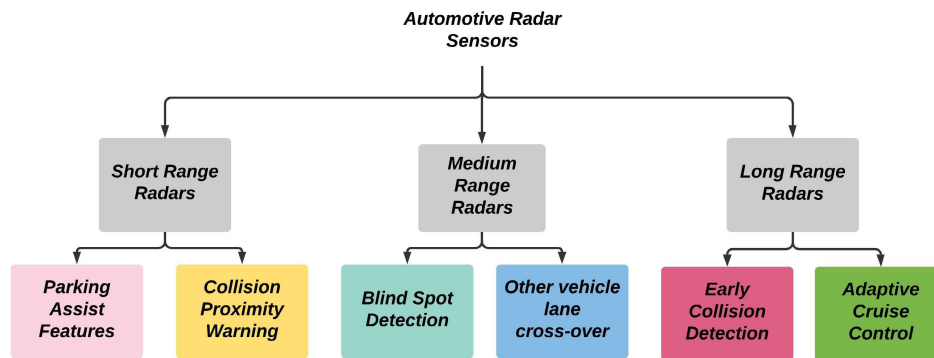


FIGURE 14. Classification of mm-Wave Automotive RADARs in terms of Range and Applications.

Neyman-Pearson framework, the probability of detection is maximized subject to a constraint. As a constraint, the false-alarm probability should not exceed a specified threshold. The noise variance is estimated that effects the false-alarm probability. If the noise variance is altered, the threshold to maintain a constant false-alarm rate is adjusted. Adaptive procedures are implemented using constant false-alarm rate detectors.

- **RCS Estimation and Guardrail RADAR>Returns:** Road guardrails present a distinctive corner case challenge to car RADAR sensors because of their huge RCS that can prompt bogus targets alarms. In [166], investigators show how guardrails can muddle essential targets, such as people on foot and close by fixed vehicles. An epic guardrail framework for high-person on-foot thickness zones is proposed. Further RCS decrease of this plan is accomplished through a proposed diffraction alleviation strategy. Reenactments utilizing this proposed guardrail framework foresee more than a 25-dB decrease in guardrail RCS. Results from this paper show that guardrails with low RCS improve the visibility of adjacent stationary targets, and thus have the potential

to reduce accidents and possibly save lives.

In [167], authors introduce a method of calculating the RCS of any arbitrary complex target at near field range using computational electromagnetic methods.

## 2) LiDAR AND CAMERA SIGNAL PROCESSING

All the strict requirements for a robust operation of an autonomous vehicle cannot be met using a single sensor. A single sensor fails to produce a detailed picture of the vicinity, especially in adverse weather conditions. In most cases, more than one sensor is required, and that scenario requires integration. Although the study of LiDARs in connected vehicles has been on a rise over the past decade due to features like 3D mapping of surroundings, however, it still needs to overcome many open challenges like greater cost, size, and weight. Apart from that, computational cost and latency are the other factors that need serious attention.

Camera-based systems are pivotal in the safety aspect of advanced driver assistance systems as they are deployed in park assist, front-back, and viewing of the surroundings. There is the involvement of image signal processing on raw data in such systems. Image signal processing applies a series

of algorithms on raw images to provide an understandable view to the user [168].

A mathematical function approximates a waveform with parameters that translates into variables of interest. In [169], altimeter position is approximated by the mean of a Gaussian distribution law which is widely used in the processing of the LiDAR waveforms. Moreover, heuristics methods have also been used like in [170], but these methods do not give satisfactory results owing to mixed peak problems. In [171], statistical method is used in frequency-modulated multifunction LiDAR for signal processing. In addition, deconvolution methods are also used for high precision in LiDAR signal processing [172].

In all of the signal processing mechanisms, disorder and sparseness of the LiDAR data limit the accuracy of the 3d perception algorithms [173]. This requires upsampling of the sparse and irregular data by depth completion. Here, a method based on LiDAR-camera fusion turns out to be extremely useful as it produces high-resolution depth images [174].

There is a lot of room available for research and development in the area of LiDAR-camera fusion, especially techniques and algorithms for the transformation of 2D features to 3D space are being explored [175]. The amalgamation of deep learning algorithms in traditional LiDAR feature extraction is being studied greatly [176]. Optimization of features extracted from fused data is also a hot topic of research for scientists and engineers working in this domain [177]. Adding geometric information to fused data is another open problem that needs attention.

### 3) ULTRASONIC, GPS, GNSS SENSOR SIGNAL PROCESSING

Ultrasound sensors are the most simple and most immediate approach to the problem of obstacle detection, which is a fundamental aspect of any autonomous vehicle. The corresponding signal processing is not easy but is also well integrated into the system.

Inertial navigation systems provide a high rate and accurate measurements for the short term. However, inertial sensors errors tend to accumulate for longer terms due to the intrinsic integration in the navigation algorithm. On the other hand, global navigation satellite systems need a direct line of sight of at least four satellites, which is not always possible due to signal blockages. GNSS prevents the inertial navigation solution from drifting, whereas the inertial navigation system provides a non-stop navigational solution. In case of inefficient integration, GNSS navigation solutions and INS mechanization operate independently and provide separate navigation solutions. For improvement, the data from GNSS is fed to an optimal estimator, usually, a Kalman Filter (KF) [178]. In the case of accelerometer and gyroscope errors, the relative dynamics between spoofed GNSS solutions and that of INS are not significant for a vehicle during a typically short update interval leading to a non-detected spoofing attack [179].

Fig. 15 summarizes the perception of multiple sensors in the context of autonomous vehicles. In perception, the vehicle

utilizes a group of onboard sensors to detect, understand, and interpret the environment to enable a connected operation of autonomous vehicles. It shows the types of targets expected against each sensor and the corresponding type of classification. All of this is fused to track moving objects, and this data is fed to the vehicle state block as feedback.

## IV. EMERGING TRENDS AND FUTURE DIRECTIONS

In this section, we outline some of the crucial and challenging issues facing CAV for the widespread adoption of the technology. In addition, we also propose some of the futuristic research problems and possible directions.

### A. EMERGING TRENDS IN COMMUNICATION AND NETWORKING DOMAIN

Recent advances in the communication and networking domain for CAV include vehicular fog computing nodes, edge intelligence, Internet of vehicles with social impact (SIOV), integration of 6G in vehicular networks, and unmanned aerial vehicles.

#### 1) Vehicular Fog Nodes:

5G and beyond will realize ultra-dense deployment of users and devices requiring massive computations as well as connectivity. [180] addresses the computational needs of 5G networks by proposing the use of mobile vehicles as fog nodes to perform tasks. These computational tasks are offloaded from mobile users to connected vehicles. From latency and computation resources, prospective vehicular fog nodes become the preferred choice. However, several issues still need to be addressed, such as data packet relay, load balancing, and so on. The authors in [181] have also presented a novel fog-based architecture for real-time control application in CAV. A use case discussed in this work is connected cruise control through the use of autonomous cars as Fog nodes. [180] also introduces the concept of Vehicular Fog Communication (VFC) complementing fog nodes. This work also discusses key challenges involved in creating and sustaining VFC, such as the data packet relay, latency optimization, and load balancing (decision making for task allocation).

#### 2) Edge Intelligence in CAV:

Cooperative intelligence merged with machine learning has delivered a new research direction coined as the Edge Intelligence, which is discussed in this section. Edge intelligence (EI), a merger of artificial intelligence in edge computing devices, is an interesting research dimension for CAV. [182] has discussed EI design challenges and solutions for CAV networks. EI can help in object detection, intelligent decisions, and also in traffic flow prediction. EI is significantly different from conventional cloud computing-based methods since EI offloads the vehicular computation hence minimizing the vehicle-based computation delays. EI allows CAVs to upload sensed data to the

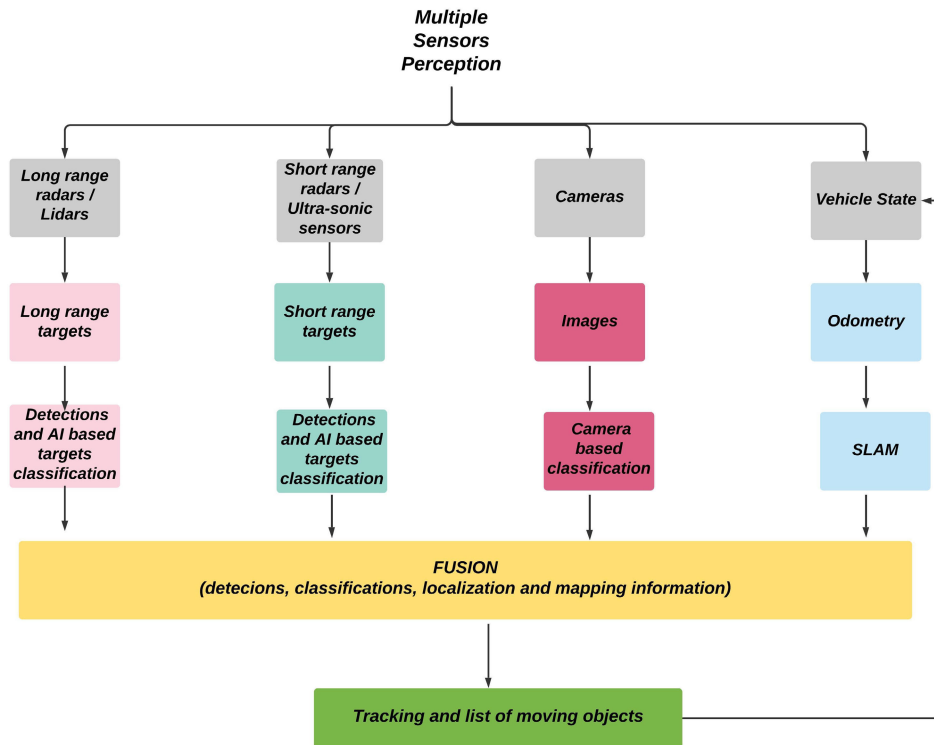


FIGURE 15. Multiple Sensors Perception.

edge server, where cloud computation is carried out on the sensed data. One computation has been carried out by the cloud the CAVs may obtain the inferring results within a limited time. This work presents a two-tier framework (AV tier and EI tier) to realize EI in CAV.

- 3) Internet of Vehicles and Social Internet of Vehicles: As more and more data sensing is carried out by CAVs by increasingly being connected to various (IoT) devices, the conventional VANET is evolving into the Internet of vehicles. Some of the works related to IoV include [183] and [2]. In [2] authors relate that IoV as being composed of three fundamental components. These are classified as the inter-vehicular network, intra-vehicular network, and vehicular mobile Internet. IoV falls in the paradigm where vehicles are connected to the Internet at the backend. This enables vehicles to provide information for different services ranging from traffic management to road safety or even infotainment. Some of the protocols being currently used for IoV include standards such as IEEE 802.11p, Directional Medium Access Control (DMAC), Vehicular Cooperative Media Access Control (VC-MAC), Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing, General Packet Radio Services (GPRS). These have been covered earlier in various sections of this paper as well.

Following IoV [184] proposes the social IoV (SIOV) architecture which leverages the same existing VANETs technologies such as V2V, V2I, and IoV communications. The authors in this paper present a vehicular social network platform following cyber-physical architecture. The cyber-physical SIOV system utilizes social relationships among physical components to support different types of communications and saves the information (e.g., safety, efficiency, and infotainment messages) as a social graph. This social graph is shared in various layers of communications, and it can offer near real-time or offline use cases for intelligent transport systems (ITS).

- 4) 6G for CAV and CAV for 6G: Authors in [185] explored two complementary directions of future research in CAV. These are 6G for CAVs and CAVs for 6G. Discussions have shown how various 6G technologies like TeraHertz (THz) or cell-less communications can be utilized for CAV in its time-critical communication. Authors have also illustrated how CAVs can be used for more effective and efficient deployment and operation of 6G systems. CAV can help the 6G network in the extension of communication infrastructure, mobile edge computing, and network performance monitoring. The intersection of CAV systems and 6G networks will bring significant innovations and momentum to both areas. [182] also

presents in detail the envisioned role of edge computing in a 6G network. The authors highlight the application scenarios associated with such intelligent edge computing before focusing on the technical challenges.

#### 5) Unmanned Aerial Vehicles:

Unmanned Aerial Vehicles (UAVs) are another key ingredient in realizing intelligent transportation systems for connected autonomous vehicles. Some of the applications that can be enabled by UAVs include incident or accident reporters, dynamic roadside units (RSUs), movable speed cameras, flying trackers for policing, and flying dynamic traffic signals [186]. These applications sometimes require multiple UAVs to fly together, collaborate, and communicate among themselves and with ground stations/vehicles to execute a specific task.

Another key application for autonomous UAVs is for logistical purposes [187]. [188] presents a UAV-based infrastructure to replace the traditional cloud-computing-based infrastructure for computing and storage facilities to be available near CAVs. Owing to the widespread fame of unmanned aerial vehicles (UAVs), tremendous amounts of information will be shared between edge devices and UAVs. In this scenario, traffic monitoring using UAVs and edge computing devices is supposed to become an essential part of the next generation of intelligent transportation systems.

#### 6) Visible Light Communication:

With the scarcity of free RF bandwidth, a new way of communication known as Visible Light Communication (VLC), which uses visible light (380-780 nm) as an information carrier and can provide 1000 times more bandwidth than RF communication, is being pursued vehicular communication. Light-Emitting Diodes (LED) are deployed to transmit messages at frequencies ranging from 430 THz to 790 THz [210]. In VLC technology, the data can be modulated to the instantaneous power of light by On-Off-Keying (OOK) and Variable Pulse Position Modulation (VPPM). At the receiver, photodetectors or cameras are used to detect data. The IEEE 802.15.7 standard defines the PHY layer and the MAC layer for short-range wireless optical communication. Some works highlighting the trend of implementing VLC for vehicular communication are [189]–[191]

## B. EMERGING TRENDS FOR CAV SENSORS AND SENSOR FUSION

Following are a few of the points extracted from the section on multi-modal sensors and data fusion.

#### 1) Enhanced Capabilities of Sensors:

There are a number of performance parameters that are expected in an automotive RADAR like range/velocity precision, range/angular resolution, and the angular

width [79]. Moreover, as mentioned in the paper, it should have a number of features like automatic cruise control, collision warning, emergency braking, parking slot measurement, pre-crash sensing, blind-spot detection, and lane change assistance, etc., and this list keeps on increasing with time. All of these features demand an interference-free environment which is an area with a lot of research potential. The automotive industry assured a fully autonomous car that can drive itself without any assistance. These vehicles will need powerful RADAR sensors that can provide accurate data about the surrounding of the vehicle. This area has a lot of potential for embedded systems engineers working in the automotive industry. Self-localization is an area that has a lot of research potential that can be exploited by scientists and researchers working in this domain. As mentioned in the paper, the landmarks offer a better approach than the conventional satellite-based approach, which is prone to changing weather conditions.

#### 2) Integration of Sensors:

The integration of sensors holds a key as there are different kinds of sensors mounted on the same platform. The study of the realization of sensors' accuracy and speed in an integrated system according to varying environmental conditions is of great significance to the future development of the automotive industry. Interconnection of automotive vehicles should be well integrated with the existing mobile network in its locality. The emergence of 6G communication and the gradual deployment of 5G mobile networks has created a lot of room for research in this domain. Integrated automotive sensors need a computing platform that can ensure real-time processing of the received signals. The increase in complexity is one of the most important issues that is faced during the fusion process of a large number of sensors as it compromises the smooth integration of multiple data sets into a consistent, accurate, and useful representation. This is an area with a considerable research gap.

Hybrid techniques for data fusion are being considered for efficient and robust operation for fully autonomous connected vehicles. Time synchronization between individual sensors to avoid interference is another area of research for communication engineers working in this domain. Extensive research is required to design layers to process the RADAR data prior to the data fusion in order to remove the filter in the RADAR data. The study of the robustness of neural fusion approaches against spatial and temporal miscalibration of the sensors needs to be evaluated. The application of fusion to 3D object detection is another direction that needs further in-depth analysis. In addition to this, removal of clutter from the fused data is an area that would require multidimensional research and development hence enabling an

increase in the performance of connected autonomous vehicles.

### 3) Quantum Sensing:

Research and development in the area of AI-enabled communication-based automotive RADARs have been on a high over the last few years for different target ranges. Quantum sensing is an emerging area that promises to improve performance and transform navigation and positioning capabilities for autonomous vehicles that will be driven by laws of quantum physics. The sensors require nano-engineered mechanical devices fabricated on a silicon chip. Although quantum sensing frameworks are costly and complex, however another generation of smaller, more affordable sensors should open up new applications. The signals utilized by quantum navigation frameworks are secure as they are difficult to get replicated for malicious activities as they depend on key properties of nature.

### 4) Re-configurable Intelligent Surfaces:

Autonomous vehicles produce a large amount of data that is also required to be exchanged for safety and security-based applications. Some of the critical issues faced by Vehicular networks, such as coverage and connectivity issues, can be addressed by using re-configurable intelligent surfaces-based solutions because of their capabilities of controlling waves and programming the environment. In order to resolve the increasing demand for emerging applications in the vehicular communication domain, new state-of-the-art technology is needed.

## V. CONCLUSION

The field of vehicular communication and intelligent transportation systems has been progressing fast since the last decade. This article provides a comprehensive review of connected and autonomous vehicles in the context of vehicular communication, networking, signal processing and multimodal sensor fusion. Research issues and challenges for connected and autonomous vehicles of the near future are also highlighted, and guidelines for future research are proposed with high priority use-case scenarios. This survey covers the recent and future trends in these sub-domains. Moreover, emerging applications connected to these areas have also been highlighted. The cutting-edge communication and networking technologies and potential bottlenecks for use case scenarios are also presented. Hence, a detailed perspective on CAVs are jointly reviewed from a communication and sensor fusion perspective in this article.

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**FARAN AWAIS BUTT** received the B.Sc. degree in electrical engineering from the University of Engineering and Technology (UET) Lahore, Lahore, Pakistan, in 2009, and the master's degree in computer engineering from the Lahore University of Management Sciences (LUMS), in 2012. From 2018 to 2019, he worked as a Visiting Researcher at the Radar Group, University College London (UCL), London, U.K. He is currently working as an Assistant Professor with the University of Management and Technology (UMT), Pakistan. He is also associated with the Center for Global and Strategic Studies, Islamabad, as a member board of experts in electronic warfare and communications. He has more than ten years of experience in academia and research. He has a number of research articles, including a U.S. patent in the area of radar signal processing. His research interests include phased array, MIMO radars, FMCW, and optimization. He also won the Young Leaders Development Award and the Research Productivity Award in year 2016 and 2017, respectively. He is a reviewer of a number of renowned journals in his areas of research.



**JAWWAD NASAR CHATTHA** received the bachelor's degree in electrical engineering from the University of Engineering and Technology, Lahore, in 2006, the master's degree in electrical engineering from the Virginia Tech, in 2009, and the Ph.D. degree in the area of communication theory from the Lahore University of Management Sciences, Lahore, in 2018. During master's, he worked as a Research Assistant with the National Science Foundation (NSF) Funded Project. He is currently

teaching at the University of Management and Technology, Lahore, as an Assistant Professor. His research interests include communication theory and computer networking related works.



**JAMEEL AHMAD** received the B.Sc. degree in electrical engineering from the UET Peshawar, in 1993, the M.S. degree in systems engineering from Quaide Azam University, Islamabad (CNS Campus), in 1996, the M.Sc. degree in electrical engineering from the University of Southern California (USC) at Los Angeles, USA, in 2005, and the Ph.D. degree in electrical engineering from the UET Lahore. From 1996 to 2002, he worked as a Hardware Engineer with PAEC. He also worked at

the Department of Electrical Engineering, SEN, UMT, for about ten years, and the Director of final year projects for four years. He is currently working as an Assistant Professor with the Department of Computer Science, University of Management and Technology (UMT), Lahore, Pakistan. His research interests include distributed control and optimization of smart microgrids for energy internet, cloud computing, parallel and distributed computing, machine learning techniques applied to face recognition, energy, wireless systems, and connected and autonomous vehicles. He was a recipient of the MOST Scholarship from the Ministry of Science and Technology, Pakistan (2002–2006) and received the Best Researcher Award in 2019 from UMT for publishing a paper in the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS. He is a reviewer of numerous journals and conferences.



**MUHAMMAD UMER ZIA** received the master's degree in communication engineering from the University of Management and Technology, UMT, Pakistan, and the master's degree in communication engineering from the Chalmers University of Technology, Sweden. He is currently pursuing the Ph.D. degree with James Cook University (JCU), Australia. Prior to joining JCU, he worked on several research projects at the Lahore University and Management Science (LUMS), Pakistan, and

the University Modena and Reggio Emilia (UNIMORE), Italy. His research interests include channel quality feedback, time reversal UWB systems, estimation and detections for MIMO, and massive MIMO systems as well as deep learning aided estimation for multi-antenna systems.



**MUHAMMAD RIZWAN** received the Doctor of Philosophy (Ph.D.) degree in electrical and computer engineering from the Georgia Institute of Technology, USA. He is currently with the Department of Computer Science, University of Management and Technology (UMT), Pakistan. He is also a machine learning expert with a diverse experience of working in practical and challenging problems. He is skilled in deep learning, big data analytics, and information visualization. He has

strong research and analytical skills.



**IJAZ HAIDER NAQVI** (Member, IEEE) received the B.Sc. degree in electrical engineering from the University of Engineering and Technology Lahore, Pakistan, in 2003, the master's degree in radio communications from SUPELEC Paris, in 2006, and the Ph.D. degree in electronics and telecommunication engineering from INSA de Rennes, France, in 2009. He is currently working as an Associate Professor with the Department of

Electrical Engineering, Lahore University of Management Sciences, Lahore, Pakistan. His research interests include wireless communications, signal processing, and life cycle engineering, including beamforming strategies for 5G and 6G wireless systems, communication under imperfect channel information, and reliability and degradation analysis of lithium ion batteries. He was a recipient of the Ministerial Scholarship of French Ministry of Research for his Ph.D. studies and the HEC Overseas Scholarship for his M.S. studies.

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