Sensor Technology for Autonomous Vehicles

Henry Alexander Ignatious, Hesham El-Sayed, and Manzoor Ahmed Khan, College of Information Technology, United Arab Emirates University, Abu Dhabi, United Arab Emirates

Nomenclature

ABS Anti-Lock Braking System
ACC Adaptive Cruise Control
ADAS Advanced Driver Assistance System
ADC Analog to Digital Converter
ADS Autonomous Driving System
AV Autonomous Vehicle
BSD Blind Spot Detection
CAS Collision Avoidance System
DSP Digital Signal Processing
DSRC Dedicated Short-Range Communication
EM Electro Magnetic Waves
FoV Field of View
FPS Frame per Second
FPS Frames per Second
GNSS Global Navigation Satellite System
GPS Global Positioning System
HFoV Horizontal Field of View
HMI Human Machine Interface
HRO Horizontal Resolution
IF Intermediate Frequency
IMU Inertial Measurement Units
INS Inertial Navigation System
IR Infra Red
LCA Lance Change Aid
L-FMCW Linear Frequency Modulated Continuous Wave

LiDar Light Detection and Range
LNA Low Noise Amplifier
LRR Long Range RADAR
MEMS Micro Electro-Mechanical System
MIR Mid Infra Red
ML Machine Learning
MMW Millimeter Wave
MRR Medium Range RADAR
NHTSA National Highway Traffic Safety Association
NIR Near Infra Red
PA Power Amplifier
PCB Printed Circuit Board
PCD Point Cloud Data
PPS Pulses Per Second
RADAR Radio Detecting and Ranging
RF Radio Frequency
RGB Red Green Blue
RNG Detecting Range
ROS Robotic Operating System
RPM Revolution per Minute
SAE Society of Automotive Engineers
SOC System-on-Chip
SRR Short Range RADAR
SSL Secured Socket Layer
ToF Time-of-Flight
V2I Vehicle-to-Infrastructure
V2V Vehicle-to-Vehicle
VCO Voltage-Controlled Oscillator
VFoV Vertical Field of View
VIS Visible
VR Vertical Resolution

Abstract

Autonomous systems including Autonomous Vehicles (AV) operate with or without human intervention. To achieve partial (or) full-fledged autonomy, the AVs must be able to sense and react to their surrounding environment. Autonomous vehicles (AVs) use a variety of sensor technologies to observe their surroundings and make logical decisions based on the data gathered, just as humans do. Perception systems (sensors onboard AVs) provide enough information to enable autonomous transportation and mobility under optimal operating conditions. Comprehensive sensing of the environment requires multiple sensors to operate simultaneously to acquire precise information from the surroundings and the internal state of the vehicle. In reality, there are still a number of challenges that might obstruct the operation of AV sensors and, as a result, reduce their effectiveness under more realistic situations. This chapter discusses various features and facts related to physical AV sensors, including the categories of sensors, their functionality, characteristics, behavior toward climate conditions, and their applications.

Introduction

Autonomous Vehicles (AVs) have the same transportation capabilities as regular vehicles but they can also sense their surroundings and navigate themselves with little or no human intervention. According to Precedence Research, the global AV market size reached over 6500 units in 2019 and is anticipated to expand at a compound annual growth rate of 63.5% between 2020 and 2027. In 2009, Google began the development of their self-driving car project, which is now known as Waymo (a subsidiary of Alphabet, the parent company of Google). In 2014 (Edelstein, 2020; Glon and Edelstein, 2020), Waymo deployed a completely autonomous car prototype that did not have any pedals or a steering wheel. Waymo has already achieved a significant milestone, with its self-driving cars having travelled over 20 million miles on public roads in 25 different sites throughout the United States (USA). Jaguar Land Rover

(JLR) worked with an autonomous car center in Shannon, Ireland, to test its next-generation AV technology by driving 450 km on public roads. SAE International, formerly known as the Society of Automotive Engineers (SAE), introduced the J3016 "Levels of Driving Automation" standard in 2014. According to the SAE, the Advanced Driver Assistance System (ADAS) is a six-tiered system that categorizes varying levels of autonomy. As illustrated in Fig. 1, the automation levels span from cars that are purely human-driven to those that are completely autonomous or self-driving (Gonzalez-de-Santos et al., 2020; Mehra et al., 2021; Mozaffari et al., 2020).

AVs must rely on a combination of sensors and software to sense the surrounding environment and maneuver without human involvement in order to attain increased levels of autonomy. Cutting-edge sensor technologies are currently being developed at a quick pace to improve autonomous transportation and mobility that is safe for pedestrians and riders. This has prompted more academics and engineers from a wide range of subjects and backgrounds to participate in the process and handle all of the related difficulties. Because of the increased interest in autonomous vehicles, many testing and validation techniques have been created to enhance their performance for optimum safety before being deployed on public roads and infrastructures. Henceforth, virtual verifications and testing have the potential to bridge the gap, allowing AV systems to be reviewed in a rigorous, controlled, and timely manner.

Most AD systems encounter various challenges and limits in real-world scenarios, including those of safe driving and navigating in bad weather, as well as safe interactions with people and other cars. Glare, snow, mist, rain, haze, and fog, among other harsh weather conditions, can have a significant influence on perception and navigation performance of perception-based sensors. Aside from poor weather, other constrained AD settings such as agriculture and logistics confront the above-mentioned issues. These challenges grow more complex for on-road AVs due to the unexpected conditions and behaviors of other automobiles. For example, putting a yield sign in a junction might change the behavior of approaching cars. As a result, in order to limit collision hazards, AVs must have a thorough prediction module that can identify all position future motions. Despite the fact that AD systems face many of the same issues in real-world circumstances, they differ dramatically in a number of ways. For example, unmanned tractors in agriculture farms travel between crop rows in a stable environment, whereas on-road vehicles must navigate through complex dynamic situations such as people and traffic. The ability of an AV to detect through a range of sensors is an important part of the entire AD system; the cooperation and performance of these sensors can have a direct impact on an AV's practicality and safety. The selection of an appropriate array of sensors and their ideal configurations, which will be used to imitate the human capacity to detect and create a trustworthy image of the surroundings, is one of the most essential elements in any AD system.

Sensors translate perceived events or changes in the environment into mathematical calculations that may later be processed. Based on their operating principle, sensors are classified into two primary groups. Internal state sensors, also known as proprioceptive sensors, that record and detect the state of a dynamic system, such as force, angular rate, wheel load, battery voltage, and so on. Proprioceptive sensors include inertial measurement units such as (IMUs), encoders, inertial sensors (gyroscopes and magnetometers), and position sensors (Global Navigation Satellite System (GNSS) receivers). An AV's relative localization refers to the vehicle's coordinates being referenced concerning nearby landmarks, while absolute localization refers to the vehicle's position being referenced in relation to a global reference frame (world). External sensors perceive the external environmental information related to the AVs. In a moving car, the reader will appreciate the more comprehensive coverage of the vehicle's surroundings. Individual and relative sensor orientation is crucial for precise and accurate object recognition to perform reliable and safe actions. In general, obtaining sufficient data from a single reliable source is difficult in AD. For a safe ride, the internal heath status of the components and external surrounding information of the AVs are essential for effective decision-making.

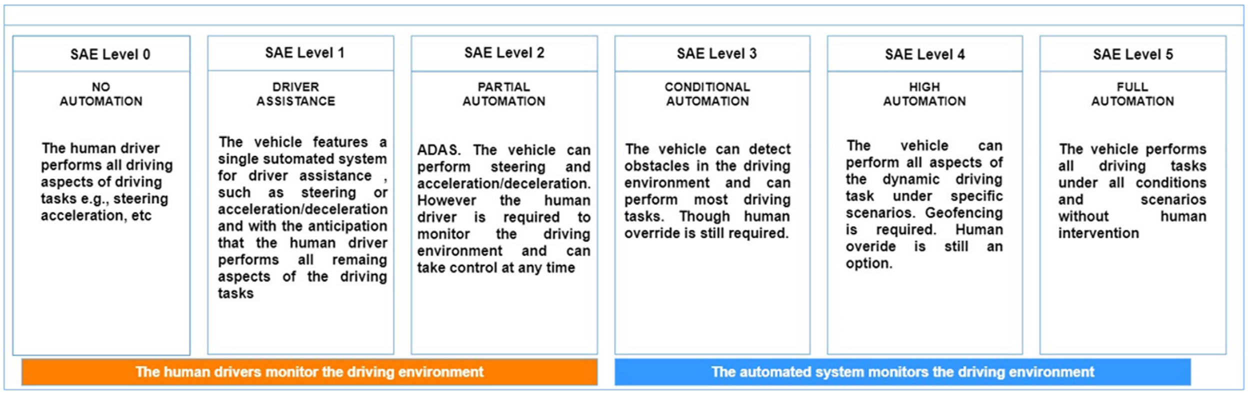

Fig. 1 Society of automotive engineer's automation levels.

Sensor characteristics

Before going into detail about the numerous sensors used in autonomous vehicle systems, it is crucial to first define the broad features of these sensors. In both fused and other approaches, the following technical qualities play a critical role in sensor selection (Özgüner et al., 2011).

i **Accuracy:** The difference between the actual and measured values, recorded by the sensor. Some mandatory factors such as irrelevant data and parameters for reducing external intervention will influence the accuracy of this measurement.
ii **Resolution:** The minimal variation between two measured values, considerably smaller than the real precision of the sensor.
iii **Sensitivity:** The minimal value that is identified and quantified.
iv **Dynamic Range:** The minima and maxima values obtained from the sensors, presented with accuracy.
v **Perspective:** This is commonly referred to as the field of view (FoV).
vi **Active and Passive:** A passive sensor relies on ambient conditions to deliver information, whereas an active sensor releases a sort of energy to perceive the surroundings.
vii **Time scale:** The rate of the measuring range and the frame rate of the sensors over a period.
viii **Output Interface:** This is the sensor's output, which could be an analog voltage, analog current, digital signal, linear data stream, or data transmission flow.

Autonomous vehicle sensing technology

RADAR, LiDAR, ultrasonic, GNSS, and cameras are the most representative sensors in the AVs sensors ecosystem. These sensors monitor wave sources and identify various physical processes. They have unique characteristics that allow them to perform a variety of jobs under specific situations. The sensors use an electromagnetic spectrum for advanced operations. This will reveal their vulnerability to deteriorating surroundings, such as extreme weather conditions. Exteroceptive sensors or external state sensors, on the other hand, perceive and gather information from the system's environment, such as distance measurements or light intensity. Exteroceptive sensors include cameras, radio detection and range (Radar), light detection and range (LiDAR), and ultrasonic sensors. Additionally, sensors might be either passive or dynamic in nature. Passive sensors, such as vision cameras, receive energy from their environment and provide outputs. Active sensors, such as LiDAR and radar sensors, emit energy into the environment and detect the environmental "response" to that energy to provide outputs. Sensors are vital in AVs for perception of the environment and vehicle localization for path planning and decision-making, which are necessary before managing the vehicle's movements. To sense its surroundings, AV relies on numerous vision cameras, radar sensors, LiDAR sensors, and ultrasonic sensors. Other sensors, such as the GNSS, the IMU, and vehicle odometry sensors, are also utilized to identify the vehicle's relative and absolute positions. An AV's relative localization refers to the vehicle's coordinates being referenced with regard to nearby landmarks, while absolute localization refers to the vehicle's position being referenced in relation to a global reference frame (world). **Fig. 2** illustrates various types of sensors used in AVs.

Overview of autonomous vehicle systems

While AV systems vary differently from one another, they are always sophisticated systems with several subcomponents. From multiple viewpoints, the layout of an AD model is presented as two stages: In the first stage, technological standpoint incorporates the hardware and software tools. The second stage explains the functional viewpoint necessary for the operational units of the AD system. Hardware and software are the two main layers from a technical viewpoint, with each layer having discrete components, which represent different elements of the entire AD platform. Certain sub-components serve as a communication infrastructure between the hardware and software layers of the AD. Interpretation, mobility, vehicle control, system tracking, organization, and decision-making are the primary operational components of the AVs. These operational units' functions based on the data acquisition, data analyzing followed by the information flow from the perceived data to the vehicle control. **Fig. 3** depicts the technical and functional aspects of the design of an audio-visual system. From **Fig. 3**, it is very clear that the entire AD system functions only after the sensors acquire appropriate environmental data. However, for accurate decision-making, clarity in sensor data is mandatory, for which advanced pre-processing techniques are used to remove the bias from the heterogeneous multimodal sensory data (Giacalone et al., 2019). The remaining sections will explain various categories of sensors in detail based on their different characteristics. Sensors are broadly classified as (i) internal sensors and (ii) external sensors. Internal sensors perceive information related to the internal components of an AV and external sensors collect the environment data of the AVs. Internal sensory information is used to monitor the health status of the AV and versatile applications embedded in the AVs use this information to alert the vehicle in cases of any malfunctions identified. The decision-making modules of the AVs effectively use the external data collected from the external sensors to guide the AVs to take instant and accurate decisions to avoid major accidents (Yeong et al., 2020).

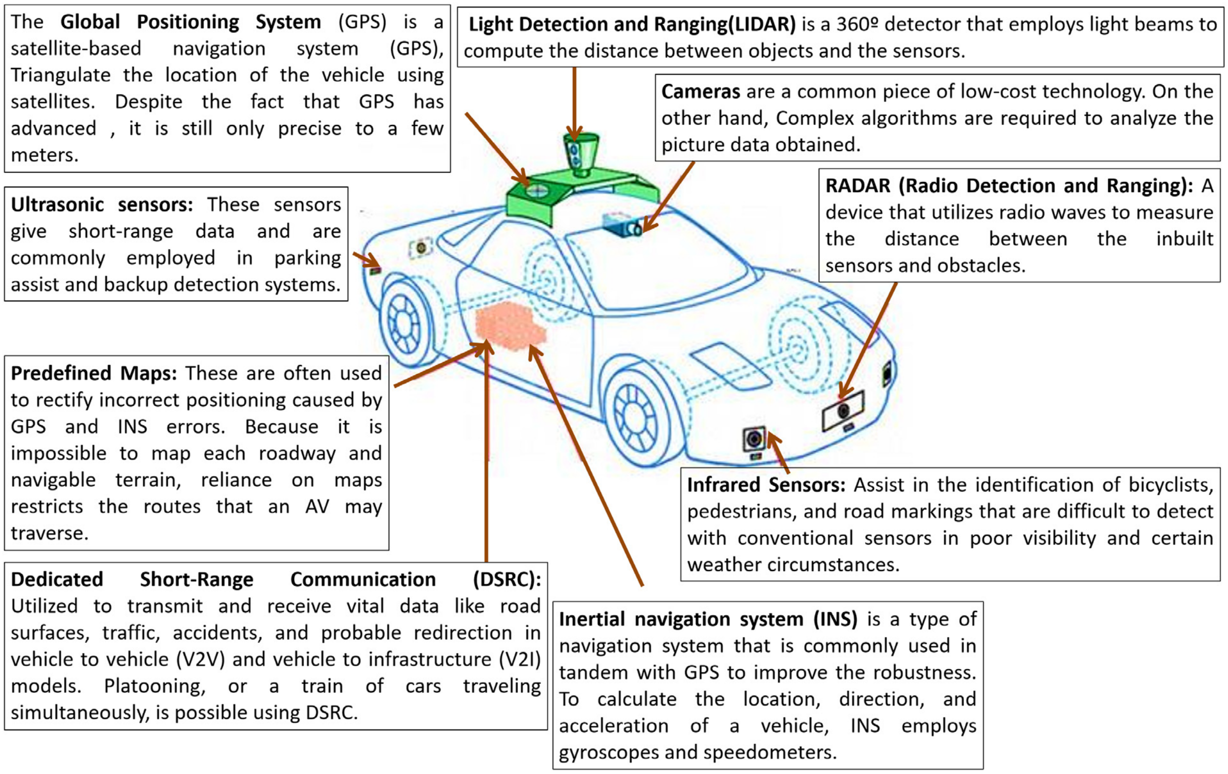

Fig. 2 Sensor positions in the AV.

Internal vehicle systems

Most of the information utilized by AVs is derived from existing sensing technologies. These signals are present in the AVs Controller Area Network and used to communicate vehicular data as well as produce responses based on sensor outputs. Most of the AV's components are not intended to deal with the increased load which the vehicles experience during prolonged usage. To sustain the increasing workload, most of these sensing devices and their components need to be more resilient (Fossen et al., 2017). Among the signals and interconnected systems are:

- Wheel spanner sensor: Commonly, a Hall Effect sensor is installed on every wheel and generates a signal, which is further translated to the velocity of the wheel. This is a kind of speedometer that is commonly found in Anti-lock braking system (ABS) and adaptive speed control mechanisms.
- Yaw Rate Sensor: This piezoelectric gyroscope (also known as a rotational speed sensor) monitors the AV's angular velocity around its vertical axis in degrees to identify the orientation of the AVs, when it attempts to flip over. This device periodically monitors the functioning of the electronic components within the AV.

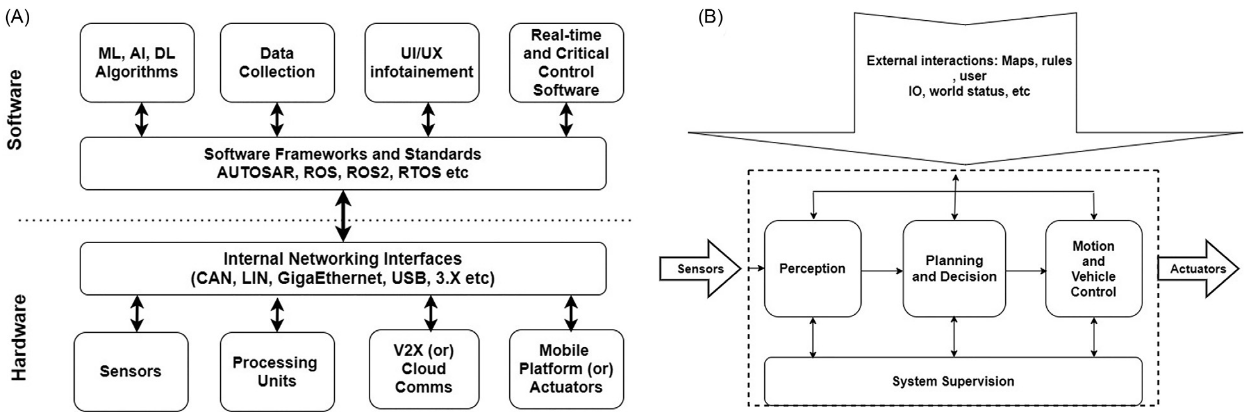

Fig. 3 (A): Architecture of an autonomous driving (AD) system. (B): A functional perspective that describes four main functional blocks.

- Lateral/Longitudinal Sensors: These MEMS (Micro-Electro-Mechanical System) provides lateral/longitudinal acceleration and are used in modern automobiles to identify the obstacles and maintain a stable digital control.
- Steering Inputs: autonomous vehicles interpret and require diverse responses, use electronic power steering signals and capabilities. The steering torque sensor and steering wheel position are two of the specific inputs that are monitored.
- Hydraulic brake booster/Hydraulic pump: These pumps integrated with ABS, distributes sufficient and equal quantity of brake oil to the braking system. This mechanism effectively controls the speed of the vehicle.
- Driver Inputs: Modern vehicles recognize the driver attributes such as braking requests, acceleration pedals, direction signals, steering force, headlamps, windscreen wipers, and transmission options.
- Transmission Outputs: Current gear, gear status, and next gear selection are among the transmission output signals used.
- Powertrain outputs: With the exception of the transmission, the remaining powertrain components produce data such as drivetrain speed, coolant temperature, Nitrogen Oxide levels, revolution per minute (RPM), spark plug firing time, Oxygen levels, and more that can be used to control autonomous vehicles.
- HMI: This might be anything from a chime to a message displayed onscreen. Autonomous vehicles use current-generation HMI for a variety of reasons, including relaying information to the driver.

External world sensing

RADAR

RADAR stands for Radio Detection and Ranging technology, which is a gadget that detects objects within a particular range using radio waves. When transmitted waves collide with an object along their course of propagation, the object's surface reflects them back to the RADAR antenna, which captures the backscattered signal (echo) inside its field of vision (FoV). The round-trip delay period, together with the known velocity of radio waves, allows the RADAR system to precisely determine the object's distance and velocity. Eq. (1) shows the RADAR range equation, which links the received echo power (P_r) to the distance of an object (R) meters away (Buller, 2018).

$$P_r = \frac{P_t G^2 \lambda^2 \sigma L}{4\pi^3 R^4} \tag{1}$$

where (P_t) denotes the transmitted power, (G) denotes the gain, (λ) denotes the wavelength, (σ) is the target cross-section, and (L) denotes all losses, including multipath, atmospheric, and environmental losses. The millimeter-wave (MMW) frequencies used by AV RADAR systems are 24, 74, 77, and 79 GHz, which are split into short-range, medium-range, and long-range RADAR systems (SRR, MRR, and LRR, respectively). An LRR can be used to detect distant targets or items in front of the ego automobile, while MRR and SRR are utilized for parking assistance or side view detection, respectively. Because of its simplicity, linear frequency-modulated continuous-wave (L-FMCW) RADARs are extensively employed in AVs among the many RADAR technologies available today. The voltage-controlled oscillator (VCO) module generates an L-FMCW chirp signal, which is amplified by the power amplifier (PA) and transmitted by the antenna, as shown in Fig. 4. The echo signal is captured by the receiving antenna, which is amplified by the low noise amplifier (LNA) before being mixed with the VCO signal to form the intermediate frequency (IF) or beat signal. The signal is then digitized and passed to the digital signal processing (DSP) module by the analog to digital converter (ADC). Fig. 4, illustrates the functional flow of FMCW RADAR system.

Most AV RADAR systems currently use an array of tiny antennas that can generate a set of antenna lobes. A 77 GHz radar with printed circuit board (PCB) antennas and a 24 GHz radar with horn antennas, are depicted in Fig. 5 (Toker and Kuhn, 2019). With system-on-chip (SOC) designs, this antenna lobe has become more prevalent, as it allows digital beam shaping, among other

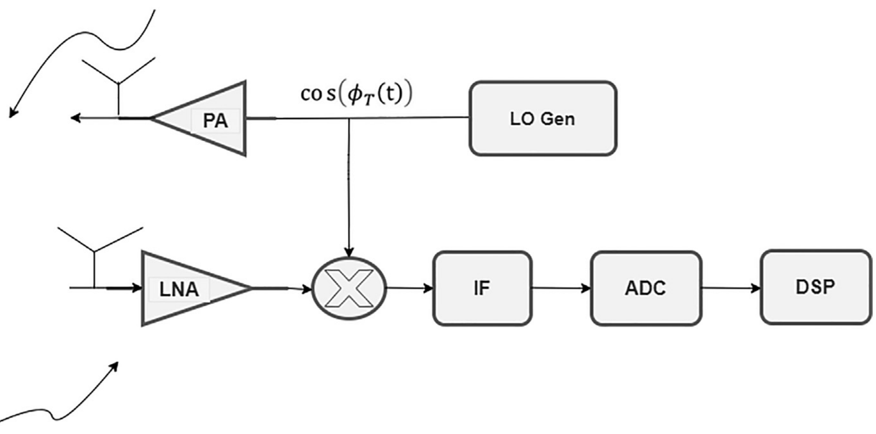

Fig. 4 High-level block diagram for FMCW RADAR system.

(A) (B)

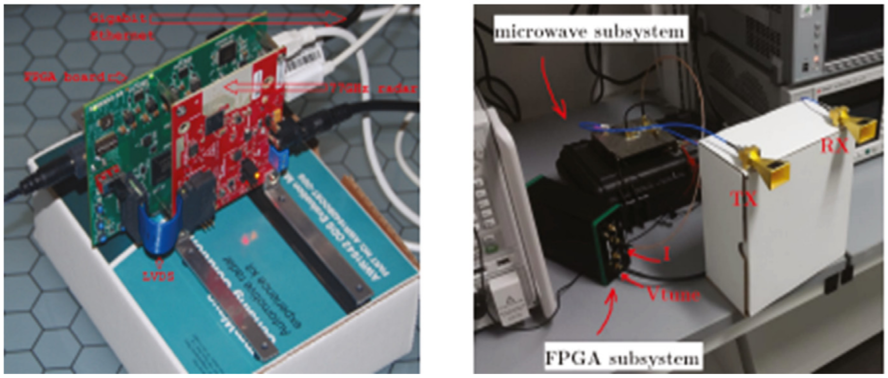

Fig. 5 (A) A 77 GHz radar with PCB antennas. (B): 24 GHz radar with horn antennas.

approaches, to limit the receiver's spatial FOV and eliminate electromagnetic interference from other active sensors running at similar center frequencies. Smart car improvements have prompted the introduction of this type of gadget in the automotive industry to increase safety (Gourova et al., 2017). The following are some examples: adaptive cruise control (ACC), collision avoidance systems (CAS), blind-spot detection (BSD), and lane change aid (LCA). Figs. 5A and B depicts radars operating with different antennas and frequencies (Vargas et al., 2021).

Due to the propagation of EM waves, radar may operate on day or night in foggy, snowy, or overcast conditions. Radar is resistant to inclement weather and works regardless of poor lighting conditions. One of the major disadvantages of radar sensors is the misidentification of metal items in their observed environment, such as road signs or guardrails, as well as the difficulty in distinguishing static and stationary objects. Due to the similarities in Doppler shift, the radars will find difficult to distinguish between static objects like an animal skeleton and dynamic roadside events (Deka and Chowdhury, 2019; Wang et al., 2020). Radar sensors are often hidden in plain sight of AD automobiles; few examples are fixing the sensors above the rooftop, around the top of the windshield, behind the vehicle bumpers, or at the rear side of brand insignia. It is crucial to maintain the precision of mounting positions and orientations of radars in production. Table 1, portrays general specifications of radars manufactured by different vendors. Fixing the sensors in the wrong positions of the AVs might lead to wrong data perceiving which leads to erroneous vehicle operation. Thus, it is important to maintain the accuracy of fixing positions and alignments of radars in production. The three basic categories of automotive radar systems are Medium-Range Radar (MRR), Long-Range Radar (LRR), and Short-Range Radar (SRR) (Steinbaeck et al., 2017). SRR is used for packing assistance and collision proximity warning by AV manufacturers, AV

Table 1 General specification of RADAR sensors.

	Aptiv Delpi		*Continental*	*SmartMicro*
Category	*ESR2.5*	*SRR@*	*ARS 408-21*	*UMMR-96-T-153*
Freq(GHz)	76.5	76.5	76…77	79(77..81)
HFOV(^{o})				
Short-Range		±75	±9	≥ 130
Mid-Range	±45			≥ 130
Long-Range	±10		±60	≥ 100 (squint beam)
VFOV(^{o})			20	
Short-Range	4.4	10	14	15
Long-Range				
Range(m)	–			
Short-Range		±0.5 noise and $\pm0.5\%$ bias	–	<0.15 (or) 1% (bigger of)
Mid-Range				<0.30 (or) 1% (bigger of)
Long-Range				<0.50 (or) 1% (bigger of)
Vel Range (km/h)				
Short-Range	–	–		$-400\ldots+100$
Mid-Range			$-400\ldots+200$	$-340\ldots+140$
Long-Range				$-340\ldots+140$
IO Interfaces	CAN/Ethernet	PCAN	CAN	CAN/Automotive Ethernet

Acronyms first from first column top to bottom, Frequency(Freq), horizontal FoV(HFOV), Vertical FoV(VFOV), Range Accuracy (Range Acc), Velocity Range(Vel Range), ROS (Robotic Operating System).

manufacturers use MRR to avoid side and rear collisions between the AVs and to detect blind spot conditions, while the manufacturers to detect adaptive cruise control and to identify early internal and external faults use LRR associated with the AVs. Fig. 6 illustrates the current radars used in the AVs.

LiDAR

Light detection and ranging, or LiDAR, was initially designed and introduced in the 1960s and has since become broadly used in aligning aeronautical and aerospace topography. The first commercial LiDARs with 2000 to 25,000 pulses per second (PPS) for topographic mapping applications were manufactured and supplied in the mid-1990s by laser scanner manufacturers. Over the past few years, LiDAR technology has progressed at an incredible rate, and it is currently one of the most essential sensing technologies for autonomous driving. LiDAR is a remote sensing method, which uses infrared/laser beam impulses to scatter the rays from the target objects. The equipment detects these reflections, and the time between emission and reception of the light pulse allows for distance estimate. The LiDAR produces a point cloud, which is a 3D depiction of the region it scans. For instance, the latest LiDARs can record approximately two lakhs points per second covering 360-degree rotation and a vertical field view of 30- degrees, which is achieved by the key attributes like wide measuring range, reliability on the perceived environment data, and high scan rate (or refresh rate). Due to the increasing demand in LiDAR sensor technology, many companies have emerged in recent years. It is estimated that the revenues of LiDAR manufacturing industry will reach $6910 million within 2025. The latest LiDAR sensors used in the AVs have a wavelength of 905 nm and absorb less water over the previous 1550-nm sensors. According to a study, 905 nm sensors can deliver greater point cloud resolution in bad weather circumstances such as fog and rain. On the other hand, they are still susceptible to snow and ice precipitates. In this context, the performance of a LiDAR can drop by 25% (Kutila et al., 2016).

1D, 2D, and 3D LiDAR sensors are the three main types of LiDAR sensors that can be used in a variety of applications. In 1D, 2D, and 3D regions, LiDAR sensors provide data as a sequence of points, commonly known as point cloud data (PCD). The PCD comprises x, y, and z coordinates as well as the intensity information of the obstacles perceived by the 3D LiDAR sensors. LiDAR sensors with 64 or 128 channels are often used in AD applications to provide high-resolution laser pictures (or point cloud data).

- 1D (one-dimensional) sensor are used to measure the data preferably the (x-coordinates) values associated with the area of the objects perceived from the surrounding environment.
- Additional information regarding the angle (y-coordinates) of the targeted objects is provided by 2D or two-dimensional sensors.
- 3D sensors, also known as three-dimensional sensors, use laser beams to determine the height (z-coordinates) of the objects in their environment.

LiDAR sensors can further categorized as mechanical LiDAR (or) solid-state LiDAR. In the realm of AV research & development, the mechanical LiDAR is the most desired long-range environment scanning solution. It directs laser beams and captures the desired field of view (FoV) around the AV using high-grade optics and rotational lenses controlled by an electric motor. The revolving lenses may span a horizontal field of view of 360 degrees covering the surrounding vehicle. The SSLs, on the other hand, do not use rotating lenses, eliminating mechanical failure. SSLs direct laser beams via a network of micro-structured waveguides to sense their environment. Due to their resilience, consistency, and less costs involved over other mechanical peers, these LIDAR's have added popularity in recent years as an alternative to spinning LIDAR's. They do, however, have a smaller and more limited horizontal FoV (120 degree) or less than classic mechanical LIDAR's. LiDAR systems, like RADARs, work by measuring the time it takes for a pulse of light emitted from a laser diode to reach the system's receiver in the infrared or near-infrared wavelengths, which is also known as the time-of-flight (ToF) principle. In ToF technology, the LiDAR emits a pulse of light with a predetermined duration (τ) that triggers the internal clock in a timing circuit at the time of emission. When a laser pulse is intercepted and reflected by the targets, laser returns are recorded as discrete observations. Modern sensors may record up to five returns from each laser pulse, allowing LiDARs to collect several returns from the same laser pulse. A photodetector detects the reflected light pulse from the target and generates an electrical output that disables the clock. This electronically measured ToF (Δt), is used to compute the distance of the reflection point using Eqs. (2) and (3)

$$P(R) = P_{op}\frac{A_o}{\pi R^2}\mu_o \exp - 2UR \tag{2}$$

(A) (B) (C)

Fig. 6 (A): ARS540 Radar Sensor. (B): ARS441 Radar Sensor. (C): SRR 600 Radar Sensor.

$$R = \frac{1}{2\Pi} c\Delta t \tag{3}$$

Where (P_o) is the optical peak power of the emitted laser, (ρ) is the reflectivity of the target, (A_o) is the receivers aperture area, (μ_o) is the detection optics spectral transmission. (U) is the atmospheric extinction coefficient, (c) is the speed of the light, in a vacuum, and (π) is the index of refraction of the propagation medium ($\sim$1 for air). Fig. 7, illustrates the high-level block diagram for ToF LiDAR.

Depending on the laser return mode configurations, the Velodyne VLP-32C LiDAR analyses several returns and portrays the reflected laser beam based on their intensity levels namely (strong, last, or dual return). In single laser return mode (strongest return or last return), the sensor examines the light gathered in a single track from the laser beam to derive distance and intensity information. The sensors use this data to differentiate between the last and strongest returns. Sensors in dual return configuration mode, on the other hand, will return both the strongest and the most recent return data. If the strongest return measures are the same as the last return readings, the second-strongest measurements will return as the strongest. Furthermore, points with insufficient intensity will be ignored. Due to broad field of vision, longer detection range, and depth perception, 3D spinning, LIDAR's are now more often used in the AVs to afford a dependable and exact insight of information gathered during day and night. The point cloud data generates a detailed 3D spatial representation (or "laser image") of the AVs' environments. LiDAR sensors, unlike camera systems, do not give the ambient background color, which is one of the prime reasons why point cloud data (PCD) is fused with the heterogeneous data acquired from other sensors using advanced fusion models. Although LIDAR systems are more accurate than RADAR, they are more expensive and need more packaging space, which limits their utilization. The spinning LIDAR system used in Google's driverless vehicle, for example, costs over $70,000. In addition, LIDAR systems are not always as accurate as RADAR systems when it comes to detecting speed. When compared to RADAR, this is owing to the inability to use the Doppler Effect. Fig. 7, depicts the high-level block diagram of a LiDAR sensor system and Fig. 8 illustrates Velodyne sensors. Table 2, demonstrates the general specifications of LiDAR sensors manufactured by different sensor manufacturers.

Ultrasonic sensors

Ultrasonic sensors can be used for a variety of detection tasks in industrial settings. They are capable of detecting particles that are solid, liquid, granular, or powdered. For automotive applications, ultrasonic sensors use sonic transducers to emit sonic waves in the 40–70 kHz range. This frequency range is beyond the human audible range, making it safe for human ears. A car's parking system can generate more than 100 dB of sound pressure to ensure clear reception, which is similar to the audible sound pressure from a jet engine. The majority of ultrasonic sensors work by measuring the ToF of sonic waves between transmission and reception (Terzic, 2013). The distance (d) to an object or a reflector within the measuring range is calculated by using the measured ToF, as shown in Eq. (4)

$$d = Speed\ of\ Sonic\ Wave \times \frac{ToF}{2} \tag{4}$$

Sonic waves travel at $\sim$340 m/s in air and are affected by temperature, pressure, and humidity (the speed of sound rises by 0.6 m/s for every degree Celsius). A sonic wave travels a distance of one meter approximately in 3×10^{-3},seconds, compared to 3.3×10^{-9} seconds for light and radio waves. Low-speed signal processing in ultrasonic systems is possible due to these multiple orders of magnitude disparities. However, pressure-based air conditions can degrade ultrasonic sensor performance, encouraging the adoption of SRRs and other technologies instead (Nagaoka, 2018). Fig. 9, illustrates the usage of ultrasonic sensors in vehicles. Ultrasonic systems are the least expensive among the different sensors. However, due to the physical conditions discussed above,

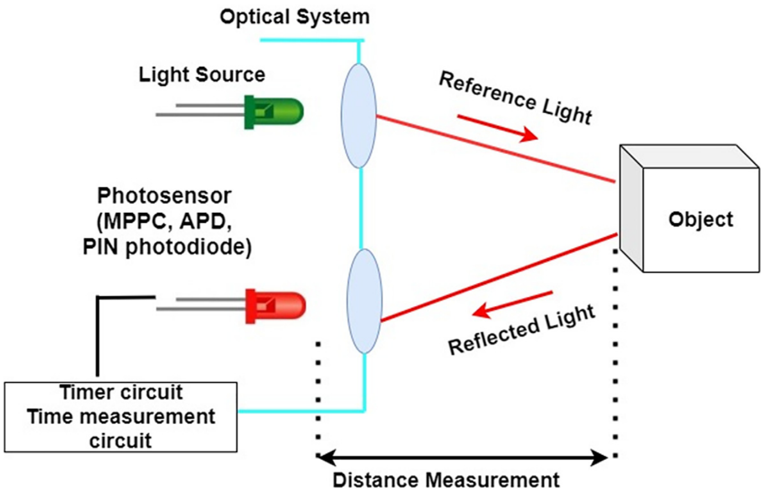

Fig. 7 High-level block diagram for time-of-light LiDAR system.

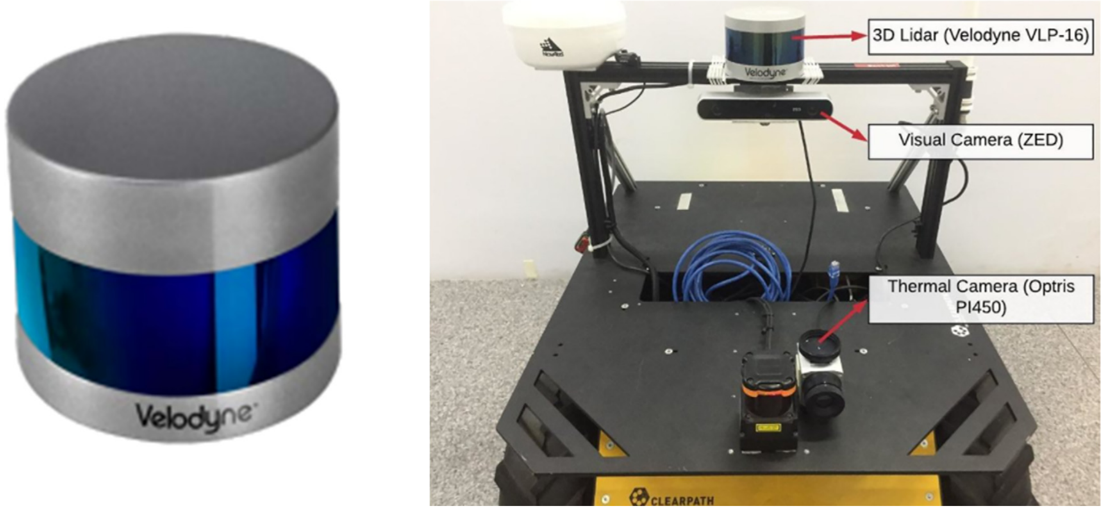

Fig. 8 Velodyne PUCK LiDAR and its set up details.

they are more often affected by obstruction or disturbances than RADAR systems. They are significantly influenced by the medium of sound wave propagation because they can only operate in a medium, unlike an electromagnetic wave. The ultrasonic sensor's sensing capabilities change as the medium's temperature, humidity, and environmental variables change. Many sensors use an algorithm that adjusts readings based on ambient temperature to account for temperature variations. Ultrasonic sensors are short-ranged sensors, typically utilized for parking solutions or other near- range applications due to their limitations. In addition, ultrasonic sensors are the most accurate of the technologies discussed in close proximity scenarios. Fig. 9, illustrates the usage of ultrasonic sensors in the AVs.

Cameras

Cameras are one of the most widely used technologies for observing the environment. A camera produces crisp images of the surroundings by detecting lights produced from the surroundings on a photosensitive surface (image plane) through a camera lens (placed in front of the sensor). Cameras are relatively cheap, and with the right software, they can identify both moving and stationary impediments in their range of vision, as well as offer high-resolution photographs of their surroundings. These characteristics enable the vehicle's perception system to recognize road signs, traffic lights, road lane markings, and obstacles in road traffic vehicles, as well as a variety of other items in off-road vehicles. An AV's camera system may use monocular or binocular camera, or a combination of the two. The monocular camera system, as the name suggests, uses a single camera to create a succession of images. Traditional RGB monocular cameras are essentially more limited than stereo cameras. RGB cameras lack native depth information, which is obtained using complicated algorithms implemented in specific situations (or) fixing more modern monocular cameras that use dual-pixel focusing hardware. As a result, two cameras are frequently put side by side in autonomous vehicles to form a binocular camera system.

Most cameras can be classed as visible (VIS) or infrared (IR) (Gade and Moeslund, 2014; Olmeda et al., 2011), based on their electromagnetic spectrum (IR). Similar to human eyes, VIS cameras (e.g., monocular vision and stereo vision) catch wavelengths ranging from 400 to 780 nm. They are popular because of their inexpensive price, great resolution, and ability to distinguish between colors. Stereo vision can be achieved by combining two VIS cameras with a specified focus distance, resulting in a 3D picture of the scene around the vehicle. Even in a stereoscopic vision camera system, however, the predicted depth accuracies are lower than those obtained from active range finders like RADARs and LIDARs. Infrared cameras work with wavelengths spanning from 780 nm to 1 mm. For some applications, IR cameras can be expanded to the near infrared (NIR: 780 nm–3 mm) and mid-infrared (MIR: 3–50 mm; known as thermal cameras). In situations where there are peaks of illumination, IR cameras are less vulnerable to weather or lighting conditions, and they can overcome some of the disadvantages of VIS cameras (e.g., at the exit of a tunnel). IR cameras can also be used to detect warm bodies, such as pedestrians and animals. Furthermore, using the ToF principle and the phase difference between broadcast and received light pulses, NIR cameras can be employed for range detection. The distance varies depending on the number of light emitting diodes (LEDs) in the LED array, ranging from 10 m for internal scenarios to about 4 m for external sceneries. Table 3, displays the general specifications of different camera types manufactured by various vendors.

Performance comparison of sensors in adverse weather conditions

This section discusses the performance of sensors in adverse weather conditions such as rain, fog, lightning and thunder.

Table 2 General specifications of LiDAR, Frame per second (FPS), Accuracy (Acc), Detecting Range (RNG), Vertical FoV(VFOV), Horizontal FoV (HFOV)Horizontal resolution (HR0), Vertical Resolution (VR), Wavelength(λ), Diameter(∅).

Category	*Company*	*Model*	*Channels/Layers*	*FPS(Hz)*	*Acc(m)*	*RNG(m)*	*VFOV(°)*	*HFOV(°)*	*HR*	*VR*	λ	*∅(mm)*
	Velodyne	VLP-16	16	5–20	±0.03	1..100	30	360	0.1–04	2	903	103.3
		VLP–32C	32	5–20	±0.03	1..200	40	360	0.1–04	0.33	903	103
		HDL-32E	32	5–20	±0.02	2–100	41.33	360	0.08–0.33	1.33	903	85.3
		HDL-64E	64	5–20	±0.02	3..120	26.8	360	0.09	0.33	903	165.5
Mechanical/ Spinning	Hesai	VLS 128 (Alpha Prime)	128	5–20	±0.03	Max 245	40	360	0.1–0.4	0.11	903	165.5
		Pandar64	64	10,20	±0.02	0.3..20	40	360	0.2,0.4	0.167	905	116
LiDARS	Ouster	Pandar40P	40	10,20	±0.02	0.3..200	40	360	0.2,0.4	0.167	05	116
		OSI-64 Gen1	64	10,20	±0.03	0.8—120	33.2	360	0.7.0.35	0.53	850	85
		OSI-16 Gen 1	16	10.20	±0.03	0.8120	33.2	360		0.53	850	85
	RoboSense	RS-LiDAR 32	32	5.10,20	±0.03	0.4–200	40	360	0.18,10.36	2	905	102
	LeiShen	C32-151A	32	5,10,20	±0.03	0.5-..70	32	360	0.09	1	905	120
		C16-700B	16	5,10,20	±0.02	0.5..150	30	360	0.18,0.36	2	905	102
	Hokuyo	YVT-35LX-F0	–	20	±0.05	0.3..35	40	210	–	–	905	0
	IBEO	LUX 4L Standard	4	25	0.1	50	3.2	110	0.25	0.8	905	0
Solid State		LUX HD	4	25	0.1	50	3.2	110	0.25	0.8	905	0
LiDARS		LUX SL	8	25	0.1	30	6.4	110	0.25	0.8	905	0
	SICK	LD-MRS400102S01 HD	4	50	–	30	3.2	110	0.125–0.5	–	–	0
		LD-MRS8001S01 HD	8	50		50	6.4	110	0.125–0.5	–	–	0
	Cepton	Vista P60	–	10	–	200	22	60	0.25	0.25	905	0
		Vista P90	–	10	–	200	27	90	0.25	0.25	905	0
		Vista X90	–	40	–	200	25	90	0.13	0.13	905	0

Rain

The maximum diameter of a rain droplet is 6 mm (Hadj-Bachir, 2019). If the diameter of a rain droplet exceeds this value, the air resistance combined with the droplet's terminal velocity will exceed its cohesive force, tearing it into smaller pieces. According to Mie's solution to Maxwell's equation (Bertoldo et al., 2017), Mie scattering occurs when the transmission wavelength (λ) is similar to or less than the droplet diameter of 6 mm. Mie scattering can affect EM signal propagation in two ways: first, EM energy is absorbed by water drops and vapor, creating attenuation; and second, rain volume backscattering or rain clutter can cause false alarms or obscure true targets in front of the sensor, causing attenuation. Mie scattering from rain will have a significant impact on LiDARs broadcasting in the 905 and 1550 nm wavebands. However, LiDAR vulnerability to rain is not as obvious within the range of 250 m required for rangefinders on AVs until more extreme rain rates occur. The effect of attenuation is not substantial at short distances for 77 GHz RADAR systems used in AVs ($\lambda = 3.9$ mm). Mie scattering, fluctuates between 0.0016 dB/m for 1 mm/h to 0.032 dB/m for 100 mm/h. However, rain backscattering or rain clutter might reduce the maximum range of detectability. Rain clutter is also a problem since the received backscatter from rain is based on R^2 rather than R^4 for the target echo, where R is the range. The intensity of picture pixels in camera systems on-board AVs is determined by scene brightness. Different weather conditions can cause dramatic intensity changes, resulting in poor image and video quality. Snow and severe rain, for example, might obscure an object's outlines, making it unidentifiable. Fortunately, several digital image-processing algorithms can reduce the impact of precipitation on image quality and increase image quality in changing weather circumstances.

Fog

Fog is created due to the presence of dust (or) pollution in the air. When water vapor condenses around these small solid particles, droplets ranging in size from 1 to 20 μm are developed (Awan et al., 2009; Gultepe, 2007). As a result, LiDAR systems with operating wavelengths shorter than fog particles will be affected by Mie scattering. Water absorption has a significant impact on the NIR

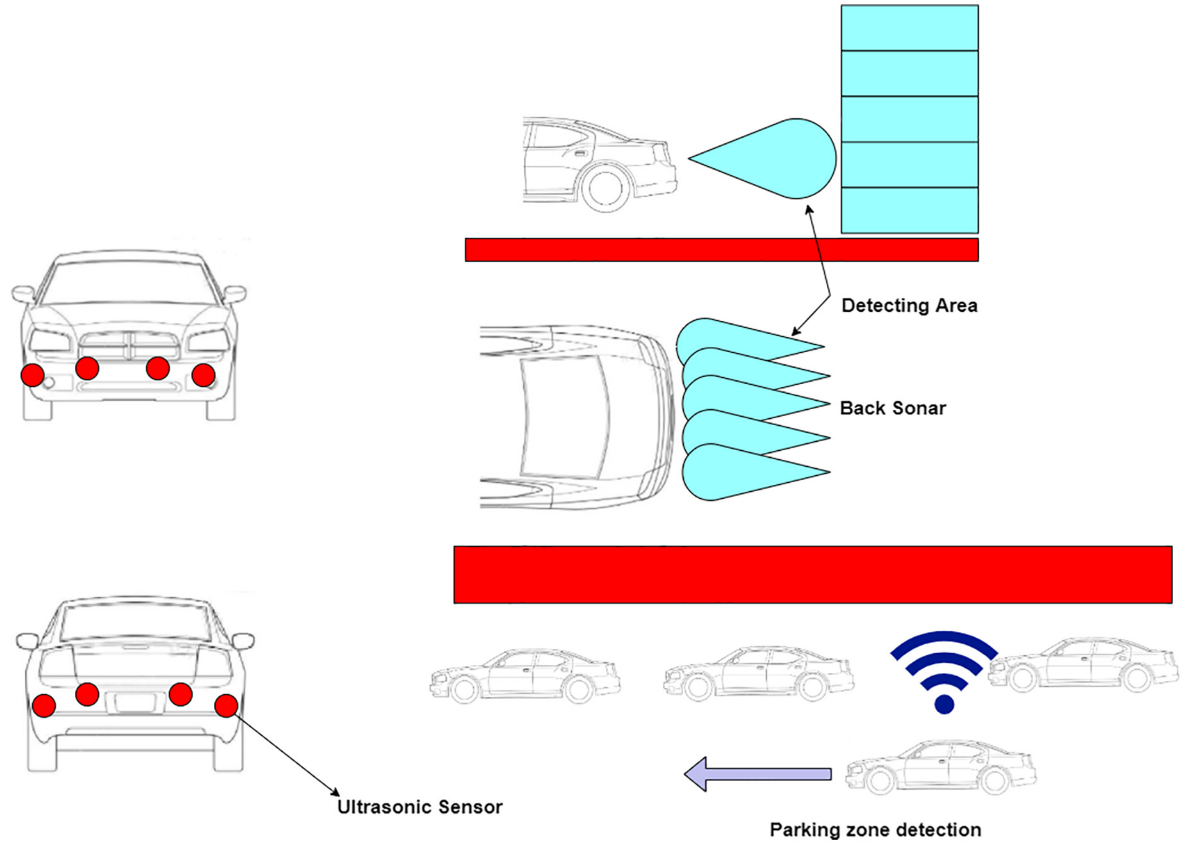

Fig. 9 Applications of ultrasonic sensors in vehicles.

spectral band, in addition to the negative effects of scattering. In contrast to most other sensors, ultrasonic sensors are not immediately impacted by scattering. However, because this is a system that works with sound waves, air quality and temperature will have an impact on its function. Since ultrasonic sensors are utilized for applications that require very short-range detection, precipitation has a little effect. NIR signals can be attenuated by up to 130 dB/km and 480 dB/km in moderate continental fog and heavy marine fog, respectively (Kaplan, 2005). Due to the huge magnitude disparity in particle to wave size, fog would display minor Rayleigh

Table 3 General specifications of stereo camera, Horizontal-field-of-view (HFOV), Vertical-field-of-view (VFOV), Frames per second (FPS), Image Resolution in mega pixels (Img Res), Depth frames per second (FPS).

								Deep Information		
	Model (mm)	*Baseline*	*HFOV(°)*	*VFOV(°)*	*FPS(Hz)*	*Range*	*Img Res*	*Range*	*Res*	*FPS*
Roboception	RC Viscard 160	160	61	48	25	0.5–3	1.2	0.5–3	0.03–1.2	0.8–25
Carnegie Robotics	MultiSense S7	70	80	49/80	30 max	–	2/4	0.4 min	0.5–2	7.5–30
	MultiSense S21B	210	68–115	40–68	30 max	–	2/4	0.4 min	0.5–2	7.5–30
Ensenso	N35–606-16	100	58	52	10	4max	1.3			
Framos	D435e	55	86	57	30	0.2–10	2	0.2 max	0.9	30
Nerian	Karmin3	50/100/250	82	67	7		3	0.23/0.45/1.14 min	2.7	–
Intel	D455	95	86	57	30	20 max	3	0.4 min	≤ 1	≤ 90
	D$35	50	86	57	30	10 max	3	0.105 min	≤ 1	≤ 90
	D415	55	85	40	30	10 max	3	0.16 mm	≤ 1	≤ 90
Flir	Bumblebee2	120	66		48/20	0.3/0.8				
	Bumblebee							–		
	XB3	240	6		16		1.2			

scattering on millimeter waves. If temperature criteria are reached by condensing on the radome i.e. a structural weather-proof enclosure that protects radar antenna or target in question, fog may have an indirect effect on RADAR. The camera, on the other hand, is highly influenced by Mie scattering due to its working wavelengths (400–750 nm) (Zang et al., 2019), which are substantially shorter than the size of fog particles. Fog also diminishes the perception clarity of the cameras. The visibility of the cameras is reduced to 30 m compared to 60 m in cameras when the effect of fog is intense.

The presence of air-light should also be considered since fog enables it. The dispersion of light caused by particle interference is known as air-light. Air-light interference makes it impossible to view objects in close proximity to the light source. As the distance between the camera and the object increases, the camera's perception of other things depends on how the air-light interacts with the camera. Object distinction becomes more difficult in fog, which in turn reduces the object-reflecting characteristic. The higher an object's reflectivity, the darker it appears in fog. Fog would also damage ultrasonic sensors that rely on air composition. The water density of the air can range from 0.01 *to* 0.2 g/cm^3 depending on the type of fog.

Humidity

Humidity is divided into two categories: absolute and relative. The amount of water vapor in a cubic meter of air is known as absolute humidity. The amount of water vapor and other particles stored in a container within a volume varies depending on the temperature of the environment. The relative humidity is determined by comparing absolute humidity with the present temperature. When the dew point temperature and actual temperature are the same, relative humidity is 100% or saturated. With this in mind, the relative humidity is estimated by the ratio between the actual vapor pressure and saturated vapor pressure (EDinformatics, 1999). Fog forms may be aided if saturation is reached in conjunction with specific weather conditions. Humidity should affect ultrasonic sensors since humidity affects pressure directly. The attenuation of ultrasonic waves is affected by humidity levels in a variety of ways. For all frequency to humidity levels, this effect is not always the same. Maximum attenuation is observed at saturation at 200 kHz, however at 60 kHz, maximum attenuation is observed at 60% humidity. High humidity should contribute to the attenuation of LiDAR performance due to the high absorption coefficient of water. The extinction coefficient of 905 nm is typically around double that of 1550 nm under normal conditions. Similarly, due to the robust nature of RADARs, the humidity will not have a significant impact on the performance of the RADARs.

Lightening

Since the AVs are using technology that requires energy and electromagnetism, it is essential that the sensors operate with electromagnetic stability on their own in perfect conditions. Hence unpredicted conditions involving electrical interferences like lightning must be considered in advance to avoid further damages to the sensors. Lightning is a weather phenomenon in which a huge electrical discharge happens and then balances by creating a brief flash of up to 30,000 K in less than 10 microseconds (National Lightning Safety Institute, 2021). Since clouds are not particularly monitored to see when and where lightning can strike, all AV sensors are at risk, especially if they're on the outside of the vehicle. The surface of the car will hold the electrical charge when struck, depending on the car's material and structural design. Passengers may still be harmed if they make contact with the vehicle's shell or components attached to the shell, such as the steering wheel, gear shift, doors, or windows. Passengers may even be harmed by interacting with equipment that has electrical capacity. Even when not directly struck by lightning, AV sensors can be affected; this includes automotive technologies, as the sensors are usually mounted to the vehicle. The new electromagnetic field formed by the electrical discharge from the clouds can have an impact on electromagnetic stability. The effects of lightning discharge can be preserved by using materials with low electrical conductivity and using controllers with low noise immunity. Structural approaches, circuitry methods, electromagnetic shielding, and filtering can all be used to ensure noise immunity. **Table 4**, provides a comparison between different sensor types in bad weather conditions.

Thunder

Thunder is the sound that follows lightning; they both happen while the other is present, even if the thunder is not audible. The excited particles emit sound in an explosion that can be heard up to 30 km away as the air is heated along the path of the electrical discharge. The noise is heard after the flash because the speed of light is faster than the speed of sound. Despite the fact that sound may travel a considerable distance, audibility is impacted by a variety of factors. Noise distorters include humidity, wind velocity, temperature inversions, topographical features, and clouds; this is especially significant for ultrasonic sensors (National Lightning Safety Institute, 2021). Buildings or landscapes can also cause echoes, resulting in repeated instances of the sound. Thunder has the ability to act at both sonic and infrasonic frequencies. Although 100 Hz is the dominating frequency, infrasonic frequencies below 20 Hz are inaudible to humans (Kithil, 2021). As a result, the pressure waves associated with thunder can cause damage to both interior and external structures (Kithil, 2021). Thunder's effect on sound for various sensors may be insignificant depending on the baseline circumstances such as temperature and relative humidity. Thunder, on the other hand, has a much higher temperature (at 30,000 K due to lightning); RADAR, LiDAR, ultrasonic, and perhaps GNSS will be damaged due to wavelength disturbances.

Overall performance comparison of sensors

Both RADAR and LiDAR sensors can operate in adverse weather conditions and both align with today's emerging technologies. The prime drawback associated with both these sensors is they need the support of a perpetual system to enhance decision-making. On the other hand when the illumination changes, the weather is bad, or visibility is low, cameras can lose their capacity to comprehend

Table 4 Performance of sensors in weather conditions.

AV Sensors	*Role(s)*	*Direct Lighting Effect Levels*	*Indirect Lightning Levels*
RADAR	Electromagnetic	High	Medium
LiDAR	Electrical	High	High
Ultrasonic Sensors	Electromagnetic	High	Medium
GNSS	Electrical, Electromagnetic	High	Medium
Camera	Electrical	High	Hugh

their perception. LiDAR sensors are widely used in spacecraft missions, but they are not the optimal choice for autonomous vehicles, due to their size and cost. Self-driving cars can rely largely on cameras to understand their surroundings. As a result, cameras are usually fixed in the AVs due to reduced cost, high resolution, and ability to distinguish between colors. Computer stereo vision is done by connecting two visible (VIS) cameras with a predefined focus distance, resulting in a 3D depiction of the scene around the vehicle. However, the estimated depth accuracy achieved from stereoscopic vision camera systems is lower than that gained from active range finders such as RADARS and LIDARs. Adverse weather conditions can pose problems for AV sensors and even cause them to fail. With the help of satellite monitoring, and existing vehicular infrastructures like traffic lights, etc. control centers can detect and avoid many roadside events such as collision avoidance via mobile devices. As a result, leading semiconductor companies are working on circuits that will turn self-driving cars into mobile data centers, allowing them to make critical choices in real-time. Table 5, portrays the overall comparison of different sensors based on different metrics.

Sensory data fusion

Sensor fusion is a process of integrating data collected from multiple sensors to provide complete information about the environment with less uncertainty. Fusing the data improves data accuracy and availability. In the worst-case scenarios, the calibration and accuracy of the sensors are debatable. Therefore, it is important to fuse data perceived from multiple sensors to improve the data accuracy and data reliability. Furthermore, multiple data streams collected from different sensors are used to discover inherent flaws that rise with sensor aging or failure. Sensors are fixed in AVs to ensure data availability rather than obtaining data accuracy. Based on various analyses, data collected from a single sensor type cannot offer a comprehensive experience of AV due to their limitations and inability to handle multiple use-cases. To make the right choice, inputs from several sensors (or) combinations of sensors are fused and supplied into an ML algorithm for improved perception and object recognition, especially in low-light situations and adverse weather conditions, like fog, snow, rain, moist, etc.

Observational data are fused at different levels that are listed below

a) **Observation level fusion:** If the sensor data are comparable (i.e., if the sensors are monitoring the same physical phenomenon, such as two visual image sensors or two sound sensors), raw sensor data can be directly merged. Classic detection and estimate methods are commonly used in raw data fusion techniques. On the other side, if the sensor data are incompatible, the data must be fused at the feature/state vector level to enhance the decision- making process.

b) **Feature level fusion**: The extraction of representative features from sensor data is the first step in feature-level fusion. Using the features of a human's face to recognize an image of the individual is an example of feature extraction. Cartoonists and political satirists utilize this method to recognize well-known people. There is evidence that people recognize things using a feature-based cognitive function. Feature-level fusion involves extracting features from numerous sensor data and appending them into a single feature vector, which is then fed into pattern recognition algorithms such as neural networks, clustering algorithms, and template techniques.

Table 5 Overall comparison of the sensors.

Type	*Proximity Detection*	*Range*	*Resolution*	*Works in Dark*	*Works in Bright*	*Works in Snow/ Fog/Rain*	*Provide Color Contrast*	*Detects Speed*	*Object Classification*	*Lane Detection*	*Size*	*Sensor Cost*
LiDAR	Poor	Good	Good	Good	Good	Good	Average	Yes	Good	Poor	Large	High
RADAR	Poor	Good	Average	Good	Good	Good	Average	Yes	Good	Poor	Medium	Average
Ultrasonic	Good	Poor	Poor	Good	Good	Poor	Average	No	Good	Average	Medium	Low
Camera	Average	Poor	Average	Average	Good	Average	Good	Yes	Poor	Good	Small/ Medium	Average

c) **Decision level fusion:** includes fusion data, after each sensor has produced a preliminary evaluation of an entity's location, characteristics, and identity. Weighted decision methods (voting techniques), classical inference, Bayesian inference, and Dempster–method Shafer's are all examples of decision level fusion methods.

Figs. 10A–C, illustrate the architecture of the above specified fusion methods.

Application of AV sensors

The use of autonomous vehicles necessitates a thorough understanding of both the vehicle and the surrounding environment in a controlled environment. As a result, complete autonomy may only exist in controlled conditions, or NHTSA Level 3, yet full autonomy may be too expensive in the mainstream sector (Waldrop, 2015). The following are some examples of autonomous environments where sensors play a vital role to perceive internal and external environmental data:

- Highway Conditions: LiDAR/RADAR (or) GPS sensors, fixed in important areas like main junctions, crossovers (or) market dwelling places, will alert (or) predict some catastrophic road events based on which the AVs will take instant decision to avoid major calamities.
- System Operations: When a vehicle enters a controlled environment, scenario-specific autonomy becomes conceivable. Parking, lane changes, and intersection handling are all examples of this. When a system approaches a potential autonomous event, it can either inform the driver or interact via HMI. The HMI will take suitable decisions based on the environment data captured by the sensors fixed in them.
- Off-Road Applications: This might be anything from a washed-out road to off-roading in its pure state. In this situation, camera systems are limited in their capabilities, necessitating precise GPS and object detection (ultrasonic, LIDAR, and RADAR). In addition, navigating the terrain requires a thorough understanding of vehicle dynamics. Since certain sensors are partially blocked, sensor changes based on fusion data and vehicle dynamics will be required. Off-roading challenges embody many of the challenges that come with inclement weather. Based on their general functioning principles, all of the sensors listed are susceptible to ice, torrential downpours, sandstorms, and other extreme weather conditions.
- Urban Applications: This feature would entail the simultaneous tracking of multiple objects.
- In an incredibly dynamic environment, there might be several pedestrians, bicyclists, merging traffic, exiting vehicles, and different signal interferences. Continuous real-time data is essential to observe the active behavior of various elements

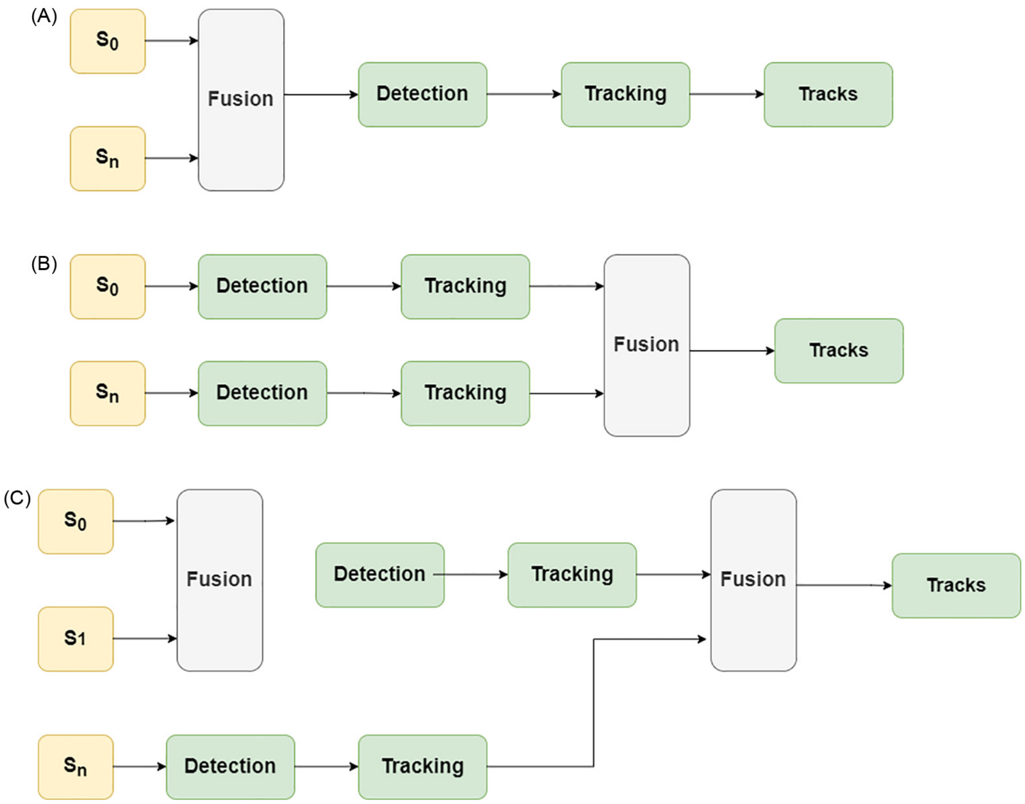

Fig. 10 (A): Low-level fusion. (B): High-level fusion. (C): Hybrid fusion.

mentioned above based on their environment by the AVs for effective decision-making and advanced analytics. To achieve this, sensors are placed in important areas to collect dynamic environmental data.

- In vehicle-to-vehicle communications (V2V) and vehicle-to-infrastructure (V2I), the use of AV sensors can improve data dissemination for instant decision-making, congestion, and obstacle avoidance, traffic flow management and ensure automobile safety.

Conclusion

This chapter provided the basics of Autonomous Vehicles (AVs), their hierarchy of evolution, and the contribution of the sensing devices toward the enhanced performance of the AVs. It has also analyzed and summarized the major concepts of the AV sensors and discussed in detail the different categories of internal and external sensors. More emphasis is given to external sensors and the four prime external sensors namely LIDARs, RADARS, Ultrasonic sensors, and Cameras are widely explored. Key aspects like the theory behind the operation of the sensors, their salient features, and performance in adverse weather conditions are deliberated and summarized. Adequate information related to the performance of different sensors manufactured by several vendors is provided. The pros and cons associated with the sensors are also highlighted as well as the applications of sensors in various areas of AVs. Moreover, the significance of sensory data fusion, their impact on the data accuracy, and different fusion architects used to fuse the sensory data are discussed in detail. In addition, the impact of sensors in ensuring safety and security in the AVs is covered in this chapter.

References

Awan, M.S., Leitgeb, E., Loeschnig, M., Nadeem, F., Capsoni, C., 2009. Spatial and time variability of fog attenuations for optical wireless links in the troposphere. In: 2009 IEEE 70th Vehicular Technology Conference Fall. Presented at the 2009 IEEE 70th Vehicular Technology Conference (VTC 2009 Fall)IEEE, Anchorage, AK, pp. 1–5. https://doi.org/10.1109/VETECF.2009.5379065.

Bertoldo, S., Lucianaz, C., Allegretti, M., 2017. 77 GHz automotive anti-collision radar used for meteorological purposes. In: 2017 IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications (APWC). Presented at the 2017 IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications (APWC)IEEE, Verona, Italy, pp. 49–52. https://doi.org/10.1109/APWC.2017.8062238.

Buller, W., 2018. Radar Congestion Study (No. Report No. DOT HS 812 632). Washington, DC.

Deka, L., Chowdhury, M.A., 2019. Transportation Cyber-Physical Systems. Elsevier.

Edelstein, S., 2020. Audi Gives up on Level 3 Autonomous Driver-Assist System in A8. 2020. https://www.motorauthority.com/news/1127984_audi-gives-up-on-level-3-autonomous-driver-assist-system-in-a8 (accessed 12.9.21).

EDinformatics, 1999. What is Humidity? How Is It Measured? EDinformatics. https://www.edinformatics.com/math_science/what-is-humidity.html.

Fossen, T.I., Pettersen, K.Y., Nijmeijer, H., Nijmeijer, H. (Eds.), 2017. Sensing and Control for Autonomous Vehicles: Applications to Land, Water and Air Vehicles, Lecture Notes in Control and Information Sciences. Springer, Cham. https://doi.org/10.1007/978-3-319-55372-6.

Gade, R., Moeslund, T.B., 2014. Thermal cameras and applications: A survey. Machine Vision and Applications 25, 245–262. https://doi.org/10.1007/s00138-013-0570-5.

Giacalone, J.-P., Bourgeois, L., Ancora, A., 2019. Challenges in aggregation of heterogeneous sensors for Autonomous Driving Systems. In: 2019 IEEE Sensors Applications Symposium (SAS). Presented at the 2019 IEEE Sensors Applications Symposium (SAS)IEEE, Sophia Antipolis, France, pp. 1–5. https://doi.org/10.1109/SAS.2019.8706005.

Glon, R., Edelstein, S., 2020. The History of Self-Driving Cars. The History of Self-Driving Cars. https://www.digitaltrends.com/cars/history-ofself-driving-cars-milestones (accessed 1.12.20).

Gonzalez-de-Santos, P., Fernández, R., Sepúlveda, D., Navas, E., Emmi, L., Armada, M., 2020. Field robots for intelligent farms—Inhering features from industry. Agronomy 10, 1638. https://doi.org/10.3390/agronomy10111638.

Gourova, R., Krasnov, O., Yarovoy, A., 2017. Analysis of rain clutter detections in commercial 77 GHz automotive radar. In: 2017 European Radar Conference (EURAD). IEEE, pp. 25–28.

Gultepe, I., 2007. Fog and Boundary Layer Clouds: Fog Visibility and Forecasting, Pageoph Topical Volumes. Birkhäuser, Basel Boston.

Hadj-Bachir, M., 2019. LIDAR sensor simulation in adverse weather condition for driving assistance development. HAL 14.

Kaplan, 2005. Understanding GPS Principles and Applications. Artech House, Boston, MA.

Kithil, R., 2021. The Thunder Mechanism. National Lightning Safety Institute. http://lightningsafety.com/nlsi_info/thunder.html (accessed 10.9.21).

Kutila, M., Pyykonen, P., Ritter, W., Sawade, O., Schaufele, B., 2016. Automotive LIDAR sensor development scenarios for harsh weather conditions. In: 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC). Presented at the 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)IEEE, Rio de Janeiro, Brazil, pp. 265–270. https://doi.org/10.1109/ITSC.2016.7795565.

Mehra, A., Mandal, M., Narang, P., Chamola, V., 2021. ReViewNet: A fast and resource optimized network for enabling safe autonomous driving in hazy weather conditions. IEEE Transactions on Intelligent Transportation Systems 22, 4256–4266. https://doi.org/10.1109/TITS.2020.3013099.

Mozaffari, S., Al-Jarrah, O.Y., Dianati, M., Jennings, P., Mouzakitis, A., 2020. Deep learning-based vehicle behavior prediction for autonomous driving applications: A review. IEEE Transactions on Intelligent Transportation Systems 1–15. https://doi.org/10.1109/TITS.2020.3012034.

Nagaoka, S., 2018. Evaluation of attenuation of ultrasonic wave in air to measure concrete roughness using aerial ultrasonic sensor. Geomate 14. https://doi.org/10.21660/2018.42.7242.

National Lightning Safety Institute, 2021. Vehicles and Lightning. National Lightning Safety Institute. http://lightningsafety.com/nlsi_pls/vehicle_strike.html (accessed 7.23.21).

Olmeda, D., de la Escalera, A., Armingol, J.M., 2011. Far infrared pedestrian detection and tracking for night driving. Robotica 29, 495–505. https://doi.org/10.1017/S0263574710000299.

Özgüner, Ü., Acarman, T., Redmill, K.A., 2011. Autonomous Ground Vehicles. Artech House, Boston (Massachusetts).

Steinbaeck, J., Steger, C., Holweg, G., Druml, N., 2017. Next generation radar sensors in automotive sensor fusion systems. In: 2017 Sensor Data Fusion: Trends, Solutions, Applications (SDF). Presented at the 2017 Sensor Data Fusion: Trends, Solutions, Applications (SDF)IEEE, Bonn, pp. 1–6. https://doi.org/10.1109/SDF.2017.8126389.

Terzic, J., 2013. Ultrasonic Fluid Quantity Measurement in Dynamic Vehicular Applications: A Support Vector Machine Approach. Springer, Cham, New York.

Toker, O., Kuhn, B., 2019. A python based testbed for real-time testing and visualization using TI's 77 GHz automotive radars. In: 2019 IEEE Vehicular Networking Conference (VNC). Presented at the 2019 IEEE Vehicular Networking Conference (VNC)IEEE, Los Angeles, CA, USA, pp. 1–4. https://doi.org/10.1109/VNC48660.2019.9062830.

Vargas, J., Alsweiss, S., Toker, O., Razdan, R., Santos, J., 2021. An overview of autonomous vehicles sensors and their vulnerability to weather conditions. Sensors 21, 5397. https://doi.org/10.3390/s21165397.

Waldrop, M.M., 2015. Autonomous vehicles: No drivers required. Nature 518, 20–23. https://doi.org/10.1038/518020a.

Wang, Z., Wu, Y., Niu, Q., 2020. Multi-sensor fusion in automated driving: A survey. IEEE Access 8, 2847–2868. https://doi.org/10.1109/ACCESS.2019.2962554.

Yeong, D.J., Barry, J., Walsh, J., 2020. A review of multi-sensor fusion system for large heavy vehicles off road in industrial environments. In: 2020 31st Irish Signals and Systems Conference (ISSC). Presented at the 2020 31st Irish Signals and Systems Conference (ISSC)IEEE, Letterkenny, Ireland, pp. 1–6. https://doi.org/10.1109/ISSC49989.2020.9180186.

Zang, S., Ding, M., Smith, D., Tyler, P., Rakotoarivelo, T., Kaafar, M.A., 2019. The impact of adverse weather conditions on autonomous vehicles: How rain, snow, fog, and hail affect the performance of a self-driving Car. IEEE Vehicular Technology Magazine 14, 103–111. https://doi.org/10.1109/MVT.2019.2892497.