

Hybrid Fusion of RADAR, Range-Finder LiDAR, and Ultrasonic Level Meter Sensors for Linear Sensing Applications

Received 05/14/2025
Review began 06/29/2025
Review ended 12/24/2025
Published 02/11/2026

© Copyright 2026

Adewuyi et al. This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

DOI:

<https://doi.org/10.7759/s44388-026-00024-z>

Oluwasanmi A. Adewuyi¹, Olumuyiwa A. Lasode¹, Jayeola F. Opadiji²

1. Department of Mechanical Engineering, University of Ilorin, Ilorin, NGA 2. Department of Computer Engineering, University of Ilorin, Ilorin, NGA

Corresponding author: Oluwasanmi A. Adewuyi, sanmi.adewuyi@gmail.com

Abstract

Collision avoidance systems serve as a major aspect of autonomous vehicles, while sensors form a crucial section of collision avoidance systems. The challenge of assembling sensors that can perceive the environment in a manner similar to human senses is being continuously explored by researchers to enhance the abilities of collision avoidance systems; more affordable and simpler methods are also being considered to reduce their complexity. This paper considers sensor fusion of radio detection and ranging (RADAR), Range finder light detection and ranging, and Ultrasonic sensors for a collision avoidance system. The concept of this paper is to exclude vision sensors from the fusion method. While vision sensors have been considered a fundamental sensor for collision avoidance systems by many researchers, the flaws of vision sensors when detecting transparent objects or under poor visibility conditions cannot be ignored. At distances below 1 m, the RADAR sensor will be rendered inactive, while at distances above 15 m, the ultrasonic sensors will be rendered inactive. All sensors are active at distances between 1 m and 15 m. The fusion method in this paper establishes an algorithm for sensor-fusion of the three sensors based on their linear accuracies.

Categories: Automotive Safety and Crashworthiness

Keywords: sensors, sensor-fusion, ultrasonic-sensor, lidar, radar, collision avoidance, autonomous vehicles, weighted fusion, complementary fusion, object detection

Introduction

The incorporation of advanced technologies in vehicles has improved the protection afforded to vehicle occupants and pedestrians significantly. These have reduced road accidents despite increase in the number of vehicles and mobility [1]. These new capabilities have profound global impacts that can significantly change how the society operates. With an estimated 10 trillion automobile miles driven every year, there are still complex conditions that can present significant problems for self-driving cars [2]. There have been events to showcase major achievements in autonomous vehicles over the last three decades. In 1995, Carnegie Mellon University's Navigation Laboratory demonstrated progress with a 5000 km drive across US on 98% autonomous driving [3]. Others include the Intelligent Vehicle Future Challenges from 2009 to 2013 [4], Hyundai Autonomous challenge in 2010 [5], the Vislab Intercontinental Autonomous Challenge in 2010 [6], the Public Road urban Driverless Car Test in 2013 [7], and the autonomous drive of the Bertha-Benz historic route [8]. Most notable of these include Google Self-Driving car (Waymo), Tesla's Autopilot system, and Uber's self-driving technology which are already in commercial use with known issues [9,10]. With such possibilities and danger involved, the most important aspects of the self-driving cars/autonomous vehicles can be considered to be the ability to avoid accidents. The human senses of vision, hearing, and smelling are crucial senses in avoidance of accidents or major road issues and the biggest tasks of self-driving cars is the availability to get sensors that can perceive the environment like the human senses. In this paper, we consider a sensor suit that excludes vision sensor and we test their accuracies in detecting opaque and transparent objects with the aim of generating a fusion-logic for the three sensors. It is important to note that vision sensors or cameras make up a large section of autonomous sensing capabilities. Vision sensors are extremely important in navigation. However, its weaknesses can be devastating when collision avoidance is considered. Vision sensor will usually fail when they have to detect transparent objects or objects that are perceived to be transparent, part of the environment, or closer than they appear on the image [11]. Such example can be a large truck with a sky blue colored cargo section, which may be interpreted as the sky instead of an object within range. Such flaws from vision sensors have made us consider how well other sensors will perform when the vision sensors fails. For this paper, we considered three sensing technologies to be fused together, which are radio detection and ranging (RADAR), light detection and ranging (LiDAR), and Ultrasonic sensors. This paper seeks to achieve high object detection accuracy from the fusion of three sensors and to also provide a theoretical model for the sensor fusion algorithm.

Background literature

How to cite this article

Adewuyi O A, Lasode O A, Opadiji J F (February 11, 2026) Hybrid Fusion of RADAR, Range-Finder LiDAR, and Ultrasonic Level Meter Sensors for Linear Sensing Applications. Cureus J Eng 3 : es44388-026-00024-z. DOI <https://doi.org/10.7759/s44388-026-00024-z>

Sensors and actuator-based embedded technologies have been used for years to develop responsive environments [12]. Data from multiple sensors can be collected to develop better and efficient systems. Types of sensors used for autonomous driving are object detection sensors and the most common ones are ultrasonic sensors, RADAR, LiDAR and Vision sensors [13]. Ultrasonic sensors are devices that generate or sense ultrasound energy. Ultrasound is generally regarded as sound signals of frequency as high as 40 kHz. Ultrasonic sensors function in three broad categories: transmitters, receivers, and transceivers. Transmitters convert electrical signals into ultrasound, receivers convert ultrasound into electrical signals, and transceivers can both transmit and receive ultrasound [14]. Because ultrasonic sensors use sound wave, they work in applications where light emitting sensors may fail. Ultrasonic sensors function properly under various weather conditions and can be considered to be highly reliable. Ultrasonic sensors provide solution for transparent object detection and for liquid level measurement.

RADAR sensors use radio waves for object detection. RADAR sensors transmit high-frequency electromagnetic waves and receive the reflection of the waves to estimate the position and velocity of the objects within range [15,16]. As with other range sensors, the distance of the object within range is determined using the temporal delay between the transmitted and received signals. However, with RADAR sensors the velocity of the object can be calculated using Doppler Effect, which considers the frequency shift of the reflected waves in respect to the transmitted waves. A RADAR sensor can use continuous waves (CW) which are electromagnetic waves with constant amplitude and frequency. Using CW, only the speed of the object can be measured using Doppler Effect [15,17,18].

LiDAR technology enables the accurate determination of an object's attributes. LiDAR makes use of light waves, which are at shorter wavelength regime compared to radio waves, and hence has potential to achieve higher precision in 3D sensing. LiDAR is widely used in metrology [19] and increasing popularity in automobile collision avoidance system. LiDAR's high resolution is valuable for identifying objects and can provide static maps for the immediate environment as well as identify moving objects [13].

Vision sensors are cameras or image generating devices with image identification abilities. This type of sensor often relies on image-related processes for extracting useful information about environment and obstacles. There are several advantages of visual sensors; such as smaller equipment size and light weight. Vision sensors have a size advantage compared to other sensors as they can be built much smaller; however, they require larger processor capability to interpret their data [20]. Depending on visibility, an object can appear as a small, low-contrast dot and does not change remarkably until it gets very close to the vehicle which can lead to an unavoidable accident.

The environment perception of different sensing technology is based on their principles of operation. There is not a single type of sensor that can perfectly simulate the human mind while driving, and hence the need for sensor fusion. Sensor fusion involves combining the capabilities of multiple sensing technologies for a better output performance. Ultrasound sensors can work in different weather conditions but typically have very limited range for compact models; RADAR sensors have long range but poor resolution, while LiDAR sensors have good resolution with mid-level range, but offer poor resolution in bad weather. In order to have the best sensing results, more than one type of sensing technology is required.

The main environment perception conditions considered in sensor fusion are range, range resolution, angular resolution, performance under different weather conditions and dark mode/night vision, color/contrast effect. All these conditions are crucial for autonomous driving technology, however, for the Collision Avoidance; with primary focus on object detection, color or contrast of the object are not primary concerns. Table 1 shows a comparison of these conditions for the common range sensing technologies [15], where + is good, - is poor and o is not applicable. Range simply refers to the maximum distance the sensor can cover in terms of linear distance. Range resolution refers to how sensitive the sensor is in determining little changes in the position of objects within range. Angular resolution refers to the ability of the sensor to distinguish or characterize small details on the objects within range.

Sensor	RADAR	LiDAR	Vision
a. Range	++	+	++
b. Range resolution	+	++	o
c. Angular resolution	o	++	+
d. Bad weather	++	o	-
e. Night mode	++	++	--
f. Bright daylight	++	+	+
g. Color/contrast	--	--	++
h. Radial velocity	++	o	-

TABLE 1: Comparison of environment perception for three different sensors [15]

(-): Poor performance; (+): good performance; (o): not applicable. RADAR, radio detection and ranging; LiDAR, light detection and ranging

Table 2 shows the comparison of sensors with the addition of ultrasonic sensors. From Table 2, we can see that the advantages of ultrasonic sensors can add to the efficiency of sensor suites during poor visibility.

Sensor	RADAR	LiDAR	Vision	Ultrasonic
a. Range	++	+	++	--
b. Range resolution	+	++	o	o
c. Angular resolution	o	++	+	o
d. Bad weather	++	o	-	++
e. Night mode	++	++	--	++
f. Bright daylight	++	+	+	++
g. Color/contrast	--	--	++	o
h. Radial velocity	++	o	-	o

TABLE 2: Comparison of environment perception of different sensors (four sensors)

(-): Poor performance; (+): good performance; (o): not applicable. RADAR, radio detection and ranging; LiDAR, light detection and ranging

There are multiple sensor-fusion methods to consider based on the desired application of the sensors. Three common types of sensor fusion methods will be discussed briefly which are late fusion, complementary fusion, and weighted fusion.

Late sensor fusion, also known as decision-level fusion, involves processing data from individual sensors independently to generate separate decisions or outputs. These decisions are then combined at a higher level using methods such as voting, averaging, or more sophisticated techniques like fuzzy logic or machine learning. Each sensor processes data independently, often optimized for its specific modality. Applications include: medical diagnostics, such as combining decisions from MRI, CT scans, and lab tests;

multimodal biometric systems, such as combining fingerprint, face, and voice recognition; and autonomous systems, such as integrating LiDAR, camera, and RADAR outputs [21].

Complementary sensor fusion combines data from sensors that measure different aspects of a system, with little or no direct overlap in the information provided. The goal is to create a more complete understanding of the system by integrating complementary datasets. A typical example of complementary fusion can include data from an accelerometer, which provides short-term dynamic information, and data from a gyroscope, which provides angular velocity, and together they provide accurate motion tracking. Complementary fusion is utilized in areas such as attitude and orientation estimation in drones, which requires combining accelerometer and gyroscope data. It is also utilized in autonomous vehicles, which can combine LiDAR for precise object detection and cameras for scene understanding [22]. Complementary sensor fusion requires using each sensor in its specific area of strength for particular obstacles/scenarios.

Weighted sensor fusion assigns different weights to the outputs of multiple sensors based on their reliability, accuracy, or importance. The fused result is a weighted combination of the sensor inputs, ensuring that more reliable sensors have a greater influence on the final outcome. Weights can be static (predefined) or dynamic (adapted based on real-time conditions). It prioritizes high-quality or more reliable sensor data. Weights can be determined using statistical measures or error models. It enhances robustness and reduces noise or inaccuracies from less reliable sensors. Applications include: navigation systems with GPS and inertial sensors using weight-based priority dependent on signal quality; multimodal systems such as image sensors and LiDAR fusion with weights adjusted for lighting conditions [23]. These weights can be dynamically adjusted based on the environmental conditions or sensor performance. Equation (1) is commonly used for weighted fusion [24],

$$x_f = \sum_{i=1}^N \omega_i x_i \quad (1)$$

Where x_f is fused estimate, x_i is measurement from the i th sensor, ω_i is the weight for the i th sensor and satisfying, and N is the number of sensors. The weight for each sensor can be obtained through inverse variance, Equation (2) [25].

$$\omega_i = \frac{\frac{1}{\sigma_i^2}}{\sum_{j=1}^N \frac{1}{\sigma_j^2}} \quad (2)$$

Where σ_i^2 is the variance (or uncertainty) of the i th sensor.

Materials And Methods

Materials

The sensors used for this research are Ultrasonic, LiDAR and RADAR sensors. Figure 1(a) shows the Ultrasonic sensor; Level Metre KEJUNCS501 (Kejun, China). It has a range of 0 to 20 m and comes with an LCD display, which shows the distance relative to the maximum distance and comes with 4-20 mA communication protocol and also offers RS485 communication protocol. The baud rate of the sensor can be configured within the ranges of 300-38,400 and offers an instrument calibration system. The LiDAR sensor used is a mid-range sensor that can measure distance up to 100 m; the TF03-100 Range Finder LiDAR sensor (Benewake, China); see Figure 1(b). It is a budget LiDAR sensor and only works as a distance measuring device, which does not provide a 3D perspective view of the environment. This LiDAR sensor senses only the range of the objects in its path. It comes with both UART and Controller Area Network (CAN) communication protocols and provides a maximum baud rate of 115,000 on UART and 1 Mbaud on the CAN protocol. It requires a 5 V power supply which can be connected via USB to a computer.

FIGURE 1: (a) Level Meter KEJUNCS501 Ultrasonic sensor, (b) TF03-100 Range Finder LiDAR sensor, and (c) ARS408-21 RADAR sensor

RADAR, radio detection and ranging; LiDAR, light detection and ranging

The RADAR sensor is ARS408-21-12 V DC (Continental Corporation, Germany); see Figure 1(c). It is a Frequency Modulated Continuous Wave (FMCW) RADAR that comes with CAN communication protocol and has a speed of 1 Mbaud. It is equipped with a microprocessor capable of detecting and processing data

of multiple objects in real time with the capability of detecting objects 250 m away and the velocity of the object in view [26].

Method

Data from the sensors were obtained through field testing. The field testing was used in a similar method to how optical testing is used for vision sensors [27]. Three different objects were used, covering opaque objects and transparent objects as discussed in [26]. Objects were targeted within the range of 0.6-50 m. This was done to identify the accuracy and strength of the sensors at different distances.

The linear nature of the experiments suggests that weighted fusion will be most appropriate for these sensors. After collating the results from the accuracy testing, we assigned weights or priority for each sensor based on the range in question. The average margin of error when the sensors are used by the fusion method was evaluated using Equation (3),

$$A = \frac{1}{n} \sum_{i=1}^n |a_i| \quad (3)$$

Where a_i is the i th error margin for n number error margins considered for the fusion algorithm.

Results

Tables 3-5 show results and the error margin taken from the three different sensors for object distances of 0.6-50 m. Results from five different ranges are presented here for analysis. Figure 2 shows the data observed at 0.6 m, Figure 3 shows data observed at 4.8 m, Figure 4 shows data observed at 15 m, Figure 5 shows data observed at 20 m while Figure 6 shows data observed at 50 m.

Key findings from our results show that the RADAR sensor struggled only at distances below 1 m, while the Ultrasonic sensor, which had a maximum range of 20 m, could not effectively measure target objects above 15 m. For the LiDAR sensor, it struggled with transparent object at distance below 1 m and distance above 20 m.

Actual distance (m)	RADAR	RADAR error margin (%)	LiDAR	LiDAR error margin (%)	Ultrasonic	Ultrasonic error margin %
0.6	1	-66.67	0.64	-6.67	0.591	1.5
1.2	1.2	0.00	1.24	-3.33	1.174	2.166667
1.8	1.6	11.11	1.84	-2.22	1.769	1.722222
2.4	2.4	0.00	2.42	-0.83	2.359	1.708333
3	2.6	13.33	3.03	-1.00	2.932	2.266667
3.6	3.6	0.00	3.635	-0.97	3.529	1.972222
4.2	4.2	0.00	4.23	-0.71	4.115	2.02381
4.8	5	-4.17	4.84	-0.83	4.703	2.020833
10	9.8	2.00	9.55	4.50	9.751	2.49
15	15	0.00	16.69	-11.27	14.652	2.32
20	19.4	3.00	19.97	0.15	11.36	43.2
30	29.2	2.67	29.88	0.40		
40	40.8	-2.00	40.04	-0.10		
50	49.6	0.80	50.09	-0.18		

TABLE 3: Results from measurements taken from all sensors for light brown object

Ultrasonic sensor has a maximum range of 20 m. RADAR, radio detection and ranging; LiDAR, light detection and ranging

Actual distance (m)	RADAR	RADAR error margin %	LiDAR	LiDAR error margin %	Ultrasonic	Ultrasonic error margin %
0.6	1	-66.67	0.655	-9.17	0.6	0
1.2	1.2	0.00	1.275	-6.25	1.19	0.833333
1.8	1.8	0.00	1.82	-1.11	1.763	2.055556
2.4	2.2	8.33	2.42	-0.83	2.35	2.083333
3	3	0.00	3.015	-0.50	2.93	2.333333
3.6	4	-11.11	3.635	-0.97	3.54	1.666667
4.2	4	4.76	4.245	-1.07	4.112	2.095238
4.8	4.8	0.00	4.85	-1.04	4.702	2.041667
10	9.8	2.00	9.55	4.50	9.756	2.44
15	14.6	2.67	14.67	2.20	14.649	2.34
20	19.8	1.00	19.93	0.35	11.39	43.05
30	29.6	1.33	30.07	-0.23		
40	40	0.00	40.03	-0.08		
50	49.6	0.80	49.5	1.00		

TABLE 4: Results from measurements taken from all sensors for black colored object

RADAR, radio detection and ranging; LiDAR, light detection and ranging

Actual distance (m)	RADAR	RADAR error margin %	LiDAR	LiDAR error margin %	Ultrasonic	Ultrasonic error margin %
0.6	1	-66.67	DND		0.586	2.33
1.2	1.2	0.00	1.56	-30.00	1.181	1.58
1.8	1.8	0.00	1.97	-9.44	1.754	2.56
2.4	2.4	0.00	2.76	-15.00	2.349	2.12
3	2.8	6.67	3.13	-4.33	2.929	2.37
3.6	3.6	0.00	3.81	-5.83	3.517	2.31
4.2	4	4.76	4.37	-4.05	4.102	2.33
4.8	4.6	4.17	5.04	-5.00	4.69	2.29
10	9.6	4.00	9.54	4.60	9.756	2.44
15	14.8	1.33	14.69	2.07	14.635	2.43
20	19.8	1.00	20.12	-0.60	11.76	41.20
30	29.2	2.67	DND			
40	40.2	-0.50	DND			
50	49.8	0.40	DND			

TABLE 5: Results from measurements taken from all sensors for transparent object

DND, Did not detect; RADAR, radio detection and ranging; LiDAR, light detection and ranging

FIGURE 2: Accuracy chart for object distance of 0.6 m

FIGURE 3: Accuracy chart for object distance of 4.8 m

FIGURE 4: Accuracy chart for target object distance of 15 m

FIGURE 5: Accuracy chart for target object distance of 20 m

FIGURE 6: Accuracy chart for target object distance of 50 m

Discussion

Sensor fusion architecture

The linear nature of the experiments makes a compelling argument for weighted fusion to be the most appropriate for this sensor-fusion. However, given the specific display of strength and weaknesses at different ranges; a hybrid combination of complementary and weighted fusion is deduced. This allows all sensors to be fully weighted in their range of priority and become inactive at the ranges where they have poor accuracy. The sensor fusion architecture obtained for the data acquired is shown in Figure 7.

RADAR sensor is inactive for any data output below 1 m, but it will serve as the priority sensor for all distances above 1 m. The LiDAR sensor, due to its inaccuracy with transparent objects, will be considered as the second option for distance of 0-1 m, third option for distances between 1 m and 15 m, and second option at distances above 15 m. The ultrasonic sensor is the priority sensor for distances below 1 m and the second option for distance of 1-15 m; its data will be classified as inactive for distances greater than 15 m. In order to have an efficient sensor fusion architecture for collision avoidance, it is important to note that a split second can be vital in avoiding a collision, and therefore it is desired that all sensors should be able to feed data to the collision avoidance logic center in parallel. With the sensor fusion architecture proposed in Figure 7, we can make a mathematical logic expression in Boolean algebra:

We consider sensor X, Y, and Z as RADAR, LiDAR, and Ultrasonic, respectively, and the range categories as: a, b, c, where a represents range of $d < 1$ m, b represents a range of $1 < d < 15$ m, and c represents $d > 15$ m. According to our desired logic we will have a logic table as shown as below:

	x	y	z	f_{used}	
a	0	1	1	1	
b	1	1	1	1	
c	1	1	0	1	

(4)

This is due to the fact that some sensors are rendered inactive at certain ranges, which gives them a weight of 0 at those ranges, but the ones that are active are not utilized on a weight scale, but rather based on priority and availability of data.

FIGURE 7: Sensor fusion architecture

RADAR, radio detection and ranging; LiDAR, light detection and ranging

Mathematical expressions for ranges a, b, and c for the three sensors are as follows:

If distance recorded by LiDAR and Ultrasonic sensors are below 1 m (Category a), then the logic will be as follows:

$$d_{fused} = d_{Radar} (Weight * 0) + d_{LiDar} (Weight * 1) + d_{Ultrasonic} (Weight * 1) = 1 \quad (5)$$

If distance recorded by RADAR and LiDAR are in the range of $1 < d < 15$ m (category b) then all data from any sensor will be utilized with the expression below:

$$d_{fused} = d_{Radar} (Weight * 1) + d_{LiDar} (Weight * 1) + d_{Ultrasonic} (Weight * 1) = 1 \quad (6)$$

If the data recorded by the RADAR and LiDAR sensors are above 15 m (Category c) then the data from the ultrasonic sensors are invalid to the logic center with expression below:

$$d_{fused} = d_{Radar} (Weight * 1) + d_{LiDar} (Weight * 1) + d_{Ultrasonic} (Weight * 0) = 1 \quad (7)$$

While weights can be assigned to each sensor based on variance in accuracy, however, due to the nature of CAS systems and complimentary fusion desired, it is important that all sensors have equal weight for data published to the control unit.

Conclusions

It can be concluded that introducing a mid-long range Ultrasonic sensor can greatly improve the efficiency of a collision avoidance system within the established working range of the sensors. With a collective accuracy above 97% within their range of strength, the sensor suite of Ultrasonic, LiDAR, and RADAR sensors can efficiently detect all objects in their path when fused together.

With the results from the sensor fusion, it shows that non vision based sensors can operate at high-level accuracies and can serve as a perfect backup system to vision based sensors or be deployed independently. They are also less susceptible to being deceived by illusions and will also perform excellently under poor visibility and weather conditions. If incorporated in vehicles, this can nearly eliminate road accidents caused by drivers' inability to respond on time. The simplistic nature of the fusion algorithm also reduces the chances of computer software/hardware failure, therefore providing a very durable platform for collision avoidance.

In terms of sensor fusion, more research should be conducted under environments that can simulate different weather conditions, which have the potential to limit the efficiencies of the sensors, thereby providing a better platform for more fusion methods.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Oluwasanmi A. Adewuyi, Olumuyiwa A. Lasode, Jayeola F. Opadiji

Acquisition, analysis, or interpretation of data: Oluwasanmi A. Adewuyi, Olumuyiwa A. Lasode

Drafting of the manuscript: Oluwasanmi A. Adewuyi, Olumuyiwa A. Lasode, Jayeola F. Opadiji

Critical review of the manuscript for important intellectual content: Oluwasanmi A. Adewuyi, Olumuyiwa A. Lasode, Jayeola F. Opadiji

Supervision: Oluwasanmi A. Adewuyi, Olumuyiwa A. Lasode, Jayeola F. Opadiji

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from

any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

The work was partially supported by the University of Ilorin through tuition scholarship.

References

1. Jiménez F, Naranjo JE, García F: An improved method to calculate the time-to-collision of two vehicles. *International Journal of Intelligent Transportation Systems Research*. 2013, 11:34-42. [10.1007/s13177-012-0054-4](https://doi.org/10.1007/s13177-012-0054-4)
2. Daily M, Medasani S, Behringer R, Trivedi M: Self-driving cars. *Computer*. 2017, 50:18-23. [10.1109/mc.2017.4451204](https://doi.org/10.1109/mc.2017.4451204)
3. Paden B, Čáp M, Yong SZ, Yershov D, Frazzoli E: A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on Intelligent Vehicles*. 2016, 1:33-55. [10.1109/tiv.2016.2578706](https://doi.org/10.1109/tiv.2016.2578706)
4. Xin J, Wang C, Zhang Z, Zheng N: China future challenge: beyond the intelligent vehicle. *IEEE Intelligent Transportation Systems Society*. 2014, 16:8-10.
5. Cerri P, Soprani G, Zani P, et al.: Computer vision at the Hyundai autonomous challenge. *International IEEE Conference on Intelligent Transportation Systems (ITSC)*. 2011, 777-83. [10.1109/ITSC.2011.6082859](https://doi.org/10.1109/ITSC.2011.6082859)
6. Broggi A, Cerri P, Felisa M, et al.: The VisLab Intercontinental Autonomous Challenge: an extensive test for a platoon of intelligent vehicles. *International Journal of Vehicle Autonomous Systems*. 2012, 10:147-64. [10.1504/ijvas.2012.051250](https://doi.org/10.1504/ijvas.2012.051250)
7. Broggi A, Cerri P, Debattisti S, et al.: PROUD—public road urban driverless-car test. *IEEE Transactions on Intelligent Transportation Systems*. 2015, 16:3508-519. [10.1109/tits.2015.2477556](https://doi.org/10.1109/tits.2015.2477556)
8. Ziegler J, Bender P, Schreiber M, et al.: Making Bertha Drive—an autonomous journey on a historic route. *IEEE Intelligent Transportation Systems Magazine*. 2014, 6:8-20. [10.1109/imits.2014.2306552](https://doi.org/10.1109/imits.2014.2306552)
9. Cannella T, Snyder R: The hidden dangers of self-driving technology: Are consumers at risk?. *Cannella Snyder LLC*, 2025.
10. Kusano KD, Beatty K, Schnelle S, Favaro F, Cray C, Victor T: Collision avoidance testing of the Waymo automated driving system. *arXiv*. 2022, [10.48550/arXiv.2212.08148](https://doi.org/10.48550/arXiv.2212.08148)
11. Tong J, Xing X, Guo R, Jiang W, Xiong L, Chen J: Performance limitations analysis of visual sensors in low light conditions based on field test. *SAE Technical Paper 2022-01-7086*. SAE International. 2022, [10.4271/2022-01-7086](https://doi.org/10.4271/2022-01-7086)
12. Yun J, Song MH: Detecting direction of movement using pyroelectric infrared sensors. *IEEE Sensors Journal*. 2014, 14:1482-489. [10.1109/jsen.2013.2296601](https://doi.org/10.1109/jsen.2013.2296601)
13. Hecht J: Lidar for self-driving cars. *Optics & Photonics News*. 2018, 29:26-33.
14. Koval L, Vaňuš J, Bilik P: Distance measuring by ultrasonic sensor. *IFAC-PapersOnLine*. 2016, 49:153-58. [10.1016/j.ifacol.2016.12.026](https://doi.org/10.1016/j.ifacol.2016.12.026)
15. Steinbaeck J, Steger C, Holweg G, Druml N: Next generation radar sensors in automotive sensor fusion systems. *Sensor Data Fusion: Trends, Solutions, Applications (SDF)*. 2017, 1-6. [10.1109/SDF.2017.8126389](https://doi.org/10.1109/SDF.2017.8126389)
16. Gibilisco S, Monk S: *Teach Yourself Electricity and Electronics*. McGraw-Hill Education, 2022.
17. Schneider M: Automotive radar - Status and trends. *Proceedings of the German Microwave Conference (GeMiC)*. Ulm, Germany; 2005. 144-47.
18. Kawakubo A, Tokoro S, Yamada Y, Kuroda K, Kawasaki T: Electronically-scanning millimeter-wave RADAR for forward objects detection. *SAE Technical Paper Series*. 2004, [10.4271/2004-01-1122](https://doi.org/10.4271/2004-01-1122)
19. Li N, Ho CP, Xue J, Lim LW, Chen G, Fu YH, Lee LY: A progress review on solid-state LiDAR and nanophotonics-based LiDAR sensors. *Laser & Photonics Reviews*. 2022, 16:2100511. [10.1002/lpor.202100511](https://doi.org/10.1002/lpor.202100511)
20. Pham H, Smolka SA, Stoller SD, Phan D, Yang J: A survey on unmanned aerial vehicle collision avoidance systems. *arXiv*. 2015, [10.48550/arXiv.1508.07723](https://doi.org/10.48550/arXiv.1508.07723)
21. Dasarthy BV: Sensor fusion potential exploitation-innovative architectures and illustrative applications. *Proceedings of the IEEE*. 1997, 85:24-38. [10.1109/5.554206](https://doi.org/10.1109/5.554206)
22. Mahony R, Hamel T, Morin P, Malis E: Nonlinear complementary filters on the special linear group. *International Journal of Control*. 2012, 85:1557-573. [10.1080/00207179.2012.693951](https://doi.org/10.1080/00207179.2012.693951)
23. Luo RC, Kay MG: Multisensor integration and fusion in intelligent systems. *IEEE Transactions on Systems, Man, and Cybernetics*. 1989, 19:901-31. [10.1109/21.44007](https://doi.org/10.1109/21.44007)
24. Liu H, Fang S, Jianhua JI: An improved weighted fusion algorithm of multi-sensor. *Journal of Physics: Conference Series*. 2020, 1453:012009. [10.1088/1742-6596/1453/1/012009](https://doi.org/10.1088/1742-6596/1453/1/012009)
25. Hartung J, Knapp G, Sinha BK: *Statistical Meta-Analysis with Applications*. John Wiley & Sons, Hoboken, NJ, USA; 2008.
26. Adewuyi OA, Lasode OA, Opadiji JF: Object detection accuracy of level metre ultrasonic sensor, range Finder LiDAR and FMCW RADAR systems: A preliminary assessment. *University of Namibia International Engineering Conference on Sustainable Emerging Innovations and Technological Advancements (UNAM-IEC24)*, 2024.
27. Chin LC, Basah SN, Yaacob S, Din MY, Juan YE: Accuracy and reliability of optimum distance for high performance Kinect Sensor. *2nd International Conference on Biomedical Engineering (ICoBE)*. 2015, 1-7.