Multi-Sensor Fusion in Autonomous Driving

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Abstract. Multimodal sensor fusion plays a significant role in vehicle driving, improving environmental perception accuracy and reliability. Subsequently, applications and challenges in environmental perception, positioning and navigation, attitude perception are discussed. And cutting-edge technologies such as the fusion of millimetre-wave radar and cameras are analyzed, especially the emerging integration of LiDAR with infrared sensors to enhance low-light environment perception capabilities. Innovations in environmental perception and modeling are also explored. Point cloud generation of multimodal data fusion is likewise studied. New fusion architectures and related hardware upgrades are researched as well. Two-dimensional image conversion methods with multi-adaptive high-precision depth completion are also analysed. The challenges in this field, such as sensor performance differences, data fusion problems, system safety and reliability, and the lack of standard specifications, are analyzed. Finally, it is pointed out that in the future, sensor performance needs to be optimized and data fusion algorithms improved to promote technological development and contribute to the construction of intelligent transportation systems.

Keywords: Autonomous Driving; Multi-Sensor Fusion; Environmental Perception; Sensor Performance; Data Fusion

1 Introduction

With the development of intelligent transportation systems, autonomous driving has become a research hotspot in recent years. Self-driving vehicles rely on a variety of sensors to obtain environmental information and make safe and efficient driving decisions. However, individual sensors each have their limitations. For example, cameras are significantly affected by lighting and weather conditions; LiDAR is expensive and performs poorly in adverse weather; and millimetre-wave radar has relatively low resolution. Multi-sensor fusion technology can overcome these shortcomings by integrating data from different sensors, thereby providing more comprehensive and accurate environmental information and enhancing the reliability and robustness of autonomous driving systems.

A. J. Moshayedi (ed.), *Proceedings of the 2025 2nd International Conference on Electrical Engineering and Intelligent Control (EEIC 2025)*, Advances in Engineering Research 279,
https://doi.org/10.2991/978-94-6463-864-6_79

Wang et al. pointed out that the development of autonomous driving places high demands on environmental perception, with 3D object detection being a critical component. In this context, multi-sensor fusion-based 3D object detection networks have become a major research focus [1]. Sensor fusion technology enables autonomous vehicles to perceive their surroundings more accurately, enhance cognitive capabilities, and make more reliable decisions. Nawaz et al. found in their study that environmental perception is a core technology in autonomous driving, and multi-sensor information fusion significantly improves the accuracy and reliability of perception systems [2]. Therefore, studying the applications and challenges of multi-sensor fusion technology in autonomous driving is of great practical significance.

2 Sensor types

For autonomous navigation and environmental awareness, self-driving automobiles use a range of sensors. These sensors can be roughly divided into visual sensors, radar sensors, and positioning and attitude sensors. A single sensor may not be able to meet all the requirements of level 5 autonomous driving, so data from multiple sensors need to be fused. Khan et al. The study noted that this fusion might compensate for the limitations of a single sensor and offer more thorough and trustworthy environmental perception capabilities [3].

2.1 Visual Sensors

Visual sensors mainly consist of cameras, which can capture rich visual information such as road signs, traffic signals, vehicles and pedestrians, etc. High-resolution cameras, which provide clear images and help vehicles precisely identify the details of various objects, have been widely used in autonomous driving. However, the performance of cameras is significantly influenced by lighting and weather conditions. In strong light, weak light or bad weather, the image quality drops significantly, thereby affecting the accuracy of object recognition. Multi-camera systems can provide a 360-degree panoramic view by installing multiple cameras around the vehicle, offering more comprehensive visual information for the vehicle. In addition, new types of visual sensors are also emerging in autonomous driving. For example, event cameras, which obtain image information by sensing changes in light intensity, have the characteristics of high dynamic range and low latency, and can capture the movement information of objects in rapidly changing scenes, making up for the shortcomings of traditional cameras in dynamic scene perception. Another example is the new theoretical model proposed by Ghasemieh & Kashef, in which deep learning significantly improves the performance of the VO, especially in the estimation of camera motion in complex environments. Current deep learning models can handle a variety of tasks, such as pose estimation, self-localization, etc., and have seen significant improvements inaccuracy and robustness [4].

2.2 Radar Sensors

Radar sensors also play an important role in autonomous driving systems. Millimeter-wave radar uses electromagnetic waves in the millimeter-wave band to detect the distance, speed and Angle of the target object. It offers the benefit of functioning around the clock, with no limitation from ambient light or weather factors, and can work stably in rainy and foggy weather, providing reliable environmental perception information for the vehicle. This showcases the advantages of sensor fusion. According to Biswas et al., sensor fusion can classify traffic signal movements very accurately (about 98%), and it outperforms the classification results when using radar or lidar alone (about 7% and 4% higher, respectively) [5]. Millimeter-wave radar exhibits superior measurement precision and enables real-time monitoring of objects moving around the vehicle, serving as a critical foundation for decision-making in autonomous driving systems. In parallel, lidar measures the distance and form of target objects through the emission of laser beams and reception of reflected signals, generating high-accuracy three-dimensional point cloud data to provide vehicles with comprehensive spatial information about the ambient environment. Luo et al. highlighted in their study that 3D point cloud-dependent location recognition (3D-PCPR) has become increasingly prevalent, a trend largely fueled by the broad integration of LiDAR scanners into autonomous driving research [6]. Zhao et al. Also demonstrated in his study that its high-precision ranging and 3D modeling capabilities give it an irreplaceable advantage in obstacle detection, road boundary recognition, and scene reconstruction [7]. Nonetheless, the comparatively high cost of LiDAR imposes certain restrictions on its large-scale deployment in autonomous vehicles to a degree. In addition, ultrasonic radar is mainly used for object detection and distance measurement at close range of vehicles and is often applied in functions such as automatic parking systems and blind spot monitoring. It works by emitting ultrasonic waves and receiving reflected waves to determine the position and distance of objects. Ultrasonic radar offers benefits including low cost, a simple structure, and straightforward installation, enabling it to efficiently detect close-range obstacles around the vehicle and enhance safety during low-speed driving and parking procedures. The fusion of radar and lidar can enhance perception in different weather and lighting conditions, as well as the ability to detect and classify static and dynamic objects in the environment. Zhuang et al.'s research expenditure, Kalman filters and their variants, graph optimization methods, and deep learning techniques can all be applied to the fusion process of radar and lidar data for more accurate and robust navigation and positioning systems [8].

2.3 Positioning and Attitude sensors

Positioning and attitude sensors are crucial for global positioning and attitude estimation in autonomous vehicles. Gu et al. explain that the Global Navigation Satellite System (GNSS) is capable of furnishing vehicles with global positional information, such as longitude, latitude, and altitude. This is mainly achieved through the design and implementation of data collection, calibration, synchronization and fusion algorithms for three sensors: Camera, LiDAR and Radar [9]. Its positioning accuracy can reach several meters or even higher in open environments, providing a foundation for macroscopic position perception of vehicles. Nonetheless, in environments with complex geometries—such as urban canyons, tunnels, and underground parking structures—GNSS signals are prone to obstruction and interference, leading to diminished positional accuracy or even complete loss of positioning. The application of multi-constellation GNSS systems is also becoming more widespread, which can improve satellite visibility and positioning accuracy by receiving signals from multiple satellite constellations simultaneously. Inertial measurement units (IMUs) measure the vehicle's acceleration and angular velocity through built-in accelerometers and gyroscopes, thereby estimating the vehicle's position and attitude changes. The advantage of the IMU is that it does not rely on external signals and can provide high precision information about the vehicle's attitude in a short period of time, which is important for dynamic perception of the vehicle. However, for the problem of error accumulation in IMUs, Fawole & Rawat stated that fusion with other positioning sensors is needed to achieve more accurate positioning and attitude estimation. By combining the advantages of different sensors, the accuracy and robustness of detection can be improved [10]. Fusing GNSS, IMU and LiDAR data, for example, enables fast and stable state estimation from coarse to fine. According to the research by Silva et al. And Das et al., autonomous vehicles rely on the collaborative work of multiple sensors that generate large amounts of data that are used to train and evaluate autonomous systems. To achieve safe and effective autonomous driving, increase the precision and dependability of environmental perception [11,12]. Figure 1 shows the locations of various sensors on the vehicle, including radar, LiDAR, cameras, GNSS and IMU. (See Figure 1)

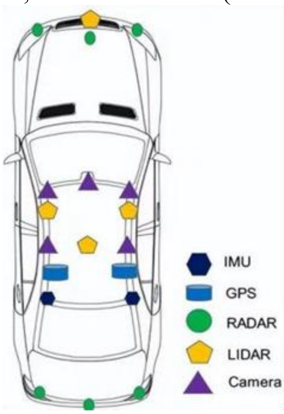

Fig. 1. Positions of various sensors on the vehicle [5]

3 Application of Multi-Sensor Fusion Technology in Autonomous Driving

3.1 Environmental Perception

Multi-sensor fusion technology is crucial for the environmental sensing of autonomous driving. Shi et al. pointed out that cameras can provide rich visual information such as color, texture and shape for target detection and recognition, but their performance is limited in light variations and bad weather [13]. LiDAR can precisely measure distances, provide high-precision 3D point cloud data, and enable three-dimensional reconstruction of the environment, but it is also more sensitive to environmental conditions. Millimeter-wave radar remains unaffected by illumination and can work in bad weather, precisely gauging the speed and distance of objects, but with lower resolution. Through the integration of data from these sensors, complementary benefits can be realized to enhance perception of the surrounding environment. For example, in complex urban traffic scenarios, cameras can identify traffic signs and pedestrians, LiDAR can precisely determine the position and shape of objects, and millimeter-wave radar can monitor the speed of objects in real time. The combination of the three can provide autonomous vehicles with comprehensive and accurate environmental information, enabling them to make better decisions.

3.2 Positioning and Navigation

Accurate positioning and navigation are the foundation of autonomous driving. Global Navigation Satellite Systems (GNSS) and inertial measurement units (IMUs) are commonly used positioning sensors. GNSS can provide high precision positioning information in open areas, but signals can be blocked and interrupted in environments such as urban canyons and tunnels. IMU can measure the attitude and acceleration of vehicles in real time, but there is a problem of error accumulation. Yang et al. proposed a method of fusing GNSS and IMU in conjunction with sensors such as LiDAR and cameras, which can enhance the precision and dependability of positioning. Through the fusion of multiple sensors, the vehicle can accurately determine its position in different environments and achieve reliable navigation, providing strong support for autonomous driving [14].

3.3 Target Detection as well as Tracking

Target identification and pursuit is an important function of autonomous driving systems. Target detection and tracking algorithms based on multi-sensor fusion take advantage of the strengths of different sensors to improve the accuracy and robustness of detection and tracking. For example, Wang et al. and Nawaz et al. can more accurately determine the position and shape of target objects by combining visual information from cameras with distance information from LiDAR, reducing misjudgement. Meanwhile, sensor fusion technology can be used to continuously track the target, predict its movement trajectory, provide a basis for decision-making of autonomous vehicles and ensure driving safety [2,15].

4 Frontier developments of Sensors in Autonomous Driving

4.1 Three-Dimensional Object Detection with the Fusion of Millimeter-Wave Radar and Cameras.

A novel approach for feature-level fusion in bird's-eye view (BEV) is put forth for three-dimensional object detection using the fusion of millimeter-wave (MMW) radar and camera sensors to achieve better feature representation, given the high cost of lidar. This is done in order to better apply multimodal sensor fusion technology in intelligent driving. To extract radar features, the radar points are first delivered to a spatiotemporal encoder after being improved by time accumulation. In the meantime, image backbone and neck models are used to extract two-dimensional properties of multi-scale images that are suited to different spatial scales. The designed view converter is then used to convert the image features to BEV. Additionally, this work fuses multimodal characteristics using two-stage fusion models: ROI fusion and point fusion. Lastly, the three-dimensional position and object category are regressed by the detecting head. (As illustrated in Figure 2) The trials' findings demonstrate that the suggested approach achieves state-of-the-art (SOTA) performance in the two most important detection metrics, mean average precision (MAP) and NuScenes detection score (NDS), on the difficult Nuscenes dataset.

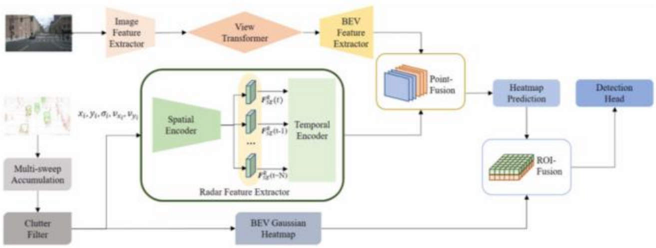

Fig. 2. Illustration of the new fusion method [16]

4.2 Innovations in environmental perception and modeling

Multimodal data fusion point cloud generation, generating high-precision 3D point cloud maps of the environment by integrating 3D point cloud data from liDAR with 2D image information from cameras. This method not only accurately measures the distance of objects around the vehicle, but also combines the texture and color information provided by the camera to greatly enrich the perception ability of the lidar, making the vehicle's perception of the surrounding environment more three-dimensional and comprehensive. At the same time, based on the principle of stereoscopic vision, parallax calculation is used to generate parallax maps and further create depth maps. This method provides the vehicle with precise depth information, which helps the vehicle better understand the spatial relationships of surrounding objects, thereby assisting in tasks such as object detection, navigation, and path planning. (As shown in Figure 3) The performance of two disparity map algorithms

(StereoBM and StereoSGBM) is also compared in this paper providing a reference for practical applications [17,18].

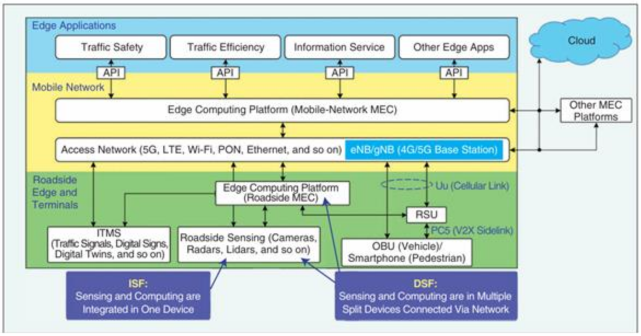

Fig. 3. Three-dimensional point cloud of the environment [17]

4.3 Modular, Real-Time Available Multi-Sensor Fusion Framework

It combines data from dispersed automobile sensors (lidars, radars, and cameras) at the object list level. Each sensor provides object lists (untracked items) to the modular multi-sensor fusion architecture. A coordinate transformation module, an object association module (Hungarian algorithm), an object tracking module (untraced Kalman filter), and a motion compensation module are among the traditional data fusion techniques that are combined in the fusion framework. The fusion framework is flexible and independent of the quantity or kind of sensors because of its modular nature. Furthermore, even if one sensor fails, the approach can still function because of its adaptable nature. This is a crucial feature for situations where safety is a top priority. The architecture is meant to be environmentally conscious in demanding real-time applications. Experimental data from the public domain and simulation were used to test the established fusion framework. It takes significantly less than 10 milliseconds to compute sensor fusion using the proposed framework, an AMD Ryzen 75800H mobile CPU, and the Python programming language. The object-level multi-sensor technique can also identify possible sensor failures and modifications in the external calibration of sensors. A strategy for detecting sensor failures using a multi-sensor architecture was created. In order to guarantee the functional safety of sensors in autonomous driving, this aspect will become crucial [19].

4.4 Communication technology

In terms of V2X communication technology, DSRC (Dedicated Short-Range Communication) is based on the IEEE 802.11p protocol, operates in the 5.9GHz band, uses OFDfM modulation, has a certain data transmission rate and reliability, and is suitable for short-range communication. The DSRC technology is relatively mature, but it has some limitations in large-scale applications, such as limited communication range and limited network capacity. C-V2X (Cellular Vehicle-to-everything) is based on the evolution of 4G LTE and 5G technologies, with higher data transmission rates, lower latency and higher reliability. C-V2X includes PC-5 (sidelink) and Uu interface communications, enabling direct communication between vehicles as well as communication between vehicles and the network. 3GPP Release 14 and Release 15 standardized the basic security services of C-V2X, and Release 16 and later versions further enhanced the performance of C-V2X, such as supporting higher data rates, lower latency, and higher reliability.5G NR V2X: 5G NR (New Radio) V2X is a further evolution of C-V2X with higher performance. 5G NR V2X supports a variety of transmission technologies such as Enhanced Mobile broadband (eMBB), ultra-reliable low latency communication (URLLC), and massive machine Type communication (mMTC), which can meet the requirements of autonomous driving for high data rates, low latency, and high reliability. 5G NR V2X also introduces flexible technologies such as numerology and mini-slot scheduling to enhance spectral efficiency and communication performance [20]. The RAT (Wireless Access Technology) approach employs a multi-RAT communication protocol architecture to address different connectivity issues such as latency, reliability, bandwidth, etc., as well as different traffic conditions. More reliable communication is achieved by combining multiple wireless access technologies (such as IEEE 802.11p, LTE-V2X, 5G-V2X, etc.) and choosing the most suitable communication profile based on the parameters of the current situation [20].

4.5 Computing architecture

Mobile edge computing (MEC) as a paradigm shift technology to push computing power to the edge of the network reduces data transmission latency by processing data close to the data source and the user, improving system real-time performance and response speed. MEC, typically deployed in locations such as base stations or roadside units (Rsus), can support real-time data analysis and decision-making, reduce the computing burden on vehicles, and improve system reliability and availability. For example, in autonomous driving, the MEC can process data from vehicle sensors and communication networks to provide real-time environmental perception and decision support [21].

4.6 Deep learning fusion methods

The issue with data fusion in most of the earlier research is that the network topology does not incorporate the sensor fusion process. With positive outcomes, the most recent image recognition networks have been extensively used in region segmentation and object recognition. However, integrating diverse data into the end-to-end network structure is challenging. Using a partially concurrent network structure, numerous sensor data as input, and concurrent processing results as input in the intermediate layer of the network are two ways that deep learning can be utilized to accomplish multi-sensor fusion. Recognize the features of different sensors' data and be able to combine them in the intermediate feature layer. The data volume, sampling rate, and channel number of various sensor data must all be considered when determining the network's depth. Utilizing the concept of supervised learning to accomplish data fusion is an additional strategy. To improve the data of the supervised sensor, one sensor's data oversees that of another sensor. GAN is utilized, for instance, to monitor lidar point cloud data or radar data to produce more accurate data [22].

4.7 Cameras combined with multiple rangefinders

Combining cameras and light detection and ranging (LiDAR) to create vehicle detection systems is an example of a representative technique. This framework has characteristics like resilience, high real-time performance, and multi-adaptability. In order to synchronize the two sensors at the data level, a multi-adaptive high-precision depth completion two-dimensional image conversion approach is first developed. This method transforms a lidar sparse depth map into a dense depth map. For identifying color images and dense depth maps, there is also the You Only Look Once Version 3 (YOLOv3) real-time object detection model. Lastly, a method for decision-level fusion was suggested. The final vehicle position and distance information is obtained by combining the two results from the previous step, which is based on boundary box fusion and the improved Dempster-Shafer (D-S) evidence theory. This improves the algorithm's robustness and detection accuracy [23, 24].

5 Challenges Facing Multi-sensor Fusion Technology

5.1 Sensor Performance Differences

There are performance differences among different types of sensors, which brings difficulties to multi-sensor fusion. Cameras are greatly affected by light and weather. Kovacs et al. Found in their study that image quality deteriorates at night or in bad weather conditions, resulting in lower accuracy in object detection and recognition [25]. While LiDAR provides high precision distance information, it is costly, and adverse weather conditions like rain, snow, and fog scatter and absorb the laser signal affecting its detection performance. Millimeter-wave radar features low resolution and is difficult to distinguish small objects at close range. In addition, there are differences in sensor measurement accuracy, data update frequency, etc. Effectively integrating the data of these sensors with different performance is an important challenge for multi-sensor fusion technology

5.2 Data Fusion Issues

Data fusion is a core part of multi-sensor fusion technology, but there are many problems in its practical application. To address this issue, Wang et al. proposed that data collected by different sensors vary in format, dimension and time, and that synchronization and registration are necessary for ensuring data consistency and accuracy [1]. Selecting appropriate data fusion algorithms is equally vital. Different fusion algorithms perform differently in different scenarios. How to choose the appropriate algorithm or combine multiple algorithms to improve the fusion effect is an issue that requires resolution. In addition, information redundancy or loss may occur during the data fusion process, affecting the reliability of the fusion results.

5.3 System Reliability and Safety

Autonomous driving systems have extremely high requirements for reliability and safety, and failures in multi-sensor fusion systems can lead to serious consequences. The sensors themselves may malfunction, such as sensor hardware damage, data transmission errors, etc., which may lead to incorrect fusion results and affect the decision-making of the autonomous vehicle. Paluszczyszyn et al. found that cyber-attacks could also pose a threat to sensor fusion systems, where hackers could tamper with sensor data, causing vehicles to make wrong decisions and endangering driving safety and other issues [26]. Therefore, methods to enhance the reliability and security of multi-sensor fusion systems represent one of the important challenges facing autonomous driving.

5.4 Lack of Standards and Norms

At present, there is a lack of unified standards and norms for fusion technology in autonomous driving. Paluszczyszyn et al. pointed out the problem that the interfaces, data formats and communication protocols of different sensors are not uniform, resulting in poor compatibility among sensors and increasing the difficulty of system integration [26]. The lack of unified test standards and evaluation metrics renders it challenging to accurately assess and evaluate the performance of multi-sensor fusion systems. This limits the development and application of sensor fusion technology with multiple sensors, and it is necessary to formulate unified standards and norms as soon as possible to promote the standardization and industrialization of the technology.

6 Conclusions

This paper discusses the application prospects of sensor technology in the field of intelligent driving of automobiles, the challenges it faces, and the current cutting-edge technological research results. In terms of application, the fusion of multiple sensors can achieve complementary advantages, and the combination of vision sensors, radar sensors, positioning and attitude sensors can provide more comprehensive and reliable environmental perception capabilities, which will have a significant effect on reducing costs, improving accuracy and system robustness. At the same time, this paper also points out that sensors have certain problems in terms of performance differences, specific data fusion, system reliability and security, and the lack of standard specifications. This paper reviews the cutting-edge technologies in the field of sensor fusion, including state-of-the-art data fusion algorithms, related hardware upgrades, and assistance from strongly related fields such as communication technology research, as well as applications of deep learning. To advance the development of autonomous driving technology, in-depth research is needed in the following areas: first, develop high-performance, low-cost sensors that adapt to various environments, and improve the reliability and stability of sensors; second, optimize data fusion algorithms to improve fusion accuracy and efficiency, and solve problems such as data synchronization, registration, and information redundancy;

third, strengthen research on system reliability and security to enhance the system's resilience against failures and attacks; fourth, establish unified standards and norms to promote compatibility and interoperability among sensors and facilitate the industrial application of multi-sensor fusion technology. With the continuous advancement and improvement of technology, multi-sensor fusion technology will play an even more important role in the field of autonomous driving and provide strong support for achieving safe and efficient intelligent transportation systems.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

1. Shi, B., Huang, K., Li, X., Li, X., Huang, S., & Li, Y. Multi-modal Sensor Fusion for Auto Driving Perception: A Survey, arXiv preprint arXiv:2202.02703v3, 2024.
2. Wang, Y., Liu, D., & Matson, E. Accurate Perception for Autonomous Driving: Application of Kalman Filter for Sensor Fusion, In 2020 (1-7), IEEE, 2020.
3. Wang, X., Li, K., & Chehri, A. Multi-Sensor Fusion Technology for 3D Object Detection in Autonomous Driving: A Review, IEEE Transactions on Intelligent Transportation Systems, 25(2), 1148-1162(2024).
4. Nawaz, M., Tang, J. K.-T., Bibi, K., Xiao, S., Ho, H.-P., & Yuan, W. Robust Cognitive Capability in Autonomous Driving Using Sensor Fusion Techniques: A Survey, IEEE Transactions on Intelligent Transportation Systems, 25(5), 3228-3243, 2024.
5. Khan, M. A., Sayed, H. E., Malik, S., Zia, T., Khan, J., Alkaabi, N., & Jgnatious, H. Level-5 Autonomous Driving—Are We There Yet? A Review of Research Literature, ACM Computing Surveys, 55(2), 1-38, 2022.
6. Ghasemieh, A., & Kashef, R. Towards Explainable Artificial Intelligence in Deep Vision-Based Odometry, Computers and Electrical Engineering, 115, 109127, 2024.
7. Biswas, S., Ball, J. E., & Gurbuz, A. C. Radar-Lidar Fusion for Classification of Traffic Signaling Motion in Automotive Applications, 2023 IEEE International Radar Conference (RADAR), 1-5, 2023.
8. Luo, K., Yu, H., Chen, X., Yang, Z., Wang, J., Cheng, P., & Mian, A. 3D Pointcloud-Based Place Recognition: A Survey, Artificial Intelligence Review, 57(4), 2024.
9. Zhao, T., Xie, Y., Ding, M., Yang, L., Jomizuka, M., & Wei, Y. A Road Surface Reconstruction Dataset for Autonomous Driving, Scientific Data, 11(1), 2024.
10. Zhuang, Y., Sun, X., Li, Y., Huai, J., Hua, L., Yang, X., Cao, X., Zhang, P., Cao, Y., Qi, L., Yang, J., El-Bendary, N., El-Sheimy, N., Thompson, J., & Chen, R. Multi-Sensor Integrated Navigation/Positioning Systems Using Data Fusion: From Analytics-Based to Learning-Based Approaches, Information Fusion, 95, 62-90, 2023.
11. Gu, J., Lind, A., Chhetri, T. R., Bellone, M., & Sell, R. End-to-End Multimodal Sensor Dataset Collection Framework for Autonomous Vehicles, MDPI AG, 2023.
12. Fawole, O. A., & Rawat, D. B. Recent Advances in 3D Object Detection for Self-Driving Vehicles: A Survey, AI, 5(3), 1255-1285, 2024.
13. Silva, I., Silva, H., Botelho, F., & Pendao, C. Realistic 3D Simulators for Automotive: A Review of Main Applications and Features, Sensors, 24(18), 5880, 2024.

14. Das, D., Adhikary, N., & Chaudhury, S. Sensor Fusion in Autonomous Vehicle Using LiDAR and Camera Sensor, 2022 IEEE 10th Region 10 Humanitarian Technology Conference (R10-HTC), 336-341, 2022.
15. Yang, B., Li, J., & Zeng, T. A Review of Environmental Perception Technology Based on Multi-Sensor Information Fusion in Autonomous Driving, World Electric Vehicle Journal, 16, 20, 2025.
16. Xu, X., Zhang, L., Yang, J., Cao, C., Wang, W., Ran, Y., ... & Luo, M. A Review of Multi-Sensor Fusion for Autonomous Driving, IEEE Transactions on Robotics and Automation, 2022.
17. Zhou, T., Shi, Y., Chen, J., Jiang, K., Yang, M., & Yang, D. Bridging the View Disparity Between Radar and Camera Features for Multi-Modal Fusion 3D Object Detection, IEEE Transactions on Intelligent Vehicles, 8, 1523-1535, 2022.
18. Wang, X., Li, K., & Sbebri, A. Multi-Sensor Fusion Technology for 3D Object Detection in Autonomous Driving: A Review, IEEE Transactions on Intelligent Transportation Systems, 25(2), 1148-1165, 2023.
19. Lei, M., Yang, D., & Weng, X. Integrated Sensor Fusion Based on 4D MIMO Radar and Camera: A Solution for Connected Vehicle Applications, IEEE Vehicular Technology Magazine, 17(4), 38-46, 2022.
20. Das, D., Adhikary, N., & Chaudhury, S. Sensor Fusion in Autonomous Vehicle Using LiDAR and Camera Sensor, 2022 IEEE 10th Region 10 Humanitarian Technology Conference (R10-HTC), 336-341, 2022.
21. Senel, N., Kefferputz, K., Doycheva, K., & Elger, G. Multi-Sensor Data Fusion for Real-Time Multi-Object Tracking, Processes, 11(2), 501, 2023.
22. Guan, L., Chen, Y., Wang, G., & Lei, X. Real-time Vehicle Detection Framework Using Multi-Sensor Fusion, IEEE Transactions on Intelligent Transportation Systems, 2020.
23. Wang, Z., Wu, Y., & Niu, Q. Multi-Sensor Fusion in Automated Driving: A Survey, IEEE Access, 8, 2847-2868, 2020.
24. Xiang, C., Feng, C., Xie, X., Shi, B., Lu, H., Lv, Y., ... & Niu, Z. Multi-sensor Fusion and Cooperative Perception for Autonomous Driving: A Review, IEEE Intelligent Transportation Systems Magazine, 15(5), 36-58, 2023.
25. Paluszczyszyn, D., Stamenkovic, V. R., & Lane, B. Toward Development of Ecosystem for Connected Autonomous Vehicles: Challenges of Modeling and Testing Sensors, IEEE Sensors Letters, 8(3), 5500802-1-5500802-4, 2024.
26. Kovacs, L., Baranyai, D., Giraszi, T., Majoros, T., Kovacs, A., Vagner, M., Palkovics, D., & Berczes, T. Sensor Design and Integration into Small Sized Autonomous Vehicle, In 2022 IEEE 2nd Conference on Information Technology and Data Science (CITDS) (171 - 176), IEEE, 2022.