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Research on Intelligent Driving Sensor Technology

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Abstract. The core of intelligent driving technology relies on the collaborative work of multiple types of sensors to achieve environmental perception, decision-making planning, and vehicle control. As global autonomous driving technology enters the L3 level mass production stage, sensor systems, as the core carriers of environmental perception, have seen a significant acceleration in their technological iteration speed. This report focuses on lidar, millimeter-wave radar, and ultrasonic sensors in intelligent driving systems, analyzing their differences in principles, performance, and applicable scenarios, and evaluating the role of multi-sensor fusion in enhancing environmental perception accuracy and system robustness. The report compares data-level, feature-level, and decision-level fusion strategies, identifying key technical points in fusion pathways. It also summarizes trends in sensor technology development, including miniaturization and integration, AI-adaptive perception, point cloud accuracy improvement, and new sensor technologies (such as terahertz imaging and quantum detection), providing reference for the evolution of perception architectures in high-level autonomous driving systems.

Keywords: Sensor fusion, self-driving cars, radar, smart driving

1. Introduction

The commercialization of intelligent driving technology is at a key turning point. According to SAE standards, L3 autonomous systems must achieve full-time environment perception and autonomous decision-making. However, challenges such as dynamic obstacle recognition in complex traffic scenes and adaptability to inclement weather remain core bottlenecks. As the vehicle's "sensory system," sensor performance directly determines perception accuracy, driving safety, and user experience. Currently, no single sensor can fully meet all-scenario requirements due to physical limitations—for example, LiDAR performance degrades in rain and fog, millimeter-wave radar has limited spatial resolution, and ultrasonic sensors have restricted detection distance. Therefore, overcoming these limitations through multi-sensor synergy and fusion has become a major focus in both academia and industry.

This paper reviews key sensor technologies in autonomous driving systems, analyzing them from three dimensions: principle characteristics, technology boundaries, and fusion strategies. Following the framework of "principle–validation–fusion," it aims to provide theoretical support for addressing long-tailed perception challenges, enhancing system robustness, and promoting the large-scale commercialization of autonomous driving.

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2. LiDAR technology

By transmitting a laser beam and receiving a return signal, LiDAR can measure the distance between an object and a vehicle to construct a high-precision three-dimensional environment model. The high ranging accuracy and spatial resolution of LiDAR can be used to assist autonomous driving in obstacle detection and map construction. LiDAR systems can be divided into laser ranging system and scanning system. The laser ranging system consists of a laser transmitter, a photodetector, optical components, and signal processing electronics. The laser transmitter irradiates the target with a modulated wave. The photodetector generates an electronic signal from the reflected photons that have undergone optical processing and photoelectric converted. The optical assembly collimates the emitted laser and focuses the reflected signal onto the photodetector. The signal processing electronics estimate the distance between the laser source and the reflective surface based on the received signal. Scanning systems are typically used to direct the laser beam at various azimuthal and vertical angles to cover the entire field of view [1,2].

2.1. Laser distance meter

A laser distance meter is a laser device that measures the distance to a target. It working principle depends on the type of signal modulation applied to the laser beam. Laser rangefinders mainly contains direct detection laser rangefinders and coherent detection laser rangefinders.

2.1.1. Direct detection laser distance meter

Direct detection laser distance meter use a pulsed laser for signal modulation and determine the target distance by measuring the Time-of-Flight (ToF) of the pulsed laser.

The laser emitted by LIDAR is attenuated in the propagation medium and diffused after reflection on the target surface. Part of the laser is captured by the receiving optics system and eventually converted into an electrical signal by the photodetector. For a target at distance r, the power Pr received by the photodetector can be approximated as:

$$Pr = \frac{Ep \times c \times Ar \times \eta \times \beta}{r^2} \tag{1}$$

which, Ep is the total energy of the emitted pulsed laser; c is the speed of light; Ar is the area of the receiving optical system's aperture; η is the overall efficiency of the system; β is the reflectivity of the target surface (which depends on the surface properties and the angle of incidence).

Under adverse weather conditions (e.g. fog, rain, dust, snow), airborne particles scatter and absorb photons, resulting in a proportional decrease in the received signal power, Pr, as a function of the square of the distance, r. As a result, the reflected signal strength of a long-range target is much weaker than that of a close-range target. In addition, the increase in laser emission power is limited by eye safety standards (IEC 60825), so the overall system efficiency must be improved by optimizing optical systems, photodetectors, and signal processing algorithms.

2.1.2. Coherent detection laser distance meter

Coherent detection laser rangefinders use Frequency Modulated Continuous Wave (FMCW) technology to indirectly measure the distance and speed of a target using the Doppler effect. ToF

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laser rangefinders measure distance by calculating the time difference between the transmitted and received laser. The formula is as follows:

$$r = \frac{c \times \Delta t}{2n} \tag{2}$$

which, n is the refractive index of the propagation medium (approximately 1 in air); Δt is the time interval from emission to return of the laser.

ToF LIDAR dominates the current automotive LIDAR market due to its simple structure and straightforward signal processing method. It is capable of providing high-precision 3D point cloud data, suitable for tasks such as target detection, obstacle localization, and distance measurement, and insensitive to ambient light [3]. However, its maximum measurement range is limited by the transmit power, so the echo signal may be affected by strong light or interference from other ToF LIDARs.

2.1.3. Case - NIO ET7 super sense system

The NIO ET7, a flagship intelligent driving model, is equipped with the Aquila supersensing system, whose core is the Innovusion Falcon 1550 nm LiDAR—the world's first mass-produced LiDAR at this wavelength. Compared with traditional 905 nm lasers, it achieves a 500 m maximum detection distance and maintains 250 m at 10% reflectivity, significantly outperforming industry averages. With a 120° horizontal FoV and 0.06×0.06° resolution, it can identify low obstacles (e.g., 8 cm curbs) and dynamic targets (e.g., pedestrians), reducing missed and false detections. The "watchtower" roof layout optimizes FoV and aerodynamics, increasing drag coefficient by only 0.002.

Functionally, the LiDAR supports "Fixed Eye Gaze" dynamic focusing (40°×9.6°), capturing fine details—for instance, depicting a 1.8 m pedestrian at 200 m with 54 point clouds, 4–5× higher than traditional radar. It tracks pedestrian speeds up to 60 km/h versus 40 km/h for conventional solutions, and its integrated transceiver design reduces calibration time by 65%. Even in heavy rain, it maintains 120 m effective range, while 905 nm LiDAR falls to 60 m. Based on ToF principles, it emits 1550 nm pulses and calculates distance via emission–reception time difference, with FMCW technology further enhancing Doppler-based speed and distance accuracy [1].

The ET7's application demonstrates LiDAR's core value in autonomous driving: reliable long-range detection, robustness in adverse weather, and high data fidelity. Its efficient point cloud output reduces algorithmic burden and, combined with multi-sensor redundancy, provides the technological foundation for all-weather, high-precision intelligent driving.

2.2. Radar

2.2.1. Theory

Millimeter-wave radar, widely applied in active braking systems, features high resolution, no blind zone, strong anti-jamming, and precise detection of small targets. Based on the Doppler effect, it transmits electromagnetic waves, processes echoes, and measures target speed, distance, and angle [4]. Based on its strength in tracking moving target, millimeter-wave radar can effectively detect targets at medium and long range, and obtain the road information in front of the vehicle in real time. By predicting travel trajectory in advance, the system is able to react quickly before encountering obstacles, substantially improves the safety performance of active braking system [5].

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In addition, millimeter waves can penetrate rain and fog, giving millimeter-wave radar strong all-weather adaptability due to its good adaptability to bad weather (e.g., fog and heavy rain). However, it has limitations in detecting static objects and recognizing the shape of objects, for example, detecting metal objects may cause “ghosting” interference [6].

Millimeter-wave radar utilizes the Doppler effect of electromagnetic waves (frequency 24 GHz or 77 GHz) and echo time to measure target parameters. Specifically, ranging calculates distance from the time difference between transmitted and reflected waves. Velocimetry calculates the relative speed of the target from the Doppler shift (frequency variation). Angle measurement determines the target’s azimuth angle from the phase difference of the multiple antenna array. The formula is as follows [7]:

$$\Delta f = \frac{2v \times f0}{c} \tag{3}$$

Which, v is the target velocity and $f0$ is the firing frequency.

2.2.2. Case-huawei 4D radar tunnel scene optimization

Tunnel environment is one of the challenging scenarios in intelligent driving. Since tunnels walls and tops resemble reflective materials, electromagnetic waves from traditional millimeter-wave radar are prone to scattering. This can cause a large number of false targets to interfere with 4D millimeter-wave radar, and this interference becomes more pronounced as the number of antenna units increase. In response to this pain point, Huawei conducted 4D radar tests on multi-tunnel roads in Chongqing. Through high-precision target detection and tracking algorithms, it ensures seamless tracking of surrounding targets when vehicles enter and exit tunnels, with track interruption time under 0.1 seconds. In addition, the height detection capability of 4D millimeter wave radar can accurate identification of hanging objects in the tunnel with height measurement errors controlled within ±5 cm, thus effectively avoiding safety hazards caused by misjudgment. In terms of anti-interference, the use of multiple-input multiple-output (MIMO) and digital beam forming (DBF) has increase the co-channel interference suppression by 18dB, ensuring the stability of the radar in complex environments. Huawei's 4D radar is a breakthrough iteration of millimeter-wave radar technology. It retains the electromagnetic wave reflection principle of traditional millimeter-wave radar, and upgraded from3D perception to 4D holographic perception through of Doppler frequency-shift analysis and high-density antenna arrays. The essence of the MIMO technology and the DBF algorithms lies in optimizing millimeter-wave radar's signal emission patterns and echo resolution, thereby enhancing its capability to capture details of complex targets. The physical properties of electromagnetic waves enable millimeter-wave radar to operate in all-weather conditions, and it can still output target motion parameters stably in inclement weather such as heavy rain and dense fog, which is significantly better than cameras relying on optical imaging. This case demonstrates that millimeter-wave radar has become an irreplaceable core component in multi-sensor fusion systems, with its anti-interference capability, motion target tracking capability, and environmental adaptability providing reliable underlying perception guarantee for intelligent driving in complex scenarios.

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2.3. Ultrasonic Sensors

2.3.1. Theory

Ultrasonic Sensors measure the presence and relative position of objects at short distances by transmitting ultrasonic waves and receiving echoes, and are widely used in parking assistance and low-speed autonomous driving scenarios. Due to its unique operating principle, the device can maintain stable detection performance in rainy and snowy weather or dusty operating environments, ensuring functional reliability [8,9]. Ultrasonic sensors can suppress water reflection through algorithms, achieving 93% interference suppression in heavy rain, providing strong environmental adaptability. In addition, its effective detection distance is usually 0.1-5 meters, with an accuracy of ±2 cm, characterized by short distance and high accuracy. Ultrasonic sensors show significant technical advantages in obstacle detection. It can adjust its transmitting frequency and amplitude based on real-time feedback information to ensure that the signal transmission is in optimal condition in various environments. In addition, it significantly improves the anti-interference performance of the system and ensures that the electro-acoustic signal maintains high quality transmission in changing environments [10]. However, the ultrasonic sensor has a limited detection distance, cannot be used for long-distance object detection, and are susceptible to environmental noise interference.

2.3.2. Case-BYD Han EV ultrasonic parking assist system

BYD Han EV, a high-end intelligent electric vehicle model, is equipped with a new generation ultrasonic parking assistance system featuring 12 48kHz digital ultrasonic sensors, which provide 360° proximity sensing of the vehicle. The system is specially optimized for complex parking scenarios (e.g. vertical parking spaces, diagonal parking spaces, narrow lane access).

Table 2. Typical scenario performance verification

Application Scenario	Performance	Technological Breakthrough
Vertical Parking	Minimum parking space length = vehicle length + 35cm	Support 0.3m narrow lane passing
Inclined train position recognition	Angle tolerance ±45°	Fusion Surround View Camera Semantic Understanding
Moving Obstacle Warning	Real-time tracking of moving targets above 0.5m/s	Doppler effect algorithm upgrade

As shown in Table 2, test results in typical scenarios indicate that the system supports the minimum parking space length of 35 cm plus the length of the vehicle when parking in a vertical space, with an angle tolerance of ±45° for slanted parking space recognition. and moving obstacle warning that can track dynamic targets moving at speeds exceeding 0.5 m/s in real time. This shows that BYD Han EV ultrasonic parking assistance system significantly improves safety and user experience in low-speed scenarios.

BYD Han EV's parking assistance system uses ultrasonic sensors as its core sensing unit, with its technical implememtation relies deeply on the sensors’s short-range, high-precision characteristics. The 48kHz high-frequency ultrasonic sensor in this system calculates distances to obstacles through the TOF principle, achieving accuracy of ±2cm. They also transmits signals in time-sharing through the Time Division Multiple Access (TDMA) technology to solve the problem of multiple sensors

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interfering at the same frequency. Under heavy rainfall (rainfall 50 mm/h), the sensor suppresses water reflection interference through adaptive filtering algorithm, and the effective detection distance is maintained at 380 cm (with attenuation rate of only 15%). Meanwhile, the system realizes 20ms-level spatial and temporal synchronization with the surround view camera, the ultrasonic wave provides accurate distance data, and the vision system completes the obstacle type recognition (classification accuracy 99.2%). This verifies the role of ultrasonic sensors as the bottom layer support in multimodal fusion.

The system fully demonstrates the unique value of ultrasonic sensors in intelligent driving. Combining the short-range detection capability (0.1-5 meters) based on the physical characteristics of sound waves with high-precision ranging functionality (±2 centimeters), the sensor can accurately identify parking space edges and low obstacles (such as steps and curbs). In addition, the small size and low cost of ultrasonic sensors support the dense deployment of multiple nodes, and together with cameras and millimeter-wave radar to solve the problem of insufficient detection of blind zones in close proximity.

3. Sensor fusion technology

In intelligent driving systems, using only a single sensor for perception often results in omissions and false detections due to its physical characteristics and technical limitations, which leads to a degradation of the target detection performance and fails to satisfy all the demands for environment perception. Therefore, intelligent driving usually adopts multi-sensor fusion technology to improve the system's environment perceive ability, realize the complementary advantages of each sensor, and make the system more robust and accurate [11,12]. Multi-sensor information fusion techniques are usually categorized into data-level fusion, feature-level fusion, and decision-level fusion based on different processing objects and implementation methods [11].

3.1. Data level fusion

Data-level fusion directly integrates raw data collected by multiple sensors at the raw data layer. It generates a unified perceptual input through the comprehensive processing such as spatio-temporal alignment and coordinate system conversion, and realizes in-depth fusion of heterogeneous data through technical such as data calibration [12]. Its operation process is usually divided into three steps, firstly, the data timestamps of different sensors are aligned through hardware clock synchronization (e.g. PTP protocol) or software interpolation algorithm. Secondly, spatial calibration is required to unify the coordinate systems of sensors such as LIDAR and cameras into the vehicle coordinate system (e.g., by calculating the external reference matrix via the calibration board). Finally, data fusion is performed by overlay processing of multiple sources data.

Data-level fusion can maximize the retention of original information features, make full use of the data from each sensor, and improve the accuracy of environment perception [13]. It is mainly applicable to tasks requiring high-precision target detection and recognition, such as target detection and depth estimation in autonomous driving. However, the overall computational effort is large because it has to deal with the variability of different sensors in terms of sampling frequency and measurement accuracy, as well as the synchronization, calibration and correction of data. In addition, data-level fusion is highly sensitive to temporal synchronization error in sensor data and is prone to information mismatch.

In practical applications, common data-level fusion includes LiDAR and camera fusion, and millimeter wave radar and camera fusion. In LiDAR and camera fusion, LiDAR provides 3D

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structure information, while cameras provide texture and color information,. The fusion can improves the accuracy of target detection and classification. In addition, in millimeter-wave radar and camera fusion, millimeter-wave radar provides the velocity information of the object and camera provides the target category. The combination can improve vehicle recognition and tracking capabilities.

3.2. Feature-level fusion

Feature-level fusion, as an intermediate layer paradigm for multi-sensor cooperative sensing, achieves complementary optimization of cross-modal information through feature extraction and integration phases. Its core process is divided into three stages: feature extraction, feature alignment and feature fusion.

In the feature extraction session, specialized algorithms or neural networks are used to extract higher-order features from different sensor data [14]. For example, cameras utilize convolutional neural networks (e.g., ResNet) to capture image texture, edge features, and semantic information. LiDAR extracts geometric structure and spatial distribution features through point cloud processing networks (e.g., PointNet++). And millimeter-wave radar resolves the Doppler shift and distance parameters of targets using Fast Fourier Transform (FFT) and Constant False Alarm Rate (CFAR) algorithms. The feature alignment phase addresses the consistency in temporal and spatial dimensions, e.g., using interpolation algorithms to compensate for temporal differences between sensors, or using calibration parameters to map multimodal features to a uniform bird's-eye view (BEV) coordinate system. Finally, the fusion phase employs channel splicing, attention mechanisms, or graph neural networks (GNNs) to dynamically weight key features. For example, the Transformer module can focus on the motion trajectories of dynamic obstacles, or cross-modal correlation maps can be constructed to connect image regions with point cloud clusters.

The advantage of feature-level fusion lies in its anti-interference ability and information compression efficiency. By filtering out the noise from raw data and using an attention mechanism to strengthen the key features, the system robustness is significantly improved. However, information redundancy remains a limitation. of feature-level fusion, which allows feature selection and dimensionality reduction, thus avoiding storage waste [11]. Cross-modal feature dimensionality differences tend to bias the model toward visual modalities, requiring a weighted loss function to balance training objectives. In addition, the acquisition and annotation costs of synchronized multi-sensor labeled datasets (e.g., nuScenes) are extremely high. The single-frame processing time of a typical fusion network (e.g., PointPainting) reaches 80-120 ms, which is difficult to meet the real-time demand of L4-level autonomous driving. Nevertheless, its accuracy advantage in target recognition and tracking tasks makes it a key technical paths for high-level autonomous driving systems.

3.3. Decision-level fusion

Decision-level fusion synthesizes independently processed results from each sensor at the decision level. It generates a synthesized judgment by integratomg these results through weighted voting, probabilistic statistics, or rule engine, utimately producing the finally perception output [12]. Its core processing flow contains of three key modules: information preprocessing, target matching, and target information fusion.

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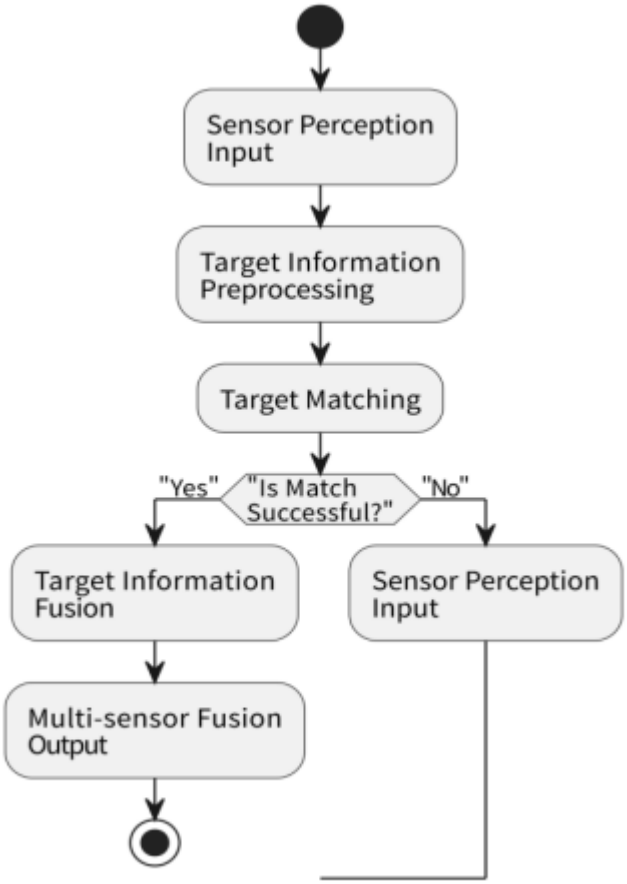

Figure 1. Flowchart of the decision-level fusion algorithm

First, after receiving the sensory data collected by each sensor, the system effectively eliminates the noise and abnormal fluctuations in the raw data after preprocessing, thus ensuring the stability and accuracy of the target information. Then, it sequentially matches each target, establishing accurate correspondence between detection information from different sensors for the same target. After matching, the system judges whether matching is successful based on the matching score. If the matching fails, the target is regarded as a false alarm or non-concerned target and the system proceeds to the next target. If the matching is successful, it enters the target information fusion stage, where the data are weighted and merged according to the characteristics of each sensor to obtain more accurate and reliable sensing results. Ultimately, the fused data output provides a key basis for subsequent decision-making and planning [15].

Unlike data-level and feature-level fusion methods, decision-level fusion methods and analyzes each sensor individually before fusing their detection results. Then, it adjusts the weights of different sensors and finally makes a final decision. The methods of decision level fusion include weighted decision-making, classical inference, and Bayesian inference [16]. The core advantage of decision-level fusion are computational efficiency and system fault tolerance. Since it does not require processing raw data or complex feature alignment, its computational overhead is significantly lower than that of data-level and feature-level fusion, making it suitable for resource-constrained embedded platforms. Meanwhile, the sensor-independent operation ensures that the system can still degrade gracefully when some modules fail. For example, in the evern of camera failure, the system

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relies on millimeter-wave radar to maintain basic target tracking capability. However, the limitation of decision-level fusion is the risk of information loss, i.e., the high-level result fusion may lose the underlying details (e.g., point cloud structure or image texture), resulting in degradation of static obstacle classification accuracy. In addition, if the single sensor false detection rate is high (e.g., ultrasound interfered by ambient noise), erroneous results may propagate to the global output through the fusion weights. In practice, decision-level fusion is often used in combination with the underlying fusion strategy. For example, in a low-speed parking scenario, the ultrasonic sensor provides the distance to the obstacle, the camera recognizes the type of parking space, and the decision results of both are cross-validated to enhance reliability. This layered fusion architecture has become a common choice for intelligent driving system design in balancing the needs of accuracy and efficiency.

3.4. Case-HUAWEI ADS 3.0 intelligent driving system

HUAWEI ADS 3.0, as a representative of high-level intelligent driving technology, has achieved a core breakthrough in its multi-sensor deep fusion perception system. The system adopts a heterogeneous combination of LIDAR, camera, millimeter-wave radar and ultrasonic sensors, and realizes efficient data fusion through a full stack of self-developed algorithms, which significantly improves the environment perception capability and decision-making reliability in complex scenes [17].

In terms of sensor configuration, the system is equipped with 192-channel high-precision LiDAR, which makes the detection distance reach more than 300 meters and meets the requirement for accurately acquiring 3D contour information of obstacles in harsh conditions such as haze and bright light. In order to complement the LiDAR, the system is equipped with a vision camera that supports multi-view semantic parsing and recognizes traffic signs, lane lines, and shaped obstacles (such as special construction signs). Meanwhile, the 4D millimeter-wave radar has a detection range of about 280 meters, with an accuracy of 5 centimeters and latency as low as 65 milliseconds, which enables real-time tracking of dynamic targets (e.g., crossing pedestrians, fast-moving vehicles) [17].

In fusion strategy, Huawei ADS 3.0 integrates heterogeneous data complementarity, redundancy, and fault tolerance. Through spatio-temporal alignment, it fuses LiDAR 3D point clouds, camera 2D images, and millimeter-wave radar trajectory predictions to build a 360°high-precision environment model. In hazy weather, LiDAR compensates for camera degradation, while radar enhances fast-target detection. A multi-sensor cross-validation mechanism further reconstructs environmental information when a single sensor is disturbed, reducing misjudgment risk [17].

The optimization and enhancement of Huawei ADS 3.0 system is fully reflected in the application scenarios of omnidirectional active safety (Collision Avoidance System 2.0) and full-scene autonomous parking. In complex scenarios such as pedestrian crossing and left-turning with oncoming traffic, multi-sensor fusion data enables the system to achieve humanized "braking while steering" decision-making. For example, when the camera detects the sudden appearance of an e-bike on the side, with millimeter-wave radar synchronously tracking the e-bike's trajectory and the assistance of the obstacle-avoidance spatial information provided by LiDAR for the vehicle, the Emergency Steering Assist (ESA) function can be triggered, thus avoiding the vehicle from having a collision. In autonomous parking, through ultrasonic sensors and vision fusion, the system can recognize non-standard parking spaces (e.g., diagonal parking spaces) and tiny obstacles (e.g., step edges), and monitor dynamic interferences (e.g., pedestrians intruding) in real time. The multi-sensor data collaboratively plan the optimal path to ensure the safety and efficiency of the parking process [17].

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Huawei ADS 3.0's sensor fusion solution realizes three major breakthroughs in environmental adaptability, system controllability, and iterative upgrades for intelligent vehicles.These breakthroughs enable the vehicle to operate with reliability under extreme conditions such as rain, fog, nighttime, and backlighting (with the system's false detection rate reduced by over 40%), effectively protecting driver safety. Additionally, the system has been localized from sensor hardware (such as self-developed LIDAR) to fusion algorithms, and fully owns the rights to the relevant technologies, which ensures the system's uniformity and stability. Furthermore, relying on Huawei Cloud's 3.5E FLOPs arithmetic power and 30 million kilometers/per day training data, the system model can realize rapid iteration to adapt to new scenarios [17].

4. Trends in sensor technology

Intelligent driving sensor technology is developing multidimensionally, with an urgent need for standards and specifications. At the compliance level, systems must meet road access norms and technical standards in vehicle operation, safety performance, and data protection [18].

In detection, multimodal sensors are moving toward ultra-high precision. LiDAR point cloud density is growing geometrically, enabling centimeter-level 3D modeling. Miniaturized integration via heterogeneous packaging combines millimeter-wave and optical modules, cutting power use by over 30% and enhancing vehicle compatibility. Next-generation sensors embed algorithms for self-test and adaptive operation through machine learning. With MEMS advances and mass production, sensor costs are expected to drop ~15% annually, bringing L3 kits to the 10,000-yuan range by 2028, accelerating commercialization.

Meanwhile, novel sensing principles such as quantum entanglement detection and terahertz imaging have entered engineering verification. These technologies may overcome classical physical limits, achieve sub-nanosecond obstacle recognition, and provide revolutionary safety solutions. Such multidimensional evolution is reshaping the sensor capability architecture and driving the transformation of vehicles into intelligent mobile terminals [19].

5. Conclusion

This paper focuses on sensor technologies and their multimodal fusion methods in intelligent driving systems, with an emphasis on analyzing the principles, performance characteristics, and synergistic mechanisms of LiDAR, millimeter-wave radar, camera and ultrasonic sensors. The study reveals that LiDAR plays a central role in complex scenarios due to its high-precision 3D modeling capability. Millimeter-wave radar becomes a key sensor for dynamic target tracking with its excellent all-weather adaptability. Camera supports human-like decision-making through semantic parsing of visual information, and ultrasonic sensors safeguard safety in low-speed scenarios with their short-range and high-precision advantages. Multi-sensor fusion significantly improves the system's environment perception robustness through data complementarity and redundancy design. However, this paper has limitations. First, the selection of sensor types is inclined toward traditional sensor technologies, with relatively insufficient discussion of emerging sensing technologies (e.g., quantum sensors, terahertz imaging). In addition, although multi-sensor fusion method are introduced, challenges in real-time processing, especially the real-time problem of high-dimensional data fusion, are not explored in depth. Future research could focus on two aspects. First, exploring the application of novel sensor technologies and their potential in improving system performance. Meanwhile, improving real-time data fusion algorithms to support higher levels of automation (e.g., L4 or L5 level autonomous driving) and addressing the reliability and redundancy of sensors in

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complex environments will be critical to improving the robustness and safety of intelligent driving systems.

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