Review of Automotive Sensors Based on Autonomous Driving

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Abstract. With the development of autonomous driving technology towards L3-L5 level, high-precision environment sensing becomes a core challenge for system safety and reliability. This paper systematically reviews the latest advances in autonomous driving sensor technologies, covering performance optimization and multimodal fusion strategies for optical sensors (lidar, camera, infrared thermal imaging), electromagnetic wave sensors (4D imaging radar), acoustic and inertial sensors. However, existing sensors still have significant limitations in scenarios such as extreme weather (rain, snow, haze), dynamic target recognition and computational power bottlenecks, and cutting-edge technologies such as solid-state LDAR and vehicle-circuit-cloud collaborative sensing offer potential paths to address these challenges. By analyzing the edge computing acceleration, spatio-temporal synchronization verification and reliability testing methods, this paper further emphasizes the necessity of interdisciplinary collaboration (mechanical engineering, material science, artificial intelligence) to balance the sensor reliability, environmental robustness and cost controllability, and provides theoretical support and technical references for the engineering of the autonomous driving sensing system.

Keywords: Autonomous Driving, Sensor Fusion, Environment Sensing, Solid-State Lidar, Edge Computing

1 Introduction

The rapid iteration of autonomous driving technology (SAE L3-L5 level) has put forward higher requirements on the accuracy, real-time and environment adaptability of the sensing system. The limitations of traditional sensors (e.g., camera, millimeter-wave radar) exposed in complex scenarios (e.g., light sensitivity, insufficient resolution) have become a major bottleneck for technology upgrades. For example, cameras have limited dynamic range in backlight or low illumination conditions, leading to a significant increase in the target detection leakage rate. Mechanical LDAR can generate high-precision point clouds, but its cost and mechanical reliability issues hinder large-scale mass production applications. Meanwhile, extreme weather (e.g., dense fog, heavy rain) and dynamic interaction scenarios (e.g., multipath reflections in urban canyons) further exacerbate the performance

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degradation of sensing systems. In autonomous driving systems, environment sensing is the core foundation for safe and efficient decision- making. Its functionality can be decomposed into the following six dimensions, each of which relies on specific sensor technologies and is critical in autonomous driving systems. The first dimension is target detection, which recognizes dynamic and static objects in the surrounding environment, such as pedestrians, buildings, and vehicles. Current target detection techniques have many challenges, such as for smaller targets and for different lighting environments under interference. One of the major challenges for object detection at night is low light, which leads to low image brightness, low contrast and noise [1]. The second dimension is localization, which is defined as accurately obtaining the attitude and position of the vehicle itself in the global coordinate system. The third dimension is path planning, which is the generation of safe and efficient driving trajectories based on environmental information. Sensors such as Imaging radar and cameras are usually used. The fourth dimension is dynamic prediction, which predicts the future motion trajectory of the surrounding targets; i.e., predicting position, velocity, and acceleration. Dynamic prediction is more demanding on the camera, which needs to have a high frame rate to accurately capture the motion details of fast-moving objects. The fifth dimension is redundancy fault tolerance, which ensures that the system can still maintain basic functionality when some sensors fail. The design of redundancy requires the complementarity of different principle sensors (e.g., optical vs. radar). The sixth dimension is real-time, where the latency of sensory data acquisition, processing and transmission needs to meet the system control cycle (typically <100 ms). The purpose of this paper is to systematically review the engineering progress and multimodal fusion strategies of autonomous driving sensor technologies (e.g., solid- state LIDAR, 4D imaging radar, infrared thermal imaging), quantitatively analyze the performance boundaries of sensors in extreme environments (e.g., LIDAR point cloud density decreases by 95%), and explore the technological optimization paths of edge computation acceleration, spatio-temporal synchronization validation, and reliability testing methods [2,3]. Finally, combining the trend of bionic design and vehicle- road-cloud collaboration, standardization framework and interdisciplinary research direction for the scaled-down landing of autonomous driving sensing systems.

2 Automotive Sensors

In this paper, sensors are categorized into optical sensors, electromagnetic wave sensors, acoustic sensors, inertial sensors and satellite positioning sensors based on the technical principles of the sensors. Further details of the relevant sensors will be presented as follow.

2.1 Optical Sensors

Commonly used optical sensors in autonomous driving nowadays are mainly LiDAR, cameras and infrared imagers. The principle of optical sensors are roughly the use of light reflection to obtain information, through a variety of types of light from the launch to the reflection of the sensor to receive the time interval to calculate the distance. But there are exceptions. Such as infrared imager is to directly capture the environment of a specific wavelength of infrared radiation to achieve the purpose of imaging. This article will be around the above three optical sensors to describe.

Lidar Sensors. Lidar sensors work by emitting laser beams and receiving reflected signals, measuring the time interval from the emitted laser to the received laser, thus calculating the distance and generating a higher-precision 3D point cloud. The Figure 1 shows a common appearance of vehicle Lidar [4]. Lidar used in autonomous driving technology is categorized into mechanical radar and solid-state radar. Solid-state radar uses MEMS galvanometer and optical phased array technology, which is smaller in size and lower in cost than mechanical radar. Although solid-state LiDAR technology is not yet fully matured, the concept of solid-state LiDAR for automotive applications is expected to meet the requirements of automobile manufacturers while being cost-effective, robust and compact enough to be integrated into consumer vehicles [5]. For applications, the fifth generation Waymo Driver utilizes LiDAR technology that allows the vehicle to sense its surroundings at different distances and map 3D point clouds. Objects up to 300 meters away can be detected even in poor lighting conditions. The two wavelengths currently used in automotive LiDAR are 905 nm and 1550 nm, giving an optical spatial resolution of 0.1 degrees, which enables high-resolution 3D representations of objects around the vehicle. 905 nm wavelengths were used in early LiDAR systems because they were compatible with silicon detector technology, and pulsed diode laser emitters were readily available at a very low cost. 1550 nm wavelengths were used in early LiDAR systems because they were compatible with silicon detector technology. Light above 1400 nm wavelengths is absorbed before it reaches the retina, it is harmless to the human eye and offers better performance, but is more expensive to manufacture [6].

Camera. The camera captures visible light (RGB) thus recognizing the color and texture of the environment and judging the surroundings. It captures near infrared (NIR) to realize the function of night vision. It can be categorized into monocular camera, binocular camera and fisheye camera. In the practice of autonomous driving, cameras are often used to recognize targets and detect lane lines. More than one camera is often used in automatic driving applications, and generally vehicle cameras can be divided into front-view camera, side-view camera, rear-view camera, surround-view camera and built-in camera to resize 360° dead-angle-free observation around the vehicle [7].

Fig. 1. Lidar [4]

Infrared Thermal Imagers. Infrared thermal imaging cameras work by using microbolometers to capture infrared radiation at long wavelengths of 8–14 μm, generating an image of the temperature distribution. Infrared imaging technology has significant advantages in nighttime driving situations. Infrared thermal imagers can operate 24 hours a day, and due to the strong air transmission of thermal radiation, the imaging of infrared imagers can still be effective in observing the environment around the vehicle at night under low-light conditions [8]. In today's stage of development of autonomous driving sensors, thermal imagers have become an important alternative to some traditional optical sensors that cannot accurately detect certain scenes [9].

2.2 Electromagnetic wave sensors

Electromagnetic wave sensors have a high application rate in modern automatic driving systems. Their working principle is to transmit millimeter waves in the 30–300GHz frequency band to the outside world, and then get the reflected wave after reflecting through the target object, and receive the reflected wave to measure and calculate the distance, speed and azimuth of the obstacle. The wavelength of millimeter wave is 3–4 times that of light wave. So electromagnetic wave is more advantageous than optical sensor in rain, snow and haze weather scenes. In cutting-edge autonomous driving systems, 4D millimeter waves are often used 4D imaging radars emit millimeter waves in the frequency band from 24 GHz to 77 GHz. It can provide remote detection, velocity measurements, and weather robustness.4D radars also provide higher resolution point clouds than 3D radars. 4D radars already provide target ranges, azimuthal counts, and Doppler velocity measurements, making their share of applications in autonomous driving sensing.4D imaging radar is also used in modern autonomous driving technology applications as an aid to LIDAR. When the M2-Fusion model fused LIDAR and 4D imaging radar, the detection performance of the automotive class was significantly improved relative to the unimodal model [10]. This proves that 4D imaging radar can provide an important auxiliary role to LIDAR's imaging [11]. Figure 2 shows a radar-camera fusion system.

Fig. 2. Radar and Camera [12]

2.3 Acoustic sensors

The acoustic sensors commonly used in the field of automatic driving are ultrasonic sensors, which work on the principle of emitting ultrasonic waves outward, reflecting them after encountering an obstacle, receiving the reflected ultrasonic waves, and calculating the distance to the obstacle according to the ToF. Ultrasonic sensors can measure a small range, so they are suitable for the detection of close-range obstacles. Such as in the automatic parking system is widely used. Figure 3 shows a Disturbuted Ascoutic Sensor [13].

Fig. 3. DAS [13]

2.4 Inertial sensors

Inertial sensors accomplish the measurement of 6 degrees of freedom by using accelerometers, gyroscopes and integrated magnetometers. Inertial sensors can compensate for positioning in scenarios where GNSS does not work, such as underground parking lots and tunnels. Inertial sensors can also assist in controlling the vehicle's attitude stabilization through real-time monitoring of swing and pitch angles when emergency obstacle avoidance maneuvers occur in vehicles on the road. Inertial sensors (IMUs) can be used as a sensing tool to provide the inertial navigation system (INIS) with data such as acceleration and deceleration of the vehicle, which can be used in conjunction with algorithms to provide better path planning for autonomous driving. In study, the focus is on solving the Sim2Real problem in simulating autonomous driving with IMU sensors, i.e., to reduce the error that exists in IMU sensors in the simulator comparing to the real environment, which is helpful in simulating autonomous driving systems [14].

2.5 Satellite positioning sensors (GNSS)

GNSS technology relies on the fusion of multiple systems, and nowadays the combined positioning of GPS, BeiDou, Galileo, and GLOPASS allows for more accurate positioning of vehicle locations. In the application of autonomous driving technology, GNSS is often used for global planning of vehicle paths, in combination with mapping software. Combined with inertial navigation systems (INIS) in the practice of autonomous driving path planning, the navigation system can be more accurate and reliable, and safety can be improved. In the experiments, a navigation-grade IMU was used in conjunction with GNSS to produce high- definition point cloud maps, and a multi-frequency GNSS receiver was utilized to reduce the error resolution of the estimated positioning [15].

3 Sensor Fusion and Data Processing

In the application of automatic driving, individual sensors are often unable to complete the accurate observation of the surrounding environment or the accurate planning of the path under different road conditions or different weather conditions, so it is necessary to fuse multiple sensors to complete the processing of complex scenarios in the automatic driving to give full play to the advantages of different sensors and make up for the shortcomings of individual sensors. This paper will discuss the development of sensor fusion technology in three aspects: multimodal fusion architecture, edge computing and AI acceleration, and real-time and reliability verification.

3.1 Multimodal fusion architecture

Multi-modal fusion is a common method for multi-sensor applications in autonomous driving technology. Multimodal fusion can be divided into three fusion methods according to the level of fusion: data-level fusion, feature-level fusion, and decision-level fusion, and the difference between the three is that the fusion of data from different sensors takes place at different points in time. Data-level fusion is to directly fuse the raw data, feature-level fusion is to extract features (edges, shapes) before fusion, and decision-level fusion is to process the data independently for each sensor and fuse the processed data [16]. This paper will introduce multimodal fusion architecture with these three methods.

Data-level Fusion. Data level fusion, also called primary fusion, raw measurements or only preprocessed data from several different sensors are fused in a deep learning stage [17], in the fusion method of [17], a scheme that fuses the radar with the camera is used. In some of the radar-camera data-level fusion studies, radar data is first used to generate regions of interest (ROIs) in the image, and then image-based detection methods are executed in the ROIs to verify the target, which is to utilise the observations from one sensor to enhance the observations from the other sensor [18]. Although data-level fusion is less utilized in practice compared to feature-level fusion and decision-level fusion due to computational overload, etc., it is mentioned that data-level fusion (early fusion) can provide coarse texture information to the point cloud, which is helpful in improving the point cloud of a scene [19].

Feature-level Fusion. Feature-level fusion, also known as mid-term fusion, is an emerging sensor fusion method compared to data-level fusion and decision-level fusion. There are many applications in autonomous driving technology, the radar-based fusion method mentioned in [20], where the detection information obtained from the radar is transformed into image form, so that the detection model can learn both visual features and radar information data [20]. Another example is the sensor fusion algorithm mentioned, which detects the optimal drivable area based on the feature-level fusion of LiDAR and video data [3].

Decision-level Integration. Decision-level fusion, also known as late fusion, is the more mainstream sensor fusion method in the field of autonomous driving, where each sensor independently performs detection to obtain the final data, and the final data is fused. There are two different modes in decision level fusion, one is to match the outputs using a Kalman-like filter, and the other is to determine the positional relationship between the two modes using a transformation matrix between sensors such as between radar and camera sensors [17].

3.2 Edge computing and AI acceleration

The development of automated driving technology has benefited from the rapid development of AI technology nowadays, and AI acceleration technology is the most important driving force for the evolution of automated driving technology from L3 to L5. Reducing the latency of data processing, for example, using the lightweight model and the TensorRT inference model can reduce the latency of data processing of the camera or the radar from the level of a hundred milliseconds to less than 10 milliseconds. Edge computing can significantly optimise the real-time, reliability and safety of autonomous driving systems by sinking data processing and storage capabilities to nodes close to the vehicle or roadside. The core approach, mentioned in the overview, uses edge computing integration, which uses edge nodes to handle non-latency sensitive tasks (e.g., high-precision map updates), and reduces the load on in-vehicle computing by handling complex computations in the cloud [21]. Hardware gas pedals for Artificial Intelligence (AI) models, especially Deep Neural Networks (DNNs), are becoming commonplace in many real-time applications, and another emerging application area for AI hardware is the perception modules in a wide variety of Autonomous Vehicles (AVs), ranging from self-driving cars to mobile robots, that can perform critical computer vision tasks [22].

4 Functional Requirements For Automated Driving

In the practice of autonomous driving, real-time and reliability are the core guarantees to ensure the safe conduct of autonomous driving.

4.1 Real-time

Real-time performance requires the system to complete the sensing-decision-control loop within a specified period of time so as to reflect the information of the surrounding environment in a timely manner. Strict latency constraints are required to be met in a series of autonomous driving task chains, for example, emergency braking latency is required to be less than 100 ms. Existing commonly used technologies to ensure real-time performance include time-sensitive networks (TSNs) and real-time operating systems (RTOSs).In the simulation experiments, a TSN integrated environment simulator was developed, which verified that TSN can compensate for the latency time caused by interruptions in the AVB stream transmission, and that the latency of TSN with ST is lower when using E2E than when using only AVB [23].

4.2 Reliability

Reliability is the ability to guarantee the continuous and stable operation of an autonomous driving system in a complex environment. There are two metrics commonly used to judge reliability, one is based on the standard ISO 26262, which includes random hardware failures and systematic failures, and the other is ISO 21448, which judges the risk due to algorithmic limitations or environmental uncertainties. At the level of verifying reliability, commonly used techniques are Fault Injection Testing (FIT) and Monte Carlo simulation. Among them, FIT is used to judge the reliability of an autonomous driving system by simulating hardware and software failures such as voltage fluctuations and process crashes.

5 Challenges And Future

The development of autonomous driving sensor technology has always been accompanied by the contradiction between performance improvement and engineering landing. This section analyzes both technical challenges and future trends. Existing sensor technologies face many challenges. For example, in extreme weather (rain, snow, haze), the sensors responsible for sensing the surrounding environment will be affected, and when there is insufficient light, the sensors may encounter interference, which leads to degradation of image quality and reduction of detection accuracy, and can cause certain safety hazards [2]. It is also difficult for today's sensors to handle complex scenarios such as urban canyons and temporary construction roads. Radar signals are reflected multiple times by buildings leading to false detections, and tall buildings can block certain GPS satellite signals leading to errors in positioning. At the mechanical level, the sensor design should consider the impact resistance of the material and heat dissipation performance. The above problems are the main bottlenecks of sensor technology, and also restrict the further development of autonomous driving technology. The future development of sensor technology tends to be multi-sensor fusion,. The research and development of new sensors and the addition of AI technology in the late data processing. At the same time, in the process of the development of automatic driving system will also be some laws and regulations of the social system needs to be improved. The development of automatic driving technology will also explore the future development trend and potential challenges of information fusion according to the market trend, and clearly define the direction of future technological progress [24].

5.1 Technical Challenges

Extreme weather has always been a major challenge in the development of autonomous driving sensor technology, extreme weather such as haze, rain and snow weather conditions will largely affect the normal operation of various types of sensors, especially those based on optical principles. In the pollution experiment, the LIDAR sensor of the car was covered with pollutants for testing, and the test response when the pollutants covered the LIDAR sensor compared to the normal operation, the intensity and the number of points were reduced by up to 95.1% and 99.9%, respectively [2]. It can be seen that the influence of the outside world on the normal operation of the sensor is huge. Fast dynamic target recognition is also a major challenge for autonomous driving sensor technology, and for today's algorithms and hardware, the false detection rate of sensors is still high. In addition, the complexity of multi-sensor fusion is also a major challenge for autonomous driving sensor technology. For example, clock drift of different sensors can lead to misalignment of fused data. Finally, the bottleneck of arithmetic power is also a major challenge. The accuracy and reliability improvement of autonomous driving technology requires massive data processing. It needs to be supported by high-computing-power chips. The larger power consumption and heat dissipation design are also problems that need to be solved.

5.2 Future Trends

The rapid development of autonomous driving technology has also led to the development of sensor technology, such as the gradual popularization of 4D imaging radar and solid-state LiDAR, as well as the emergence of some bionic sensors. Group intelligence sharing technology is also one of the future developments such as the Azera HCP+ technology, which jointly learns sensor data from multiple vehicles and stores it in the cloud to generate high-precision dynamic maps. There is also the intelligence of fusion architecture, which makes the multimodal fusion of sensors more efficient.

6 Conclusion

The rapid development of autonomous driving sensor technologies (e.g., 4D imaging radar, solid-state LiDAR) has significantly improved the environment sensing capability, but its scaled application is still limited by challenges such as environment adaptability and complexity of multimodal fusion. Insufficient robustness in extreme environments: existing sensors have significant performance degradation in rain, snow, backlight and other scenes, and need to be combined with anti-jamming algorithms (e.g., fusion of thermal imaging and millimeter-wave radar) and biomimetic optical design to improve reliability. Convergence Architecture Intelligence Requirements: end-to-end Transformer model and spatio-temporal synchronization technology (e.g., time-sensitive network TSN) can optimize the consistency of multimodal data, but the contradiction between computing power and energy consumption needs to be further resolved through heterogeneous computation and lightweighting models. Engineering Innovation Paths: Vehicle-Road-Cloud Collaborative Sensing and Self-Healing Materials (e.g., polymer coatings) provide new directions for reducing sensor loads on a single vehicle and extending the life of the hardware. Future research needs to integrate the interdisciplinary strengths of mechanical engineering materials science and artificial intelligence to promote the practicalization of technologies such as photonic computing chips and quantum sensing. Meanwhile, standardised regulations (e.g. ISO 50831 LiDAR performance test) and ethical priority perception strategies (e.g. pedestrian avoidance rules) will become the key support for the technology to be put into practice. Through the collaboration of the whole industry chain, the automatic driving perception system is expected to move from laboratory verification to large-scale deployment, and ultimately realize all-wearher, all-scene safe and reliable operation.

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