Key Challenges Restricting Autonomous Driving Perception Systems

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Abstract. This article focuses on the research of autonomous driving sensor technology, pointing out that sensor systems—acting as the "perceptual organs" of autonomous driving—have a direct impact on its safety and reliability. Currently, three core issues need to be addressed: synchronization errors, environmental perception errors, and electromagnetic interference. In terms of synchronization errors, differences in sampling frequencies among different sensors, clock drift, installation deviations, and other factors cause spatiotemporal misalignment. This can be addressed by unifying the clock source via the Global Positioning System (GPS)/Beidou Navigation Satellite System. Environmental perception errors are affected by weather, lighting, obstacle occlusion, and other factors, and can be resolved through hardware protection, multi-sensor fusion (e.g., the Dynamic Gaussian algorithm), and algorithm optimization. Electromagnetic interference originates from signal conflicts between radars and requires breakthroughs in hardware shielding, algorithm-based anti-interference technologies, and system redundancy design. At the same time, the article mentions that in the future, sensor technology can be enhanced in three aspects: dynamic calibration, extreme environment adaptation, and vehicle-road collaborative electromagnetic monitoring—thereby assisting in the development of autonomous driving.

Keywords: Autonomous Driving Sensor Technology, Sensor Synchronization Errors, Environmental Perception Errors, Electromagnetic Interference (EMI), Multi-Sensor Fusion.

1. Introduction

With the rapid development of modern science and technology, autonomous driving has become a hot topic among many new energy vehicle companies. Autonomous driving refers to a technological system that utilizes artificial intelligence (AI), sensors, computer vision, and decision-making systems to enable vehicles to autonomously perform driving tasks including environmental perception, path planning, and vehicle control—without the need for continuous human intervention.

The goal of autonomous driving is to ensure traffic safety, improve transportation efficiency, and enhance travel convenience, as it can bring revolutionary changes to the future development of transportation. As a key area of the new round of technological revolution, autonomous driving is gradually shifting from technological breakthroughs to lifestyle upgrades. Its impact has gone beyond a mere "change in driving mode" and has reshaped multiple domains, including transportation safety, social operations, economic models, and industrial ecosystems. However, while it creates unprecedented opportunities, it also presents challenges that must be addressed [1].

The sensor system serves as the "perceptual organs" of the autonomous driving system and is the core foundation for realizing autonomous driving. Without accurate perception by sensors, the decision-making, planning, and control functions of autonomous driving cannot be achieved. Sensors provide environmental data input for autonomous driving—this is a prerequisite for the system to understand its surroundings, avoid risks, and drive safely. Since the safety of autonomous driving technology largely depends on its sensor system, engineers are focusing on how to further advance sensor technology to enhance overall safety.

Currently, autonomous driving technology is mainly divided into four levels based on SAE International standards: Level 2 (partial autonomous driving), Level 3 (conditional autonomous driving), Level 4 (highly autonomous driving), and Level 5 (fully autonomous driving). Under Level 3 (conditional autonomous driving), AI can autonomously control the vehicle under specific road conditions, but the driver still needs to take over control when necessary. A key breakthrough of this

level is the shift of partial driving responsibility from the driver to the system, which has also given rise to numerous legal disputes. Currently, known systems using this technology include the Audi A8 Traffic Jam Pilot (not yet widely deployed) and the Mercedes-Benz DRIVE PILOT (the first joint-venture Level 3 model). Engineers are still striving to develop Level 4 (highly autonomous driving) and Level 5 (fully autonomous driving) technologies [2].

Therefore, to develop and implement advanced autonomous driving technology, several flaws and challenges in sensor technology must be addressed. For example: Sensors are easily affected by factors such as the appearance and color of objects, leading to deviations in object recognition that may trigger unnecessary braking and subsequent rear-end collisions. Adverse weather conditions—such as raindrops, heavy snow cover, or strong sandstorms—can obscure the vehicle's "vision," causing temporary "blindness" of the sensor system. The reliability of current sensors is also limited: long-term vehicle vibration during driving can cause camera misalignment and radar calibration failures, while sensors also face issues related to aging. Additionally, radar signals from different autonomous vehicles may interfere with each other; cameras may suffer from overexposure under strong light; and the alternation of light and dark when entering/exiting tunnels can also cause short-term system "blindness." Finally, data fusion poses significant challenges: data from different sensors vary in format, accuracy, and update frequency, making it extremely difficult to integrate these data accurately and efficiently to build a complete, precise environmental perception model.

There are also approaches to enhance sensor stability in the future. For instance: Integrating more types of sensors to obtain more comprehensive environmental information, while adopting more advanced data fusion algorithms to improve the accuracy and reliability of fused data. Beyond that, collecting massive training samples based on big data and deep learning—while fully accounting for different operating scenarios—can enhance the algorithm's adaptability in complex environments, enabling the system to recognize and predict the intent of targets more accurately. To prevent hardware aging, engineers can optimize sensor manufacturing processes to enhance anti-interference performance and durability, thereby reducing performance issues caused by hardware aging, vibration, and other factors, while further improving sensor accuracy. Finally, multiple types of sensors can be used in redundancy to provide precise positioning for the vehicle in the event of sensor signal loss or hardware damage, ensuring safe perception and control of the vehicle.

This review introduces methods such as unified clock sources, multimodal fusion anti-interference, and electromagnetic protection, and explores solutions to issues including sensor synchronization errors, environmental perception errors, and electromagnetic interference.

2. Key Challenges and Solutions in Autonomous Driving Perception Systems

2.1. Sensor Synchronization Errors

To start with, multi-sensor spatiotemporal synchronization and calibration are fundamental engineering aspects of autonomous driving perception systems. Their main goal is to effectively integrate perception data from different types of sensors (such as radar and cameras) in a unified timeline and spatial coordinate system [3]. However, due to differences in the physical characteristics, installation environments, and dynamic operating conditions of the sensors, this process is highly complex and directly affects perception accuracy and decision-making safety. Below, I will analyze the main issues in detail from two perspectives: time synchronization and spatial calibration.

Sensor synchronization requires that the sensing data from different sensors correspond to the same moment in the real world; otherwise, information such as target location and speed will lose accuracy and timeliness due to time differences. However, inherent differences in sensor sampling frequencies and delay characteristics can lead to errors in results. Because the "data generation rhythm" and "internal delay" of different sensors vary significantly, the timing of data acquisition will be misaligned.

The typical sampling frequency of LiDAR is 10–20 Hz (generating a point cloud frame approximately every 0.05–0.1 seconds), the camera is 30–60 Hz (generating an image frame

approximately every 0.016–0.033 seconds), the millimeter-wave radar is 50–200 Hz (updating detection results approximately every 0.005–0.02 seconds), and the IMU is 1000 Hz (outputting motion status approximately every 0.001 seconds). These varying sampling frequencies can cause coordination errors between different sensors. For example, when a vehicle is traveling at a speed of 100 km/h, within the 0.1-second interval between two LiDAR frames, the vehicle has moved 2.78 meters. If the time difference between the camera and LiDAR is 0.05 seconds, the position deviation of the same target in the image and point cloud can reach 1.39 meters—resulting in a mismatch between "pedestrians in the image" and "obstacles in the point cloud".

Additionally, the time reference of sensors usually relies on their respective local clocks (such as crystal oscillators), and the "tick rate" of different clocks may deviate. The frequency error of a standard crystal oscillator is approximately ±20 ppm (parts per million), meaning the cumulative error can reach 1.7 seconds per day. In autonomous driving, if the clock drift between the LiDAR and camera is not compensated, the time difference can accumulate to 7.2 ms after one hour—corresponding to a position deviation of 0.2 meters at a speed of 100 km/h, which is sufficient to cause missed detection of nearby obstacles. Even with a unified external clock source (such as Global Positioning System (GPS) time), delays may still occur in the "time synchronization trigger" of sensors. For example, when transmitting synchronization signals via the CAN bus, the jitter of bus delay (±5 ms) leads to inconsistent response times of different sensors to the "same trigger signal", further exacerbating timing misalignment.

Beyond time errors, there is also the issue of spatial calibration. Its core is to determine the positional offset and attitude rotation relationship between different sensors, ensuring that all sensor data are mapped to a unified vehicle coordinate system.

Inevitable mechanical deviations during sensor installation—such as the pitch angle of LiDAR and the horizontal offset of cameras—will be significantly amplified in long-range perception. There are a total of 3 translation parameters (X/Y/Z) and 3 rotation parameters (rotation around the X/Y/Z axes). For instance, if a 0.5° pitch angle error exists during LiDAR installation, the target height calculation error at 100 meters can reach 0.87 meters ($\approx 100\ \text{m} \times \tan(0.5°)$), which is enough to misclassify a "low guardrail" as a "pedestrian". A lateral offset error between the camera and LiDAR (e.g., a 1 cm X-axis offset) can cause a 17 cm lateral position deviation of the target at 100 meters (based on the principle of similar triangles). If the target is at the edge of the lane, this may lead to incorrect judgments about the vehicle deviating from lane lines.

In addition, dynamic factors during vehicle operation—such as vibration, temperature changes, and road bumps—can cause deformation or displacement of sensor brackets, rendering statically calibrated external parameters invalid. For example, engine vibration or rough road surfaces can cause slight changes in the relative position between sensors and the vehicle body; the long-term accumulation of these errors may significantly reduce perception accuracy. Meanwhile, extreme temperatures—from summer exposure or severe winter cold—can cause thermal expansion or contraction of sensor brackets. For example, the linear expansion coefficient of aluminum alloy is approximately 23.2 × 10-6/℃ (refer to GB/T 6892-2015 Aluminum Alloy Profiles for Building), with a typical temperature adaptation range of -40 ℃ to 120℃. When the temperature drops below -20 ℃, the shrinkage per meter can reach 0.5 mm (calculated based on a 10 ℃ temperature difference); in environments above 80℃, the expansion per meter exceeds 1.8 mm. Inertial forces during rapid acceleration and braking may also loosen screws, causing sudden changes in external parameters. If not detected promptly, this can distort all subsequent perception data.

Time errors can be minimized by using a unified clock source. The core goal of a unified clock source is to provide a globally consistent time reference for the entire system, eliminating time deviations caused by internal clock drift among different devices. Engineers can leverage the high-precision timing function of global navigation satellite systems such as GPS or Beidou. Satellites provide nanosecond-level precision time signals via atomic clocks; on-board receivers obtain UTC (Coordinated Universal Time) by resolving satellite signals and output synchronization signals. The sensor receives the PPS (Pulse Per Second) signal, resets the sub-millisecond portion of its internal

clock to zero, and restarts counting from the rising edge of the PPS signal. The sensor then parses the UTC in the NMEA (National Marine Electronics Association) message and combines it with the timestamp of the PPS signal to complete the calibration of the device's absolute time [4].

2.2. Environmental Judgment Errors

Secondly, external environmental influences on autonomous driving sensing systems are key challenges limiting their reliability. Core sensors such as LiDAR, cameras, and millimeter-wave radar are highly susceptible to external factors including weather, lighting, and extreme temperatures [5]. According to data from the U.S. National Highway Traffic Safety Administration (NHTSA), approximately 37% of autonomous driving test accidents are directly related to sensor perception biases caused by environmental factors. Weather is the most direct threat to autonomous driving sensing systems. Natural weather conditions—such as rain, fog, or snow—can directly interfere with sensor signal acquisition and data analysis through physical effects like scattering, occlusion, and reflection. The impact mechanisms and severity vary significantly across different weather scenarios [6]. For cameras: In rainy conditions, raindrops adhering to the lens cause image blurring or speckle interference, making it difficult for the system to accurately recognize lane markings, traffic signs, and other vehicles. On snowy days, snowflakes can block the camera lens; some snow may also melt and refreeze into ice, forming opaque obstructions that further obscure the field of view. In foggy weather, severe light scattering reduces image contrast, leading to a camera false detection rate of up to 40% at night or in heavy fog.

For radars and LiDAR: Snowflakes and sandstorms tend to accumulate on their detection components, interfering with the transmission and reception of detection signals. This impairs accurate perception of the surrounding environment and reduces the ability to recognize target objects. In extreme rainfall or low-temperature environments, radars may also experience signal attenuation, power loss, and measurement errors. While some radars have a certain ability to penetrate adverse weather, their accuracy remains relatively low. Of course, there are corresponding solutions to these problems. For instance: Equip LiDAR and cameras with heating devices to prevent frost or ice formation on their surfaces; Design high-efficiency wipers or water-spray systems to promptly remove rainwater, snow, and other debris from lens surfaces; Use passive devices like hydrophobic coatings to enhance the sensor's anti-interference capability; Adopt multi-sensor fusion: Combine the advantages of multiple sensors (e.g., LiDAR, cameras, and millimeter-wave radar) and integrate their data via intelligent data fusion algorithms. For example, in rainy or foggy weather, leverage the strong penetration of millimeter-wave radar and the high precision of LiDAR to complement each other in environmental detection.

In 2024, Wang Yongtao's research team at the Wang Xuan Computer Research Institute of Peking University proposed the Driving Gaussian algorithm—a surround-view dynamic scene reconstruction algorithm based on state-of-the-art 3D Gaussian reconstruction technology. This algorithm achieves highly realistic and consistent multi-camera surround-view image synthesis [7]. This research demonstrates the feasibility of combining multiple types of sensors to build a more comprehensive and accurate perception system. Improvements can also be made at the software level, such as optimizing perception algorithms for specific weather conditions. By connecting the sensing system to external weather monitoring systems, the current weather status can be identified, and corresponding optimized algorithms can be activated. For example: On rainy days, the relationship between rainfall intensity and LiDAR performance degradation can be quantified to support more robust decision-making; In foggy weather, use waveform processing and multi-echo technology to recover hidden targets; Build a bad-weather training dataset: Collect large volumes of driving data under various adverse weather conditions, and perform accurate labeling (including target type, location, size, as well as weather type and severity). These labeled data can form accurate samples for algorithm training, enabling the autonomous driving system to better adapt to bad weather.

2.3. Electromagnetic Interference

Finally, when the perception system of an autonomous vehicle is subjected to electromagnetic interference (EMI), its ability to accurately assess the surrounding environment is significantly impaired. When multiple autonomous vehicles operate simultaneously on the road, their millimeter-wave radars may be interfered with by strong signals from other radars—causing background noise to increase. As a result, small targets may be obscured by noise, shortening the detection distance for real vehicles, pedestrians, or obstacles, and narrowing the dynamic detection range. Therefore, to achieve large-scale deployment of autonomous driving, effective solutions must be developed to overcome this problem. Additionally, if the waveforms of two radars are nearly synchronized in time but have a slight phase delay, deceptive false targets may be generated. This leads the radar to incorrectly identify non-existent obstacles ahead and react to these false targets. A more detailed explanation is provided below.

First, electromagnetic interference may affect the time-of-flight (ToF) circuit of LiDAR. Attackers can use EMI to transmit specific noise signals, deceiving target detection models and causing object classification errors, false detections, or the generation of non-existent obstacles. Research shows that EMI can reduce LiDAR's classification accuracy for pedestrians by more than 50%.

Second, some low-quality in-vehicle devices—such as wireless charging phone mounts and LED ambient lights—generate high-frequency harmonics that pollute the in-vehicle electromagnetic environment. This impairs camera imaging quality and increases image noise. At night, the intelligent driving system may suffer reduced recognition accuracy due to this elevated noise.

Finally, since ultrasonic radar operates on the principle of transmitting and receiving ultrasonic waves, EMI may disrupt its signal transmission and reception circuits—resulting in inaccurate distance measurements or even misjudgments. For example, in environments with strong EMI, ultrasonic radar may misidentify distant objects as nearby ones or fail to detect nearby objects entirely.

Several solutions exist to address these issues: (1) Strengthen Electromagnetic Shielding: Engineers can adopt aviation-grade electromagnetic protection designs and multi-layer shielding technologies. For instance, using metal shielding enclosures, shielding meshes, and similar materials to shield key components (e.g., sensors and circuit boards) reduces the intrusion of external EMI. Simultaneously, ensuring the vehicle's exterior has robust electromagnetic shielding prevents external electromagnetic waves from interfering with internal electronic systems—addressing obstacles to large-scale autonomous driving deployment. Wu Qiuyu and Gao Yong from Peking University proposed a deep complex convolutional recurrent network based on an attention mechanism to resolve mutual interference between automotive radars, achieving frequency-domain interference suppression. This model uses complex networks to integrate the real and imaginary parts of signals for feature learning and introduces attention mechanisms in skip connections to focus on critical feature information. Experimental results show the model effectively suppresses interference and improves target signal-to-noise ratio (SNR) [8]. (2) Optimize Sensor Installation and Device Selection: Reasonably planning sensor installation locations and orientations reduces mutual interference. For example, installing millimeter-wave radar and LiDAR separately avoids signal overlap. Additionally, increasing physical isolation between sensors (e.g., using isolation plates) mitigates EMI impacts. When selecting in-vehicle electronic devices, priority should be given to products with strong anti-EMI capabilities—such as those certified to 3C standards and automotive-grade specifications. For sensors, choose models with built-in anti-EMI features or modify existing sensors to enhance interference resistance. (3) Enhance Software Algorithms: Improvements can also be made at the algorithm level, such as using adaptive noise cancellation algorithms. An adaptive noise canceller dynamically adjusts filter parameters based on changes in the interference signal to better suppress EMI. Common adaptive noise cancellation algorithms include the minimum mean square error (MMSE) algorithm, recursive least squares (RLS) algorithm, and Kalman filter algorithm. These effectively eliminate EMI impacts on radar signals and improve radar SNR. Alternatively, EMI recognition and compensation can leverage deep learning: deep learning techniques learn and identify EMI signals, establishing an interference signal model. Sensor data is then compensated and corrected

based on the identified interference, enhancing sensor accuracy in EMI environments. For example, convolutional neural networks (CNNs) can identify and remove EMI noise from camera images, while recurrent neural networks (RNNs) can predict and compensate for interference in radar signals. (4) System-Level Improvements: Combine data from multiple sensors (e.g., millimeter-wave radar, LiDAR, cameras, and ultrasonic radar) to comprehensively assess the surrounding environment via data fusion algorithms. When one sensor is affected by EMI, others can provide supplementary information to ensure autonomous driving system reliability. Simultaneously, adopt redundant designs by increasing the number of critical sensors: if one sensor fails or is interfered with, a backup sensor can be activated immediately to maintain normal system operation. Additionally, install EMI monitoring devices on the vehicle to track the surrounding electromagnetic environment and real-time sensor working status. When EMI intensity exceeds a threshold, the system can issue a warning to remind the driver to exercise caution, automatically switch to a backup driving mode (e.g., manual mode), or downgrade the autonomous driving level.

3. Conclusion

In summary, this article focuses on autonomous driving sensor technology, analyzes the core issues currently constraining its performance and reliability one by one, and proposes targeted solutions—providing key references for the optimization of autonomous driving perception systems.

In terms of sensor synchronization errors, spatiotemporal synchronization and calibration are fundamental engineering tasks for autonomous driving perception systems, directly affecting perception accuracy and decision-making safety. In the temporal dimension, the sampling frequencies of different sensors vary significantly; the combination of local clock drift and synchronization signal transmission delay can easily cause spatiotemporal misalignment of target information. In the spatial dimension, errors in the six-degree-of-freedom (6DoF) installation parameters of sensors will be significantly amplified. Additionally, vibrations, temperature changes, and rapid acceleration during vehicle operation can invalidate statically calibrated parameters, further reducing perception accuracy. To address this, using nanosecond-level precision time signals provided by global navigation satellite systems (e.g., GPS/Beidou), combined with a PPS (Pulse Per Second) signal to reset the sensor's internal clock, and parsing NMEA (National Marine Electronics Association) messages to calibrate absolute time, can effectively minimize temporal errors.

Environmental perception errors are a key factor limiting the reliability of autonomous driving sensors. In terms of weather: Rain can cause camera lens blurring and millimeter-wave radar signal attenuation; snow easily leads to sensor occlusion and freezing; and foggy weather can increase the camera's false detection rate by up to 40%. Lighting and temperature can also interfere with sensor performance—for example, strong light causing camera overexposure, or the alternation of light and dark in tunnels leading to transient system "blindness." To resolve these issues: (1) Hardware-level measures: Enhance anti-interference capabilities through heating devices (to prevent frost), high-efficiency wipers or water-spray systems (to clear obstructions), and hydrophobic coatings; (2) Multi-sensor fusion: Technologies such as the Driving Gaussian surround-view dynamic scene reconstruction algorithm—proposed by Wang Yongtao's research group at Peking University in 2024—can integrate the high precision of LiDAR and the strong penetration of millimeter-wave radar, enabling accurate perception in complex environments. (3) Software-level optimization: Link the perception system with external meteorological systems to optimize algorithms for specific weather conditions (e.g., quantifying the relationship between rainfall intensity and LiDAR performance degradation, or using waveform processing technology to recover hidden targets in fog). Meanwhile, construct a severe weather training dataset containing weather types and target information to improve the algorithm's environmental adaptability.

Electromagnetic interference (EMI) also severely impairs sensor functionality. When multiple vehicles operate in parallel: Signal interference between millimeter-wave radars can increase background noise, causing small targets to be obscured, detection distances to shorten, and dynamic

ranges to narrow—even generating false targets due to waveform delays. High-frequency harmonics from low-quality in-vehicle devices can pollute the in-vehicle electromagnetic environment and reduce camera imaging quality. Additionally, EMI can disrupt LiDAR's time-of-flight (ToF) circuits and the signal transmission/reception of ultrasonic radars. Solutions span multiple dimensions: (1) Hardware: Adopt aviation-grade electromagnetic protection designs, reasonably plan sensor installation locations, and prioritize devices certified to 3C standards or automotive-grade anti-EMI specifications; (2) Algorithms: Dynamically suppress interference via adaptive noise cancellation algorithms and use deep learning to identify and correct interference signals; (3)System-level: Integrate multi-sensor data fusion and redundancy designs and install EMI monitoring devices to trigger warnings or switch driving modes when interference exceeds thresholds.

The future development of autonomous driving sensor technology needs to pursue breakthroughs in higher precision and accuracy based on existing solutions.

In the field of synchronization and calibration: Explore AI-based dynamic real-time calibration technology, which uses the vehicle's motion state and environmental characteristics to automatically correct external parameter offsets caused by vibrations and temperature changes—further improving spatiotemporal synchronization accuracy. Leverage the low-latency transmission capabilities of 5G/6G to optimize sensor time synchronization mechanisms in multi-vehicle collaborative scenarios, reducing inter-vehicle interference.

In terms of environmental adaptability: Strengthen R&D on sensor performance in extreme environments—for example, developing ultra-low-temperature-resistant LiDAR transmission/reception components and strong-wind-resistant camera stabilization brackets. Meanwhile, integrate environmental data from satellite remote sensing and vehicle-road collaboration to predict weather and road conditions in advance, providing "prior information" for sensor perception and mitigating the impact of sudden environmental interference.

For EMI response: In the future, construct a vehicle-road collaborative electromagnetic environment monitoring network to share real-time EMI intensity data for road sections and guide vehicles to dynamically adjust sensor operating parameters. Develop new anti-interference materials or sensor structures to enhance hardware anti-interference capabilities at the source. Additionally, based on federated learning technology, collaborate with multiple automakers to jointly train EMI identification and compensation models while protecting data privacy—accelerating algorithm iteration.

From a system perspective, as autonomous driving advances toward L4 and L5 levels, sensors will be deeply integrated with artificial intelligence (AI) and big data to form a "perception-decision-control" closed-loop optimization system. For example, use real-time sensor data to update digital twin models, simulate complex interference scenarios in virtual environments, and verify anti-interference solutions in advance. Meanwhile, establish more comprehensive sensor reliability evaluation standards covering the entire lifecycle of performance testing—providing safety guarantees for the large-scale deployment of autonomous driving.

In conclusion, although current autonomous driving perception systems are relatively well-equipped, further research is still needed in specific areas. I believe that large-scale deployment of autonomous driving technology will be achieved soon.

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