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Core AI Technology and Development Trend of Autonomous Vehicle Safety Perception

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Abstract

With the rapid development of artificial intelligence (AI) technology, autonomous vehicle have become an important part of the future transportation system. As the core link of auto drive system, environment awareness has a direct impact on the performance of the whole system. Therefore, this paper systematically combs the development process of core AI technology in the field of autonomous vehicle perception through comparative analysis, and deeply discusses the evolution of different technology paths. First of all, this paper reviews the historical background of the safety development of autonomous vehicle, and analyzes the main challenges facing the current perception technology; Then, this article compares the research results of different representative scholars and different key technology routes from three key dimensions, revealing the inherent logic and future trends of the development of perception technology. This article aims to provide theoretical reference for technological innovation and safety system construction in the field of autonomous driving safety, and to assist in the large-scale application of autonomous driving technology under the premise of safety and controllability.

Keywords

autonomous driving, environmental perception, AI, driving safety, core technology, future trends

1. Introduction

As a product of the deep integration of artificial intelligence (AI) technology and the automotive industry, autonomous vehicle are reshaping the development pattern of the global transportation system. As the largest automobile market in the world, China's autonomous driving technology has developed particularly rapidly. For example, the “Apollo Go” of Wuhan Autonomous Taxi has achieved the world's first urban level commercial operation of fully unmanned autonomous taxi [1]. Tesla's Full Self Driving (FSD) also continues to advance the development of advanced intelligent autonomous driving technology [2]. However, the large-scale commercial application of autonomous vehicle still faces many challenges, in which the safety and reliability of the environmental awareness system are particularly critical [3]. As the basis of the auto drive system, environment awareness is responsible for identifying the road environment, detecting obstacles, predicting behavioral intentions and other core functions. Its technical level directly determines the safety boundary of autonomous vehicle [4, 5].

The in-depth study of the development of core AI technology in the perception field of autonomous vehicle has important theoretical value and practical significance for understanding the evolution law of technology, identifying key technical bottlenecks, and predicting future development trends. This paper will systematically compare the advantages and limitations of different technology paths, analyze the innovation contributions of different representative scholars, provide important theoretical guidance for subsequent technology innovation, and then promote the autonomous vehicle perception technology to a higher safety level.

2. The Current Safety Status of Autonomous Driving

The statistics of autonomous vehicle safety accidents show that autonomous driving technology is not absolutely safe, and its unique technical defects have led to new traffic accidents. According to the global autonomous driving accident statistics from 2024 to 2025, accidents related to perception systems accounted for more than half of the total number of accidents, with target recognition errors, poor weather perception failures, and sensor malfunctions being the main causes of accidents. For example, Xiaomi SU7 caused a collective collision due to radar recognition failure during automatic parking, and Tesla FSD misjudged signal lights on rainy days, resulting in red light running accidents [6].

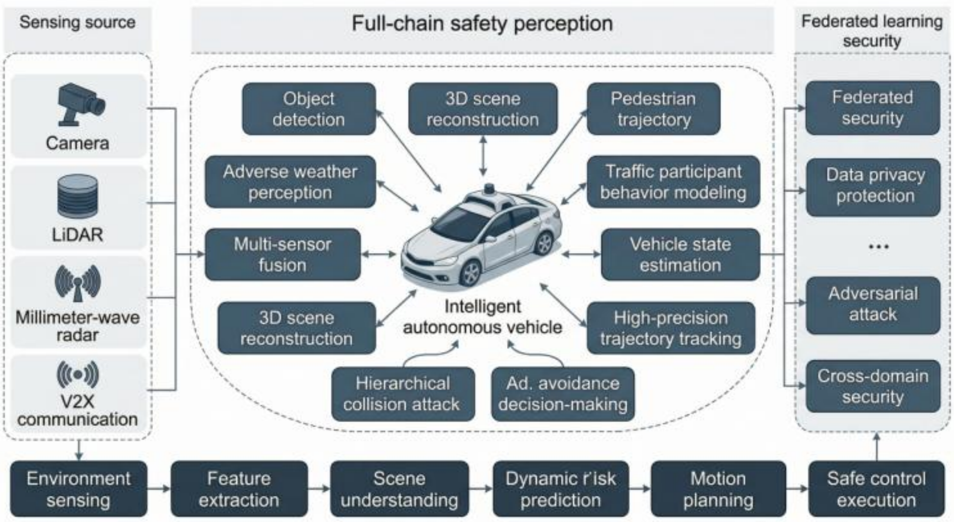
These typical cases collectively reveal the limitations of autonomous driving perception technology, mainly reflected in three core dimensions: environmental adaptability, algorithm robustness, and system integration [7]. The main limitations of its perception technology are compared and analyzed in Table 1.

Table 1. Comparative analysis of limitations of main perception technologies

Technical Type	Main Limitations	impact level	Typical Failure Scenarios	Current solution maturity
visual perception [8]	Light sensitivity [9]	tall	Backlight, nighttime	moderate
LiDAR	Adverse weather conditions [10]	moderate	Heavy rain and dense fog	lower
millimeter wave radar	Metal reflection interference	moderate	Tunnels and bridges	moderate
multimodal fusion	Real time challenge [11]	tall	high-speed scenario	lower
Deep learning algorithms	Vulnerable to adversarial attacks	tall	malicious attack	lower

AI plays an irreplaceable core role in the safety system of autonomous vehicle, especially in the field of environmental awareness. The synergy of these AI technologies has formed a multi-level safety assurance mechanism, which not only improves the accuracy and robustness of the perception system, but also provides a technical basis for coping with safety challenges in complex traffic scenarios [12]. The panoramic diagram of the autonomous driving safety perception technology system is shown in Figure 1.

Figure 1: Panoramic Block Diagram of Autonomous Driving Safety Perception Technology System



3. Key AI Technology System for Autonomous Driving Safety

3.1 Basic Environmental Perception Technology

3.1.1 Evolution and Performance of Complex Road Object Detection Algorithms

The target detection technology in complex road environments has undergone a significant transformation from traditional machine learning to deep learning [13]. As the most fundamental and core functional module in the unmanned driving environment perception system, object detection directly determines the recognition accuracy and response efficiency of vehicles to road targets, and is the first technical line of defense to ensure the safe driving of vehicles.

Early traditional object detection methods relied on manually designed features and traditional machine learning models, which had weak feature expression ability and poor generalization, and could not adapt to the complex changes in real traffic scenes. To solve this problem, Girshick et al. successively proposed R-CNN and Fast R-CNN series algorithms, applying convolutional neural networks to the field of object detection, greatly improving detection accuracy. Especially, Faster R-CNN improved the object detection accuracy to over 85% by introducing the region recommendation network RPN, laying the foundation for the application of deep learning in the field of autonomous driving perception [14,15]. The YOLO series algorithm developed by Redmon et al. further optimized the detection speed, and YOLOv3 achieved 57.9% mAP on the COCO dataset, reducing inference latency to below 20ms. More and more research is applying these YOLO series to the field of transportation [16–18].

In recent years, the CenterNet algorithm proposed by Pandey et al. has achieved high-precision target localization through keypoint detection, with a vehicle detection accuracy of 89.6% AP on the KITTI dataset [19]. The PointPillars algorithm developed by Zhang and Zhou is specifically designed for LiDAR point cloud data, achieving accurate detection of 3D targets and obtaining a comprehensive NDS score of 58.1% on the nuScenes dataset [20].

Overall, the core demand for technological evolution is the dual improvement of accuracy and real-time performance. In the future, research in this field will focus on lightweight Transformer model design, deep fusion of multimodal features, breakthroughs in complex extreme scene detection performance, and further achieve collaborative optimization of detection accuracy, real-time performance, and robustness.

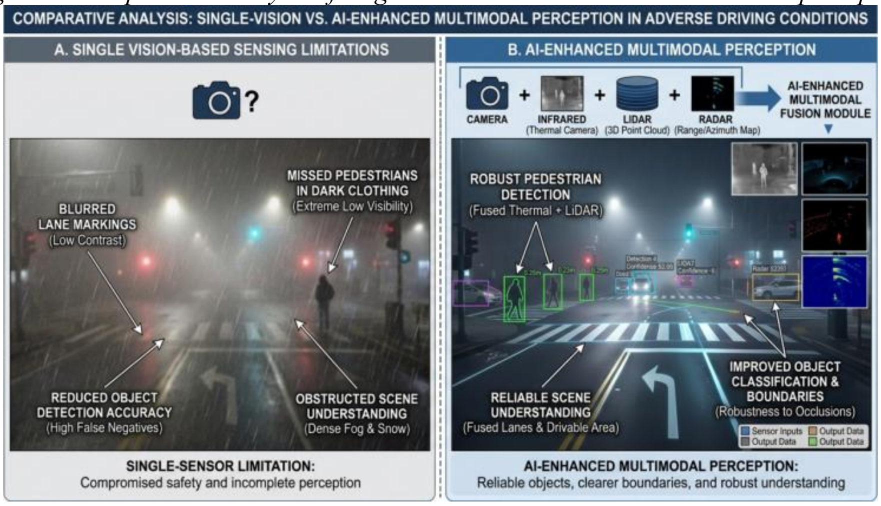
3.1.2 Breakthrough in Perception Algorithms for Harsh Environments

Perception algorithms under adverse weather conditions face severe challenges such as image degradation and increased sensor noise. Deep learning methods have brought revolutionary improvements to the perception of harsh environments. Tang et al. proposed a simple but effective RDT method for dehazing nighttime images based on dark channel precedents. The method uses atmospheric light images and latent dehazing images to obtain the final dehazing image [21]. However, RDT is prone to failure in bright areas such as the sky and has a high computational complexity. Subsequently, the introduction of optimization techniques such as guided filtering improved algorithm efficiency, but the fundamental problem has not yet been fundamentally solved [22].

Regarding the problem of image degradation in foggy environments, scholars at home and abroad have conducted extensive research on image dehazing and perception enhancement based on deep learning. Zhang et al. proposed a spatial dual branch attention dehazing network SDBAD Net based on meta learning paradigm to address the shortcomings of insufficient feature extraction and poor detail preservation in traditional dehazing networks. The SDBAD Net extracts global semantic features and local detail features through a dual branch structure [23]. Wang et al. focused on the adaptation challenges of foggy environments with different concentrations and constructed a TFRHaze multimodal image dehazing network based on a dynamic fog concentration evaluation mechanism. The network adopts an independent dual branch architecture and can process and fuse the data features of infrared and visible light modes separately. Compared with a single modal dehazing network, its target detection accuracy is significantly improved [24].

Multimodal fusion technology further enhances the perceptual robustness in harsh environments. The comparative analysis of single vision and AI enhanced multimodal perception is shown in Figure 2. By combining visible light, infrared, and lidar data, the system can maintain a detection accuracy of over 85% even under extreme weather conditions [25].

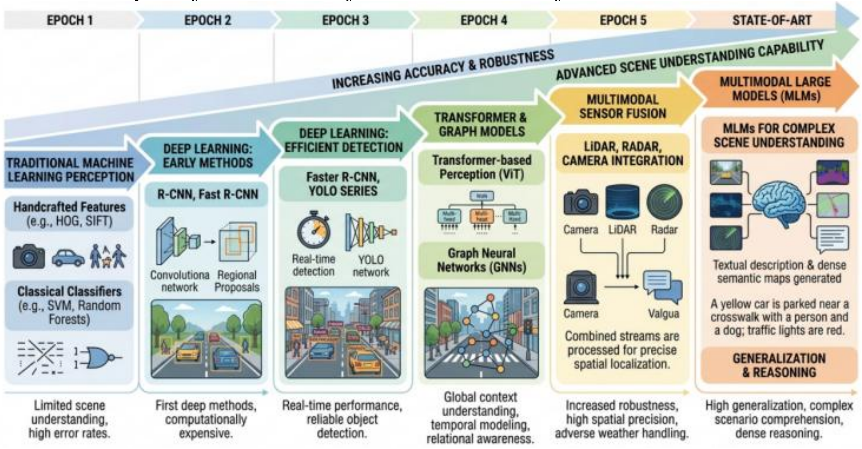
Figure 2: Comparative analysis of single vision and AI enhanced multimodal perception



3.1.3 Multi Sensor Fusion Strategy and Architecture

Multi sensor data fusion technology is a key way to improve the reliability of autonomous driving perception. The panoramic analysis of the robust multi-sensor fusion architecture for autonomous driving perception is shown in Figure 3.

Figure 3: Panoramic analysis of multi-sensor fusion architecture for robust autonomous driving perception



Early fusion methods mainly used simple data level fusion, which had problems such as difficulty in spatiotemporal registration and information redundancy when processing heterogeneous sensor data [26]. The introduction of Kalman filtering algorithm significantly improves the multi-sensor fusion effect The linear optimal estimation theory proposed by Kalman in 1960 provided a mathematical basis for dynamic system state estimation and has been widely applied in autonomous driving target tracking [27]. Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) further expand the applicability of the algorithm and can handle nonlinear system fusion problems. The state prediction during the fusion process can be expressed as:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_K u_k \tag{1}$$

The status update process is as follows:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + k_k \left(z_k - H_k \hat{x}_{k|k-1} \right) \tag{2}$$

The Kalman gain is:

$$K_k = P_{k|k-1} H_K^T \left(H_K P_{K|K-1} H_K^T + R_K \right)^{-1} \tag{3}$$

The arrival of the deep learning era has driven significant innovation in fusion technology. Yao et al. proposed a network architecture called Octree Grouping PointNet++(OG PointNet++) based on the PointNet++network structure, which achieved efficient processing of point cloud data and provided new ideas for the fusion of LiDAR and cameras [28].

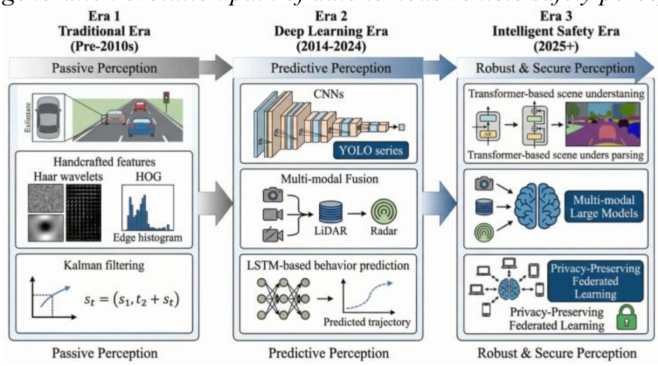
Through performance comparison analysis, feature level fusion has achieved a good balance between accuracy and efficiency, becoming the mainstream choice for current industrial applications [29].

3.2 Dynamic Behavior Perception Technology

3.2.1 Pedestrian Trajectory Perception and Risk Prediction Mechanism

Pedestrian track perception and risk prediction is one of the most challenging technical links in the auto drive system, which is directly related to the safe operation of vehicles in complex urban environments [30-32]. The three generation evolution path of autonomous vehicle safety perception technology is shown in Figure 4. The Histogram of Oriented Gradients (HOG) feature descriptor proposed by Dalal and Triggs significantly improves this problem by capturing pedestrian contour information through calculating HOG, laying the foundation for subsequent trajectory tracking [33]. The rise of deep learning technology has completely changed the traditional rule-based pedestrian behavior prediction model. In the field of trajectory prediction, Qiao et al. developed a pedestrian trajectory prediction model using the Spatial Social Force Graph Neural Network (SSF-GNN), which constructs an interaction graph structure between humans and combines distance and velocity factors from the social force model to achieve accurate prediction of pedestrian trajectories in complex scenarios [34]. The current multimodal perception technology based on Transformer architecture can integrate visual, LiDAR, and high-precision map data, improving prediction accuracy by about 25% compared to traditional Kalman filtering methods [35].

Figure 4: Three generation evolution path of autonomous vehicle safety perception technology



3.2.2 Modeling of Traffic Participant Behavior and Interaction Perception

The evolution of traffic participant behavior modeling technology reflects a paradigm shift from individual modeling to group interaction modeling, as shown in Table 2. Early traffic participant behavior modeling was mainly based on the classic vehicle following model. Gipps' proposed safety distance model describes the following behavior between vehicles through mathematical formulas. Although the calculation is simple, it is difficult to handle complex multi vehicle interaction scenarios [36]. The social force model proposed by Helbing and Molnar provides a new theoretical framework for the interaction perception of Gipp among traffic participants. This model considers traffic participants as particle systems subject to driving, repulsive, and frictional forces, and can effectively describe basic interaction behaviors such as lane changing and pedestrian crossing [37].

With the development of machine learning technology, Hidden Markov Models have been widely used for traffic participant intention recognition. Zhang et al. research shows that HMM has an accuracy rate of up to 85% in vehicle steering intention recognition [38]. After entering the era of deep learning, the modeling technology of traffic participant behavior has achieved a qualitative leap. The convolutional social pooling network proposed by Deo and Trivedi extracts spatial features through CNN and combines LSTM to model temporal dependencies, achieving a behavior prediction accuracy of over 92% in complex traffic scenes [39]. In recent years, interactive perception methods based on graph neural networks (GCN) have become a research hotspot. The TrafficGCN model proposed by Li et al. models traffic participants and their relationships as dynamic graph structures, and achieves more accurate group behavior prediction through graph convolution operations. The prediction error in multi vehicle cooperative lane changing scenarios has been reduced by 30% [40]. Qiao et al. proposed a social attention long short-term memory (LSTM) model using a social pooling layer to predict the future trajectories of neighboring vehicles and achieve higher accuracy, effectively capturing cooperative behavior and mutual influence between carriers [41]. The dynamic behavior perception technology based on deep learning has achieved significant improvement in prediction accuracy compared to traditional methods. The multimodal fusion algorithm of Transformer architecture reduces trajectory prediction error to less than 0.5 meters, laying a solid technical foundation for achieving the safety requirements of L4 level autonomous driving.

Table 2: Comparison of the Development of Behavior Modeling Techniques for Traffic Participants

Technical method	Propose year	Core Features	prediction accuracy
Hidden Markov Model	1999	State transition modeling	85%
CNN-LSTM fusion	2018	Deep learning feature extraction	92%
TrafficGCN	2021	Graph Neural Network Modeling	95%
LSTM	2024	Social pooling layer	>95%

3.3 Control Execution Perception Technology

3.3.1 Vehicle State Perception and High-precision Trajectory Tracking

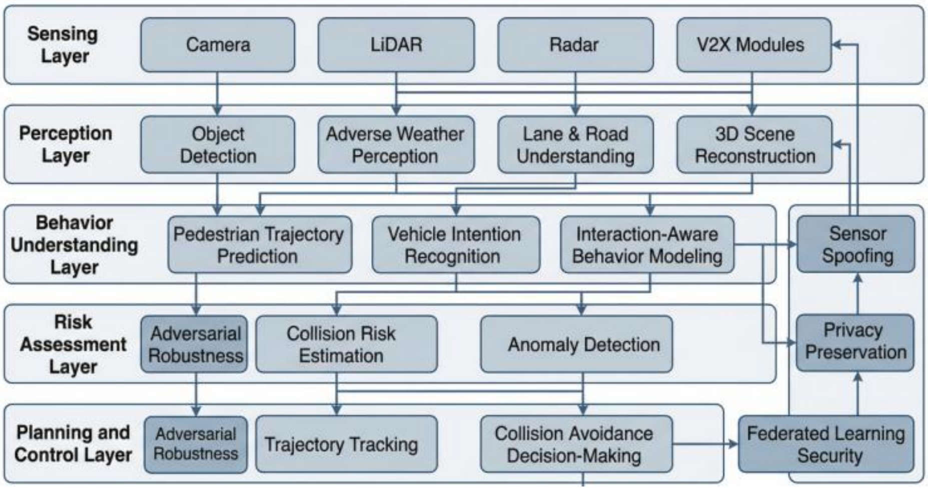
As the end link of the auto drive system, the control execution awareness technology bears the key responsibility of transforming the environmental awareness results into precise vehicle control commands [42]. The accuracy of vehicle state perception and trajectory tracking directly affects the safety and riding comfort of autonomous vehicle. The traditional vehicle state estimation methods mainly rely on probability estimation algorithms such as extended Kalman filter and unscented Kalman filter, and achieve real-time estimation of vehicle pose by integrating sensor data such as IMU, GPS, and wheel encoder [43, 44]. In recent years, Xin et al. have proposed a novel Difficulty Guided Feature Enhancement Network (DGFNet) for multi-agent trajectory prediction by combining model predictive control with deep reinforcement learning. This network enhances the adaptability and robustness of the system while maintaining control accuracy [45]. At the same time, promote the engineering deployment of hybrid intelligent control models to achieve precise and reliable trajectory tracking.

3.3.2 Hierarchical Perception and Decision Mechanism in Collision Avoidance Scenarios

The hierarchical perception and decision-making mechanism in collision avoidance scenarios constitutes the final line of defense for the autonomous driving safety system, which achieves rapid response from threat detection to emergency braking through a multi-level perception architecture. The hierarchical safety perception architecture for autonomous driving is shown in Figure 5.

The development of hierarchical perception decision-making technology began with the theoretical framework of vehicle collision warning system proposed by Reif, which quantitatively evaluates collision risk through time to collision and collision threat index [46]. Kaempchen et al. introduced Bayesian networks into collision risk assessment and processed perceptual uncertainty through probabilistic inference, improving the reliability of the system in sensor noise environments. However, the high computational complexity limits real-time applications [47]. With the maturity of deep learning technology, Yuan et al. proposed a new Temporal Multi task Mixture of Experts model for simultaneously predicting vehicle trajectories and driving intentions, considering the interrelationships between tasks, which can significantly improve the accuracy of vehicle trajectory prediction [48]. The latest research trend focuses on multi-agent interaction modeling based on graph neural networks, which can dynamically predict the behavioral intentions of traffic participants and formulate collision avoidance strategies in advance [49].

Figure 5: Layered Safety Perception Architecture for Autonomous Driving



4. Core Challenges Facing AI Safety in Autonomous Driving

4.1 Information Cross Domain Fusion Security Threats

At present, the auto drive system has significant weaknesses in the integration protection of functional safety and information safety, and there are essential differences in the design concepts and protection mechanisms of the two security domains. Functional safety follows the ISO 26262 standard, focuses on safety risks caused by system failures, and adopts redundant design and fail safe strategies; Information security follows the ISO 21434 standard, with a focus on preventing malicious attacks and data leakage threats. The two security systems lack effective collaboration in risk assessment methods, security architecture design, and emergency response mechanisms [50]. Functional security design often assumes that attackers do not exist, while information security protection may introduce new functional failure points. During the processing of sensor data, encryption and authentication mechanisms may increase processing latency and affect real-time requirements [51]. In practical systems, there are significant mechanism conflicts and performance constraints between dual domain protection. The encryption and authentication mechanisms used in information security will increase data processing latency, affect the real-time requirements of autonomous driving, and thus conflict with functional safety goals.

4.2 AI Model Robustness Defects and Model Poisoning Threats Adversarial Sample and Sensor Deception Vulnerability

The perception system of autonomous vehicle shows significant vulnerability in the face of well-designed anti sample attacks, which seriously threatens the security and reliability of the system. The patch attack against Tesla's fully auto drive system in 2025 proves the severity of these vulnerabilities, in which the strategically placed visual disturbance reduces the confidence of target detection of stop signs and pedestrian recognition by 67%. The incident involved patches with pixel modifications below the human perception threshold, but caused the perception system to misclassify critical road elements, resulting in catastrophic impacts on vehicle safety. Similarly, the 2026 sensor spoofing attack on Waymo's LiDAR based sensing stack revealed a systemic weakness in the multimodal sensor fusion method, where coordinated electromagnetic interference resulted in an 89% false alarm rate under specific ambient lighting conditions of 2400-2600 lux.

Sensor deception attacks take advantage of the physical weaknesses of perception devices such as LiDAR and cameras, creating false targets or obscuring real obstacles through laser projection, infrared interference, and other means, causing the fusion perception system to fall into a chaotic state [52]. The main types and impacts of adversarial attacks are shown in Table 3.

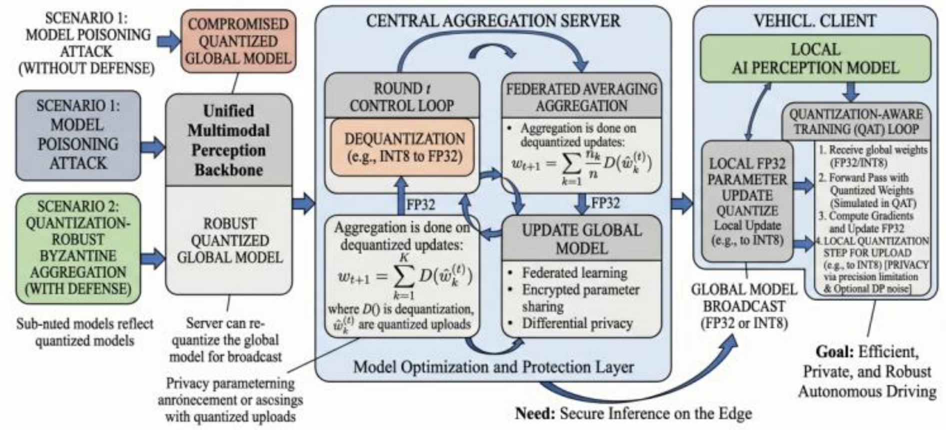
Table 3: Main types of adversarial attacks and impact assessment

Attack Type	Target sensor	Implementation difficulty	Difficulty of detection	Potential hazard level	Current situation of protection
Physical Adversarial Patch	camera	moderate	difficulty	tall	Partial protection
Laser deception	LiDAR	tall	moderate	extremely high	research phase
radio interference	millimeter wave radar	low	easy	moderate	Basic Protection
deepfake [59]	multi-sensor	extremely high	extremely difficult	extremely high	No effective protection

4.2.1 Federated Learning and Model Poisoning Threats

Federated learning, as an important technological path to address data privacy issues in autonomous driving perception systems, achieves collaborative learning without data leaving the local environment through distributed training. However, this distributed architecture also introduces new security threats [54, 55]. In a federated learning environment, malicious actors may launch poisoning attacks on the global model by uploading tampered model parameters or gradient information, leading to a decrease in perception algorithm performance or even erroneous judgments. Especially in autonomous driving perception tasks, model poisoning attacks may lead to serious consequences such as target detection failure and lane recognition errors, directly threatening driving safety [56]. The privacy protection quantification model based on federated learning is shown in Figure 6.

Figure 6: Federated Learning-Based Privacy-Preserving Quantized Model



In the aggregation process of federated learning, the server-side usually uses weighted averaging to fuse the model updates of each client [57]. The mathematical expression is:

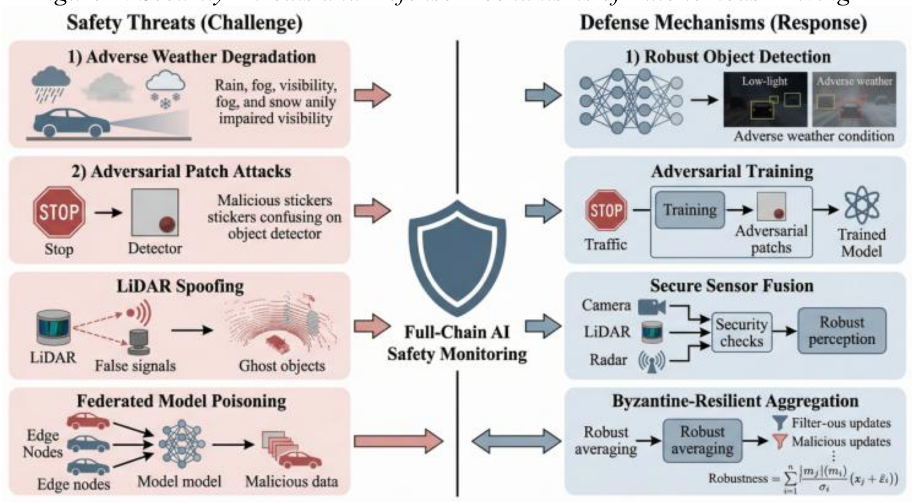
$$\mathrm{w}_{t+1} = \sum_{k=1}^{k} \frac{n_k}{n} w_k^{(t+1)} \tag{4}$$

Among them, w_{t+1} represents the global model parameters of the t+1 round, $w_k^{(t+1)}$ represents the k model parameters uploaded by the *th* client, n_k represents the data volume of the k client, and n represents the total data volume. However, this simple weighted aggregation method is susceptible to model poisoning attacks. When malicious clients upload abnormal model parameters, it can seriously affect the convergence and accuracy of the global model, thereby threatening the safety and reliability of the entire autonomous driving perception system.

5. Future Development Trends and Countermeasures Suggestions

As autonomous driving technology enters the advanced stage of mass production and commercialization, precise understanding of complex scenarios and full chain safety assurance have become the core direction of technological breakthroughs. On the one hand, multimodal large models provide key technological empowerment for autonomous driving to break through the limitations of a single sensor and achieve deep understanding of complex traffic scenes through cross modal perception, universal feature extraction, and complex logical reasoning capabilities. On the other hand, the entire chain of autonomous driving AI systems, from perception, decision-making to model training, faces security risks such as malicious attacks, environmental interference, and model vulnerability. Building a full chain AI security perception system has become an inevitable requirement to avoid technical risks and ensure system reliability. The specific security threat and defense mechanism framework is shown in Figure 7.

Figure 7: Security Threats and Defense Mechanisms of Autonomous Driving AI



6. Conclusion

This paper provides a systematic review of the current state of core AI technologies for autonomous driving safety perception, confirming that perception system failures are the primary cause of autonomous driving accidents. The key contributions include: conducting a comprehensive analysis of the inherent limitations and typical failure scenarios of various perception sensors and deep learning algorithms; elucidating the technical evolution patterns in object detection, multi-sensor fusion, and traffic behavior modeling while defining the applicable boundaries of mainstream algorithms; delineating three evolutionary stages of autonomous driving perception technology and establishing a hierarchical safety perception decision architecture; revealing cross-domain conflicts between functional safety and information security based on dual safety standards, and systematically addressing adversarial attack risks and model poisoning hazards in federated learning. Current perception technologies still suffer from weaknesses such as poor adaptability to extreme environments, insufficient algorithmic robustness, and vulnerability to physical deception attacks. Moving forward, leveraging multimodal large-scale models to build a comprehensive AI security protection framework across the entire system chain will serve as the cornerstone for scaling advanced autonomous driving applications.

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Conflicts of Interest

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