Proceedings of the 3rd International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/141/2025.22055

Research on the Evolution and Integration of Advanced Driving Systems in Intelligent Vehicles

Liqun Niu

Chang'an Dublin International College of Transportation, Chang'an University, Xi'an, China
2796949858@qq.com

Abstract: In recent years, intelligent vehicle technology has developed rapidly, with major breakthroughs in autonomous driving as well as advanced driver-assistance systems. Due to advances in sensors, artificial intelligence (AI), and vehicle-to-everything (V2X), intelligent vehicles have seen significant improvements in environmental perception, path planning, and decision-making. However, society lacks clarity on the development, implementation, and classification of autonomous driving in intelligent vehicles. Thus, this paper explores the evolution of advanced driving systems in intelligent vehicles, clarifies key component relationships, and analyzes the prospects and challenges of autonomous driving technology. Through an analysis of recent literature and data from the Society of Automotive Engineers (SAE) and official websites of auto parts suppliers, the latest developments are highlighted. Besides, it defines intelligent vehicles as integrated systems of perception, decision-making, and control, and investigates their progression toward L3 to L5 autonomous driving. The results suggest that intelligent vehicles will be at the core of the future automotive industry, with autonomous driving technology, powered by sensors, algorithms, and control systems, enabling full automation.

Keywords: Intelligent vehicles, PID control systems, Advanced Driver Assistance Systems (ADAS), Autonomous driving technology, Vehicular LiDAR sensors

1. Introduction

Intelligent vehicles merge sensors, artificial intelligence (AI), communication, positioning, as well as control systems, driving advancements in automotive technology. In recent years, the adoption of 128-line LiDAR, the development of self-learning AI models, and the use of 5G have accelerated the evolution of intelligent connected vehicles (ICVs) toward higher-level autonomous driving [1]. Despite advances in intelligent vehicle technology and new smart driving systems from major automakers, public understanding of smart vehicle classification, functions, and capabilities remains limited. Existing research mainly examines individual technologies in intelligent vehicles, with fewer comprehensive reviews on their evolution, integration, and future trends. Thus, an in-depth study is needed to trace the evolution of intelligent vehicle technologies, explore the integration of various systems, and examine their future development trajectories. This paper aims to explore the technological framework and development trends of intelligent vehicles, focusing on the role of intelligent driving systems in advancing autonomous driving. As such, it investigates the historical development, technological progress, and integration of components, highlighting the impact of driving assistance systems. By analyzing existing literature and industry data, this paper explores

DOI: 10.54254/2755-2721/141/2025.22055

the challenges and development directions of intelligent driving technology, offering insights for innovation in the intelligent vehicle sector.

2. Overview of the Intelligent Vehicles

2.1. The Evolution of Intelligent Vehicles

The intelligent vehicle technology has evolved from computer-assisted control to AI-driven systems, advancing perception, decision-making, and control. In the 1950s, the introduction of computer technology laid the foundation for vehicle automation, driving the early development of Electronic Control Units (ECUs) and supporting the evolution of intelligent driving systems [2]. In the 1980s, the application of neural networks enhanced the adaptability of autonomous driving in complex environments, accelerating progress in pattern recognition, path planning, and intelligent control systems. In the 21st century, intelligent vehicle technology advanced toward higher levels of automation and commercialization. In 2011, the Hongqi HQ3 autonomous driving test validated the stability of intelligent decision-making systems in complex environments, providing a reference for commercialization [3]. This test proved long-distance autonomous driving feasible and validated key modules like sensor fusion, path planning, and decision control, supporting L3+ systems. In 2018, NVIDIA launched the Jetson AGX Xavier platform with high-performance GPUs and deep learning accelerators. This boosted computing power for real-time perception, decision-making, and control. In 2024, Tesla's FSD V12 adopted an end-to-end neural network architecture, achieving autonomous driving control through large-scale data training. Compared to traditional rule-based and modular autonomous driving systems, this end-to-end learning approach reduces the limitations of manually defined rules, improves adaptability to complex traffic environments, and marks a shift from symbolic logic reasoning to data-driven deep learning models. This breakthrough refines path planning and driving strategies, speeding up L4-L5 autonomy.

2.2. Key Technological Breakthroughs and Innovations in Intelligent Vehicle Systems

The autonomous driving has evolved via three key phases, high-definition (HD) mapping, map-free planning, and AI-based learning, which aims to minimize dependencies, enhance adaptability, and improve autonomous decision-making.

The HD mapping phase (2022-2023) relied on mapping vehicles to create high-precision road models for navigation. While this approach provided accurate positioning, its dependence on static data limited real-time adaptability, making it unsuitable for dynamic road conditions. The map-free planning phase (2023-2024) adopted rule-based path planning, utilizing code-driven algorithms to interpret traffic signals and driving logic for better adaptability in complex environments. Tesla's early FSD versions (pre-V12) utilized this approach. However, since rule-driven systems cannot predefine all possible scenarios, human intervention remained necessary, restricting full autonomy. The AI-based autonomous learning phase (2024-present) marks a shift to data-driven autonomous driving. End-to-end neural networks use large-scale driving data to train models that mimic human decision-making, reducing dependence on pre-programmed rules. Tesla's FSD V12 exemplifies this shift, thus marking the transition from rule-based logic to deep learning-driven autonomy. However, challenges such as data quality, training costs, and algorithm generalization persist, posing obstacles to full implementation.

The trend in intelligent driving is toward reduced human intervention, increased adaptability, and advancement toward L4-L5 autonomy. And breakthroughs will hinge on optimizing data training, boosting computational efficiency, and refining real-time decision-making to ensure safer and more reliable autonomous driving systems.

DOI: 10.54254/2755-2721/141/2025.22055

2.3. Autonomous Driving Classification and Sensor Distribution

The classification of autonomous driving technology was initially introduced by the U.S. National Highway Traffic Safety Administration (NHTSA), which developed a five-level system from L0 (manual driving) to L5 (fully autonomous driving). This classification provided a framework for the global development of intelligent driving technology and influenced standardization efforts in other countries. Many countries have localized this system, such as Germany, which refined it to meet the requirements of its automotive industry, China, which emphasizes the integration of intelligent and connected technologies while aligning with international standards, and the European Union, which introduced a six-level system for a more precise depiction of technology development stages [2].

Despite varying standards across countries, the core principle remains: classification depends on automation level and driver involvement. For example, the EU emphasizes driver monitoring, while the U.S. focuses on automation capabilities.

At L0, there is no automation, and the driver is responsible for all driving tasks. At L1, driving assistance features like Adaptive Cruise Control (ACC) are introduced, but the driver must be ready to take control at any moment. L2 adds lane-keeping to longitudinal control, requiring the driver to remain attentive and intervene when needed. L3 enables the vehicle to autonomously manage all driving tasks in certain conditions, but the driver must intervene in more complex environments. At L4, the vehicle can drive autonomously in most situations without driver intervention and will enter a minimal risk state if the driver fails to respond to a takeover request. L5 represents full autonomy, where the vehicle can manage all driving tasks in any environment without any need for driver intervention. Figure 1 illustrates the sensor distribution for L4 and L5 vehicles, ensuring accurate perception and decision-making in complex driving environments [4]. These classifications reflect the gradual progress of autonomous driving technology, from driver assistance to full automation.

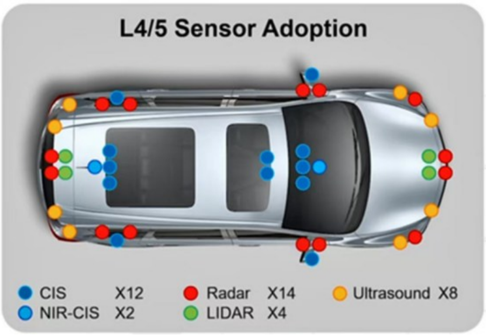

Figure 1: Distribution of Autonomous Driving Sensors

3. The Perception System and Technological Evolution in Autonomous Driving Systems

3.1. Perception Systems and Intelligent Driving Technologies

The Autoware architecture is the world’s first “All-in-One” open-source software for autonomous driving, consisting of sensing, computing, and actuation. The computing module handles perception, planning, and decision-making, with perception focused on positioning, detection, and prediction through cameras, radars, sensor fusion, and deep learning [2,5].

3.1.1. Vehicular Camera Technologies and Applications

Vehicular cameras are essential components of autonomous driving and driver assistance systems, providing environmental perception. These cameras are categorized by their installation positions: front, rear, and side-mounted. Each serves a specific function, such as lane boundary detection,

DOI: 10.54254/2755-2721/141/2025.22055

rearview imaging, and lateral safety monitoring. As autonomous technology advances, the number and precision of cameras improve, with monocular, binocular, and triocular cameras providing accurate three-dimensional data for complex driving tasks. Table 1 shows the installation positions and functions of these cameras: front cameras detect lanes, rear cameras assist with parking, and side cameras ensure lateral safety.

Table 1: Installation Positions and Functions of Vehicular Cameras

Type	**Front-mounted**	**Rear-mounted**	**Side-mounted**
Installation	Front upper windshield, grille, or bumper	Outside the trunk lid	Bottom of door mirror, B-pillar
Function	Detect lane boundary, Distinguish warm body objects during nighttime driving	Provide rear-view image, work together with rear-view radar, assist to back a car	Provide lateral vision, ensure safety when overtaking

The number of lenses in vehicular cameras plays a crucial role in boosting depth perception and stereoscopic vision capabilities. Monocular cameras are suitable for basic object detection, while binocular and triocular cameras provide accurate three-dimensional information through disparity, meeting the high precision requirements of autonomous driving systems. Binocular cameras utilize the principle of disparity to capture three-dimensional information, thus providing high frame rates, enhanced reliability, and reduced sensitivity to lighting conditions. And they are commonly used in EyeSight driving assist technology. Triocular cameras, equipped with three lenses arranged in a 120-degree configuration, provide a broader field of view, minimize data errors, and are better suited for complex driving environments, as demonstrated by the use of Tesla's triocular lenses [1]. The application of SLAM (Simultaneous Localization and Mapping) technology in autonomous driving depends on three-dimensional environmental data provided by binocular cameras. SLAM collects real-time data from the surrounding environment to assist autonomous driving systems in path planning and decision-making, which enhances the precision and dependability of autonomous driving, particularly in challenging conditions. Binocular cameras collect three-dimensional data via disparity calculations, facilitating precise path planning. Leading automakers like Subaru and Tesla have widely adopted this technology, integrating SLAM to enhance decision-making capabilities.

3.1.2. Vehicular Radar Technologies and Functions

Vehicle radar technologies are mainly divided into millimeter-wave radars, LiDARs, and ultrasonic radars. These radars work by emitting waves or lasers and receiving echoes to measure information such as the distance, speed, and azimuth of target objects, which is crucial for autonomous driving. Millimeter-wave radars measure distance with high resolution, performing well in various weather conditions. They are mainly used for short- and medium-range detection but can be impacted by severe weather. LiDARs create high-precision 3D maps using lasers, thus allowing accurate object detection and shape identification, making them ideal for obstacle detection and path planning in complex environments. The main disadvantage of LiDARs is their high cost and limited scanning range [6]. Ultrasonic radars are used for short-range detection, like parking and low-speed driving. They are cost-effective and lightweight but vulnerable to interference from noise, dust, and weather. And temperature also affects the operation of ultrasonic radars, and the specific impact mechanism is as follows:

$$c = c_0 + 0.607T \tag{1}$$

DOI: 10.54254/2755-2721/141/2025.22055

where = 332m/s (T = 0), and T is the temperature (in Celsius). Temperature variations affect the propagation speed of ultrasonic waves, thereby influencing detection accuracy. Reverse-parking ultrasonic radars are the most widely used application of ultrasonic radar [3].

The working principle of LiDARs is similar to that of millimeter-wave radars. They primarily emit lasers, receive the reflected waves, and process the data. By emitting lasers and receiving the echoes, LiDARs generate 3D point clouds. To accurately locate targets and convert them into real-world 3D coordinates, LiDARs use Cartesian coordinate transformation:

$$\begin{cases} x = r\cos\omega\sin(\alpha+\delta) \\ y = r\cos\omega\cos(\alpha+\delta) \\ z = r\sin\omega \end{cases} \tag{2}$$

where $r$is the distance between LiDAR and detection target, ω is the laser vertical angle, α is laser horizontal rotation angle, δ is channel horizontal offset angle. By utilizing these parameters, LiDARs can convert point cloud data into 3D maps, thus providing accurate spatial information for autonomous driving systems [1].

As illustrated in Table 2, different radar technologies have unique advantages and limitations. Millimeter-wave radars excel in short- and medium-range detection and perform well in various weather conditions. LiDARs generate high-precision 3D point cloud maps, but they are expensive and have a limited scanning range. Ultrasonic radars are commonly used for short-range obstacle detection due to their low cost but are easily affected by external interference.

Table 2: Comparison of Radar Technologies in Automotive Applications

Type	**Function**	**Advantages**	**Disadvantages**	**Common Models**	**Detection Error**
Millimeter-Wave Radar	Monitor the distance, speed, and azimuth of the target	High resolution, suitable for various weather conditions	Poor long-range accuracy; insensitive to non-metallic materials	ARS408	$\pm$0.05m for 0-20m; $\pm$0.4m for 0-100m
LiDAR	Create 3D point cloud maps of the surroundings, help with path planning and obstacle detection	High precision, strong object recognition ability, not affected by light	Expensive, limited scan range	RoboSense 128-line	$\pm$0.03m for 0-230m
Ultrasonic Radar	Detect close-range obstacles, assist with parking and low-speed operation	Low cost, suitable for short-range detection	Affected by external interference, less accurate at long distances	AK2	Large error for long distances

The vehicle's kinematic model, integrated with radar technology, enables target prediction and trajectory planning, as illustrated in Figure 2. The Ackermann steering model is commonly applied to calculate a vehicle's speed, angle, and other parameters, aiding autonomous driving systems in decision-making [1]. And the system processes vehicle state information, including speed, angular velocity, wheel angle, and curvature, to control the vehicle's actuators.

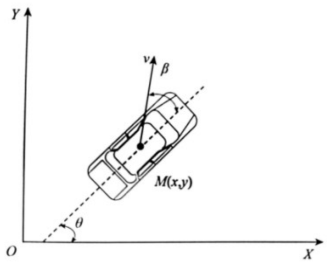

Figure 2: Vehicle Kinematic Model

$$\frac{d_x}{d_t} = v\cos(\beta + \theta) \tag{3}$$

$$\frac{d_y}{d_t} = v\sin(\beta + \theta) \tag{4}$$

where M represents the vehicle's center of mass, v represents the current velocity vector of the vehicle, θ represents the current heading angle of the vehicle, and β represents the angle between the current velocity direction of the vehicle and the vehicle's heading angle, which can be called the vehicle's center of mass offset angle.

3.2. Design and Implementation of Driver Assistance Systems

Adaptive Cruise Control (ACC) and Lane Keeping Assistance (LKA) aretwo of the most advanced and mature driver assistance systems. And the combination of these two functions enables partial automation of driving and plays a crucial role in advancing higher levels of autonomous driving [7]. As the evolution of cruise control, ACC addresses the limitations of conventional systems that are unable to adjust to the varying speeds of surrounding vehicles, thus making them suitable only for simple traffic scenarios [8]. In contrast, ACC uses millimeter-wave radars and sensors, employing PID control to adjust speed based on errors, effectively responding to speed changes in real-time. For full-speed adaptive cruise control, accurate and timely speed adjustments at low speeds require continuous tuning of PID parameters. However, traditional PID control alone cannot address the complexities of real-world driving conditions. To improve safety, comfort, and efficiency, ACC must integrate additional control algorithms that combine data from various sources for more comprehensive control [9]. The LKA utilizes high-resolution front cameras, millimeter-wave radars, and LiDAR to detect lane boundaries. The system monitors the vehicle's position and body posture in the lane through multiple sensors. Wheel speed sensors and the Inertial Measurement Unit (IMU) measure the vehicle's speed, distance, and angle changes. The system calculates data including the vehicle's deviation from the lane centerline and the angle between its driving direction and the lane markings. When the vehicle starts to drift out of the lane, the control system calculates the required steering angle using preset PID control and model predictive control algorithms, automatically adjusting the steering to keep the vehicle centered within the lane [10]. As shown in Figure 3, the function of PID control is illustrated [11].

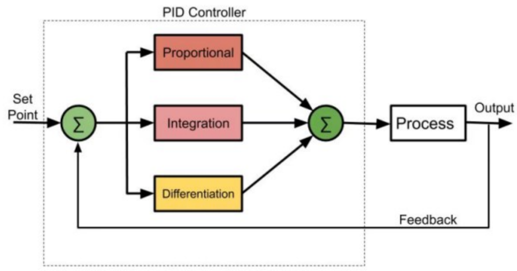

Figure 3: Function of PID control

3.3. Functions and Impacts of Advanced Driving Assistance Systems

Advanced Driving Assistance Systems (ADAS) are vital to the progress of intelligent vehicles and act as a key factor in achieving complete autonomous driving. By enhancing a vehicle's perception, decision-making, and control abilities, ADAS not only increases driving safety and comfort but also significantly eases the driver's workload, improving the overall driving experience. In terms of safety, ADAS features like ACC, LKA, and Forward Collision Warning monitor the surrounding road environment in real-time. When potential risks are identified, the system quickly alerts the driver or takes automatic actions such as braking or steering, thus greatly lowering the chances of a collision. ADAS proves particularly advantageous in extreme weather conditions. Vehicle radar and cameras are less affected by weather, continuously providing accurate environmental information to the driver, which improves judgment and enhances safety. In addition, ADAS greatly enhances driving convenience and comfort. For example, the automatic parking system allows for precise parking, reducing the need for driver intervention. ACC adjusts the vehicle's speed according to the traffic ahead, reducing the frequency of accelerator and brake pedal use. Additionally, the system can automatically adjust the chassis stiffness to improve ride comfort, thus enhancing the overall user experience. Future intelligent driving technology will integrate AI and visual language models, improving vehicle adaptability in real-world scenarios. Through continuous learning, the system will improve its accuracy in tasks such as traffic sign recognition, lane changing, and overtaking, thereby enhancing the intelligence of autonomous driving [12].

4. Conclusion

This study explores the application of Advanced Driving Assistance Systems (ADAS) in intelligent vehicles and the challenges of autonomous driving technology. The results indicate that with the upgrades in perception systems, the introduction of artificial intelligence, and improvements in chip computing power, future intelligent driving systems will be more accurate and effective. Despite progress in safety, convenience, and comfort, intelligent driving systems still encounter technical bottlenecks, particularly in adapting to traditional vehicles and handling performance challenges in complex environments and extreme weather. Limitations of the study include limited predictions about future technologies, lack of empirical data, and insufficient analysis of system performance in different environments. Future research will aim to improve the adaptability of intelligent driving systems, resolve technical challenges, optimize communication, and explore advanced AI and deep learning algorithms to enhance decision-making and adaptability.

References

[1] He, J. (2021) Development and verification of automotive intelligent driving systems. China Machine Press.
[2] Xue, S. (2024) Research on the application of mechatronics in automotive mechanical systems. Automotive Maintenance Technician, 18: 31-33.

DOI: 10.54254/2755-2721/141/2025.22055

[3] *[Rui, P.E. (2021.) Intelligent vehicle autonomous driving and autonomous driving assistance technology. Chemical Industry Press.*

[4] *Patnzar, J. (n.d.) The Challenges to Achieve Level 4/Level 5 Autonomous Driving. https://www.gsaglobal.org /forums/the-challenges-to-achieve-level-4-level-5-autonomous-driving/*

[5] *Bagi, S., et al. (2021) Blind Spot Detection System in Vehicles Using Fusion of Radar Detections and Camera Verification. International journal of ITS research, 19(2): 389-404.*

[6] *Guo, Q., Su, Y. and Hu, T. (2023) LiDAR Principles, Processing and Applications in Forest Ecology. Higher Education Press.*

[7] *Zhang, W. (2022) The technological development status and trends of advanced driver assistance systems and automotive chips. Metal Functional Materials, 29(04), 70-77.*

[8] *Liu, Z., et al. (2021) A Multi-Objective Model Predictive Control for Vehicle Adaptive Cruise Control System Based on a New Safe Distance Model', International journal of automotive technology, 22(2): 475-487.*

[9] *Wang, L. (2020) PID Control System Design and Automatic Tuning using MATLAB/Simulink.*

[10] *Chen, W.W, et al. (2020) Lane departure warning systems and lane line detection methods based on image processing and semantic segmentation: A review. Journal of Traffic and Transportation Engineering (English Edition), 7(6): 748-774.*

[11] *SMLease Design. (2022). What is PID (Proportional-Integral-Derivative) control? SMLease Design. https://www.smlease.com/entries/automation/what-is-pid-proportional-integral-derivative-control/*

[12] *Jimenez, F. (2018) Intelligent Vehicles: Enabling Technologies and Future Developments. Butterworth-Heinemann*