

A Review of Automated Driving and ADAS Technologies

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Abstract

Automated driving and advanced driver assistance systems (ADAS) are transforming road mobility, promising enhanced safety, improved traffic efficiency, and greater accessibility. This review presents a comprehensive synthesis of core technologies, system architectures, sensor modalities, perception, and decision-making algorithms, and evaluation methodologies underpinning contemporary ADAS and automated driving. We provide a detailed discussion of the functional components, such as sensors (camera, radar, light detection and ranging (LiDAR), ultrasonic), localization, perception, prediction, planning, control, and human-machine interfaces, and how these integrate within modular and end-to-end architectures. A two-page literature survey distills seminal and recent contributions across academic research and industrial deployments, highlighting breakthroughs in deep learning-based perception, sensor fusion strategies, robust localization, and simulation-based validation. Methodological approaches for developing and validating ADAS systems are summarized, including data-driven model training, closed-loop simulation, hardware-in-the-loop testing, and on-road trials. Key challenges are examined, such as safety assurance, handling edge cases, sensing limitations in adverse weather, regulatory and ethical considerations, cybersecurity, and human factors. Finally, we outline future directions such as scalable validation frameworks, V2X integration, artificial intelligence (AI) interpretability, and shared autonomy paradigms. The review aims to serve researchers, engineers, and policymakers with a structured overview and practical recommendations for advancing safe, reliable automated driving systems. Automated driving and ADAS represent a significant evolution in intelligent transportation, aiming to improve road safety, traffic efficiency, and driving comfort. This review paper provides a structured overview of key ADAS and automated driving technologies, including system architecture, sensor technologies, perception, decision making, and control algorithms. It surveys major advancements in camera, radar, LiDAR-based sensing, sensor fusion, and deep learning techniques for environmental understanding. Additionally, the paper discusses validation methodologies, safety challenges, human-machine interaction, and regulatory aspects. Future research directions, such as V2X integration, scalable testing, and explainable AI, are also highlighted.

Keywords: ADAS, automated driving, localization, perception, planning, safety assurance, sensor fusion, V2X

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INTRODUCTION

Today, automated driving and advanced driver-assistance systems (ADAS) encompass a broad set of functionalities designed to assist or replace human driving tasks. From basic lane-keeping assistance and adaptive cruise control to fully autonomous vehicles capable of performing all driving tasks under defined conditions, these technologies rely on sensing, perception, decision-making, and control systems. The automotive industry, academia, and regulatory bodies have made significant progress in recent years; however,

achieving robust and deployable autonomy in various real-world scenarios remains a complex multidisciplinary challenge. This review organizes the field into component layers, summarizes influential literature, discusses common methodologies for development and validation, and identifies open problems and future research avenues [1–5].

Road transportation is a critical component of modern society, enabling economic growth, social connectivity, and mobility of people and goods. However, rapid motorization has also led to serious challenges such as traffic congestion, road accidents, environmental pollution, and increased energy consumption. According to global road safety reports, human error contributes to the majority of traffic accidents, including errors in perception, decision-making, fatigue, distraction, and improper vehicle control [6–9]. These challenges have driven significant research and industrial interest in ADAS and automated driving technologies, which aim to enhance vehicle safety, efficiency, and driving comfort by reducing the reliance on human judgment alone (Figure 1).

ADAS represents the first major step toward vehicle automation. ADAS technologies assist drivers by providing warnings, partial control, and automated responses in critical situations. Common ADAS features include anti-lock braking systems (ABS), electronic stability control (ESC), adaptive cruise control (ACC), lane departure warning (LDW), lane-keeping assist (LKA), automatic emergency braking (AEB), blind spot detection (BSD), and parking assistance systems. These systems use a combination of sensors, electronic control units (ECUs), and control algorithms to monitor the vehicle surroundings and support safer driving decisions. ADAS has evolved from simple warning systems to more complex functions capable of actively intervening in vehicle control [10–13].

Automated driving technologies extend the capabilities of ADAS by enabling vehicles to perform driving tasks with reduced or no human intervention. The Society of Automotive Engineers (SAE) has classified driving automation into six levels, ranging from Level 0 (no automation) to Level 5 (full automation). Although most production vehicles today operate at levels 1 and 2, research prototypes and limited commercial deployments have demonstrated levels 3 and 4 automation in controlled environments. Fully autonomous vehicles (Level 5) remain a long-term goal, requiring breakthroughs in perception, decision-making, validation, and regulatory frameworks [14–17].



Figure 1. Exploring the future of safe driving.

The core of automated driving systems lies in their ability to perceive, understand, and interact with complex and dynamic environments. Unlike controlled industrial automation, road environments are highly uncertain and involve diverse actors such as pedestrians, cyclists, animals, and human-driven vehicles. Automated vehicles must operate reliably under various lighting conditions, weather scenarios, traffic densities, and road infrastructure. To address these challenges, modern ADAS and automated driving systems rely heavily on multisensor architectures that integrate cameras, radars, LiDAR, ultrasonic sensors, global navigation satellite systems (GNSS), and inertial measurement units (IMUs). These sensors provide complementary information that enhances the robustness and redundancy of the system (Figure 2).

Recent advances in artificial intelligence (AI), particularly in machine and deep learning, have significantly accelerated the progress of automated driving. Deep neural networks have achieved remarkable performance in tasks such as object detection, lane recognition, traffic sign classification and semantic scene understanding. Sensor fusion techniques combine data from multiple sensors to overcome individual limitations and improve their reliability. In addition, high-definition (HD) maps and localization algorithms enable precise vehicle positioning, which is essential for accurate planning and control. Together, these technologies form a layered system architecture comprising sensing, perception, localization, prediction, planning, and control modules [18].

Despite substantial technological progress, the widespread deployment of automated driving systems faces several challenges. Ensuring safety is the most critical concern, as automated vehicles must demonstrate performance equal to or superior to that of human drivers across a vast range of scenarios, including rare and hazardous edge cases. The validation and verification of these systems are difficult because of the numerous driving situations encountered in real-world applications. Furthermore, ethical considerations, legal liabilities, cybersecurity threats, and public acceptance play crucial roles in determining the pace of adoption. Human-machine interaction is another important factor, particularly in partially automated systems, wherein a safe and timely transfer of control between the vehicle and driver is essential.

This review article provides a comprehensive overview of automated driving and ADAS technologies, focusing on the system components, key research developments, and evaluation methodologies. A detailed literature survey highlights the foundational and recent contributions of academia and the industry.

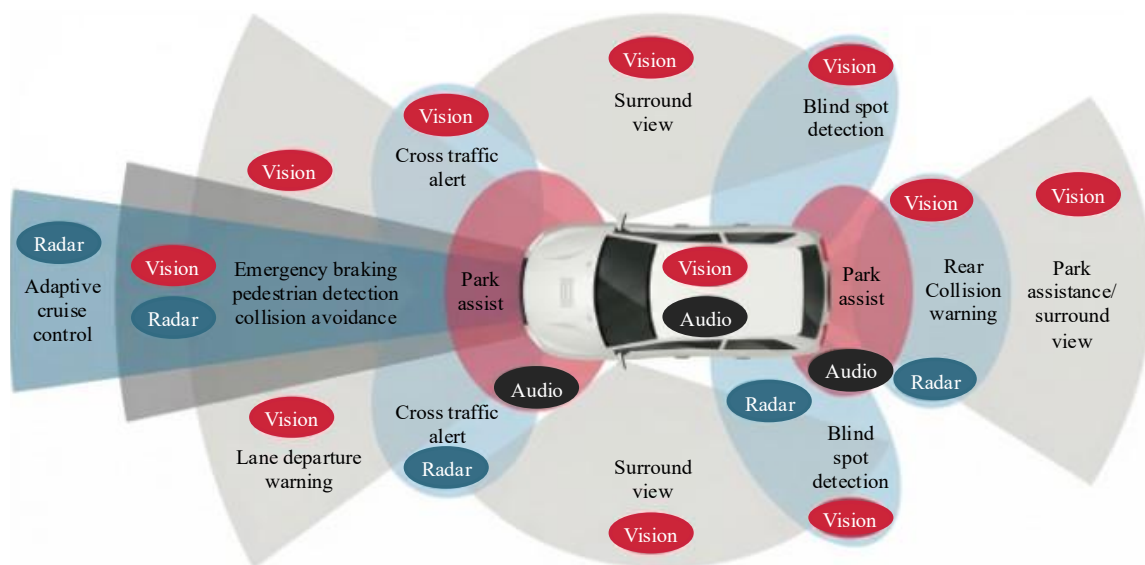


Figure 2. Vision and image processing in automotive ADAS/AD development.

This paper also discusses common development methodologies, major technical and nontechnical challenges, and emerging research directions. By synthesizing existing knowledge and identifying future opportunities, this review serves as a useful reference for students, researchers, engineers, and policymakers in the fields of intelligent transportation and automotive automation.

COMPONENTS OF AUTOMATED DRIVING AND ADAS SYSTEMS

Automated driving and ADAS are designed using a layered architecture. Each component performs a distinct function, thereby enabling the perception, decision-making, and control of the vehicle. Figure 3 presents a functional overview of the major components of the system.

Sensing Systems

Sensing systems provide real-time information about the vehicle surroundings. Cameras, radars, LiDAR, ultrasonic sensors, GPS, and inertial sensors are commonly used. Cameras capture visual cues, such as lanes, signs, and obstacles. Radar offers accurate distance and speed measurements, even in poor weather, and LiDAR generates high-resolution three-dimensional (3D) point clouds for environmental mapping. Ultrasonic sensors are effective for short-range detection of obstacles.

Perception and Sensor Fusion

Perception systems interpret the sensor data to identify objects, lanes, and free spaces. Sensor fusion combines multiple sensor inputs to improve reliability and reduce uncertainty. Modern perception systems extensively use deep-learning algorithms.

Localization and Mapping

Localization estimates the position of the vehicle within the environment. GNSS provides global positioning, whereas simultaneous localization and mapping (SLAM) and HD maps ensure lane-level accuracy. Accurate localization is essential for path planning and navigation.

Prediction

Prediction modules estimate the future motion of road users. These estimates consider the uncertainty and interactions among multiple agents, thereby enabling safe maneuver planning.

Planning and Decision Making

Planning algorithms generate collision-free trajectories that satisfy the traffic rules and vehicle constraints. Decision making determines maneuvers such as lane changes, overtaking, and stopping at intersections.

Vehicle Control System

The control system converts the planned trajectories into actuator commands for steering, braking, and the acceleration. Controlling algorithms, such as proportional–integral–derivative (PID) and model predictive control, ensure stability and comfort of the user.

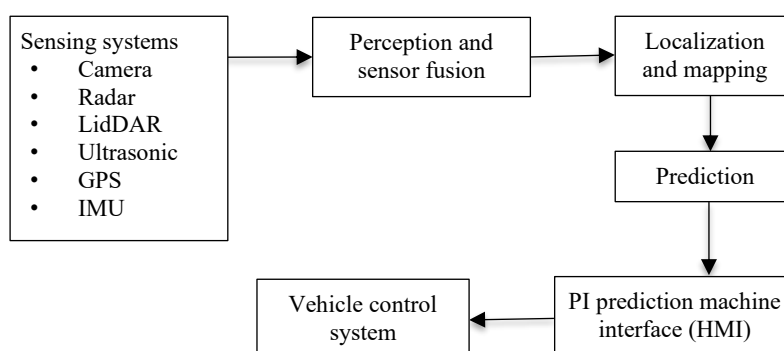


Figure 3. Architecture of automated driving and ADAS.

Human–Machine Interface (HMI)

The HMI enables communication between the driver and automation system. Visual, auditory, and haptic feedback inform the driver of the system status and takeover requests.

V2X Communication

Vehicle-to-everything communication enhances situational awareness by sharing data with other vehicles and infrastructure.

LITERATURE SURVEY

The following literature survey highlights the influential academic and industry contributions that have shaped the current state of ADAS and automated driving. The selection emphasizes widely cited studies, foundational standards, and recent trends in perception, planning, validation, and safety.

SAE International: Levels of Driving Automation (J3016)

The SAE J3016 taxonomy standardizes automation levels (0–5) and provides a common language for researchers and regulators. It is fundamental to define system capabilities and regulatory requirements.

Kalra and Paddock (2016): Driving to Safety

This study analyzed the safety paradox of autonomous vehicles by discussing probabilistic approaches to safety validation and the challenges of deriving acceptable risk levels compared with those of human drivers [2].

Bojarski et al. (2016): End-to-End Learning for Self-Driving Cars

This study demonstrated end-to-end deep learning from raw pixels to the steering commands. Although promising, end-to-end approaches raise questions regarding interpretability and safety guarantees compared with modular pipelines [3].

Geiger et al. (Karlsruhe Institute of Technology and Toyota Technological Institute (KITTI) Dataset, 2012–2013)

The KITTI benchmark has accelerated research in vision-based perception by providing high-quality datasets for stereo, optical flow, object detection and tracking. Benchmarks such as the KITTI have spurred rapid progress in algorithms [4].

Chen et al. (2017): Multi-View 3D Object Detection (MV3D)

MV3D and subsequent multisensor fusion methods combine LiDAR and camera data to improve 3D detection accuracy, establishing fusion as a standard practice for robust perception [5].

Waymo/Google and Waymo Open Dataset (2019)

Waymo's dataset and industry-scale efforts have provided large-scale, labeled sensor data capturing complex urban driving scenarios, enabling data-hungry deep learning models and evaluations at scale [6].

Ziegler et al. (Berkley/Uber/Others): Motion Planning Frameworks

Classical motion planning techniques (graph search and sampling-based planners) combined with optimization approaches have provided robust solutions for trajectory generation under constraints, and modern systems often hybridize these with learned components [7].

Ulbrich et al. (2015): Pedestrian Intention Prediction

Prediction research focuses on modeling uncertainties and multi-modal futures. Bayesian approaches, Gaussian processes, and deep learning planners have contributed methods for anticipating the behaviors of other agents [8].

Shalev-Shwartz et al. (2016): Formal Safety Frameworks

This study argues for formal and provable safety frameworks and decompositions that enable system-level safety arguments and influence how industries approach verification [9].

NVIDIA DRIVE, Mobileye, and Industrial Perception Stacks (2015–2021)

Commercial platforms have integrated high-performance computing, optimized perception stacks, and mapping solutions into their systems. These efforts have highlighted the engineering challenges of moving from research prototypes to production systems [10].

Simulation and Validation: Car Learning to Act (CARLA) and LG Silicon Valley Lab (LGSVL)

Open-source simulators provide reproducible environments for training and testing perception and planning algorithms, and simulation has become essential for covering rare edge cases and scaling validation.

Sensor Failure and Robustness Studies

Research on adverse weather sensing, sensor degradation, and redundancy strategies has emphasized the need for robust fusion and fallback behavior.

Human Factors and Takeover Studies

Empirical studies have examined driver behavior under partial automation, attention, trust, and the dynamics of safe handover between vehicles and drivers.

METHODOLOGY

Currently, the development and validation of ADAS and automated driving systems typically follow an iterative, multistage methodology:

1. *Data collection*: Multi-sensor logging (camera, LiDAR, radar, IMU, and GNSS) across diverse environments and edge cases.
2. *Algorithm development*: Supervised, self-supervised, and reinforcement learning were used for the perception and decision modules. Classical model-based methods are vital for control and verification purposes.
3. *Simulation and synthetic data*: Leveraging simulators for scenario generation, corner case exploration, and training data augmentation.
4. *Hardware-in-the-Loop (HIL) and Software-in-the-Loop (SIL) testing*: Hardware-in-the-loop and software-in-the-loop frameworks for validating real-time performance and integration.
5. *Field trials*: Controlled track tests followed by instrumented on-road trials with safety drivers and phased deployments.
6. *Safety assurance*: Fault injection testing, formal verification where applicable, and safety cases aligned with standards (ISO 26262, ISO/PAS 21448).

The evaluation metrics included detection and tracking accuracy, localization error, trajectory tracking error, collision rates in the simulation, and reliability metrics under different environmental conditions.

CHALLENGES

- Safety assurance and validation across the long tail of edge cases.
- Perception limitations in adverse weather or occlusion.
- Explainability and interpretability of deep learning models.
- Regulatory harmonization and legal liability for automated actions.
- Cybersecurity risks and secure over-the-air updates.
- *Human factors*: handover, driver monitoring, and trust calibration.
- HD mapping dependence vs. map-less approaches.
- Cost, scalability, and energy consumption of sensors and computing platforms.

FUTURE SCOPE

Research and industry trends indicate several promising directions:

- *Scalable validation*: statistical validation methods, scenario-based testing, and distributed real-world data-sharing.
- V2X and infrastructure augmentation to reduce sensing ambiguity in complex environments.
- Lightweight, efficient perception models for edge compute and energy-constrained platforms.
- Explainable AI methods to support safety cases and regulatory acceptance.
- Shared autonomy paradigms enabling flexible handover and cooperative driving among connected agents.
- Standardized datasets and benchmarks for safety-critical evaluation and cross-vendor interoperability.

CONCLUSION

Automated driving and ADAS technologies have advanced significantly, driven by breakthroughs in sensing, artificial intelligence (AI), and computing. However, robust deployment at scale requires continued progress in safety assurance, validation and human-centered design. A balanced approach that combines data-driven learning with provable system-level guarantees, extensive simulations, and careful real-world validation is crucial for achieving the societal benefits of automation while managing risks.

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