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Technical Survey on Sensor-Aided Automatic Parallel Car Parking Systems for Effective Vehicle Navigation

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Abstract

Sensor-aided automatic parallel parking systems represent a cornerstone of modern Advanced Driver Assistance Systems (ADAS) and emerging autonomous vehicle technologies. These systems alleviate urban parking challenges by automating space detection, path planning, and precise vehicle control, thereby reducing driver stress, low-speed collisions (by up to 75%), circling time, and associated emissions. Early implementations (2000–2015) relied primarily on ultrasonic sensors for basic reverse aids, evolving into sophisticated multi-modal architectures incorporating radars, cameras, Light Detection and Ranging (LiDAR), infrared, magnetic, and electromagnetic sensors. Sensor fusion strategies leveraging Kalman filters, probabilistic occupancy grids, and deep neural networks address individual sensor limitations such as weather sensitivity, noise, and limited range, achieving detection accuracies exceeding 95% in controlled settings. Recent advancements (2023–2025) integrate Reinforcement Learning (RL), diffusion models, 4D imaging radars, transformers, and end-to-end deep learning for robust performance in dynamic, low-visibility urban environments. Path planning employs geometric (Reeds-Shepp), optimization-based Particle Swarm Optimization (PSO), and Model Predictive Control (MPC) methods, while perception benefits from CNNs (YOLO) and RL for adaptive decision-making. Commercial systems (Tesla Autopark, BMW Parking Assistant Plus, Ford Active Park Assist) vary in their strengths in vision-based autonomy, precision, and reliability. However, challenges persist in adverse weather, computational constraints, sensor interference, regulatory compliance (ISO 26262), and user trust. Real-world benchmarks reveal success rates of 85-99% under ideal conditions but highlight degradation in clutter, rain, or unstructured lots. This review underscores the transition toward fully Autonomous Valet Parking (AVP) and smart-city integration via Vehicle-to-Everything (V2X), while identifying critical needs for weather-resilient fusion, verifiable AI, and enhanced human-machine interfaces to accelerate safe, widespread adoption.

Keywords: Sensor-aided, Car parking systems, Vehicle navigation, Advanced driver assistance systems.

1 | Introduction

Parking assistance systems, often integrated into Advanced Driver Assistance Systems (ADAS), are designed to aid drivers in locating, maneuvering into, and monitoring parking spaces, thereby reducing accidents, stress, and time spent searching for spots. These technologies are particularly vital in urban environments, where parking scarcity contributes to traffic congestion, increased emissions, and economic losses estimated at

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billions of dollars annually due to inefficient space utilization [1], [2]. At their core, sensor technologies enable real-time detection of obstacles, free spaces, and environmental conditions, evolving from simple audible alerts to fully Autonomous Valet Parking (AVP) systems where vehicles self-park without human intervention. The foundational concept of parking assistance dates back to the 1990s, with basic ultrasonic sensors for reverse parking aids. Still, advancements in the 21st century have incorporated a broader array of sensors, Artificial Intelligence (AI), and Internet of Things (IoT) connectivity [3], [4]. Modern systems distinguish between Automatic Parking Assist (APA), where the vehicle controls steering. At the same time, the driver manages acceleration and braking, while AVP handles the entire process autonomously. Key drivers include urbanization, the rise of electric and autonomous vehicles, and sustainability goals, such as optimizing space in smart cities to reduce "circling" traffic. Sensor fusion, combining data from multiple sources, has become essential for robustness, addressing individual sensor limitations such as weather sensitivity or limited range [5]. As of 2026, these technologies not only enhance safety (reducing low-speed collisions by up to 75%) but also support broader Intelligent Transportation Systems (ITS), including predictive analytics for space availability and integration with Vehicle-to-Everything (V2X) communication. The sensor technologies for parking assistance span from early sensor-focused implementations to recent AI-driven, multi-modal systems [6], [7]. This review synthesizes key developments in a thematic framework, drawing on systematic reviews, empirical studies, and technological analyses published between 2000 and 2025. It highlights historical evolution, sensor classifications, fusion techniques, AI integration, recent advancements, and persistent challenges.

1.1 | Historical Evolution and Early Developments (2000-2015)

Early research emphasized basic detection for roadside and structured parking, transitioning from manual monitoring to automated systems. Initial studies focused on single-sensor approaches, such as ultrasonic sensors for proximity alerts in reverse parking, as seen in early 2000s work [8]. For instance, laser scanners and 3D stereo vision cameras were explored for occupancy detection in on-street parking, achieving accuracies around 95% but limited by high costs and environmental factors such as lighting conditions. By the mid-2010s, hybrid methods emerged, combining sensors with image processing for better reliability. A 2014 review on automatic parking systems classified approaches into sensor-based (ultrasonic for path planning), vision-based (cameras for slot recognition), and control strategies, noting challenges in real-time computation and unstructured environments. Investigations around 2012–2015 highlighted Wireless Sensor Networks (WSNs) for open lots, with ultrasonic and infrared sensors dominating due to their low power and ease of deployment. However, they are prone to interference [9]. These early works laid the groundwork for Smart Parking Systems (SPS), emphasizing cost-effective, scalable solutions to reduce search times by up to 30%.

1.2 | Sensor Classifications and Technologies (2016-2022)

Subsequent studies classified sensors based on detection principles, invasiveness, and application contexts, with ultrasonic sensors emerging as the most prevalent (35% of studies) due to their affordability and precision for short-range occupancy detection [10]. Cameras followed (26%), leveraging computer vision for wide-area monitoring, though they are vulnerable to weather and require AI for processing. Other types included magnetometers for magnetic field disruptions (effective in buried installations), infrared for heat-based detection, radars for long-range all-weather performance, and smartphones' embedded sensors (accelerometers, GPS) for crowd-sourced data. Ultrasonic sensors offer high accuracy but limited range, while radars provide robustness in fog/rain but at a higher cost. Cameras enable semantic understanding but demand computational resources [11]. For open parking lots, non-invasive sensors like geomagnetics were favored for durability, while IoT integration via protocols like ZigBee (60% usage) enabled low-power networking. Emerging LPWAN technologies (LoRa) addressed range limitations in large urban areas, reducing deployment costs by minimizing wiring.

1.3 | Sensor Fusion and AI Integration (2020-2023)

Fusion techniques gained prominence to mitigate single-sensor weaknesses, combining ultrasonics for close-range, radars for velocity/elevation, and Light Detection and Ranging (LiDAR) for 3D mapping. Probabilistic frameworks like Kalman Filters handled uncertainty, while tightly coupled LiDAR-IMU fusion improved SLAM in GPS-denied environments [12]. AI, particularly CNNs and YOLO, enhanced detection accuracies to 99%, integrating with UAVs for aerial monitoring and AVM for 360° views. Studies from 2020 to 2023 emphasized hybrid systems, such as sensor-camera fusion for roadside parking, reducing emissions by 45% through real-time updates. Challenges included computational overhead and weather degradation, with solutions such as event-based cameras for low-latency operation in dynamic scenarios.

1.4 | Recent Advancements (2023-2025)

Pivotal studies from 2023 to 2025 focused on AI-centric innovations. Reinforcement Learning (RL) (SAC with Reeds-Shepp paths) achieved high success rates in dynamic environments, while diffusion models generated smooth trajectories. 4D imaging radars and monocular VIO offered all-weather, cm-level accuracy [13]. End-to-end datasets and transformers improved fusion performance in low-visibility conditions, achieving 85% success on benchmarks. Commercial systems like Hyundai's AAPS integrated cameras/ultrasonics for seamless deployment. Trends include verifiable AI, multi-agent coordination, and federated learning for data scarcity.

2 | Vehicle Parking Challenges

Parking maneuvers include perpendicular, angled, and parallel types, with parallel parking being the most complex due to tight spaces and the need for precise steering. It involves detecting a suitable gap, typically 1.5 times the vehicle's length, and executing a multi-stage trajectory as shown in *Fig. 1* [14]. Sensor-aided systems automate this by measuring space and controlling the vehicle, reducing the 15% of drivers who avoid it due to anxiety.

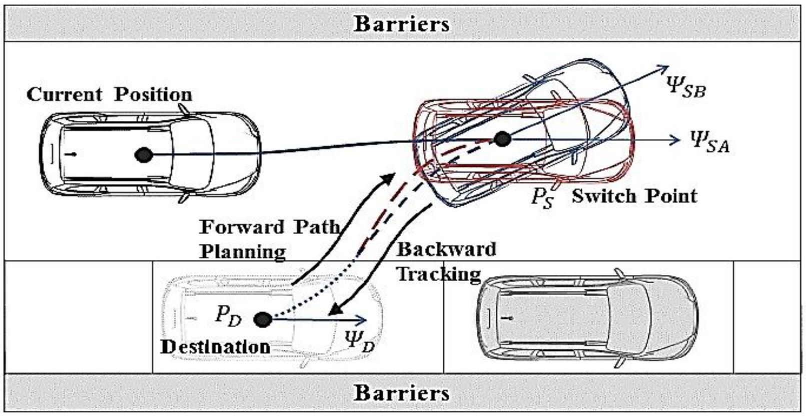

Fig. 1. Illustration of the path planning algorithm applied to parallel parking maneuver [15].

2.2 | Limitations of Manual Parking and Driver Assistance Needs

Manual parking is prone to errors, especially in low visibility or crowded areas, leading to collisions and inefficiencies. Drivers often require assistance for blind spots, distance estimation, and maneuver precision [16]. Sensor-aided systems mitigate these issues by providing real-time feedback, with studies showing that automated parking requires fewer maneuvers and achieves greater accuracy. Assistance needs include obstacle detection, path guidance, and emergency braking to enhance safety.

2.3 | Navigation in Urban Environments

Navigation systems integrate GPS, IMU, and sensors to guide vehicles to parking spots, optimizing routes in urban congestion. They play a crucial role in smart cities by incorporating real-time data on availability, reducing circling time by up to 30%. V2X communication further enhances this by sharing infrastructure data for cooperative parking [17], [18].

2.3.1 | Types of sensor technologies for parking assistance

Parking assistance systems, also known as parking aids or ADAS for parking, rely on various sensor technologies to detect obstacles, measure distances, and guide vehicles into parking spaces. These technologies are used in both in-vehicle systems (reverse parking sensors) and broader parking guidance systems (in parking lots). Below is a comprehensive list of the main types, based on common implementations.

I. Ultrasonic sensors: these are the most common type used in vehicle parking assistance. They emit high-frequency sound waves (ultrasound) that bounce off nearby objects, measuring the time taken for the echo to return to calculate distance. Typically installed on bumpers, they provide audible or visual alerts for obstacles during low-speed maneuvers like reversing or parallel parking (see *Fig. 2*). This sensor is very affordable and effective for close-range detection (up to about 5-6 feet). Still, it is less accurate in bad weather and can be fooled by certain surfaces [19].

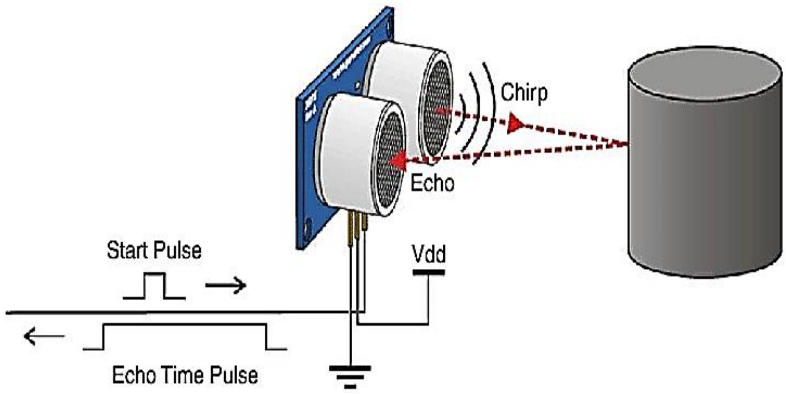

Fig. 2. Ultrasonic sensors [20].

II. Radar sensors use radio waves to detect objects and measure their speed/distance. In parking assistance, it's often used for longer-range detection than ultrasonic, making it suitable for features such as blind-spot monitoring integrated with parking aids [21]. This sensor works well in poor visibility conditions (e.g., fog, darkness) and can detect moving objects (see Fig. 3). It is more expensive and may experience interference issues in crowded environments. It can be applied to adaptive cruise control, extended to parking, and to pedestrian detection during parking.

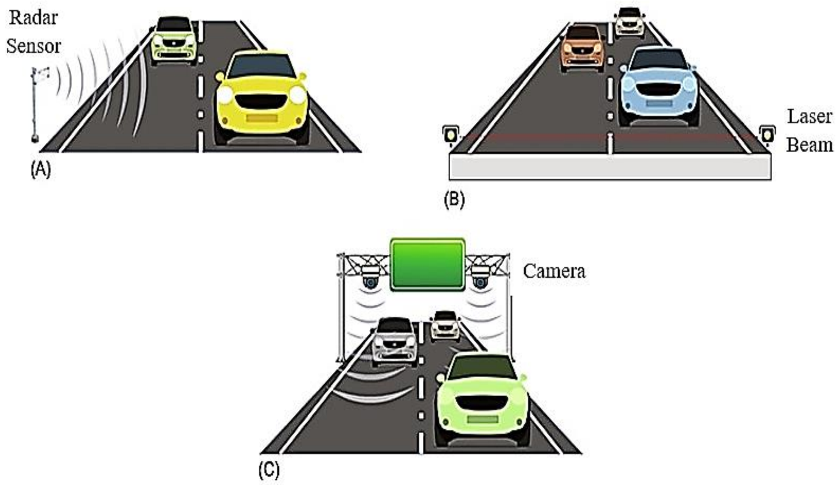

Fig. 3. Radar sensor configuration [22].

III. Camera-based sensors: these types of sensors use optical cameras (often with image-processing AI) to provide visual feedback, such as 360-degree views or bird's-eye perspectives. They detect parking lines, curbs, and obstacles through computer vision [23]. It provides real-time video feeds for better situational awareness and can integrate with displays for guided parking (see *Fig. 4*). The sensor's performance degrades in low light, with dirt on the lenses, or under adverse weather conditions. Its common applications include rear-view cameras and automated parking systems.

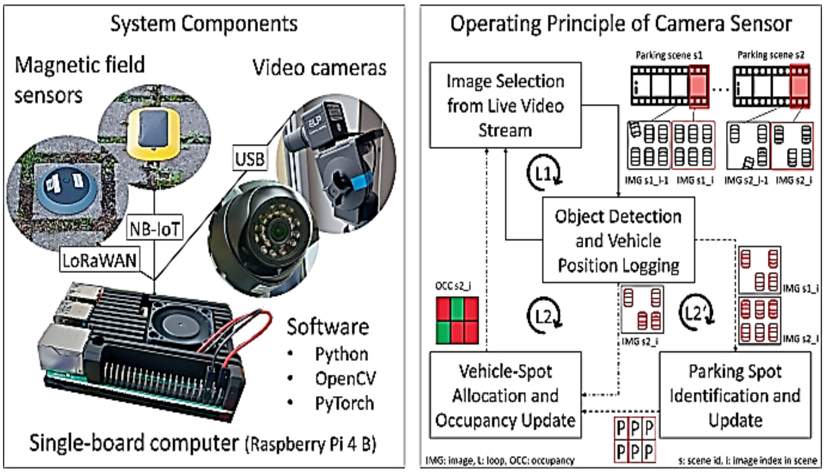

Fig. 4. Camera-based sensors in vehicle parking.

IV. Electromagnetic sensors: these types of sensors generate an electromagnetic field around the vehicle to detect metallic objects or changes in the field caused by nearby obstacles [24]. Often hidden behind bumpers for a seamless look. It can be installed discreetly with no visible holes in the bumper, and it can also detect stationary objects well. However, its limitation stems from its limited range (shorter than radar) and its lesser effectiveness on non-metallic objects. The electromagnetic sensors are seen in *Fig. 5*.

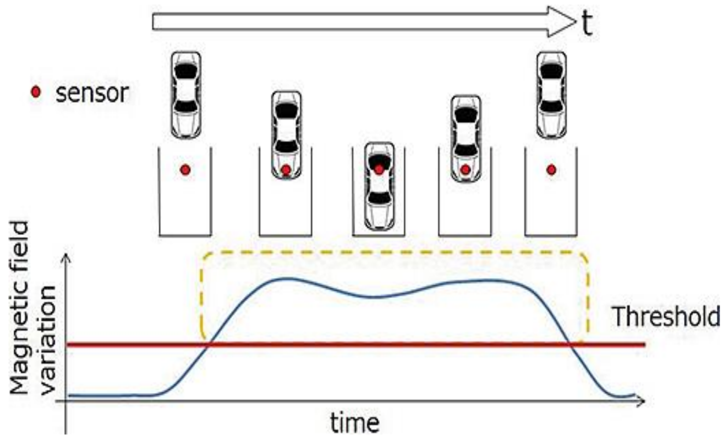

Fig. 5. Electromagnetic sensors [25].

V. LiDAR sensors: LiDAR uses laser pulses to create a 3D map of the surroundings, offering precise distance measurements. It's emerging in advanced autonomous parking systems [26]. It has high accuracy and detailed environmental mapping, even in complex scenarios. LiDAR sensors are expensive and very sensitive to weather conditions such as rain or fog (see *Fig. 6*).

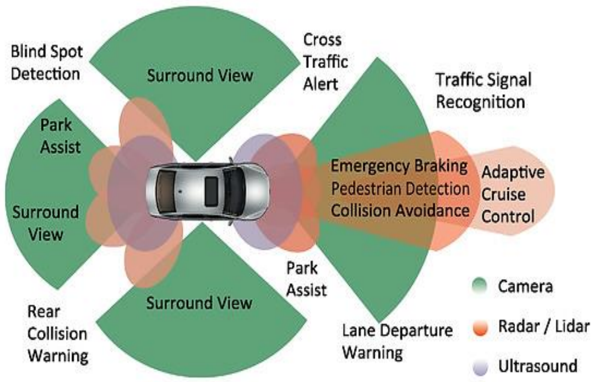

Fig. 6. LiDAR sensors [27].

VI. Infrared sensors: infrared sensors detect heat or infrared radiation from objects, useful for identifying vehicles or obstacles in parking guidance systems. It is very effective in low-light conditions and can distinguish between objects based on temperature [28]. However, it is limited in range and also affected by ambient temperature variations (*Fig. 7*).

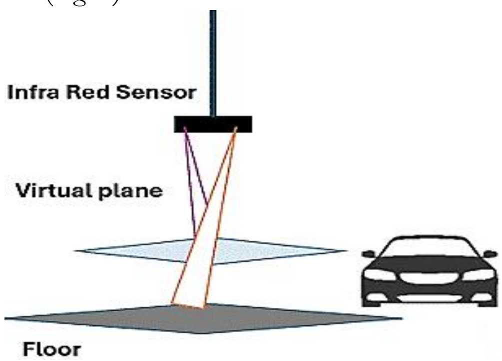

Fig. 7. Infra-red sensors for smart parking management system [29].

VII. Magnetic sensors: magnetic sensors detect changes in the Earth's magnetic field caused by vehicles (which contain metal). Often used in in-ground or puck-style sensors for parking lots. It has low power consumption, and it's very durable for embedded installations, but it is less effective for non-metallic vehicles or in areas with magnetic interference [30]. It is commonly applied for parking space monitoring in guidance systems (*Fig. 8*).

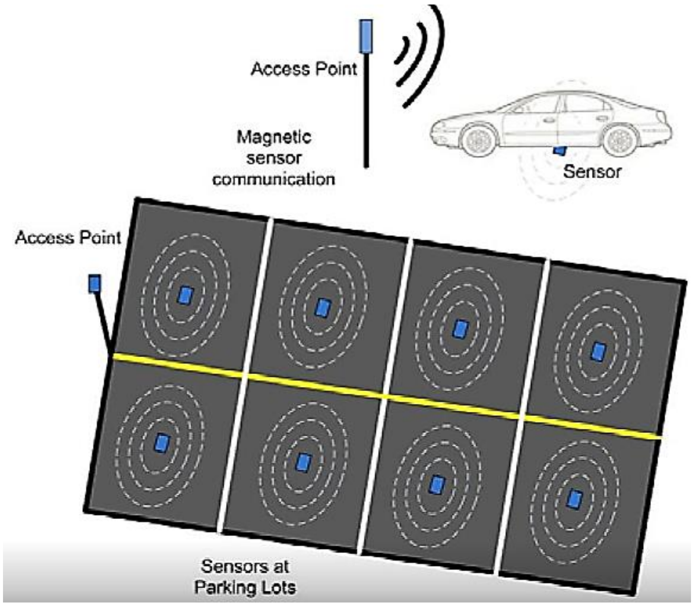

Fig. 8. WSN system with magnetic sensor [31].

2.4 | Sensor Fusion Strategies for Enhanced Accuracy

Sensor fusion, as shown in *Fig. 9*, combines data from ultrasonics, radar, LiDAR, cameras, and other sources to mitigate individual limitations, using approaches such as low-level (raw data merging), mid-level (feature extraction), and high-level (decision integration). Techniques include Kalman filters for state estimation and DNNs for early fusion, improving obstacle detection by 20-30%. In automatic parking, fusion creates 3D environmental models for precise localization, as in Early Grid Fusion (EGF), which outputs 4 cm-resolution height maps. Strategies like consensus frameworks adaptively weight sensors to improve urban reliability, achieving superior performance compared to single modalities. Multi-modal fusion with AI enhances decision-making, reducing false positives in varied conditions [32].

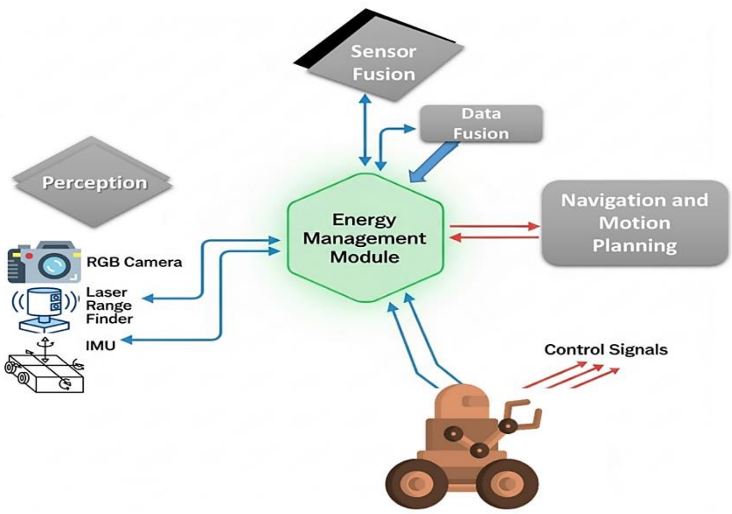

Fig. 9. Functional overview of the energy-aware channel robot [33].

3 | System Architecture of Sensor-Aided Automatic Parallel Parking

The system architecture of sensor-aided automatic parallel parking integrates hardware, software, communication protocols, and navigation systems to enable precise, real-time vehicle control. This framework processes sensor data for environment perception, plans parking maneuvers, and executes them via actuators, ensuring safety and efficiency in urban settings [34]. Key elements include modular designs for scalability, real-time processing to handle dynamic conditions, and fusion of multiple data sources for robust performance.

3.1 | Hardware Components (Sensors, Actuators, and ECUs)

Hardware forms the foundation of automatic parallel parking systems, comprising sensors for perception, actuators for vehicle control, and Electronic Control Units (ECUs) for processing. Sensors, such as ultrasonic, radar, and camera sensors, detect parking spaces and obstacles, with ultrasonic sensors providing short-range distance measurements via sound waves [35]. Actuators, including steering motors, brakes, and throttle controls, execute maneuvers in response to ECU commands. ECUs integrate sensor data, run path-planning algorithms, and interface with vehicle systems, such as the Body Control Module (BCM), for centralized management. For instance, systems like Bosch's Park Assist use ultrasonic sensors in bumpers to scan the surrounding area, while ECUs process this data to control steering and braking. Advanced setups incorporate LiDAR for 3D mapping and IMUs for vehicle orientation, fused in ECUs for accuracy (see *Fig. 10*). In Tesla's Autopark, multiple cameras and ultrasonics connect to a central ECU for vision-based parking [36]. Hardware integration often uses System-on-Chip (SoC) platforms with FPGAs for parallel processing, ensuring low-latency responses in confined spaces.

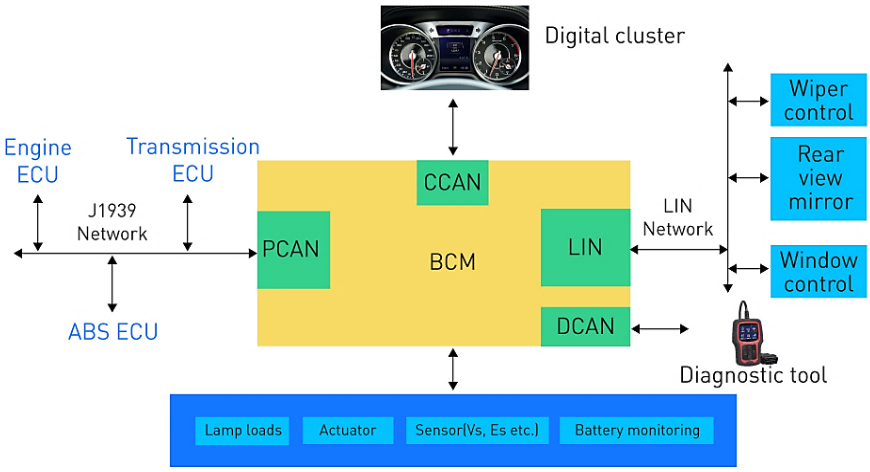

Fig. 10. Electronics components in vehicles [37].

3.2 | Communication Protocols (CAN, Ethernet, and Wireless Interfaces).

Communication protocols enable seamless data exchange between sensors, ECUs, and actuators in parking systems. Controller Area Network (CAN) provides robust, low-speed communication for real-time control signals, such as sensor data to ECUs, with variants like CAN-FD offering higher bandwidth (see *Fig. 11*). Automotive Ethernet supports high-speed data transfer (up to 10 Gbps) for video from cameras or LiDAR point clouds, using topologies with switches for point-to-point connections, reducing wiring complexity [38]. Wireless interfaces, including LoRaWAN for long-range, low-power sensor networks in smart parking and WiFi/Bluetooth for V2X integration, facilitate the exchange of external data, such as parking availability.

Protocols like IEEE 802.11p (WAVE) ensure secure, low-latency vehicle-to-infrastructure communication. Security features, such as MACsec and IPsec, protect against attacks via VLAN segmentation. In hybrid setups, MQTT enables efficient IoT data exchange for real-time updates, while DSRC and C-V2X support ad-hoc routing for dynamic environments [39].

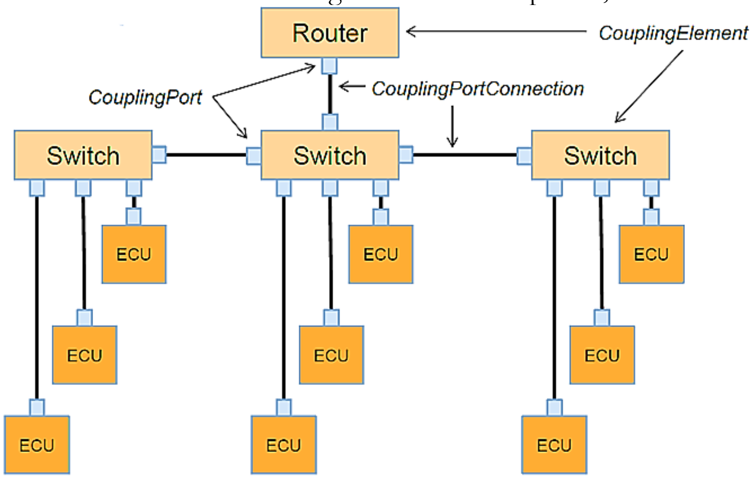

Fig. 11. Automotive Ethernet and its applications [40].

3.3 | Integration with Vehicle Navigation Systems.

Integration merges parking assistance with navigation for end-to-end guidance, from route planning to spot execution. Systems use GPS and IMUs for positioning, fused with sensor data for precise localization in urban areas [41]. Navigation interfaces, like BMW's iDrive or Android Auto, display parking options on maps, with features such as saved locations for automatic parking activation. Multi-sensor ensembles recognize spaces under both parallel/nonparallel states, dynamically adapting trajectories. In Kia's remote smart parking assist, infotainment screens display maneuvers, integrating with collision-avoidance systems for safety. V2X enables cooperative parking by sharing availability data. Toyota's IPAS ties sonar and cameras to navigation displays for steering guidance. Advanced systems like Nissan's use around-view monitors for a bird's-eye view, enhancing user interaction.

4 | Algorithms and Methods for Parallel Parking

Algorithms and methods for parallel parking form the core of sensor-aided automatic systems, enabling vehicles to detect parking spaces, plan paths, generate trajectories, control movements, and avoid obstacles in real time. These techniques integrate sensor data with computational models to execute precise maneuvers, often under constraints like limited space and dynamic environments [42]. Common approaches include geometric modeling for simple paths, optimization for complex scenarios, and machine learning for adaptive perception, with control strategies ensuring stable tracking.

4.1 | Space Detection and Measurement Algorithms

Space detection algorithms process sensor data from ultrasonics, radar, LiDAR, or cameras to identify and measure suitable parallel parking spots, typically requiring a gap at least 1.2-1.5 times the vehicle's length. Methods include edge detection in camera images using Canny filters, or Hough transforms to locate lines and curbs, while point cloud analysis from LiDAR employs clustering to segment free spaces [43]. Ultrasonic-based algorithms scan laterally as the vehicle passes, using time-of-flight to map distances and fit rectangles for spot validation. Advanced techniques fuse multi-sensor data with Kalman filters to achieve 5-10 cm accuracy, while handling noise and occlusions. For instance, in simulation environments, algorithms achieve 94% detection rates by combining occupancy grids with probabilistic models. Deep learning variants, such as CNNs, classify spots from overhead views, improving robustness across varied lighting conditions.

4.2 | Path Planning Techniques: Geometric and Optimization-Based

Path planning generates feasible routes from the vehicle's current position to the parking spot, accounting for kinematic constraints and obstacles. Geometric techniques use circular arcs and straight lines based on the vehicle's turning radius, such as the Reeds-Shepp model for shortest paths with forward/reverse segments [44]. For parallel parking, a common method involves two arcs: one for initial alignment and another for backing in, ensuring collision-free curvature continuity. Optimization-based approaches, like A or Hybrid A, discretize the space into grids and search for optimal paths using heuristics, incorporating vehicle constraints via state lattices. Improvements include dynamic replanning and B-spline smoothing for curvature-limited paths, reducing computation time by 30-50% in narrow spaces. Particle Swarm Optimization (PSO) refines paths by minimizing cost functions for smoothness and safety [45].

4.3 | Trajectory Generation and Tracking

Trajectory generation refines planned paths into time-parameterized profiles, incorporating velocity and acceleration for smooth execution. Techniques use polynomials to interpolate waypoints, ensuring jerk minimization and kinematic feasibility. Tracking employs feedback loops to follow the trajectory, using pure pursuit for geometric steering or Stanley controllers for lateral error correction. In parallel parking, trajectories which often include multi-phase segments, approach, reverse, and straighten, with adaptive adjustments for sensor updates, simulations show tracking errors under 10 cm using kinematic bicycle models (see *Fig. 12*). Integration with SLAM enhances localization for precise tracking in unmapped areas [46].

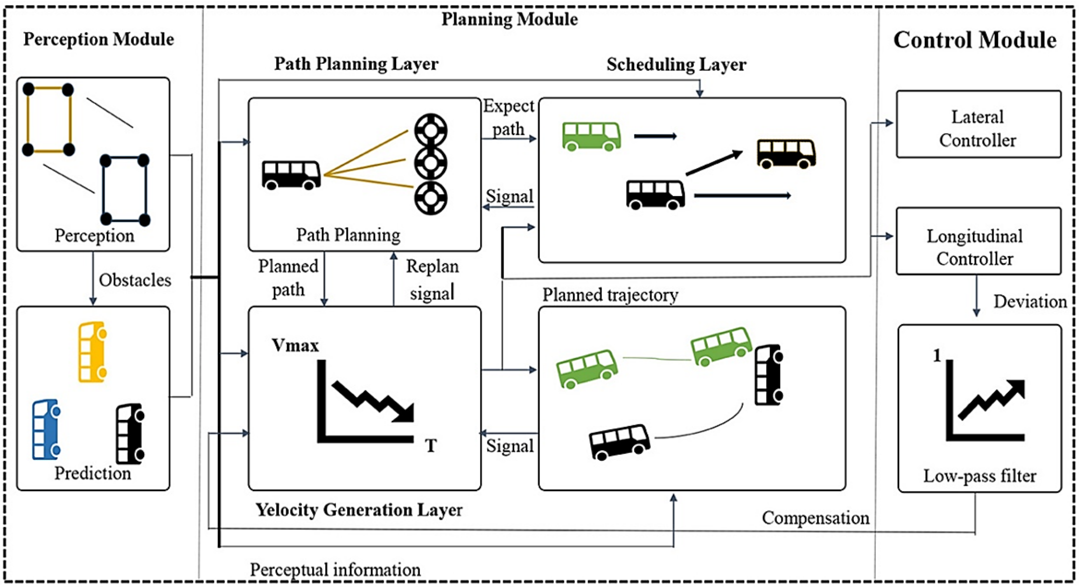

Fig. 12. Overall algorithm flowchart [47].

4.4 | Control Algorithms

Control algorithms regulate steering, throttle, and braking to execute trajectories. Proportional-Integral-Derivative (PID) controllers provide simple feedback for lateral and longitudinal control and tune gains for stability during low-speed maneuvers, though they struggle with nonlinearities [48]. Model Predictive Control (MPC) optimizes future states over a horizon, solving quadratic programs to handle constraints such as wheel slip and obstacles, achieving sub-centimeter parking accuracy. Fuzzy Logic mimics human reasoning with rule-based systems for uncertain environments, fuzzifying inputs like distance errors and outputting defuzzified controls, ideal for variable conditions. Hybrid approaches combine PID for basics with MPC for predictions, reducing computation while improving robustness. Q-learning enhances fuzzy systems for adaptive parking [49].

4.5 | Machine Learning and Deep Learning Approaches for Perception and Decision Making

Machine learning, particularly deep learning, enhances perception by processing raw sensor data to extract features. CNNs like YOLO or Faster R-CNN detect parking spaces and obstacles from camera feeds, achieving 89-95% accuracy in real-time. RL trains agents for decision-making, optimizing parking policies via rewards for successful maneuvers, as in Q-learning for path selection [50]. End-to-end DL models map sensor inputs directly to controls, using architectures such as LSTMs for sequential data. In perception, auto-encoders denoise LiDAR points, while GANs generate synthetic scenarios for training. These approaches adapt to unseen environments and outperform traditional methods in complex urban settings.

4.6 | Real-Time Obstacle Avoidance and Collision Detection

Real-time obstacle avoidance integrates detection with reactive planning, using algorithms such as the Dynamic Window Approach (DWA) or artificial potential fields to repel from threats while attracting to goals. Collision detection uses bounding boxes or voxel grids on sensor data to predict trajectories with constant-velocity models for dynamic objects. In parking, hybrid systems replan paths via A upon detection, fusing MPC for evasive controls [51]. Techniques achieve response times of 20-50 m/s, ensuring safety margins of 20-30 cm. SLAM-based mapping updates environments dynamically, while fuzzy Logic handles uncertainty in avoidance decisions.

5 | Real-World Testing Scenarios and Benchmarks

Real-world testing validates simulation results by exposing systems to unpredictable conditions, using structured scenarios and benchmarks to measure performance. Scenarios include urban parking lots with clutter, varying weather (rain reducing sensor accuracy by 10-20%), lighting (95% accuracy in daylight and 90% at night), and angles (93% for 45-degree plates). Benchmarks like PS 2.0 and SNU datasets evaluate slot detection with metrics such as 99% precision in controlled tests, but real-world failures highlight gaps in complex scenes [52]. NHTSA frameworks outline testable cases, including lane changes, vehicle following, and parking at speeds up to 15 mph, with failure modes like unresponsive drivers. Proving grounds dominate with 34% market share for controlled tests. At the same time, virtual-to-real transitions use HiL for safety. Challenges include environmental robustness and human behavior, with datasets like CRPS-D improving models for diverse conditions, achieving 95% in shadows but lower in damaged lots. These tests ensure systems like AVP meet reliability standards for urban deployment.

5.1 | Comparative Analysis of Existing Systems

A comparative analysis of commercial automatic parallel parking systems reveals variations in technology, performance, and usability among leaders such as Tesla, BMW, and Ford. Tesla's Autopark relies on vision-based cameras for parallel/perpendicular parking and remote summon, excelling in autonomy but slower and prone to failures in tight spaces or curbs [53]. BMW's Parking Assistant Plus uses ultrasonics and cameras for precise maneuvers, achieving better curb alignment and speed, and earning greater user trust due to its reliability. Ford's Active Park Assist 2.0 integrates sensors for automated steering and braking, reducing curb distance by 37%, but it still ignores curbs in some models, leading to inconsistencies. In tests, BMW and Ford outperform Tesla in parallel parking success (Tesla fails in narrow spots), while all reduce manual time by 20-30 seconds. Overall scores from evaluations like Consumer Reports favor Ford's BlueCruise at 84/100 for integrated assistance, highlighting Tesla's innovation but BMW's precision in real-world scenarios. Future improvements focus on sensor fusion for enhanced reliability across brands [54].

Table 1. Comparative analysis table of existing systems.

System	Technology	Accuracy (cm)	Speed (s)	Reliability (%)	Strengths	Weaknesses
Tesla autopark	Vision-based	10-20	40-60	80-90	Remote summon	Slow, curb issues
BMW parking assistant	Ultrasonics + cameras	5-10	20-30	95+	Precise alignment	Costly option
Ford active park assist	Sensors + cameras	10-15	25-40	85-95	Easy activation	Ignores curbs

6 | Challenges and Limitations

Despite advancements, sensor-aided automatic parallel parking systems face numerous challenges that impact their reliability, efficiency, and adoption. These limitations stem from environmental sensitivities, sensor imperfections, and resource constraints in vehicle hardware, safety and compliance requirements, and user interaction issues [55]. Overcoming them requires ongoing research in robust sensor fusion, AI enhancements, and user-centered design.

6.1 | Environmental Factors

Environmental conditions pose significant challenges to sensor performance in automatic parking systems, often resulting in degraded accuracy or system failures. Weather elements like rain, snow, fog, and extreme temperatures can distort sensor readings, such as those from ultrasonic sensors, which experience signal attenuation in heavy precipitation or strong winds. At the same time, cameras misinterpret wet surfaces as obstacles due to reflections [56]. Snow accumulation can block sensors entirely, reducing detection range by up to 50%. Lighting variations exacerbate issues: low-light conditions in garages or at night impair camera-based systems, leading to failures in line detection, while sunlight glare creates shadows or false positives. Urban clutter, including pedestrians, debris, irregular markings, and occlusions from nearby vehicles, complicates space recognition and path planning, resulting in aborted maneuvers or collisions in dense areas. These factors can degrade performance by 20-30%, necessitating weather-resilient sensors like radar, though even they struggle with clutter-induced multipath interference [57] (*Fig. 13*).

Fig. 13. Environmental effects on automatic parallel car parking systems [56].

6.2 | Sensor Limitations (Noise, Interference, and Calibration Issues)

Inherent sensor limitations undermine the precision of automatic parking systems. Noise from ambient sources or internal sensor variability leads to false readings; ultrasonic sensors, for instance, produce sparse data and struggle with soft or angled surfaces, while radar encounters clutter and multipath reflections in urban settings. Interference arises from electromagnetic sources or environmental factors, such as jamming in dense areas for radar or temperature-induced distortions for ultrasonic, causing up to 10-20% error rates [58]. Calibration drift due to vibrations, heat, or damage requires frequent maintenance, but misalignment can amplify fusion errors, leading to poor object classification. Limited ranges of 0.2-3m for ultrasonic and narrow fields of view necessitate multiple sensors, increasing complexity and cost, while soiling or occlusions further reduce reliability. *Fig. 14* posits a driverless technology and the key Components of autonomous vehicles.

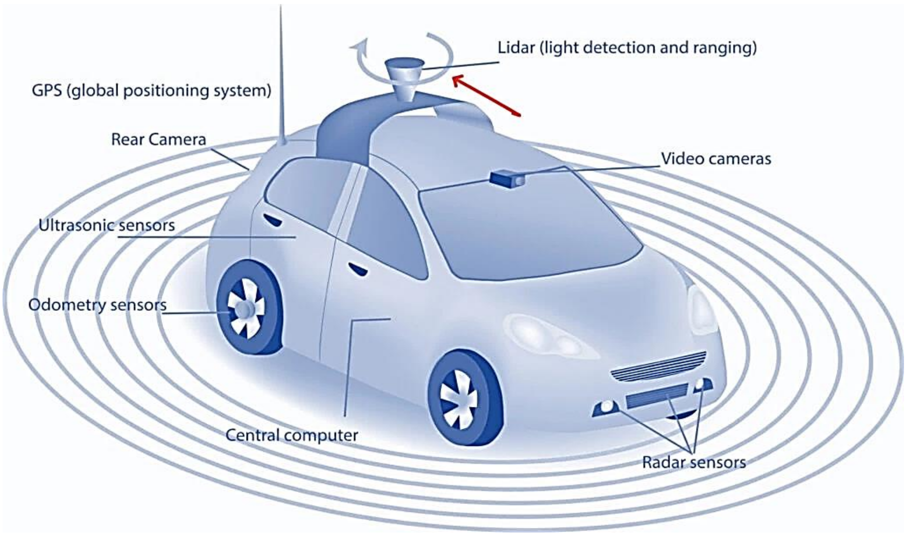

Fig. 14. Driverless technology and the key components of autonomous vehicles [59].

6.3 | Computational and Power Constraints in Embedded Systems

Embedded systems in vehicles must handle real-time processing of high-volume sensor data, but limited computational resources create bottlenecks. Complex algorithms for fusion and planning demand powerful ECUs, yet automotive hardware prioritizes cost and energy efficiency, leading to latency in dynamic scenarios and trade-offs in accuracy [60]. Power constraints are acute in electric vehicles, where sensor arrays and AI models accelerate battery drain, especially in high-accuracy modes, significantly reducing battery life. Data from LiDAR or cameras overwhelms low-power processors, risking overheating or delayed responses in tight parking maneuvers. Non-deterministic AI components further strain resources, requiring optimizations like model compression, which may compromise subtle feature detection [61]. These issues limit scalability, leading systems to often underperform in resource-intensive urban environments.

6.4 | Safety and Regulatory Considerations

Safety remains a core challenge, as systems must handle unpredictable factors such as dynamic obstacles and sensor failures without human intervention. Non-deterministic AI hinders verification, with reality gaps between simulations and real-world behaviors risking accidents in OOD scenarios. Regulatory standards such as ISO 26262 require rigorous certification, but black-box models complicate compliance, especially for fusion and planning uncertainties [62]. Liability concerns arise from errors, necessitating fail-safes such as overrides, though these can be overly conservative and reduce usability. Global variations in regulations require adaptable designs, while cost limits advanced redundancies, potentially compromising safety in adverse conditions.

6.5 | Human-Machine Interaction and User Acceptance

HMI challenges include building trust, as users often perceive systems as unreliable due to past failures or lack of transparency, leading to mis-calibrated trust and reduced adoption (80% prefer manual parking). Disadvantages such as skill degradation, imbalances in mental workload, and loss of situation awareness deter acceptance [63]. Interfaces must provide clear feedback for overrides and explanations, but vague notifications or black-box decisions erode confidence. User studies reveal anxiety over loss of control and ethical issues, with media influencing perceptions negatively. Enhancing XAI and adaptive HMIs can improve acceptance, but cultural factors and error-proneness continue to limit reliance on them (*Fig. 15*).

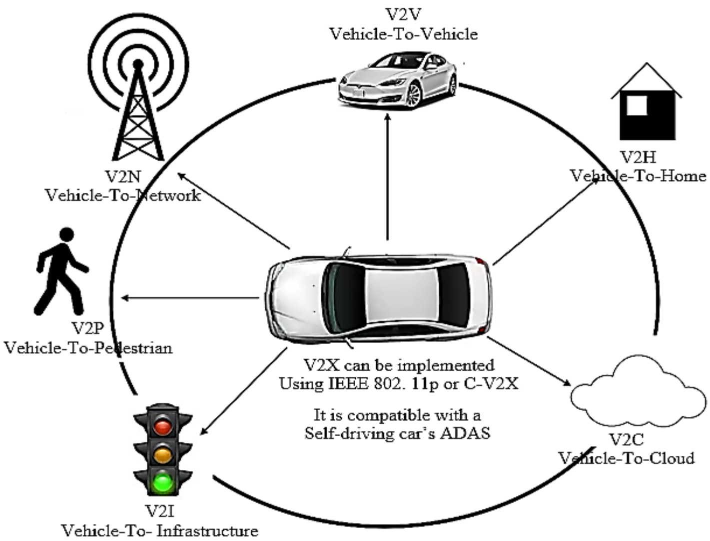

Fig. 15. V2X communications protocols for self-driving cars [35].

7 | Conclusion

Sensor-aided automatic parallel parking systems have advanced dramatically from basic ultrasonic alerts to AI-driven, multi-sensor autonomous solutions that significantly enhance vehicle navigation, safety, and urban efficiency. By fusing ultrasonics, radars, cameras, LiDAR, and emerging modalities with sophisticated algorithms ranging from geometric path planning and MPC to deep RL and transformer-based perception, these technologies achieve high precision, robustness, and adaptability in complex environments. Commercial implementations validate substantial reductions in parking time, collision risk, and driver workload, supporting broader intelligent transportation goals, including reduced congestion and emissions. Nevertheless, persistent challenges include adverse weather, sensor noise/calibration, embedded computational limits, regulatory verification of non-deterministic AI, and building user trust, which continue to hinder full reliability and mass adoption. Future progress depends on developing cost-effective, all-weather fusion architectures, verifiable and explainable AI frameworks, energy-efficient edge computing, and seamless V2X-enabled cooperative parking ecosystems. As electric and autonomous vehicles proliferate in smart cities, overcoming these barriers will be essential to realizing safe, stress-free, and sustainable automated parking that transforms urban mobility and realizes the long-term vision of fully AVP.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Data Availability

The datasets generated and/or analyzed during the current study are included in this article.

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