

# A Review of Obstacle Avoidance Path Planning Technologies for Intelligent Vehicles

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## Abstract

As a core component of autonomous driving systems, obstacle avoidance path planning technology for intelligent vehicles aims to achieve safe and efficient navigation in dynamic environments through the coordination of multiple modules. This paper systematically reviews the current state of research on the overall architecture and key algorithms of this technology, focusing on the technical developments of the three core modules: perception, decision-making, and control. In the realm of environmental perception, technologies such as multimodal fusion, V2X collaboration, and vehicle–road–cloud integration have significantly enhanced the robustness and global awareness of perception; the path decision-making module encompasses diverse developments ranging from classical graph search algorithms to intelligent optimization methods, balancing the real-time performance and optimality of decision-making algorithms; and the motion control section summarizes the trend toward integrating deterministic methods with heuristic strategies, thereby enhancing the accuracy and adaptability of trajectory tracking. The review notes that while current technologies have progressed in modular collaboration, future breakthroughs are still needed in areas such as end-to-end learning and lightweight deployment to drive the system toward higher reliability.

## Keywords

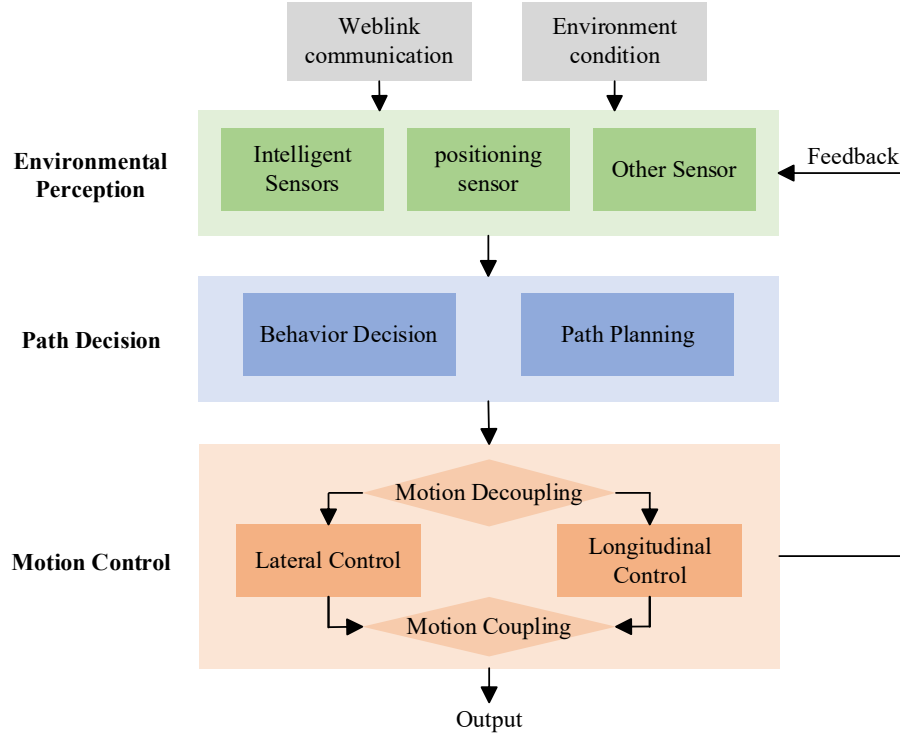
intelligent vehicles, obstacle avoidance, environmental perception, decision-making algorithms, motion control

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## 1. Core Modules and System Architecture

The core modules and system architecture serve as the foundational framework, enabling the efficient implementation of obstacle-avoidance path planning in intelligent vehicles. Their design is driven by the need for autonomous decision-making in complex traffic scenarios. Through the modular decomposition and collaborative integration of “sensing–decision–control”, a full-chain technical pathway is established, spanning from environmental perception to motion execution [1]. Its core value lies in using a systematic approach to overcome the limitations of individual modules. By fostering deep intermodule coordination, it enhances overall robustness, enabling intelligent vehicles to maintain decision-making consistency and controllable execution in uncertain environments. Through the synergy of these three components, the goal of obstacle-avoidance path planning is achieved [2]. The system architecture, which illustrates the coordination of these three modules, is shown in Figure 1.

Figure 1: System architecture for intelligent car sensing, decision-making and control



In this context, the division of core modules serves as an engineering solution to address the complexity of intelligent vehicle systems. Essentially, it achieves a modular restructuring of the technical workflow through functional decoupling. This decomposition strategy not only reduces the development difficulty and coupling risks associated with individual modules but also provides an expandable architectural foundation for multimodule collaboration through standardized interface design. In obstacle avoidance scenarios, modular design effectively isolates the cascading effects between perception noise interference, decision-making logic iterations, and control execution jitter, enabling the system to achieve independent optimization of functional units and dynamic resource allocation within limited computational power. Under this modular division of labor and dynamic collaboration, the closed-loop chain of “environmental perception → path decision-making → motion control → execution feedback” is realized, thereby establishing the overall system architecture comprising the three major modules of intelligent vehicle obstacle avoidance path planning.

As the system’s “sensory hub”, the sensing module’s core objective is to collect real-time information about the vehicle’s surrounding environment—including obstacle locations, motion states, road boundaries, and traffic signs—via multisource heterogeneous sensors. By leveraging data fusion algorithms to construct a high-precision environmental model, it provides reliable environmental prior information for subsequent decision-making [3].

The decision-making module, which serves as the system’s “intelligent brain”, has the core task of generating obstacle avoidance paths from the starting point to the destination on the basis of the environmental model provided by the perception module and vehicle dynamics constraints [4]. This module must integrate global and local dynamic programming, balance trade-offs through a cost function, and update decisions in real time to respond to dynamic obstacle interference; simultaneously, it must combine traffic rules and driving intent to achieve multiobjective cooperative optimization.

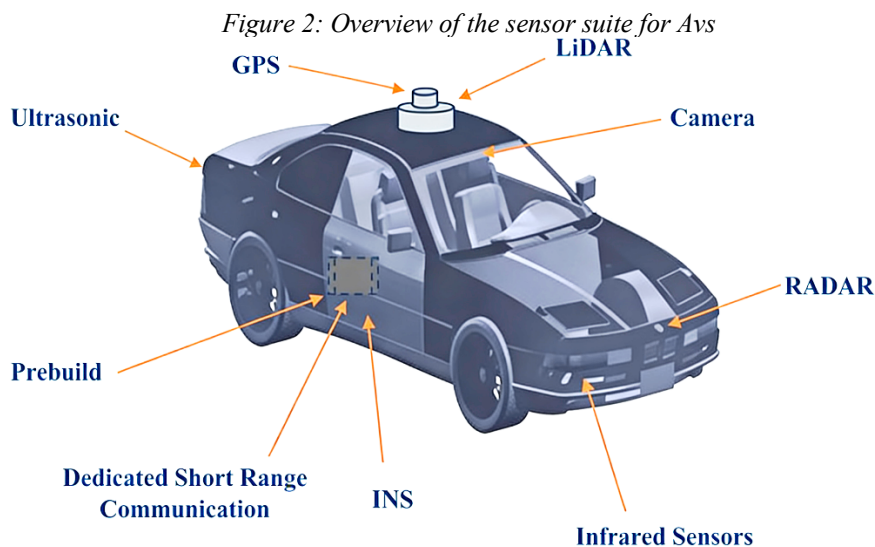
The control module serves as the system’s “execution terminal”. Its core function is to convert the path commands generated by the decision-making module into control signals for the vehicle’s actuators, ensuring that the vehicle stably tracks the target trajectory through lateral and longitudinal control [5]. This module requires the design of a multidegree-of-freedom controller to compensate for actuator delays and modelling errors and ensures motion safety through lateral dynamic constraints. Additionally, closed-loop control must be implemented using vehicle state feedback to improve path-tracking accuracy.

## 2. Environment Perception Algorithms

Environmental perception algorithms serve as the core technological engine enabling autonomous decision-making and safe driving in intelligent vehicles. Essentially, they continuously perceive complex environments composed of dynamic and static obstacles through the deep integration and intelligent analysis of multisource, heterogeneous data, providing reference information for path planning modules [3]. Today, sensor systems such as LiDAR, ultrasonic devices, GPS/GNSS modules, and vehicle-to-vehicle (V2V) communication units form the foundation of an autonomous system's environmental awareness [6]. However, in complex road scenarios, individual sensors are often limited by their physical characteristics and adaptability to the environment. Modern environmental perception algorithms are needed to overcome traditional perception frameworks and establish a three-dimensional perception system through methods such as multimodal data fusion. This system must address not only fundamental issues such as sensor noise suppression and robust target tracking but also challenges to perception reliability in scenarios involving extreme weather, communication vulnerabilities, and cyberattacks, thereby providing high-precision, low-latency descriptions of the environmental state for subsequent path planning and control decisions [7].

### 2.1 Multimodal Fusion Sensing

Multimodal fusion sensing refers to the combination of data from various sensors to gain a more comprehensive and accurate understanding of the environment, thereby enabling the system to make informed decisions [8]. This is the core approach in environmental perception algorithms for overcoming the limitations of single-sensor systems. Faced with diverse challenges in complex scenarios, where a single sensor struggles to balance accuracy and adaptability, multimodal fusion, by leveraging the strengths of heterogeneous data, has emerged as a key technological direction for enhancing the reliability of perception systems, providing a multidimensional foundation for environmental understanding to support subsequent decision-making. An overview of a typical sensor integration design for an autonomous vehicle is shown in Figure 2.



There are numerous applications of multimodal fusion sensing. For instance, Shim et al. [9] proposed the EURECAR autonomous driving system, which broke away from traditional methods that rely on prebuilt road and traffic signal maps and instead use a unified map constructed from various onboard sensors to detect obstacles; however, Roselyn et al. [10] utilized the concept of multisensor fusion to develop a comprehensive software module for autonomous vehicles. By employing convolutional neural network (CNN) algorithms in software stacks for object and lane detection and by applying sensor fusion principles and semantic segmentation to filter out erroneous object detection outputs, they provided a robust and efficient solution for the vehicle's fused perception; to improve the accuracy and robustness of yaw angle estimation for distributed-drive electric vehicles under extreme manoeuvring conditions, Chen et al. [11] proposed a redundant estimation scheme based on multisource sensor information fusion, significantly enhancing the lateral stability of the vehicle; and Barua et al. [12] integrated longwave infrared, near-infrared

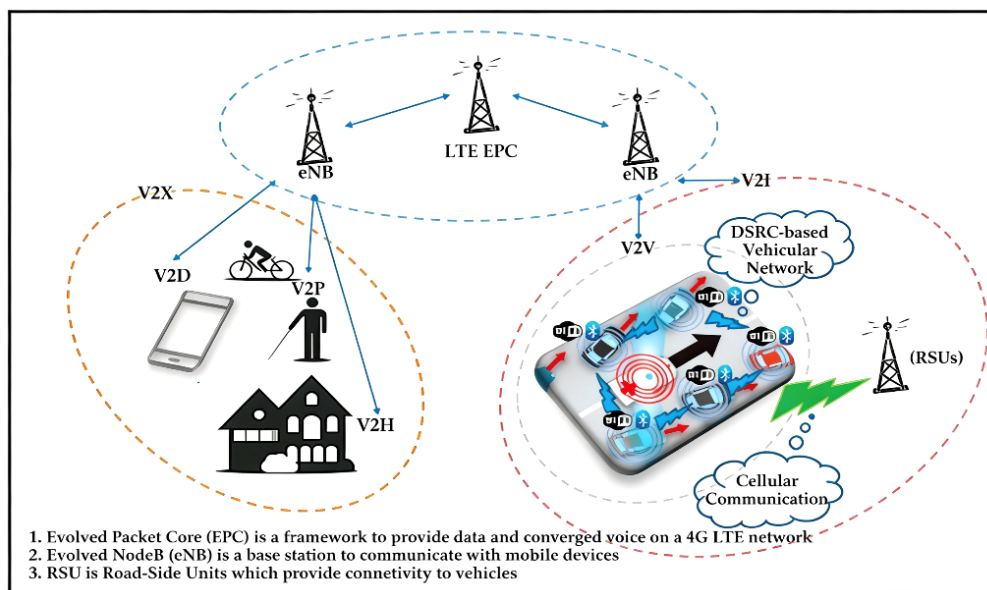
stereo, and ultrasonic sensors to establish an advanced fallen object detection system, proposing a targeted solution to avoid collisions with fallen pedestrians.

Furthermore, since individual sensors operate in concert within a multimodal fusion sensing system, a decline in the efficiency of any single sensor can compromise the reliability of the entire system. Therefore, through a literature review and analysis, Csikor et al. [13] identified weather factors that affect sensor performance and the extent of their impact on detection performance, thereby providing further theoretical support for the operational stability of all the components within a multimodal fusion sensing system.

## 2.2 V2X Cooperative Perception

Vehicle-to-everything (V2X) refers to “information exchange between vehicles and the external environment” and is a technology that supports real-time wireless communication between vehicles and their surroundings. Today, it has evolved into a new form of vehicle communication, building a multidimensional, wide-coverage dynamic perception network through real-time information exchange between vehicles, vehicles and roads, and vehicles and people [14]. In complex urban traffic scenarios, individual vehicles are limited by the sensor field of view and computational capabilities, making it difficult to address risks such as obstructions, blind spots, and beyond-line-of-sight situations. V2X collaborative perception, however, significantly enhances the completeness and real-time nature of environmental awareness through cross-domain data sharing and fusion, providing global perception support for collaborative decision-making and safety control. The overall concept of V2V, V2I, and V2X is illustrated in Figure 3.

Figure 3: The overall concept of V2V, V2I, and V2X



With respect to V2X technology, many improvements have been proposed, such as the invention of visible light communication (VLC), which leverages the visibility of SLC to facilitate the installation of roadside equipment [15]; Furlotov et al. [16] developed a hardware-software integrated system using generalized cross-correlation and phase transformation algorithms to accurately determine the coordinates of simulated accident sound sources, thereby enhancing V2X infrastructure; and Yu et al. [17] proposed a target tracking method that incorporates target identity information provided by V2X to improve data correlation, effectively enhancing target tracking performance.

Cellular V2X (C-V2X) is a wireless communication technology for V2X networks that has evolved from cellular mobile communication technology. It is among the mainstream approaches in V2X technology [18]. Since vehicles exchange driving intentions, thereby providing situational awareness beyond the capabilities of autonomous vehicle (AV) sensors, vehicle data will dominate network traffic; thus, novel network architectures are needed to support this growth [19]. Salim et al. [20] designed a communication module that enables all vehicles equipped with the OBD standard to reliably transmit and receive relevant V2X data over cellular networks using cost-effective embedded systems. Moreover, with the emergence of new 5G radio

technology, C-V2X leverages the ultrareliable and low-latency advantages of 5G networks to achieve high-bandwidth and low-latency cellular connectivity, which is crucial for V2X applications [21].

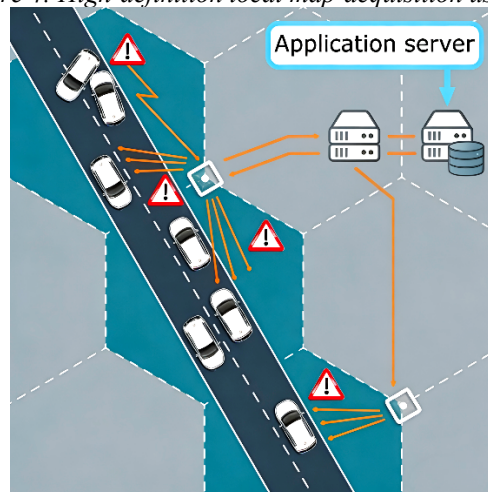
### 2.3 High-Definition Maps and Vehicle–Road–Cloud Collaborative Perception

High-definition map (HD map) technology and vehicle–road–cloud collaborative perception technology establish a foundation for comprehensive perception and collaborative decision-making by integrating the centimeter-level static positioning capabilities of HD maps with real-time dynamic data exchange enabled by vehicle–road–cloud collaboration. In complex urban traffic scenarios, traditional single-vehicle perception systems are constrained by sensor performance limitations and the complexity of dynamic environments, making it difficult to address long-tail challenges such as extreme weather and road construction zones. HD Maps supplements perception blind spots with beyond-line-of-sight semantic information, while vehicle–road–cloud collaboration leverages V2X communication and cloud computing power to fuse multisource heterogeneous data. This creates a three-dimensional perception network that integrates static prior knowledge with dynamic perception, effectively resolving issues such as high-precision temporal synchronization and unified positional reference for intelligent vehicles, thereby establishing a spatiotemporal reference for obstacle avoidance planning in smart cars [22].

#### 2.3.1 HD Map Technology

HD maps refer to maps designed for robots that feature high accuracy, more detailed map elements, and richer attributes and typically have a data error margin of less than 0.2 m while also incorporating 3D information. They not only assist intelligent vehicles in achieving localization but also provide lane-level information to the planning layer of autonomous driving systems, thereby helping intelligent vehicles achieve centimeter-level path planning [23]. Its core value lies in providing vehicles with beyond-line-of-sight environmental awareness and a high-precision positioning reference, thereby overcoming the limitations of single-vehicle sensor performance. The operating principle of typical high-definition mapping technology is illustrated in Figure 4.

Figure 4: High-definition local map-acquisition use case



HD maps not only store detailed information on global reference road networks and lane layers but also provide the entire appearance of unique landmarks or the surrounding environment, thereby aiding in the self-localization of vehicles [24]. However, matching in-vehicle sensor data with high-definition maps often poses a challenge. To address this challenge, some researchers have conducted studies and achieved certain results, such as Zhou et al. [25], who utilized the distinctive visual features of road markings as landmarks. On the basis of their detection results, they employed the RASAC for line matching using edge points to remove outliers. Finally, they fused distance and position data from an integrated navigation system using a proposed linear Kalman filter based on a second-order Markov model, achieving accurate and robust vehicle localization; Lai et al. [26] proposed a new high-precision map matching algorithm based on a semantic likelihood model and a particle filter framework, enabling intelligent vehicles to perform simultaneous localization and target detection tasks.

On the other hand, vehicles can also provide feedback to the world model to update high-definition maps; thus, timely and rapid data updates have become key to enabling high-precision maps to perceive environmental changes in real time. Pannen et al. [27] proposed a solution based on crowdsourced data to detect changes in maps independently of change types, automatically trigger map update tasks for affected areas, and create and integrate map patches, ensuring that the map remains up-to-date; Doer et al. [28] proposed an iterative method based on graphical SLAM that uses fleet data from production vehicles to create high-definition maps, relying solely on advanced sensor measurements provided by advanced driver-assistance systems. This reduces the required bandwidth and enables the method to be scaled to fleet data.

### 2.3.2 Vehicle–Road–Cloud Cooperative Perception Technology

Virtual–road–cloud cooperative perception leverages V2X communication and cloud computing power to achieve integrated perception, collective decision-making, and coordinated control among multiple dimensions—including people, vehicles, roads, and the cloud—thereby enhancing the comprehensive performance of road traffic systems in terms of safety, efficiency, and environmental sustainability and forming a comprehensive dynamic perception network [29]. This technology overcomes the limitations of single-vehicle perception blind spots, provides global optimization capabilities for traffic management, and drives the evolution of intelligent connected vehicles toward cooperative perception.

In recent years, although significant progress has been made in the research, development, and commercialization of autonomous driving technology, the large-scale commercial deployment of autonomous driving still faces enormous challenges, and there is an urgent need for vehicles to integrate multisource, multidimensional information from vehicle-side, roadside, and cloud-side sources. Zhang et al. [30] proposed a vehicle infrastructure-cooperated autonomous driving (VICAD) system framework for autonomous driving. This framework unifies the modelling of various vehicle–road–cloud coordination deployment strategies with autonomous driving algorithms and uses evaluation results to continuously iterate and optimize the VICAD system, thereby enhancing autonomous driving capabilities. To address the trade-off between perception accuracy, computational resources, and communication bandwidth in this system, Xin et al. [31] proposed a joint resource and intelligent optimization method, C<sup>4</sup>I-JO, for vehicle–road–cloud cooperative perception, ensuring superior performance in terms of both resource efficiency and perception quality compared with the baseline.

In addition to the accuracy and reliability of perception in vehicle–road–cloud integrated systems, low latency is also a critical metric that such systems should pursue given the massive volume of data. Liu et al. [32] proposed a distributed computing framework utilizing multiple edge computing devices while also taking into account factors such as trajectory smoothness and velocity consistency. This reduces the processing latency of the vehicle–road–cloud integrated system and enhances the driver experience.

## 2.4 Other Auxiliary Perception Technologies

In addition to the aforementioned multimodal fusion perception, V2X, HD map, and vehicle–road–cloud collaborative perception technologies, other auxiliary perception technologies help address the limitations of automotive environmental perception systems and enhance the reliability of environmental awareness in complex scenarios. For example, Adnan Yusuf et al. [33] addressed safety issues concerning vulnerable road users (VRUs), such as pedestrians, cyclists, and e-scooter riders, by proposing an end-to-end autonomous vehicle motion control architecture based on temporal deep learning algorithms. By integrating the dynamic behaviors of both visible and out-of-sight VRUs and critically evaluating various AI technologies, this approach enhances VRU detection, tracking, and localization; Bhardwaj et al. [34] addressed the challenge of poor visibility caused by adverse weather conditions by proposing an associative learning circuit based on memory storage, which enhances fault tolerance by dynamically adapting to multisensor inputs; to address the limitations of tracking vehicles with nonlinear trajectories using distributed magnetic sensor networks, Yang et al. [35] proposed a novel grid search–particle swarm optimization–strong tracking interactive multimodel algorithm, which significantly improved the tracking of complex manoeuvres while maintaining computational efficiency; Chu et al. [36] proposed a sustainable vehicle detection technique based on self-powered sensor data and an improved YOLOv8 model, addressing privacy and visibility issues associated with mainstream video-based detection methods; Chaurasia et al. [37] developed a hybrid edge-cloud

method that combines ultrasonic ranging data with CNNs to enable object detection, stopping time prediction, and braking control under various environmental conditions.

### 3. Path Planning Algorithm

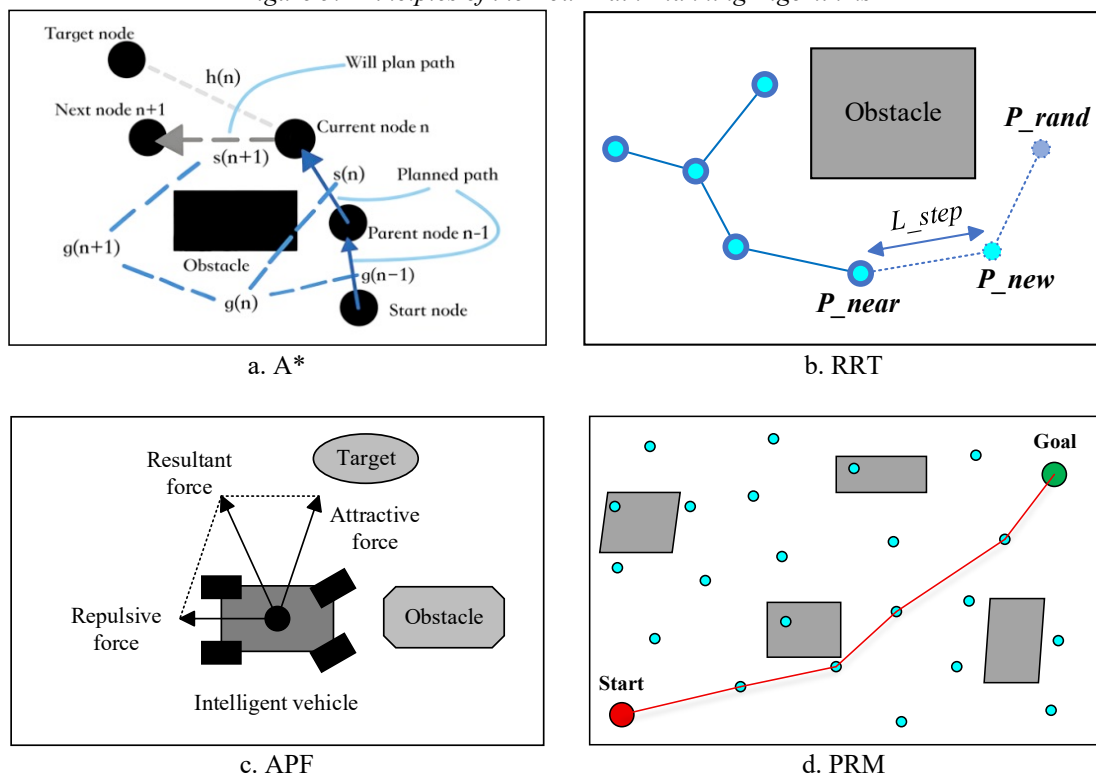
The decision-making layer of an intelligent vehicle can generally be divided into two parts: behavioral decision-making and path planning. Behavioral decision-making is inspired by perception data; predicting the trajectories of surrounding vehicles at future time steps helps the autonomous driving system better predict and understand the traffic environment, thereby adjusting its driving strategy, such as decelerating, changing lanes, or stopping [38]; path planning, on the other hand, involves finding a navigable path on the basis of environmental perception and the position of the vehicle within the environment, using specific search algorithms to enable autonomous navigation of the intelligent vehicle [4].

In the field of path planning, numerous algorithms have been developed to find optimal obstacle avoidance paths. Classic methods include the artificial potential field (APF) method, rapid-exploring random tree (RRT), the A\* algorithm, and Dijkstra's algorithm, among others [39]. Subsequently, many new intelligent optimization methods have been developed, such as genetic algorithms (GA) and neural network algorithms [40]. Since this paper focuses on path planning, the following discussion focuses on algorithms related to path planning within the decision-making module.

#### 3.1 Classical Path Planning Algorithms

There are numerous classical path planning algorithms, including graph-search-based methods such as Dijkstra's algorithm, the A\* algorithm, and the D\* algorithm, as well as random-sampling-based methods such as the RRT algorithm and the Probabilistic Roadmap Method (PRM). Schematic diagrams illustrating the principles of some of these mainstream algorithms are shown in Figure 5.

Figure 5: Principles of the Four Path Planning Algorithms



However, each traditional path planning algorithm has its own performance advantages and limitations and cannot be applied to all scenarios simultaneously. A specific performance comparison is shown in Table 1.

Table 1: Comparison of Principles and Performance of Different Algorithms

| Algorithm Name | Advantages                                                                                                                                                                                | Limitations                                                                                                               |
|----------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
| A*             | This heuristic-guided algorithm offers high search efficiency in global path planning for static environments and has many well-established variants [41].                                | Performs poorly in dynamic environments and high-dimensional spaces [42], and lacks smoothness, affecting comfort [43].   |
| RRT            | Performs well in high-dimensional spaces, relies less on prior environmental modelling, and can quickly find paths through rapid sampling [44].                                           | Path smoothness cannot be guaranteed, and it struggles with dynamic environments and has poor real-time performance [45]. |
| APF            | It offers strong real-time performance, is suitable for dynamic obstacle avoidance, and features a simple, easy-to-implement model with low computational cost [46].                      | Prone to getting stuck in local optima too early and may result in unreachable goals [46].                                |
| PRM            | It adapts well to high-dimensional spaces, and by separating the offline construction and online query processes, it improves real-time performance in slowly changing environments [47]. | Sampling points lack directionality, struggle to cover narrow passages, and exhibit insufficient smoothness.              |

Consequently, building upon these classic algorithms, researchers have developed numerous optimization algorithms to address their original shortcomings. Below, we introduce several representative algorithms from among these methods.

### 3.1.1 A\* Series Algorithms

The A\* algorithm is a heuristic search algorithm that combines Dijkstra's algorithm with a breadth-first search (BFS). Compared with Dijkstra's algorithm and BFS, it offers higher search efficiency and can simultaneously find the optimal path [41]. The core of the A\* algorithm lies in the design of the cost function, which generally takes the following form:

$$f(n) = g(n) + h(n) \quad (1)$$

where  $f(n)$  is the estimated cost from the initial state through state  $n$  to the goal state;  $g(n)$  is the actual cost from the initial state to state  $n$ ; and  $h(n)$  is the estimated cost of the optimal path from state  $n$  to the goal state.

However, the A\* algorithm still has shortcomings in terms of search patterns and the smoothness of route planning and is constrained by the limitations of traditional heuristic functions [41]. Consequently, many researchers have proposed improvement strategies. For example, Chu et al. [48] introduced a steering penalty function and an obstacle grid coefficient into the search cost function of the A\* algorithm and proposed an effective search strategy for solving the problem of trajectories passing through sparse obstacles, as well as a redundant node elimination strategy based on discrete smoothing optimization, which improved the accuracy and robustness of the generated paths to a certain extent; Wang et al. [49] considered tracking errors caused by vehicle speed and size, as well as the vehicle's own kinematic constraints and path smoothness during actual driving, and designed an obstacle position-based collision cost heuristic function and a heading angle difference-based steering cost heuristic function, thereby improving the quality of the generated paths; to address the challenges of safety, smoothness, and search efficiency in autonomous vehicle path planning, Chen et al. [50] proposed an improved hybrid A\* algorithm based on the learning optimization algorithm, which effectively optimized the path by introducing the Reed-Shepp algorithm.

Many researchers have also improved the A\* algorithm for specific scenarios, thereby expanding its scope of application. For example, Du et al. [51] proposed an improved A\* algorithm based on a dynamic multiobjective path planning mechanism and an adaptive congestion index, effectively addressing the limitations of existing congestion index models; Li et al. [52] proposed an improved sampling-based hybrid A\* algorithm for intelligent vehicle path planning, enabling smart cars to operate more effectively in complex urban environments while possessing the ability to rapidly explore complex, unstructured scenarios; Lv et al. [43] To address the issues of low efficiency and limited robustness in indoor autonomous vehicle path planning, proposed an AI-driven enhanced adaptive A\* algorithm, further enhancing the practical applicability of intelligent vehicles in real-world scenarios.

### 3.1.2 RRT Series Algorithms

The RRT algorithm is a classic tree-based algorithm. On the basis of control theory, it uses control inputs to incrementally transition from the initial state to a new state within a short time. This algorithm directly searches the entire state space through randomly expanding nodes, obtaining collision-free paths via random sampling. It requires no preprocessing, resulting in fast search speeds while simultaneously accounting for kinematic and dynamic constraints [46].

However, owing to shortcomings such as instability caused by randomness and fast execution but low efficiency, RRT cannot be directly applied to path planning. Consequently, many variants have been developed, such as RRT\* [53], RRT-connect [54], and bidirectional RRT [55]. Recently, with respect to obstacle avoidance algorithms for intelligent vehicles, more scholars have proposed more targeted optimization strategies. For example, Wang et al. [56] integrated probabilistic goal deviation, adaptive steps, and bidirectional exploration to propose an optimized PAB-RRT, enhancing RRT's exploration efficiency, path performance, and robustness in complex environments; Zong et al. [57] proposed a region-sampling RRT that combines Gaussian distribution sampling with local bias sampling, improving search efficiency during the sampling phase and giving the algorithm advantages in terms of the number of nodes, path length, and runtime; Huang et al. [58] employed a cyclic sampling strategy to generate random points and designed an extended random point rule based on a cost function to filter random points, enabling the improved RRT to shorten convergence time while enhancing path quality; Abdoumi et al. [59] proposed an enhanced variant of the RRT algorithm specifically designed for local vehicle path planning, while adhering to basic RRT principles, they integrated novel modifications to improve search efficiency during the sampling phase; Zhang et al. [60] further improved the existing Bidirectional RRT variant by introducing vehicle constraints that account for driver habits and a barrier-free direct connection mode between two random trees, thereby ensuring vehicle ride comfort and stability.

### 3.1.3 APF and Its Fusion Algorithms

The fundamental concept of the APF is to model the surrounding environment as a potential field and to view the motion of an intelligent vehicle in state space as its motion within a virtual field. The gravitational field of the target point exerts an attractive force on the robot, causing it to move toward the target; the repulsive field acts as a unique constraint to prevent collisions with objects. The robot moves collision-free along the downwards gradient of the potential field formed by the superposition of gravitational and repulsive fields, ensuring path safety. Since the potential field varies continuously in free space without state discontinuities, the path generated by the APF algorithm is relatively smooth. APF is widely used in path planning because of its simple mathematical principles, low computational complexity, and strong real-time capabilities [4].

However, APF also has limitations, such as a tendency to become stuck in local minima and a failure to account for the speed of dynamic obstacles. Consequently, many improvements to the APF have been proposed; for example, Park et al. [61] designed an APF that obtains the desired vehicle longitudinal velocity and yaw angle in real time, enabling the vehicle to quickly follow the target path and enhancing safety performance; Zhang et al. [62] optimized the APF by combining a distance adjustment factor, a safe distance protection model, and a virtual subgoal potential field, thereby addressing the issues of unreachability and local minima and improving the obstacle avoidance efficiency, safety, and adaptability to the dynamic obstacles of autonomous vehicles.

In addition to the above improvements, the APF has been increasingly integrated with classical path planning algorithms such as A\* and RRT. For example, Yang et al. [63] integrated the repulsive field concept of APF with an improved A\* algorithm to develop AAPF\*, a global planning algorithm tailored specifically for autonomous vehicle path planning, thereby improving vehicle safety and smoothness; Zhang et al. [64] also combined APF with A\*, resulting in a new algorithm that excels in improving execution efficiency and reducing the number of turning points; Guan et al. [65] integrated RRT\* with APF to propose a bidirectional APF-RRT\* algorithm, addressing issues with the traditional RRT\* algorithm such as high sampling randomness, slow convergence, and insufficient path smoothness; and Tao et al. [66] proposed a variable-probability sampling RRT\* algorithm combined with APF, which significantly optimizes vehicle performance in terms of path quality and convergence speed.

### 3.2 Intelligent optimization algorithms

With advances in society and technology, traditional algorithms have become less efficient and reveal certain shortcomings when they are operating in complex environments. Consequently, intelligent optimization algorithms such as ant colony optimization (ACO) and particle swarm optimization have begun to emerge. This category of stochastic search and optimization methods is inspired by natural phenomena or biological intelligence. It proposes various improvement mechanisms for both local and global path planning to better enhance the algorithm's optimization performance [67].

ACO is among the most representative intelligent optimization algorithms. It is a heuristic search algorithm that simulates ant foraging behavior and uses distributed computing, positive feedback mechanisms, and heuristic search to find approximate optimal solutions in complex problem spaces. However, when applied to path planning for autonomous vehicles, this algorithm may encounter issues such as slow convergence and rough cornering, and the solutions may become stuck in local extremes [68]. Therefore, Xu et al. [69] proposed a direction-aware ant colony optimization framework that integrates four complementary mechanisms in a unified manner, addressing the issues of jagged paths with excessive turns, the slowing of high-quality solution emergence due to homogeneous pheromone updates, and delayed convergence in traditional ACO; Liu et al. [70] proposed an improved heuristic ACO, incorporating four enhanced mechanisms: adaptive pheromone concentration settings, a direction-aware heuristic mechanism, an improved pseudorandom transition strategy, and dynamic adjustment of pheromone evaporation rates. This addresses the original algorithm's shortcomings, such as low search efficiency and susceptibility to stagnation; Guo et al. [71] further incorporated green and low-carbon principles and proposed a low-carbon vehicle routing planning model based on an adaptive multistrategy ant colony optimization algorithm, namely, the adaptive cooperative graph neural network, which enhances traffic efficiency while advancing low-carbon and environmental sustainability goals.

In addition, many intelligent optimization algorithms have drawn inspiration from nature, such as the immune algorithm (IA), which was developed on the basis of the principles of the immune system; the GA, which was developed on the basis of the theory of natural selection; and the artificial bee colony (ABC) algorithm, which simulates the foraging behavior of bees. These algorithms are grounded in biological intelligence or physical phenomena, making path planning calculations more intelligent [72]. Building upon these intelligent optimization algorithms, many researchers have proposed their own improvements. For example, Pan et al. [73] proposed a dynamic path planning method that combines adaptive potential fields with hierarchical replacement IA to achieve optimal navigation paths and real-time obstacle avoidance; Xie et al. [74] combined Bezier curves with a GA, incorporating path limits and risk values into the GA's fitness function, and improved the selection and mutation operators to better avoid risk points; Ni et al. [75] proposed a multistrategy ensemble ABC algorithm based on Q-learning, introducing more effective state and action configurations within the Q-learning framework to enhance search performance during the solution process.

In addition to these mainstream intelligent optimization algorithms, researchers have proposed many other innovative ideas regarding decision-making algorithms. For example, Kurdi et al. [76] proposed tide path planning (TPP), which effectively avoids search-blocked routes; in benchmark tests against mainstream algorithms such as A\* and GA, the TPP algorithm successfully found the shortest path while visiting the fewest cells; Nai et al. [77] proposed a mixed policy gradient actor-critic (AC) model with a stochastic escape term and filter operations, in which policy weights are both data-driven and model-driven, and innovatively introduced filter optimization. Ultimately, this AC model not only improves the solution accuracy without sacrificing precision but also accelerates convergence and enhances data utilization.

## 4. Motion Control Algorithms

The control architecture includes longitudinal and lateral control, where the longitudinal controller requires the vehicle to follow the desired speed by applying acceleration, while the lateral controller manipulates lane tracking by adjusting the steering to maintain vehicle stability [78]. In the control analysis of vehicles, it is common to decouple longitudinal and lateral control, establish geometric kinematic and dynamic models for analysis, and finally couple them using various techniques [79]. Over time, a wide range of control strategies have been developed, evolving from classical methods such as proportional-integral-

derivative (PID) control to more complex adaptive methods such as sliding mode control (SMC), model predictive control (MPC), and GA. In recent years, the integration of advanced control technologies and machine learning algorithms has significantly enhanced the adaptability and robustness of path-following systems, enabling AVs to navigate complex, nonlinear environments and adapt to road changes [80].

On the basis of previous research on intelligent vehicle control algorithms, the aforementioned algorithms can generally be categorized into two types: deterministic methods and heuristic methods [80]. Among these, deterministic methods include classical control algorithms such as PID and SMC, whereas heuristic methods encompass adaptive optimization techniques such as the DA algorithm and cluster optimization, as well as certain learning-based strategies. The following section introduces representative technological advancements.

#### 4.1 Deterministic Algorithms and Their Hybrid Methods

Many control algorithms are widely applied in both lateral and longitudinal control; the most common examples include SMC, MPC, and PID. Like decision-making algorithms, they each have their own strengths and weaknesses and must be flexibly applied to specific scenarios. Only by integrating different algorithms can stable control of intelligent vehicles be better achieved. Table 2 presents a performance comparison of these control algorithms.

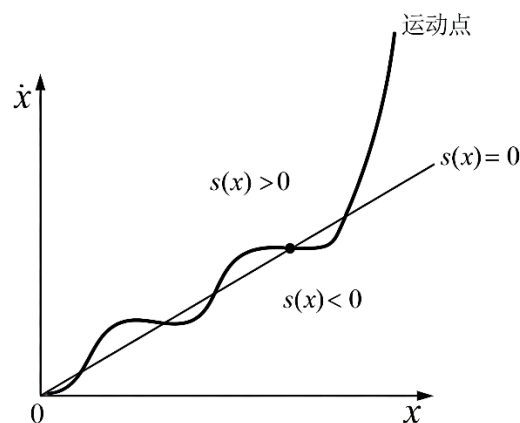
Table 2: Performance Comparison of Three Typical Control Algorithms

| Algorithm Name | Advantages                                                                                                                                                                 | Limitations                                                                                                    |
|----------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------|
| SMC            | High robustness against external disturbances and uncertainties, with excellent stability [81].                                                                            | The occurrence of "chatter" can easily affect control accuracy and smoothness [82].                            |
| PID            | systems have a simple structure and low computational requirements [83]; model design and tuning are easy to implement.                                                    | It struggles with nonlinear control and has shortcomings in terms of longitudinal and lateral coupling [83].   |
| MPC            | Effectively handles multi-input multioutput and nonlinear problems [85]; and can incorporate vehicle dynamics constraints during processing, ensuring high stability [81]. | High computational complexity, with stringent requirements for real-time performance and system accuracy [85]. |

##### 4.1.1 SMC Algorithm

An SMC is a typical nonlinear control method that involves designing a sliding surface and driving the system state to reach that surface within a finite time, after which the system moves along the sliding surface. It differs from other control algorithms in that the "system" architecture is not fixed but changes purposefully and continuously during the dynamic process based on the system's current state. Traditional SMC involves primarily two aspects: First, the sliding surface function  $s(x)$  is designed to move the moving point to the sliding surface  $s(x) = 0$ ; second, the convergence rate is designed to ensure that the moving point continuously converges to the sliding surface  $s(x) = 0$  and enters "sliding mode" motion [79]. The phase trajectory generated by SMC is shown in Figure 6.

Figure 6: Phase trajectory generated by the SMC



Since the dynamic characteristics of the sliding mode are determined solely by the sliding surface and are largely independent of system parameter perturbations and external disturbances, this method is strongly robust to model uncertainty and external disturbances. However, a major challenge with traditional SMC is that high-frequency switching of control inputs can introduce chattering, which must be suppressed using methods such as boundary layers, higher-order sliding modes, or filtering [81].

There are also many improvement strategies for this algorithm. For example, El Hajjami et al. [82] proposed a novel robust adaptive neural sliding mode steering angle controller and employed a new neural network optimization algorithm to provide optimal values for controller settings; Akermi et al. [83], based on fuzzy system gain scheduling, radial basis function neural networks, and disturbance observer algorithms, proposed a novel robust, accurate, and fast SMC algorithm for control under uncertainty, effectively improving control performance; and Demirci et al. [84], based on SMC theory, proposed two new disturbance observer methods for vehicle steering control, both of which demonstrated satisfactory reference tracking performance in tests.

#### 4.1.2 PID Algorithm

The core of PID technology lies in the linear combination of proportional, integral, and derivative terms based on the error between the setpoint and the actual output. In this technique, the deviation  $e(t)$  from the proportional, integral, and derivative terms is linearly combined to form the control signal, which controls the system—this is known as a PI controller. The control law is as follows:

$$u(t) = K_p [e(t) + \frac{1}{T_i} \int_0^t e(t) dt + \frac{T_D de(t)}{dt}] \quad (2)$$

where  $K_p$  is the proportional gain,  $T_i$  is the integral time constant, and  $T_D$  is the derivative time constant.

This is the most widely used control strategy and is capable of performing effectively in various process control applications [78]. However, distributed disturbances such as road conditions and friction are difficult to handle when an integral controller is used; thus, improvements are necessary.

Li et al. [85] proposed a fractional-order PID semiactive suspension control strategy. This method combines fractional-order theory with traditional PID control to improve the controllability range and control accuracy of the suspension system, addressing issues such as imprecise parameter tuning and performance degradation in complex nonlinear systems associated with traditional PID control; Wang et al. [86] noted the dynamic coupling between vertical and pitch motions in active suspension systems caused by traditional velocity feedback control. They introduced a novel acceleration-difference-feedback-based decoupling with a PID control strategy, combining ADF decoupling with PI control to independently regulate the vertical and pitch accelerations of the vehicle; Kim et al. [87] proposed a feedback-based lane-changing control strategy. The proposed PID feedback controller monitors traffic conditions in the inner lane and systematically manages the number of vehicles changing lanes, thereby balancing lane traffic at merging bottlenecks and mitigating capacity degradation in connected vehicle environments.

In addition, many intelligent methods can be integrated with PID algorithms to achieve better vehicle control performance. For example, Wu et al. [88] proposed a vehicle lateral electronic stability control algorithm based on a backpropagation neural network and a PID control algorithm. This algorithm not only improves the processing efficiency of complex road condition data and the accuracy of parameter tuning but also identifies subtle and elusive patterns in noisy and ambiguous data, providing a feasible approach for developing more intelligent and versatile vehicle lateral electronic stability systems; Anandan et al. [89] optimized PID controller parameters using GA technology based on the integral time absolute error criterion, successfully improving vehicle ride comfort; Abdullah Hashim et al. [90] developed and validated an automotive pedal force feedback control system using an optimized PID controller and a hybrid spiral-cosine algorithm, optimizing it for low-speed driving scenarios in traffic congestion and addressing challenges such as stop-and-go motion, vehicle jolting, and energy efficiency; at the lane level, Xu et al. [91] introduced a deep reinforcement learning-based proportional-integral-derivative Q-network, which utilizes an ID control

mechanism to enhance the accuracy and adaptability of lane selection, demonstrating significant improvements in the success rate and convergence speed of path planning tasks.

### 4.1.3 Hybrid Methods

Classical algorithms such as PID, SMC, and MPC are widely applied in the field of automotive control technology; however, each has its own advantages and disadvantages. Therefore, many researchers have integrated these methods to leverage their respective strengths and complement their functionalities.

With respect to the integration of PID and SMC technologies, Xu et al. [92] proposed a control strategy based on an improved extended Kalman filter-PID-modified sliding mode control and rear-wheel steering and experimentally validated the effectiveness of the parameter estimation method and control strategy. Nguyen et al. [93] studied a five-state-variable dynamic model to simulate vehicle vibrations under four road-based excitation scenarios and developed a sophisticated control solution for active suspension, termed SMPIDF; their experiments demonstrated its effectiveness and applicability to increasingly complex models.

Furthermore, numerous studies have investigated the fusion of PID and MPC; for example, Li et al. [94] introduced a PID channel into traditional MPC to enhance controller performance and proposed a collision avoidance method based on Q-learning-optimized ABSAS, successfully aligning the vehicle's motion state with the driver's expectations, thereby improving driver comfort and driving safety; Yang et al. [95] also proposed a control method based on MPC and fuzzy PID to avoid excessive trajectory tracking errors and ensure better trajectory tracking performance.

In addition, functional integration between SMC and MPC is possible; for example, Dai et al. [96] proposed a novel algorithm that combines robust SMC and tubular MPC, in which MPC is used to derive the control law for the nominal system, while the sliding surface and arrival law of SMC are used to derive the auxiliary tubular SMC control law. This helps the actual system keep pace with the nominal system and achieves robustness, enhancing lateral path tracking control under conditions of unmodelled uncertainty and external disturbances; Yang et al. [97] further integrated these three approaches, proposing a dual-PID-based longitudinal controller and an MPC lateral controller with SMC compensation to achieve dynamic coupling between the longitudinal and lateral domains, thereby improving vehicle safety and stability on wet, snowy, and icy roads.

## 4.2 Heuristic Methods

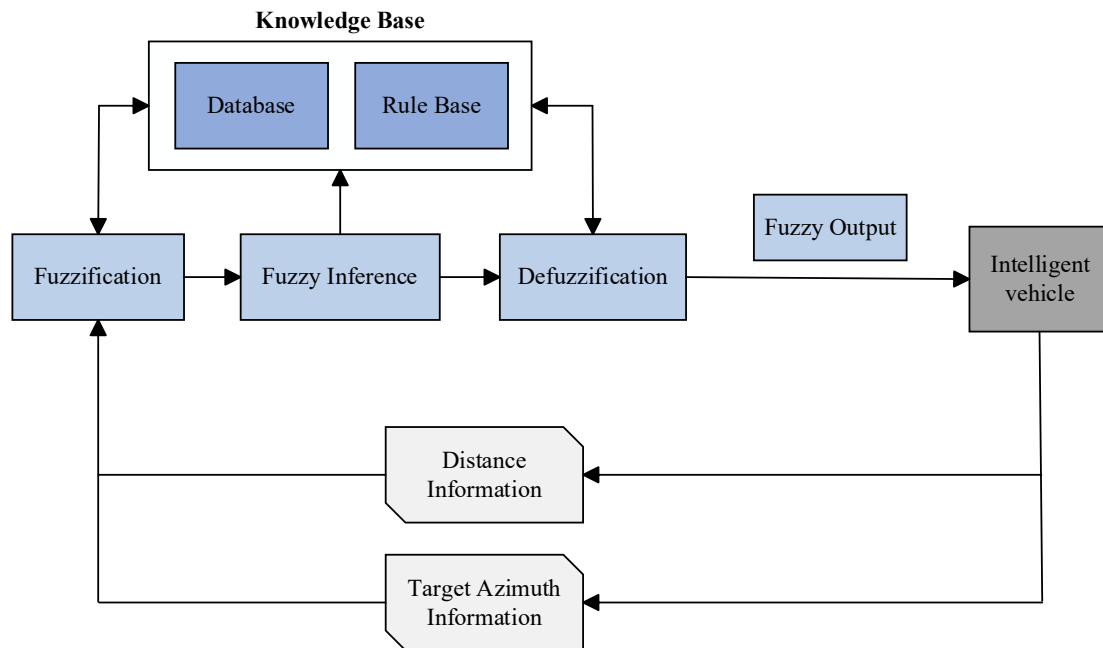
Traditional deterministic methods often rely on predefined mathematical models, offering simplicity and computational efficiency; however, complex situations such as noise and modelling uncertainties remain major challenges. Heuristic methods, including adaptive and learning-based strategies, can further address these limitations through real-time adaptability, thereby compensating for some of the shortcomings of traditional algorithms and demonstrating their importance in the control modules of intelligent vehicles [98].

Fuzzy logic control systems are a typical example of heuristic methods. They primarily consist of input variables, a fuzzy controller, a controlled object, and an error term and do not require prior knowledge of the exact mathematical model of the controlled object. Fuzzy rules are generally derived from the experience of skilled operators or experts and are expressed as conditional statements, making them easy to learn and understand [99]. The relevant principles and framework of fuzzy controllers are shown in Figure 7.

However, fuzzy control itself has limitations such as limited adaptability and insufficient accuracy, making it difficult to modify and optimize. Therefore, Naderi et al. [100] proposed a novel structure based on fuzzy control, in which an antiskid fuzzy controller for each wheel and another fuzzy controller were designed to control the yaw angle, thereby improving the vehicle's braking stability under critical driving conditions; Soudani et al. [101] proposed a new fuzzy logic controller that uses acceleration error as a third input, thereby effectively improving ride comfort by reducing body acceleration caused by road disturbances. To investigate multichannel quantized output feedback tracking control of electric vehicle lateral dynamic systems under sensor failure, Pan et al. [102] designed nonfragile fuzzy observers and elastic controllers, incorporating a Takagi–Sugeno fuzzy model with norm-bounded uncertain parameters established by the author. Finally, experimental simulations verified the effectiveness of the proposed design under road conditions with varying friction coefficients and during high-speed cornering.

In addition, many other heuristic methods have been applied in control modules. For example, Guangwen et al. [103] proposed a novel method that combines deep reinforcement learning with vehicle dynamics systems. On the basis of the double deep Q-learning algorithm, they introduced a trajectory tracking algorithm that combines PID and feedback control into the vehicle dynamics system, significantly improving the algorithm's reward values and control performance; Wang et al. [104] designed a controller that incorporates a multistep prediction and memory mechanism (MPM), calculated the eigenvalue root locus and stability time of the model controlled by the MPM controller, and subsequently, addressed the limitations of the MPM controller, further proposed a hybrid controller that combines the MPM controller and PID, achieving a wider range of stability bifurcation parameters and stability times; Zheng et al. [105] addressed the lateral motion control problem in the structural system of intelligent vehicle autopilots by proposing a forward-plus-predictive LQR lateral motion control algorithm that is based on GA parameter optimization and PID compensation, thereby improving tracking accuracy performance.

Figure 7: The relevant principles and framework of fuzzy controllers



## 5. Conclusion

As a core research direction in the field of autonomous driving, obstacle-avoidance path planning technology for intelligent vehicles has achieved significant progress through interdisciplinary integration and technological innovation. This paper systematically reviews the evolutionary trajectory of algorithmic technologies across the three core modules of environmental perception, path decision-making, and motion control. It analyses the current status and development trends of key technologies, including various perception techniques, classical algorithms, intelligent optimization algorithms, and advanced control strategies. The research findings indicate the following:

(1) Multimodal perception fusion, by integrating data from multiple sensor sources, significantly enhances the completeness and robustness of environmental modelling; moreover, V2X cooperative perception and vehicle-road-cloud integrated architectures overcome the perception limitations of single-vehicle intelligence, providing global decision-making support for complex traffic scenarios.

(2) Path planning algorithms are evolving in diverse directions. Classical algorithms such as A\* and RRT are being continuously optimized through improvements to heuristic functions and sampling strategies, whereas intelligent optimization algorithms such as ACO and GA offer new approaches for searching in high-dimensional spaces.

(3) Motion control technology, which builds upon traditional methods such as PID, SMC, and MPC, integrates deep reinforcement learning and adaptive mechanisms, significantly improving trajectory tracking

accuracy and disturbance rejection capabilities and enhancing the control performance of intelligent vehicles when commands from upstream modules are executed.

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## **Conflicts of Interest**

The authors declare no conflict of interest.

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