Review of Control Strategies for Autonomous Vehicles

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Abstract. With the rapid advancement of artificial intelligence, computer vision, and vehicle-to-everything (V2X) technologies, autonomous driving is increasingly becoming an integral part of future intelligent transportation systems. As the core mechanism ensuring safe and stable vehicle operation, control strategies directly affect trajectory tracking accuracy, dynamic response capabilities, and adaptability to environmental disturbances. This paper provides a comprehensive review of current research on control strategies for autonomous vehicles, categorizing them into four main groups: traditional PID control and its enhancements, adaptive and model predictive control, intelligent control methods based on deep learning and reinforcement learning, and hybrid and robust control strategies. From the perspectives of theoretical foundations, structural design, and representative applications, the advantages and limitations of each category are analyzed in depth. The study further highlights the emerging trend toward the integration of model-based and data-driven approaches, aiming to develop high-performance control systems that are adaptive, robust, and verifiable. This review offers both theoretical insights and practical references for future research and engineering applications in autonomous driving control.

Keywords: Autonomous Driving, Pid Control, Model Predictive Control, Deep Learning, Reinforcement Learning

1 Introduction

With the advancement of artificial intelligence, computer vision, sensor technologies, and vehicle-to-everything (V2X) communications, autonomous driving has moved from laboratory research into real-world applications, gradually becoming a key component of future intelligent transportation systems [1]. Continuous progress in core modules such as perception, path planning, environmental understanding, and motion control has significantly improved the decision-making accuracy and control stability of autonomous driving systems [2]. However, the design of control strategies that are robust, real-time, and capable of generalization remains a critical challenge,

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particularly under complex traffic scenarios, multi-source dynamic disturbances, and nonlinear vehicle dynamics [3].

As the core mechanism enabling the safe and stable operation of autonomous vehicles, control strategies directly influence the system's tracking accuracy, dynamic responsiveness, and adaptability to varying environments. The traditional Proportional-Integral-Derivative (PID) controller, known for its simple structure and ease of implementation, is still widely used in basic tasks such as low-speed straight-line driving and lane keeping. However, it suffers from large tracking errors and high sensitivity to disturbances under complex conditions. To overcome these limitations, researchers have developed enhanced control methods such as adaptive control, Model Predictive Control (MPC), deep learning-based strategies, reinforcement learning policies, and hybrid and robust control frameworks [4]. These methods incorporate mechanisms like online learning, state prediction, control switching, and disturbance observation, significantly improving control performance in uncertain environments.

In recent years, path tracking based on MPC has become a research hotspot [5-6]. Leveraging dynamic system modeling and receding horizon optimization, MPC generates optimal control inputs while satisfying vehicle constraints, and has been widely applied in trajectory tracking and motion planning. Additionally, adaptive control and Model Reference Adaptive Control (MRAC) offer online adjustment capabilities in dynamic environments, demonstrating strong stability in scenarios such as platooning, lane changing, and obstacle avoidance. These methods adjust control gains in real time based on vehicle state, reference models, and communication data to maintain inter-vehicle distance and coordination [7].

Meanwhile, the introduction of artificial intelligence has greatly expanded the design space for autonomous driving control strategies. Data-driven methods, especially those based on deep learning, eliminate the dependence on accurate system modeling. End-to-end neural network architectures can directly map sensor or image data to control commands, enabling a seamless "perception-to-control" pipeline [8-9]. Multimodal fusion techniques further enhance environmental understanding by integrating multi-source information. At the control level, reinforcement learning emphasizes trial-and-error interactions to derive optimal policies, making it well-suited for dynamic, uncertain, and high-dimensional state spaces. Algorithms such as DDPG, PPO, and SAC have been extensively validated in tasks like trajectory tracking, lane changing, and multi-vehicle obstacle avoidance, offering notable advantages in policy flexibility and generalization [10-12].

In practical autonomous driving scenarios, a single control strategy often fails to meet all performance requirements simultaneously. As a result, the integration of hybrid and robust control approaches has become a prevailing trend. By modularly combining multiple controllers, researchers have designed multi-layered control architectures with clearly defined roles to address varying levels of task complexity and stability demands [13]. Robust control methods, on the other hand, are particularly effective in environments with incomplete system modeling and significant external disturbances, delivering strong performance in applications that require high path-tracking precision and disturbance rejection under real-world conditions [14].

To systematically present the current research landscape of autonomous vehicle control strategies, this paper reviews four major control paradigms: traditional PID control, model predictive and adaptive control, intelligent control based on deep and reinforcement learning, and hybrid and robust control strategies. From the perspectives of theoretical foundations, control architectures, and representative applications, this paper summarizes and compares the characteristics and applicability of each method, aiming to provide theoretical insights and practical guidance for the optimization and engineering implementation of future autonomous driving control systems.

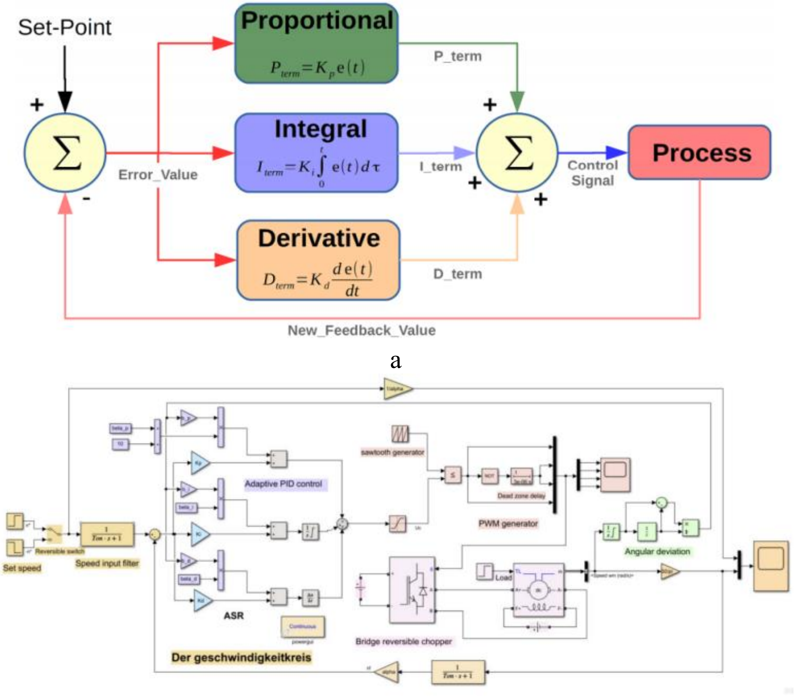
2 PID Control in Autonomous Driving

2.1 Traditional PID Control

The Proportional-Integral-Derivative (PID) controller, as a classical feedback control strategy, has been widely applied in autonomous driving systems due to its simple structure, ease of implementation, and intuitive parameter tuning. It is particularly effective in low-complexity tasks such as path tracking, steering control, and speed regulation. Traditional PID controllers generate control signals dynamically based on the feedback error and its integral and derivative terms, thereby maintaining the desired system output. However, as the complexity of autonomous driving scenarios continues to increase, the limitations of traditional PID control methods have gradually become more apparent.

Farag et al. designed and tested a representative lateral PID control system that uses the cross-track error (CTE) as its primary input to generate steering commands via a PID controller, thereby enabling the vehicle to follow the centerline of the desired trajectory [15]. As illustrated in Fig.1(a), the PID controller computes control actions based on the current error, where the proportional term governs the response speed, the integral term addresses steady-state error, and the derivative term mitigates oscillations. The study emphasized that while the PID controller performs well during initial testing phases, it encounters significant tuning challenges as the path curvature increases and vehicle speed rises. To address this, the authors introduced a manual tuning approach called "WAF-Tune" and compared it with traditional methods such as the Ziegler–Nichols technique and the Twiddle algorithm. Although acceptable error levels can be achieved within certain speed ranges, the PID controller still heavily relies on an extensive trial-and-error process to prevent deviation from the intended trajectory. This underscores a critical limitation of traditional PID control in dynamic environments—namely, its lack of robustness due to the unsystematic and non-adaptive nature of its tuning process.

Ren et al. further pointed out that in longitudinal speed regulation tasks, traditional PID controllers, due to their fixed gain parameters, struggle to cope with the dynamic changes in vehicle speed and road conditions [16]. Through simulations conducted on MATLAB's Simulink platform, they found that under intensified environmental disturbances or abrupt changes in driving conditions, traditional PID controllers exhibit degraded response speed, pronounced oscillations, and steady-state errors, with even risks of control failure. As shown in Fig.1(b), they developed an adaptive PID control system that integrates speed feedback, PWM modulation, and angular error compensation modules within a Simulink-based model. The simulation results demonstrate the shortcomings of conventional PID controllers, including slow response and large oscillations. This work provides a theoretical and experimental baseline for subsequent improvements through adaptive PID control strategies.



a

b

Fig. 1. Comparative structure diagrams of PID control systems (a) Structure of the PID controller [15]; (b) Adaptive PID control system [16]

A more comprehensive comparison was conducted by Anil et al, who applied both PID and Model Predictive Control (MPC) strategies to the same trajectory tracking task and carried out detailed simulations using MATLAB Simulink [17]. The experimental results revealed that although the PID controller performed well during the initial phase, it exhibited slower error convergence, greater overshoot, and inadequate handling of nonlinear state transitions and input constraints, especially at higher speeds. These limitations negatively impacted the overall tracking performance. In contrast, the MPC controller demonstrated superior control accuracy and robustness, further confirming that conventional PID methods suffer from precision bottlenecks and a lack of adaptability when confronted with complex autonomous driving scenarios.

In summary, although traditional PID controllers offer advantages in terms of structural simplicity and ease of implementation, making them suitable for path control in straightforward scenarios, they exhibit significant limitations under dynamic conditions such as large speed variations and complex road environments. These limitations include reliance on empirical tuning, sluggish response, and poor robustness, highlighting the need for enhanced strategies to improve control performance and adaptability.

2.2 Adaptive and Intelligently Enhanced PID Control

As autonomous driving environments grow increasingly complex, traditional PID controllers—with fixed parameter settings—are gradually revealing their limitations under nonlinear and disturbance-rich conditions, such as slow response and poor system stability. To overcome these drawbacks, researchers have proposed adaptive PID control strategies, as well as intelligent-enhanced PID controllers that integrate fuzzy logic, neural networks, and fractional-order theory, in order to improve system responsiveness and environmental adaptability.

One of the most widely adopted approaches in adaptive PID controller design is gain tuning based on feedback mechanisms. For example, Ren et al. proposed an adaptive PID control system that dynamically adjusts the proportional, integral, and derivative gains based on real-time differential speed signals and angular deviation feedback from the vehicle [16]. This method effectively reduces oscillations, shortens adjustment time, and enhances response speed. Moreover, by combining the PID controller with a PWM modulator, the system achieves greater control precision, making adaptive PID control particularly well-suited for complex autonomous driving scenarios. In terms of validation, Simorgh et al. implemented and verified an adaptive PID strategy for longitudinal velocity control using the MATLAB/Simulink platform [18]. In particular, under complex road conditions, the adaptive PID controller demonstrates superior tracking accuracy for target velocities, while effectively suppressing oscillations and enhancing the overall stability of the control system.

In the pursuit of improved control performance, intelligent-enhanced PID controllers have been developed by integrating advanced computational methods such as fuzzy logic, fractional-order calculus, and neural networks, thereby significantly enhancing adaptability and robustness. Yao et al. proposed an adaptive fuzzy PID control strategy that dynamically adjusts PID parameters in real time based on driving scenarios identified by onboard sensors, such as cornering, overtaking, and following [19]. As shown in Fig.2, the architecture of the fuzzy PID controller includes key components such as fuzzification, rule inference, and parameter output. By establishing a“fuzzy rule partition table”that maps specific driving conditions to corresponding control laws, the system is able to select optimal fuzzy rules for each scenario. Simulation results in the Panosim environment demonstrated that this approach consistently outperforms conventional PID control in terms of accuracy across a range of typical driving conditions, particularly excelling in highly dynamic maneuvers like sharp turns and lane changes, where it achieves superior stability and faster response.

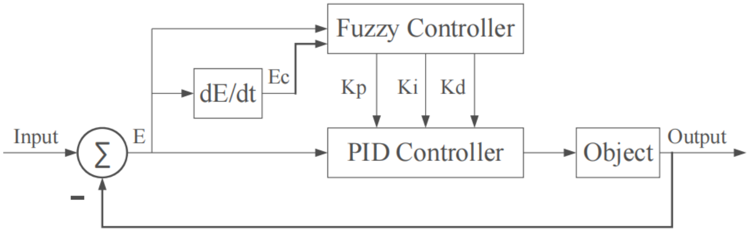


Fig. 2. Structure of fuzzy PID controller [19]

To address the characteristics of non-integer-order systems, Dong et al. proposed a lateral control approach based on a Fractional-Order PID (FOPID) controller, with parameter tuning performed using a Particle Swarm Optimization (PSO) algorithm [20]. This control strategy maintains low tracking error and ensures ride comfort even under conditions of rapidly changing path curvature. Compared with conventional PID and Linear Quadratic Regulator (LQR) controllers, the FOPID approach demonstrates enhanced robustness against model uncertainties while preserving high path-following precision. These advantages make it particularly suitable for complex curves and unstructured road environments.

Han et al. introduced a data-driven control architecture by integrating a Recurrent Fuzzy Neural Network (RFNN) with a PID controller, forming a hybrid "RFNN + PID" structure [21]. In this framework, the RFNN is responsible for predicting the optimal control trajectory at the next time step, while the PID module compensates for prediction errors and suppresses disturbances. This architecture leverages the strong nonlinear modeling and trajectory generation capabilities of neural networks, along with the stability and simplicity of PID control. Simulation experiments demonstrated that this combined system performs effectively in tasks such as dynamic obstacle avoidance and trajectory deviation correction. The resulting vehicle trajectory closely follows the desired path, and the control system maintains high robustness and fast convergence even under environmental disturbances.

Adaptive and intelligent-enhanced PID control represents a key evolutionary direction of PID-based strategies in autonomous driving applications. By incorporating mechanisms such as online parameter tuning, fuzzy rule inference, neural network-based prediction, and fractional-order regulation, these advanced approaches significantly enhance the responsiveness and environmental adaptability of control systems under complex and dynamic operating conditions.

3 Model Predictive and Adaptive Control

3.1 Path Planning and Trajectory Tracking Based on Model Predictive Control

Predictive Optimization Mechanism of MPC. The core advantage of Model Predictive Control (MPC) lies in its predictive optimization mechanism. By constructing a dynamic model of the system, MPC forecasts future state trajectories over a finite time horizon and computes the optimal control input at each time step through a receding horizon optimization strategy. This enables the system to achieve optimal control performance while satisfying operational constraints. In the context of trajectory tracking for autonomous vehicles, MPC is particularly effective in handling complex road environments, rapidly changing velocities and directions, and nonlinear system dynamics.

Chang et al. proposed an adaptive MPC algorithm that dynamically adjusts the weight matrices in real time to accommodate varying road conditions, thereby enabling the vehicle to rapidly reduce trajectory tracking errors while improving overall stability and ride comfort [22]. The study demonstrates that the adaptive MPC controller is capable of modifying its control strategy in response to the vehicle's dynamic requirements at different speeds, significantly enhancing both the accuracy and robustness of trajectory tracking performance.

In addition, Song et al. designed an MPC-based trajectory tracking strategy for four-wheel independent drive electric vehicles utilizing differential steering [5]. This approach optimizes control inputs such as individual wheel speeds to enable smooth and high-precision trajectory tracking under various driving conditions. Particularly in non-ideal scenarios like low-speed cornering, the MPC controller effectively addresses torque coordination among wheels, thereby enhancing both path stability and control responsiveness.

In summary, Model Predictive Control, with its receding horizon prediction and constraint optimization mechanisms, demonstrates significant advantages in trajectory tracking and path planning tasks. It is particularly well-suited for handling multi-constraint and highly nonlinear control problems. By enhancing system accuracy, response speed, and stability, MPC has become one of the key control strategies in advanced autonomous driving systems.

Advantages and Applications of MPC in Path Planning and Trajectory Tracking. Model Predictive Control (MPC) has demonstrated broad applicability in autonomous driving systems, particularly excelling in the core control tasks of path planning and trajectory tracking. By predicting future system states and optimizing control inputs in a receding horizon framework, MPC not only meets the stringent requirements for control accuracy and system stability in multi-objective tasks but also provides effective support for intelligent decision-making in complex driving environments.

In trajectory tracking tasks, MPC exhibits strong capabilities in handling multiple constraints. The controller can incorporate constraint variables such as velocity, acceleration, and steering angle, alongside performance indicators like tracking error, into a unified cost function. This allows for precise path fitting even under complex road conditions [22]. Additionally, by explicitly modeling system dynamics, MPC enables global optimization and coordinated scheduling of control actions. The predictive model accounts for nonlinear factors such as vehicle dynamics and environmental disturbances, allowing the controller to proactively adjust control strategies and improve responsiveness and adaptability. Song et al. highlighted that in four-wheel independent drive electric vehicles with differential steering, MPC effectively coordinates wheel torques to enhance system stability and control responsiveness, especially during turning maneuvers [5]. As shown in Fig.3(a), the control architecture integrates the MPC module with a PI-based wheel speed controller, slip rate compensation module, and a kinematic vehicle model, thereby achieving a closed-loop linkage between trajectory reference and feedback control. In terms of robustness, MPC has demonstrated strong resilience to dynamic obstacles, low-adhesion surfaces, and uncertain environments. Ma introduced a control scheme that incorporates obstacle-state constraints and pose stability metrics into the MPC formulation, enabling effective obstacle avoidance on low-friction roads while maintaining continuous and stable trajectory tracking [6]. As illustrated in Fig.3(b), the method employs a simplified point mass model for trajectory planning and constructs a multi-objective optimization path, which then serves as an accurate reference for the downstream controller.

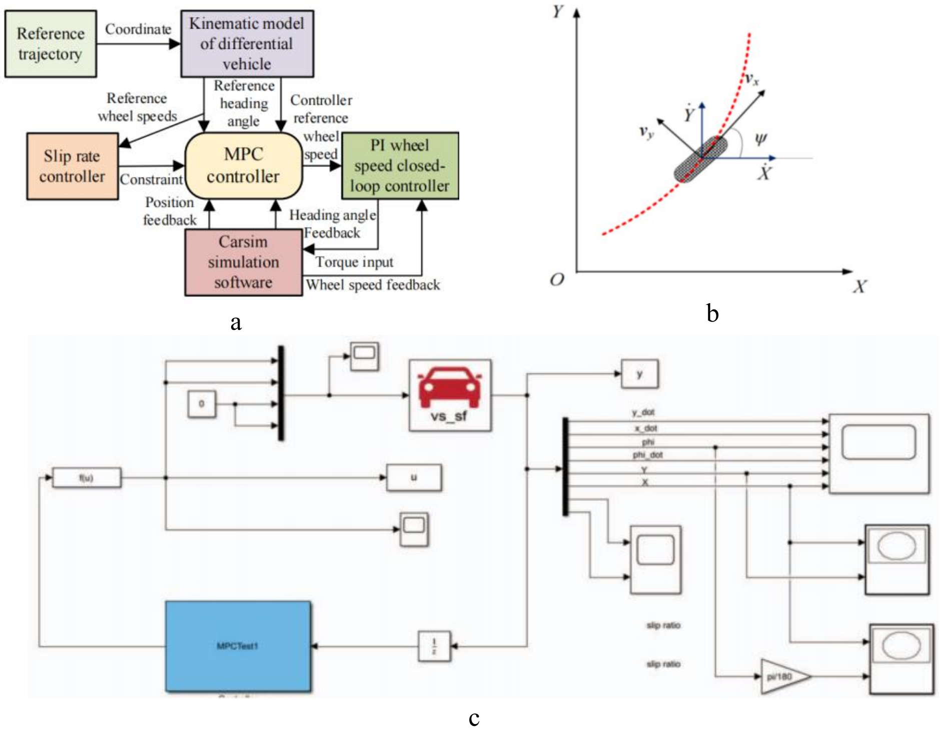


Fig. 3. Representative MPC-based frameworks for trajectory tracking and obstacle avoidance (a)Trajectory tracking controller architecture [5]; (b) Point mass model [6]; (c) Carsim-Simulink joint simulation platform structure diagram [23]

In addition to trajectory tracking, MPC also plays a crucial role in the path planning phase. By integrating path generation and control execution into a unified framework, MPC enables the system to rapidly generate feasible paths and adaptively update them upon perceiving road targets. Ling et al. proposed a tightly coupled framework that fuses path planning with control optimization. Their MPC-based path correction strategy significantly improved control accuracy and path smoothness during navigation execution [24]. As illustrated in Fig.3(c), the authors implemented the path control system using a co-simulation platform built on Carsim and Simulink. In this setup, vehicle state feedback, tracking error, and dynamic model inputs are integrated into the MPC module, enabling multidimensional optimization for closed-loop path execution.

By integrating path planning and trajectory tracking, MPC enables a closed-loop perception–control interaction framework. Through continuous prediction and optimization, the controller can iteratively adjust the future path, equipping the vehicle with strong adaptability and global path planning capabilities under complex driving conditions. Particularly in typical scenarios such as high-speed driving, sharp turning, and obstacle avoidance during lane changes, the MPC strategy provides a robust foundation for enhancing driving safety and system intelligence.

3.2 Applications of Adaptive and Model Reference Control in Dynamic Systems

In highly dynamic autonomous driving control tasks, conventional fixed-structure controllers often struggle to cope with system model variations, external disturbances, and rapid transitions between operating scenarios. In contrast, Adaptive Control and Model Reference Adaptive Control (MRAC) have emerged as promising advanced control strategies. By incorporating reference models or feedback-based adaptation mechanisms, these approaches enable real-time adjustment of control parameters, thereby enhancing the system's ability to handle uncertainties and complex environments.

Zhu et al. proposed a vibration control method based on MRAC for wheeled-legged multi-mode vehicles equipped with both wheeled and legged locomotion modes [7]. In this system, an equivalent dynamic model is reconstructed using external force feedback, enabling the controller to adaptively adjust based on the deviation from a target reference model. This allows the vehicle to maintain stable vibration suppression while navigating rugged terrains. Compared to traditional methods, MRAC does not rely on precise system modeling and can effectively accommodate the nonlinear variations resulting from frequent switching between chassis configurations. As such, it is well-suited for complex mobile platforms requiring high terrain adaptability.

In the domain of vehicle platoon control, string stability is a critical metric for evaluating system performance. When the leading vehicle in a convoy experiences speed disturbances, effectively suppressing the propagation of these disturbances along the longitudinal chain becomes a central challenge for Cooperative Adaptive Cruise Control (CACC) systems. To address this, Kayacan et al. introduced a multiobjective H∞-based adaptive control method, which optimally balances trade-offs among spacing error, velocity deviation, and acceleration fluctuation [25]. This controller does not rely on an accurate model of the system and adopts a robust control framework to strictly attenuate external disturbances. As a result, it significantly enhances the overall stability of vehicle platoons operating in high-density formations and at high speeds.

On the other hand, Tian developed an adaptive cruise control system based on a model predictive control algorithm. By modeling the vehicle's longitudinal dynamics in real time and adaptively tuning system parameters, the controller dynamically adjusts the following distance and plans vehicle speed accordingly [26]. Simulation results verified the system's strong responsiveness to vehicle nonlinear behavior and traffic flow fluctuations, providing a practical and effective solution for intelligent cruise control in highly variable urban traffic scenarios.

Therefore, adaptive control and MRAC methods exhibit distinct advantages in dynamic systems characterized by high-dimensional parameter variations, structural changes, and incomplete information. Whether in the stable control of heterogeneous platforms or in disturbance attenuation and communication dependency reduction within cooperative platooning systems, their flexibility and generalization capabilities offer robust support for autonomous driving control architectures.

4 Deep Learning and Reinforcement Learning-Based Control

4.1 End-to-End Perception and Control Models Based on Deep Learning

Image-Driven Steering Control. With the rapid advancement of computer vision and deep learning technologies, end-to-end control methods have emerged as a central research focus in autonomous driving. These approaches leverage deep neural networks to establish a direct mapping from sensor perception to control commands, aiming to bypass multiple intermediate modules traditionally present in the perception–decision–control pipeline. By simplifying the overall system architecture, end-to-end models significantly improve operational efficiency. Compared to conventional rule-based and feature-engineered methods, end-to-end learning offers a distinct data-driven advantage by automatically extracting critical features through large-scale data training. This enables superior adaptability and generalization in real-world scenarios involving complex road environments, variable lighting conditions, and visual occlusions. As a result, such methods provide a novel paradigm for developing lightweight and robust intelligent driving systems.

Mygapula et al. proposed an end-to-end steering angle prediction method based on a Convolutional Neural Network (CNN) architecture [8]. In this approach, steering angle prediction is formulated as a regression problem and trained using the publicly available SullyChen driving dataset. To enhance model efficiency and convergence, the input images undergo a series of preprocessing operations including normalization, dimensional resizing, and color space transformation (from RGB to HSV). The CNN model is composed of three core components: a feature extractor, a steering angle predictor, and an optimizer. Specifically, the feature extractor comprises multiple convolutional and pooling layers, and the final prediction is generated via a fully connected layer that regresses to a single continuous angle value. The authors tested multiple CNN configurations and determined that the model with four convolutional layers and four fully connected layers achieved the best performance, with a minimum Mean Squared Error (MSE) of 0.0354 and a coefficient of determination (R^2) of 0.819. This demonstrates the model's ability to accurately predict real-world steering angles from image inputs, validating the effectiveness of their architecture in autonomous driving tasks.

Simmons et al. validated an end-to-end image-to-action control system in a real-world setting using a low-cost, remote-controlled car platform [9].They designed both DNN and CNN models to map single-frame grayscale images to four discrete actions: forward, reverse, left, and right. A dataset of 5,222 labeled images was collected through manual driving for training and validation. The CNN model achieved the highest validation accuracy of 94.61%, outperforming both the DNN and pre-trained models like VGG16. Additionally, a finite state machine was introduced to handle stop signs and obstacles, enabling the vehicle to switch to a "stopped" state automatically, enhancing safety and interpretability.

In summary, image-based end-to-end steering control leverages deep neural networks to directly map perception to control, significantly simplifying the system architecture and enhancing generalization. Related studies have demonstrated its predictive accuracy and feasibility in real-world scenarios, offering an effective pathway toward building lightweight and highly robust autonomous driving systems.

Applications of Multimodal Fusion and Multi-Task Learning. In end-to-end autonomous driving systems, conventional methods relying solely on single-modality visual input (e.g., RGB images) often suffer from limited perception capabilities and delayed control responses. To improve perception accuracy and enhance the robustness of control strategies, researchers have begun incorporating multimodal sensory inputs (such as depth maps and semantic segmentation maps) and multi-task learning frameworks. These approaches enable the simultaneous estimation of multiple control variables—such as steering angle, velocity, and distance—within a unified network architecture, thereby achieving integrated optimization of perception and decision-making.

Azak et al. proposed a unified monocular vision-based multi-task end-to-end driving model named TS2DNet [27]. The model preprocesses a single RGB image to generate corresponding depth and semantic segmentation maps. These three modalities are independently encoded using separate EfficientNet sub-networks, whose features are then fused to jointly predict steering angle and vehicle speed. To enhance temporal awareness, an LSTM module is incorporated to capture sequential dependencies from historical steering and speed data, improving the stability and consistency of predictions. Experimental results on the Udacity, CARLA, and Sully Chen datasets show that TS2DNet reduces the root mean square error (RMSE) for steering angle by 44.96% and the speed prediction error by 4.39% compared to state-of-the-art methods, demonstrating excellent multi-task performance and strong generalization across different driving environments.

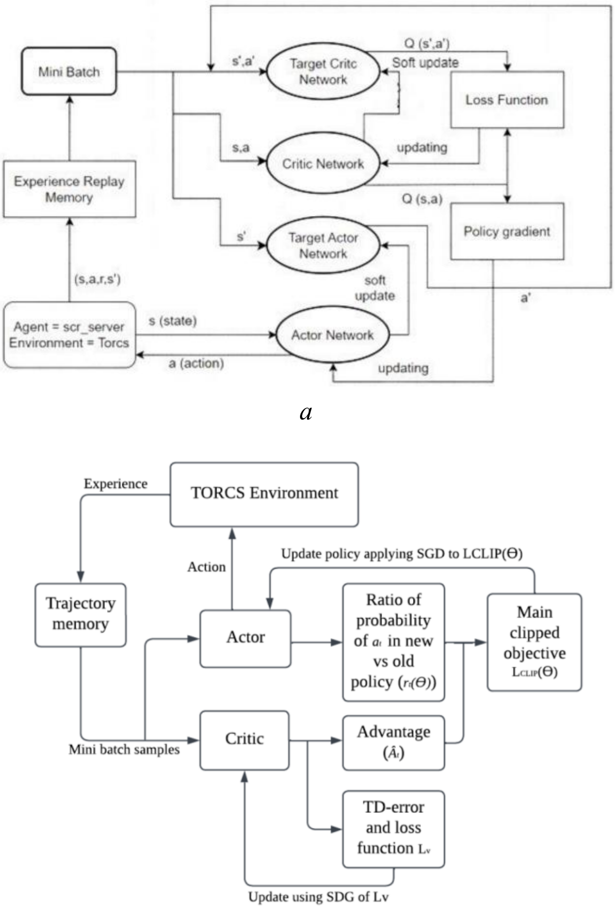
Beyond multimodal fusion, jointly modeling object detection and distance estimation has become an important direction in recent research. Ding et al. proposed a deep neural network architecture that integrates a distance estimation module into a conventional detection framework to form an end-to-end system for vehicle recognition and localization [28]. The backbone network is designed based on multi-scale feature fusion, allowing shared feature maps to be used simultaneously for object classification, bounding box regression, and distance prediction. The distance estimation module, appended after the detection head, utilizes both geometric modeling and neural regression to calculate the distance to detected vehicles. Experimental results on the KITTI dataset demonstrate that the proposed model outperforms ResNet50 and YOLOv3 in both precision and recall. Additionally, it achieves better area coverage under the precision-recall (PR) curve and exhibits superior prediction stability, validating the feasibility and effectiveness of integrating detection and control tasks into a unified framework.

Therefore, the integration of multimodal perception and multi-task learning has significantly enhanced the perception accuracy and control stability of autonomous driving systems in complex environments. Studies have shown that end-to-end models incorporating visual, semantic, and depth information perform exceptionally well in predicting steering angle, speed, and distance, providing strong support for the development of more intelligent and reliable control systems.

4.2 Innovative Applications of Reinforcement Learning in Decision-Making and Path Control

In recent years, with the continuous advancement of deep learning and reinforcement learning algorithms, Reinforcement Learning (RL) has emerged as a core technology for autonomous decision-making and path control in intelligent driving systems. Compared to traditional control methods, RL offers capabilities such as online learning, adaptive policy optimization, and effective handling of high-dimensional dynamic environments. It demonstrates notable advantages in unstructured traffic scenarios, complex action spaces, and uncertainty modeling. To further enhance its stability, computational efficiency, and safety in real-world autonomous driving systems, researchers have explored various improvements in algorithm design, model integration, and control mechanism development.

Siboo et al. investigated the challenges of continuous action spaces and high-dimensional state representations in autonomous driving decision-making by conducting a comparative study of two deep reinforcement learning algorithms: Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimization (PPO) [10]. They implemented two typical scenarios—lane keeping and multi-agent obstacle avoidance—on the TORCS simulation platform and trained both algorithms under identical conditions. Fig.4(a) and 4(b) illustrate the control architectures of DDPG and PPO, respectively: DDPG employs an Actor-Critic structure with experience replay and target network updates, while PPO builds its optimization framework based on advantage estimation and clipped surrogate objectives.Results showed that DDPG outperformed PPO in terms of convergence speed and cumulative reward, particularly excelling in the lane-keeping task where precise continuous control is required. This suggests that DDPG's policy update mechanism, grounded in its Actor-Critic structure, makes it more suitable for fine-grained control problems. Although PPO offers higher policy robustness, it exhibited slower responses under high-precision demands. The study further analyzed the strengths and limitations of both algorithms from multiple perspectives, including reward function design, experience replay, and training episodes, providing valuable insights for reinforcement learning algorithm selection and architecture design in autonomous driving systems.



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b

Fig. 4. Comparison of reinforcement learning architectures for autonomous driving (a) DDPG block diagram [10]; (b) PPO block diagram [10]

To improve control efficiency, Dang et al. proposed an event-triggered model predictive control (eMPC) framework integrated with deep reinforcement learning (DRL), aiming to mitigate the computational burden typically associated with high-frequency MPC updates [11]. The framework employs a DRL agent based on algorithms such as PPO, DDQN, and SAC to learn a triggering policy that determines when the MPC should be re-executed. As shown in Fig.5(a), the RL agent is embedded into the control loop to dynamically govern the triggering logic, significantly enhancing the system's responsiveness and execution efficiency. The authors further incorporated Long Short-Term Memory (LSTM) networks and prioritized experience replay (PER) to improve training efficiency and the robustness of the learned policy. Simulation results demonstrate that the proposed RL-eMPC method outperforms traditional threshold-based eMPC and linear Q-learning approaches in path-tracking accuracy, while also reducing the frequency of control updates. This effectively lowers communication and computational demands without compromising control performance. The study introduces a novel paradigm that blends reinforcement learning with predictive control, offering a promising direction for building lightweight and efficient path control systems in autonomous driving.

From the perspective of system stability, Hejase et al. proposed a Lyapunov Stability-Regulated DDPG (LSR-DDPG) framework to ensure that the learned reinforcement learning (RL) policy satisfies stability conditions for nonlinear systems during training [12]. The framework first employs neural networks to jointly learn the system dynamics and the associated control Lyapunov function (CLF). The violation of the Lyapunov condition is then formulated as a regularization term and incorporated into the DDPG training objective. In a simulated highway lane-following scenario, the LSR-DDPG method significantly improved trajectory stability and action smoothness without compromising training efficiency. By embedding control-theoretic stability constraints into the policy optimization process, the framework effectively addresses the challenge of unverifiable or unstable behavior in RL-based policies for safety-critical tasks. The results demonstrate the practical potential of LSR-DDPG in developing stable and reliable autonomous driving controllers.

In addition to deep reinforcement learning, Adaptive Dynamic Programming (ADP) has been increasingly applied to path tracking, offering the advantage of learning control strategies without relying on an accurate system model. Guo et al. proposed a path tracking control method based on Dual Heuristic Programming (DHP), where a nonlinear tire model and vehicle dynamics are constructed to support an online learning mechanism for optimizing control inputs [29]. As illustrated in Fig.5(b), the control architecture consists of an Actor-Critic network and a nonlinear system model. The Critic approximates the derivative of the value function, while the Actor adjusts the control strategy in real time based on the Critic's feedback. Validated through simulations on a co-simulation platform integrating Carsim and Simulink, the proposed method maintains high tracking accuracy under varying speed conditions, particularly excelling in high-speed sharp-turn scenarios. These results highlight the engineering feasibility of ADP-based approaches in handling nonlinear control problems in autonomous vehicle systems.

In summary, reinforcement learning has demonstrated strong capabilities in path control and decision optimization for autonomous driving systems. Recent studies encompass performance comparisons between mainstream algorithms such as DDPG and PPO, improvements in control efficiency through eMPC, enhanced policy stability via Lyapunov-based constraints, and the application of ADP to trajectory control in nonlinear systems. These advancements collectively highlight the broad adaptability and engineering potential of reinforcement learning in complex dynamic environments.

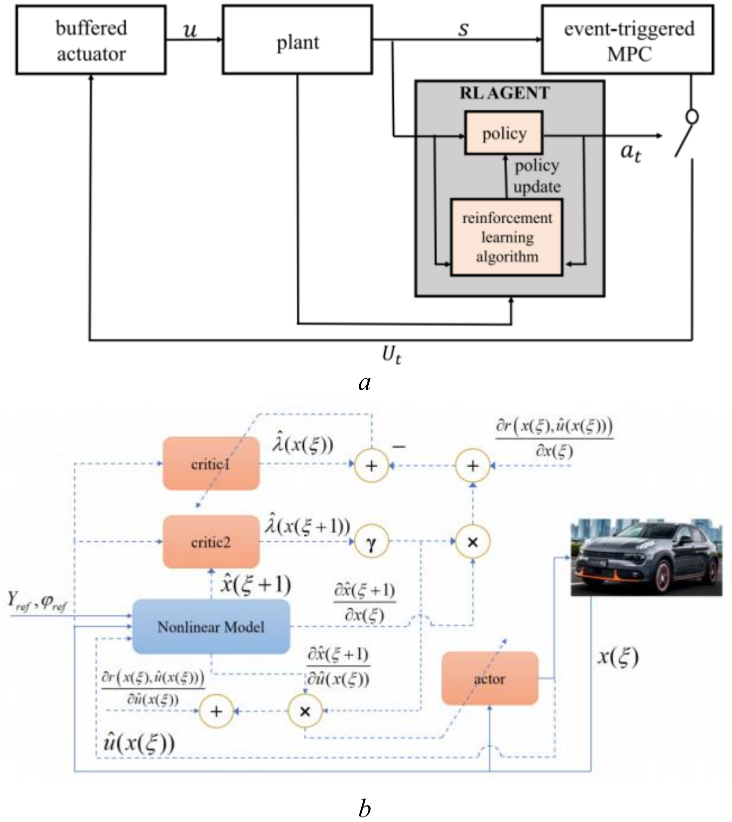


Fig. 5. RL- and ADP-based control architectures for efficient trajectory tracking (a) Scheme of RL based event-triggered MPC [11]; (b) DHP Control Block Diagram [29]

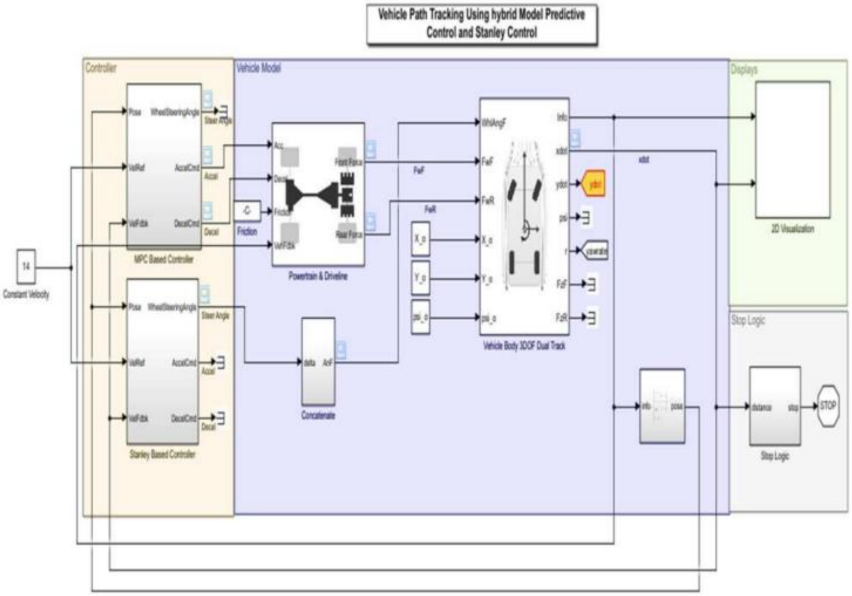
5 Applications of Hybrid and Robust Control

In autonomous driving systems, environmental uncertainty, nonlinear vehicle dynamics, and unpredictable external disturbances pose significant challenges to the stability and accuracy of control systems. To address these issues, hybrid control and robust control strategies have been widely adopted in trajectory tracking, path planning, and obstacle avoidance. These approaches serve as essential means to enhance system adaptability and improve fault tolerance.

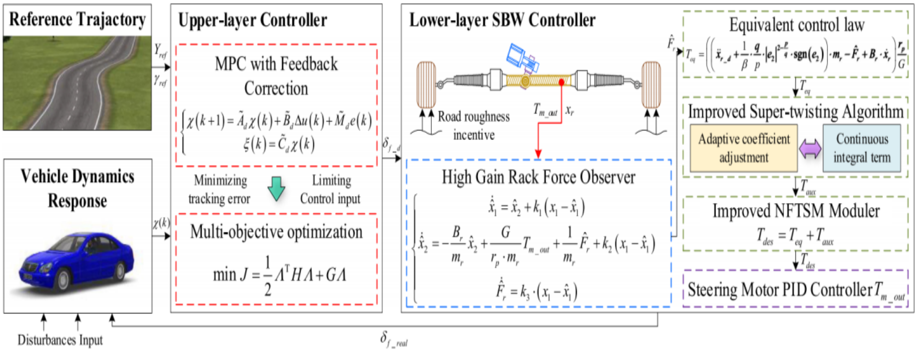
Al-Jumaili et al. proposed a hybrid control architecture named MPS, which integrates Model Predictive Control (MPC) with the Stanley controller to enhance path tracking performance under various road conditions [13]. In this framework, the

Stanley controller is utilized for lateral control, leveraging its simplicity and fast response, while the MPC component handles longitudinal speed control, taking advantage of its predictive capability for precise acceleration and deceleration. Comparative experiments in both straight and curved road scenarios demonstrated that the MPS controller outperforms standalone MPC and Stanley controllers in terms of stability, response time, and control accuracy. Particularly in sharp turns, MPS significantly reduces steering angle fluctuations and mitigates lateral deviation. As illustrated in Fig. 6(a), the MPS framework achieves effective decoupling and coordination between longitudinal and lateral control through modular integration of the controllers and feedback mechanisms.

To further enhance the system's resistance to complex disturbances, Liu et al. proposed a hierarchical anti-disturbance path tracking control scheme [14]. In this approach, the upper layer employs MPC as the main controller to generate reference control inputs, while the lower layer introduces a robust compensation mechanism based on a Fast Terminal Sliding Mode Control (FTSM) strategy to address terrain-induced vibrations, wind disturbances, and model uncertainties. Additionally, a nonlinear Extended State Observer (ESO) is integrated to estimate and compensate for both external disturbances and unmodeled dynamics in real time. As illustrated in Fig.6(b), the proposed architecture features a clearly modular design, coordinating the upper and lower layers through dual-layer control and disturbance observation. Simulation and experimental results demonstrate that the method achieves low steady-state errors and high control stability even under diverse combinations of disturbances, highlighting its strong potential for real-world engineering applications.



a



b

Fig. 6. Representative architectures of hybrid and robust control strategies (a) MPS hybrid control architecture combining MPC and Stanley controller [13]; (b) Hierarchical anti-disturbance control scheme [14]

In addition to disturbance rejection in path tracking, robust control strategies have also proven effective in multi-vehicle coordination and obstacle avoidance. Poveda et al. proposed a robust hybrid control strategy for multivehicle systems that integrates source seeking and obstacle avoidance in unknown environments [30]. The method employs a switching-based hybrid control law that alternates among a set of cooperative model-free controllers, enabling vehicles to search for an unknown signal source while simultaneously avoiding obstacles. The stability of the closed-loop system is analyzed using cooperative Lyapunov functions and singular perturbation theory for hybrid dynamical systems, demonstrating that the system maintains global asymptotic stability even under arbitrarily small disturbance signals. Furthermore, the framework was extended to accommodate vehicles with general nonlinear dynamics. Experimental validation on a TurtleBot platform confirmed the method's effectiveness in real-world scenarios.

In summary, hybrid and robust control strategies provide significant practical benefits in autonomous driving. Hybrid control enhances system adaptability by integrating multiple controllers, balancing response speed and control precision. Robust control, on the other hand, improves system reliability under uncertainty through disturbance compensation and stability constraints. The combination of both approaches is applicable not only to single-vehicle control but also to multi-vehicle coordination and dynamic obstacle avoidance, and is expected to play an increasingly critical role in complex traffic scenarios.

6 Conclusion

This paper provides a comprehensive review of recent advances in autonomous vehicle control systems, systematically summarizing four mainstream categories of control strategies: PID control and its extensions, model predictive and adaptive control, intelligent control based on deep learning and reinforcement learning, as well as hybrid and robust control strategies. Each approach presents unique advantages in terms of structural design, response capability, environmental adaptability, and engineering deployment complexity. Traditional PID control remains valuable in basic tasks such as low-speed trajectory tracking due to its simple structure and implementation efficiency. However, it faces performance limitations in complex traffic environments. To address these challenges, researchers have developed enhanced variants such as adaptive PID and fuzzy PID controllers, enabling online parameter tuning and improved control accuracy. Model Predictive Control (MPC), with its explicit modeling and receding horizon optimization, offers superior performance in high-speed dynamic scenarios and has become a key technology in advanced autonomous driving systems. Adaptive control and Model Reference Adaptive Control (MRAC) enhance system stability under uncertainty through feedback adaptation and model compensation, making them suitable for cooperative platooning and challenging terrain navigation. Meanwhile, the integration of deep learning and reinforcement learning has accelerated the evolution of data-driven control strategies, showing remarkable potential in tasks such as path planning and obstacle avoidance. Hybrid and robust control approaches have demonstrated superior disturbance rejection and system stability, particularly in multi-vehicle systems, dynamic scenario transitions, and unstructured road conditions.

Prospectively, future autonomous vehicle control systems will increasingly emphasize the integration of model-based and data-driven strategies, aiming to establish intelligent control architectures that are adaptive, learnable, and verifiable. In complex application scenarios such as multi-sensor fusion, heterogeneous platform control, and cooperative traffic systems, achieving an optimal balance among control performance, system safety, and resource efficiency will be a critical research frontier. The continued convergence of control theory and artificial intelligence algorithms is expected to drive the development of high-performance control frameworks with strong generalization and robustness, providing essential technical support and engineering pathways toward realizing truly high-level autonomous driving.

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