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A Review of Vehicle Longitudinal Speed Control in Autonomous Driving

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Abstract

With the continuous development of the automotive industry and intelligent transportation technologies, vehicles are gradually moving toward unmanned operation. Within this context, longitudinal control, which mainly focuses on regulating speed, acceleration, and braking, has become a core component of intelligent driving systems and has attracted significant attention. In recent years, various approaches have been proposed in both academia and industry; however, existing studies still lack systematic reviews and comprehensive classifications, limiting the overall understanding of their characteristics and applications. To address this gap, this paper provides a systematic review of longitudinal control methods for autonomous vehicles. These methods are categorized into three groups: rule-based control, optimization-based control, and learning-based control. This review summarizes the state of the art, highlights the strengths and limitations of existing methods, and provides a reference framework and potential directions for future research and applications.

Keywords

autonomous driving vehicles, longitudinal control, control method, model predictive control

1. Introduction

With the rapid development of the automotive industry and intelligent transportation technologies, vehicles are gradually evolving toward unmanned operation, autonomous driving has emerged, and their impact on society and human life will be significant (Zhang et al.,2017). Autonomous vehicles are expected to fundamentally reshape the way transportation systems operate by improving road safety (Michałowska et al.,2017), reducing traffic congestion, increasing mobility, and enabling sustainable travel. Among the numerous enabling technologies, vehicle control is regarded as a cornerstone of autonomous driving, ensuring that high-level planning decisions are effectively executed in complex and dynamic traffic environments.

Despite the increasing number of studies on vehicle longitudinal and speed control, literature reviews are still limited in several aspects. First, most prior reviews focus on specific methods or application contexts, such as adaptive cruise control or eco-driving, but lack a comprehensive classification that systematically organizes a wide range of approaches. Second, relatively few studies have compared the advantages and limitations of approaches within a unified framework, which is essential for identifying their respective roles and complementarities in the future of autonomous driving.

To address these gaps, this paper proposes a comprehensive review and classification of longitudinal control strategies for autonomous driving. Instead of limiting the discussion to a single technique or application scenario, this paper systematically organizes the existing approaches into a framework, covering rule-based control, optimization-based control, and learning-based control. Furthermore, we conduct a comparative analysis of their strengths and weaknesses, highlighting complementarities and potential synergies. This unified perspective is expected to serve as a foundation for future research and practical implementations.

2. Classification of Typical Longitudinal Control Methods

2.1 Rule-Based Control

Rule-based control represents one of the earliest and most widely adopted approaches to speed regulation in autonomous vehicles, and it continues to play an important role in the field. These methods typically rely on explicit system models or error-based feedback mechanisms to achieve reference tracking and disturbance rejection, thereby providing stable control performance under simple operating conditions. Although they face limitations when dealing with strong nonlinearities and multivariable couplings, rule-based approaches remain extensively applied in longitudinal speed control for autonomous driving because of their maturity, and a variety of enhanced strategies have been developed on this foundation.

2.1.1 PID control and Its Improvements

Proportional–integral–derivative (PID) control is a classical error-feedback method in which the control signal is generated through a weighted combination of proportional (P), integral (I), and derivative (D) terms. Owing to their simple structure, ease of implementation, and intuitive parameter tuning, PID controllers have been widely applied in both industrial control and autonomous driving. In the context of longitudinal control, PID is commonly used for tasks such as speed regulation and car-following, where it can provide stable and reliable performance even in the presence of modeling inaccuracies.

However, conventional PID controllers have limited adaptability to parameter variations and external disturbances, and they often fail to maintain optimal performance in highly nonlinear or constrained environments. These challenges have motivated the development of improved variants such as adaptive PID and fuzzy PID control. Kebbati et al. (2021) proposed two optimized self-adaptive PID controllers for autonomous vehicle speed regulation: a genetic algorithm-based PID (GA-PID) and a neural network-based PID (NN-PID). The simulation results showed that GA-PID performs well under fixed conditions requiring high accuracy, whereas NN-PID is more effective in dynamic environments with varying slopes and wind disturbances. Similarly, George (2021) introduced a multiobjective fuzzy FOPID controller for speed regulation, in which the ant colony optimization (ACO) algorithm was applied to tune the controller parameters and fuzzy membership functions. This approach achieved faster and more responsive tracking than fuzzy integer-order PID (IOPID), FOPID, and classical PID controllers, with minimal overshoot and negligible steady-state error. Similarly, Naranjo et al. (2020) applied three metaheuristic optimization methods, the genetic algorithm (GA), the magnetic algorithm (MA), and the mesh adaptive direct search (MADS), to tune the PID parameters. The simulation results demonstrate that all three methods outperform classical IAE-based tuning, with the memetic algorithm achieving the best performance, reducing the error by approximately 12%. Furthermore, robustness tests under signal disturbances and varying vehicle weights confirm the stability of the optimized controllers. In another direction, Chen et al. (2020) developed a PID controller integrated into an MPC-based path tracking framework to simultaneously manage longitudinal and lateral control, where simulations showed only minor tracking errors in both the lateral and longitudinal positions.

2.1.2 Others

Kim et al. (2020) proposed a disturbance observer (DOB)-based longitudinal speed control method for hybrid electric vehicles (HEVs). In this approach, a simplified vehicle model was developed in which model uncertainties and external disturbances were aggregated into a single disturbance term and compensated by the DOB. Both simulations and vehicle experiments demonstrated that the DOB-based controller provides superior robustness against uncertainties and disturbances compared with conventional PI control. Similarly, Zhang et al. (2020) introduced a Lyapunov-based real-time compound controller that integrates vehicle speed tracking with energy management of a battery–supercapacitor hybrid energy storage system (HESS). This method not only reduces battery stress and extends lifetime but also avoids the high computational burden of optimization-based strategies. The simulation results confirmed that the proposed controller outperforms heuristic and certain optimization approaches under both standard and real-world driving cycles.

2.2 Optimization-Based Control

Unlike traditional control approaches that rely on empirical tuning, optimization-based optimal control methods formulate longitudinal velocity control as a mathematical optimization problem. The core idea is to define an objective function (e.g., minimizing speed tracking error, improving fuel economy, or enhancing ride comfort) subject to constraints such as maximum acceleration, minimum headway distance, and safety requirements. Analytical or numerical algorithms are then employed to derive the optimal control input. These methods can explicitly handle multiple constraints and flexibly adapt to different application requirements, which makes them highly attractive in longitudinal control. Representative approaches include linear quadratic regulator (LQR), model predictive control (MPC) and scenario-oriented analytical optimization.

2.2.1 Linear Quadratic Regulator (LQR)

LQR is one of the most widely used optimal control methods. It models the longitudinal vehicle dynamics in a state-space form and minimizes a quadratic cost function consisting of state error and control effort, thus achieving a trade-off between tracking accuracy and energy consumption. A key advantage of LQR is that it provides an analytical solution with high computational efficiency and simple implementation. However, LQR is based on linear system models, and its applicability is limited in highly nonlinear or time-varying scenarios. Therefore, it is more suitable for systems that can be well approximated by linear models or operate under relatively stable conditions. Shakouri et al. (2011) developed an ACC simulation model using gain-scheduled PI (GSPI) and gain-scheduled LQ (GSLQ) controllers for throttle control, where controller gains are tuned at multiple operating points and applied to a nonlinear model. The simulation results under various traffic scenarios demonstrate good performance.

2.2.2 Model Predictive Control (MPC)

Model predictive control (MPC) has emerged as one of the most widely adopted optimization-based control methods in recent years. Its principle lies in predicting the future behavior of the vehicle over a finite horizon via a system model and solving an optimization problem at each sampling step within a receding-horizon framework. MPC can explicitly handle multiple constraints, such as acceleration limits, braking forces, and intervehicle safety distances, making it particularly suitable for adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC). Moreover, the framework is highly flexible: linear MPC is applicable to moderately complex systems, whereas nonlinear MPC (NMPC) can address more complicated nonlinear vehicle dynamics. The main drawback of MPC lies in its relatively high computational burden, which may limit real-time implementation. Nevertheless, with the advancement of onboard computing hardware and efficient optimization algorithms, MPC has become a mainstream approach in longitudinal vehicle control research and applications.

For example, Lee and Jo (2024) proposed an MPC framework incorporating a first-order plus dead time (FOPDT) model to capture signal transmission delays and actuator lags while employing nonlinear torque maps of the motor and brake system to convert the desired driving force into throttle and brake commands. The simulation results revealed that the proposed controller significantly outperforms the conventional PID and delay-agnostic MPC methods by achieving higher speed tracking accuracy, eliminating overshoots during acceleration and deceleration, and maintaining real-time performance. Similarly, Yuan et al. (2016) developed an NMPC-based wheel slip control strategy, which ensures vehicle safety while providing satisfactory longitudinal acceleration and braking performance, ride comfort, and energy consumption optimization. Luciani et al. (2020) designed an MPC framework that integrates both lateral and longitudinal dynamics under various driving conditions, where passenger comfort was maximized by selecting the weighting parameters through a novel offline method. In addition, Chen et al. (2020) combined an offline optimization approach based on Pontryagin’s maximum principle (PMP) with an online MPC controller. Their results demonstrated energy savings of up to 7% without increasing travel time or deviating from normal driving patterns and further highlighted that an MPC with a prediction horizon of approximately 1000 meters can closely approximate the offline optimal solution. The study also emphasized that urban driving offers greater potential for fuel savings than highway driving does. Long et al. (2024) proposed VLM-MPC, a novel autonomous driving framework that integrates vision-language models (VLMs) with model predictive control (MPC). The motivation stems from the strong reasoning and environmental understanding abilities of foundation models, which are limited by slow response times when they are directly applied to vehicle control. VLM-MPC adopts a two-layer asynchronous structure: the upper-level VLM interprets front-view images, vehicle states, traffic context, and reference memory to generate high-level driving parameters (e.g., desired speed and headway), whereas the lower-level MPC executes real-time control while considering vehicle dynamics and safety constraints. Experiments on the nuScenes dataset demonstrated that VLM-MPC consistently maintains safe postencroachment time, improves trajectory smoothness compared with real-world driving and VLM-only baselines, and achieves high completion rates with minimal hallucinations. Ablation studies further validate the importance of the environment encoder and reference memory in ensuring stable responses.

2.2.3 Scenario-Oriented Analytical Optimization

Within optimization-based control, a specific category of research focuses on scenario-oriented analytical optimization, where mathematical models are formulated for particular traffic situations and optimal speed trajectories are computed directly through analytical or numerical methods. Typical applications include intersection crossing under signal control, eco-driving on roads with varying gradients, and energy-efficient car-following. The core idea is to define an optimization problem under given traffic constraints—such as traffic signal timing, speed limits, or vehicle dynamics—and solve it to obtain the optimal trajectory that minimizes travel time, fuel consumption, or emissions. These methods typically operate at the decision or planning layer of autonomous driving systems. On the basis of information from onboard sensors or vehicle-to-everything (V2X) communication, they compute an optimal speed or speed trajectory for a given scenario to achieve objectives such as energy efficiency or travel time minimization. However, they do not directly generate the control signals required by the execution layer (e.g., throttle or braking commands) and therefore rely on low-level longitudinal controllers, such as PID or MPC, to track the optimized trajectories.

Malikopoulos (2018) proposed an optimization method based on traffic flow dynamics, enabling automated vehicles to adjust their speeds smoothly while ensuring traffic safety on highways. The simulation results revealed that this approach reduced the frequency of acceleration and deceleration, enhanced the stability of vehicle platoons, and thereby lowered fuel consumption and emissions. Similarly, Xu et al. (2018) developed a cooperative strategy that integrates traffic signal optimization with the speed control of connected vehicles, where the Legendre pseudospectral method was employed to address the vehicle optimal control problem. Their results demonstrated significant reductions in average vehicle delays and improvements in traffic throughput. In another study, Du et al. (2018) proposed a velocity control strategy that prioritized passenger comfort by employing weighted root mean square acceleration (WRMSA) as the evaluation metric for speed regulation, thereby improving ride comfort. Zamanpour et al. (2025) proposed an energy-efficient speed control framework for connected and autonomous vehicles (CAVs) that explicitly incorporates lane-change prediction at signalized intersections. The predicted lane changes were then integrated into an optimal speed control strategy via the sequential least squares programming (SLSQP) method to minimize energy consumption. The simulation results for two-lane signalized corridors with mixed traffic revealed that considering lane-change prediction yields up to 13% additional energy savings compared with models without lane-change anticipation. Anon et al. (2024) proposed a multiprofile quadratic programming (MPQP) framework for optimal speed planning in autonomous driving. Building on the path–speed decomposition approach, the method involves constructing a space–time graph to represent interactions with dynamic obstacles and employs a breadth-first search to identify multiple feasible passage profiles. Each profile was then optimized via quadratic programming, ensuring smoothness, safety, and global optimality while integrating both hard and soft constraints to handle feasibility issues. A funnel technique was further introduced to account for the lateral acceleration and curvature limits. Extensive validation in the CARLA simulator across diverse traffic scenarios, including merging, intersections, and lane changes, as well as real-world road demonstrations, highlighted the algorithm's efficiency, robustness, and passenger comfort.

2.3 Learning-Based Control

In recent years, learning-based control approaches have emerged as promising directions for vehicle speed regulation in autonomous driving. Unlike traditional rule-based or optimization-based methods, learning-based techniques leverage historical data or online interactions to capture complex driving environments and derive optimal control strategies. For example, supervised learning can approximate human driving behaviors from large-scale datasets, whereas reinforcement learning enables autonomous agents to improve acceleration and deceleration decisions through continuous interaction with dynamic traffic environments. These methods exhibit strong adaptability and generalization capabilities, making them particularly suitable for scenarios involving multivehicle interactions, dynamic signal control, and mixed traffic conditions. As such, learning-based speed control shows significant potential for advancing the efficiency, safety, and sustainability of intelligent transportation systems.

Zhang et al. (2018) proposed an approach that integrates double Q-learning with deep neural networks, and the experimental results revealed significant improvements over a single deep Q-network. Similarly, Zhu et al. (2020) developed a deep reinforcement learning–based method for autonomous car-following control, aiming to imitate human driving behavior while optimizing safety, efficiency, and comfort. They trained a deep deterministic policy gradient (DDPG) model guided by a reward function incorporating these objectives, and the results demonstrated that the model outperformed human drivers, highlighting the potential of deep reinforcement learning to enhance autonomous driving performance. In another study, Du et al. (2022) presented a deep reinforcement learning (DRL)-based speed control framework addressing the challenges of ride comfort and energy efficiency. Compared with the conventional MPC approach, the DRL model improved ride comfort by 8.22%, energy efficiency by 24.37%, and computational efficiency by 94.38%. Furthermore, Lu et al. (2019) introduced a personalized behavior learning system (PBLS) based on neural reinforcement learning (NRL) to achieve human-like longitudinal speed control. The experimental results demonstrated that PBLS could adapt to different drivers and successfully reproduce their car-following behaviors. Kang et al. (2018) introduced a deep Q-network (DQN)-based active speed management approach to enhance traffic safety and efficiency in autonomous driving environments. By developing a variable speed limit (VSL) control model within a microscopic traffic simulation and designing reward functions on the basis of time-to-collision (TTC) and vehicle speed, this study evaluated performance under varying market penetration rates of autonomous vehicles. The results demonstrated that the proposed DQN-VSL strategy significantly reduces crash risk and improves traffic density, with the most notable benefits observed in congested scenarios and at medium-to-low penetration levels of autonomous vehicles.

3. Method Evaluation and Future Perspectives

To provide a more intuitive comparison of the different approaches, the advantages and limitations of rule-based, optimization-based, and learning-based longitudinal control methods are summarized in Table 1. The table contrasts these approaches across several dimensions, including computational complexity, adaptability, safety, interpretability, and application scenarios, thereby offering a clear overview of their respective strengths and weaknesses.

Table 1: Advantages and limitations of the three methods

Method	Advantages	Limitations
Rule-based Control	- Simple structure, low computational cost - High interpretability and ease of implementation - Guarantees stability and safety - Reliable under simple operating conditions	- Limited flexibility and adaptability - Weak in handling strong nonlinearities and multiconstraints - Difficult to achieve global optimality - Poor scalability in complex traffic environments
Optimization-based Control	- Explicitly models system constraints - Supports multiobjective trade- offs (safety, efficiency, energy, comfort) - Performs well in complex scenarios (e.g., intersections, eco- driving)	- High computational complexity, limited real-time applicability - Strong dependence on accurate models and predictions - Sensitive to uncertainty and disturbances - Challenging for large- scale network deployment
Learning-based Control	- Model- free, strong adaptability - Handles complex and dynamic environments - Good generalization capability - Suitable for multivehicle interaction and mixed traffic scenarios	- Low training efficiency, requires massive data or simulations - Insufficient safety assurance and interpretability - Uncertain generalization across scenarios - Practical deployment still at an exploratory stage

Although considerable progress has been made in vehicle longitudinal control, several challenges remain unsolved. Future studies are expected to move toward more integrated, adaptive, and practical approaches. As mentioned in Table 1, current methods exhibit complementary strengths: rule-based controllers ensure stability and interpretability, optimization-based approaches achieve multiobjective trade-offs, and learning-based methods provide adaptability in complex environments. Future research is expected to move toward hybrid and integrated frameworks that combine the complementary advantages of existing approaches, such as embedding reinforcement learning into model predictive control to reduce computational costs. Another important direction is multiscenario generalization, since some existing studies are limited to specific contexts, whereas practical deployment requires robust performance across diverse environments, including mixed traffic, intersections, and highways. Finally, longitudinal control is expected to be increasingly integrated with emerging technologies such as vehicle-to-everything (V2X) communication and cloud-based decision support, thereby making autonomous vehicles safer, more adaptive, and more practically deployable.

4. Conclusion

This paper provides a systematic review of longitudinal and speed control methods for autonomous vehicles, categorizing them into three major groups: rule-based, optimization-based, and learning-based approaches. Rule-based methods, owing to their simplicity and computational efficiency, have played a significant role in early applications of autonomous driving, yet they suffer from limited adaptability in complex traffic scenarios. Optimization-based methods are capable of balancing multiple objectives, such as safety, efficiency, and energy consumption, and have shown strong performance in applications such as intersection coordination and eco-driving. However, their high computational complexity and reliance on accurate models restrict their scalability for real-time, large-scale deployment. Learning-based methods exhibit strong adaptability and generalizability in dynamic environments, but challenges remain in terms of safety assurance, interpretability, and cross-scenario transferability.

Overall, the three categories of methods present complementary strengths and limitations. Future research is expected to move toward hybrid and integrated approaches and multiscenario research so that longitudinal control strategies do not overly depend on specific traffic assumptions and can be applied robustly across diverse conditions. Addressing issues of safety validation, real-time performance, and large-scale traffic network implementation will also be essential for practical deployment. By integrating diverse methodologies, validating across multiple scenarios, and building unified frameworks, more reliable, efficient, and scalable longitudinal control systems can be realized, paving the way for the large-scale deployment of autonomous driving technologies.

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