



# Analysis of Autonomous Driving Control Strategies Based on Deep Learning

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**Abstract.** As a core component of intelligent transportation systems, the development of autonomous driving technology is of milestone significance for enhancing traffic safety, optimizing traffic efficiency, and improving travel experience. Control strategies, as a key execution link in the "perception-decision-control" closed loop of autonomous driving systems, directly determine the safety, comfort, and robustness of vehicle dynamic responses. Traditional control methods such as PID control and model predictive control struggle to cope with dynamic road conditions and multi-objective coordination requirements in complex traffic scenarios like urban multi-interaction environments and extreme weather. In contrast, deep learning, with its powerful data-driven modeling capabilities, ability to capture temporal dependencies, and multi-modal information fusion capacity, provides new pathways for optimizing autonomous driving control strategies. In recent years, autonomous driving technology has made a series of advancements in optimizing control strategies, but it also faces many challenges, such as model generalization capability, interpretability, and real-time performance. This article aims to organize the current research status, analyze existing issues, and look forward to future development trends in conjunction with the latest research results, providing references to promote further and more practical development of autonomous driving technology.

**Keywords:** Autonomous driving, control strategies, deep learning.

## 1 Introduction

As a core component of intelligent transportation systems, autonomous driving technology is significantly enhancing the safety, efficiency, and comfort of traffic operations by redesigning the coordination model between people, vehicles, and roads, thus becoming a key pathway to solving urban congestion and reducing traffic accidents. However, the control aspects of autonomous driving systems face multiple challenges from complex dynamic environments (such as changing road conditions and heterogeneous traffic participants), nonlinear vehicle dynamics characteristics, and uncertain disturbances (such as sensor noise and communication delays). Traditional control strategies (such as Proportional-Integral-Derivative (PID) control, Model

Predictive Control (MPC)) rely on precise mathematical models and preset rules. They lack robustness when dealing with high dynamics and strong coupling scenarios, making it difficult to meet control demands in complex traffic conditions.

In recent years, deep learning technologies have provided a new paradigm for breakthroughs in autonomous driving control strategies, thanks to their advantages in nonlinear fitting, high-dimensional data feature extraction, and dynamic decision optimization. From environment perception and control collaboration based on convolutional neural networks (CNN) to modeling of temporal dynamic driving behavior using recurrent neural networks (RNN) and long short-term memory networks (LSTM), and then to control decision optimization in multi-agent interaction scenarios based on the Transformer architecture, deep learning-driven control methods have gradually achieved a transformation from 'model-dependent' to 'data-driven', significantly enhancing the adaptability and control accuracy of autonomous driving systems in complex scenarios.

This article presents a review study on automatic driving control strategies based on deep learning. First, from the two dimensions of lateral control (path tracking, steering angle decision-making) and longitudinal control (speed adjustment, following distance optimization), we will sort out the application scenarios and typical results of technologies such as CNN, LSTM, Transformer, and reinforcement learning. Secondly, we will analyze the three core challenges currently faced in research: the lack of interpretability, bottlenecks in real-time processing, and risks associated with data dependence; then, we will look forward to three major development directions: lightweight models, multi-task transfer learning, and dynamic collaboration in 'perception - decision - control'. Finally, summarize the core values of the research to provide theoretical references for the engineering implementation of autonomous driving technology and the construction of intelligent traffic systems.

## 2 Horizontal Control Strategy

Lateral control is the core of maintaining path tracking accuracy and ensuring driving safety for autonomous vehicles. It achieves this by adjusting the steering angle in real time, allowing the vehicle to follow the planned path in scenarios such as cornering, lane keeping, and obstacle avoidance. Deep learning, with its ability to model high-dimensional nonlinear data, has become the mainstream direction for lateral control, primarily applied in two major tasks: path tracking and steering angle decision-making.

In path tracking tasks, Convolutional Neural Networks (CNNs), with their powerful image feature extraction capabilities, are widely used to process road image data collected by onboard cameras. CNNs encode visual features such as lane lines and road boundaries, and combine the vehicle's current position with the deviation from the target path to construct an end-to-end steering control model, achieving stable tracking of straight roads and small curvature turns. Bojarski addressed the limitations of

traditional explicit decomposition methods (such as lane detection, path planning, and control) in autonomous driving by training a convolutional neural network (CNN) to directly map the raw pixels from a single front-facing camera to steering commands. This allows the system to automatically learn the internal representations of necessary processing steps (such as detecting useful road features) without explicitly training to detect road contours, ultimately enabling the system to navigate various scenarios including local roads with or without lane markings, highways, parking lots, and unpaved roads, operating at a frame rate of 30 frames per second [1].

Recurrent Neural Networks (RNN) and Long Short-Term Memory Networks (LSTM) are more suitable for processing vehicle dynamic time-series data. By modeling the changing patterns of continuous states such as body posture, speed, and acceleration, they enhance the model's dynamic adaptability for path tracking, especially demonstrating superior robustness in scenarios like continuous curves and slopes compared to traditional control algorithms (such as PID and model predictive control). Rodolfo proposed an end-to-end deep architecture that combines CNN, LSTM, and fully connected (FC) layers, using current images and future images shared via vehicle-to-vehicle (V2V) communication from the front vehicle as input. LSTM is used in the architecture to account for the temporal dependencies between image frames. The introduction of LSTM to capture temporal dependencies and the utilization of future images from V2V communication improved the existing end-to-end steering angle prediction techniques, effectively reducing errors and achieving enhanced steering angle control accuracy [2].

In recent years, the Transformer architecture has further optimized path tracking accuracy in complex scenarios due to its self-attention mechanism's ability to capture long-range dependencies—by modeling the temporal and spatial correlations of multi-frame sensor data, the model can effectively address the issue of path feature ambiguity in scenarios such as occlusions and intersections. Yao addressed the issues of inaccurate feature extraction for target objects, difficulty in adapting to different scale targets, poor robustness in complex scenarios, and insufficient real-time capability in traditional image segmentation methods under intelligent driving scenarios. Based on the Deeplabv3 architecture, a comprehensive approach was adopted that employed a "Transformer backbone network, hybrid attention mechanism, and multi-scale optimization strategy." The DenseASPP module was improved, and an enhanced DenseASPP with an adaptive strip pooling structure was designed. At the same time, advancements were made in the attention mechanism and feature fusion technology, resulting in significantly better segmentation accuracy for the proposed model compared to baseline methods, along with balanced performance in terms of mean Intersection over Union (mIoU), mean Pixel Accuracy (mPA), and computational efficiency. Ultimately, this achieved an efficient, precise imaging segmentation solution with real-time deployment potential for intelligent driving, effectively

enhancing the model's ability to capture and distinguish target objects in varying scales and complex environments [3].

In terms of steering angle decision-making, deep learning models have overcome the dependency of traditional control algorithms on precise vehicle dynamics models, directly outputting the optimal steering angle in a data-driven manner. A typical example is the end-to-end control framework proposed by NVIDIA, which uses CNN to map raw image data to steering angle commands, effectively reducing tracking errors. Reinforcement learning (such as Deep Deterministic Policy Gradient algorithm DDPG) can dynamically optimize the steering angle decision-making strategy through continuous interaction with the environment. In scenarios with low friction coefficients, such as icy roads and waterlogged sections, it can adaptively adjust the steering amplitude to avoid skidding. To address the issue of ensuring the safety of steering angles in autonomous vehicles, which can easily lead to erroneous steering decisions due to minor input disturbances, Wu adopted a technical solution based on a Deep Learning Verification (DLV) framework. By utilizing neuron coverage and relaxation relations to improve the DLV, the steering angle judgment problem was transformed into a classification problem, thereby solving the challenge of predicting behavior judgments and achieving automated verification of the steering angle safety in autonomous vehicles [4].

### 3 Vertical Control Strategy

Longitudinal control is a core technology for autonomous vehicles to achieve speed adjustment, maintaining following distance, and emergency braking. Its primary goal is to dynamically adjust the throttle position and brake pressure to ensure vehicle speed adaptation and distance control while guaranteeing driving safety. Deep learning technology, with its ability to model dynamic traffic environments, has broken through the reliance on fixed scene parameters seen in traditional PID and fuzzy control methods. It demonstrates stronger adaptability in speed optimization and distance adjustment, with applications focused on dynamic speed control and coordinated optimization of following distance.

In terms of dynamic control of vehicle speed, Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) have become the mainstream tools for handling the patterns of vehicle speed variation due to their advantages in modeling time-series data. For example, in response to the issue of needing to predict the driving trajectories of surrounding vehicles accurately in autonomous driving to plan low-risk paths, ensure safety, and improve driving efficiency, Wang utilized a Long Short-Term Memory (LSTM) network trained with information extracted from Vehicle-to-Vehicle (V2V) technology to predict the driving trajectories of surrounding vehicles. This optimized the path planning logic, achieving significantly better improvements in driving efficiency of the proposed path planning algorithm compared to constant speed

prediction methods and Nonlinear Input-Output (NIO) network prediction methods, especially when there are abrupt changes in speed and trajectory [5].

In the collaborative optimization of following vehicle distance, reinforcement learning algorithms are widely used due to their ability to interact with dynamic environments, among which deep deterministic policy gradient (DDPG) and proximal policy optimization (PPO) have become core technologies for adaptive cruise control (ACC). In view of the challenges posed to traditional algorithms in the context of adaptive cruise control (ACC) technology integrated with hybrid electric vehicles (HEV) due to system complexity, inconsistent targets, and strict constraints in vehicle-following scenarios, Peng proposed a novel ecological driving strategy (DDPG-ECO) based on Deep Deterministic Policy Gradient (DDPG). This strategy improves the energy management strategy (EMS) of HEVs in vehicle-following situations and constructs the DDPG-ECO strategy. While ensuring the following performance, the fuel economy of DDPG-ECO can reach over 90% of that based on the dynamic programming (DP) method, effectively enhancing the fuel efficiency of HEVs [6].

## 4 Challenges Faced by Control Strategies Based on Deep Learning

Although deep learning-based autonomous driving control strategies demonstrate greater adaptability than traditional algorithms in complex scenarios, the contradictions between model characteristics and engineering requirements gradually become apparent during practical implementation, facing three main challenges: lack of interpretability, real-time performance bottlenecks, and data dependency risks.

In the field of autonomous driving, the lack of interpretability caused by the 'black box' nature of deep learning models restricts the safe implementation of technology. Core standards such as ISO 26262 require that the decision-making of autonomous driving systems be auditable, necessitating a clear traceability of the complete logic chain of 'input-decision-output'. However, deep learning models rely on implicit associations of vast amounts of parameters to generate decisions, making it impossible to clearly explain 'why a particular driving action was chosen'. Shahin addresses the issue of lack of interpretability in end-to-end autonomous driving systems due to their 'black box' characteristics, which hinders user trust and affects safety certification and accident investigation. He improves the safety assessment technology for end-to-end autonomous driving by combining XAI methods with end-to-end learning paradigms such as reinforcement learning and imitation learning. Additionally, he quantifies the impact of features on driving decisions using tools like Shapley values (SHAP), effectively revealing fault patterns in the training data [7]. However, due to the significant uncertainty that typically exists in dynamic driving environments, there is an urgent need to provide reasonable justification for the actions of autonomous vehicles at an appropriate level of confidence.

In autonomous driving systems, the contradiction between model complexity and onboard computing resources has become a core bottleneck limiting real-time performance. On one hand, to achieve high-precision environmental perception (like object detection and semantic segmentation) and decision control, deep learning models need to enhance their representational capabilities by increasing the number of network layers and expanding parameter scale, which inevitably leads to exponential growth in computational costs; on the other hand, autonomous driving has stringent real-time requirements for control responses, while the onboard computing platform is constrained by space and power consumption, with inherent limits in hardware computing power (such as GPU and TPU performance), making it difficult to support real-time computation of ultra-large-scale models. Wang addressed the issue of insufficient system stability and efficiency caused by the difficulty in quantifying the complexity of intelligent driving tasks in the collaborative task scheduling supported by the In-Vehicle Computing Platform (IVCP). He improved the task scheduling and resource adaptation technology within the vehicle-edge collaborative computing framework, ultimately achieving an average task handling precision increase of approximately 1.70% and an average latency reduction of about 1.97%. Additionally, the stability and reliability of the vehicle-edge collaborative computing system were significantly enhanced during high-speed vehicle movement[8]. Although the complexity can be reduced through lightweight techniques such as model pruning and knowledge distillation, these methods often come at the cost of sacrificing some accuracy, resulting in a difficult contradiction between accuracy, real-time performance, and computing power, which still limits the practical application of autonomous driving systems.

In addition, the strong dependence of deep learning models on data makes it difficult for them to handle the 'long tail problem'. The "long tail" scenario typically refers to the rare and constantly emerging driving situations related to safety that autonomous vehicles may encounter during actual driving[9]. These scenarios may have multiple features, such as road closures, traffic accidents, traffic participants violating traffic rules, etc. Even testing millions of miles on public roads cannot list all these scenarios one by one. In rare but high-risk scenarios, due to insufficient training data, control strategies are prone to extreme errors. Safety assurance schemes for planners are one of the key areas of exploration, and one core idea is to establish a set of universal safety rules for planners, which can serve as baseline standards for decision-making, regardless of whether they encounter regular road conditions or complex situations. The conservativeness of the planner can be improved by enlarging the space occupied by obstacles around autonomous vehicles, thereby reducing the risk of potential accidental behaviors[10,11]. However, these strict constraints may lead to unnecessarily overly conservative decisions, which can severely impact driving maneuverability.

## 5 Future Development Trends

Looking to the future, the automated driving control strategies based on deep learning will present three key development directions.

Firstly, lightweight models that integrate knowledge distillation will become the mainstream choice for on-board deployment. The knowledge distillation technique builds a "teacher-student" model architecture, transferring the decision logic and knowledge contained in the complex and high-precision "teacher model" to the lightweight "student model". The intelligent driving image segmentation model (Transformer-Deeplabv3) proposed by Yao combines attention mechanisms with multi-scale optimization to optimize the image segmentation model. It reduces computational complexity by simplifying the Transformer layers; however, in some cases, the computational resources required by the model are still relatively high, with a floating point operation count (FLOPS) reaching approximately 369.05 billion, and further optimizations are needed to balance performance and efficiency [3].

Secondly, multi-task learning and transfer learning techniques will help overcome the bottleneck of scenario generalization. Multi-task learning integrates multiple control tasks such as path tracking, obstacle avoidance, and energy optimization within the same model, enabling the model to uncover potential correlations and common features between different tasks, thereby enhancing its comprehensive ability to respond to complex scenarios. Transfer learning employs domain adaptation algorithms, such as adversarial domain adaptation, to enable the model to quickly transfer and adapt the knowledge learned from the source domain to the target domain.

The dynamic collaborative optimization of control strategies and perception results will achieve a comprehensive upgrade of the "perception-decision-control" closed loop. During the operation of the autonomous driving system, the perception module collects real-time information about the vehicle's surrounding environment, the decision-making module plans the driving intention based on this information, and the control module is responsible for execution. When the multimodal fusion perception system detects an unexpected obstacle, the control model can quickly and in real time adjust the internal weights, temporarily enhancing the priority of longitudinal braking to achieve precise coordination between braking and steering. This dynamic collaborative optimization breaks the traditional static sequential model of 'perception → decision → control', with each link providing feedback to one another and interacting in real-time, significantly improving the system's response speed and decision quality in complex and changing road conditions.

## 6 Conclusion

This article systematically reviews the research progress of autonomous driving control strategies based on deep learning, covering the optimization of lateral control in path tracking and steering angle decision-making, the dynamic adjustment of vehicle speed and following distance in longitudinal control, and the scene adaptation of cooperative control in both lateral and longitudinal directions. Leveraging the modeling capabilities of high-dimensional nonlinear data and advantages in dynamic environment interaction, deep learning has gradually broken through the reliance of traditional control algorithms on precise models, laying a technological foundation for the

transition of autonomous driving from demonstration in specific scenarios to practical application in complex environments. Through the innovative application of technologies such as CNN, LSTM, Transformer, and reinforcement learning, the safety and adaptability of autonomous driving in complex road conditions have been effectively enhanced, providing a technological pathway to address real problems like frequent traffic accidents and low traffic efficiency. At the same time, the exploration of challenges such as interpretability, real-time performance, and data dependency has promoted the deep adaptation of autonomous driving technology to engineering requirements. Techniques such as knowledge distillation and multi-task learning not only provide lightweight solutions for on-board deployment but also help meet the reliability requirements of safety standards like ISO 26262. Despite currently facing risks of "black box" decision-making, bottlenecks in onboard computing power, and challenges in adapting to long-tail scenarios, the integration of an explainable AI safety control framework and cross-scenario transfer techniques enhanced by vehicle-road collaboration have become key directions for breaking through these bottlenecks. In the future, with the dynamic collaborative optimization of control strategies and perception and decision-making modules, deep learning-based autonomous driving control technology will further unleash its value, providing core support for building an efficient, safe, and intelligent smart transportation system, ultimately achieving the long-term goal of enhancing the quality of travel for the public and promoting the upgrade of the transportation industry.

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