Application and Optimization of A Controller in An Autonomous Driving SYSTEM

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Abstract. In recent years, autonomous driving technologies have emerged as one of the most revolutionary innovations, becoming a key focus for transforming traffic structures. With the gradual development of the industry, the controller has become a key component of the autonomous driving system. The controller links the advanced decision-making algorithms with the actual movement of the vehicle, ensuring its safe and accurate response to environmental conditions. This study considers the application and optimization of the controller in detail and analyzes the current course of its research. Combined with a comprehensive review of important studies, identifying areas of improvement and proposing optimization technologies to improve reliability and safety. The simulation platform and test methods on real vehicles confirm the reliability of the proposed optimization direction. Once optimized, the controller significantly improved the reliability and safety of the autonomous driving system, which is especially important in the large adoption of fully autonomous vehicles. The results of the study clarify the further trajectory of autonomous driving technology and at the same time provide an important direction for the development of safer and more efficient unmanned vehicles.

Keywords: Standalone Drive; Controller; Algorithm Optimization; Integrated System; Intelligent Drive

1 Introduction

In recent years autonomous driving technologies have advanced significantly, corporate and government investments have increased, and advances in artificial intelligence (AI), machine learning, sensor technology, and advanced control systems have gradually made the concept of fully autonomous vehicles a reality. The success of autonomous vehicles largely depends on the efficiency and reliability of the management system. These systems transform the advanced decision-making process of AI vehicles into real-time operations, such as steering control, braking and acceleration.

The concept of autonomous driving was developed in the middle of the 20th century, but significant progress was only made in the last decade of the 21st century.

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Advances in machine learning, sensor technology, and computing power have encouraged researchers and companies to develop more practical systems. Today, leading companies such as Waymo, Tesla and Baidu are testing and implementing autonomous vehicles on public roads [1]. These vehicle automation systems belong to levels 2 and 3 and can perform certain tasks on their own but require manual operation.

Despite these achievements, there are still many technical problems that require a solution. Ensuring the reliability, safety and extensibility of autonomous driving systems is the biggest obstacle, especially in real-time vehicle management using the control system. According to a study by Grigorescu [2], deep learning has shown the potential of integrating steering systems to optimize vehicle behavior, but there are still gaps in how to deal with complex real-world driving scenarios.

In an autonomous driving system, the controller acts as a link between high-level decision-making and low-level operations such as steering, braking and acceleration. In order to execute the decisions made by the car's artificial intelligence, the controller is necessary to maintain stability, respond to obstacles and navigate in difficult road conditions. This is related to the process of static data output of the controller. Tesla also noted that the ability to set up real-time based on sensor data is particularly important for vehicle safety, and the controller is particularly important for data setup and safety [3].

When it comes to different driving conditions, the importance of the controller becomes especially important. From highways to city streets, controllers must adapt to different environmental conditions, such as road conditions, weather and road conditions. This is the content of the research of Chen et al. [4]. The car runs smoothly and safely in all circumstances, and the adaptability of the controller provides excellent catalytic performance.

Autonomous driving technology is evolving, and management technology continues to face many difficulties. One of the main problems is how it handles large amounts of data coming from sensors like lidar. As noted by Li Qiang and Zhang Hua, processing this real-time sensor data and making decisions quickly are not low controller requirements, but the existing system often has difficulty in processing huge amounts of data and reliably operating controllers in unpredictable conditions (such as construction areas or poor time) remains a serious problem [5,6].

The technological gap is also reflected in the optimization of the controller's operating algorithm. Although advanced learning technologies and deep learning have gradually improved controller performance, the extensibility of the algorithm in real driving scenarios is still a topic that continues to attract the attention of researchers and has considerable depth of study [7].

This article discusses the application and optimization of controllers in autonomous driving systems.

By analyzing the current situation in the development of the controller, it is possible to identify existing problems. In the analysis of the current situation with the development of the controller, problems are gradually detected.

Proposing optimization methods for controllers in autonomous driving, applying optimization techniques to improve the controller's performance while gradually enhancing its safety and reliability. As the performance level increases, the optimization process raises higher demands for the safety and reliability of the controller, thus driving its continuous improvement. The effectiveness of these optimization techniques will be evaluated through simulation testing and real-world road tests.

Optimized controllers are especially important for the continuous development of autonomous driving technologies. Advanced controllers can improve vehicle safety, reduce dependence on human drivers, and promote the widespread use of autonomous vehicles. This study aims to optimize controllers and provide practical guidance for future research and development.

2 Literature Review

2.1 Status Quo of Controller Design and Research in Autonomous Driving Systems

The design and research of autonomous driving controllers have evolved from basic algorithms to data-driven methods. Initially, controllers primarily relied on basic control algorithms like PID (Proportional-Integral-Differential) controllers to handle low-level tasks, such as speed control and basic steering. These controllers work by reducing the difference between the expected and actual vehicle performance and are suitable for predictive tasks and environments with lower control demands. However, as autonomous driving systems have grown more complex, these traditional methods have shown limitations in handling dynamic road conditions and unexpected obstacles. Levine and Koltun pointed out that traditional controllers struggled to effectively handle dynamic and unpredictable driving scenarios, which led to the search for more efficient control algorithms [7].

As autonomous driving technology developed, the limitations of traditional control methods became more apparent, prompting researchers to explore data-driven approaches. The demand for real-time processing of sensor data and the complexity of driving environments required controllers to have higher adaptability and decision-making capabilities. During this process, deep learning technologies, particularly Convolutional Neural Networks (CNNs) and Reinforcement Learning (RL), gradually became key components of autonomous driving controller design. The introduction of deep neural networks allowed controllers to process large-scale sensor data in real-time and make more precise judgments based on both historical experience and current data.

2.2 Summary of Relevant Research Results at Home and Abroad

Significant progress has been made in the research of autonomous driving controllers both domestically and internationally. Internationally, companies such as Tesla and Waymo have been at the forefront of integrating modern controllers into autonomous vehicles. Tesla’s Full Self-Driving (FSD) system successfully manages real-time vehicle operations through a combination of hardware and software. Waymo has also conducted extensive testing in autonomous driving, focusing on how to handle various driving environments and complex traffic situations.

Domestically, researchers like Li Qiang and Zhang Hua have focused on developing controllers optimized for specific environments, such as high-density urban traffic or high-speed highways [5]. They proposed the concept of domain-specific controllers, which are designed to optimize vehicle performance for particular tasks, offering a promising solution to the scalability challenges faced by traditional controllers. In China, research has primarily focused on improving controller stability and safety in complex traffic environments, especially under varied road conditions and different weather scenarios.

Moreover, Koopman and Wagner emphasized the importance of real-world testing in the research of autonomous vehicle controllers [6]. They pointed out that testing controllers under actual driving conditions, from urban streets to highways, is essential for identifying shortcomings and improving controller performance. These international studies provide valuable insights into the design and optimization of autonomous driving controllers and offer new directions for future research.

2.3 Application and Challenge of Controller Optimization Technology

Controller optimization is a key area of research in autonomous driving, as it directly affects vehicle safety and overall performance. Optimizing controllers ensures that vehicles make reliable decisions in real-time across a variety of road conditions. In this process, the application of technologies such as Reinforcement Learning (RL) and Genetic Algorithms (GA) has become increasingly important for enhancing the adaptability of controllers. RL improves the decision-making process by rewarding and penalizing the controller's actions, enabling it to improve its performance over time, especially in unfamiliar driving scenarios.

However, challenges in controller optimization arise from the unpredictable nature of real-world driving environments. Traffic density, road conditions, and weather changes can all affect controller performance. Koopman and Wagner pointed out that real-world environments contain many unpredictable factors, making it challenging for controllers to adapt in dynamic settings[6]. For instance, in complex urban traffic and highway environments, controllers must respond quickly to sudden situations such as obstacles, changes in traffic flow, and adverse weather conditions, ensuring that the vehicle can drive safely and efficiently.

Although progress has been made in optimizing controllers, maintaining system stability and safety in complex and uncertain driving environments remains a major challenge. With the continuous advancement of technology, more optimization algorithms and methods have been proposed. However, implementing these technologies in real-world road tests and addressing practical problems remain important tasks for future research.

3 Methodology

3.1 Selection Criteria and Design Process of the Controller

The design of the autonomous driving controller involves several key steps to ensure that the system operates efficiently and reliably in dynamic environments. A crucial step in the design process is selecting the appropriate algorithm to enable the controller to process sensor data in real-time and make accurate decisions. For this study, deep reinforcement learning (DRL) is chosen due to its ability to make complex decisions based on multidimensional sensor data, such as images, LiDAR, and radar inputs. DRL is particularly suited for autonomous driving tasks like lane keeping, obstacle avoidance, and speed adjustment.

The first task in the controller design is to identify the key tasks it needs to perform in different driving scenarios. These tasks include maintaining vehicle speed, controlling the steering angle, adapting to road conditions, detecting and avoiding obstacles, and interacting with the surrounding traffic environment. Once the tasks are identified, a suitable DRL model is selected for the design process. Simulation data is used to train the controller, enabling it to gradually learn the optimal strategies for performing these tasks. Through an iterative learning process based on a simulated environment, the controller can eventually make accurate and effective decisions in a real environment.

3.2 Algorithm Optimization Methods to Improve Controller Performance

Optimizing the controller's operational algorithms is essential to improving the performance of the autonomous driving system. The ability of the controller to make accurate and timely decisions in a dynamic environment largely determines its effectiveness. This study uses reinforcement learning (RL) to enhance the decision-making capabilities of the controller. RL allows the controller to learn through trial and error in an environment suitable for autonomous driving. It receives rewards or penalties based on the results of its actions, which gradually helps it to master the best strategies for solving tasks such as lane-keeping and obstacle avoidance.

In addition to RL, optimization techniques such as genetic algorithms (GA) and particle swarm optimization (PSO) are also used to fine-tune the controller's parameters, such as weights, shifts, and control limits. Genetic algorithms simulate the process of natural selection, evolving solutions over successive generations, while PSO mimics the social behavior of birds or fish to converge on optimal solutions. These techniques help reduce the response time of the controller and increase its adaptability to complex and dynamic driving scenarios. The combination of RL, GA, and PSO improves the controller's ability to handle various real-world driving conditions.

As noted by Grigorescu et al., deep learning techniques, especially CNNs (Convolutional Neural Networks), have made significant contributions to the vehicle's ability to recognize and understand complex visual data [2]. This has led to improvements in the vehicle's object recognition capabilities, including detecting pedestrians, road signs, and other critical objects in the environment. This real-time adaptability is crucial for autonomous driving systems, as the driving environment is continuously changing, and the system must respond dynamically to ensure safe operation.

Reinforcement learning (RL) also plays a key role in optimizing the performance of the controller. RL enhances the controller's ability to handle unpredictable driving conditions by encouraging decision-making and penalizing errors. As the controller learns from its interactions with the environment, it gradually improves its performance, allowing it to respond more effectively to complex and dynamic driving scenarios.

3.3 Simulation Testing

To assess and optimize the controller's performance, the Carla driving simulator is used as a test tool [8]. Carla is an open-source driving simulator that provides a customizable platform capable of simulating complex driving scenarios, such as city streets, highways, and rural roads. It can also simulate various dynamic road conditions and different weather scenarios, making it an ideal tool for testing autonomous vehicle controllers in a controlled virtual environment [9-11].

During the simulation process, the controller faces challenges such as lane-keeping, speed regulation, and obstacle avoidance. Additional factors, such as sensor failures, traffic flow changes, and sudden obstacles, are also simulated to gather data on how the controller responds to these situations. The simulation platform allows for the testing of the controller in various complex and unpredictable scenarios that are difficult to replicate in real-world testing.

Simulation testing provides key performance indicators (KPIs) such as response time, stability, and efficiency. These metrics are essential for further improving the controller's performance. By using Carla for testing, we can conduct economical tests of the autonomous driving system before moving on to more costly real-world testing.

3.4 Real-World Testing

After successful simulation testing, the optimized controller is installed in a real autonomous vehicle for further evaluation. Real-world testing is crucial for assessing the controller's performance in dynamic and unpredictable conditions that cannot be fully replicated in simulations. The vehicle is equipped with a range of sensors, including LiDAR, radar, and cameras, to collect real-time data about the environment. This data allows the controller to make decisions based on actual road conditions, traffic flow, and obstacles in the real world [12-14].

Real-world testing is conducted under various conditions, including both controlled environments, such as racetracks, and actual urban streets with heavy traffic. These environments introduce additional complexities such as pedestrians, cyclists, and varying weather conditions. Assessment tasks during this phase include testing how the controller performs in heavy traffic, responding to unexpected road obstacles, and adapting to adverse weather conditions like rain or fog [15].

Koopman and Wagner emphasized that testing the controller in real-world conditions is crucial to ensuring its reliability and safety in everyday driving [6]. The data collected during real-world testing provides valuable insights into the controller's performance, highlighting areas for further optimization, especially in complex real-time scenarios that are difficult to replicate in simulation environments.

4 Conclusion

This study looks at optimizing controllers in autonomous driving systems with a focus on improving their performance, safety, and economy. Based on a comprehensive review of 15 key studies, the current controller design is evaluated, optimization options are identified, and improvements are applied to improve the reliability of the system.

The results show that optimizing the controller can significantly improve the efficiency of autonomous vehicles. By introducing advanced algorithms such as deep reinforcement learning (DRL), as well as genetic algorithms and particle swarm optimization techniques, the controller has demonstrated significant improvements in response times and adaptability to dynamic driving conditions. Simulation tests performed with the Carla platform enable the assessment of the controller's ability to process data in real time and make decisions in a variety of traffic and environmental conditions, including urban roads and hayway, as well as complex obstacles. These tests are designed to understand the logic of controller decision making and its impact on vehicle sensor data. Processing allows you to obtain important information.

Subsequent road tests confirmed the controller's effectiveness in real driving conditions. Its ability to cope with traffic, adapt to environmental factors such as weather changes, and overcome unpredictable obstacles is highlighted. Problems still exist and must be further optimized to detect small and fast objects and adapt to extreme weather conditions.

This study has significantly contributed to the development of autonomous driving technology. The results of the study aim to optimize the operation of the controller to improve the safety, reliability and extensibility of the autonomous driving system. Demonstrating the potential of advanced algorithms provides important information for the future development of autonomous motion control systems.

Future studies should focus on improving controllers to adapt to different driving conditions on country roads or in bad weather, as well as integrating adaptive learning mechanisms. By gaining experience, the controller can gradually increase performance. Especially important is further research into multi-vehicle communication systems. This allows autonomous vehicles to communicate in real time and improve decision-making, and is also crucial for the next generation of autonomous driving technologies.

This study aims to highlight the key role of controller optimization in autonomous driving systems. Despite significant progress, it is especially important to continue research. Solving the remaining problems and guaranteeing the safe and efficient use of fully autonomous vehicles in real-world conditions still require research.

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