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Control Strategies in Autonomous Vehicle Path Tracking: A Comprehensive Review

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Abstract - Autonomous vehicle path tracking is a critical aspect of the overall control system of a vehicle. This review paper provides a comprehensive examination of the sophisticated control strategies used for autonomous vehicle path tracking. The paper categorizes the control strategies into three main types: model-based, learning-based, and hybrid approaches. Each category is analysed for its strengths, weaknesses, and application contexts. Hybrid strategies prove to be the best approach of the three as they combine the strengths of both model and learning-based strategies, providing a balanced approach that leverages the advantages of each method. The review aims to highlight current research trends, recognise gaps in the existing works, and recommend directions for future study.

Keywords: autonomous vehicle, control strategies, learning-based control, model-based control, path tracking

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1.0 INTRODUCTION

Autonomous vehicles (AVs) represent the forefront of modern transportation technology, promising increased safety, efficiency, and convenience in various applications, from personal transport to logistics (Guanetti et al., 2018). Path tracking, the ability of a vehicle to follow a predetermined route accurately, is a fundamental challenge in AV control (Paden et al., 2016). Figure 1 shows the autonomous driving system's standard blocks, which gives a general idea on how an AV works (Kiran et al., 2022). This review focuses on the various control strategies developed to address the challenge of tracking a predetermined path accurately, providing an extensive overview of their theoretical foundations and practical implementations.

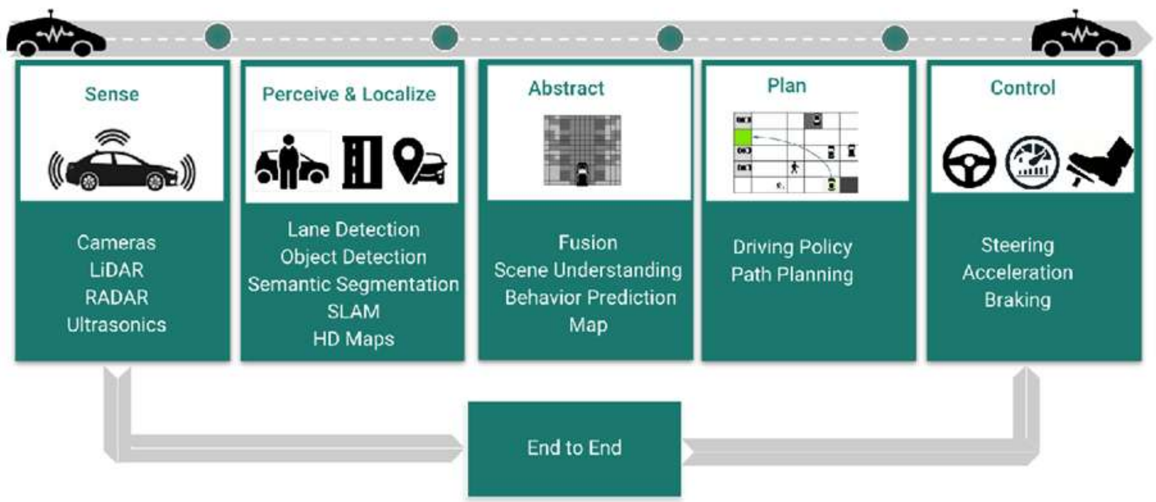

Fig. 1. Autonomous driving system's standard blocks (Kiran et al., 2022).

Model-based control strategies have traditionally dominated the field, leveraging mathematical models of vehicle dynamics to predict and control the vehicle's path (Falcone et al., 2007). These methods, while robust, often require precise modelling and can struggle with the variability and unpredictability inherent in real-world driving environments (Katrakazas et al., 2015). In contrast, learning-based approaches are now more preferable thanks to their capability to adapt and improve from experience, using data-driven methods to enhance path tracking performance (Levinson et al., 2011).

Hybrid approaches, combining elements of both model-based and learning-based strategies, provide a favourable approach for addressing the limitations of each individual method (Pinosky et al., 2023). This paper reviews these three categories in detail, providing insights into their mechanisms, applications, and performance metrics. By examining recent advancements and identifying research gaps, this review aims to guide future developments in autonomous vehicle path tracking.

2.0 MODEL-BASED CONTROL STRATEGIES

Model-based control strategies rely on mathematical representations of vehicle dynamics to predict and guide vehicle motion. These models can be linear or nonlinear, depending on the complexity of the vehicle's dynamics and the desired level of control precision (Wu et al., 2020). Some of the model-based control strategies are linear model predictive control (LMPC), nonlinear model predictive control (NMPC), and proportional-integral-derivative (PID) control.

2.1 Linear Model Predictive Control (LMPC)

Linear model predictive control (LMPC) is a widely used approach due to its balance between computational efficiency and control performance (Falcone et al., 2007). LMPC uses a linear model of the vehicle's dynamics to anticipate future states and optimize control inputs over a finite time horizon (Katrakazas et al., 2015). This method has been successfully applied in various autonomous driving scenarios, including highway driving and urban environments.

2.2 Nonlinear Model Predictive Control (NMPC)

Nonlinear model predictive control (NMPC) extends LMPC by incorporating nonlinear vehicle dynamics, allowing for more accurate predictions and control in complex driving situations (Findeisen & Allgöwer, 2002). NMPC is particularly useful in scenarios where the vehicle operates near the limits of its dynamic capabilities, such as high-speed cornering or off-road driving (Grüne & Pannek, 2017).

2.3 Proportional-Integral-Derivative (PID) Control

Proportional-integral-derivative (PID) control is one of the simplest and most intuitive model-based control strategies. It adjusts the control inputs by referring to the proportional, integral, and derivative of the error between the actual and desired path (Ogata, 2010). While PID controllers are not complicated in terms of implementation, they may not perform well in highly dynamic or unpredictable environments (Levinson et al., 2011).

2.4 Discussion of Model-Based Control Strategies

Model-based control strategies offer a structured approach to autonomous vehicle path tracking, leveraging well-established theories of control systems. However, their reliance on accurate modelling can be a limitation in real-world applications where environmental conditions and vehicle dynamics may vary (Paden et al., 2016). Integrating adaptive elements into these models or combining them with learning-based strategies can enhance their robustness and applicability (Pinosky et al., 2023). Table 1 shows the comparison between LMPC, NMPC, and PID control (Falcone et al., 2007).

Table 1: Comparison of Model-Based Control Strategies (Falcone et al., 2007)

Strategy	Design Complexity	Computational Load	Adaptability	Application Scenarios
LMPC	Low	Medium	Low	Highway, Urban
NMPC	High	High	Medium	Urban, Off-road
PID control	Low	Low	Low	Simple Routes

With reference to Table 1, each model-based control strategy has its own strengths and drawbacks. For instance, NMPC has a higher design complexity than LMPC and PID control, but its adaptability is better than them. PID control has the lowest computational load of all three strategies but it is only suitable for simple routes application.

3.0 LEARNING-BASED CONTROL STRATEGIES

Learning-based control strategies leverage machine learning techniques to develop controllers that can adapt and improve over time (Pinosky et al., 2023). These methods are particularly useful in environments where the system dynamics are complex or poorly understood. Examples of learning-based control strategies are reinforcement learning (RL), imitation learning (IL), and deep learning (DL).

3.1 Reinforcement Learning (RL)

Reinforcement learning (RL) has come out as an important strategy for autonomous vehicle control, allowing the system to learn optimal policies through trial and error (Sutton & Barto, 2018). RL-based controllers can adapt to changing environments and learn from past experiences, making them well-suited for dynamic and unpredictable scenarios (Kendall et al., 2019).

3.2 Imitation Learning (IL)

Imitation learning (IL) involves training a controller by mimicking the actions of an expert driver. This approach can be particularly effective in complex driving situations where designing explicit control rules is challenging (Pomerleau, 1989). IL has been used successfully in various autonomous driving applications, including urban driving and obstacle avoidance (Codevilla et al., 2018). An overview of IL control is illustrated in Figure 2 (Wang et al., 2022).

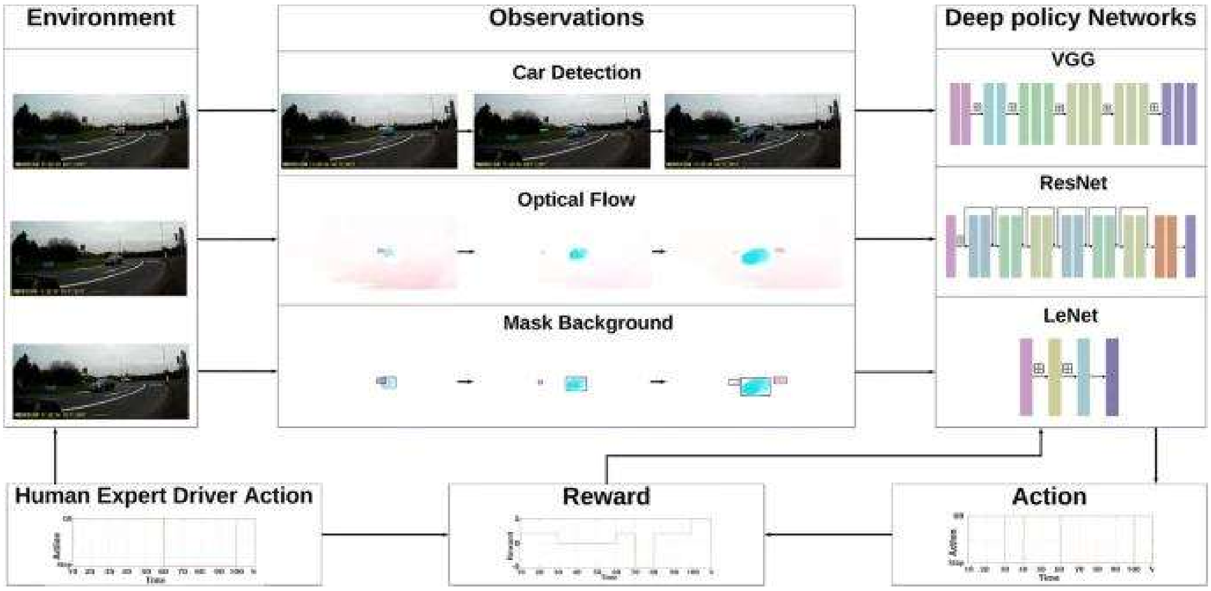

Fig. 2. Main framework of IL based decision-making system (Wang et al., 2022).

Figure 2 shows how an AV works using IL control. A decision will be made guided by human expert drivers' actions, based on the data gained by the camera mounted in front of the AV to capture a video sequence data from its surrounding. The data will be processed before an action is made at each timestamp.

3.3 Deep Learning (DL)

Deep learning (DL) techniques, especially convolutional neural networks (CNNs), have been applied to end-to-end control of autonomous vehicles (Bojarski et al., 2016). These methods learn to map raw sensor inputs directly to control actions, bypassing the need for explicit feature extraction and modelling (LeCun et al., 2015). While DL-based controllers can achieve high performance, they often need immense training data and computational resources (Arif et al., 2022).

3.4 Discussion of Learning-Based Control Strategies

Learning-based control strategies propose notable edges with regard to adaptability and performance in complex environments (Sutton & Barto, 2018). However, their dependency on huge datasets and computational resources can be a drawback, particularly in real-time applications (Levinson et al., 2011). Combining learning-based methods with model-based approaches can help mitigate these challenges and enhance overall system performance (Kendall et al., 2019).

4.0 HYBRID CONTROL STRATEGIES

Hybrid control strategies integrate elements of both model-based and learning-based approaches to leverage the strengths of each (Pinosky et al., 2023). These methods aim to combine the robustness and predictability of model-based controls with the adaptability and performance of learning-based techniques. The hybrid control strategies reviewed in this paper are adaptive model predictive control (AMPC), learning-augmented model predictive control (LAMPC), and hierarchical control systems.

4.1 Adaptive Model Predictive Control (AMPC)

Adaptive model predictive control (AMPC) adjusts the settings of the model in real-time based on observed data, which enhances the capability of the controller to handle variations in the vehicle's dynamics and environment (Aswani et al., 2013). This approach can improve the robustness and performance of MPC in real-world applications (Santos et al., 2024).

4.2 Learning Augmented Model Predictive Control (LAMPC)

Learning-augmented model predictive control (LAMPC) combines MPC with learning-based elements to enhance control performance (Hewing et al., 2020). For instance, a neural network could be utilised to predict and compensate for model inaccuracies, enhancing the overall robustness and accuracy of the control system (Xiao et al., 2023).

4.3 Hierarchical Control Systems

Hierarchical control systems use a multi-layered approach to combine different control strategies at various levels of abstraction (Talebpour et al., 2017). For example, a high-level planner might use a model-based approach to generate a global path, while a lower-level controller uses learning-based methods to handle local adjustments and obstacle avoidance (Katrakazas et al., 2015).

4.4 Discussion of Hybrid Control Strategies

Hybrid control strategies represent a promising direction for autonomous vehicle path tracking, combining the best aspects of model-based and learning-based approaches. By integrating these methods, hybrid strategies can achieve high levels of performance and robustness in a wide range of driving scenarios (Pinosky et al., 2023).

5.0 CONCLUSION

This review has provided a comprehensive examination of the control strategies used in autonomous vehicle path tracking. Model-based, learning-based, and hybrid approaches each offer unique strengths and face specific challenges. Model-based strategies provide robustness and predictability but require precise modelling. Learning-based strategies offer adaptability and high performance but depend on large datasets and computational resources. Hybrid strategies combine the strengths of both, providing a balanced approach that leverages the advantages of each method.

Future research should focus on further integrating these approaches, developing adaptive and learning-augmented control systems that can tackle the complexities and variability of real-world driving environments. Additionally, the continued advancement of computational resources and machine learning techniques will likely enhance the capabilities and performance of autonomous vehicle.

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