

Chapter 6

Study on Integrated Neural Networks and Fuzzy Logic Control for Autonomous Electric Vehicles

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ABSTRACT

This chapter presents a comprehensive study on the integration of neural networks and fuzzy logic control techniques for enhancing the autonomy of electric vehicles (EVs). The integration of these two paradigms aims to overcome the limitations of traditional control approaches by leveraging the complementary strengths of neural networks in learning complex patterns and fuzzy logic in handling uncertainty and imprecision. The chapter discusses the design, implementation, and evaluation of an autonomous EV control system that utilizes neural networks for learning vehicle dynamics and fuzzy logic for decision-making in various driving scenarios. Through extensive simulations and experiments, the effectiveness and robustness of the proposed integrated approach are demonstrated, showcasing its potential for improving the safety, efficiency, and adaptability of autonomous EVs in real-world environments.

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INTRODUCTION

Autonomous electric vehicles (AEVs) represent a transformative paradigm in the automotive industry, merging cutting-edge technology with sustainable mobility solutions. At their core, AEVs are vehicles equipped with advanced sensors, computing systems, and artificial intelligence algorithms, enabling them to navigate and operate independently without human intervention. These vehicles rely on a plethora of sensors such as LiDAR, radar, cameras, and GPS to perceive their surroundings and make informed decisions in real-time. By harnessing the power of electric propulsion systems, AEVs not only reduce reliance on fossil fuels but also contribute to mitigating environmental pollution and combating climate change (Phan, Bab-Hadiashar, Fayyazi, et al., 2020).

One of the primary objectives of AEVs is to enhance road safety by minimizing human errors and distractions, which are major contributors to accidents on roads. Through sophisticated perception algorithms and advanced control systems, AEVs can detect and respond to dynamic environments, including detecting pedestrians, cyclists, and other vehicles, with a level of precision and speed unmatched by human drivers. Moreover, AEVs hold the promise of revolutionizing urban mobility by offering on-demand transportation services, reducing traffic congestion, and optimizing travel routes for efficiency. Additionally, AEVs have the potential to redefine the concept of vehicle ownership, with the rise of autonomous ride-hailing services and shared mobility platforms, leading to a shift from individual car ownership towards mobility-as-a-service models (Angundjaja et al., 2021). As the automotive industry continues to embrace autonomy and electrification, AEVs are poised to play a pivotal role in shaping the future of transportation, ushering in an era of safer, cleaner, and more efficient mobility solutions for society.

The relentless march of technological advancement has propelled the automotive industry into a new era, characterized by the emergence of autonomous vehicles and electric propulsion systems. As the capabilities of these vehicles evolve, so too must the control techniques that govern their behavior. The need for advanced control techniques in this context stems from the unprecedented complexity and dynamism of the autonomous electric vehicle (AEV) environment (Phan, Bab-Hadiashar, Hoseinnezhad, et al., 2020). Unlike traditional vehicles, which rely primarily on human drivers to interpret and respond to changing road conditions, AEVs must navigate a multifaceted landscape of sensors, algorithms, and decision-making processes to operate safely and efficiently.

At the heart of the demand for advanced control techniques lies the inherent intricacy of AEV systems. These vehicles are equipped with an array of sensors, including LiDAR, radar, cameras, and GPS, which generate vast amounts of data about the surrounding environment in real-time. Managing and interpreting this data requires sophisticated control algorithms capable of processing complex sensor inputs, identifying relevant features, and making rapid decisions to ensure safe navigation. Moreover, the transition to electric propulsion introduces additional layers of complexity, as AEVs must dynamically manage power distribution, battery state-of-charge, and energy efficiency while navigating diverse driving conditions (Guo et al., 2021). Conventional control approaches are ill-equipped to handle such multifaceted challenges, underscoring the imperative for advanced techniques that can adapt and evolve alongside the evolving landscape of AEV technology.

Furthermore, the push towards autonomy necessitates control techniques that can accommodate uncertainty, variability, and ambiguity in the AEV environment. Unlike deterministic systems where inputs and outputs are precisely defined, AEVs operate in a world characterized by inherent unpredictability, including variability in road conditions, weather patterns, and human behavior. In such dynamic environments, traditional rule-based control approaches often fall short, as they struggle to account for

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