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Integration of Model-Based and Model-Free Approaches for Robust Autonomous System Design

Syeda Noor Fathima, P. Selvaraju
VISVESVARAYA TECHNOLOGICAL UNIVERSITY,
EXCEL ENGINEERING COLLEGE

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[1]Syeda Noor Fathima, Assistant Professor, Department of Electronics and Communication, HKBK College of Engineering, Visvesvaraya Technological University, Bangalore 560045, Karnataka, India, Fatu.phd@gmail.com

[2]P. Selvaraju, Associate Professor, Department of AIDS, Excel Engineering College, Namakkal, Tamil Nadu, India, rpselvaraju@gmail.com

Abstract

This book chapter explores the integration of model-based and model-free approaches for the design of robust autonomous systems. The chapter emphasizes the complementary strengths of both paradigms, highlighting how model-based methods provide structured predictions and model-free techniques enable adaptive learning in dynamic environments. A detailed analysis of hybrid approaches demonstrates their effectiveness in enhancing system robustness, scalability, and real-time performance across various applications, such as autonomous vehicles, robotics, and healthcare. The chapter discusses performance evaluation techniques, focusing on robustness and scalability metrics critical for real-world deployment. Case studies illustrate the practical application of hybrid systems, showcasing their ability to navigate complex, unpredictable environments. With advancements in machine learning, these integrated approaches are poised to revolutionize autonomous system design, offering innovative solutions to challenges in autonomy, adaptability, and decision-making. The chapter serves as a comprehensive guide for researchers and practitioners in autonomous system development.

Keywords:

Hybrid Approaches, Model-Based Methods, Model-Free Techniques, Autonomous Systems, Performance Evaluation, Scalability.

Introduction

The field of autonomous systems has rapidly evolved over the past few decades, driven by advancements in machine learning, artificial intelligence, and robotics [1,2]. As autonomous systems are increasingly deployed in complex, real-world environments, there was a growing demand for systems that can adapt and perform under dynamic and unpredictable conditions [3,4]. Traditional model-based approaches, which rely on predefined mathematical models to make decisions, offer a high degree of precision and predictability [5-7]. However, often struggle when faced with the uncertainty and variability inherent in real-world environments [8,9]. Conversely, model-free approaches, such as reinforcement learning and deep learning, enable systems to learn from experience and adapt to new, unforeseen scenarios, but theylack the predictability and reliability needed for critical applications [10-12]. This chapter focuses on the integration of both model-based and model-free approaches, presenting a hybrid methodology that combines the strengths of both paradigms to create more robust, adaptable, and scalable autonomous systems [13,14].

Model-based approaches in autonomous systems leverage existing knowledge about the environment, using mathematical models to predict the behavior of the system and make decisions accordingly [15,16]. These models can be highly effective in controlled settings where the environment was predictable and well-understood [17]. However, their performance can degrade significantly when faced with unknown variables, such as sensor inaccuracies, environmental changes, or unforeseen obstacles [18]. This was where model-free approaches come into play [19]. Techniques like reinforcement learning, which allow systems to learn through trial and error, provide the flexibility needed to deal with uncertainty [20]. By combining these two approaches, a hybrid model can achieve greater flexibility while maintaining the reliability and structure offered by model-based systems [21].

Hybrid approaches have gained significant attention due to their ability to overcome the limitations of both model-based and model-free methods when applied individually [22-24]. By integrating model-based predictions with model-free learning capabilities, these systems can adapt to new scenarios more effectively [25]. This combination allows autonomous systems to make predictions based on existing models while simultaneously learning from their interactions with the environment. In applications such as autonomous vehicles or robotics, this integration enables the system to navigate complex environments, account for unexpected variables, and make decisions in real-time. Hybrid systems can improve scalability, as the model-free component can enable the system to adapt to new environments without requiring complete reprogramming or redesign.