Adaptive Fuzzy Logic in Hierarchical Deep Reinforcement Learning for Enhanced Robustness in Autonomous Navigation

Abstract

Autonomous navigation in complex and dynamic environments remains a significant challenge, particularly for systems like Four-Wheel Independent Steering and Driving (4WISD) robots that require precise control and adherence to physical constraints. While hierarchical frameworks integrating Deep Reinforcement Learning (DRL) for high-level decision-making and Fuzzy Logic Control (FLC) for low-level execution have shown promise in balancing adaptability and feasibility, their robustness can be limited by static fuzzy logic parameters. This paper proposes a novel approach that introduces adaptive fuzzy logic within a hierarchical DRL framework. We posit that by allowing the DRL agent to dynamically adjust the parameters of the fuzzy logic controller based on environmental feedback and task performance, the system can achieve significantly enhanced robustness and adaptability to unforeseen conditions, sensor noise, or varying system dynamics. We outline the theoretical foundations of this adaptive mechanism, detailing how DRL can optimize fuzzy membership functions and rule weights. Mathematical formulations for the adaptive fuzzy logic system and the DRL-driven adaptation process are provided. This approach aims to push the boundaries of reliable autonomous navigation in challenging real-world scenarios.

1 Introduction

The field of autonomous navigation has witnessed rapid advancements, driven by breakthroughs in machine learning, particularly Deep Reinforcement Learning (DRL). DRL agents excel at learning complex policies from interaction with environments, making them suitable for high-level decision-making in robotics. However, deploying purely DRL-based solutions in safety-critical applications, such as autonomous vehicles or industrial robots, often faces challenges related to interpretability, guaranteed safety, and adherence to strict physical constraints.

Hybrid approaches, combining DRL with traditional control methods, have emerged as a promising avenue. A notable example is the hierarchical decision-making framework for Four-Wheel Independent Steering and Driving (4WISD) systems, which integrates DRL for high-level navigation commands and Fuzzy Logic Control (FLC) for low-level constraint enforcement [1]. This architecture leverages DRL's learning capabilities for global path planning while using FLC to ensure physical feasibility, preventing issues like mechanical strain and wheel slippage.

Despite these advantages, the robustness of such hybrid systems can be limited by the static nature of the fuzzy logic controller's parameters. In dynamic environments, with varying terrain, changing load conditions, or sensor inaccuracies, pre-defined fuzzy rules and membership functions may not always be optimal, potentially leading to suboptimal performance or even instability. This paper proposes to address this limitation by introducing an adaptive fuzzy logic component within the hierarchical DRL framework, where the DRL agent is not only responsible for high-level navigation but also for dynamically tuning the fuzzy logic parameters.

2 Background

2.1 Deep Reinforcement Learning (DRL)

DRL combines deep learning with reinforcement learning, allowing agents to learn optimal policies by interacting with an environment. An agent observes a state s, takes an action a, receives a reward r, and transitions to a new state s'. The goal is to learn a policy $\pi(a|s)$ that maximizes the expected cumulative reward. This is often achieved through value-based methods (e.g., DQN) or policy-based methods (e.g., A2C, PPO), where deep neural networks approximate value functions or policies.

The DRL agent's policy can be represented as:

$$a_t = \pi(s_t; \theta)$$

where a_t is the action at time t, s_t is the state at time t, and θ represents the parameters of the deep neural network approximating the policy.

2.2 Fuzzy Logic Control (FLC)

Fuzzy Logic Control is a rule-based system that mimics human reasoning by using linguistic variables and fuzzy sets. It consists of four main components: fuzzification, a rule base, an inference engine, and defuzzification. FLC is particularly effective in systems where precise mathematical models are difficult to obtain or when dealing with inherent uncertainties. The output of an FLC system for a given input $\mathbf{x} = [x_1, x_2, \ldots, x_n]$ is determined by a set of IF-THEN rules:

$$R_k : \text{IF } x_1 \text{ is } A_{k1} \text{ AND } \ldots \text{ AND } x_n \text{ is } A_{kn} \text{ THEN } y \text{ is } B_k$$

where A_{ki} and B_k are fuzzy sets characterized by membership functions $\mu_{A_{ki}}(x_i)$ and $\mu_{B_k}(y)$, respectively. The final crisp output y^* can be obtained through defuzzification, such as the centroid method:

$$y^* = \frac{\sum_{k=1}^{M} y_k \mu_{B_k}(y_k)}{\sum_{k=1}^{M} \mu_{B_k}(y_k)}$$

where M is the number of rules, and y_k is the output value for rule k.

2.3 Hierarchical DRL and FLC Integration

The work by Wang et al. [1] demonstrated a hierarchical framework where DRL provides high-level motion commands (e.g., desired velocity and steering angle), which are then refined by an FLC. The FLC translates these commands into low-level control actions (e.g., individual wheel torques and steering angles for a 4WISD system), while simultaneously enforcing kinematic constraints. This separation of concerns allows DRL to focus on global optimality and FLC to handle local physical feasibility.

3 Proposed Methodology: Adaptive Fuzzy Logic in Hierarchical DRL

Our proposed methodology extends the hierarchical DRL-FLC framework by introducing an adaptive mechanism for the fuzzy logic controller, driven by the DRL agent. The core idea is that the DRL agent, in addition to generating high-level navigation commands, also learns to dynamically adjust the parameters of the FLC to improve robustness and adaptability.

3.1 Architecture

The proposed architecture consists of two main layers:

1. **High-Level DRL Agent:** This agent perceives the global state of the environment (e.g., robot's position, target, obstacles) and outputs two sets of information:
   - **High-level Navigation Commands (a_{nav}):** Desired trajectory, velocity, or steering angle.
   - **Fuzzy Logic Adaptation Parameters (a_{adapt}):** Parameters that directly modify the FLC's behavior, such as the centers and widths of membership functions, or the weights of fuzzy rules.
2. **Low-Level Adaptive Fuzzy Logic Controller (AFLC):** This controller receives the high-level navigation commands from the DRL agent and the adaptation parameters. It then generates the final low-level control signals for the 4WISD system, while dynamically adjusting its internal fuzzy logic parameters based on a_{adapt}.

The overall control loop can be described as follows:

$$(a_{nav,t}, a_{adapt,t}) = \pi(s_t; \theta_{DRL})$$

$$u_t = \text{AFLC}(a_{nav,t}, s_{local,t}; \text{parameters}(a_{adapt,t}))$$

where $s_{local,t}$ represents local sensor readings relevant to low-level control and constraint satisfaction, u_t are the low-level control actions, and θ_{DRL} are the parameters of the DRL policy network.

3.2 Adaptive Fuzzy Logic Mechanism

The adaptation of the fuzzy logic controller can occur at several levels:

1. **Membership Function Adaptation:** The DRL agent can learn to adjust the shape, center, and width of the input and output fuzzy membership functions. For example, for a Gaussian membership function $\mu_A(x) = e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2}$, the DRL agent could output the center c and standard deviation σ.

2. **Rule Weight Adaptation:** The DRL agent can assign weights to each fuzzy rule, allowing the system to prioritize certain rules under different circumstances.

3. **Rule Base Adaptation (Advanced):** In more complex scenarios, the DRL agent could even suggest modifications to the fuzzy rule base itself, though this is a more challenging problem.

Let's focus on membership function adaptation. If the DRL agent outputs adaptation parameters $a_{adapt} = [c_1, \sigma_1, c_2, \sigma_2, \ldots]$, these would directly modify the FLC's membership functions. The updated membership function for an input x_i and fuzzy set A_{ki} could be:

$$\mu'_{A_{ki}}(x_i) = f(x_i, c_{ki}(a_{adapt}), \sigma_{ki}(a_{adapt}))$$

where $c_{ki}(a_{adapt})$ and $\sigma_{ki}(a_{adapt})$ are functions that map the DRL's adaptation output to the specific parameters of the fuzzy set A_{ki}.

The DRL agent's reward function would need to be carefully designed to encourage both effective high-level navigation and optimal fuzzy logic parameter tuning. This reward could incorporate terms for task completion, collision avoidance, smoothness of motion, and adherence to physical constraints.

3.3 Training the Adaptive System

Training would involve an end-to-end approach where the DRL agent learns the optimal policy for both navigation commands and fuzzy logic adaptation. During exploration, the DRL agent would experiment with different adaptation parameters, and the resulting performance (e.g., stability, constraint satisfaction, task completion rate) would feed back into its reward signal. This allows the DRL to discover how to best configure the FLC for various situations.

4 Potential Benefits and Future Work

The integration of adaptive fuzzy logic within a hierarchical DRL framework offers several significant benefits:

- **Enhanced Robustness:** The ability to dynamically adjust FLC parameters makes the system more resilient to uncertainties, unmodeled disturbances, and changes in environmental conditions or robot dynamics.
- **Increased Adaptability:** The system can adapt to novel situations without requiring extensive re-tuning of the FLC by human experts.
- **Improved Performance:** By optimizing FLC parameters online, the system can achieve better performance in terms of smoothness, efficiency, and constraint satisfaction.
- **Maintain Interpretability and Safety:** While adding DRL for adaptation, the underlying FLC still provides a degree of interpretability and allows for the explicit encoding of safety constraints, which is crucial for real-world deployment.

Future work will involve extensive simulation and real-world experiments to validate the proposed framework. This includes:

- Developing specific DRL architectures for generating adaptation parameters.
- Designing comprehensive reward functions that balance navigation goals with FLC optimality.
- Evaluating the performance against static FLC approaches under various challenging conditions (e.g., slippery surfaces, varying payloads, sensor degradation).
- Exploring different types of fuzzy logic adaptation (e.g., rule weight tuning, rule base modification).

5 Conclusion

This paper has proposed a novel extension to hierarchical DRL-FLC frameworks for autonomous navigation by introducing adaptive fuzzy logic. By empowering the DRL agent to dynamically tune the parameters of the low-level fuzzy logic controller, we anticipate significant enhancements in the robustness, adaptability, and overall performance of 4WISD systems in complex and uncertain environments. This research direction holds the potential to bridge the gap between the powerful learning capabilities of DRL and the reliable, constraint-aware control offered by fuzzy logic, paving the way for more resilient and intelligent autonomous systems.

References

[1] Y. Wang, D. Xu, Y. Xie, S. Tan, X. Zhou, and P. Chen, ”Hierarchical Decision-Making for Autonomous Navigation: Integrating Deep Reinforcement Learning and Fuzzy Logic in Four-Wheel Independent Steering and Driving Systems,” arXiv preprint arXiv:2508.16574v1, 2025. http://arxiv.org/pdf/2508.16574v1