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Abstract

The increasing complexity of distributed systems across robotics, network optimization, and intelligent infrastructure necessitates advanced decision-making frameworks capable of autonomous learning and coordination. This chapter investigates the integration of Multi-Agent Reinforcement Learning (MARL) and Genetic Algorithms (GA) as a hybrid approach to address the scalability, adaptability, and optimization challenges in decentralized environments. By combining the local policy refinement capabilities of reinforcement learning with the global search strengths of evolutionary algorithms, the hybrid MARL-GA paradigm enables agents to evolve robust strategies in dynamic, partially observable, and adversarial settings. Key components such as policy encoding, fitness shaping, co-evolution, and credit assignment are explored in detail, with a focus on their role in enhancing multi-agent cooperation and specialization. Furthermore, the chapter presents mechanisms for scalable agent policy evolution, emphasizing role differentiation and generalization across complex multi-agent tasks. Real-world applications and experimental insights are discussed to demonstrate the effectiveness of this hybrid model in scenarios demanding distributed intelligence. The proposed frameworks and methodologies offer a strong foundation for the design of resilient and adaptive multi-agent systems, setting the stage for future research in hybrid learning-based distributed decision making.

Keywords: Multi-Agent Reinforcement Learning, Genetic Algorithms, Distributed Decision Making, Policy Evolution, Co-evolutionary Learning, Hybrid Intelligence.

Introduction

The evolution of intelligent systems has accelerated the demand for decentralized decision-making frameworks, especially in domains where a central controller is either infeasible or inefficient [1]. Distributed decision-making plays a pivotal role in modern applications such as autonomous vehicle coordination, swarm robotics, decentralized sensor networks, and smart grid systems [2]. These environments require multiple agents to operate concurrently, often under partial observability and resource constraints [3]. Each agent must make independent decisions while simultaneously coordinating with others to achieve global objectives [4]. Unlike traditional centralized models, which are limited by bottlenecks such as single points of failure, scalability issues, and communication delays, distributed frameworks promote robustness, scalability, and adaptability. Enabling autonomous agents to make intelligent decisions in a distributed setting introduces substantial complexity, particularly in learning effective cooperation strategies and managing the interdependencies of actions and outcomes [5].

Multi-Agent Reinforcement Learning (MARL) has emerged as a powerful approach to tackle this complexity by allowing agents to learn from their interactions with the environment and with one another. In MARL, agents adapt their policies over time using feedback in the form of rewards, which indicate the desirability of their actions [6]. While effective in theory, practical implementation of MARL is impeded by several challenges [7]. The non-stationarity of the environment, resulting from simultaneous policy updates by multiple agents, often destabilizes the learning process [8]. The joint action space grows exponentially with the number of agents, leading to slower convergence and increased sample complexity [9]. Credit assignment also becomes non-trivial, as it is difficult to determine the exact contribution of each agent to the global reward. These limitations underscore the need for augmenting MARL with mechanisms that enhance learning efficiency, policy diversity, and convergence stability [10].

Genetic Algorithms (GAs), inspired by biological evolution, offer a complementary approach to reinforcement learning by emphasizing population-based global search rather than gradient-based optimization [11]. GAs evolves a population of candidate solutions through iterative processes involving selection, crossover, and mutation, guided by a fitness function [12]. When applied to multi-agent systems, GAs can maintain policy diversity, escape local optima, and explore complex solution landscapes more effectively than conventional methods [13]. This makes them particularly suitable for environments with sparse or delayed rewards, where reinforcement signals alone are insufficient to guide learning [14]. GAs enables the evolution of not just individual agent behaviors but also communication strategies, task allocations, and coordination mechanisms. By combining the exploratory strengths of GAs with the adaptive capabilities of MARL, hybrid systems can achieve improved performance in decentralized environments characterized by uncertainty, variability, and adversarial dynamics [15].