Deep Reinforcement Learning: Methodologies and Military Applications

1 Introduction

Deep reinforcement learning (DRL) integrates deep learning's capacity for feature extraction with reinforcement learning's trial-and-error approach to optimize decision-making in dynamic environments. This field has garnered attention for its ability to address complex strategic challenges. Wang et al. [2023] categorize DRL algorithms into value function-based and policy gradient-based approaches, emphasizing their military applications. This article synthesizes their analysis with insights from Mnih et al. [2015] and OpenAI's blog [OpenAI, n.d.] to explore DRL's methodologies, military uses, and future directions, based on research conducted in June 2025.

2 DRL Methodologies

DRL algorithms are categorized into value function-based and policy gradient-based methods. Value function approaches, such as the Deep Q-Network (DQN), estimate the value of actions in specific states. Mnih et al. [2015] demonstrated DQN's success in mastering Atari games, though its overestimation of action values led to improvements like Double DQN, which separates action selection and evaluation, and Dueling DQN, which distinguishes state and action values for enhanced stability [Wang et al., 2023]. These refinements improve DRL's reliability for practical applications.

Policy gradient methods optimize action probabilities, ideal for continuous tasks like robotics. Wang et al. [2023] highlight Deep Deterministic Policy Gradient (DDPG) for efficient data use and Proximal Policy Optimization (PPO) for stable training through constrained updates. Advanced algorithms like Twin Delayed DDPG (TD3) and Soft Actor-Critic (SAC) address overestimation and improve exploration. OpenAI's blog underscores PPO's effectiveness in strategic scenarios, suggesting its suitability for complex DRL challenges [OpenAI, n.d.].

3 Military Applications

Wang et al. [2023] identify three military applications: air combat maneuvering, task assignment, and military chess deduction. In air combat, DRL enables autonomous unmanned aerial vehicle decisions, as seen in the 2020 AlphaDogfight, where a DRL system outperformed human pilots. Unlike traditional methods reliant on precise models, DRL learns through experience, though sparse rewards present challenges. Mnih et al. [2015] highlight DRL's strength in dynamic, game-like settings, akin to air combat. Task assignment employs multi-agent DRL for dynamic resource allocation, but complex task interdependencies slow convergence. Military chess deduction, resembling strategy games, benefits from DRL's automation potential, yet its opaque decisions raise concerns, as noted in OpenAI's blog [OpenAI, n.d.].

4 Challenges and Future Directions

DRL struggles with learning efficiency and adaptability across scenarios [Wang et al., 2023]. Proposed solutions include hierarchical DRL, multi-agent systems, and transfer learning to enhance scalability. Mnih et al. [2015] suggest generalizable architectures could support these advancements. OpenAI's blog emphasizes ethical concerns about autonomous military systems, highlighting the need for responsible development [OpenAI, n.d.].

5 Conclusion

DRL's blend of deep learning and reinforcement learning holds transformative potential for military applications, from air combat to strategic simulations. Overcoming efficiency and ethical challenges will strengthen its impact. Future research should focus on scalable algorithms and transparent decision-making.

References

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