Robust DDPG Reinforcement Learning Differential Game Guidance in Low-Thrust, Multi-Body Dynamical Environments

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***Abstract*—Onboard autonomy is a critical enabler for increasingly complex deep-space missions. In nonlinear dynamical environments, designing computationally efficient and robust guidance strategies remains a significant challenge. Traditional approaches often rely on simplifying assumptions in the dynamical model or require substantial computational resources, limiting their applicability for onboard implementation. This research introduces a robust reinforcement learning-based differential game approach to develop an adaptive closed-loop controller for low-thrust spacecraft guidance in multi-body dynamical environments. The proposed controller is trained to handle large initial deviations, enhance resilience against disturbances, and augment conventional targeting guidance methods. Unlike traditional approaches, it does not require explicit knowledge of the dynamical model, allowing direct interaction with the nonlinear equations of motion to create a generalizable learning framework. High-performance computing is leveraged to train a robust neural network controller, which can be deployed onboard to generate real-time low-thrust control profiles without overloading the flight computer. The effectiveness of this method is demonstrated through sample transfers between Lyapunov orbits in the Earth-Moon system, where the controller exhibits strong robustness to perturbations and generalizes effectively across different mission scenarios and low-thrust engine models. This work highlights the potential of reinforcement learning-based differential game approaches in advancing autonomous spacecraft navigation in complex gravitational environments.**

***Index Terms*—component, formatting, style, styling, insert.**

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References

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