Transformer-Augmented Deep Reinforcement Learning for Fault-Tolerant Autonomous Navigation in Aerospace Robotics

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Abstract:
Autonomous navigation of aerospace robots in GPSdenied, radiation-rich, and dynamically uncertain environments remains one of the hardest unsolved challenges in space systems engineering. Classical controllers—PID, LQR, model predictive control—struggle to generalize across the high-dimensional, partially observable state spaces encountered during orbital debris avoidance, lunar surface traversal, and deep-space proximity operations. We present the *Transformer-Augmented Proximal Policy Optimization* (TA-PPO) framework, an integrated threemodule architecture that combines Vision Transformer (ViT)based multi-modal sensor fusion, an LSTM-augmented PPO policy network, and an autoencoder-driven fault detection and recovery subsystem within a single end-to-end pipeline. Training was carried out in AeroNav-Sim, a custom OpenAI Gymcompatible simulator with extensive domain randomization, and validated on a hardware-in-the-loop testbed featuring an NVIDIA Jetson Orin NX and ROS2 Humble middleware. Across 500 evaluation episodes, TA-PPO achieved a navigation success rate of 89.2%, compared to vanilla PPO (78.1%), Soft Actor-Critic (84.7%), and classical MPC (71.4%). Mean fault recovery latency was 1.82s, a 31% improvement over the nearest baseline. Onboard inference ran at 23.4ms per decision step. These results suggest that integrating transformer-based perception with deep reinforcement learning can yield a viable, fault-aware control stack for space robotic missions operating under sensor degradation.

Keywords:
Deep reinforcement learning, aerospace robotics, vision transformer, fault-tolerant navigation, autonomous systems, sim-to-real transfer, sensor fusion, proximal policy optimization.