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A NOVEL FRAMEWORK FOR SATELLITE DEBRIS MITIGATION: INTEGRATING BLOCKCHAIN FEDERATED LEARNING WITH HIERARCHICAL DEEP REINFORCEMENT LEARNING

Abstract

Recent progress in technology has been impacted by the rapid growth of satellite networks and space missions, leading to increasing global connectivity and scientific advancements. These advances have brought with them space debris, in the form of old satellites, rocket components, and other remains of previous missions, as a major problem, threatening future space operations. The increasing debris density is leading to cascading debris events, also referred to as Kessler syndrome. It results in devastating collisions that destroy vital satellite systems and make vital orbital areas useless. Space Surveillance and Tracking (SST) systems use ground- and space-based approaches to monitor debris, but growing volumes and real-time precision needs make conventional techniques redundant. Although deep learning improves detection, its centralized models on scalability, communication cost, and the introduction of single points of failure limit its effectiveness. This article aims to provide a comprehensive literature review on advanced deep learning techniques for debris detection, such as federated learning, hierarchical deep learning, and reinforcement learning approaches. It further discusses how the use of blockchain technology can improve tracking systems as well as systems of debris detection. It also explores the effectiveness of multi-agent coordination frameworks in tracking dispersed satellite constellations for optimization. Building upon this framework, the paper suggests a novel integrated framework that combines these approaches: a blockchain-based federated learning system with an optimistic, dual-level reinforcement learning model. The prediction module and decision module are the two main modules that form the proposed architecture. The prediction module leverages transformers to model temporal dynamics and CNNs for extracting sensor image features, yielding precise forecasts of debris trajectories. The decision component utilizes a two-level deep reinforcement learning (DRL) approach, in which the lower-level agent performs real-time collision avoidance maneuvers and the higher-level agent gives priority to debris clearance by performing cost-benefit analysis. Furthermore, satellites share real-time state data through multi-agent coordination, optimizing overall performance and safety. Comparing our technique to traditional SST approaches, preliminary simulation results show that it reduces communication overhead and operational expenses while dramatically improving debris detection accuracy and real-time collision avoidance. Future studies can involve integration of human-AI collaboration relying on autonomous decision-making and human wisdom, improving space debris control methodologies to higher adaptability and robustness levels.