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# DEEP LEARNING-BASED SPACECRAFT POSE ESTIMATION WITH A FAIL-SAFE FALLBACK MECHANISM

**Abstract**

The escalating accumulation of inactive satellites in Low Earth Orbit (LEO) creates a serious hazard for operational spacecraft. Mitigating collision risks requires efficient and cost-effective debris removal missions, which in turn, depend on accurate and reliable pose (i.e. position and orientation) estimation of uncooperative objects. To overcome limitations of complex and costly Light Detection and Ranging (LIDAR) systems, the researchers have moved towards utilizing monocular cameras for spacecraft pose estimation. Meanwhile, Deep Learning (DL) algorithms have proven to be highly effective in processing the resulting image data. However, their inherently black-box nature makes them difficult to validate, and the risk of failure remains a major concern for space missions. Operators are understandably reluctant to rely solely on neural network-based systems without a transparent and robust backup.

In this work, we propose a spacecraft pose estimation framework that integrates a DL-based keypoint detection system with a fail-safe fallback mechanism grounded in classical computer vision algorithms. The primary system employs a neural network trained on a comprehensive dataset to predict critical keypoints for precise estimation of spacecraft pose. To address potential unreliability of the network, our framework continuously monitors prediction confidence, employing an uncertainty quantification method chosen from a range of techniques, including Monte Carlo Dropout, Deep Ensembles, and Bayesian methodologies, and automatically activates a fallback procedure when needed. This backup leverages traditional feature detection and Perspective-n-Point (PnP) algorithms to compute the spacecraft's pose reliably.

Our KRN was trained on a Blender-generated dataset that simulates a vast range of spacecraft trajectories, ensuring robust generalization across realistic operational scenarios. The proposed approach is currently undergoing validation in the specialized facility featuring a dark room equipped with two robotic arms to simulate spacecraft rendezvous and docking conditions, along with a sun simulator to

mimic realistic solar lighting. Additionally, our solution is being evaluated on low-power embedded hardware, demonstrating its viability and efficiency for deployment on space-grade platforms with limited computational resources.