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Deep Learning and Simulation-Based Inference for Radiation Damage Modeling in Space Telescopes: Euclid Case Study

The Euclid Space Telescope aims to map the geometry of the dark universe with unprecedented precision, requiring exceptional data fidelity from its Visible Instrument (VIS). However, radiation damage introduces charge transfer inefficiencies (CTI), distorting observations over time. Trap pumping is a novel technique for localizing and characterizing radiation-induced defects in the detector surface, but it remains time-consuming and often fails to identify complex defect structures. My ongoing work investigates the potential of machine learning to enhance the accuracy and efficiency of trap pumping analysis, as well as the use of simulation-based inference to bridge two interrelated physical models of radiation damage simulations which are used for the generation of training datasets.

I am utilizing convolutional neural networks (CNNs) and multi-channel architectures to localize and characterize detector defects in both simulated and in-orbit calibration data. The best estimates from the nominal trap pumping method serve as a part of the training dataset for learning a quantifiable defect representation in real and simulated data, with the goal of reducing the number of necessary calibration images for successful defect detection. I will assess the performance of different models under varying calibration time constraints and present predictions for the evolution of both the nominal and CNN-based trap detection performance throughout Euclid's mission, accounting for the expected accumulation of radiation damage.

AI keywords

Convolutional networks, pattern recognition, Simulation-based inference

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Track Classification: Patterns & Anomalies