SpaceGAN: Generative Adversarial Network for High Fidelity Simulation of Spacecraft Docking

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Motivation

Recent advancements in space-grade hardware and cost of access to orbit have made modern computer vision methods a likely candidate for formation-flying and on-orbit servicing missions. However, large datasets to train deep learning architectures are difficult to obtain and often lack the illumination and texture fidelity required to guarantee high navigation accuracy. Hence, this work proposes the use of a Generative Adversarial Network (GAN) to produce high quantity of high fidelity imagery of a target spacecraft.

Problem Statement

Given an input synthetic image of a target spacecraft with a certain pose configuration, the proposed method outputs a high fidelity (illumination, texture) of the target space- craft with the same pose.

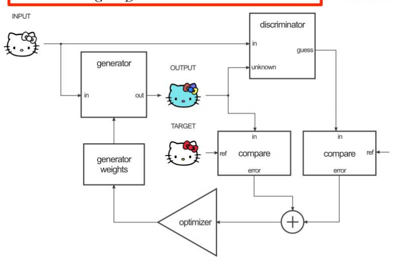
Model

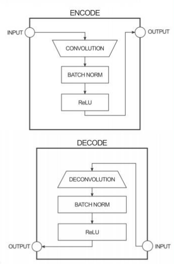
The current work utilizes the pix2pix architecture [1] proposed by Isola et al.

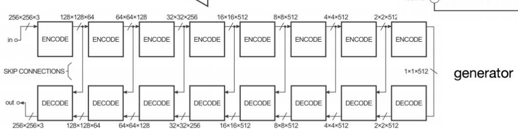
$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|_1]$$

$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G,D) + \lambda \mathcal{L}_{L1}(G)$$

$$\mathcal{L}_{GAN}(G,D) = \mathbb{E}_y[\log D(y)] + \mathbb{E}_{x,z}[\log(1 - D(G(x,z)))]$$

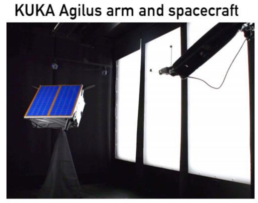


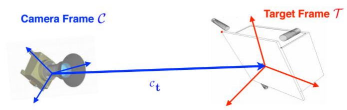


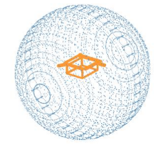


Dataset Generation

KUKA Agilus arm and spacecraft

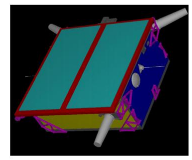




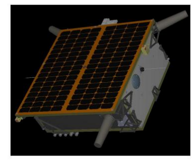


Since there are no large datasets publicly available for spacecraft in close proximity, we created our own synthetic and real image datasets. The synthetic dataset was created using an OpenGL rendering pipeline while real images were gathered using a camera mounted on a KUKA Agilus arm and a mockup spacecraft.

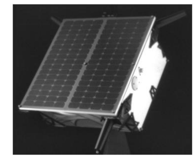
Synthetic - 1 dataset



Synthetic - 2 dataset



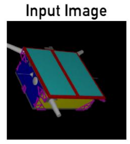
Real dataset



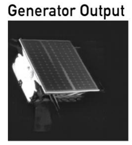
Experimental Evaluation & Conclusions

We successfully trained the pix2pix architecture with pairs of {synthetic-1, synthetic-2} and {synthetic-1, real} images. The GAN output had several notable features. Firstly, it had difficulty learning the solar panel texture, however, this was to some extent mitigated by training for larger epochs and the use of separate panels in the synthetic-1 dataset. Secondly, there were some pose deviations between the synthetic-1 and real dataset due to the measurement noise of the Vicon pose trackers.

Input Image



Generator Output



Ground Truth