# **Abstract**

With satellite constellations and the new Space Age, Space Situational Awareness (SSA) is an important area. For a sustainable Space Environment, specifically the Low Earth Orbit, preventing collisions and an increase in space debris is paramount.

Position and Orientation (Pose) estimation is a key element of space navigation systems, as this helps to

The Kelvin POSE+ challenge provides synthetic images pose labels for model development, which is tested using Tango satellite in sunlamp and lightbox modes. Develop a model to estimate POSE given limited images and associated pose values, supervised learning domain gap

This paper uses the dataset to create a model. Using set parameters, various imagenet pre-trained models are compared for feature extraction. The base models showed

Maintaining set hyperparameters across models is the limitation

Keywords: Space Situational Awareness, Pose Estimation, Space Traffic Management

# **INTRODUCTION**

Problem overview/background:

SSA

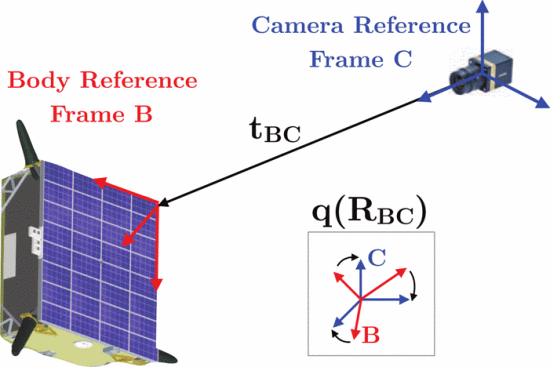
[1]

The issue of operational spacecrafts coliding with debris has significantly increased, with incidents of damage to . A recent occurrence was the Canadarm-2 attached to the International Space Station being struck by debris leaving a 14-inch hole. With the increase in satellite deployment to the low earth orbit with missions like Starlink and OneWeb’s constellation, the space environment will likely see more congestion.

Collisions with debris, other spacecrafts in orbit and asteroids is one of the main cases for Space Situational Awareness (SSA)

SPPED+

Convolutional Neural Netwoks which are trained usin images and their corresponding pose labels [2], [3]



[4]

Compared to more complex systems like the Light Detection and Ranging (LiDAR), or Range Detection and Ranging (RADAR) systems, getting a large dataset of target objects and their associated pose labels will be difficult with some experiments using previous images from space missions and had annotations to train models[2]. Synthetic data is can solve this, however it is prone to performance issues

[5]

The sensor being used is a low Sze, Weight, Power, and Cost (SwaP-C) camera which meets the low mass and power requirements of Space missions while staying cost effective.

Monocular navigation systems setermine a targets position and orientation (pose) relative to the camera based on an image. Conventional approach is to use this image-prcessing models to extract features and compare them to uk

To exploit the superior feature extraction capabilities of images and pose labls are simulated. The development dataset consists of synthetic images generated from Blender/OpengL a computer graphics rendered, although the various iluminations

The Testbed for Rendezvous and Optical Navigation (TRON/0 is used to validaed machine learning algorrithms for spacebased optical navigation. This faciity have albedo lightboxes and sun lamps to simulate the variational lghting scenarios and account for noise.

Pose is gotten from the Vicon Vero cameras which track markers on the objects with the Vicon software to report the answer. The KUKA robotic arm used provides pose data of the endeffectors in real-time as well based on joint angles.. And these two are used for accurate pose estimation between the camera and model.

Motivation and Significance

# **RELATED WORK**

## Space Situational Awareness

[1]

The safety of orbiting spacecrafts is threatened by the increase in space debris in the space environment [**REF**] particularly the low earth orbit.

Collision risks have drastically increased with the frequency of dangerous rendezvous increasing to over 80 per week as of 2022

Different space-based situational awareness systems consisting of target recognition and monitoring technology.

Near-Earth space is 100,000km extention.

[6]

SSA can be defined as the timely accurate, comprehensive and transparent positional and situationa; awareness of the space operating environment.

Safety and sustainability of space activities is a struggle as space players continue to grw with emergining nations and the rise of commercial players in the NewSpace Era. The Low Earth Orbit at a greater rist than the Geospacial orbit (GEO)

[7]

Current SSA technologies includes object detection, tracking and recognitionTo avoid damage to ritical infrastructure, a survey on the deep learning application to SSA object detection and classificationhas shown the areas that most benefit from these models.

With current trend towards space environment sustainability lookong for ways to clear debris. Some of the methods have included end of life plans for space missions which set spacecrafts into deorbiting, Astroscale is a company which works towards clearing debris using a robotic arm. Whether clearing debris oof collision avoidance,

## POSE Estimation

Traditionally this was done by manually matching image region with data.

[8]

Estimating relative positin and orientation of a non-cooperative (no active communication link) space object has been studied in mltiple contexts using a monocular camera.

The advanced Concepts Team at the European Space Agency recently held a benchmark competition using the SPPED data.

Use of Convolutional Neural Networks to avoid handcrafted features between the 2-dimentional image and 6-degree of freedom (3-dimensional) pose output using supervised learning. More recent attempts merge the deep learning and traditional geometric optimization by incorporatiing a perspective-n-point (PnP) [8], [9] like the lite- High-Resolution Network (HRNet) approach.

Although there have been different earth-based pose estimations, not all models can be applied to spaceborne devices due to the power and memory limitation which brings a tradeoff in performance.

[9]

CNNs adopted monocular pose estimation has had great performance results over traditional methods.

Uses a transformer-based method and

## Pose+ challenge

# **MATERIALS AND METHODOLOGY**

Describe and discuss the final methodology employed by the team to solve the problem.

Methodology used, data set

Data was pre-split for us

## Experimental setup

1. Data set intro
2. Where’s the data from?
3. Resolution
4. Data augmentation
5. # of images and how it’s copied

This project utilised the SPEED+ (Next Generation Spacecraft Pose Estimation Dataset) dataset which contains 59,960 synthetic images for development (80% training and 20% validation) and 9,531 simulated data for testing [4]. The synthetic data was generated using OpenGL-based Optical Stimulator (OS) camera emulator software[5]. The simulated images from this challenge includes different types of spaceborne objects like asteroids, debris and satellites.[5]. Also included arejson fileswiththe image ilenames and associted pose labels.

Figure 1: Sample SPEED+ Images. (a) synthetic training data (b) synthetic validation data (c) sunlamp test data (d) lightbox test data.

1. Proposed method with specific aspects
2. What’s the model in use?
3. Feature extraction and finetuning
4. What’s the system, code, GPU

Set hyperparameters

The L2 loss, Mean Squared Error (MSE) was used as the loss function which is generally used for regression tasks calcilates the sum of the squared digfference between the true and predicted vales [10]:

**Lite-HRNet was trained by scratch, for each of the 6 validation steps, employing the ADAM optimizer with starting learning rate = 0.001 (dropped by a 0.1 factor at the 120th and 170th epochs respectively), momentum = 0.9 and weight decay = 0.0001 parameters. A total number of 180 training epochs has been chosen.**[8]

What initially seems like a regression problem can be solved more efficiently with a classification to find the discrete pose of the target space object as shown in literature.

1. Validate effectiveness

Pose is the (q, r) vectrs which represent the quaternion and 3-dimentional distance vector. These align the camera and target reference frames, and to accurately measure the error between the predicted and true pose values the following errors ahall be calculated [2], [3], [11]:

Orientation error giving the angle of the smallest rotation:

The normalized distance between the truth and predicted positions:

2-norm is the same as the root mean squared error

The Pose error is the combined errors:

The Mean Squared Error is used as a loss function, the accuracy willalso be calculated

The general score is the sum of the pose error across the batch divided by the number of images

# **RESULTS AND ANALYSIS**

Batchsize of 128, and weight decay learning rate, set as the hyperparameters

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Base model | Rotation error | Position Error | Pose error | Computational Training time | Number of parameters | Best Accuracy |
| ResNet 50 |  |  |  |  |  |  |
| DarkNet |  |  |  |  |  |  |
| Efficientnet |  |  |  |  |  |  |
| Inception V3 |  |  |  |  |  |  |
|  |  |  |  |  |  |  |

Figure 2: Prediction Results

# **CONCLUSION AND FUTURE CONSIDERATION**

Strengths and Limitations of methodology

A major limitation of the methodology was setting fixed hyperparameter values, this became a requirement due to the cluster capacity constraint

# **REFERENCES**