



Deep learning and Unreal Engine for Spacecraft Pose Estimation

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URSO: Unreal Rendered Spacecraft On Orbit Features

- Built on UE4
- Earth:
 - 21600x10800 land and cloud images
 - Ocean specular mask
 - Atmospheric scattering
- Lighting:
 - Sun emissive body
 - Simulated albedo
 - Bloom scatter convolution + Lens flare
- Spacecrafts:
 - High poly models imported from 3D model repositories
 - UE4 materials
- Interface:
 - UnrealCV via server/client TCP connection







URSO: Unreal Rendered Spacecraft On Orbit Datasets

Random Sampling:

- Earth yaw
- Orbit height (LEO)
- Camera and object orientation
- Object location within FOV
- Object distance: [10, 40] m

Camera:

- 1080x960 px
- 90 deg horizontal FOV
- Auto-exposure

Dataset size: 5000 images







URSO: Unreal Rendered Spacecraft On Orbit Why Unreal Engine 4?

- Other space visual simulators:
 - PANGU by University of Dundee supported by ESA
 - SurRender by Airbus
 - Ray tracing
 - 'Giant textures'
- UE4 pros:
 - State-of-the-art graphics
 - Community
 - Industry (e.g. autonomous driving, robotics)
 - Source-available
 - Physical based shading (materials, lighting)
 - Physical based cameras:
 - Exposure metering mode, F-Stop, ISO, etc.

- UE4 cons:
 - Steep learning curve
 - Limited, sparse documentation
 - Max texture resolution: 8192 x 8192 px
 - World size vs precision error
 - Importing materials from other tools (e.g. Blender)

Spacecraft Pose Estimation Architecture



• To regress or to classify that is the question?

Spacecraft Pose Estimation Probabilistic orientation estimation



Testing Weighted average quaternion $\bar{q} = Null\left(\sum_{i}^{N} w_i(b_i^T b_i)\right)$

Spacecraft Pose Estimation Ambiguous orientation

Multimodal orientation estimation:

- Expectation Maximization to fit N Gaussians
- Use log likelihood to score Mixture Model







Spacecraft Pose Estimation Results: Weighting Loss Functions



Spacecraft Pose Estimation Data Augmentation and Sim-to-real

- Image Augmentation during Training:
 - In-plane rotation
 - Small camera orientation perturbations
 - Change image exposure & contrast
 - Convert to grayscale
 - Add AWG noise and blur
 - Drop-out patches

Aug.	Loc error	Ori. error	
None	1.06 m	19.5 deg	
Rotation	0.56 m	8.0 deg	













Spacecraft Pose Estimation Results

Dataset	Location error	Attitude error	
SPEED	0.17 m	4.0 deg	
Soyuz hard	0.8 m	7.7 deg	
Dragon hard	0.9 m	13.9 deg	

Error distribution



Resnet-50, 128 bottleneck filters, 24 bins per angle \sim 50 M params



Spacecraft Pose Estimation ESA competition entry

	Backbone	# bo	ttleneck	filters	# bins per Angle	Real ESA score	Synth. ESA score
	Resnet-101	512			32	0.1443*	0.0670*
			800		64	0.1630*	0.0604*
		Triple Ensemble			semble	0.1555	0.0571
				(Other Teams	Real ESA score	Synth. ESA score
				UniAdelaide		0.3752	0.0095
~500M params					EPFL_cvlab	0.1140	0.0215
				To	op 10 average	1.3848	0.1515

* Public Leaderboard

Spacecraft Pose Estimation Conclusions & Future work

Contribution:

- Effective data augmentation
- Alternative to Keypoint-based approach
- Probabilistic orientation estimation method to model orientation ambiguity
- Ablation study

Future work:

- More efficient architecture
- Improve URSO
- Address tracking

https://pedropro.github.io/project/urso/

P. Proença and Y. Gao, Deep Learning for Spacecraft Pose Estimation from Photorealistic Rendering, arXiv:1907.04298