Autonomous Image Tasking for Surface Mapping of Large Bodies

Islam Nazmy and Dr. Hanspeter Schaub

Aerospace Engineering Sciences, University of Colorado Boulder

Abstract

Surface mapping is an essential step for robotic exploration missions to other planets; however, the round-trip light-time delay makes ground-based control time-consuming and unscalable for frequent deep space missions. This work explores using shielded deep reinforcement learning (SDRL) to develop an autonomous solution to safe spacecraft imaging and poses a potential reward function to describe image quality for mapping. An SDRL approach is demonstrated on a single-target imaging problem with two image types; the agent learns the appropriate imaging behavior while staying safe. By changing the image requirements, this approach can be extended to mapping. A candidate reward function of mapping quality for stereo-photoclinometry (SPC) is proposed and simulated for different orbital parameters.

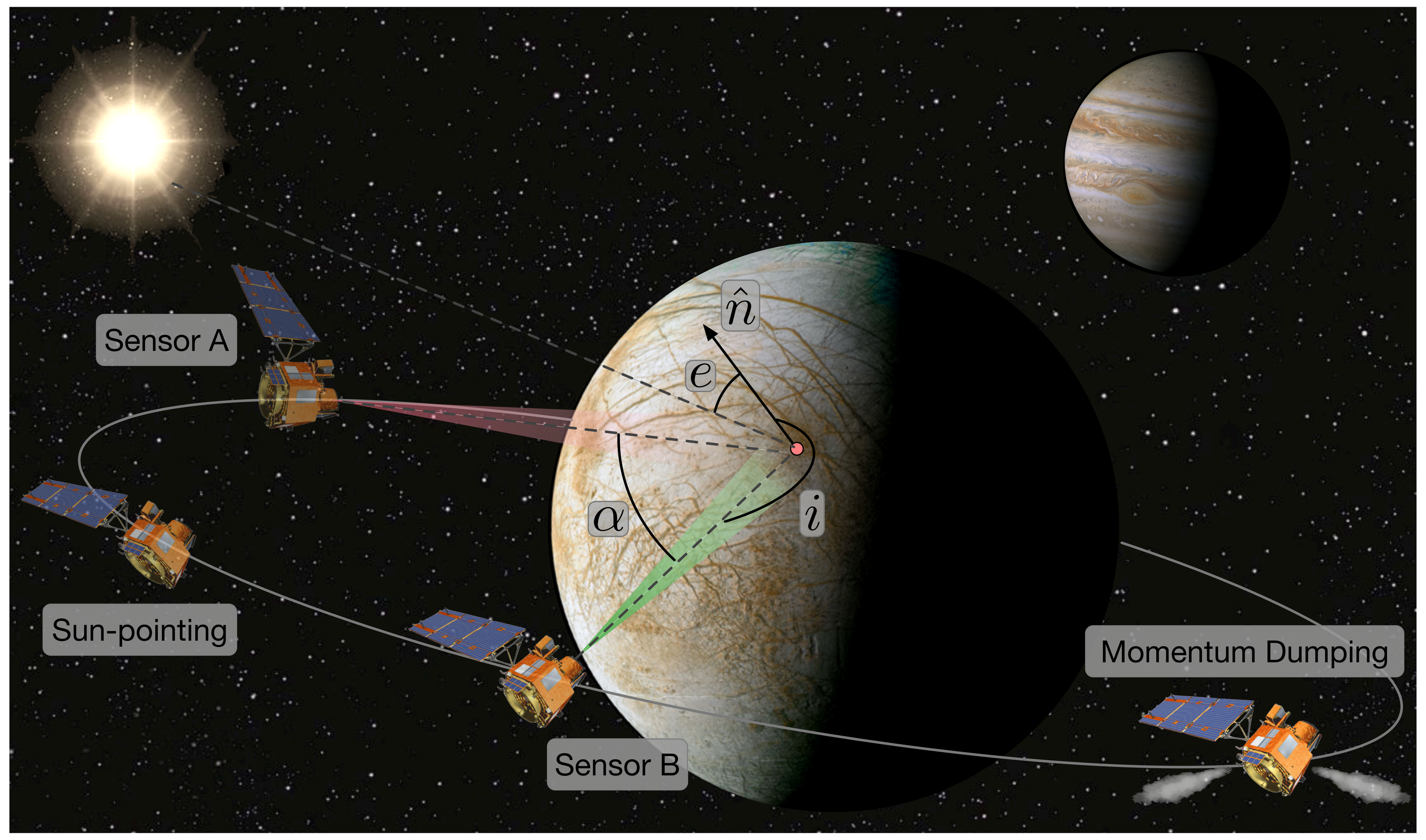
Problem Description

The spacecraft mapping problem can be cast as a multi-target imaging problem. This work approaches the problem in two parts: (1) solving the single-target imaging problem with complex image requirements; and (2) evaluating images with a metric derived from the requirements of SPC.

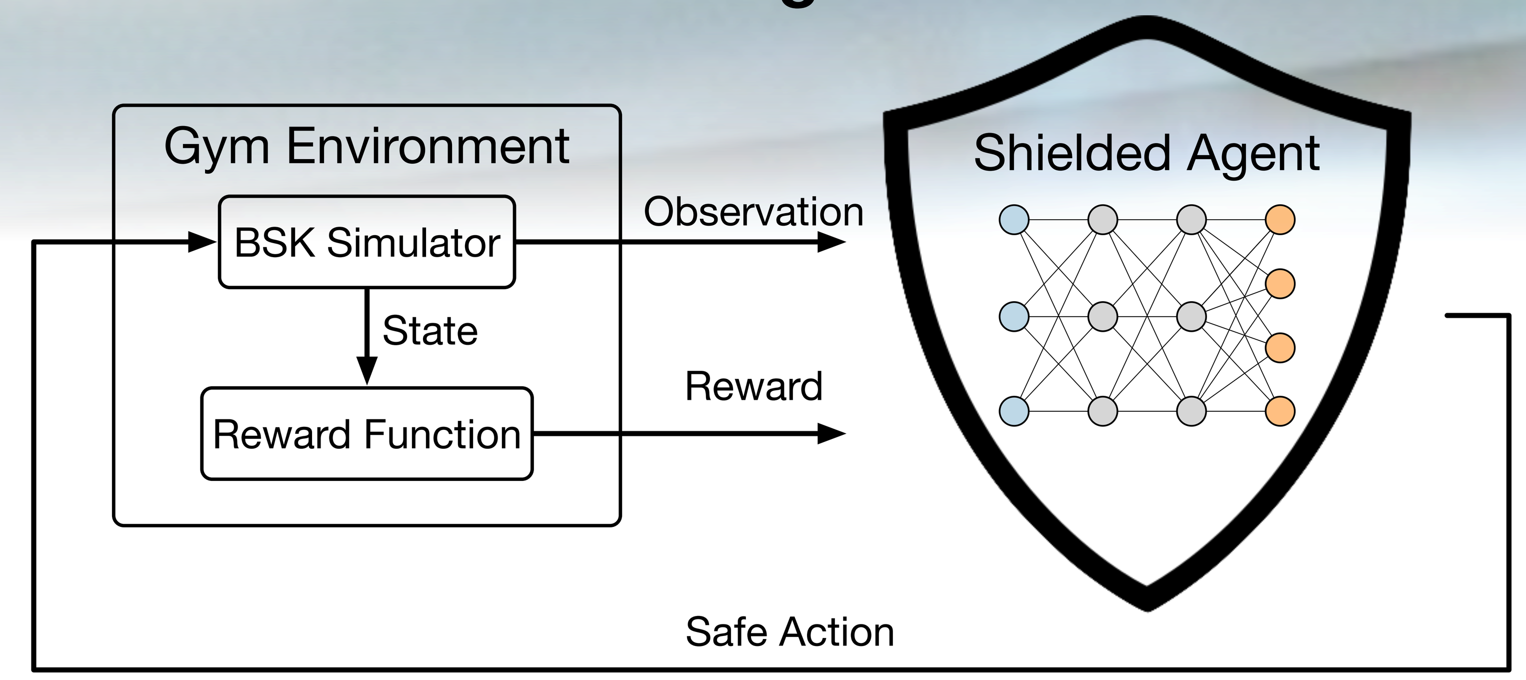
For a single target, the spacecraft must safely manage its states while meeting image requirements by sequencing the following four flight modes: *Sensor A*; *Sensor B*; *Sun-pointing*; and *Momentum Dumping* mode.

A 3-D terrain model can be constructed through SPC using spacecraft images; the mapping accuracy depends on variation in imaging angles and lighting conditions. The significant parameters that affect SPC image quality are

- Solar emission angle (e)
- Spacecraft incidence angle (i)
- Image stereo angle (α)



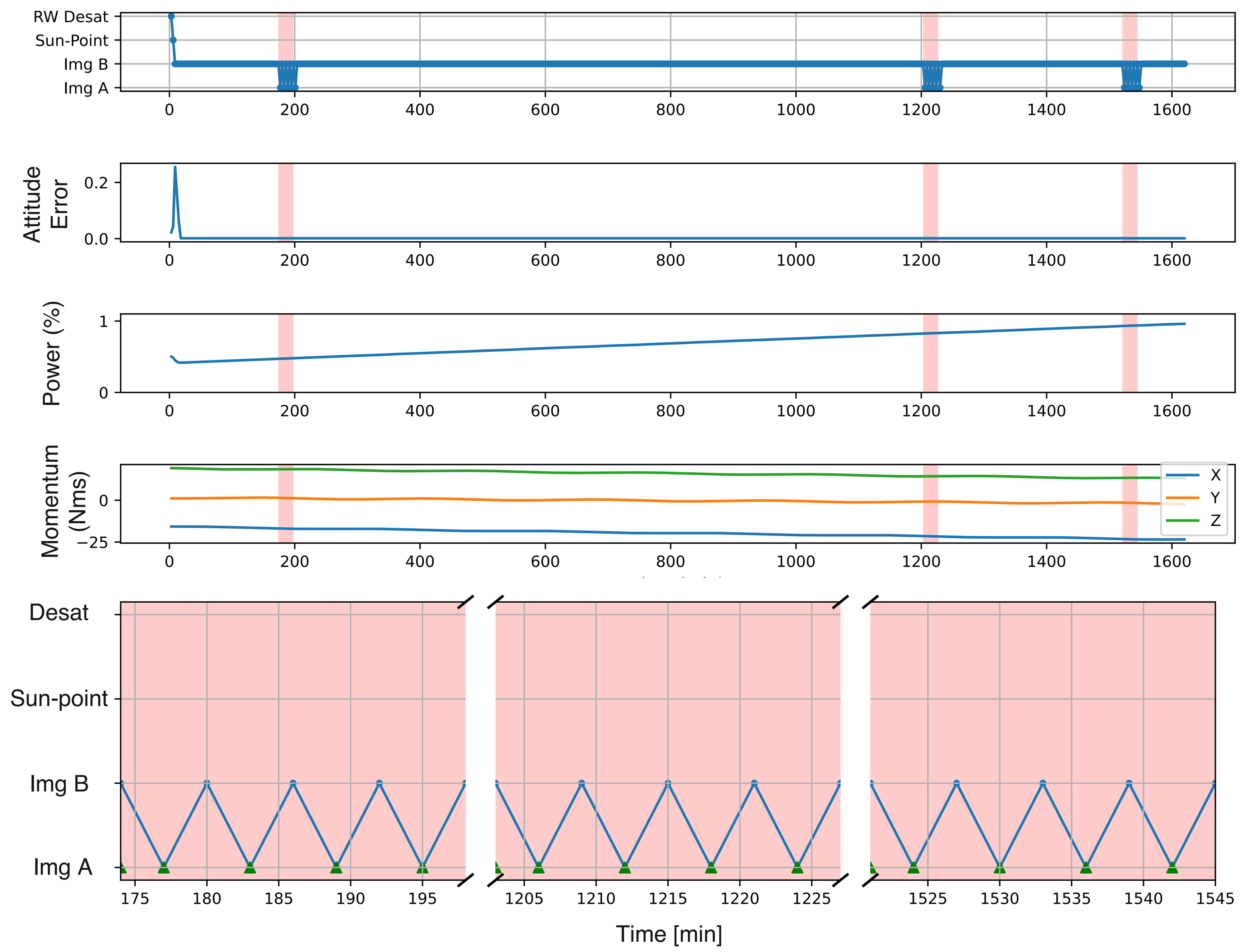
SDRL Learning Framework



A shield policy is constructed by coarsely discretizing the states by safety bounds and solving the safety MDP. SDRL provides safety guarantees by enforcing a minimal interference policy on a DRL agent; the shield only interferes if the agent selects inappropriate actions in unsafe states. The shield provides safety guarantees during execution and improves training by pruning the search space.

Single-Target Imaging Simulation Results

An SDRL agent is trained to image Boulder, CO, USA, with the requirements of imaging type A at least every 6 minutes and imaging type B every 30 minutes. The agent receives a reward if it takes an image matching these requirements. The action history below shows that the agent collects the desired image type (green markers).

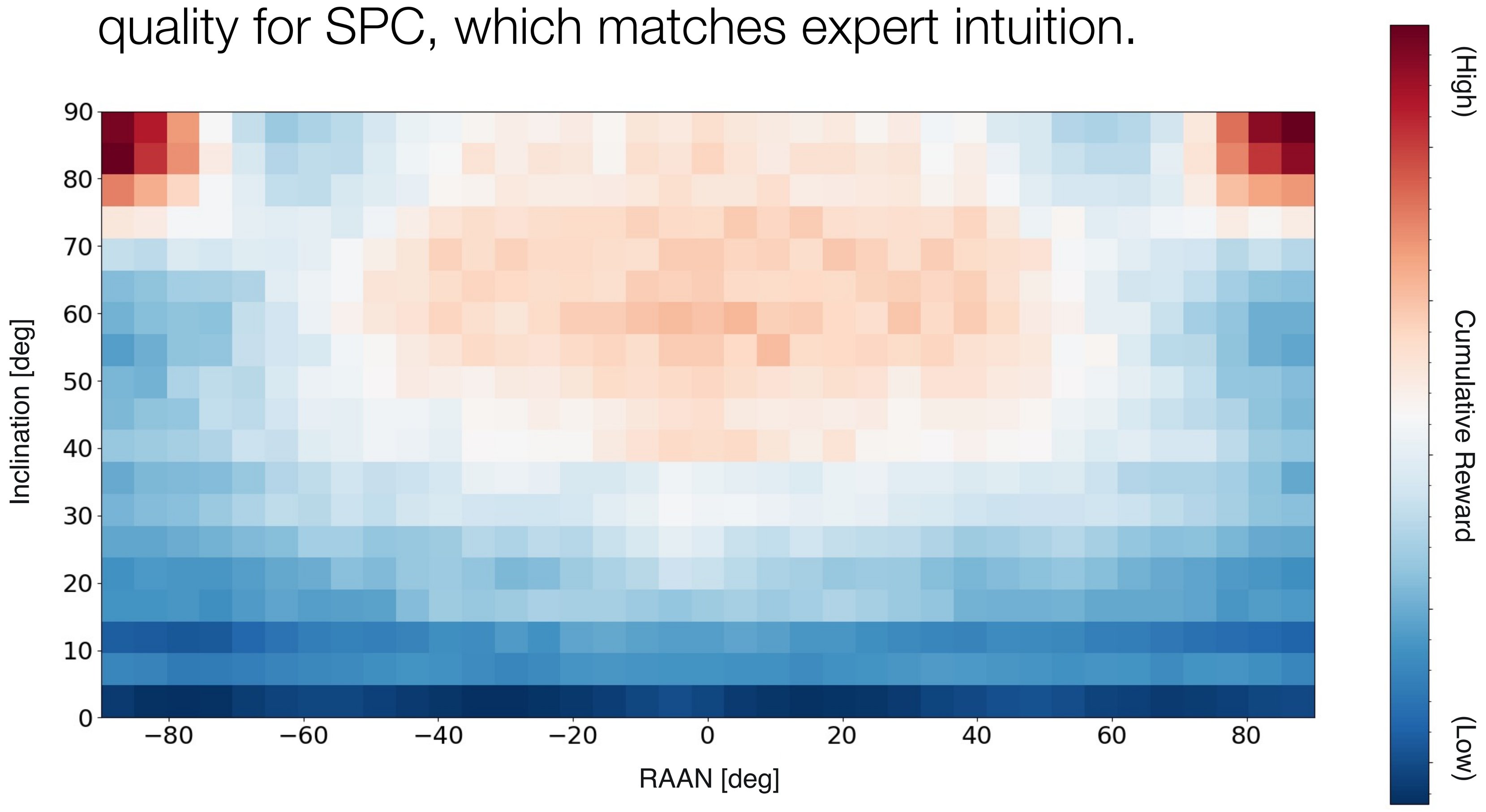


Evaluating SPC Image Quality

The significant requirements of SPC images that improve map quality are summarized in the table below. Each of these requirements maps to a reward component; each requirement that is satisfied from an image adds a contribution of +1 to the cumulative image quality reward.

	Requirement	Acceptable Range
1	0° Emission Angle	$[0°, 20°]$
2	45° Emission Angle	$[35°, 48°]$
3	0° Incidence Angle	$[0°, 20°]$
4	45° Incidence Angle	$[30°, 50°]$
5	Various 45° Emission Angles	Varying by $> 15°$
6	Various 45° Incidence Angles	Varying by $> 15°$
7	Pair of stereo images	$[70°, 110°]$
8	Triplet of Illumination Geometries	$[40°, 90°]$
9	Minimum of three images	≤ 3

The cumulative image quality reward is computed for several orbits, varying the inclination and RAAN. This case study investigating a simple SPC reward function indicates that high-inclination orbits provide the highest overall image quality for SPC, which matches expert intuition.



Conclusion/Future Work

This work demonstrates how to use SDRL for safely imaging a target with complex imaging requirements based on the sensor type. A metric for image quality corresponding to SPC is proposed according to soft requirements. Future work will combine these two research thrusts to use SPC quality as the reward function for an SDRL agent. The implications of this work will motivate greater spacecraft autonomy for deep space exploration.

9th AIAA Annual Technical Symposium, Boulder, CO, September 29, 2021