AI FOR ADDRESSING UNKNOWN UNKNOWNS IN OUTER SOLAR SYSTEM MISSIONS. E. C. Czaplinski[1], J. Cámara[2], K. Dzurilla[3], M. A. Hossen[4], B. Schmerl[5], J. Su[4], and P. Jamshidi[4]. [1]NASA Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA (ellen.czaplinski@gmail.com). [2]ITIS Software, University of Málaga, Spain. [3]University of Arkansas, Center for Space and Planetary Sciences, Fayetteville, AR. [4]College of Engineering and Computing, University of South Carolina, Columbia, SC. [5]Institute for Software Research, Carnegie Mellon University, Pittsburgh, PA.

Introduction: RASPBERRY SI (Resource Adaptive Software Purpose-Built for Extraordinary Robotic Research Yields - Science Instruments) works with existing and/or planned science instruments to autonomously adapt lander and instrument software in response to newly discovered data on the surface of planetary bodies. For example, if instruments detect an important element or compound that would ordinarily lead scientists to perform high-fidelity analysis, the system would analyze its existing resources and reconfigure itself to perform that analysis without waiting multiple hours round-trip for a new set of commands from the ground station on Earth. RASPBERRY SI increases the autonomy of a mission on the surface of another planetary body, and decreases the amount of round-trip communication data from humans. It is important for spacecraft to react to unexpected changes in radiation, surface conditions, and other uncertain environments, some of which we cannot anticipate beforehand (unknown unknowns); real-time decision-making is the key for these types of situations. In the future, software like this could be implemented on landers deployed to outer solar system targets (Europa, Titan, etc.).

Ocean Worlds: In the search for extraterrestrial life, ocean worlds have become a major focus, as most contain compounds and conditions relevant to biological and chemical processes that occur on Earth. Europa was chosen as a test case for this project due to its variable surface and active interior. A ~100 km subsurface liquid water ocean interacts with the ~25 km ice shell and potentially with the seafloor [1]. Potential interactions among the ice crust, liquid water ocean, and silicate seafloor may give rise to conditions necessary for life as we know it [1]. Furthermore, the presence of plumes on the surface could allow for sampling of this material without extreme excavation and surface manipulation [2].

Autonomy Module - Design and Evaluation: Europa's challenging environment requires a lander to be adaptive and accurately respond to unexpected events/changes in the absence of real-time communication with ground control on Earth. Improvements to intelligent, autonomous decision-making on the robotic side increases the productivity of future landers to ocean worlds.

Planning/Adaptation: Our autonomy module implements a MAPE-K (Monitor, Analyze, Plan, Execute over a shared Knowledge) [3] loop (Fig. 1) embodied by the Rainbow framework [4], and utilizes machine learning to inform quantitative planning and adaptation. A plethora of known and unknown events (e.g., quakes, high radiation events) may occur on the surface of planetary bodies; the lander can monitor and analyze these events, then integrate an intelligent plan that increases the chances of mission success.

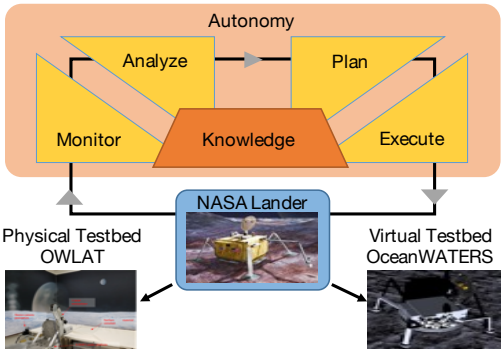


Figure 1: Design and evaluation of the autonomy.

We designed our planner (Fig. 2) by analyzing the domain in cooperation with other team members, writing prototype specifications for the PRISM [5] probabilistic model checker, and adding a plan translator to convert a high-level plan into a Plan Execution Interchange Language PLEXIL [6] plan that is then executed in the virtual and physical testbeds (described below). These specifications capture an abstract version of the sampling excavation scenario for the Europa Lander Mission [1] as a Markov decision process for which PRISM synthesizes a policy that selects which locations should be excavated, how, and in what order, for example. In an excavation scenario, the run-time provision of the list of candidate locations is supported by our machine learning component that estimates the successful probability of excavation at a candidate site, as well as the energy cost for arm movement and other excavation operations.

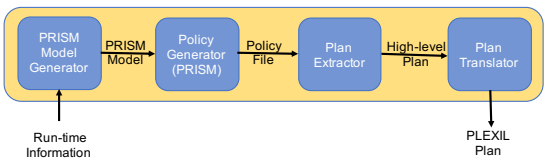
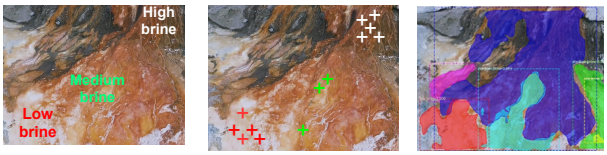


Figure 2: Planning process.

Science value and dataset: On Earth, several types of ecosystems serve as a potential analogue to Europa. Here, we focus on brines (waters with particularly high concentrations of salt), as they represent areas of the surface with low water ice components – a geologic criterion to guide the search for biosignatures [1]. Particularly, Antarctica hosts a large, subglacial brine system called Blood Falls that seeps through an outlet in the Taylor Glacier. Blood Falls has a Na:Cl and Cl:Br ratio similar to that of seawater and high levels of iron and sulfur [7]. Nitrogen/sulfate reducing bacteria, halotolerant/psychrotolerant bacteria, and methanogenic activity are present in Blood Falls [7]. Blood Falls is evidence that microbial survival is possible under a variety of temperature, pressure, and salinity conditions relevant to Europa.

A previous study on AI-driven soil nutrients prediction utilized multispectral images from Earth's surface to predict the total nitrogen content in the soil [8]. We adapted a similar approach; to train the deep neural network (DNN) model, we curated a dataset involving different brine surfaces. We annotated the dataset by performing (i) category labeling, (ii) instance spotting, and (iii) instance segmentation (Fig. 3). We performed training on the brine dataset using a DNN to predict the science values and extract the coordinates (x, y) of the selected locations, which later feeds to the autonomy module to perform planning and adaptation.



(a) Category labeling (b) Instance spotting (c) Instance segmentation

Figure 3: Image annotation pipeline.

Vision-based energy prediction: For surface operations on Europa, power consumption is extremely important throughout the lander's lifetime. Two main factors that influence energy consumption are: (i) the spacecraft's arm-dependent factors (e.g., torque) for each joint and (ii) environment-dependent factors (e.g., surface properties). We employed a method in which driving energy for planetary rovers was predicted utilizing DNN and terramechanics [9]. To generate the ground truth, we recorded the motor log (Fig. 4) for each joint of the lander's arm, as well as depth information of the surface at every timestep at different surface properties, while the arm performed various actions. We then performed training on the generated training dataset, which used DNN to predict the required energy for each of the trench locations (which was previously selected based on the science value).

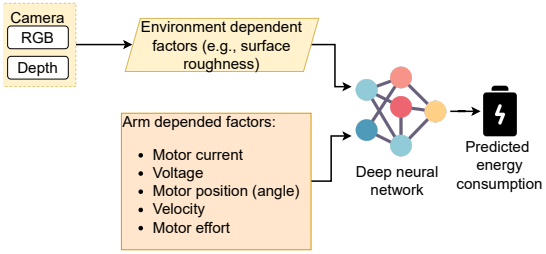


Figure 4: Overview of vision-based energy prediction.

Autonomy Testbeds:

Virtual: The Ocean Worlds Autonomy Testbed for Exploration Research and Simulation (OceanWATERS) project, led by NASA Ames Research Center, is an autonomy software testbed simulator that aids in the development and maturation of autonomy technologies, enabling increased science operations for surface missions to ocean worlds [10]. The Europa Lander mission [1] was selected for initial lander and environmental modeling. The testbed autonomy focuses on enabling continued operations with no ground control intervention in the case of sub-system failures [10]. PLEXIL is incorporated as a Robotic Operating System (ROS) component.

Physical: The Ocean Worlds Lander Autonomy Testbed (OWLAT), led by JPL, replicates the primary robotics components of a spacecraft lander system [11]. The testbed includes the lander platform, an arm manipulator, and a perception system. Several tools are adapted to the mount of the manipulator end-effector, including a pressure-sinkage plate, shear bevameter, cone penetrometer, scoop, and drill. Room-temperature surface simulates include: white quartz sand to represent loose granulated ice [12], and highly porous concrete [13].

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