MASS INFERENCING MODEL CREATION AND DEPLOYMENT TO LUNAR EXCAVATION ROBOT, RASSOR.

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Introduction: The Regolith Advanced Surface Systems Operations Robot (RASSOR) Excavator is a teleoperated mobile robotic platform with a unique space regolith excavation capability [1]. This research project developed functionality for inferencing regolith mass ingested during RASSOR operation, enhancing RASSOR's ability to successfully complete ISRU missions.

Rationale: Radio wave propagation time to the Moon and back is ~2.56 seconds [2]. Though teleoperation is possible with this delay, autonomous capability that enables RASSOR to plan and execute excavation missions intelligently and efficiently is preferred. To teleoperate or run autonomously, it is crucial for the quantity of regolith mass ingested by RASSOR to be available as a system state for efficient operation. For example, during autonomous operation, RASSOR should navigate and move to a processing plant to offload the collected regolith when the drums are full; without knowledge of how much mass is in the drums, this type of high-level planning is not possible.

Methods: RASSOR utilizes the Robot Operating System (ROS [3]) for command and telemetry. To gather modeling data, the robot was run in a simulated lunar environment and data files were recorded capturing the state data from consecutive excavation runs. After testing, the data files were converted to a format [4] that enables using state-of-the-art data analysis tools for model creation. Only a subset of states (arm/drum positions, velocities, currents, voltages, and robot pose) were used in model creation.

Four distinct modeling approaches were employed in developing a mass inferencing approach that could work on RASSOR. All take in system states and output a mass prediction for each set of the robot's bucket drums.

1) A neural network model that takes a vector of normalized system states;
2) A mathematical model that uses the integrated power consumption of an arm-raise (normalized by velocity);
3) A linear fit of average drum current over a variable interval of the drum disengaged from the surface; and
4) A real-time estimation model that aggregates excavation drum current.

ROS nodes created for these models enabled testing on the hardware. Before being deployed to RASSOR, the ROS nodes were validated by playing back the data files from the initial data collection.

Results: The developed ROS nodes run in real time, outputting predictions for the front and rear drums, timestamp of the last prediction, and the total mass in RASSOR's drums (given by the sum of the front and rear mass predictions).

The neural network model (1) was initially thought to perform well on unseen data but testing on the hardware showed that the model was overfitting to the training dataset. Work continues with developing a robust neural network model that predicts mass from recorded state data.

Further testing is required to validate the arm-raise model (2), though initial tests indicate reasonable performance (<10% mean error).

The linear fit of average drum-current model (3) had a front value of $R^2 = 0.99$ and a rear value of $R^2 = 0.98$ on the validation dataset. The realtime model (4) is still in development. Neither of these models have been tested on the hardware due to other projects making RASSOR unavailable for testing, but a ROS node has been written for model (3). This node will be deployed, tested, and refined in the coming weeks.

Conclusions: Though work remains to be done with deploying a high-fidelity model to the physical system that makes predictions with error below the desired threshold, the modular architecture for model development allows quick adjustment of parameters to increase model fidelity. This architecture can also be adapted to use lunar excavation data to create models that are reflective of RASSOR's dynamics when operating on the lunar surface. The results are promising as it has been shown that models can be developed that accurately estimate excavated regolith mass.

References: [1] Mueller, R., et al. *Regolith Advanced Surface Systems Operations Robot (RASSOR)*, IEEE Aerospace Conference, 2012. [2] Butrica, Andrew J. *To See the Unseen, a History of Planetary Radar Astronomy*, NASA Sp-4218, 1996. [3] Stanford Artificial Intelligence Laboratory et al., 2018. Robotic Operating System. [4] McKinney, W., et. al., 2010. Data structures for statistical computing in python. In *Proceedings of the 9th Python in Science Conference* (Vol. 445, pp. 51–56).