ABSOLUTE LOCALIZATION FOR SURFACE ROBOTICS IN GPS-DENIED ENVIRONMENTS USING A NEURAL NETWORK.

B. Wu[*1], R. W. K. Potter[*2,3], P. Ludivig[*4,5], A. S. Chung[*6], T. Seabrook[*7], [1]National Astronomical Observatory of Japan (benwu.astro@gmail.com), [2]Brown University, [3]GTA Travel, [4]ispace Europe, [5]University of Luxembourg, [6]Tensorlicious, [6]University of Oxford. [*]Equal Contribution.

Introduction: Accurate localization in surface robotics is essential for navigation, path planning, and science objectives. On Earth, absolute localization can be readily achieved via satellite navigation (e.g., GPS). For other planetary bodies such as the Moon or Mars, however, such systems are unavailable. Current methods for absolute localization of planetary rovers rely on time- and labor-intensive human visual matching of surface perspective features with satellite images. Relative localization also accumulates errors over time, with different methods estimating dissimilar locations (e.g., [1]). Thus, an absolute localization method that can quickly, automatically, and accurately reduce the position search space is of great benefit to future planetary exploration missions. This project [2] presents a new approach to localizing planetary rovers: training an artificial neural network to match surface-perspective imagery to corresponding satellite maps.

Methodology: We performed the following steps.

Data Generation: A simulated environment was used to generate a dataset adequate in size for training a deep neural network. The synthetic Lunar surface environment was assembled in Unreal Engine 4 with distinct zones for training, validating, and testing. A pipeline was built to place a rover at random locations, capturing surface-perspective images in each cardinal direction (Figure 1a) and a ground truth orbital map.

Data Processing: Each set of 4 surface perspective images was reprojected into an approximate aerial view using rover camera properties and assuming that the terrain is locally flat (Figure 1b).

Neural Network: A Siamese neural network was trained to classify pairs of reprojections and satellite maps as matching or non-matching. The model, PLaNNet (Planetary Localization Neural Network), is shown in Figure 1c. Each image feeds into a ResNet feature extractor, is concatenated, and then fed into a 256 neuron fully connected layer for classification.

Results: We have produced a publicly available synthetic Lunar dataset and open source code for training and benchmarking localization algorithms [3].

Dataset: In total, we generated 2.4+ million surface-perspective images corresponding to 600,000+ distinct locations split among the training, validating, and testing regions within the synthetic environment.

Localization: On average, PLaNNet returns a location within 5m of ground truth from the top 10% inferences from available candidate regions (i.e., 90% reduction of search space). The neural network performs more than a factor of 2 better than traditional computer vision benchmarks (SAD/SSD/random).

Discussion: This proof-of-concept demonstrates promising capabilities for neural network approaches to absolute localization in remote planetary surface environments. Work is currently in progress to include depth information from stereo cameras into the model.

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References: [1] Liu, Z. Q. et al. (2014) *Science China: Phys., Mech., Astro.*, 58, 1-11. [2] Wu, B. et al. (2019) *IEEE IROS*, 3262. [3] http://moonbench.space/

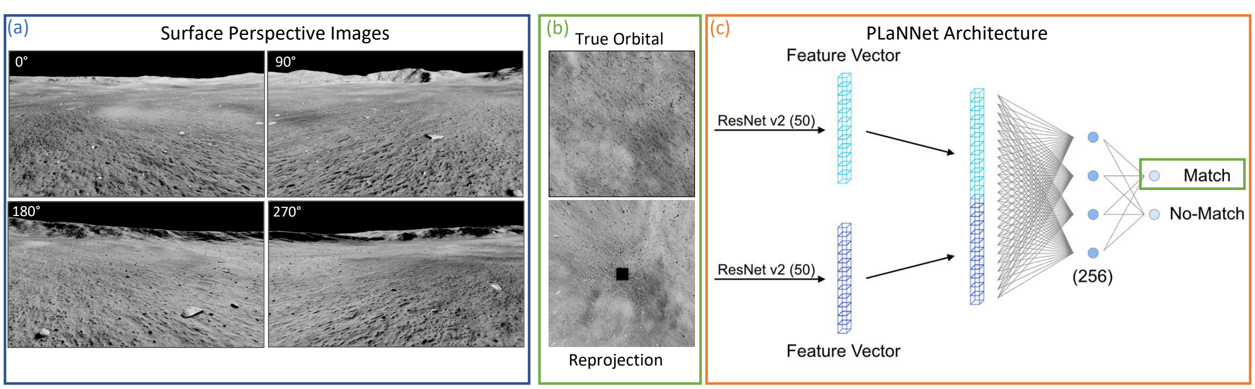

Figure 1. (a) Surface perspective images taken from a location within the 1.05km x 1.05km testing zone; (b) 50m x 50m representations of the corresponding satellite ground truth (top) and aerial reprojection based on the surface perspective images (bottom); (c) schematic illustrating the neural network architecture.