National Aeronautics and Space Administration

FY24 Strategic University Research Partnership (SURP)

Robust Machine Learning for Autonomous Visual Navigation Under Variable Illumination Conditions

Principal Investigator: Andrew Johnson (343);
Co-Investigators: Richard Linares (MIT), Jonathan How (MIT)
Graduate Student: Adriana Mitchell (MIT)

Objectives: The objective is to demonstrate the use of advanced classical and machine learning image registration techniques to dramatically expand Terrain Relative Navigation (TRN) invariance to illumination changes during planetary entry, descent, and landing. A secondary objective is to apply the same techniques to multi-modal matching (e.g., visible to SAR) for terrain relative navigation on bodies with dense atmospheres.

Background: Visual navigation is the process by which a spacecraft uses optical sensors to survey its surroundings and estimate its position. Visual navigation is a powerful tool but is limited, in part, by its sensitivity to large illumination changes. Feature-based visual navigation, where areas of interest in sequential images are identified and used to estimate the spacecraft's position over time, has been successfully used at JPL. However, large variations in illumination conditions in the set of images used by a spacecraft for position estimation can complicate the process of identifying reliable landmarks between images, and in some cases, can cause visual navigation to fail.

Current flight proven visual navigation methods for variable illumination, like natural feature tracking used on OSIRIS-REx, hand-select which features will be used based on their reliability and then render the topography to the current illumination condition.

Our alternative is to leverage the inherent terrain structure of images for feature matching, as topographical features remain invariant between images of the same terrain across different times of day, thereby skipping the human- in-the-loop process and removing the need for an accurate surface appearance map which requires many images taken during a costly orbital reconnaissance phase.

Approach and Results: JPL's current TRN pipeline estimates position by matching image patches in descent images (templates) to a map made from orbital images in two stages: coarse FFT correlation and a fine spatial correlation. Figure 1, characterizes coarse and fine sensitivity to changing illumination conditions and compares this to other classical computer vision algorithms using helicopter field test imagery taken in southern California in December 2023.

The other algorithms compared were variants on FFT correlation: frequency normalization, where all magnitudes are set to zero (aka phase correlation), frequency cropping, where bands of frequencies are removed, and a FFT correlation without normalization. While the variants on FFT correlation provided improvements over the FFT correlation alone, the standard coarse mode still had the least sensitivity to illumination differences.

In contrast, the fine mode performance, which utilizes normalized cross-correlation, can match many landmarks quickly but struggles to find matches across changing illumination. NCC's dependence upon pixel-level gradient changes leads to high sensitivity to changing illumination.

Coarse matching is computationally expensive so only a small number of templates can be matched in a fixed amount of time (e.g., 15 templates in 5s on Mars 2020). It is difficult to automatically remove outliers with so few matches, so the coarse mode is not robust. To mitigate, we investigated LoFTR, a machine learning algorithm which can potentially generate many feature matches while combining both coarse and fine phases. LoFTR performed well on field test and Mars imagery and can also be used to identify terrain patches that are insensitive to illumination conditions.

Significance/Benefits to JPL and NASA: JPL's expertise in visual navigation was combined with MIT knowledge of space-based machine learning applications to create a network that can be used on future planetary or small body vision-based navigation missions. The machine learning techniques have expanded the applicability of vision-based navigation to mission scenarios differences in illumination (e.g., landing in the morning or late afternoon for Mars Sample Retrieval Lander; autonomous navigation/exploration missions to small bodies).

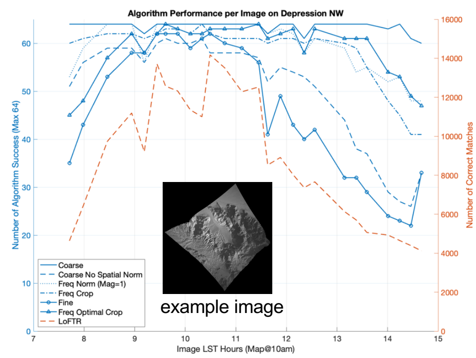

Figure 1. Comparison of algorithm performance across time of day for field test data.

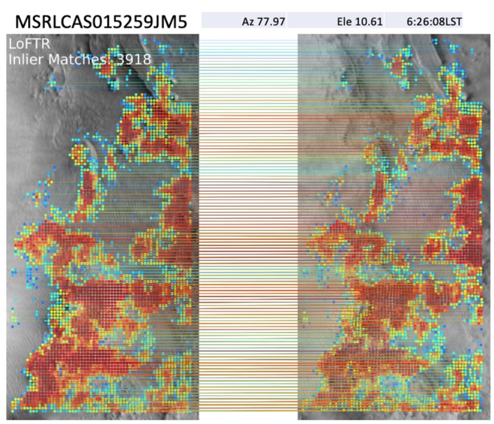

Figure 2. Example of LoFTR feature matches between a Mars image pair. Left: CaSSIS image taken at 6:30AM (az=78˚, el=11˚), Right: Jezero Crater Map from CTX Imagery taken around 3:00PM (az~270˚, el~40˚)

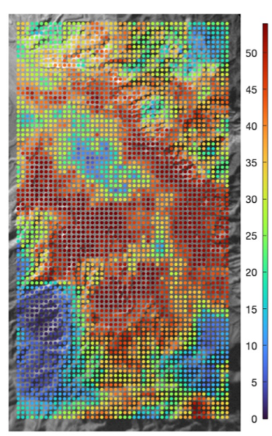

Figure 3. Heatmap of repeated LoFTR matches over 54 map-projected field test images. Warmer coloring indicates terrain regions matchable across all images (across all time-of-day differences).

National Aeronautics and Space Administration

Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

www.nasa.gov

PI Contact Information:
aej@jpl.nasa.gov
(818) 354-0357

RPD-106 Clearance Number: CL#00-0000