# Implementation of Machine Learning Methods for Crater-Based Navigation

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Increasing demand for deep space communications resources requires that spacecraft include more autonomous capabilities, particularly in navigation for dynamic mission phases like entry, descent, and landing. For spacecraft orbiting the Moon, Mars, or other solid-terrain environments, Terrain Relative Navigation (TRN) based on optical images can provide an on-board source of additional information to improve state estimates in real time. Particularly for the Moon, TRN methods often use craters as surface landmarks to compare against previously mapped areas, requiring a crater detection method to use for the subsequent measurement updates of a filter. While traditional image processing tools like edge detection rely on pixel thresholding and shadow modeling [1], these methods can fail in detecting craters with different shapes and sizes caused by varying lighting conditions. Instead, TRN systems can use machine learning (ML) methods developed by the computer vision community, leveraging the advancements in object detection and neural networks to generalize the definition of a "crater," extract them from images, and use the information to improve an orbiting spacecraft's state estimate. These ML methods can be trained using real lunar imagery, simulated renders, or a combination of both, to develop a crater detection algorithm that is robust to the varying environmental conditions.

The ongoing operations of the Lunar Reconnaissance Orbiter (LRO) enable the continued refinement of lunar mapping knowledge. From the cameras of LRO that provide global map images of the Moon [2] along with the continued efforts to create catalogs of known craters [3], this work includes an automated method of generating large sets of labeled images containing thousands of crater image samples. This component aims to solve one of the difficulties with using ML-based tools, which require many training samples for a neural network to form its internal weights and metrics to define the target crater object. The LRO maps contain crater samples with inconsistent shadows and light direction because the maps are formed by stitched images. Because of the varying light conditions from which LRO returns images of the Moon, the developed neural network pipeline benefits from the inherent variation in data. Since the neural network gains more information through each provided training sample, the inclusion of images taken at geometrically varied spacecraft orientations allow the detector to learn what a crater looks like with different shadows. This automated dataset generation implements sorting methods including controls on the number of craters, diameter limits, and entropy metrics that can be manually inspected and configured through a user interface.

The neural network implemented for crater detection uses the Mask-RCNN [4] framework, which enables localized searching to provide ellipse fit estimates of every crater detected in a single image. Unlike edge detection-based methods, Mask-RCNN also provides a confidence metric that can be used for additional pre-processing before the state estimation filter uses the crater detections. With the labeled datasets, an iterative neural network training pipeline was developed to create a set of tools to enable testing and inspection of the resulting detector's performance over time. The developed tools also allow for the inclusion of new datasets with different control parameters and test the detector performance as a result of the included changes.

Quantifying the performance of the detector through centroiding error requires an identification method to match a detection to a known crater in the input catalog. Figure 1 shows a set of images with detected craters of various shapes and sizes highlighted, along with the matched craters and their respective centers. Another performance metric that this work aims to increase is the precision of the detector, which compares the number of identified craters to the total number of detections. Preliminary results for a set of 1000 images are shown below. Figure 2 shows the number of detected and matched craters. Figure 3 shows the accuracy of the centroid estimates through the optimal subpattern assignment (OSPA) [5] localization metric. Finally, Fig. 4 shows the computed precision of the crater detector. With additional work, the crater detection tools outlined in this paper can be integrated with a state estimation filter to quantify the overall performance of a crater-based navigation pipeline.

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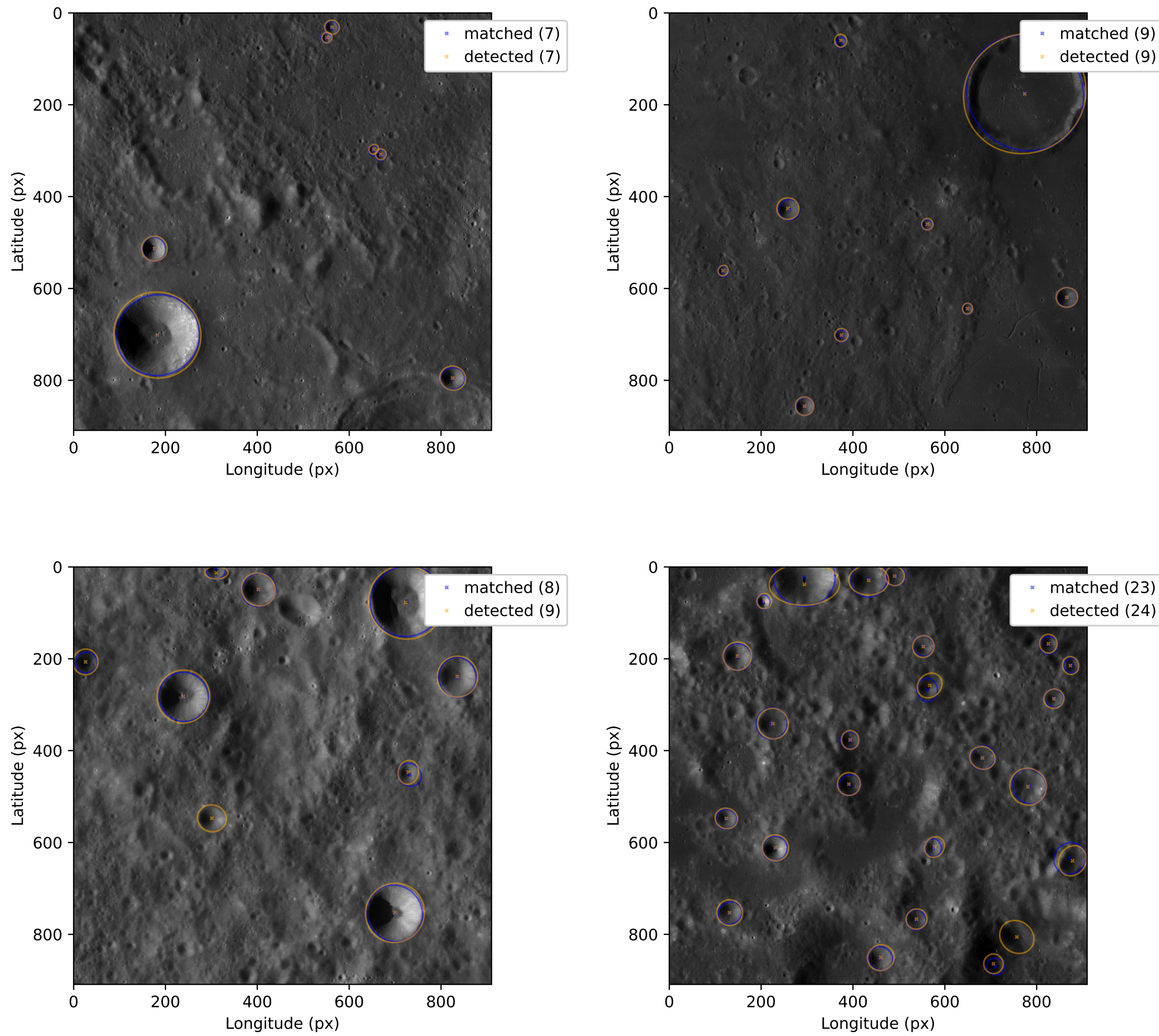


**Fig. 1 Examples of Crater Detections and Matches**

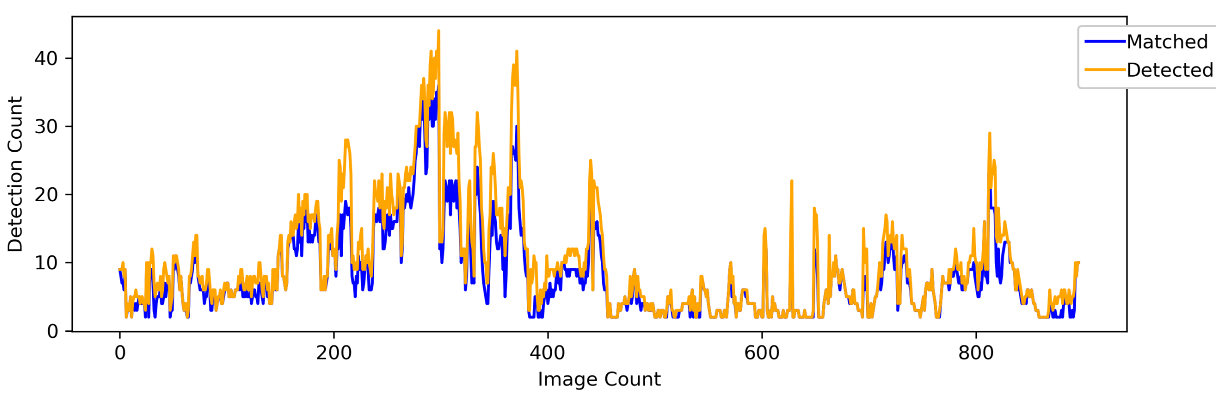


**Fig. 2 Number of Detections and Matches**

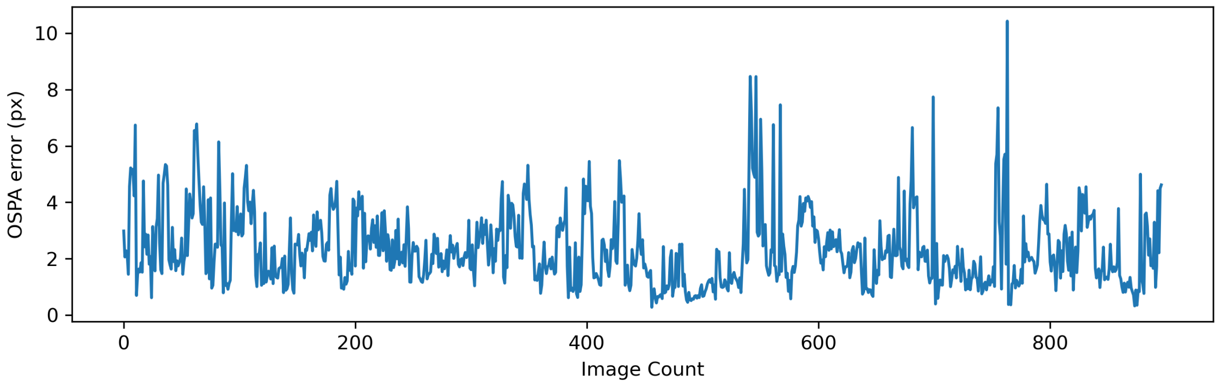


**Fig. 3 Localization OSPA Accuracy**

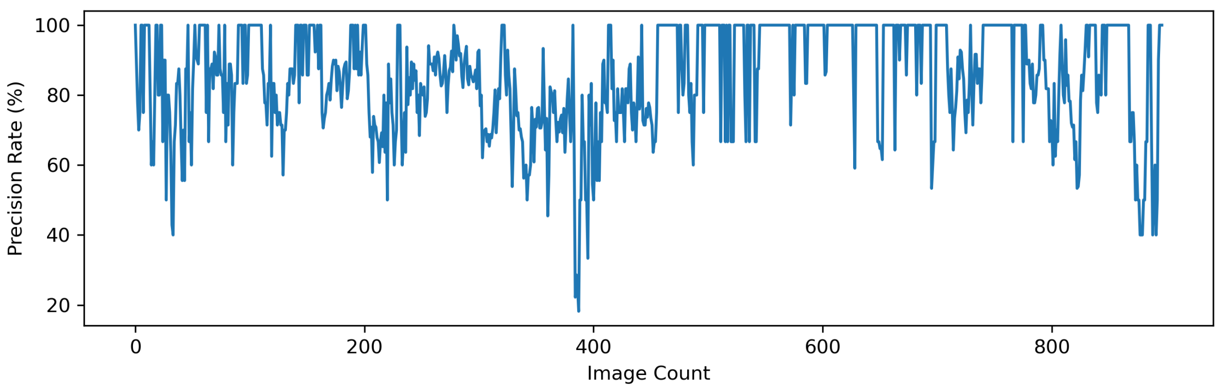


**Fig. 4 Detector Precision**

# References

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