AUTOMATED CRATER DETECTION ON THE MOON AT HIGH-RESOLUTIONS.

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Introduction: Counting craters is a key aspect in determining relative chronologies of different surfaces on terrestrial bodies. The technique has proven useful in building geological histories and establishing model ages of geological events on the Moon, Mars, and asteroids [1].

For the Moon, some surfaces have radiometric ages, determined from the collected samples obtained via the Apollo, Luna, and soon, Chang-e missions. Though those samples are local and linked to specific events, meaning they cannot be viably be attributed to chronologies on a global scale [2]. Crater counting offers a practical solution for acquiring global chronologies and targeting locations yet to be visited by sample collecting missions.

The ability to count craters has continuously improved over the years, through higher quality images and spacecraft technologies. Ultimately, the accuracy of the technique is governed by two aspects: counting area and image resolution.

The current lunar global high-resolution crater dataset has manually counted ~1.3 million craters down to 1km in diameter [2]. To date young and/or small surfaces, the ability to detect craters smaller than 1km is required. The LROC NAC images are high-resolution (0.5-2 m/px) with nearly global coverage, making them the ideal dataset for the identification of craters down to ~10m in diameter. But because crater sizes scales as a power law, the number of impact craters in the size range 10 m to 1 km is in the hundreds of millions, making automation of this process key to the continued use of this technique [3].

Our group developed for Mars (with proven success [3,4]), and is now adapting to the moon, a machine-learning based CNN (Convolutional Neural Network) Crater Detection Algorithm (CDA), which makes the crater counting task on high-resolution images many magnitudes faster. We will show and discuss the current implementation of crater detection algorithm on different lunar surfaces using the high-resolution NAC images.

The Crater Detection Algorithm: Morphologies of impact craters on the Moon and Mars are different, mostly due to differences in target properties and surface conditions. Therefore, our Mars-trained library cannot be used. A new training set is therefore a prerequisite to accurately detect and estimate crater diameter using lunar imagery. This entails feeding the algorithm a dataset of manually identified and mapped craters, which is uses for training and validation.

The current CDA model for the Moon was trained on 152 square (414x416 pixels), tiled NAC images which consist of 25,973 manually counted craters. All the images have incidence angles ranging from 50-85° (afternoon/morning lighting) which produces favorable shadows detailing the surface texture/craters. The algorithm uses an architecture called You Only Look Once (YOLOv3) [5], which specializes in fast object detection.

The NAC Image Dataset: The LROC-NAC images give us the high-resolution detail (0.5-2m/px) to count decimeter sized craters. Though the NAC images are publicly available [6], they are not in the correct format for our proposes. For our model to work they need to be in a GeoTiff file format. This has been done by adapting a series of USGS ISIS3 and GDAL scripts to batch georeference 1000s of NAC images and outputs them in a GeoTiff format.

Initial Results of the CDA: The CDA was run on two georeferenced NAC images, respectively covering a portion of Mare Serenitatis (NAC: M1320016983LE) and Terra Sanitatis (NAC: M1338833866LE). The NACs were analyzed at their highest resolution in order to detect the smallest craters possible. However, our approach allows the detection of larger craters by downsampling the resolution of the image [4], a task we used in our Mars crater counting pipeline. Results are presented in figure 1.

On the highland surface it detected 406,447 craters in ~3 mins. The smallest craters detected are 5m in diameter and largest at 270m, and the image has an area 150 km2. On the mare surface it detected 419,950 craters in ~4 mins. The smallest craters detected are 6m in diameter and the largest also at 270m with an image area 210 km^2. Over the span of ~7 mins the CDA was able to detect ~820,000 craters smaller than 300m over 360km^2 area.

To test the accuracy of the CDA in detecting fresh crater morphologies, 291 craters with clear rims,

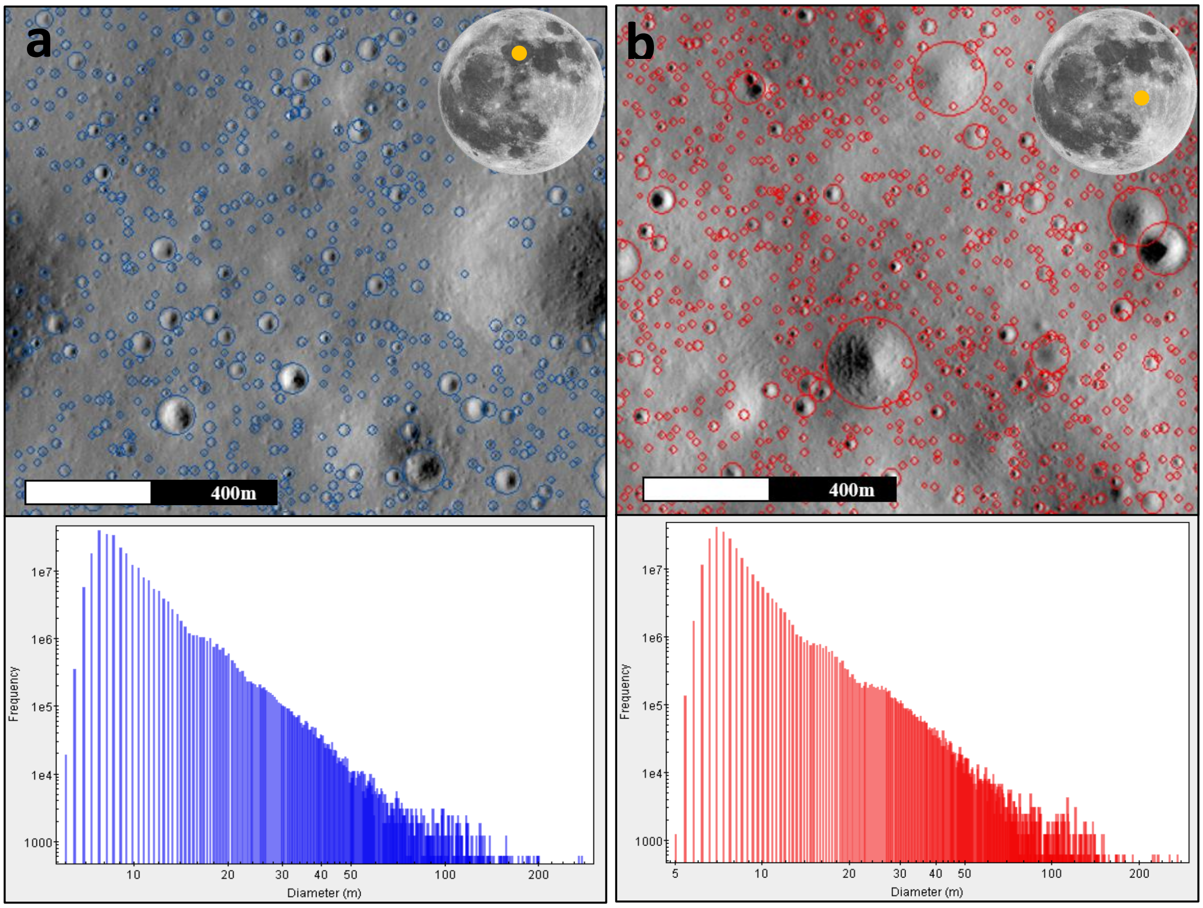

Figure 1: *Location and corresponding CSFD histograms of the CDA's detections; a. excerpt of NAC image M1320016983LE (mare surface); b. excerpt of NAC image M1338833866LE (highland surface).*

circular shapes and diameters of 4m-92m were manually marked over 860m^2 area of Terra Sanitatis (M1338833866LE). Then the results of the CDA over the same area were compared to the manual count. 286 (~98%) of the 291 chosen craters were detected by the CDA, which means within our test dataset the CDA performed outstandingly at detecting non-degraded craters.

However, the model did struggle at detecting degraded craters over the same area. 456 degraded craters, with diameters of 6m-78m, were marked, where the CDA was only able to detect 302 of them (~66%). However, this result was not unexpected when compared to human detection variability, where analysts vary by ~80% on different levels of crater degradation [7].

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References: [1] Neukum G., Ivanov B. and Hartmann, W.K. (2001). Chronology and Evolution of Mars, Kluwer. 96, 55–86. [2] Robbins, S. J. (2019). Journal of Geophysical Research: Planets. 124, 871–892. https://doi.org/10.1029/2018JE005592. [3] Benedix, G.K., et al. (2020). Earth and Space Science. https://doi.org/10.1029/2019EA001005. [4] Lagain, A., et al. (2021) Earth and Space Science (in press). [5] Redmon, J., Farhadi, A. (2018). arXiv preprint arXiv:1804.02767.[6]http://wms.lroc.asu.edu/lroc/search. [7] Robbins, S.J., et al. (2014). Icarus. 234, 109–131.