LUNAR ROCKFALL DETECTION AND MAPPING USING DEEP NEURAL NETWORKS

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Introduction: NASA's Lunar Reconnaissance Orbiter Narrow Angle Camera (NAC) has taken more than 1.6 million images of the lunar surface since it has been launched in 2009. Most of these images have not been utilized for scientific inquiry so far, due to the size of the dataset and current limitations in automated data processing and exploitation capabilities.

Amongst numerous applications, NAC images can be used to detect and map rockfalls. Investigation of the spatial distribution and magnitude of lunar rockfalls can help to improve our understanding of past and current tectonic activity [1], as well as the evolution and terramechanics of the lunar surface [2,3], among others.

Methods:

Recent advances in computer vision and deep learning allow for the automated detection of objects in images. We implemented a single-stage dense object detector (RetinaNet) [4] that is able to identify and map lunar rockfalls with boulder tracks using NAC imagery. For Deep Neural Network (DNN) training ~3000 original rockfall images have been augmented to ~240000 images, applying image rotation, flipping, and up- and downsampling. The resulting DNN is feature rotation- and scale invariant. DNN performance concerning Recall, Precision, and Average Precision has been assessed by using testing images that have been labelled by an experienced human operator.

Results: The trained DNN is able to detect rockfalls with trails in the available NAC imagery (Fig. 1). Processing time for a single NAC image in RetinaNet is about 10 seconds using a GeForce GTX 1080 Ti and a GeForce Titan Xp, which is orders of magnitude faster than an experienced human operator. The DNN achieves recall values between 98 and 39 % (% detected), precision values between 100 and 25 % (% correct detections), and average precisions (AP) ranging from 89 to 69 % (average of the maximum precisions at different recall values), depending on the used confidence threshold (CT) and Intersection-over-Union (IoU) (Table 1). Using the detections' bounding box diameter, the size of the detected boulders can be estimated.

False Negatives (FN) and False Positives (FP) can be caused by 1) insufficient spatial resolution of the used input images, 2) unfavorable illumination conditions that cause extreme shadows (Fig. 2e), and 3) conflicting objects within the immediate surrounding of the rockfall that confuse the trained network (Fig. 2d).

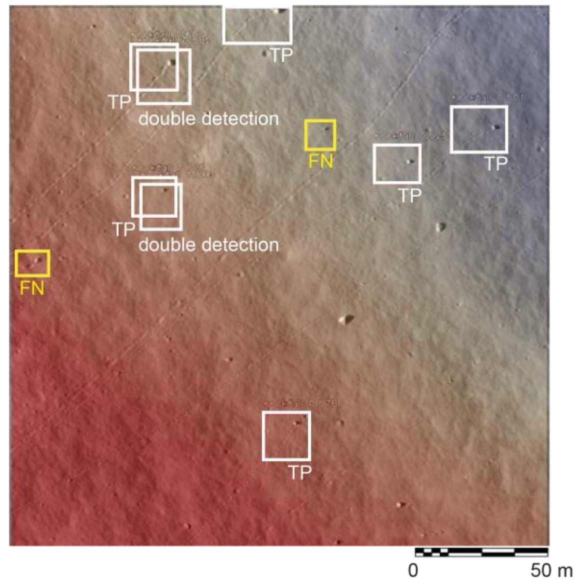

Fig. 1. Example of RetinaNet detections (white rectangles, TP). Yellow bboxes indicate false negatives (FN).

Multiple detections of the same rockfall can be effectively removed using a Non-Maximum-Suppression filter.

Conclusions: A Deep Neural Network has been implemented and trained to automatically detect and map lunar rockfalls with traces in NAC imagery. DNN performance and speed allow to exploit the entire NAC image archive and to produce rockfall distribution and magnitude maps on large or even a global scale. Preliminary results of such a map are displayed in Fig. 3.

The trained DNN is being implemented as a tool in NASA JPL's Moon Trek platform that is part of the Solar System Treks Project (trek.nasa.gov/). An on-demand web-based approach brings the user to the data, not the data to the user, thus, avoiding data download and storage limitations. This tool will eventually be available for usage by the scientific community.

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References: [1] Kumar P. S. et al. (2016) *JGR: Planets 121*, 147–179. [2] Filice A. L. (1967) *Science, 156*, 1486-1487. [3] Bickel V. T. et al. (2018) *JGR: Planets* (submitted). [4] RetinaNet 'Fizyr' (2018) GitHub.

Table 1. Validation results, reported as AP, recall, and precision results for IoU values of 0.1, 0.25, and 0.5.

	CT	AP_{10}	$Recall_{10}$	$Precision_{10}$	AP_{25}	$Recall_{25}$	$Precision_{25}$	AP_{50}	$Recall_{50}$	$Precision_{50}$
RetinaNet (ResNet50)	0.2	0.89	0.98	0.45	0.84	0.96	0.35	0.69	0.88	0.25
	0.3		0.90	0.63		0.88	0.54		0.82	0.35
	0.4		0.77	0.86		0.77	0.84		0.75	0.60
	0.5		0.69	0.98		0.69	0.95		0.65	0.79
	0.6		0.44	1		0.44	0.96		0.39	0.85

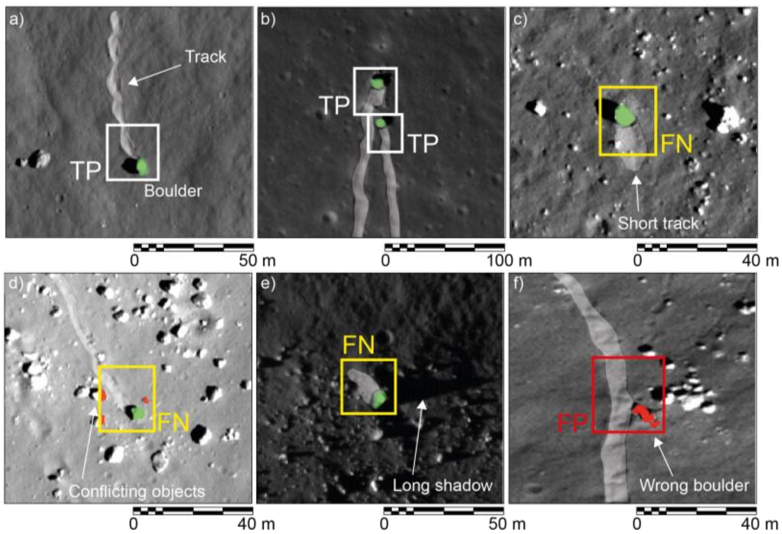

Fig. 2. Examples for influence of NAC image features and rockfall neighborhood on detection, including FPs (2f).

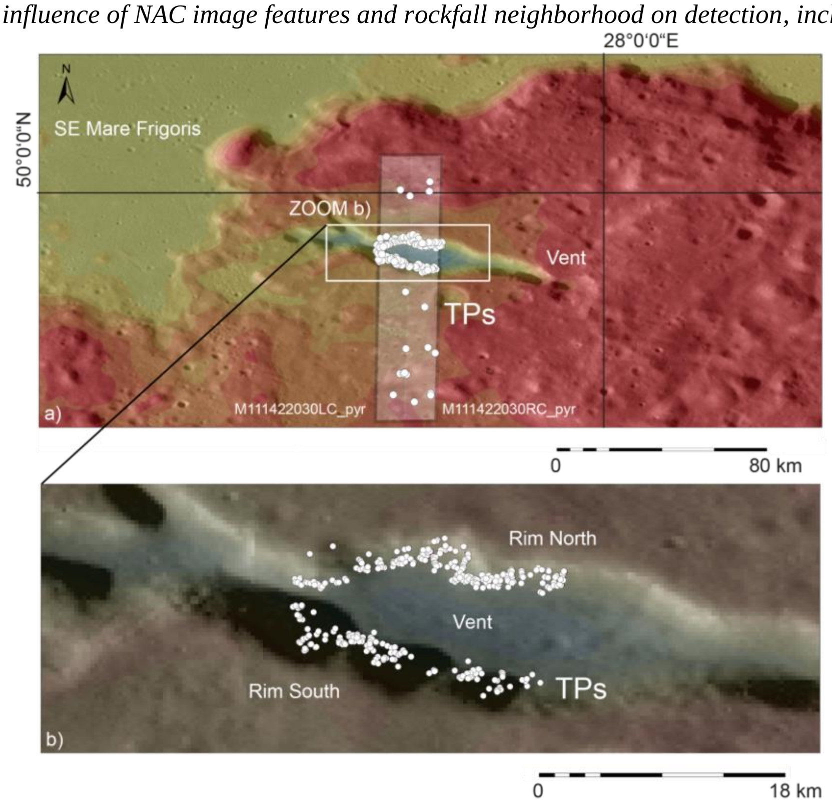

Fig. 3. RetinaNet performance illustration: White shapes mark confirmed positive rockfall detections in 2 NACs.