

Automated detection of planetary craters: open and reproducible benchmark platform for the Martian surface

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Abstract

We present an open framework to benchmark crater detection algorithms, based on infrared images of the Mars surface acquired from the THEMIS survey and a recently revised catalogue of all Martian craters with a diameter larger than 1 km, representing ~400 000 entities. Within this framework, we clearly define the problem and the model evaluation (i.e. data sets, metrics, and cross-validation). This framework is embedded in the Rapid Analytics and Model Prototyping (RAMP) computing platform which aims at providing a fair comparison of present and future methods. The platform has been deployed during a beta event to show a proof-of-concept.

1. Introduction

Impact craters are one of the most prominent geological features of telluric planets, yielding important information on their geological history [1]. Although any human with a short training can detect craters in an image, automating such process remains an open challenge. Consequently, crater detection algorithms have received a particular attention in recent years [2, 3, 4, 5, 1, 6]. As recently pointed out by Pedrosa *et al.* [7], it remains, however, difficult to make a fair comparison between those methods: the data sets and the metrics differ between studies.

To our knowledge, only Salamunićar *et al.* [8] has proposed a framework addressing those issues. However, this framework, now a decade old, uses an outdated ground-truth catalogue, lacks standard metrics for object detection, and reproducing the evaluation is not easy. Herein, we propose an open framework integrated within a computing platform allowing for fair and reproducible comparison between crater detection methods.

2. Evaluation framework

In this regard, we define a common data set based on the full Martian surface, using the latest available crater catalogue as ground-truth as presented. We also define a testing methodology and metrics to compare the algorithms.

2.1. THEMIS data

We used THEMIS [10] day-time infrared image, a huge mosaic of the full Mars surface at 100m/pixel in cylindrical projection as the main dataset. We processed the THEMIS mosaic, one quadrangle at a time. Each quadrangle was first reprojected to their local stereographic projection. From these quadrangles images, we extracted all possible 224 px × 224 px images - hereafter referred to as tiles - using an overlap of 56 px, to make sure each crater would fit entirely in one tile at least. We also down-sampled the quadrangle images to cut additional tiles, using identical methodology, to include the craters too big to fit in a tile of the original image resolution.

2.2. Ground-truth catalogue

The ground-truth catalogue used for this benchmark is currently the most accurate database of Martian craters with a diameter larger than 1 km [9]. The catalogue is based on the work of Robbins *et al.* [11], cleaned up by human-operation [9]. It contains 376,439 verified impact structures larger than 1 km in diameter.

2.3. Testing methodology

The tiles dataset created is large enough to be split into independent training and testing sets. We selected tiles from the most heterogeneous quadrangles (position, crater population, etc.) to maximize the characteristics of the data while keeping a manageable volume.

Cross-validation was applied to the training data, using the quadrangles as folds. We used the hold-out testing data to perform the evaluation as well as checks for consistency with cross-validation scores.

2.4. Performance measures

A classic metric in object detection, the Intersection-over-Union (IoU), also known as the Jaccard index [12], is used as a similarity criterion between two objects that provides a good evaluation of both the location and size accuracy of a given prediction with respect to a crater.

As the final detection score, we compute the average precision, a performance metric based on the precision-recall curve. This metric aims at penalizing algorithms that lack of balance between precision (good predictions) and recall (completeness of the predictions).

3. Benchmark platform (RAMP)

The testing methodology presented in the previous section has been implemented within the Rapid Analytics and Model Prototyping (RAMP) platform¹. The RAMP platform aims at the development of open source, collaborative, and reproducible solutions.

Concretely, the problem has been formulated as a detection problem in which the center and the radius of each crater has to be predicted. The dataset has been pre-processed and the evaluation has been fixed following the testing methodology. Therefore, the contributors willing to benchmark their algorithm are just required to provide the source code of the detector with predefined input and output format. Subsequently, each algorithm is tested on Amazon S3 on hardware with identical specification, ensuring consistency. All data and code described in this document are available online ².

4. Preliminary results and conclusions

An initial version of this benchmark platform was used during a data science course at École Polytechnique (Palaiseau, France) in November 2017. Algorithms both using computer vision and deep learning methods were implemented. A next edition will occur at the end of July 2018 at the CIFAR summer school³

in Toronto, Canada ; and a dedicated edition could be organized for the conference.

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¹<https://ramp.studio>

²<https://github.com/ramp-kits/mars-craters>

³<https://dlrsummerschool.ca>