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Automatic Detection of Sub-km Craters on Mars for Equilibrium Population Statistics

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Abstract

Small (sub-km) crater size-frequency distributions are the standard metric for dating very young surfaces on the Martian surface, because of the lack of large, infrequent impact events and the unavailability of surface samples. However, small crater population statistics are poorly understood and make accurate absolute dating of young surfaces impossible. This is because several unknown factors which affect the crater production and erosion rates – such as atmospheric filtering, secondary cratering and partial resurfacing [1]. Constraining these factors, where possible, is important if we are to understand the recent history of the Martian surface. We present an algorithm capable of detecting small crater candidates in high-resolution visible imagery of the Martian surface. The algorithm classifies craters with a state-of-the-art F1-score (91%) when compared with other algorithms on the same dataset [2-4]. We use this alongside a mean-shift clustering algorithm to detect crater candidates in an extended HRSC image with near 100% recall and roughly 50% precision. The candidates can then be marked rapidly by a human expert, greatly increasing the speed of small crater counting exercises, when compared to traditional manual marking. The detection algorithm's performance is shown in both familiar (relative to the training set) and unfamiliar terrain, which we believe demonstrates that it is a viable tool for accurate and quick crater counting on Mars.

1. Introduction

Historically, CSFD's have been constructed manually by human experts [5]. We believe this is primarily due to two reasons: 1) human experts are thought to be the most accurate crater detector, given that we have no higher authority by which to check our answers; 2) Large craters have been shown to be of far more immediate use in age-dating, and are more easily countable by humans because there are many fewer of them than sub-km ones.

Small crater statistics are not well understood. This is because of various poorly constrained stochastic processes that effect both the production and erosion of small craters [1]. These small craters reach an equilibrium population distribution quickly, and therefore many surfaces have a stable number of small craters which cannot inform us of the surface age. With substantial amounts of data, the processes effecting production and erosion may be able to be isolated in these equilibrium populations, however a very large count of small Martian craters has never been conducted.

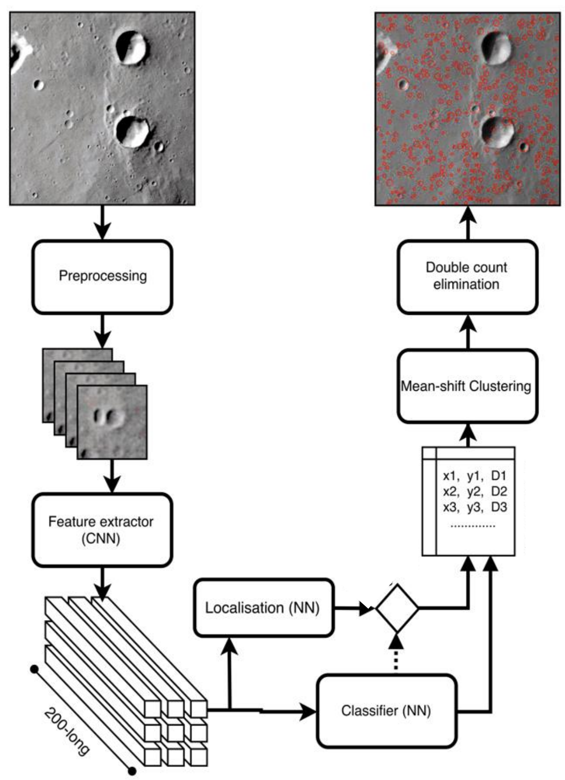

Figure 1: A flowchart of the algorithm, showing feature extraction, classification and clustering.

2. Method

Our algorithm comprises three distinct stages (see Figure 1). First, image patches are transformed by a 4-layer convolutional neural network into a set of features. Secondly, these features are used to classify the image patch as a crater or non-crater, by a neural network. A second neural network is then used on the crater candidates to estimate position and size within the image. Finally, many detections of the same crater in the extended scene are clustered using the mean-shift algorithm.

The convolutional network is initially trained in an unsupervised fashion, using an autoencoder architecture. The training data used is random patches of Martian terrain imagery from HRSC nd-4 products. After the unsupervised learning, both the convolutional network and the neural networks are trained using a dataset made available by Cohen et al. (link) in the Nanedi Valles region. We extend this dataset with additions from different terrain, and use data augmentation to increase the number of training examples.

3. Results

Our algorithm performs at the state-of-the-art when compared to other methods [2],[3],[4] using the same dataset. We perform with a 91% F1-score in a classification scenario, which will improve with more training data (Figure 2). In a detection scenario across an extended scene, the algorithm can be used to obtain crater candidates for expert marking. In this mode, the detection algorithm has a recall at or near to 100% and a precision of around 50%. This leads to a huge decrease in the time spent manually counting craters, given that errors of omission (the most time-consuming to correct) are negligible. Our detection algorithm shows robustness to a variety of terrain types, with reliable performance in areas that aren't represented in the training set. Using this tool, we aim to produce a large catalogue of small Martian craters, which will be used to constrain the effects of secondary cratering, erosion rates and partial resurfacing.

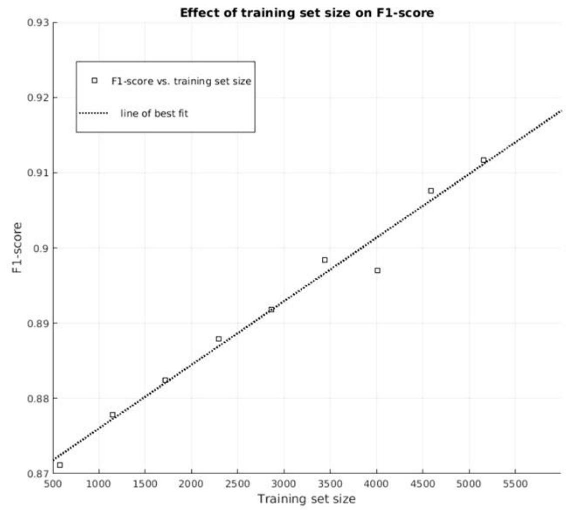

Figure 2: The classification performance (F1-score) of the algorithm, using different amounts of the available training set data. This is a clear indication that more data will increase performance.

4. Acknowledgements

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