AUTOMATED DETECTION OF CRATERS IN MARTIAN SATELLITE IMAGERY USING CONVOLUTIONAL NEURAL NETWORKS. C. J. Norman[1], J. P. Paxman[1], G. K. Benedix[2], T. Tan[1], P. A. Bland[2], M. Towner[2] [1]Department of Mechanical Engineering, Curtin University, Kent Street, Bentley, Perth Western Australia, 6102, [2]Department of Applied Geology, Curtin University, Kent Street, Bentley, Perth Western Australia, 6102.

Introduction: Impact craters are structures formed when a meteoroid strikes the surface of a planetary body. The age of a surface can be estimated through analysis of crater frequencies, assuming random impact rates with known long-term averages [1]. Considerable research effort has been invested into developing automated techniques for the detection and counting of craters [2].

Approaches to Crater Detection Algorithms (CDAs) have included image analysis techniques such as edge detection and the Hough transform [3], though many in recent years have incorporated some form of machine learning, including neural network architectures.

We propose an automated machine learning solution to the crater detection and counting problem on Mars, involving a Convolutional Neural Network (CNN), with ground truth (training) data provided by the Robbins database of Martian craters with diameters over 1km [4].

Background: Convolutional neural networks have performed well at complex classification tasks, particularly in image recognition, where pixel proximity is exploited to solve the scaling problem which exists for conventional multilayer perceptron neural networks. The OverFeat CNN architecture is capable of object classification, localisation and detection. This architecture has been used to detect people in complex, crowded scenes [6], and was able to correctly detect overlapping and occluded examples, making it promising for use in a CDA – crater overlapping is similar to the occlusion problem.

Google Tensorflow is an open-source machine learning library based on data flow graphs. The advantage of a Tensor-flow based CDA is that the algorithm can be scaled to a distributed supercomputing environment to process large volumes of planetary data.

A supervised machine learning algorithm requires a ground truth database of examples labelled by experts. Robbins and Hynek [4] coordinated a community effort to catalogue Martian craters over the entire Martian surface with diameters above 1 km, currently numbering some 384,343 entries. We assumed the Robbins database to be consistent enough for the training of an algorithm, and sought to develop a CDA with the objective of generalising to craters smaller than 1km. Even among experts, a maximum variation of up to 45% has been noted in crater identifications [5]. A CDA may provide a more consistent, less subjective, and of course faster method of crater detection compared to expert analysis of images.

Approach: A CNN-based CDA was designed using TensorBox, an open-source object detection framework based on Google Tensorflow. Images from Mars Odyssey's Thermal Emission Imaging System (THEMIS) were used to generate a ground truth database using the Robbins identifications. The USGS Astrogeology Science Centre has released mosaic images combining individual THEMIS images into a larger map. Mosaics covering the entire equatorial latitude band of N°30 to S°30 were selected for analysis. Each mosaic image spans a region of approximately 2700 km by 1800 km. The mosaics were split into a total of 6387 tiles each with width 1280 pixels and height 960 pixels. The Robbins Database craters were mapped to each tile.

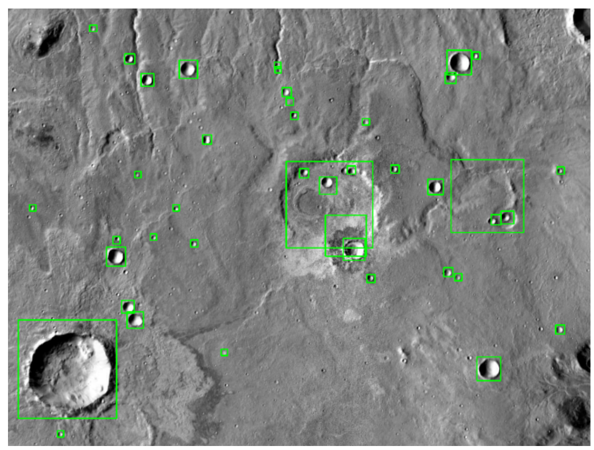

Figure 1: CDA crater detections

The CDA was trained for 20,000 iterations with a learning rate of 0.001. The neural network model that was used by the CDA was GoogLeNet-OverFeat, pretrained on the Imagenet dataset. Figure 1 shows the predictions made using the CDA. Preliminary results visually correlate with craters. The CDA is able to detect a broad range of craters that vary in size and appearance.

The algorithm was generalised to higher-resolution Context Camera (CTX) Martian satellite imagery to detect craters from approximately 100m in diameter in the vicinity of the Mojave crater. Figure 2 shows a crater size frequency distribution isochron generated through the automated workflow for comparison with earlier analysis by Werner et al. [7] based on manual counts. The crater frequencies are consistent with the results of Werner's analysis in the 0.1-1km range.

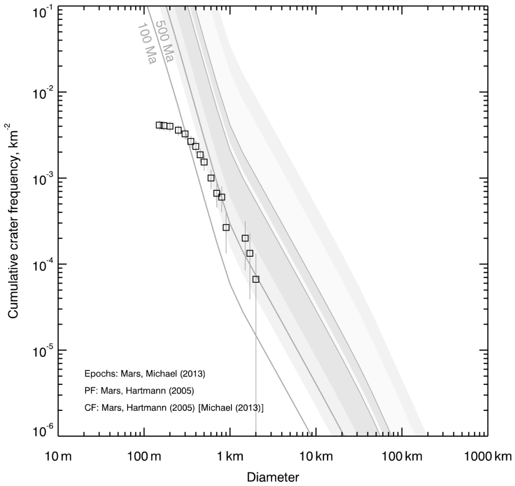

Figure 2: CDA generated crater count statistics, showing crater frequency versus diameter.

The complete workflow for the training and application of the CDA, including generation of the characteristic surface aging curve is depicted in Figure 3.

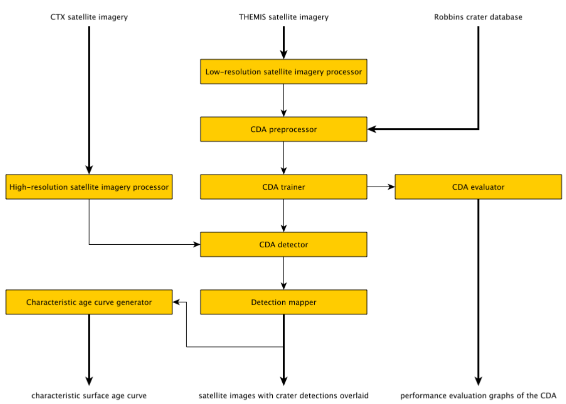

Figure 3: CDA system workflow

Conclusions: A CDA was developed, based on a Convolutional Neural Network trained using THEMIS images and the Robbins database for ground truth. The results are extremely promising, and an analysis of crater frequencies around the Mojave crater proved the concept of generalisation to higher resolution data and smaller craters.

The characteristic isochron generated automatically by the algorithm is consistent with curves generated by expert manual counting.

Future work will further refine the algorithm, and expand the training set to include examples from within a broader size range and higher resolution data. The algorithm will be applied to more surface targets, with the ultimate objective of deploying supercomputing resources to obtain crater count ages for the entire Martian surface.

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