MACHINE IDENTIFICATION AND CHARACTERIZATION OF MARTIAN CRATERS FROM DIGITAL TOPOGRAPHY. Tomasz F. Stepinski, *Lunar and Planetary Institute, Houston TX 77058-1113, USA, (tom@lpi.usra.edu)*, Michael P. Mendenhall, *Dept. of Physics, Washington Univ., St. Louis, MO 63130, USA.*.

Abstract. We present a robust two-stage system for an automated cataloging of craters from digital elevation models (DEM) data. In the first stage an innovative crater-finding transform is performed on a DEM to identify centers of potential craters, their extents, and their basic characteristics. This stage produces a preliminary catalog. In the second stage a machine learning methods are employed to eliminate false positives. Using the MOLA derived DEMs, we have applied our system to six large test sites. The system has identified 3217 craters without any false positives. This pixel-based algorithm is scale independent and can be applied to any future, higher resolution DEMs of planetary surfaces.

Introduction. Detailed analysis of the number and morphology of impact craters on Mars provides the worth of information about the geologic history of its surface. Global catalogs of Martian craters have been compiled (for example, *The Catalog of Large Martian Impact Craters* [1] by N. Barlow, or *Morphological catalogue of the craters of Mars* [2] by J.F. Rodionova et al.) However, these catalogs are only comprehensive for relatively large craters. Manual compilation of smaller craters from higher resolution data is too labor-intensive to be practical. Automation of the crater survey process is necessary in order to catalog smaller craters. An existing body of work focuses exclusively on researching methods for automatic detection of craters from images (see [3] and reference therein). Because of inherent limitations of imagery data, the resultant methods suffer from low efficiency and are not practical for global surveys. The purpose of our research is to develop a computer algorithm for detection and characterization of craters from digital elevation models (DEMs) data. DEMs are much more fundamental descriptors of planetary surfaces than images. They are suitable for a quantitative geomorphic analysis and are well-suited for automated identification of craters. At present, global Martian DEMs are constructed from the MOLA data and have resolution of of 1/128 degree, or $\sim$ 500 m at the equator. The coarse resolution of presently available topographic data limits the size of craters that can be detected by our algorithm to $\sim 3-5$ km in diameter, about the same lower limit as in [1]. However, we will catalog much smaller craters once higher resolution DEMs, derived from Mars Express HRSC images, become available.

Methods. Denote the site's DEM as a surface S. In the first step we perform a series of "crater finding" transforms of S into a new (abstract) surfaces $C(r)$. These transforms are performed for an increasing value of a parameter r, an approximate radius of craters we want to find. For a given focus pixel the transform counts the number of other pixels, within a distance r from a focus pixel, that have gradients "pointed away from" a focus pixel. Craters with radii $\sim r$ will produce local minima in $C(r)$. The transform $C(r)$ smoothes out features smaller than r and suppresses low-frequency components in the DEM, leveling out any slowly changing background gradients. As a result, we obtain a smooth surface with craters of size r forming pronounced basins in $C(r)$. These basins are delineated using curvature measure. Aggregating identified basins from $C(r_{min})$ to $C(r_{max})$ we obtain a catalog of crater candidates of all sizes. For each candidate we calculate its size, depth, and a number of coefficients that measure its shape and the distribution of slopes within it. We use thresholds on these parameters to significantly reduce a number of crater candidates.

In the second stage the remaining crater candidates are subjected to a machine learning classification algorithm designed to eliminate all false detections. A number of crater candidates is selected from a test site and manually labeled TRUE or FALSE. This labeled set constitutes an input to a machine learning algorithm which constructs a classification function. Unlabeled crater candidates are submitted to the classification function for automatic labeling. We use J48 machine learning algorithm as implemented in the software package WEKA [4] using default parameters.

Table 1. Identification of craters: automatic vs. manual

Name	Coordinates (lower left, long., lat.) (upper right, long., lat.)	Area (millions km^2)	# of craters (our code)	# of craters (Barlow)
Terra Cimmeria #1	(114.0, -18.42) (141.4, -7.58)	1.0	734	499
Terra Cimmeria #2	(117.4, -28.4) (145.4, -17.0)	0.98	748	571
Terra Cimmeria #3	(117.4, -38.6) (145.4, -26.6)	0.92	662	508
Terra Cimmeria #4	(117.4, -47.5) (145.4, -26.5)	0.73	300	409
Hesperia Planum	(107.1, -29.6) (118.5, -17.0)	0.44	305	136
Sinai Planum	(261.5, -29.7) (278.6, -10.3)	1.0	468	124

Results. We have applied our machine crater detection system to six sites, each having area of $\sim 1\times10^6$ km^2. Four of these sites are located in Terra Cimmeria and are predominantly Noachian, the remaining two are located in Hesperia Planum and Sinai Planum and are predominantly Hesperian. Table 1 summarizes our findings. The fourth column lists the number of craters identified by our system whereas the fifth column shows the number of craters present in the Barlow catalog. For all sites except the Terra Cimmeria #4 site we have identified significantly more craters than are listed in the Barlow catalog. The extra finds are predominantly small craters, at the edge of detectability, that are most difficult to fully account for in manual surveys. The Sinai Planum site with a lot of small

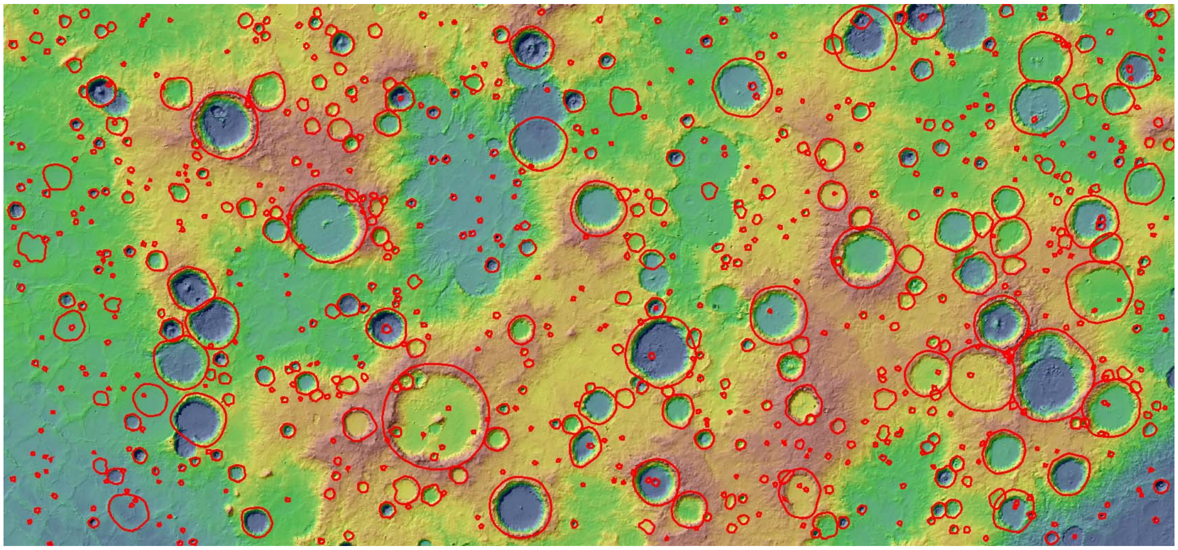

Figure 1: Detected craters in the Terra Cimmeria #2 site are shown in red on top of MOLA-derived topography.

carters provides a particularly striking example of this trend; our system finds almost four times as many craters as are listed in the Barlow catalog. Overall, for all six sites, we have identified 3217 craters, 43% more than are present in the Barlow catalog.

Fig.1 shows the Terra Cimmeria #2 site. The first stage of our algorithm resulted in identification of 1287 crater candidates. The machine learning stage eliminated many of them producing a final catalog of 748 craters. As can be seen from Fig.1 some degraded craters are not identified, but the algorithm produces a robust, predictable result.

In addition to identifying the carters the algorithm also estimates their sizes and depths. Previous studies [5] have manually estimated depths (and diameters) of 155 craters in Hesperia Planum and 94 craters in Sinai Planum. For craters in the Hesperia Planum there is an excellent agreement between crater sizes calculated manually and derived by our algorithm. For the Sinai Planum craters our algorithmic estimate of crater diameter is systematically slightly lower than the manually derived value. In both sites our derived depth is systematically higher than the manually calculated depths. This difference is attributed to a different definition of depth. Our algorithm estimates depth as the difference between the highest and lowest points within the segment identified as a crater. In [5] the depth is defined as the difference between the average elevation of the rim and the lowest point in the floor.

Conclusions. Machine identification of craters from DEM data constitutes a practical method for conducting global automated surveys of craters on Mars. Our system has been tested on large and demanding test sites and had proven to deliver robust results. The code implementing the first stage of our system is available from *cratermatic.sourceforge.net* and the machine learning software WEKA is also available from *www.cs.waikato.ac.nz/ml/weka*. Because our automated survey is DEM-based, the resulting catalog lists craters depths in addition to their positions, sizes, and measures of shape. This feature significantly increases the scientific utility of any catalog generated using our system. Our initial calculations yield a training set that will be used to identify craters over the entire Martian surface with estimated accuracy of 95%. Moreover, because our method is pixel-based and scale-independent, the present training set may be used to identify craters in higher resolution DEMs derived from Mars Express HRSC images. It also can be applied to future topography data from Mars and other planets. For example, it may be utilized to catalog craters on Mercury and the Moon using altimetry data to be gathered by Messenger and Lunar Reconnaissance Orbiter spacecrafts.

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