A STATISTICAL ANALYSIS OF AUTOMATED CRATER COUNTS IN MOC AND HRSC DATA. C. S. Plesko[1,3], S. C. Werner[2], S. P. Brumby[3], E. A. Asphaug[4], G. Neukum[2], and the HRSC Investigator team. [1]University of California, Santa Cruz, cplesko@es.ucsc.edu, [2]Geosciences Institute, Freie Universität Berlin, [3]Los Alamos National Laboratory, brumby@lanl.gov [4]University of California, Santa Cruz.

Introduction: We describe continuing efforts to develop automated crater counting algorithms for Mars surface images. Comparison of automated to manual counts yield automated counts that are within the 1-σ error of the manual counts in several adjacent diameter bins. It may be possible to develop a fitting function to completely correct the algorithm results to within manual-level accuracy.

Background:

Craters as a feature of interest. Impact craters are some of the most interesting, and most common, features on the surface of Mars. They provide clues about the relative age, local composition, and local erosional history of the surface, and are interesting features of themselves.

Automated crater counting. Manual counting done by experts can produce highly accurate crater surveys on a given image. However, it takes a long time to produce a detailed survey, and each image must be counted several times by different trained people in order to eliminate perceptual biases. This process can take months for just a few images. A variety of attempts have been made to develop algorithms that would automatically detect objects in astronomical or planetary science data. However, none have yet been able to claim a human-level of count accuracy.

GeniePro[1] is a supervised classifier algorithm development environment written by the ISIS development team at Los Alamos National Laboratory. A supervised classifier is an algorithm that sorts the pixels in an image according to patterns or definitions given by a human analyst. There are a variety of supervised classification techniques. Of these, two of the most useful are Genetic Programming (GP) and Support Vector Machines (SVMs). GP was used in previous[2] steps of this work. Support Vector Machine techniques evolve algorithms over time. Rather than using a competing population of algorithms like GP, it generates one, and then tests random modifications, which are accepted if they improve the accuracy of the classification relative to training data. SVM-generated algorithms have been found to generalize more reliably to multiple images[3] than GP-generated algorithms, so SVMs are the machine learning technique of choice for this work.

Results: Here we compare the accuracy of two automated crater-counting algorithms against expert manual surveys. These tests demonstrate the results of one single algorithm per image, with minimal post-processing. Accuracy of a final crater count can be increased by combining multiple algorithms into a voting set[4].

The algorithms are human-readable and modifiable. They consist of image processing steps (maxima, morphological open, etc.) that may be performed on part or the entire image, and combined with the results of other steps. These collections of steps are then combined and weighted to maximize the similarity of the results to the training data. The final GeniePro graphical result is then subjected to a simple post-processing step consisting of a morphological open followed by two morphological erodes in order to separate clustered detections (craters).

MOC image NA-SP1-21904[5] *results.*

Manual counts for this MOC image were conducted by W. K. Hartmann and D. Berman in their 2000 survey of craters in Elysium Planitia[6]. The area was chosen because it is young and the terrain is simple, which makes counts easier. The counts were binned as number of crater per square kilometer, as per Arvidson 1979[7], and a 1-σ confidence interval (CI) calculated. In this table, we compare the results of the automated count (Auto) to Hartmann and Berman's manual counts, in order to determine whether the automated counts fall within the confidence interval of the manual counts. We find that the automated counts are within the 1-σ confidence interval of the manual counts for diameters greater than 0.125 km.

D (km)	Hartmann	Berman	Auto	CI	In CI?
0.062	0.877	0.928	0.7	0.099	**no**
0.088	0.407	0.540	0.3	0.094	**no**
0.125	0.284	0.414	0.25	0.196	**yes**
0.176	0.0617	0.0627	0.092	0.285	**yes**
0.250	0.0370	0.0376	0.080	0.294	**yes**
0.353	0.0123	0.0251	0.031	0.227	**yes**

HRSC Pavonis Mons Caldera results. A manual survey of craters inside the caldera of Pavonis Mons, in an HRSC nadir panchromatic image[8], conducted by S. C. Werner yielded the following results.

Automated counts yielded results that were within the confidence interval at diameters greater than 0.2 km.

D (km)	Werner	Auto	CI	In CI?
0.0700	3.0400	0.0000	0.6790	**no**
0.0800	2.8900	0.0197	0.6620	**no**
0.0900	3.9100	0.0243	0.6960	**no**
0.1000	5.4700	0.0319	0.9120	**no**
0.1100	2.5800	0.0410	0.6260	**no**
0.1200	1.3700	0.0258	0.4560	**no**
0.1300	1.5200	0.0213	0.4800	**no**
0.1400	0.4560	0.0258	0.2630	**no**
0.1500	1.0600	0.0182	0.2840	**no**
0.1700	0.6080	0.0258	0.1750	**no**
0.2000	0.0456	0.0228	0.0263	**yes**
0.3000	0.0304	0.0319	0.0304	**yes**
0.3500	0.0304	0.0030	0.0304	**yes**

Future Work: Feature extraction in panchromatic imagery is one of the most difficult problems in automated image analysis. There is very little data per pixel with which to establish patterns and differentiate various features. It appears, however to be possible. In these tests we find that the computer-generated algorithms are detecting craters correctly. The next challenge is to extract the crater rim diameters. These algorithms measure the craters only out to the rims at some diameters, while they tend to detect material outside the crater rim as part of the crater (ejecta?) at other diameters.

Further tests are required to see if this offset is consistent within an image, and if it will be possible to fit algorithm results to manual count results using a fitting function. If this is possible, it will be interesting to examine how this fitting function changes across different terrain types, and the physical motivations behind it.

It would also be useful to compare and combine the results of the various machine-learning and hand-written crater-detection algorithms. Results from a variety of algorithms can be graphically summed to increase the accuracy of the result[4].

References: [1] S. Perkins et al. (2005) Proc. SPIE. [2] C. S. Plesko et al. (2002) Proc. SPIE, 4480, 139-146. [3] S. Perkins et al. (2001) Proc. SPIE, 4381, 286-295. [4] C. S. Plesko et al. (2004) Proc. LPSC. XXV Abstract #1935. [5] M. C. Malin et al. (1998) Cat. No. SP1-21904. [6] W. K. Hartmann and Berman, D. C. (2000) JGR, 105, 15011-15026. [7] R. Arvidson, (1979) Icarus, 37, 467-474. [8] G. Neukum and the HRSC investigator team (2005).

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