

AUTOMATED IDENTIFICATION OF MARTIAN CRATERS USING IMAGE PROCESSING. M. Magee¹, C.R. Chapman², S.W. Dellenback¹, B. Enke², W.J. Merline², and M.P. Rigney¹, ¹Automation and Data Systems Division, Southwest Research Institute, P.O. Drawer 28510, San Antonio, Texas 78228-0510, E-Mail: mmagee@swri.edu, ²Department of Space Studies, Division 15, Suite 426, 1050 Walnut Street, Boulder, Colorado 80302, E-Mail: cchapman@boulder.swri.edu.

Introduction: We have developed methods for detecting craters automatically, focusing specifically on complex Martian landscapes. Mars exploration is planned as the highest priority element of NASA's Solar System Exploration Program for the next two decades. Much of this interest in Mars is based on geological evidence for running water on, or just below, the surface of Mars, especially several billion years ago when the planet's climate might have been warmer, with implications for past or present life. Numerous impact craters on the southern highlands, among which the ancient river valleys weave, provide witness to the evolving surface processes on Mars.

Automation of crater detection is an important initial step toward making more efficient the work of human analysts, who face large volumes of images that are being archived by missions such as Mars Global Surveyor and Mars Odyssey. Our ongoing work^{1,2} (collaborating with J.P.L., funded by NASA's Applied Information System Program), had developed techniques for automated recognition of craters on planetary surfaces, chiefly the simpler craters on the lunar maria. To address the more complicated terrains of Mars, including varying states of degradation, Southwest Research Institute is supporting an Internal Research and Development Project, described here. Several automated methods, based on local intensity values, intensity gradients, and geometric traits have been developed and applied to detection of Martian craters. We have found that, collectively, these methods can successfully locate most craters in typical images by enforcing relatively high confidence measures.

Image Processing Algorithmic Approaches: So far, our image processing research has focused on locating craters using four separate methods. These include (1) cross-correlation based template matching, (2) applying edge detection operations whose response is greatest in the direction of the sun, (3) applying an annular crater convolution kernel whose response is greatest in the direction of the sun, and (4) detecting circular patterns in edges using a circular Hough transform. We briefly describe these methods here.

Cross-Correlation Based Template matching. For relatively small craters, a method³ based on cross-correlating a template of a typical crater extracted from the image proved to be relatively effective. In this case (Figure 1) a template is derived from the image

and its normalized cross-correlation is computed at each location in the image. A set of scaled templates provides detection of a range of crater sizes. At those locations where the cross-correlation is sufficiently high and is a local maximum, a crater is detected, as shown by the red circles. Multiple templates may be used to increase sensitivity to different crater morphologies (e.g., bowl-shaped vs. flat-floored). In practice this method – which seemed promising on bowl-shaped lunar craters in our previous work^{1,2} – worked best for small craters while other methods, below, were more sensitive and efficient in detecting larger craters.

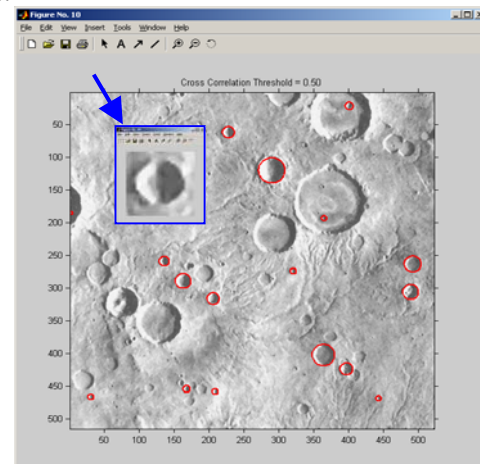


Figure 1: Cross-Correlation Based Crater Detection

Directional Edge Based Detection. Since the crater floors are vertically offset from their rims, intensity gradients may be employed to enhance their boundaries. As described by Davies⁴, many different types of edge gradient operators may be applied. For the current study, however, we developed a specialized gaussian based operator that is most sensitive in the direction of the sun. By applying this operator to the region shown in Figure 1, which has the sun off to the right (east) of the image, the gradient strengths shown in Figure 2 are produced. Note that the edge strengths are strongest (colored red) on the left and right sides of each crater rim. A rim's right side has a high response because the interior shadow falls on the left of the rim. Analogously, the left side of each crater rim has a high response because the interior of the crater wall is illuminated more directly than the neighboring surface on the left of the rim. By convolving the local maxima of

these directional edges with annular kernels of varying radii, the craters outlined in blue in Figure 3 are found.

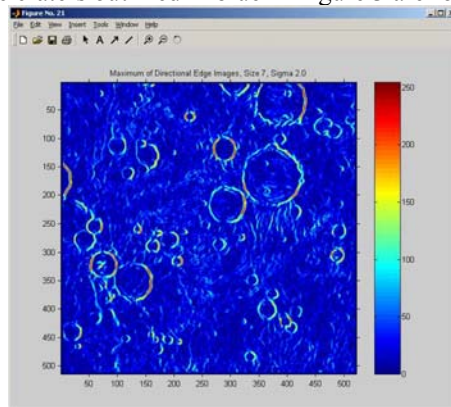


Figure 2: Directional Edge Gradient Strengths

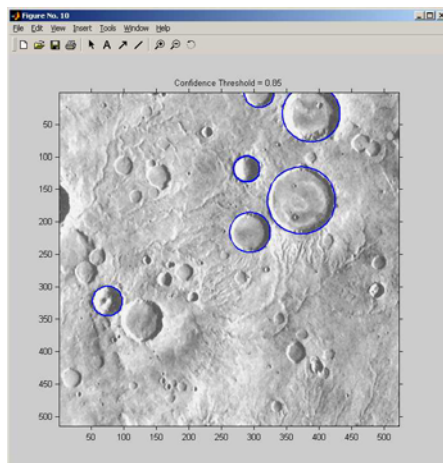


Figure 3: Craters Detected with Directional Gradients

Convolution with an Annular Crater Kernel. The third method detects craters using the annular crater kernel shown in Figure 4. The convolution kernel used is also dependent on sun angle with the blue portions of the kernel being toward the sun and the red portions being away from the sun. The purple circles show craters found using this approach.

Circular Hough Transform. A final crater-detection method is based on applying circular Hough transforms.⁴ It is a multiple step approach in which edges are computed, locally strong edges are preserved, and those that are locally linear are discarded. Edges that survive these preprocessing steps are then fit to circular arcs and parameterized into a three-dimensional space representing the center (x,y) and radius (r) of putative circles. An accumulation process is then applied evaluating from this 3-D space whether arcs represent part of the same circular feature; if so, they are consolidated into a single circle. The green circles in Figure 5 are craters found by this method. Also in Figure 5 are craters that were found using

cross-correlation (red), directional annulus (purple), and locally maximum directional edges convolved with an annular kernel (blue).

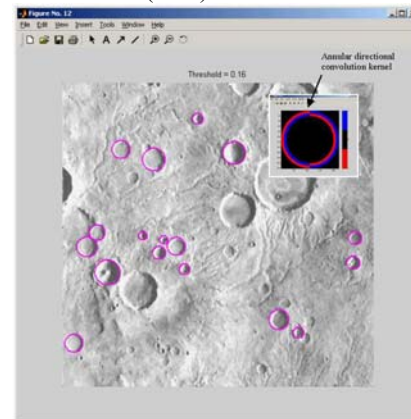


Figure 4: Craters Detected with Annular Directional Kernel

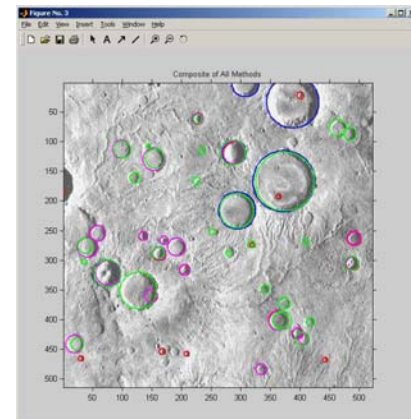


Figure 5: Composite Image of All Detected Craters

Summary: Four methods for detecting Martian craters have been implemented and applied to actual images. Enforcing relatively high confidence measures for each method generally yields reliable detection of most craters.

References:

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- [4] E.R. Davies (1990), Machine Vision: Theory, Algorithms, Practicalities.