

**CHANGE DETECTION IN MARS ORBITAL IMAGES USING DYNAMIC LANDMARKING.** Kiri L. Wagstaff<sup>1</sup>, Julian Panetta<sup>2</sup>, Adnan Ansar<sup>1</sup>, Melissa Bunte<sup>3</sup>, Ronald Greeley<sup>3</sup>, Mary Pendleton Hoffer<sup>3</sup>, and Norbert Schörghofer<sup>4</sup>, <sup>1</sup>Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr., Pasadena, CA 91109 USA (kiri.wagstaff@jpl.nasa.gov), <sup>2</sup>California Institute of Technology, 1200 E. California Blvd., Pasadena, CA 91125 USA, <sup>3</sup>Arizona State University, School of Earth and Space Exploration, Box 871404, Tempe, AZ 85287 USA, <sup>4</sup>University of Hawaii, Institute of Astronomy, 2680 Woodlawn Dr., Honolulu, HI 96822 USA.

**Introduction:** As of December 2009, there are more than 1,500,000 orbital images of Mars available on the Planetary Data System’s Imaging Node (from Mars Odyssey, Mars Express, Mars Global Surveyor, and Mars Reconnaissance Orbiter). The volume of image data is steadily increasing, as is the number of repeat images that allow for the possibility of detecting surface changes such as dark slope streaks [1], new impact craters and gullies [2], ground ice excavated by fresh impact craters [3], etc. The number of overlapping image pairs is growing quickly enough that there is a need for automated methods for detecting and characterizing those changes. In addition to greatly accelerating the analysis process, automated methods offer the opportunity to discover entirely new types of transient features, not just ones we can already search for.

**Related Work:** Most existing work on automatic detection of changes in images has focused on identifying changes in individual pixels. These methods adopt a two-step approach by first registering the two images and then subtracting or ratioing them to identify any changed pixels [4]. Registration can be accomplished through methods such as maximizing mutual information [5] or matching SIFT (Scale-Invariant Feature Transform) features [6]. The focus on individual pixels means that the results can be very sensitive to noise and, critically, the results must still be interpreted to determine what the changed pixels represent.

We have investigated a *landmark*-based approach to change detection, which first identifies areas of high visual salience (landmarks) and then looks for changes in only the landmark areas. This approach avoids a costly pixel-level registration and instead focuses on content changes in the image. Rather than providing a list of changed pixels, it can summarize the changes in an interpretable form, such as “two new dark slope streaks,” along with contours showing the location of the new landmarks.

**Landmark Identification:** The first step is to identify the landmarks in each image. We define a landmark as a surface feature that is salient in a statistical sense, with respect to its surrounding area. Examples include craters, dark slope streaks, dust devil tracks, etc. Given a grayscale image with pixel values that range from 0 to 255, we define the salience  $S$  of a pixel  $p$  with respect to

a histogram  $h$  of pixel values in a window surrounding  $p$ :

$$S(p) = \sum_{i=0}^{255} h(i)|I(p) - i|,$$

where  $h(i)$  is the histogram count for grayscale value  $i$  and  $I(p)$  is the intensity of pixel  $p$ . Computing the salience of every pixel in the image yields a salience map. To find landmarks, we specify a salience threshold to generate contours around high-salience regions. For each landmark, we extract the following attributes: mean and standard deviation of intensity, area, perimeter, and several shape attributes derived from an ellipse-fit. This process yields a catalog of landmarks for each image. Each landmark can be classified as a crater, dark slope streak, dust devil track, etc., based on its attributes.

**Landmark-Based Change Detection:** To detect changes when comparing two images, we identify the landmarks in each image and then compare the two landmark sets, marking any unmatched (new or vanished) landmarks as changes. We use the Hungarian/Kuhn-Munkres assignment algorithm [7] to find the best matching of landmarks in image 1 to those in image 2. We use cosine similarity to compare landmarks  $L_1$  and  $L_2$ :

$$Sim(L_1, L_2) = \frac{A(L_1) \cdot A(L_2)}{\|A(L_1)\| \|A(L_2)\|},$$

where  $A(L)$  is the attribute vector for with landmark  $L$ .

The Hungarian algorithm produces a matching based on landmark similarity, but ignores the spatial position of the landmarks. We incorporated this information by building a Relative Landmark Graph (RLG) for each image. The nodes are the landmarks, and the edges connect each landmark to its  $k$  nearest neighbors. No information about absolute position is encoded in the RLG. We then augment the similarity measure by averaging it with the similarity of a recursive matching computed between the nodes’ RLG neighborhoods, similar to the approach of Chevalier et al. [8]. Finally, we impose an affine transform constraint so that the matching between the two images applies consistently to all landmarks, using RANSAC [9] to estimate multiple possible transforms and selecting the one that best fits the landmarks in both images.

**Results:** Example change detection results are shown in Figure 1. We analyzed two MRO CTX images taken

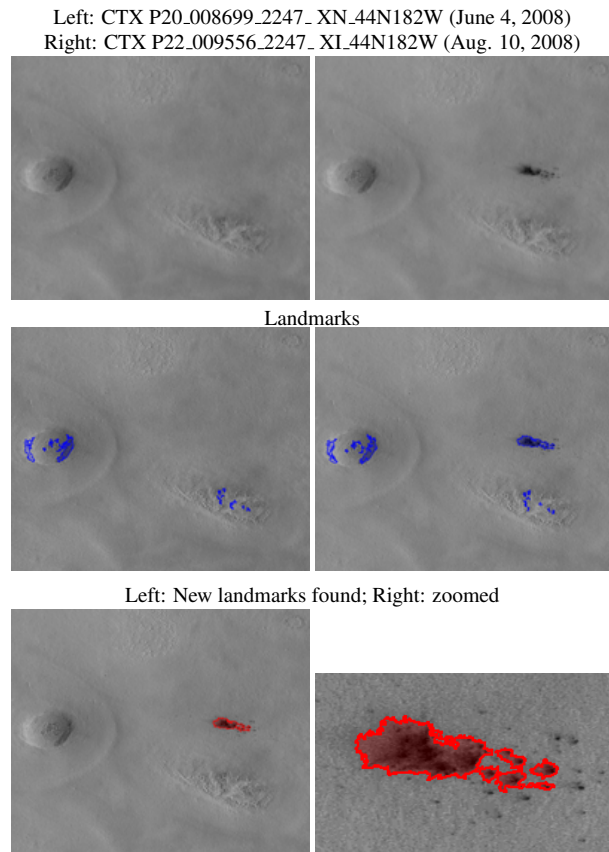


Figure 1: New impact craters (outlined in red) detected by landmark-based analysis in western Arcadia Planitia.

approximately two months apart, during which time a new impact crater formed [10]. An automated analysis identified 20 landmarks in the first image and 24 in the second image. The four new landmarks are shown in Figure 1(c) and the zoomed-in version shows that they are the surface changes caused by the impact. The same region was also imaged by HiRISE, to observe the sublimation of water ice that was exposed by the impacts [3]. In Figure 2, bright ice is apparent in a crater in the upper left of the first image but has faded in the second image. This subtle change is correctly detected by landmark analysis, as shown in the following panels.

**Conclusions:** We have described a landmark-based approach to automated detection of transient features and surface changes on Mars. This method focuses on image content (landmarks and their attributes) rather than typical methods, which identify only the changed pixels. The landmark focus also enables the automatic annotation of past, present, and future images, and ultimately content-based searches of archives (e.g., “return all images containing dark slope streaks”). Our future plans include

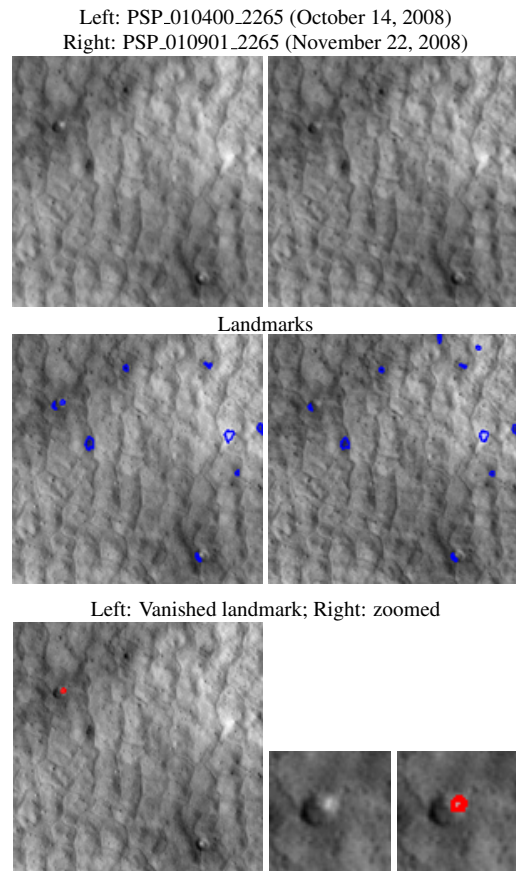


Figure 2: Sublimating ice in fresh impact craters detected by landmark-based analysis in western Arcadia Planitia.

change detection across images obtained by different instruments (e.g., MOC and THEMIS). More information at: <http://landmarks.jpl.nasa.gov/>.

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