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Mars Surface Change Detection from Multi-temporal Orbital Images

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Abstract. A vast amount of Mars images have been acquired by orbital missions in recent years. With the increase of spatial resolution to metre and decimetre levels, fine-scale geological features can be identified, and surface change detection is possible because of multi-temporal images. This study briefly reviews detectable changes on the Mars surface, including new impact craters, gullies, dark slope streaks, dust devil tracks and ice caps. To facilitate fast and efficient change detection for subsequent scientific investigations, a featured-based change detection method is developed based on automatic image registration, surface feature extraction and difference information statistics. Experimental results which use multi-temporal images demonstrate the promising potential of the proposed method.

1. Introduction

In recent years, Mars has been intensively explored by orbital missions, such as Mars Global Surveyor, Mars Odyssey, Mars Express and Mars Reconnaissance Orbiter, to understand its geology and climate as well as to evaluate its possible habitability potential. Images with higher metre- and decimetre-level resolution have been obtained by different cameras, which helped researchers identify fine-scale geological features and surface changes. Archived Mars orbital images are available to the public through the Planetary Data System (PDS) of the National Aeronautics and Space Administration (NASA). At present, several types of detectable changes on the Mars surface have been reported and studied, namely, the emergence of new impact craters [1], the formation of gullies [2], [3], dark slope streaks [4], dust devil tracks [5] and the melting of ice caps [6]. Change detection of these features is very important to scientists in determining ongoing surface changes and understanding their underlying processes, and may even discovering unknown processes. The availability of the vast amount of Mars orbital images enables Mars surface change detection through the use of repeated multi-temporal observations of the same areas.

Traditional change detection methods are mainly pixel-based approaches in which images are first registered followed by a difference or ratio operation to highlight any pixel changes [7]. The detection results which were obtained by using these methods are generally sensitive to noise, illumination changes and sensor characteristics. Thus, such results usually need considerable manual editing.

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Feature-based (also called content-based or object-based) methods [8], [9] have been used for target identification or classification, but are seldom used for change detection, especially for planetary images.

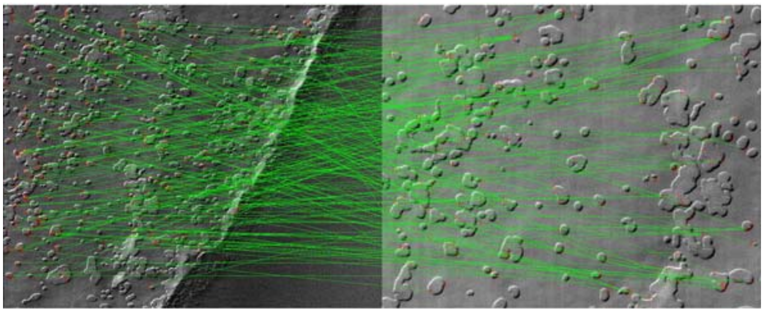
The Mars surface is very different from the Earth's surface; it has much fewer types of features and lacks texture in most areas. Changes on the Mars surface are usually of high visual salience and can be distinguished from the monotonous background. On the other hand, the tones of the multi-temporal images of the same areas may be quite different in varying solar incident angles or depending on the cameras used to acquire the images. Therefore, a feature-based method is more suitable for Mars surface change detection than a pixel-based method. Wagstaff et al. [10] identified Mars surface features and performed change detection by using a content-based method called dynamic landmarking, which performs well in new impact crater detection but barely detects dust devil tracks and dark slope streaks.

In this study, we propose a feature-based method and computational framework for change detection which can be applied to five types of changes on the Mars surface. First, an automatic registration method which uses the Scale Invariant Feature Transform (SIFT) method and the Random Sample Consensus (RANSAC) algorithm is designed for multi-temporal images. Then, a feature extraction method is developed to identify the feature regions based on edge detection and linking and pixel greyscale statistics. The feature regions in the reference and the registered images are compared to calculate their multiple difference information. Finally, the changed regions are detected according to the multiple difference information.

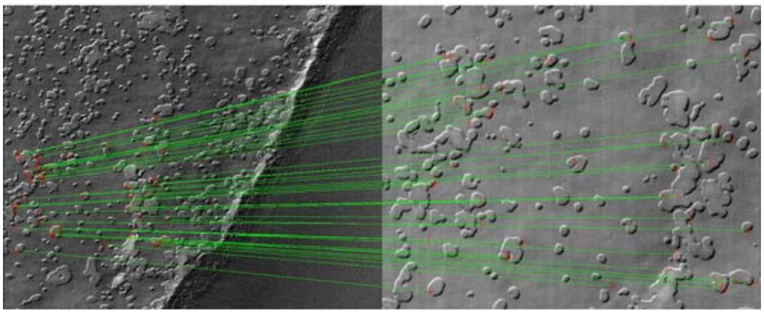
2. Method

2.1. Automatic registration

The registration of multi-temporal images is a prerequisite for change detection. The key to automatic registration is to determine the corresponding points between the reference image and the image to be registered. Considering scale and illumination changes as well as local geometric distortions caused by image orientation, SIFT matching is used to identify as many initial corresponding points as possible. RANSAC is then applied to eliminate gross error points (outliers) from the initial corresponding points. Figure 1(a) and (b) show the corresponding points (linked by green lines) from two Mars images that contain ice caps. The result indicates that the combination of SIFT and RANSAC can effectively find sufficient corresponding points for image registration. With these corresponding points, image registration is accomplished through a geometric transformation, e.g., polynomial transformation or piecewise affine transformation.



(a)



(b)

Figure 1. Corresponding points matched by using an automatic image registration method. (a) SIFT matching result, (b) corresponding points after error elimination using RANSAC.

2.2. Surface feature extraction

In the study, the surface features of Mars are generally classified into two types according to the distinctness of their boundaries. The first type refers to features that have a clear boundary, such as gullies, dark slope streaks and ice caps, while the other type refers to features that have a fuzzy boundary, such as new impact craters and dust devil tracks. As shown in Figure 2, different strategies and algorithms are adopted to extract the two types of features.

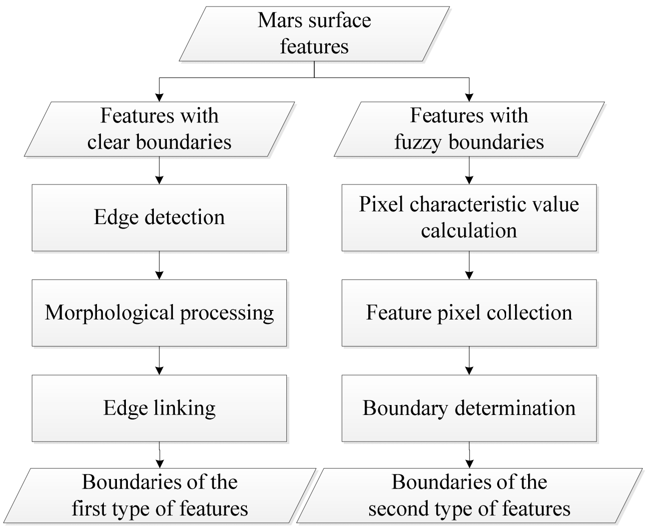


Figure 2. Flowchart of the surface feature extraction.

An edge detection method is applied for the first type of features. A Canny detector performs well in the experiments. Then, a set of morphological processing techniques (erosion and dilation) are used to link the edges and eliminate some trivial edge segments. The edges are connected by using an edge linking algorithm according to positional closeness and similarities in the directions of the detected edges. For example, for gullies, the edge linking algorithm tends to link edges that are approximated as straight lines and point towards the same direction, forming long and narrow regions. Areas enclosed by linked edges are determined as individual feature regions.

For the second type of features, their edges cannot be easily distinguished from the background of the image by using the edge detection method. However, a feature region can be identified based on the greyscale differences from the background. Thus, the method is designed to extract brighter or darker regions from the images. A context window is used to calculate the greyscale gradients of the centre of the window for each pixel in the image. The greyscale gradient is calculated in the X and Y directions separately and combined as the characteristic value of the pixel. The size of the window is adjusted according to the scale of the feature. A threshold is set to measure the characteristic value of a pixel so that pixels with high contrast against the background are chosen to form the feature regions. The edge pixels of a feature region define its boundary.

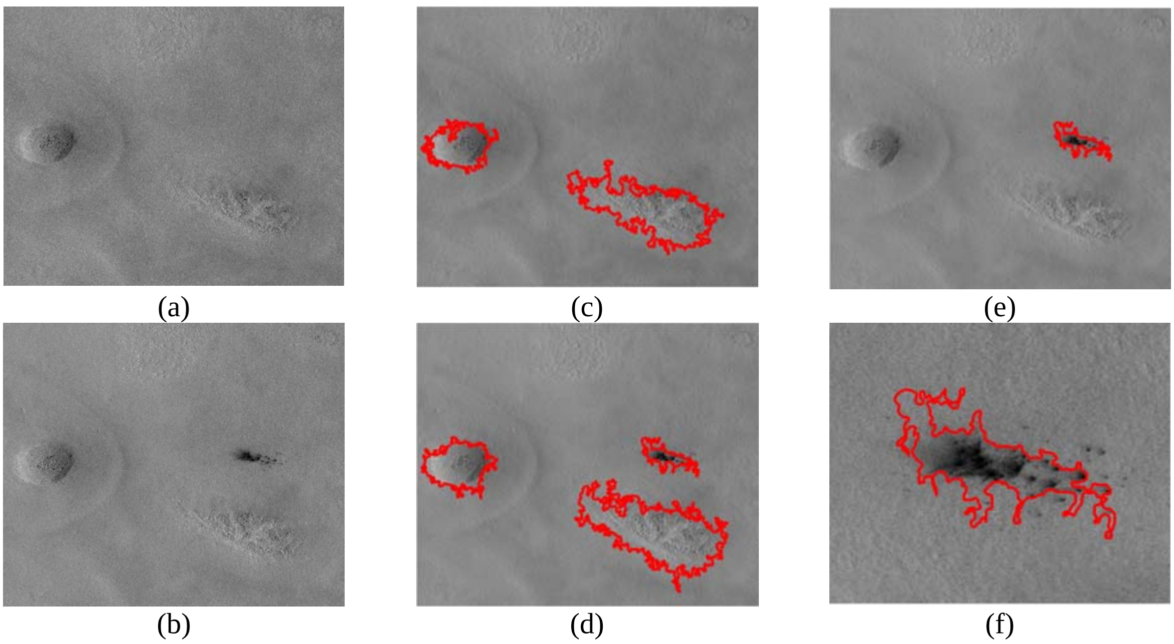
2.3. Feature region change detection

After feature regions in both the reference and the registered images are extracted, multiple difference information, which includes the location (centre and bounding rectangle), area, shape (roundness and compactness) and greyscale difference, are calculated for each pair of the two feature regions from the two images. If none of the difference values exceed the pre-set thresholds, this feature is considered unchanged. Otherwise, this feature exhibits some changes. For example, if one feature region does not have a corresponding region in the same location in the other image, a feature may have either emerged or disappeared, such as a new impact crater or dust devil tracks that have vanished. If two feature regions are of the same location but have different areas, a gully' evolution [11], a seasonal melting of ice caps [12] or other types of change could have occurred. Greyscale information is usually helpful for change detection of dark slope streaks because this kind of streaks is quite dark in the initial stage and will fade over time.

3. Experimental results

3.1. New impact crater

Two Context Camera (CTX) images (P20_008699_2247 and P22_009556_2247) of an area in the western Arcadia Planitia were selected for the experiment. A series of dark spots in the latter image indicates the emergence of a new impact location (46.7°N, 183.2W°) [1] and is successfully detected by using our developed method. Figure 3 (a) and (b) show the subregions of the two images after automatic registration. The areas enclosed by a red line, as shown in Figure 3 (c) and (d), represent the extracted feature regions. Figure 3 (e) shows the changed region detected by difference information statistics. Figure 3 (f) is an enlarged view of the changed location.



(a) (c) (e)

(b) (d) (f)

Figure 3. Change detection result for new impact crater. (a) and (b) are the registered images; areas enclosed in red in (c) and (d) are the extracted feature regions from the two images; the area enclosed in red in (e) is the detected surface change; and (f) is an enlarged view of the detected surface change.

3.2. Gully

Gullies are usually found on steep slopes, especially on crater walls. Gullies have been the subject of heated debate because they indicate the possible existence of liquid water or other substances [11], [13], [14]. A comparison between two Mars Orbiter Camera (MOC) images (E11/03412 and a mosaic image of S09/02603 and S10/01184) shows that a slim gully (around 400 metres) developed in a crater located at Terra Sirenum (near 36.5°S, 161.8°W). Change detection results are shown in Figure 4.

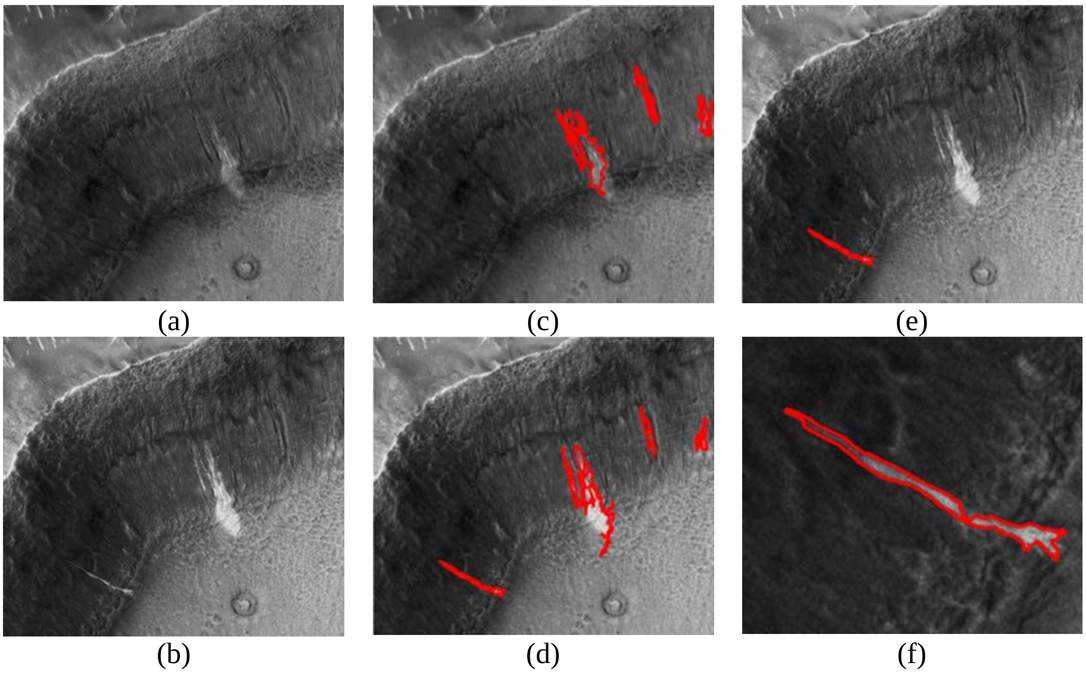
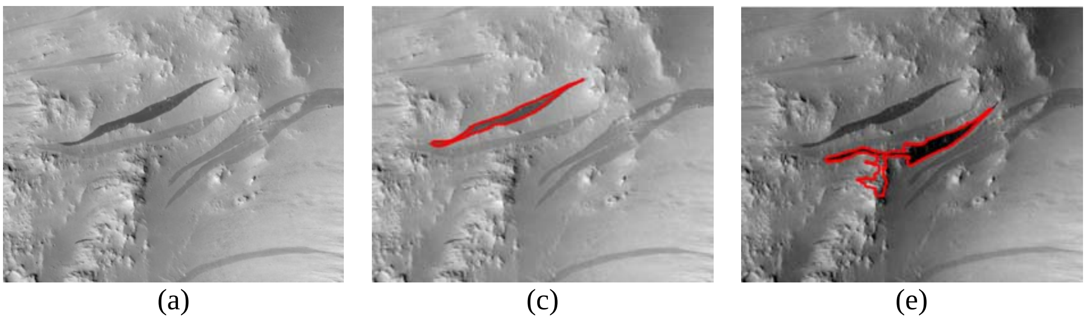


Figure 4. Change detection result for gully (similar layout as in Figure 3).

3.3. Dark slope streak

Dark slope streaks on Mars represent a currently active geological process and are usually thought to be formed by dust avalanches that remove a thin layer of bright dust from the surface [4]. However, several controversies about their formation exist [15]–[17]. From a pair of High Resolution Imaging Science Experiment (HiRISE) images (ESP_020963_1810_RED and ESP_004151_1810_RED), a 725-metre-long dark slope streak located at 0.9°N, 160.7°E is identified by using our proposed change detection method. Intermediate and final results are shown in Figure 5.



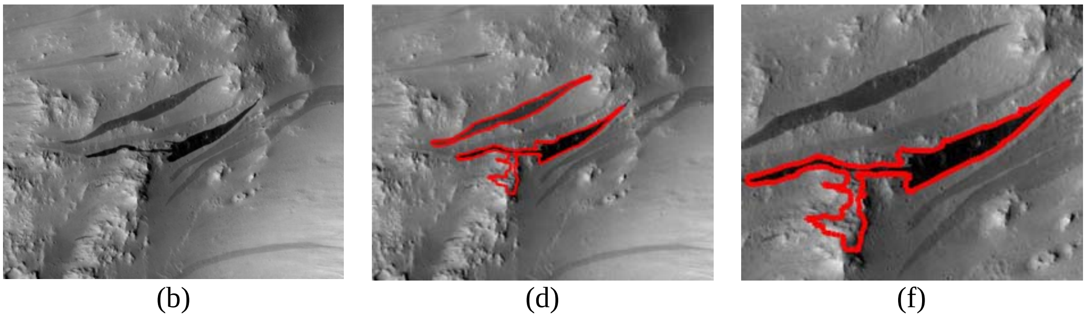


Figure 5. Change detection result for dark slope streak (similar layout as in Figure 3).

3.4. Dust devil track

Dust devils mostly occur from two narrow bands near 60°N and 60°S during their respective spring and summer [18]. Dust devils scour away loose surface materials to reveal different colored soils beneath and leave tracks which indicate the path and lifetime of dust devils crisscrossing the surface. Dust devil tracks are difficult to extract through change detection because of their abundance and their complicated net-like texture. Several crisscross tracks usually form a large feature region, and the boundary for each track could not be distinguished. A detection result with a pair of HiRISE images (ESP_004249_1255_RED and ESP_005383_1255_RED) at 54.3°S, 13.0°E is shown in Figure 6. The feature regions for both images are all marked in red (see Figure 6 (c) and (d)). The detection result is shown in Figure 6 (e).

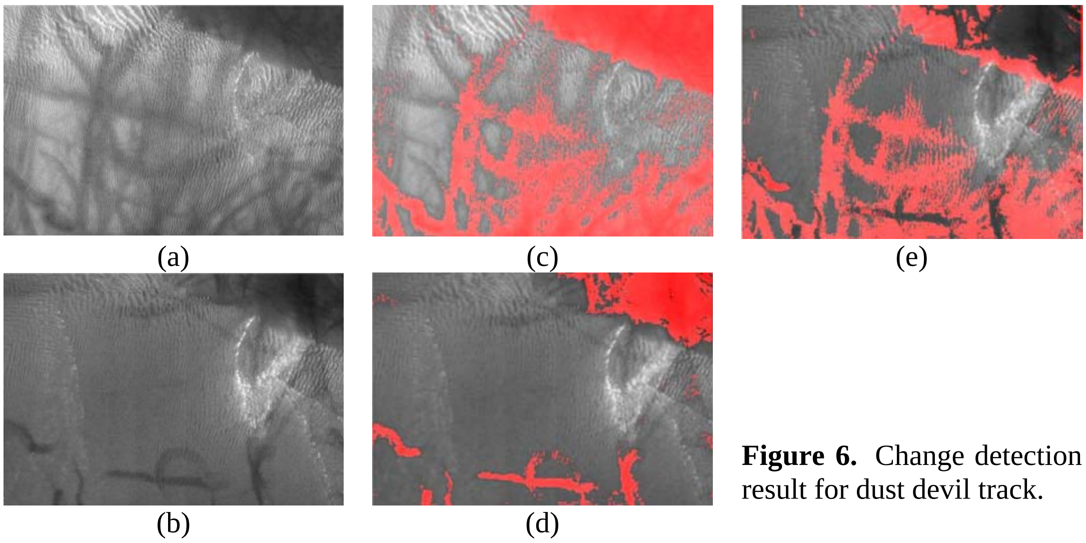


Figure 6. Change detection result for dust devil track.

3.5. Ice cap

Ice caps in the Mars polar regions are usually divided into two layers. The top layer mainly consists of frozen carbon dioxide, and the bottom layer is made of iced water [6], [12]. Seasonal or long-term climate changes may result in the sublimation and melting of the ice caps [19], [20]. The changes in ice caps are detected by using a pair of MOC images (M08/04518 and E07/01565) that show polar ice caps at 87.0°S, 108.0°E. The results are shown in Figure 7. A binary image of changed regions is shown in Figure 7 (e), which indicates that ice cap melting is a fairly common occurrence. Figure 7 (f) shows a detailed view of a region (shown in a red rectangle in Figure 7 (a) and (b)) of ice caps that exhibit apparent changes. To show the changes more clearly and intuitively, the two subimages in Figure 7 (f) are rotated 180°.

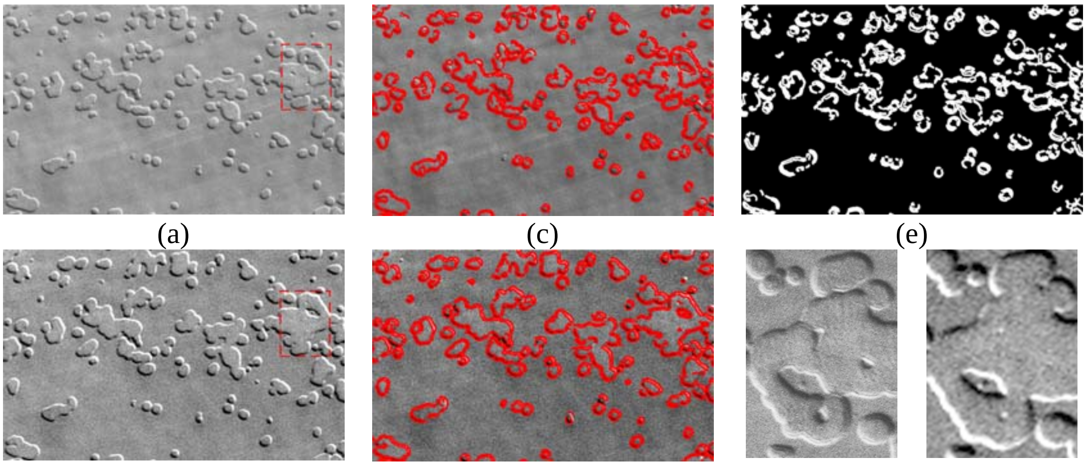


Figure 7. Change detection result for ice cap.

4. Conclusions and Discussions

A feature-based change detection method which uses multi-temporal images to detect changes on the Mars surface was proposed. The primary steps in the method are automatic registration by using SIFT and RANSAC, surface feature extraction by using edge- or region-based algorithms and change detection based on the difference information statistics of the feature regions. Preliminary experimental results obtained by using CTX, MOC and HiRISE images demonstrate the promising potential of the proposed method for the detection of new impact craters, gullies, dark slope streaks, dust devil tracks and ice caps.

In the experiments, the thresholds used in the algorithms of the change detection method were set empirically. In the future, we will develop a self-adaptive threshold selection algorithm to improve the method. Automatic feature classification will also be incorporated. More multi-temporal images will be used to further validate the change detection method.

Acknowledgments

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References

[1] Malin M C, Edgett K S, Posiolova L V, McColley S M and Noe Dobrea E Z. 2006 *Science* **314** 1573–77
[2] Malin M C and Edgett K S 2000 *Science* **288** 2330–35
[3] Malin M C and Edgett K S 2001 *J. Geophys. Res. Planets* **106** 23429–570
[4] Sullivan R, Thomas P, Veverka J, Malin M, and Edgett K S 2001 *J. Geophys. Res. Planets* **106** 23607–33
[5] Balme M R, Whelley P L and Greeley R 2003 *J. Geophys. Res. Planets* **108** E8 5086 doi: 10.1029/2003JE002096
[6] Thomas P C, Malin M C, Edgett K S, Carr M H, Hartmann W K, Ingersoll A P, James P B, Soderblom L A, Veverka J and Sullivan R 2000 *Nature* **404** 161–4
[7] Radke R J, Andra S, Al-Kofahi O and Roysam B 2005 *IEEE Trans. Image Process.* **14** 294–307
[8] Walter V 2004 *ISPRS J. Photogramm.* **58** 225–38
[9] Zabih R, Miller J and Mai K 1995 Feature-based algorithms for detecting and classifying scene breaks *Computer Science Department Report Cornell University, Ithaca, NY.*

[10] Wagstaff K L, Panetta J, Ansar A, Greeley R, Pendleton H and Bunte M 2012 *ACM TIST* **3** 49.1–22
[11] Head J W, Marchant D R and Kreslavsky M A 2008 *Proc. Natl. Acad. Sci. USA* **105** 13258–63
[12] Malin M C, Caplinger M A and Davis S D 2001 *Science* **294** 2146–8
[13] Dickson J L, Head J W and Kreslavsky M 2007 *Icarus* **188** 315–23
[14] Dundas C M, Diniega S, Hansen C, Byrne S and McEwen A S 2012 *Icarus* **220** 124–43
[15] Phillips C B Burr D M and Beyer R A 2007 *Geophys. Res. Lett.* **34** L21202
[16] Kreslavsky M A and Head J W 2009 *Icarus* **201** 517–27
[17] Schorghofer N, Aharonson O and Khatiwala S 2002 *Geophys. Res. Lett.* **29** 2126
[18] Whelley P L and Greeley R 2008 *J. Geophys. Res. Planets* **113** E07002.1–12
[19] Zuber M T, Smith D E, Solomon S C et al. 1998 *Science* **282** 2053–60
[20] Nye J F, Durham W B, Schenk P M and Moore J M 2000 *Icarus* **287** 1788–93