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Crater detection, classification and contextual information extraction in lunar images using a novel algorithm

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ABSTRACT

This study presents the development and implementation of an algorithm for automatic detection, classification and contextual information such as ejecta and the status of degradation of the lunar craters using SELENE panchromatic images. This algorithm works by a three-step process; first, the algorithm detects the simple lunar craters and classifies them into round/flat-floor using the structural profile pattern. Second, it extracts contextual information (ejecta) and notifies their presence if any, and associates it to the corresponding crater using the role of adjacency rule and the Markov random field theory. Finally, the algorithm examines each of the detected craters and assesses its state of degradation using the intensity variation over the crater edge. We applied the algorithm to 16 technically demanding test sites, which were chosen in a manner to represent all possible lunar surface conditions. Crater detection algorithm evaluation was carried out by means of manual analysis for their accuracy in detection, classification, ejecta and degraded-state identification along with a detailed qualitative assessment. The manual analysis depicts that the results are in agreement with the detection, while the overall statistical results reveal the detection performance as: $Q \sim 75\%$ and precision $\sim$0.83. The results of detection and classification reveal that the simple lunar craters are dominated by the round-floor type rather than flat-floor type. In addition, the results also depicts that the lunar surface is predominant with sub-kilometer craters of lesser depth.

1. Introduction

Impact craters are not just depressions; they are the record holders for the planetary body, which hold information and changes that happened on it over time. They are the dominant surface features on any planetary body including the Moon. The recording nature and the dominant character bring forth the hidden information of the planetary surface through such natural pits on their surface. Their dominant presence is used for age estimation by crater count (Baldwin, 1964). The morphological analyses on the crater reveal the recorded event variations in terms of the geological process (Melosh, 1989) and the effects on the target characteristics (Cintala et al., 1977; Bray et al., 2008). Craters occur in all shapes and sizes and with currently available high spatial resolution planetary images, even smaller dimension craters can be analyzed.

Recognizing craters and distinguishing them is not an easy task even for human observers because of their smaller size and their vast presence. In this regard, most of the manual analyses on lunar craters have been carried out for simple craters (Pike, 1976; Ravine and Grieve, 1986) and complex craters (Allen, 1975) on small number. But, the craters with small diameter form the largest population on the lunar surface. The rugged surface and different illumination condition on the lunar surface pose difficulty in extracting the crater and its features. Even morphologically identical craters may differ due to illumination conditions (Ding et al., 2010). In addition, the topography of the terrain in which the crater formed also plays a role in illustrating the crater. On global analysis, the craters look more similar; but, there is notable difference between them when viewed locally, because they all are individual features. Moreover, most of the small craters will not be visible on a global image and thus they will not be detected or accounted (interestingly they are the dominant features). This indicates that the global model only focuses on the statistics of large craters. Since, each crater is unique by their size, shape, texture, etc., crater mapping becomes a tedious process. Thus, in this study, local analysis was aimed to capture the local co-dependences of the simple lunar craters.

Due to the availability of voluminous data on planetary bodies, the need for an automatic algorithm is inevitable. Automatic crater detection algorithm is one of the applications developed to detect the craters on any planetary surface like Moon (Honda et al., 2002),

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Mars (Bandeira et al., 2007; Martins et al., 2009) and even asteroids (Leroy et al., 2001). Several works (Salamuniccar and Loncaric, 2008; Salamuniccar et al., 2011; Stepinski et al., 2012) listed the existed crater detection algorithms. From the data source point of view, two types of algorithm were most common; they are image based (often panchromatic) and elevation (DEM/DTM) based. Image-based approach widely uses techniques such as gradient approach and pattern recognition to extract craters (Sawabe et al., 2006; Urbach and Stepinski, 2009). DEM/DTM-based approach uses machine learning, identify craters by depression, etc., (Kim et al., 2005; Stepinski et al., 2009). However, almost all the previous CDA are restricted to detection and counting (Bue and Stepinski, 2007; Salamuniccar et al., 2011) and further information about each crater was lacking. Most of the above said currently available CDA are not designed to classify the craters and also fall short in extracting the contextual information associated with the crater. These untouched direction led us to explore an automatic approach which considers the crater characteristics and its associated surrounding. In this regard, the proposed algorithm aims to detect, classify and extract contextual information from the simple lunar craters. Along with the detection, the ability of our algorithm is to classify the craters into round/flat-floor type, to indicate the presence of ejecta, to associate the ejecta with the corresponding crater and to assess the status of degradation. However, the current algorithm was designed to detect simple lunar craters of diameter >~50 m and exclude the craters lesser than this diameter, because from which less morphological information can be extracted. Thus, this algorithm is built to detect the simple lunar craters and extract vital information from each of them.

Fig. 1 shows the simple lunar round- and flat-floor craters with various shadow sizes along with their respective panchromatic, DTM and Getis–Ord cross-section profiles. In the first column, the occurrence of round- and flat-floor craters with different sizes and shadow are illustrated. The second column represents the panchromatic image-derived profile; the next column represents the DTM image-derived profile and the last column represents the Getis–Ord (G–O) derived crater profile. All the crater profiles are extracted along the horizontal direction through the center of the crater. This gives an overall view of the occurrence of crater on the lunar surface and their respective variations in the 2D (panchromatic, Getis–Ord) and 3D (DTM) profiles. The crater sizes and its profiles are projected first itself to give an overall view of the pattern by which they are analyzed and classified by this algorithm.

The paper is organized as follows. Section 2 describes the algorithm in detail, which is used to detect, classify and extract the contextual information from each crater. In Section 3 we present the results of applying our algorithm to sixteen demanding test sites. The results are discussed separately for each of the above said methodology with a detailed evaluation factors for each of the detection process. Conclusions and future work of this approach are presented in Section 4.

2. Methodology for crater – detection, classification and contextual information extraction

The simple craters form the majority of the population on the lunar surface and this crater detection algorithm (CDA) was developed to detect and classify them accordingly. In this work, an image based crater detection algorithm using the pattern recognition approach was developed. This study utilized the SELENE Terrain Camera (TC) and its derived DTM data for the automatic crater detection process. The SELENE ortho images are available in L3D PDS format with a spatial resolution of ~7 m. This CDA works on the panchromatic images, however, the CDA also uses the DTM data to extract the elevation details from the crater.

A schematic image-based framework of the crater detection algorithm is shown in Fig. 2. In addition to crater detection, this CDA has three more modules, they are, (i) to classify the craters using its structural profile pattern, (ii) identify and associates ejecta to its corresponding crater and (iii) assess the crater status of degradation. Subsequent section below describes each of these modules in detail.

2.1. Crater bright and shadow pair selection

The first step in this CDA is to identify and discriminate the bright and shadow parts of the crater. The threshold technique is the widely used approach to discriminate crater parts in most of the detection algorithms (Urbach and Stepinski, 2009; Ding et al., 2010). The selection of threshold decides the crater detection; in this study, it was chosen based on the histogram and density slicing techniques. This implies a clear cut-off limit to discriminate the shadow and bright part of a crater. For proper selection of the threshold, a trial and error approach is suggested by Jain et al. (1995). Due to uneven illumination on the lunar surface, a fixed threshold is not adequate for all the images. Thus, the threshold used in this algorithm is an adaptive and image dependent, which varies for each image. Separate thresholds are chosen to discriminate the shadow- and bright-part of the crater. For the shadow part detection, the lower and upper limit is used, whereas for the bright part detection only the upper limit is used to distinguish them. It is given as:

$$\mathrm{IMS} = \begin{cases} 1 & \text{if } T_1 \leqslant \mathrm{img}[i,j] \leqslant T_2 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$\mathrm{IMB} = \begin{cases} 1 & \text{if } \mathrm{img}[i,j] \geqslant T \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where T, T_1 and T_2 represent the threshold values, IMS represents the image with blobs of detected shadow region and IMB represents the image with blobs of detected bright region. The output obtained after applying threshold is a pair of image, which consist of the detected bright and shadow blobs of all sizes respectively. The role of this threshold technique is to identify and delineate all bright and shadow part of the crater. However, it also includes the ejecta patches whose intensity is similar to that of the crater bright part. This extra blob is an unwanted one for the crater detection, but this is the contextual information adjoining the ejecta. This extra blob will be analyzed in detail in Section 2.3. The detected blobs consist of all sizes, which poses difficulty in narrowing down to the crater candidature. In order to overcome this, a regional threshold (T_r) was applied to limit the minimum dimension of the crater to be detected. It was decided to choose those bright (B_b) and shadow (B_s) blobs whose region is greater than the given region threshold. It is given as:

$$B_{b/s} > T_r \quad (3)$$

where T_r = 50 pixels and this limits the minimum feature to be detected. Candidates with values lesser than the threshold are rejected; only the fitting candidates are kept for pairing them. The regional threshold (T_r) value is image independent and thus the minimum detectable region is kept constant for all the images. The images obtained after applying the region threshold consist of required dimension of bright and shadow parts, which is further analyzed to pair them to form the crater.

2.2. Crater-pair matching

The matching of corresponding bright and shadow blob was one of the crucial parts in delineating the crater candidate. Due to