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# Ellipsoidal Features Extraction for Planetary Image Registration

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## ABSTRACT
Using greyscale texture features recently become a new trend in supervised machine learning crater detection. Need to be analysed image data preferably by automatic technique as the data is in huge amount. Automatic feature extraction method is proposed and utilised for earth remote sensing images. These are not always applicable to planetary data which is having low contrast and uneven illumination features. Proposed a new method which is unsupervised for different ellipsoidal feature extraction for planetary image registration. Approach is based on combination of various techniques including Hough Transform and watershed segmentation technique. This is mainly applicable for geometrically compact shapes rocks, craters, and other geological features.

## Keywords
Hough transform, Watershed segmentation, feature extraction, Crater detection.

## 1. INTRODUCTION
IN THE PLANET-SURFACE imagery among the typical features craters play primary role. Craters display great variety and complexity of morphologies because of the wide range of ages on the surfaces on which they are located and multiplicity of degradational processes to which they are subjected. Detailed analysis of craters' morphology and their spatial statistics is an important source of information about geologic processes and properties of surface. Selection of appropriate features is discussed. Features such as edges or wavelet extremes [1]. The usual features used for earth image registration might not be as reliable for planetary images. In general features that are uniformly distributed over the entire image are required for image registration. Such features can easily indentified in the earth images.Planetary feature extraction can be manually performed by human experts, but this process can be very time consuming.

Therefore, a reliable automatic approach to detect the position, structure, and dimension of each feature is highly desirable. This is a critical task for various reasons, i.e., limited data are usually available, the image quality is generally uneven (i.e.,it depends on illumination, surface properties, and atmospheric state), and the features that are present in the images can be barely visible due to atmospheric erosion, and they may be based on different structure types of variable sizes.

Detection of craters has been widely addressed and different approaches have been recently proposed in the literature, based on the analysis of planetary satellite images [2] in the visible spectrum and the infrared spectrum and topography data [3]. Here, we focus on optical image-based approaches for crater and rock detection. The existing techniques can be divided into two main categories, i.e., supervised and unsupervised. Supervised methods require input labeled data to train the algorithm for feature extraction. Unsupervised methods do not involve any training process and search for the structures of interest in the image. Different approaches have been presented based on template matching [2], [4], texture analysis [5], neural networks [6], boosting approaches [7], or a combination of these techniques [8]. In particular, in [9], the identification of impact craters was achieved through the analysis of the probability volume created as a result of a template matching procedure. Kim and Muller [5] presented a crater detection method based on texture analysis and ellipse fitting. This method was not robust when applied to optical images; hence, it was performed by using fusion techniques exploiting both Digital Elevation Model (DEM) and optical images. In subsequent work [10], in order to automatically detect craters on Mars, the authors proposed a combination of edge detection, template matching, and supervised neural network-based schemes for the recognition of false positives. In a different approach, Martins *et al.* [11] adopted a supervised boosting algorithm, which was originally developed by Viola and Jones [12] in the context of face detection, to identify craters on Mars. In [13], the authors presented a different approach for crater detection in panchromatic planetary images. The method in [13] is based on using mathematical morphology for the detection of craters and on supervised machine learning techniques to distinguish between objects and false alarms.

Other typical ellipsoidal features in planetary images are represented by rocks. Rock detection in ground imagery has been addressed in the literature. In particular, in [14], the authors presented a supervised method for segmentation, detection, and classification of rocks on data collected by rovers. This approach, which is based on a probabilistic fusion of data from multiple sensor sources, was tested on earth data. In [15], the same authors tested different rock detection approaches on Mars Exploration Rover data. In [16], rock detection was addressed using a segmentation method on data collected by the Spirit Mars Rover Planetary Camera. Moreover, in [17], an automatic algorithm for rock detection both on ground imagery and on High Resolution Imaging Science Experiment (HiRISE) data, based on cylinder fitting, was proposed. Registration of planetary images has been addressed in the literature as well. Kim *et al.* [18] proposed a method for crater extraction from Mars Digital Image Mosaic (MDIM) and Mars Orbital Laser Altimeter (MOLA) tracks, for their alignment. However, registration errors occurred due to shape distortions of the detected craters. In [19], a method for the automatic recognition of impact craters onMars was proposed and applied to remeasure the coordinates of big craters (exceeding 10 km in diameter) in a catalog. In [20], the authors proposed a method for the coregistration of topographic data by surface matching. Nonetheless, here, we focus on the analysis of optical data. In order to overcome the typical problems of planetary images with limited contrast, poor illumination, and a lack of good features, we propose here a new unsupervised region-based approach to the extraction of different planetary features for registration purposes. The main contribution of this letter is a novel unsupervised approach for feature extraction on planetary images, aimed at extracting curvilinear structures, relevant for this typology of images as a typical model for craters and rocks. In particular, the proposed approach is based on a novel combination of robust image processing techniques such as the Canny operator, the Hough transform, and the watershed. Moreover, the approach allows not only locating the features but also reconstructing their shape.

## 2. EXISTING SYSTEM

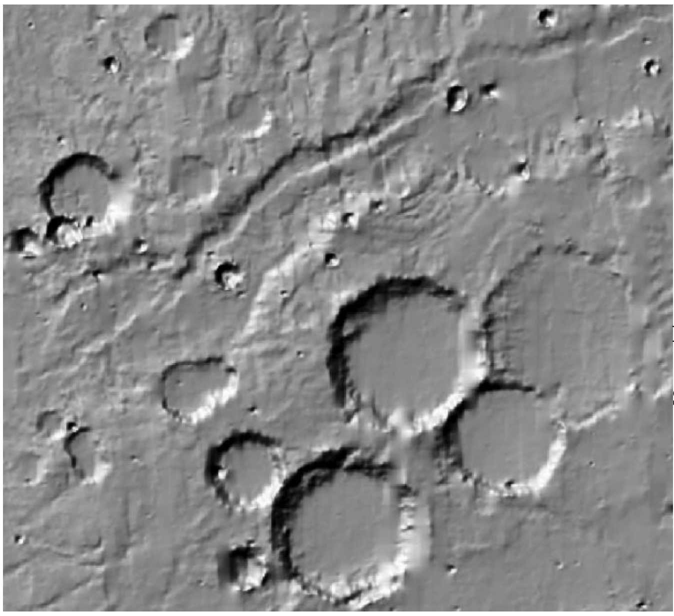

**Fig. 1. Topography of the Tisia test site on Mars.**

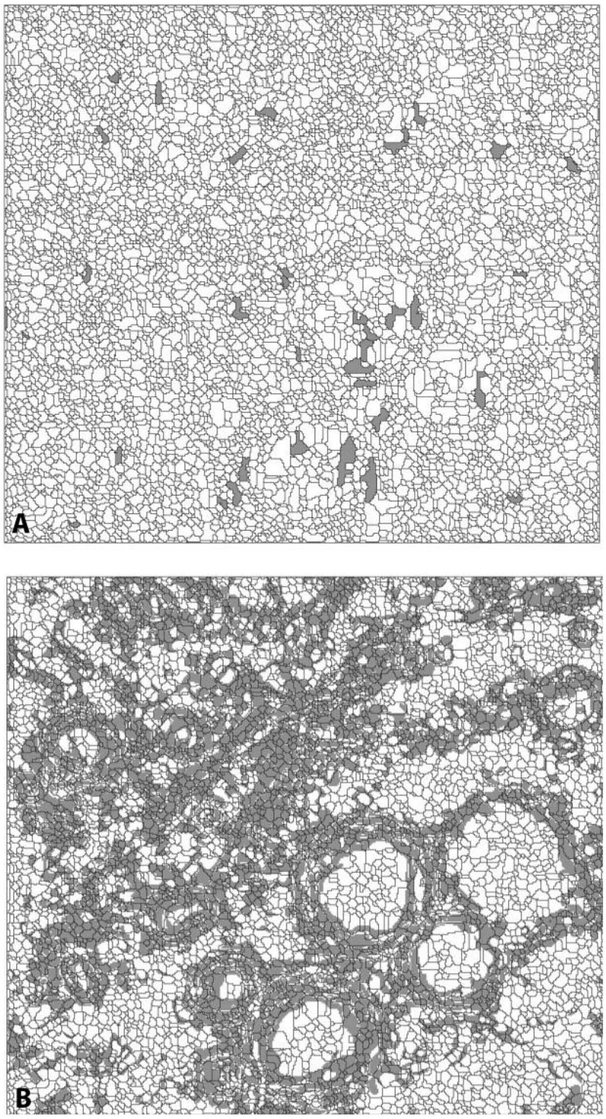


**Fig. 2. Comparison of segments elongation in the Tisia site. Gray-colored segments indicate elongated segments with SCI _ 1:75. (A)The watershed based segmentation. (B) The K-means based segmentation.**

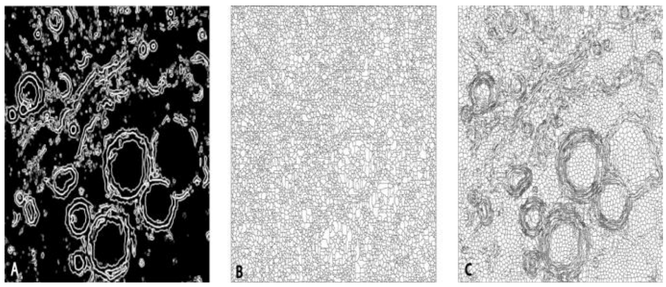


**Fig. 3. Tisia site segmentation. (A) The H-image used for watershed based segmentation. (B) The watershed based segmentation. (C) The K-means based segmentation.**

Martian craters display great variety and complexity of morphologie because of the wide range of ages on the surfaces on which they are located and multiplicity of degradational processes to which they are subjected. Detailed analysis of craters' morphology and their spatial statistics is an important source of information about geologic processes and properties of martian surfaces. Regional differences in crater size distributions form the basis for geological stratigraphy of Mars (Crater Analysis Technique Working Group, 1979; Wise and Minkowski, 1980; Tanaka, 1986; Hartmann and Neukum, 2001). Craters are natural probes of target surface properties; spatial variations in crater morphologies indicate variations in geologic material (Cintala et al., 1976), including the presence of sub-surface volatiles (Cintala and Mouginis-Mark,1980; Kieffer and Simonds, 1980; Kuzmin et al., 1988; Costard,

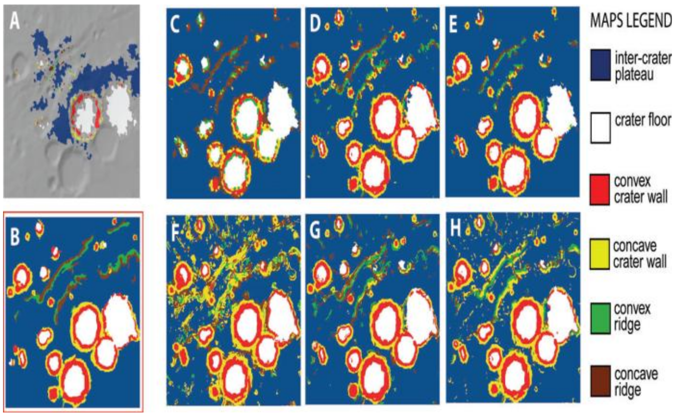


**Fig. 4. Geomorphic maps of the Tisia site generated by different segmentation/classification methods. (A) Labeled regions; different landform classes are coded by different colors as given by the legend. Unlabeled regions are displayed in gray. (B) The analyst-drawn map ("ground truth"). Maps based on the watershed segmentation (C – Naive Bayes, D – Bagging, E – SVM). Maps based on the K-means segmentation (F – Naive Bayes, G – Bagging, H – SVM).**

1989; Mouginis-Mark and Hayashi, 1993; Barlow and Perez,2003; Barlow, 2005; Reiss et al., 2006). In addition, the nature, timing, and location of past surfacial processes are inferred from observedcrater morphologies and their spatial distributions (Soderblom et al., 1974; Craddock et al., 1997; Boyce et al.,2005). For all of these reasons, impact craters are among the most studied features on Mars, and a number of catalogs listing crater positions and their morphological attributes have been compiled (Barlow, 1988; Costard, 1989; Kuzmin et al., 1988; Roddy et al., 1998; Rodionova et al., 2000; Salamuniccar and Loncaric, 2008) to facilitate the crater-related research. These datasets, some global while others regional in extent, are all based on visual inspection of images. The image-based catalogs provide numerical parameters pertaining to planar geometry of craters and categorical parameters pertaining to their observed morphologies, but they lack any information about crater depths and other topographical parameters. The most widely used image-based dataset is The Catalog of Large Martian Impact Craters (Barlow, 1988) (hereafter referred to as the Barlow catalog). It lists locations and eight parameters for 42,283 craters distributed over all of Mars. Another global dataset is the Morphological Catalogue of the Craters of Mars (Rodionova et al., 2000) that lists locations and 15 parameters for 19,308 craters. The positions of craters in these two catalogs are not aligned with actual craters as registered in the more modern imagery and topographic data conforming to the Mars Digital Image Model (MDIM) 2.1 standard. Recently, Salamuniccar and Loncaric (2008) have corrected the subsets of the two aforementioned catalogs and compiled a catalog of 57,633 craters that conforms to the MDIM 2.1 standard. It is worth noting that a revision.

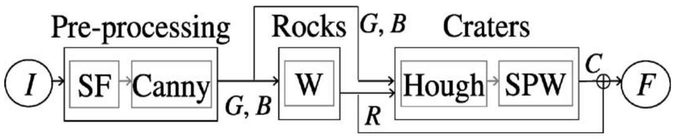


**Fig. 5. Flowchart of the proposed approach.**

## 3. PROPOSED APPROACH

Different types of features are present in the planetary images, and their sizes, shapes, and positions are estimated by applying different methods. The extracted features can be used for registration purposes.

The extraction of these spatial features is a difficult task because planetary images are blurry, quite noisy, present lack of contrast and uneven illumination, and the represented objects are not well defined. For these reasons, a regionbased approach, based on segmentation, has been chosen in order to address such problems. Segmentation is the process of partitioning an image into multiple regions, for instance, in order to distinguish objects from the background. A frequent approach to segmentation introduces a set of characteristic points that are related to the objects to be detected, automatically selected and used as "seed points" (SPs) to segment the images. Many segmentation approaches have been explored in the literature. Here, the watershed algorithm [21] has been chosen, a method which is automatic, robust, and fast. The flowchart of the proposed technique for feature extraction is shown in Fig. 5.

Planetary images show the surface of a planet and its structures.The aim here is to propose a technique for the extraction of different structures on a considered planetary surface for the registration of optical planetary images. The proposed approach is based on image analysis techniques and is potentially useful for the detection of craters and rocks.

The main features to be extracted are craters and rocks. Craters are objects of approximately elliptical (and generally circular) shape with shadows due to their deep concave shape and uneven illumination. Rocks are objects of ellipsoidal shape, smaller than craters, with almost no shadows (because of their convex shape).

Before applying feature extraction techniques, an input image $I$ needs to be preprocessed. First, the noise is reduced by a smoothing filter. Then, in order to detect edges, the image gradient is computed by using the Canny edge detector [22].

As an intermediate result of this operation, intensity gradient *G* is generated. Then, by applying a nonmaximum suppression algorithm followed by hysteresis thresholding to *G*, a binary gradient image *B* is obtained, but this image shows the contours of the objects represented in the original image.

Rocks generally appear similar to closed contours in *B* because of the almost absence of shadows. In order to extract these features, the watershed segmentation algorithm *W* is applied to *B*, and closed contours are extracted. All the areas included within a closed contour correspond to "SP areas" and are identified as regions. The result of this first step is a binary image *R* that shows boundaries of small ellipsoidal features of regular shapes, such as rocks. While rocks generally appear similar to closed contours and can be easily detected, craters have a more complex structure and, due to their depth and uneven illumination, often exhibit internal shadows. Their borders can be approximated with incomplete elliptical curves. A generalized Hough accumulator [23] is used to identify the SPs to detect these structures from *B*. For every pair of pixels that are detected as edge points in *B* and exhibit opposite gradient directions (being the relation of opposition defined with tolerance _), an accumulator, corresponding to the median point between them in the image plane, is incremented of a unit value. The maxima of the accumulator are taken as centers of ellipses. The three parameters describing the ellipse centered in each detected maximum are then computed, and a 3-D accumulator is used to estimate the two semi-axes and the direction angle of the ellipse from all the pairs of points that contributed to the accumulator in the considered center. The center of each ellipse that has been generated is used as an SP for segmentation. Starting from all the detected SPs, a watershed algorithm, denoted SPW in the flowchart, is applied to *G*, and the craters are identified. *G* is used in this case because it represents not only the edges but also the elevation information. As a result, a binary image *C* shows the boundaries of elliptical features, such as craters, that were not detected by the previous step. In a post processing step, features are approximated by ellipses and their attributes (i.e., ellipse semi-axes and rotation angle) are estimated. Features with eccentricity $e > 0.6$ are discarded, being features of larger *e* unlikely to be either craters or rocks. A binary image *F*, which represents the contours of all detected features, is created. The binary image *F* shows the boundaries of the features, identifies their locations, and estimates their shapes.

The proposed technique for feature extraction can be used to register image pairs representing the same scene. For registration, two binary images (*Ir* and *I*in) need to be extracted from both images to be registered, and their match can be estimated.

## 4. CHALLENGES

Impact craters, the structures formed by collisions of meteoroids with planetary surfaces, are among the most studied geomorphic features in the solar system because they yield information about the past and present geological processes and provide the only tool for measuring relative ages of observed geologic formations.

4.1 Challenge : Lack of distinguishing features. Craters, as a landform formation, lack strong common features distinguishing them from other landform formations. Their sizes di_er by orders of magnitude. Their rims have often been eroded since their formation millions of years ago, resulting in shapes that depart signi_cantly from circles. They frequently overlap, complicating the task of their separation from background.

4.2 Challenge : Heterogeneous morphology in images. Planetary surfaces are not homogeneous where nonuniform surface morphology frequently exhibits. Furthermore, planetary images may be taken at different lighting conditions, at different resolutions, and their quality varies so that even morphologically identical craters may have different appearances in different images.

4.3 Challenge : Huge amount of sub-kilometer craters in high resolution planetary images. The size distribution of craters follows power-law [Tanaka1986]; large craters that can be easily identified manually are rare and small sub-kilometer craters are abundant.

## 5. CONCLUSION

In this letter, a novel unsupervised region-based approach has been proposed for automatic detection of spatial features that characterize planetary surfaces. The proposed approach has been applied to the registration of planetary data.

In the future, we plan to expand the experimental validation. The approach will be applied on different types of data and registration of multisensor images will be addressed. In order to address registration of multitemporal data, the use of boulders in the matching process is an additional concern. Indeed, such features could move or be moved between two temporally consecutive images representing the same scene. In our future work, we plan to integrate the shadow information around the features in order to improve the reliability of the edge detection Illumination correction, based on the knowledge of the orbital angle and the acquisition time, will be useful to reduce the bias in the reconstruction of the exact feature shape.

Furthermore, crater and rock detections could be separately addressed for specific applications. The different features couldbe distinguished in a postprocessing step using the shape information. A crater detection algorithm able to detect features of small size would be useful to identify small craters. Craters that are not catalogued yet could be identified, and this information would increase the importance of Mars catalogues completed only down to a certain diameter range [24]. Finally, the proposed method could be used to extract other features of elliptical shape, such as volcanoes. Additionally, features of other shapes, such as ridges or polygonal patterns among others, could be extracted, by adapting the generalized Hough transform to the detection of the shape of interest.

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