Crater and Boulder Detection Using Image Processing

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ABSTRACT

Planetary surface crater and boulder detection is required for geological studies, space navigation, and autonomous navigation. The paper is a pure image-processing-based crater and boulder detection technique irrespective of deep learning or machine learning techniques. The pipeline created uses conventional image processing methods, including histogram equalization for contrast adjustment, Gaussian blurring for noise reduction, Sobel edge detection for enhancing feature boundaries, and morphological operations for enhancing detected features. Contour detection is applied afterwards for crater and boulder detection. The method is implemented in OpenCV and Python and is tested on high-resolution planetary surface images. The outcomes show that classical image processing is highly effective at geological feature extraction and analysis with a computationally straightforward and interpretable strategy for planetary surface analysis.

Keywords: Image Processing, Crater Detection, Boulder Detection, Edge Detection, Morphological Operations, Planetary Surface Analysis

1. INTRODUCTION

Space exploration and surface studies of planets have played a very vital role in creating the geological evolution and history of celestial bodies. Craters and boulders are the most evident surface features mapped on planets, moons, and asteroids. The identification and awareness of the features are very important for planetary mapping, planning missions, and threat analysis to robotic and human exploration. However, crater and boulder identification from high-resolution planetary data are labour-intensive and time-consuming. This work introduces an image-processing-based, computationally light method for boulder and crater detection using traditional techniques instead of deep learning, which is computationally expensive. The need for this work stems from the need for a lightweight, efficient detection algorithm that can be utilized in systems with limited processing resources, e.g., onboard space missions or real-time rover path planning. Using simple image processing techniques like contrast stretching, edge detection, morphological processing, and contour detection, the proposed technique is aimed at demonstrating a stable and clear framework for feature extraction of planetary surface imagery.

The broader objective of this project is to develop a systematic pipeline that can process planetary images and identify craters and boulders based on their morphological characteristics. The approach balances computational expense with detection strength against changes in terrain and illumination. The research findings add to the science of planetary science as they deliver an effective means of automated surface surveying that can be used to support future space travel and planetary geology missions.

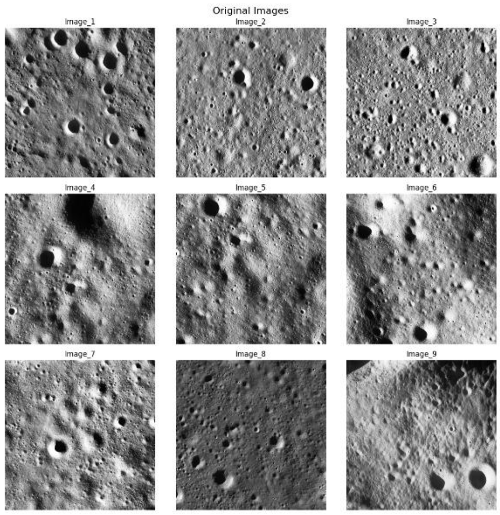


Fig 1.1 Original grayscale images

2. BACKGROUND

Planetary surface study, i.e., by detection and identification of craters and boulders, is of extreme significance in our quest to know the celestial body's geological evolution and history. Researchers have used different methods of image processing conventionally to automate detection and analysis of these features using non-computational power-intensive techniques.

2.1 Traditional Methods of Image Processing for Crater Detection

Crater detection has been among the primary areas of research in planetary science, and traditional image processing techniques provided the foundation for early techniques. In early techniques, techniques such as edge detection and the Hough Transform were applied for circular feature detection typical of craters. For example, Bandeira et al. studied the use of edge detection filters and the Hough Transform to enhance and detect crater edges in lunar images, proving the effectiveness of the proposed methods in certain lunar missions [1]. Morphological processing, which is one of the key pillar techniques, involves functions like erosion and dilation that serve to emphasize or suppress details in an image. Such functions have served to screen out the output from initial edge detection operations and, in turn, improve the accuracy of the end output crater detection [2].

2.2 Boulder Detection Techniques

Alternatively, boulder detection on planetary surfaces has applied traditional image processing methods to segment and identify large rock outcrops. Typically, thresholding and contour detection are applied to border and identify boulders in the landscape. Sato et al.'s research showed how thresholding assisted by contour detection could be used to simply extract and analyse Martian boulders on the surface to provide rich information for navigational and geological studies [3].

2.3 Integration and Application of Techniques

Such classical image processing algorithms in combination form a robust pipeline that can effectively process planetary images to detect and analyse craters and boulders. The pipeline typically starts with the image enhancement algorithms like histogram equalization for image contrast enhancement, followed by edge detection to establish distinguishing features. Additional morphological processing further sharpens the features prior to utilizing them for final analysis, e.g., contour detection, which annotates the features of interest with high accuracy.

While the traditional image processing methods have been the foundation for boulder and crater detection on planetary surfaces, they are prone to struggle with flexibility in handling various environmental conditions and require manual adjustment of parameters, which is time-consuming and prone to errors [4]. Moreover, these methods are prone to fail in an accurate detection of features in low-contrast regions and complex shadow behaviour. This project aims to bridge these gaps by enhancing the robustness and flexibility of conventional image processing techniques. Optimization of histogram equalization and tightening of morphological operators will be done to improve detection accuracy in changing imaging conditions. Integration of structured contour detection also aims to provide more accurate and reliable outputs, which are needed for planetary exploration missions with consideration for computational efficiency and operational reliability.

3. METHODOLOGY

This project employs a series of standard image processing techniques to detect boulders and craters on planetary surfaces. Every step in the approach is designed to emphasize some features in the images for easier detection and more accurate results.

3.1 Image Enhancement through Histogram Equalization

The first segment of our pipeline is responsible for enhancing the contrast of images of planetary surfaces to make boulders and craters stand out more. This is accomplished by histogram equalization, which is a highly popular image processing method for adjusting the contrast level in an image. Histogram equalization re-allocates an image's intensity distribution so that areas with lower contrast are made clearer without compromising the visual quality of the image. This initial step is useful insofar as it brings out subtle detail, which is lost in under-contrasted images, thus setting the stage for more successful subsequent processing, e.g., edge detection.

In planetary imaging, especially, where the lighting can be quite different, it is particularly important that all surface detail is made as visibly apparent as possible. Histogram equalization makes these lighting variations uniform across the image, still enhancing the ability to make out geological formations. The technique is particularly useful in planetary missions where images tend to be over- or underexposed and can make an even image out so that further analysis can be made [5].

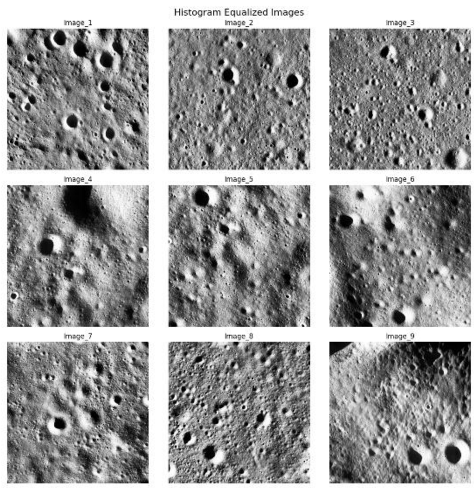


Fig. 3.1 Histogram Equalized Images

Beginning here with this first improvement step, the pipeline leads the way to increasingly finer and more sophisticated feature extraction in later steps of the image processing pipeline. OpenCV's cv2.equalizeHist, yet another grizzled old salt of the image processing war effort, is a priceless contribution to the success of this step.

3.2 Noise Reduction with Gaussian Blurring

Once the image contrast has been improved, our second most critical step in the order of operations is noise reduction, which is a critical processing step before further intensive examination. This process is undertaken by utilizing Gaussian blurring, and this technique is established to smooth noise and minor detail not significant in the identification of large-scale geology. With the application of a Gaussian filter using kernel (5,5), the process can suppress the noise without disrupting the integrity of the essential features like craters and boulders. Gaussian blurring serves to protect the subsequent image processing edge detection process from disruption by spurious positives of the small noise features.

The process reduces the image data detail, concentrating the detection algorithms on more significant and larger features. The Gaussian-blurred images, provide a concise visualization of texture smoothing of the image and reduction of noise, which plays a very crucial role in highly varying illumination conditions like on planetary surfaces. Besides preconditioning images before improved detection accuracy in edge detection, its well-timed application contributes to overall detection reliability in subsequent operations [6].

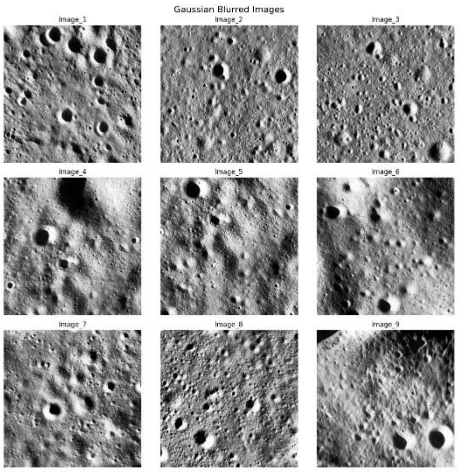


Fig. 3.2 Gaussian Blurred Images

Application of the method at the second stage of the pipeline serves as a platform for better and more effective feature analysis, which plays a crucial role in detailed planetary geological research. Application of the OpenCV function cv2.GaussianBlur serves here to create an efficient mechanism of fulfilling the pipeline's needs for noise reduction.

3.3 Edge Detection Using Sobel Operator

Following noise elimination, the pipeline proceeds to edge detection, a pivotal process in the detection of edges of geological features on planetary surface. The operation is carried out using the Sobel operator, a gradient-based technique specifically designed for the use of edge detection in images. Through the calculation of the gradient magnitude at each pixel in the x and y directions, the Sobel operator identifies areas of high spatial frequency where edges are present.

The Sobel operator in fact is being applied with the x and then y blurred images, both 5x5 kernels. It's the best choice of a kernel size that's intended to most sacrifice sensitivity to edge detection over not having it be so sensitive to artifacts that the noise causes. It naturally follows that by averaging the two gradient directions, a complete edge map is achieved. This map is significant because it makes the boundaries of both boulders and craters more identifiable by demarcating them.

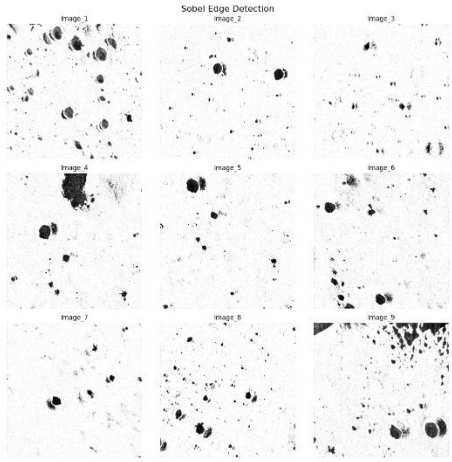


Fig. 3.3 Sobel Edge Detection

This step of methodology, with the help of [7], improves the precision and efficacy of detection, which opens to more complex analysis in subsequent pipeline stages.

3.4 Morphological Processing: Erosion and Dilation

As a reaction to the building block formed via edge detection, the subsequent step in our pipeline utilizes morphological processing to emphasize the edges that have been detected further. The operation here utilizes the erosions and dilations, two basic morphological operations modifying the image structure in a way that makes features of interest apparent and continuous to a greater extent.

The process begins with binary conversion of Sobel edge-detected image based on Otsu's technique to automatically determine the optimum threshold value. The binary image is critical because this will be the starting point to perform morphological transformations depending on high contrasts of background and foreground [8].

The image is converted into a binary state first and dilation is performed. With the help of a structuring element of size (3,3) in the shape of an ellipse, dilation-based stretching stretches the edges found during the Sobel process. The stretching fills in disconnected segments of edges, and in essence, this is highly important in images where craters and boulders are likely to have openings as their edges might not be closed by uniform edge detection. The dilated image is then eroded with the same structuring element. Erosion removes small noise pixels that could have been expanded by dilation, cleaning up feature edges and leaving only structures of significance behind that can be attributed to boulders and craters.

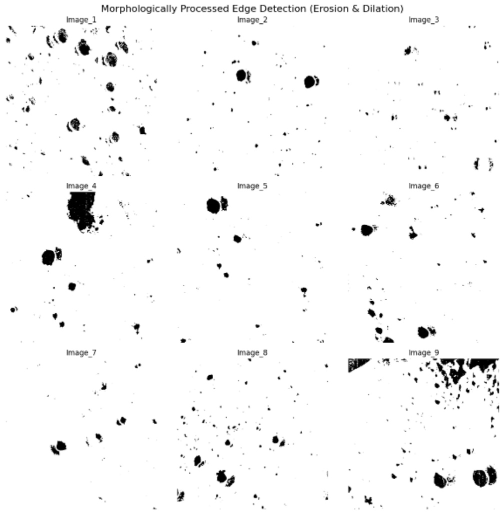


Fig. 3.4 Morphologically Processed Edge Detection (Erosion & Dilation)

3.5 Contour Detection

The final operation in our image processing routine is contour detection, a crucial step towards defining the precise boundaries of the geological features detected in the previous steps. With the edges sharpened and the outlines of features enhanced by morphological processing, the next task is to trace these features' contours from the processed images. This is done by inverting the morphologically processed images back to binary through an inverse thresholding method, prepared for contour detection.

Binary images are converted into contours using OpenCV's cv2.findContours. The RETR_EXTERNAL mode is used within this function, which will find only the outer contours and is ideally suited to outline discrete features like boulders and craters without considering any nested contours within the said features above. To minimize storage space and computation time, CHAIN_APPROX_SIMPLE is utilized which shortens horizontal, vertical, and diagonal lines to a single line and only stores their ends, rather than storing whole horizontal, vertical, or diagonal line segments [9].

For visualization, contours are subsequently superimposed on the original images, which are reloaded in BVR format for colour processing compatibility. For grayscale original images, conversion to colour is done to ensure that green contours utilized in highlighting the features can be seen. Green contour lines superimposed on original planetary surface images help in visually ascertaining the correctness and accuracy of the detected features.

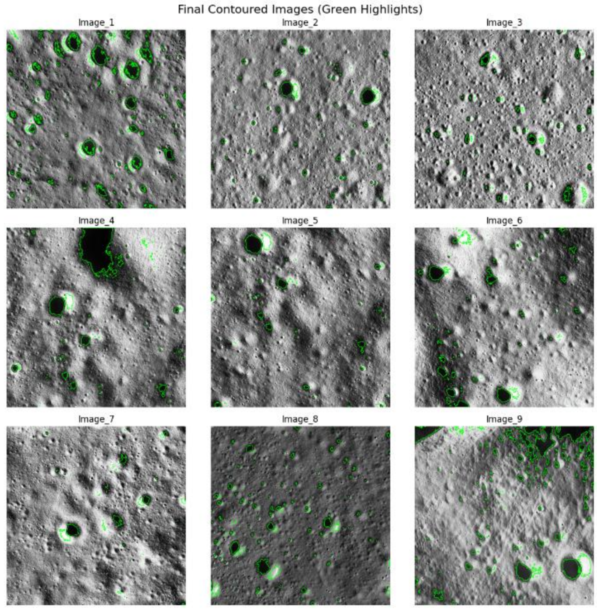


Fig 3.5 Final Contoured Images (Green Highlights)

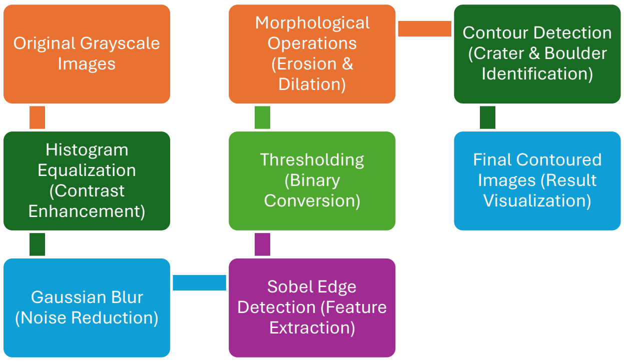
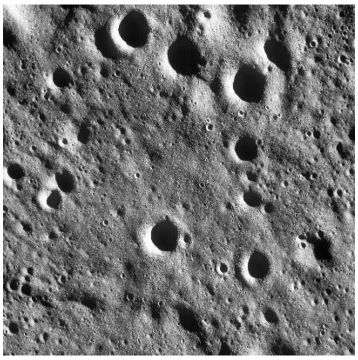


Fig. 3.6 Image Processing Pipeline

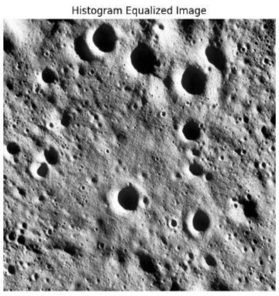
RESULTS

Data Description: The test data used here is a collection of nine randomly selected grayscale images blended from the training and test subsets of a commonly accessed dataset stored on Roboflow [10], in this instance the Crater and Boulder Detection set. These are typical examples of planetary surface topography under random lighting and texturing conditions that represent a significant base for illustrative purposes upon which to make the claim of effectiveness of the image treatment techniques.

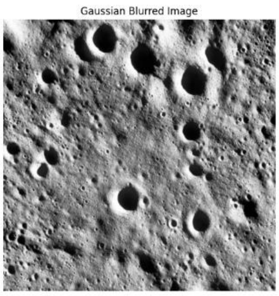
4.1 Qualitative Analysis



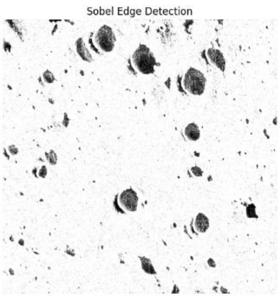
Original Grayscale Image



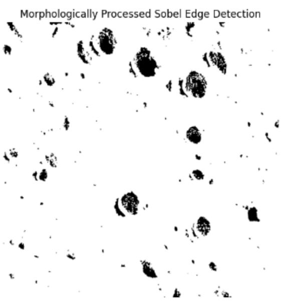
Histogram Equalization: 'Histogram Equalized Image' has improved contrast with geological structures more represented than in the 'Original Image'.



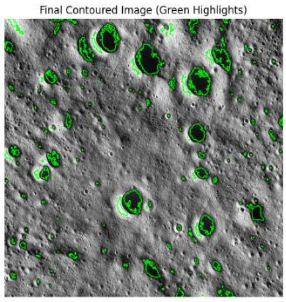
Gaussian Blur: 'Gaussian Blurred Image' displays high-frequency noise removal, surface details blurring, and image preparation for finer edge detection.



Sobel Edge Detection: The 'Sobel Edge Detection' image greatly amplifies the edges of the biggest craters and boulders' for application in future morphological processing.



Morphological Processing: The 'Morphologically Processed Sobel Edge Detection' has purer edges, where morphological processing closes the edges with broken edges and noise, producing more precise edges.



Final Contouring: The 'Final Contoured Image (Green Highlights)' is the truest form of the contours superimposed on the extractions of the features, and proof that feature extraction is completed.

4.2 Evaluation of Results

- **Visual Inspection:** A sequence of pictures from each processing step is a visual inspection of the pipeline's performance. Input-to-output transformation can be visually inspected in terms of accuracy and precision of detected features.
- **Comparative Analysis:** Comparative analysis of the resulting and original images will provide qualitative measures of edge definition and contrast in feature visibility. Contoured images derived using the process provide a qualitative description of where the algorithm performs best and where the algorithm isn't performing as well now.

4.3 Success and Failure Cases

- **Success Cases:** On comparatively contrast images with less noise artifacts, the pipeline correctly detects and contours the boulders and craters, e.g., in the 'Final Contoured Image (Green Highlights)'.
- **Failure Cases:** The performance is reduced in highly low contrast or highly noisy images and results in missing or spurious feature detection specially boulders. These are future directions of work on noise handling and contrast adjustment.

CONCLUSION

Development of this project has led to an image processing pipeline that works well and is well adapted to the specific requirements of planetary surface imagery, with greatly enhanced feature detection capability without the cost of processing of complex machine learning schemes. Inquiry into the promise of classical image processing algorithms revealed that they are highly promising where simplicity and speed are desired. One of the strongest aspects of the project is its ability to increase feature visibility by large orders of magnitude through methods such as histogram equalization and Gaussian blurring, which work best in conditions of fluctuating light levels typical on planetary surfaces.

The project also addressed some of the limitations, particularly in images with extremely low contrast or high noise, where current methods could not clearly define features. This also has the potential to create avenues for future work, where adaptive thresholding and morphological operations of higher order are combined to enhance the pipeline's robustness even further. In addition, the application of feedback systems to adjust processing parameters adaptively as a function of image content can lead to large gains in flexibility and system accuracy in different operating conditions. In summary, the project was successful in its initial objectives and proved the scalability of conventional image processing techniques in modern planetary studies paradigms and laid a solid ground for future development and research.

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