Automatic extraction of foreground objects from Mars images

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A novel method is proposed to automatically extract foreground objects from Martian surface images. The characteristics of Mars images are distinct, e.g., uneven illumination, low contrast between foreground and background, much noise in the background, and foreground objects with irregular shapes. In the context of these characteristics, an image is divided into foreground objects and background information. Homomorphism filtering is first applied to rectify brightness. Then, wavelet transformation enhances contrast and denoises the image. Third, edge detection and active contour are combined to extract contours regardless of the shape of the image. Experimental results show that the method can extract foreground objects from Mars images automatically and accurately, and has many potential applications.

**Keywords:** automatic object extraction; Mars images; homomorphic filtering; wavelet transformation; active contour; edge detection

1. Introduction

It is difficult to extract foreground objects from intensity images of planetary surfaces because there is no uniform morphology, color, texture, or other quantitative measures to characterize them from other features \((1, 2)\). With the development of space exploration technology, the capabilities for analyzing data from outer space exploration tools are also increasing, especially for such planets as Mars on which creatures might live. It is imperative to analyze the imagery data from Mars exploration, especially differing foreground objects, e.g., rocks, gravels, or creatures, from background information in an image. In future Mars rover missions, the rovers will travel much longer distances than those achieved by the Mars Exploration Rover (MER) spirit and opportunity \((1)\). Autonomous foreground object extraction will be one of the major parts of an image analysis system for Mars exploration. Onboard autonomous image analysis is highly desirable in future Mars rover missions \((3)\). Compared to normal images, Mars images have singular features, e.g., less color, monotonous scenery, an unsteady light source, and so on. In addition, objects are often covered by dust, occlude each other, becoming blurred in the distance, or partially embedded in terrain \((1)\). Foreground objects are one of the major features exposed on the Martian surface. If foreground objects are automatically extracted from Mars images, people are able to separate the focus, and carry out further study on interested partitions.

It is valuable for hazard avoidance and rover localization in rover missions to automatically extract foreground objects from Mars images. Some foreground objects, e.g., rocks, are one of the major obstacles for rovers traversing the surface and even endanger the rovers’ safety if they cannot be detected correctly in advance. Foreground objects are also the ideal tie points for vision-based rover localization and navigation \((2)\). Automatic extraction of foreground objects may assist in finding available route automatically for the Mars rover, and even with nonstone object (e.g., creatures) discovery. In addition, foreground objects may be used to judge the image information content for helping image compression and prioritizing data transmission from Mars to Earth, or for understanding the planet’s chemical composition, geologic environment, and climate mechanics \((4)\).

Current Mars image processing is developing rapidly. The representative methods include edge detection, Fourier transformation, wavelet transformation (WT), threshold extraction, and active contour recognition. In edge detection, there are the Sobel, Canny, and LoG methods. For solving the variable illumination problem, histogram equalization, homomorphic filter are given \((5)\). Modeling requires that the image has same features \((6, 7)\). Histogram equalization \((8)\) is particularly suited to process a uniform illumination image. Although traditional edge detection is less sensitive to the brightness of image, it is so sensitive to texture details resulting in too much noise. While threshold extraction can, in turn, eliminate
the interference of detail information, but is too sensitive to unsteady light sources, resulting in halo phenomenon. Fourier transformation and WT filtering are good at compression and denoising images, but difficult to use alone. Gulick et al. developed a rock detector with cast shadows (9). Thompson et al. developed a rock detection method based on segmentation, detection, and classification (10). Song and Shan (11) developed a framework for automated rock segmentation from Mars rover imagery. Li et al. extracted large rocks from three-dimensional ground points generated from stereo images (3). Hence, for natural image extraction, especially fully automated extraction without human operation, so far there is no general method. However, an organic combination of current image processing method can overcome relatively simple natural interference with satisfactory results; especially, the processing of spatial natural data like Mars images.

To get results that are more precise, in this paper a comprehensive method is proposed that automatically extracts foreground objects from Martian surface images. The rest of this paper is structured as follows: Section 2 presents the fundamentals. In Section 3, images acquired by the Spirit rover of the Mars exploration are studied as a case study and Section 4 draws conclusions.

2. Fundamentals
The method aims to extract automatically foreground objects from Martian surface images in context (Figure 1).

As shown in Figure 1, the method is composed of four parts: image preprocessing, image enhancement, edge detection, and image segmentation. Preprocessing adjusts images to a more suitable form for later processing, including homomorphic and Gaussian filtering, and intensity normalization. The former will eliminate the problem of uneven illumination; the latter will adjust histogram to most appropriate status. Image enhancement is responsible for multiscale WT and filtering texture details, enhancing the differences between foreground and background to the maximum extent. Edge detection is common operation in image processing, locating an images edge. It uses the Canny algorithm to acquire approximate edges with single response, then encloses the edge using active contour extract edge precisely based on the result of Canny. Image segmentation uses a connecting area algorithm, combined with geometry and graphics, extracting precisely positioned objects from an original image.

2.1. Homomorphic filtering
Based on illumination–reflectance, homomorphic filtering is an approach to image enhancement by simultaneous brightness range compression and contrast enhancement (12). In order to achieve simultaneous dynamic range compression and contrast enhancement, the transfer function of the frequency domain filter decreases the overall spectral energy of the illumination component while amplifying the spectral energy of the reflectance component of the image. Next is to select the filter function and cutoff frequency.

2.1.1. The frequency domain filter function
Different filter function $H(u, v)$ may impact high and low frequency components of a Fourier transform in different ways. Figure 2 is the state of filter function.

Here, $RH$ is the high frequency, $RL$ means low frequency, and $D(u, v)$ denotes the distance from frequency $(u, v)$ to the center of the two-dimensional Fourier transform $(u_0, v_0)$. $D_0$ means the cutoff frequency.

The curves shape in Figure 2 is similar to a high-pass filter that includes a Gaussian high-pass filter, a Butterworth high-pass filter, and an exponential high-pass filter. It was shown in experiments that a, (12, 13) Butterworth equation is most compatible with the homomorphic filter approach if it is modified as Equation (1).

$$H(u, v) = (RH - RL) \left[ \frac{1}{1 + (D_0/D(u, v))^{2c}} \right] + RL \quad (1)$$

where constant $c$ is introduced to control the slope of the whole range. When $RL \wedge 1$ and $RH \vee 1$, the filter can reduce the low frequency and enhanced high frequency, make the illumination range compression and amplify the image details. But it is difficult to choose $D_0$.

Figure 1. Fundamental procedure.
Figure 2. Filter function.
because it relates to the spectrum amplitude of illumination field and reflectance coefficients.

2.1.2. The selection of filter parameters
The traditional homomorphic filtering method determines the cutoff frequency $D_0$ by using many experiments. The proposed method selects the filter cutoff frequency by analyzing the frequency spectrum to obtain light features.

Supposing light to be absolutely uniform, and the spectrum of illumination only includes direct current components (the average value of original gray). The proportion of harmonic waves increases when the uneven level of illumination increases. By calculating the proportion of $n$ harmonic wave in the condition of variable light, the greater part of the harmonic component is captured. Thus, the corresponding frequency is the cutoff frequency. The algorithm is given below:

- Calculate the natural logarithm of the image firstly, multiply $(-1)^{x+y}$ for the center transformation, and then apply the Fourier transform to get the frequency center coordinate in $(M/2, N/2)$.
- Calculate the distance from point $(u, v)$ to the frequency center:
  \[ D(u, v) = \sqrt{(u - M/2)^2 + (v - N/2)^2} \]
- Calculate the frequency amplitude $F(u, v)$ where the point $(u, v)$ is under the same distance $D(u, v)$. They are in a circle that the radius is $D(u, v)$.
- Calculate the ratio $\alpha_d$ of image power $|F(u, v)|$ in the total image power, where the frequency is surrounded by the circle with different $D(u, v)$.

\[
\alpha_d = \sum_{i,j} |F(u, v)|^2 / \sum_{i} \sum_{j} |F(u, v)|^2
\]

\[
\{i,j | D(u, v) \leq d \}
\]

- Stop calculation when $\alpha_d \leq 0.7$, and the corresponding radius $D(u, v)$ is the cutoff response $D_0$.

The contrast between the original image and the filtered image is given in Figure 3. It is clear that there is halo phenomenon caused by uneven illumination in the original image (Figure 3(a)). Due to uneven illumination, it may become dim (Figure 3(b)), the filtered image is further equalized (Figure 3(c) and (d)). Figure 3(c) is the Butterworth homomorphic filtering. Seen from Figure 3(c), the brightness of the image has basically been corrected, and the high frequency part of the image is enhanced. When compared Figure 3(c) with Figure 3(d), the natural logarithm function is shown. Without calculating the natural logarithm of the image, the component of the shadow was changed after filtering.

2.2. Intensity normalization
After filtering, the whole image will become dim and not suitable for further processing. In order to enhance the differences between foreground and background after WT, it is necessary to use the histogram to transfer into the appropriate range. The image is processed first by intensity normalization.

\[
N_{x,y} = \frac{N_{\text{max}} - N_{\text{max}}}{O_{\text{max}} - O_{\text{min}}} \times (O_{x,y} - O_{\text{min}}) + N_{\text{min}}
\]

\[
\forall x, y \in 0, N - 1
\]

Where $O_{\text{max}}$, $O_{\text{min}}$ mean the maximum brightness degree and minimum brightness degree, respectively, $N_{\text{max}}$ and $N_{\text{min}}$ are output intensity degrees. The determination $N_{\text{max}}$ and $N_{\text{min}}$, is related to the parameters of wavelet of the task.

2.3. Lifting WT enhancement
WT analyzes images at different scales or resolution. It controls the precision and range of image processing. Through lifting schema, WT retains its core function and becomes more effective and easier to implement. Lifting wavelet transformation (LWT) separates the high-frequency information and low-frequency information into the image’s odd pixels and even pixels. It yields an image composed of four divided subimages: the upper left one saves the low-frequency information, the lower right one saves the high-frequency information, and others save mixed information (Figure 4).

In Figure 4, it is obvious that LWT can partition the image into high-frequency information and low-frequency information under different scales. When the scale increases, the compressed image with the smallest
scale will emerge, simultaneously keeping the high-frequency information at all scales. LWT produces a compressed image that the smallest scales’ low-frequency information save as the main information of the image while detailed information is saved in all odd pixels. Thus, a large amount of noise and details may be denoised if the image is inverse transformed and rebuilt after the odd pixels are filtered. However, this operation will also affect the edge information that is one piece of the detailed information. So it is meaningless to use this method alone.

Unlike a normal image enhancement algorithm, lifting wavelet transformation enhancement (LWTE) handles the same function at different scales for achieving the best effects. The enhanced image will be handed over to the Canny operator that needs the most differentiate between foreground objects and background information. After Canny operator proceeds, the detailed information of foreground and the noise from background will bring certain negative effects to the result. LWTE provides an easy way to reduce noise with high-pass filtering at different scales, and magnifying the difference by enhancing the image at different resolution. As an appendage, it can identify the edge that Canny operator produces as close as possible.

Because the image itself is often saved as byte data, the histogram of the image will get stretched when each image data has multiplied by a constant. Additionally, when the original data are more than 255, its multiplication will lead to data overflow (Equation (4)):

$$1111:1111 + 1 = 1'0000:0000$$  \hspace{1cm} (4)

As byte data can only save eight bit data, the overflowed data will lose its top bit. In other words, when data are larger than 255, it will restart at 0, namely white will turn to black. Hence, this method brings a way that let the serial date turn to extremely different data, which make the fuzzy edge information distinct after denoising enhanced (Figure 5).

Even though the LWTE has good effect on enhancing the image, there are still problems, for example, selecting wavelet basis, deciding the scale and amplification for enhancement, and choosing high-pass filter selection. First, the wavelet basis is under lifting schema. $s^0_l = s_{2l}, d^0_l = s_{2l+1}$ present the way of divided image data into odd terms and even terms (pixels start from 0), and odd terms save high-frequency information while even terms save low-frequency information. $d^l_l = d^0_l - \frac{1}{2} (s^0_l + s^0_{l+1})$, is the prediction to extract the high-frequency information. $s^0_l = s^0_l + \frac{1}{2} (d^l_l + d^l_{l+1})$ is the update for saving the low-frequency information. $s_l = \sqrt{2} \cdot s^1_l, d_l = \frac{d^l_l}{\sqrt{2}}$ are to wave band coefficient to adjust the result to the available luminance. Second, Figure 4 shows that the image is divided into four parts when scale is one. With the scale increases, the upper left part is divided into another four parts. Thus, choosing larger scale will produce more information, which brings LWTE different effects on denoising and enhancement. At the same time, the amplification is a constant that will multiply the image data at each scale of image so that it can enhance the image partially. It has certain relationship with the scales. Third, the high-pass filter is the main factor in denoising. There are two ways to denote, one is to rebuild the image by using the same filter on each split partition of the image and the other is to use the filter at each scale through rebuilding.

2.4. Canny edge detection

Canny edge detection operator is a popular edge detection technique. There are three main objectives: (1) optimal detection with few spurious responses, (2) good localization with minimal distance between detected and true edge position, and (3) single response to eliminate multiple responses to a single edge. In this paper, the third objective will provide a good support to the connected component partition step which will reduce replication of partition, and provide the snake operator enough accurate start points. Meanwhile, the second objective can bring an optimal position of edge, especially after LWTE. Almost all foreground objects’ edges that are worth to be interested in can be located precisely. Additionally, the first objective pays low attention to noise and detail but to guaranteeing the accuracy. Canny edge detector includes three steps:

1. Denoise. It is a preprocessing step for Canny to convolute the data with a Gaussian operator to get blurred image contrast from the original
image. After Gaussian smoothing, a single pixel noise such as salt and pepper noise will not affect the next edge detection steps.

2. Find the maximum gradient of brightness. The edge of the image may point to any different direction. Two masks are used to convolute the image for getting the gradient in horizontal and vertical. Then the edge’s direction is obtained by calculating the ratio of these two gradients, and the edge’s value is got by calculating the Euclidean distance of these two gradients. Through the direction and the value, those points with the maximum in its direction are chosen. A series of points that may be the real edge are finally collected.

3. Trace edge. The points that have higher value are more possible to become the real edge, but there is not a clear value to distinguish how high the value. The hysteresis threshold is presented. Two accurate thresholds are necessary, one is to determine the start point of the real edge named high threshold, the other is to find the real edge that connects to the start points named low threshold. Because the edge is not one point alone, when a point has a high value that can be determined as the real edge, the points next to it with higher values become the real edge than others, even it has a lower value. Through this hysteresis threshold to trace all edge, all edge information are extracted accurately.

Because Canny is sensitive to noise, the extracted edges are closure, and they have poor effect on edge detection under different illumination, the LWTE has reduced the noise and improved the edge detection result, and the homomorphic filter has made the different illumination into a close illuminate environment.

Taking a close look at Canny, there are some parameters that impact the Canny’s execute time and result. The size of the Gaussian filter is a common. The larger size filter will get more blurred image that is used for detecting bigger and smoother image, while the smaller size is used for detecting the smaller and obviously changing image. The threshold will determine the final result. The lower the threshold is the more detailed information and the more noise as well.

2.5. Precise positioning with an active contour model
Active contour model, or Snake model, was proposed by Michael Kass in “Snakes: Active Contour Models” (14). It defines an energy function of the object’s contour of interest. The contour changes in shape and behavior in order to decrease the energy function until it reaches its minimum value when the contour stops changing and converges to the edge of the object. The principle of designing energy function includes continuity of curve, flatness of curve, high-gradient region close to the curve, and other specific prior knowledge that leads to the decrease of energy function. With the guide of the energy function, the active contour can converge to the local edge that is smooth and continuous. Traditionally the object boundary is detected only with the image data but without considering the nature of the object (15). First, the initial contour must be close to the true boundary of the object of interest or else it may converge to a wrong boundary. Second, though the active contour model provides a unified solution for computer vision on certain application, appropriate energy function (16) should be designed so that the contour can converge to the right boundary, if not, it would lead to wrong result. By changing the energy function, some improved algorithms were given (17) for active contour model. It has been widely used in cell detection, X-ray analysis and image analysis of clinical bone marrow, (5) achieving quite good performance for edge detection, image matching, segmentation, and target tracking. After initialization, the active contour could automatically converge to minimum energy status with energy function.

When extracting foreground objects from Mars images, the input of connected component partition must be a closed contour, while in fact using Canny operator after WT could not always get closed contours. In order to extract all foreground objects from Mars images correctly, the nonclosed inputs should firstly be enclosed. Here, to achieve the result through active contour model greedy algorithm (18) in which the result of Canny operator is used to initialize the contour that is close to the true boundary and Sobel operator is used to provide the image gradient energy part.

2.5.1. Sobel operator
After the preprocessing of denoising by Gaussian filter and normalization to improve the contrast, the edge detection of Sobel operator can be used via Sobel template (St).

1. Use the smoothing function S, and differencing function d, to generate the horizontal and vertical template, respectively. To set the size of the template W, the horizontal template and the vertical template are computed

\[ S_{x}(x_{win}, y_{win}) = S_{win} * d_{win} \]  \hspace{1cm} (5)

\[ S_{y}(x_{win}, y_{win}) = S_{win} * d_{win} \]  \hspace{1cm} (6)

\[ S_{win} = \frac{(w - 1)!}{(w - 1 - x_{win})!x_{win}!} \]  \hspace{1cm} (7)

\[ d_{win} = P(x_{win}, w-2) - P(x_{win} - 1, w-2) \]  \hspace{1cm} (8)

Where P is defined as follows:
\[ P(k, n) = \begin{cases} \frac{n!}{k!(n-k)!}, & 0 \leq k \leq n \\ 0, & \text{otherwise} \end{cases} \]  

(1) Scan the image data with the horizontal and vertical template, respectively, getting \( G_x \) and \( G_y \).

(2) Compute image data \( G \) under \( G = \sqrt{G_x^2 + G_y^2} \) as the image gradient energy of the energy function in snake model.

### 2.5.2. Greedy algorithm

Active contour model is to enclose all the nonclosed contours from Canny operator. Active contours are actually expressed as an energy minimizing process. When the contour converges to the true edge, the energy function reaches its minimum value. After initializing, the contour acquires the results from Canny operator, and greedy algorithm iterates the initial contour until the energy function reaches its minimum. Finally connect the set of points to a line so that the contour is closed.

The initial contour consists of a set of discrete points. Greedy algorithm iterates the set of points until it reaches the ending conditions. Before the iteration, it is suggested to set the energy part weights, and the ending condition of the iteration, i.e. the threshold of moving points and the threshold of iteration times. Calculate the moved points as variable number every iteration. For each point in the set, calculate the energy of the point and the adjacent size according to the searching space. If the energy of the point with the smallest energy of the adjacent points is smaller than that of the point under control from the set, replace it with the point with the smaller energy and plus the variable number with one. At the end of each iteration, adjust the set of points by deleting the points that are too far from the center point. If the number is smaller than the set threshold or the iteration times are bigger than the set threshold, end the iteration. Finally connect all the concrete points in the set to be a closed line. Figure 6 shows that the greedy algorithm can approach the rock contour well.

### 2.6. Connecting area partition

After edge detection, each foreground is surrounded by different contours \([19, 20]\). However, before locating a certain object and extracting it from the image, it is necessary to binarize and label the image. Labeling connecting area in binary image is a process of identifying each distinctive connecting area in a black and white bitmap image. Distinctive connecting area represents different target objects. Normally, by using label tags, a mark-matrix of the origin image is used to describe the different divisions. Labeling is firstly a horizontal scanning from left to right and from top to bottom. If the value of pixel is the same with adjacent value, it means they are connected. On the contrary, they are not connected. Then marks this point and saves it into the mark-matrix.

Because connected domain which contains connected components with different labels can exist, it is necessary to mark equal sets in order to consolidate these subconnected components. After scanning, to rectify the integral labels and remove those which are united.

After labeling each connecting area, it is possible to extract its contour outline according to label matrix. Then separate target stone from original image according to the extracted contours. Separation of a connecting area should be done in accordance with its smallest rectangular boundary. In the end, create a result graph in accordance with the separation. After the recognition and labeling of connecting area and target separation, the foreground objects were extracted from original image. Figure 7 shows the results of extracted foreground rocks.

### 3. Experiment

The objective is to extract foreground rocks from Mars images. The experimented images are Navcam and Pan-cam images taken by MER Spirit rover (downloaded from MER Analyst’s Notebook). In order to get the best result, the scale is 4 and the amplification is 1.4. At this scale and using this amplification, the image can contain the most data, while differentiating the foreground and the farthest background. Concerning that detailed information is useless for the following steps, this paper...
filtered all high-frequency information to get the best performance. The size of the Gaussian filter is set as three because LWTE has blurred once before Canny. Otsu threshold is used as the low threshold, and double low threshold is used as high threshold. The edge pixel is converted into 225 (foreground) while non-edge pixel is 0 (background). In addition, each object is differentiated by marking this binarized area.

3.1. Foreground objects extraction

After the overall implementation of the application, the foreground rocks from the Mars image are identified (Figure 8). Figure 9 is the enlarged view of the result image in Figure 8(b).

Comparing the original image to the resulting image, the foreground of the image including stone, sand, and shadow is well circled by the white lines. The white lines providing an accurate location are derived through the process of homomorphic filtering, WT, and edge extraction. The following enlarged view shows the result of image segmentation after edge detection. It shows that rocks can be well separated with clear texture and little background information. The resulting images indicate that foreground rocks can be extracted from Mars image comparatively completely with the proposed method.

3.2. Comparative analysis

Figure 10 shows the comparative results of different combinations of the algorithms.

Figure 10(a) is the original image, in which there exists uneven illumination. The center part is brighter than the surrounding parts.

Figure 10(b) is the result of only using Canny edge detection on the original image. The central brighter part obtains a comparatively good edge detection result. However, the surrounding darker part obtains an incomplete result because some of the edge lines are discrete and are difficult to extract.

Figure 10(c) is the result after only Otsu binarization processing on the original image. The influence of uneven illumination is more obvious. It is difficult to get any useful foreground information.

Figure 10(d) is the result of combined processing including LWTE with Canny edge detection on the original image. It is still affected by uneven illumination. However, owing to the effect of denoising and LWTE, which weakens the noise and increases the differences of the background and the foreground, the rocks of the center part can be detected completely. The stone edge is closed so that it is easy to extract. On the other hand, the rocks in the surrounding part impacted by uneven illumination are mixed with the background and therefore also hard to extract.
Figure 10(e) is the result after the processing of homomorphic filter and Otsu binarization. The halo is significantly weakened and the rocks can be identified vaguely but not complete. In addition, compared with other binary image, that this binary image has white background and black foreground, which is in the opposite way to others. It is not good for segmentation.

Figure 10(f) is the result of the proposed method. Here, the halo is basically removed. The edge of the foreground is located precisely. Moreover, the enlarged image in Figure 11 shows that the contour of rocks is clear and complete and forms a closed geometry graphic. It provides the right input for the segmentation algorithm. The results of segmentation are shown in five small images on the right of Figure 11.

In summary, the results show that the method can extract foreground objects from Mars images automatically and precisely, and it has potential applications, e.g. supervising the moving Mars rover, Mars image interpretation. The comparisons indicate that edge detection without using LWTE beforehand might introduce noise easily which resulted in incomplete and nonclosed stone edge. In addition, because of uneven illumination, the different enhanced rate of the background caused halo phenomenon and jeopardizes the processing result. The homomorphic filter overcame this problem. After the whole procedure, the shadow of stone could be easily regarded as real stone and shadows can be considered into foreground.

4. Conclusion

After analyzing the features of a Mars image, a comprehensive method was proposed to extract foreground object automatically. It preprocessed the image with homomorphic filter to make up for the shortcomings of uneven illumination, and chose the cutoff frequency of the filter function automatically by analyzing the features of image spectrum. When the situation of uneven illumination was improved, it further expanded the histogram of the image so as to adjust the background to the available range. Then LWTE was used to enhance and invert the image to avoid the overflow of background information. For improving the whole image’s contrast, it was necessary to make the background restart from 0 and the foreground stay near 255. Then, rough edges of rocks were got by Canny edge detection. Precise locations were further achieved through active contour models. Finally, connecting area partition is used to divide all the rocks successively.

However, because of the effect of illumination, the shadow of stone can easily be regarded as real stone incorrectly. Therefore, the next step is to make further texture analysis of the rocks extracted from Mars images so as to remove the shadow from the extracted objects.

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