Matching Method of Lunar Remote Sensing Image Based on Laplacian

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Abstract. In recent years, there is an emerging interest in the exploration of the lunar surface. We can use many images of the lunar with different resolutions sent by more and more satellites that launched to the Moon. However, research on the lunar image matching still faces various difficulties. Significantly differing from the complex physical structure of the Earth's surface, the lunar surface is mainly craters, ridges and mountains, and its simple physical structure directly leads to the difficulty of extracting the same name points; satellite sensors are easily influenced by multiple factors while imaging, such as the shooting angle of the forward-looking and backward-looking linear array, the sun's angle of incidence, which is likely to cause some differences in the brightness of the images, and it makes the image matching choose the appropriate image enhancement method. In this paper, taking Chang'e II CCD lunar image as an example, firstly we propose a method of extracting the same-name point of lunar images based on Laplacian and image grayscale matching, and compare it with the commonly used SIFT + RANSAC algorithm, the accuracy rate and processing speed rate increases by 4.55\% and 58.3\% respectively, which verifies the scientificity and rationality of this method. Our work provides a new idea for the study of lunar image matching technology and lays foundation for the image-based lunar surface research and development.

1.Introduction

Since the 1960s, our neighboring satellite moon has been an important topic of research to understand the origin and the lunar crustal evolutionary processes. Such as China's Chang’e series, Japan's Selene, India's Chandrayaan-1, and NASA’s Lunar Reconnaissance Orbiter Camera (LROC) have been launched to explore the moon\textsuperscript{1}. Lunar Remote Sensing image matching technology has always been one of the key research directions in the fields of graphic image processing, GIS, photogrammetry and remote sensing, and is also a basic research field\textsuperscript{2}. In many lunar image
processing, such as DOM (Digital Orthophoto Map) production, image stitching, 3D reconstruction and object detection, one of the core steps is the same name point extraction and image matching technology, which establishes reliable correspondence of points between two images. At present, lunar image matching algorithms can be basically divided into matching algorithms based on image gray values, matching algorithms based on image features (including imaging arts, colors, spectra, geometric features), and matching algorithms based on artificial intelligence technology3, 4. However, under some circumstances such as on the lunar surface, there are various factors that make the image matching problem difficult. The satellite sensor imaging is easy to cause partial brightness difference between the images. In addition, due to the large difference between the lunar surface image and the earth surface image, the surface coverage of the lunar surface image is rather monotonous5. The meteorite craters are the main types. The meteorite craters do not have significant geometrical features, nor do they have obvious linear intersection points. Lunar images are characterized by single texture6 and inconspicuous gray-scale changes, which bring great difficulty to lunar image matching. At present, in the research on the same name point extraction and image matching technology, the matching method based on image features is mainly used, such as Kun Chen, Lu Wang and others, who matched the Chang’e II CCD lunar image basing on the SIFT algorithm combined with the image characteristics7. Ahua Yang, Jianwei Xie, Liu Tao, etc. used the SIFT algorithm, combined with the same orbit characteristics of the lunar images to automatically extract and match the Chang’e II CCD lunar image8. Yuren Zhang, Xu Yang, etc. constructed a keypoint correspondence algorithm for lunar images using SIFT algorithm based on graph matching. The local affine-invariance constraint is utilized to tackle point ambiguity caused by repetitive patterns and outliers9. These studies have achieved some results, but also have some shortcomings. In view of the problems such as large volume, single texture, inconspicuous geometric features, ground object distortion and differences in brightness between front and rear view images10, the same name matching technology of lunar image is still one of the most difficult issues to overcome during the pretreatment.

In view of the above problems, this paper presents a simple image matching method based on Laplacian and image grayscale: (1) Select the low-pass filter to smooth and denoise the image, filter out the image Gaussian noise, isolated point noise. (2) Then according to the geometric characteristics of the lunar craters, such as the place with steep edges and smooth edges, Laplacian is selected to extract and enhance the edges of the smoothed images, enhance the image gray mutation and reduce the low-frequency component of the image. (3) Finally, the gray matching algorithm based on NCC algorithm is used to match the pixels with the same name, the match error is reduced, and the lunar image registration result is obtained.

2. Dataset used

Datasets from China’s lunar exploration satellite Chang’e II, the spatial resolution of the image is 7m, the linear texture information of the front and rear images of the CCD image is not significant, and the difference of the brightness is obvious. From Chang’e II’s launch to May 20, 2011, Chang’e II satellite equipped with CCD stereo camera has covered the latitude 85° north latitude and lunar two regions of the three-dimensional imaging, and successfully returned 607 rail data during orbital operation. The CCD stereoscopic camera component carried by it is a time delay integral charge-coupled device (TDICCD), which carries out the three-dimensional imaging of the lunar surface in a continuous push-broom by a bilinear array with the pixel size of 10.1um * 10.1um and the number of pixels 61445,11. The main technical indicators are shown in Table 1.
Table 1. Specifications of CE-2 CCD stereo camera

| Name                        | Specifications                  |
|-----------------------------|---------------------------------|
| Spectral Range              | 450-520 nm                      |
| Spectral Channel Number     | 1                               |
| Quantification Level        | 8bit                            |
| MTF                         | ≥0.2                            |
| S/N(ρ=0.2 θ=60°)            | ≥100                            |
| Gain Selection              | Three Level                     |
| Imaging Width               | ≥43km(100km Height) ≥6km(15km Height) |
| Number of CCD Pixels        | 6144                            |
| Base Ratio                  | 0.45                            |
| Pixel Spatial Resolution    | Better than 10m (100km Height), Better than 1.5m (15km Height) |

Optical System Parameters

| Focal Length | 144.3mm |
|--------------|---------|
| Relative Aperture | F/9 |
| ExposureTime  | Five Level |
| Perspective  | Front view +8° rear view -17.2° |

3. Methods

3.1 Image Enhancement

3.1.1 Low-pass spatial domain filtering

While sensors are gathering spatial images, the ground object forms the incident light by reflecting the sunlight, after the incident light shines into the CCD camera, the image noise comes into being during the photoelectric conversion of the incident light by CCD camera due to the reflection of the ground object, CCD components and other factors. In addition, the weather, temperature, manual errors and other factors during the image transmission can easily lead to the formation of image noise. Image noise usually includes salt and pepper noise, normal noise, speckle noise and so on. The existence of image noise will damage the image quality, and have an impact on the image processing, image analysis and image visual effects in varying degrees. Therefore, image denoising is an important means to improve image quality, enhance images and restore images. Common denoising methods include: 1. Spatial domain denoising, that is, image denoising in two-dimensional space, including linear and nonlinear spatial denoising, such as median filtering, low-pass spatial domain filtering, Wiener filtering, multi-image averaging denoising; 2. the frequency domain denoising, that is, the image denoising domain transforms from the spatial domain to the frequency domain, the mathematical theory of spatial transformation is based on the Fourier function, and the commonly used frequency domain denoising methods include: frequency domain low-pass filter denoising, wavelet transform and so on.

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Low-pass spatial domain filtering is a spatial domain processing method based on the convolution operation, which smooths the image isolated noise points through the image neighborhood points in order to remove the noise. Using the gray value of all the pixels in the neighborhood $\Omega$ of a pixel of image $(a,b)$ to linearly predict the gray value of this pixel $f(a,b)$, we can get the estimated value:

$$f(a,b) = \frac{1}{N^*N} \sum_{(i,j) \in \Omega} k * f(a-i,b-j)$$  \hspace{1cm} (1)
Wherein, $\Omega$ denotes the neighborhood of a pixel, $f(a-i,b-j)$ denotes the gray value of each point in the neighborhood, N denotes the size of the neighborhood, and $k$ denotes the weight coefficient.

Low-pass spatial domain filtering is a commonly used image enhancement technique, which has good application effect for Gaussian noise removal and image smoothing. Through low-pass filtering, the image can reduce the erroneous response of the operator to the isolated noise in the subsequent image enhancement, so as to improve the extraction accuracy of the same-name point. There are two main factors that affect the filtering performance of spatial domain low-pass filter, one is the filtering function and the other is the size of the filtering window. Therefore, it is very important to select the filtering function and set the size of the filtering window in the image enhancement processing. The spatial low-pass filter also filters out the Gaussian noise point, and also makes the edge of the image obscure. The larger the filter window value is, the more obvious the image smoothing effect is and the more ambiguous the contour of the image is, which may result in Geometric features are not obvious or disappear. Therefore, in the practical application process, the low-pass filter function and the window size value are often selected reasonably according to the size of the object and the application requirements.

In practice, images has the characteristics of too much Gaussian noise and isolated noises, the need of Laplacian image sharpening after image processing, as well as the consideration of the algorithm complexity and the efficiency of denoising, spatial low-pass filtering is the best image denoising and smoothing filter.

3.1.2 Laplace Operator

As for low-pass filter, from the spectral point of view, the part of the image signal which changes more intense called the high-frequency, as well as the part of the image signal which changes more slowly called the low-frequency part, are reflected in the spatial domain by showing sharp and smooth gray change differently. The low-pass filter sets the threshold in advance, then by comparing the threshold, to select the image signal to cut off the high-frequency components, and pass the low-frequency components. After the image is processed by the low-pass filter, the outline and edge of the image tend to be more blurred than the original image. In order to eliminate the ambiguity and make the image outline, edge, isolated points and lines and others become clear, it is often necessary to sharpen the image, and common operators include: Roberts operator, Prewitt operator, Laplacian operator and so on. According to the different functions of various operators, various edge extraction operators have different characteristics and application fields. For example, Prewitt operator is a direction operator, which has good effect on the directionality detection of the edge of the image and shows a larger value of the width of the edge part; sobel operator is also a group of direction operators, which also has good on the detection of fine edge of the image, and shows a higher value of the edge of the gray as well as better the visual effect.

Laplace Operator, a second-order differential operator in n-dimensional Euclidean space. Although it is difficult for common image enhancement techniques to determine the edge line position of steep edges and flat edges, laplace operator can produce a steep zero crossing(The zero-crossing point, generated by the second-order derivative between the positive peak and the negative peak at the edge of the image is referred to as zero-crossing) at the edge of the image, so that it is more sensitive to outliers or endpoints, as a result, often used for image sharpening and edge enhancement.

A continuous binary function $f(x,y)$, $x,y$ represents the Cartesian coordinates in the plane, the Laplace operation is defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$  \hspace{1cm} (2)
To be more suitable for digital image processing, the Laplacian can also be expressed in discrete form:

\[ g(i, j) = 4f(i, j) - f(i + 1, j) - f(i - 1, j) - f(i, j + 1) - f(i, j - 1) \]  

(3)

Its convolution form can be expressed as:

\[ g(i, j) = \sum_{r=-k}^{k} \sum_{s=-l}^{l} f(i-r, j-s) H(r,s) \]  

(4)

In equation (3), (4), \( i, j = 1, 2, 3, \ldots; \ k = 1, \ l = 1 \), the \( H(r,s) \) filtering template is sampled as follows:

\[
H_1 = \begin{bmatrix}
0 & -1 & 0 \\
-1 & -4 & -1 \\
0 & -1 & 0
\end{bmatrix}
\]  

(5)

Laplacian template representation, as shown in equation (6).

\[
G_x = \begin{bmatrix}
0 & -1 & 0 \\
-1 & -4 & -1 \\
0 & -1 & 0
\end{bmatrix}, \quad G_y = \begin{bmatrix}
0 & -1 & 0 \\
-1 & 5 & -1 \\
0 & -1 & 0
\end{bmatrix}
\]  

(6)

Where \( G_x \) is a discrete Laplacian template, \( G_y \) is its expansion template. Since Laplacian has rotation invariance, and it is an isotropic filter, and its linearity as well as displacement are invariable. At the same time as a result of its sensitivity to the image edge, it can solve problems that other operators (such as Sobel, Prewitt, etc.) cannot solve, such as the steep edge, slow edge changes, which is very beneficial to solve the problem of the Chang'e II CCD image that grayscale changes steeply and image edge changes slowly as well as the extraction and identification of isolated edge-shaped and linear features on the image. Like the other gradient operators, the Laplacian also increases the noise in the image. Therefore, in order to extract linear and point features more effectively, it is also very necessary to do the edge extraction Smooth noise reduction before using the Laplace operator to extract the image.

3.2 Image gray matching

Gray-based image matching is a method for measuring the similarity between images by directly using the gray information on the matching image. Selecting the appropriate similarity measure algorithm is the key point of gray-based image matching. Common similarity measure algorithms include:

1. MAD (Mean Absolute Difference)

\[
D(u,v) = \frac{1}{n \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} |x_{i+u,j+v} - y_{i,j}| 
\]  

(7)

2. SAD (Sum of Absolute Difference)

\[
D(u,v) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} |x_{i+u,j+v} - y_{i,j}| 
\]  

(8)

3. SSD (Sum of Squared Difference)

\[
D(u,v) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (x_{i+u,j+v} - y_{i,j})^2 
\]  

(9)
4. Prod(Product correlation)

\[ R(u,v) = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} x_{iuv} - y_{ij} \]  

(10)

5. NCC(Normalized Cross-Correlation)

\[ R(u,v) = \frac{p(u,v)Q(u,v)}{D(u,v)Q(u,v)} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} [S_{uv}(i,j) - E(S_{uv})] \bullet [T(i,j) - E(T)]}{\left[ \sum_{i=1}^{n} \sum_{j=1}^{n} [S_{uv}(i,j) - E(S_{uv})]^2 \right]^{\frac{1}{2}} \left[ \sum_{i=1}^{n} \sum_{j=1}^{n} [T(i,j) - E(T)]^2 \right]^{\frac{1}{2}}} \]  

(11)

In the above algorithms, \( D(u,v) \) is the energy of the region from the template corresponding to the source image, which is related to the pixel position \((u,v)\), \( n \times n \) is the template size, \( y_{ij} \) is the gray value of the \((i,j)\) pixel in the template image, \( x_{iuv} \) represents the image grayscale of the \((u,v)\) pixel point of \(f(u,v)\) in the search map, \( E(S_{uv}) \) represents the average gray value of the subgraph at \((u,v)\), \( E(T) \) is the average gray value of the template.

The above five algorithms, the principles of MAD, SAD, SSD are basically the same with a slight modification in their formulas, that is, taking \((u,v)\) as the upper left corner in the image, taking \(n \times n\) size of the subgraph, calculating the similarity of the remaining templates, then traversing throughout the matching graph to find the most similar subgraph to the template from all the subgraphs as the final matching result. Since the algorithm measures the matching accuracy by measuring the distance between the image vectors \( x_{(u,v)} \) and \( y \), the smaller the average difference \( D(u,v) \) (or the absolute difference, the square of the error) is, the more similar they are, and the minimum value is 0, so we only need to find the minimum value of \( b \) to determine the location of the matching subgraph. Prod and NCC algorithms are similar to the above-mentioned distance measurement algorithms, and still use the gray value of the subgraph and the template to do the calculation. The normalized correlation metric formula is used to calculate the degree of matching between the two, and the bigger the value of \( R(u,v) \) is, the better it is, and the maximum value is 1. The closer the value of \( R(u,v) \) is to 1, the higher the image similarity is.

By comparing the matching accuracy of the above gray-level matching algorithms under different conditions, it is helpful for us to select the algorithm that is suitable for the lunar image matching. Under the condition of the same template image and fixed gray threshold, the matching accuracy of different algorithms is calculated by the variation of image brightness and the edge ambiguity of image, and the operation under normal conditions can be obtained: When the brightness value of the image changes, the MAD and NCC algorithms perform well against the change of brightness and have no significant effect on the image gray-scale matching; with the condition of vague edges of the image meteorite craters, the SSD and NCC algorithms show their advantages and can still accurately recognize the transformation of the meteorite craters, and can still accurately match the image grayscale; under the conditions of normal brightness and sharpness, MAD, SAD and SSD algorithms are relatively simple, but their computational complexity is relatively high, and their sensitivity to noise is high, and the computational complexity of Prod and NCC is relatively complicated. However, the computational complexity is relatively small and insensitive to noise. Comparing the test results, according to the actual situation of the lunar image in terms of brightness and sharpness, this article will select the NCC algorithm as the image grayscale matching algorithm afterwards.
4. Experiment Results

The image matching experiments are run over the ENVI / IDL 8.2 platform in this paper. We select two tracks of the Chang'e II CCD stereo pair, the image numbers are: B0606/ F0606, B0607/ F0607. Before the extraction of the same name point, the image was geocoded and smoothed using a low-pass filter. The image matching process is shown in Fig. 1.

![Image matching flow chart](image)

**Figure 1.** Image matching flow chart

4.1 Smooth image noise reduction

According to the experimental procedures, firstly, the data of Lunar image is analyzed and found that the Gaussian noise and isolated noises are relatively dense. In the light of the demand of image enhancement processing based on Laplacian in the later period, combining the complexity of the algorithm and the computational efficiency, in this paper, we select the low-pass spatial domain filter as the best filter for lunar image denoising and smoothing. In this paper, we select the low pass filter function and use the low pass filter with 3 * 3 convolution kernel to filter the experimental image. The filtered image is smoother and the noise is reduced greatly. The denoising effect is shown in Fig. 2.

![CCD image smoothing and denoising](image)

(a) Original image; (b) After smoothing denoising

**Figure 2.** CCD image smoothing and denoising:

4.2 Image Edge Extraction and Enhancement

In view of the characteristics of the widely distributed isolated points and the linear ground objects in the lunar image, the significant change of the grayscale of the image and the slow change of the edge of the crater, combining the characteristic of the Laplacian isotropic filter, on the IDL 8.2 platform, we use the Laplacian and the convolution kernel set as 3 * 3 to enhance and extract the smoothed image after filtering. The processing results is shown in Fig. 3.

![CE-2 CCD Image Edge Enhancement Based on Laplace Operator](image)

(a) Original image; (b) After smoothing denoising; (C) After the Image edge sharpening enhanced

**Figure 3.** CE-2 CCD Image Edge Enhancement Based on Laplace Operator:
4.3 Image gray matching and Mismatch point removed

After image preprocessing of lunar image, such as geocoding, smoothing and denoising, edge enhancement and so on, in this paper, we use NCC (normalized product correlation algorithm) gray matching algorithm, to conduct the same name point image matching experiment with the window size of 9*9. We get 436,431 image points of the same name from the selected two-track lunar image experimental images. By matching the experimental data directly, the precision error of the same name point extracted is 4.76 pixels, while the matching precision error of the same name point is 0.39 pixels by using the Laplacian-processed image for gray-level matching. Using the control point correction module of ENVI software, based on the error parameters of control points, we check and remove the same name of the mismatched points. After checking, the number of the error matching points is 6 and 8 respectively, the accuracy of image matching is up to 98%. Thus it can be seen that the Laplacian-based algorithm of the same name point extraction method significantly improve the accuracy of image matching. The example of image processing is shown in Fig. 4.

![Image processing example](image.png)

**Figure 4.** Partial matching rendering image of the CE-2 CCD the entire orbit lunar image. (a) Front magnified view (b) Rear magnified view

4.4 Comparison with SIFT algorithm

Feature-based image matching algorithm does not require the whole image information the same as the gray-scale matching algorithm, but only require partial image information. The basic principle is to extract some local invariant features first, and describe the local invariant features, and then match by comparing the coincidence level of the feature descriptor. Therefore, the key issue of performing feature point matching is the feature point. The feature points, that is, the largest part of the image mutation, such as point features, turning point and so on. Therefore, selecting the feature extraction
algorithm with high matching accuracy, excellent robustness and fast computing speed is the key to feature matching. Common feature matching algorithms include: Moravec operator, SUAN operator, Harris operator, Harris-Laplace operator and SIFT operator.

SIFT (Scale Invariant Feature Transform) algorithm is a commonly used descriptor with scale invariance, which is used mostly for feature point detection. The algorithm was first proposed by David Lowe, a professor at Columbia University in 1999. Since this operator has immutability in different scales space, gray space and image space shift, deflection and so on, along with strong scalability, it is widely used in the field of image processing.

RANSAC (Random Sample Consensus) is a kind of method of fitting a model with experimental data that can be used to smooth data with a large amount of interference, and therefore it also can be used for data generated by a feature extractor which is prone to errors.

In order to verify the accuracy and superiority of the proposed method, in this paper, we perform the same-point matching process on the same region of the same image based on the commonly used SIFT + RANSAC algorithm (Algorithm 1), compared with the Laplacian + NCC image gray matching algorithm (Algorithm 2), and the results is shown in Table 2.

| Algorithm | Front view feature points | Rear view feature points | Matching point pairs | Match success rate (%) | Time consuming |
|-----------|--------------------------|-------------------------|---------------------|----------------------|---------------|
| Algorithm1 | 502 | 425 | 346 | 23 | 93.35 | 12min |
| Algorithm2 | 436 | 436 | 430 | 9 | 97.9 | 5min |

As can be seen from the table above, for the lunar image, the technical solution based on the Laplacian matching with the grayscale obviously shows its superiority in terms of the extraction accuracy and the efficiency.

By using the feature-based SIFT operator and gray-based image matching method for the same name point of lunar image extraction and matching, we find that with the use of the above method for lunar grayscale images, especially for the same name point lunar image extraction, due to the influence of lunar image quality and data volume, the feature-based SIFT operator has a large mismatch rate and requires complex mismatching points to be screened out. In the meantime, due to the large amount of CCD image data of the monorail Chang’e II, extracting points of the same name takes a large amount of computation and a long time. However, the method of extracting points of the same name based on grayscale is affected by image noises and single feature, and the extraction accuracy is very poor.

5. Discussion and Conclusions

The lunar image usually has a narrower field of view, and it is more susceptible to the sensor attitude/orientation, perspective projection center, panoramic distortion, undulating terrain and other factors while imaging which leads to the partially geometric distortion, scale changes, displacement and other image distortion phenomenon on the image, so it brings a certain degree of difficulty to the same name point matching of the lunar image.

Aiming at the above problems, combining with the gray-scale characteristics of the lunar image, in this paper, we taking Chang’e II lunar image as an example, present a matching method of the same point of lunar image based on Laplacian and NCC gray scale matching. And by randomly select a track of lunar image three-dimensional image pair, we perform the same name point matching running over the ENVI / IDL8.2 platform. Comparing with the extraction efficiency of SIFT algorithm, we have verified the feasibility and accuracy of this method. We provide a reliable technical solution for lunar image matching and this work is of great significance for homogeneous studies. However, in the process of extracting DEM, there are more strict requirements on the error precision of the same point quantity and pixel. The method proposed in this paper needs to be further verified and studied in the future.
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