

SURF-Based Image Matching Method for Landing on Small Celestial Bodies

Yu-lang CHEN and Jing-min GAO*

Beijing Information Science & Technology University, Beijing, 100192, China

*Corresponding author

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Abstract. In deep space exploration missions, one of the main methods used to achieve accurate landing of small celestial body by detectors is the terrain-matching navigation method based on optical images. Image matching technology is the key technology of this method. This paper proposed a small celestial image matching method based on SURF (*Speeded Up Robust Features*) to improve the adhesion accuracy of small celestial bodies. Firstly, we used the SURF feature detector to perform feature point detection on the surface image of the target celestial body then, the feature points are matched by the fast nearest neighbor search method. And mismatches are eliminated with NNDR and RANSAC. Finally, under the influence of image rotation, Gaussian noise, etc., the matching results of the algorithm were simulated and analyzed. The simulation results demonstrate that the proposed method has good robustness in complex environment of small celestial and high matching accuracy. It can provide effective landmark information and attitude information for subsequent visual navigation.

Introduction

The scientific significance of small celestial exploration is very significant, whether it is the study of the formation and evolution of the solar system, the origin and evolution of life, or the defense against foreign celestial bodies in the future. Exploration of small celestial bodies are gradually developed to the current detection methods of landing, etc.[1]

During the attachment process, the detector relies on identifying the keypoint in the image captured by the optical camera for autonomous optical navigation. Among them, the detection and matching of image features play a crucial role[2,3]. The extracted keypoint must have high uniqueness, for example, the edge of the crater on the surface of the small celestial body, the edge of the groove, etc. What's more, the keypoint need to have scale invariance and rotation invariance. And it should have good adaptability to light changes.[4]

The image feature matching process is mainly divided into three steps: keypoint detection, feature descriptor generation and feature matching. At present, the keypoint detection algorithms mainly include SIFT, SURF, ORB, KAZE, etc.

SIFT (*Scale-invariant feature transform*) has a good image matching effect with different image scales, different brightness and different rotation, and the application range is very wide[5,6]. SURF(*Speeded Up Robust Features*) has the invariance of translation, scaling and rotation. At the same time, it is also relatively robust to illumination, affine and projection variability[7]. As the requirements for keypoint matching speed increase, Edward Rosten et al.[8] proposed the FAST algorithm in 2006. Then the ORB[9] and the BRISK[10] algorithm were generated on the basis of FAST. In terms of speed, ORB is the fastest among them, followed by BRISK, and the slowest is SIFT. In terms of feature extraction, especially in the context of small celestial attachment, ORB is not suitable for working in this context because it does not have scale invariance. BRISK is fast, but not as robust as SIFT and SURF, and SURF is faster than SIFT. Therefore, this paper chooses SURF algorithm as feature detector[11,12,13].

The surface atmosphere and geological environment of small celestial bodies are complex, especially the difference of illumination. At the same time, the detector landing needs to complete image matching in high speed. In this paper, SURF is used for image keypoint detection, and then

matched by fast nearest neighbor search method. This method use the NNDR(*Nearest Neighbor Distance Ratio*) to initially reject the mismatch and use RANSAC(The Random Sample Consensual) to finally reject the mismatch. Finally, this paper uses the photos of comet 67P/Churyumov-Gerasimenko to simulate and verify the image matching algorithm for image rotation, illumination variation, Gaussian noise and scale change.

Literature Review

SURF

SURF (Speeded Up Robust Features) has been published by Bay et al. The algorithm has greatly improved the speed of the keypoint extraction and stability of the keypoint. The implementation method is used to integrate the original image and use the Harr wavelet derivative instead of the Gaussian filter to achieve the purpose of speeding up the calculation. At the same time, the Hessian matrix is used to increase the robustness of the feature points. The feature detection process is mainly divided into four steps: Interest Point Detection, keypoint location, determining dominant orientation and generating feature descriptors.

FLANN

Muja et al. [11] proposed *Fast Library for Approximate Nearest Neighbors* (FLANN) in 2009. FLANN matches feature points based on the *KD-TREE*. Firstly, the method constructs a *KD-TREE* structure based on the detected keypoint set. Then, according to the FLANN, the nearest neighbor feature points of the target point are searched from the root along the tree node.

NNDR

Nearest Neighbor Distance Ratio (NNDR) was used by D.G. Lowe for matching SIFT features in [6]. Subsequently, ratio of nearest neighbor to the second nearest neighbor is calculated for each feature descriptor and a certain threshold ratio is set to filter out the preferred matches.

RANSAC

The Random Sample Consensual(RANSAC) algorithm was first proposed by Fischler et al.[12] in 1981. It is an algorithm that calculates the mathematical model parameters of the data based on a set of sample data sets containing abnormal data and valid sample data. In this paper, these anomalous data are mismatched or matches which contain large error. Through RANSAC, a large number of mismatches can be effectively eliminated, resulting in a more accurate match.

Image Matching Strategy in This Paper

The satellite captures the image of target small celestial body on the orbit and extracts the features of the image to form a set of keypoints. The small celestial body is also photographed during the landing of the detector, and the image is extracted to form an another keypoint set of the image. Based on the FLANN matching algorithm, the Euclidean distance is used as the similarity measure to match the keypoints in the two sets. This method use NNDR and RANSAC to eliminate the wrong match and finally output the correct matching result. As shown in Fig.1.

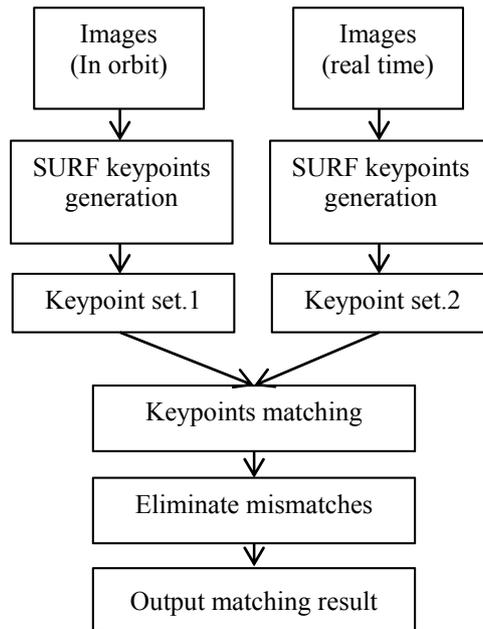


Figure 1. Image matching method

Experiment & Results

During the detector's descent, due to different shooting angles, shooting time and shooting height, real-time images and on-orbit images will produce changes in rotation angle, light illumination darkness, image noise and scale estimation error, thus affecting the extraction of feature points. This paper simulates these four kinds of external interference effects, and experiments on the image matching method. The matching performance is judged by verifying the correct matching number, the correct matching rate, and the total image matching time (Interest Point Detection, keypoint location, determining dominant orientation, generating feature descriptors, feature matching and culling error matching).

The number of correct match divided by the number of total match is defined as the correct match rate. The total matching number is M . The correct matching number is the matching number N after the RANSAC culling error matching, then the correct matching rate P is as following.

$$P = \frac{N}{M} \times 100\% . \quad (1)$$

Experimental Setup

Python3.7 with *OpenCV 3.4.2* has been used for performing the experiments presented in this article. Specifications of the computer system used are: *Intel(R) Core(TM) i5-4200U CPU @1.60GHZ 2.30GHZ, 8.00GB RAM*. In order to verify the validity of the image matching algorithm, experiment with photos of comet *67P/Churyumov-Gerasimenko*. As shown in Fig.2. The image was taken by *Rosetta's Onboard Scientific Imaging System (OSIRIS)* on August 6, 2014. The image was taken from a distance of 80 miles. *Rosetta* is an *ESA* mission with contributions from its member states and *NASA*.

In terms of parameter setting, in the FLANN matching method, the number of KD-TREES is set to 5, the number of recursions is 30. The threshold of NNDR is set to 0.5. The error threshold of RANSAC is 3.

Table 1. Performance under varying scale

σ	Total matches [pair]	Correct matches [pair]	Accuracy rate [%]	Time [sec]
1	2894	2894	100	1.67
0.5	2894	2894	100	1.71
-0.5	1729	1725	99.77	1.69
-1	1729	1725	99.77	1.61

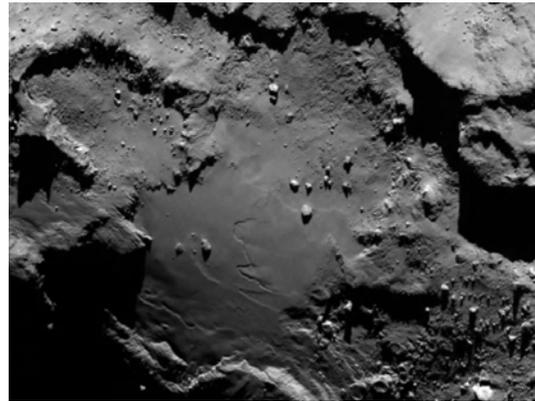


Figure 2. Image of 67P/Churyumov-Gerasimenko

Change in Scale

The Gaussian function is used to convolve the image to change the scale of the image. The two-dimensional Gaussian function is shown in Table 1..

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}. \quad (2)$$

It can be seen from the experimental results that the matching method in this paper is robust to scale changes, can detect a large number of keypoints, and the correct rate of match is very high.

Change in Brightness

This paper uses Gamma Correction to change the brightness of the image. The gamma correction is defined by the following power law expression. The value γ is changed to achieve the brightness change of the picture, and A is a constant.

$$V_{OUT} = AV_{IN}^\gamma. \quad (3)$$

The experimental results are shown in Table 2. Through experiments, it can be verified that the matching method of this paper has strong adaptability to images with obvious illumination changes, can identify a large number of keypoints, and has high matching accuracy.

Table 2. Performance under light change

γ	Total matches [pair]	Correct matches [pair]	Accuracy rate [%]	Time [sec]
0.3	306	302	98.69	2.19
0.5	753	749	99.47	2.17
0.8	2404	2254	93.76	2.16

Table 3. Performance under rotation

α ($^{\circ}$)	Total matches [pair]	Correct matches [pair]	Accuracy rate [%]	Time [sec]
45	494	489	98.99	2.16
90	2937	2936	99.97	1.89
180	2808	2807	99.96	1.79
320	494	486	98.38	2.2

Change in Rotation

The image is rotated at different angles, where the image is rotated 45°, 90°, 180°, and 320°, respectively. Record the number of rotation is α° . It can be seen from Table 3. That the image matching method is still excellent in the case where the angle changes significantly, and a large number of keypoints can still be recognized while ensuring a high correct matching rate.

Adding Gaussian White Noise

The probability density of Gaussian noise follows a Gaussian distribution (normal distribution), as shown below, with two parameters, the mean μ and the standard deviation σ . Change μ and σ to apply different Gaussian white noise to the image.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right). \quad (4)$$

Table 4 .Performance under Gaussian white noise

μ	σ	Total matches [pair]	Correct matches [pair]	Accuracy rate [%]	Time [sec]
0.2	0.004	842	829	98.46	2.77
0.2	0.008	448	444	99.11	3.2
0.2	0.01	389	388	99.74	3.21
0.1	0.004	863	856	99.19	2.71
0.1	0.008	465	413	88.82	3.16
0.1	0.01	383	332	86.68	3.32

The experimental results are shown in Table 4. The results show that the matching method still performs well under different Gaussian noises, and it can still accurately identify and correctly match a large number of keypoints.

Multifactorial Influence

Apply gamma correction, rotation, scale change, and add Gaussian noise to the test image. The specific parameter settings are shown in Table 5.

Table 5. Parameter setting

Gaussian noise		Gamma correction	Rotation	Scale
μ	σ			
0.1	0.01	0.5	45	-0.5

Table 6. Performance under multifactorial influence

Method	M [pair]	N [pair]	Accuracy rate[%]	Time [sec]
This paper	43	41	95.35	2.18
SIFT	399	396	99.25	5.15

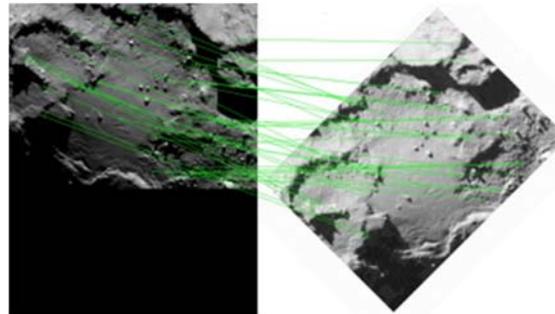


Figure 3. Image matching result under comprehensive influence

The validity of the matching method can be verified from the Table 6. And the Fig 3. Under the influence of the rotation, light change, the image noise and the scale, the matching algorithm can still identify the significant effective feature points and achieve high accuracy matching. Although the matching method in this paper detects fewer feature points than SIFT, the accuracy is reduced, but the accuracy is still high. More importantly, the matching method in this paper takes less than half of the time of SIFT.

Conclusion

Since the image matching technology is the key technology to realize the accurate landing of small celestial detectors, this paper uses SURF feature detector as the basis to quickly match through FLANN, thus reducing image matching time, improving real-time performance, and eliminate mismatch through NNDR and RANSAC. Finally, it is verified that the matching method is highly robust in the background of detector attachment, which can efficiently and accurately identify and match a large number of effective feature points, thus providing a large amount of effective information for the small celestial landing process. However, the matching method still has a lot of room for improvement. It can analyze and debug various parameter settings, research and improve the feature point detection algorithm and matching algorithm, so that the image matching technology can achieve the best performance under the background of small celestial body attachment.

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