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Crater Detector using Haar-Like Feature for Moon Landing System

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Abstract– A crater detector for moon landing system using Haar-Like feature is proposed. This proposal assumes that it is applied to SLIM(Smart Lander for Investigating Moon) project aiming at the pin-point landing to the moon surface. In the SLIM project, 400kg-class lander is assumed, therefore, high-performance computers for image processing cannot be equipped. The image processing is going to realize high-speed processing by using the FPGA circuit for parallel computation. Furthermore, as the crater detection method, we try to apply a object recognition method using Haar-Like feature. It seems that the Haar-Like feature is suitable for rapid object detection based on distribution of the light and shade of the image, such as the surface image of moon.

In this paper, the precision and rapidity of the crater detection using Haar-Like feature is shown by computer simulation.

1. Introduction

Recently, JAXA(Japan Aerospace Exploration Agency) examines the SLIM(Smart Lander for Investigating Moon) project[1] aiming at the pinpoint landing to the moon surface. One of the success criteria is defined to guide the lander to the target point within 100 meters with detecting and avoiding the obstacles autonomously. Therefore, a technique about autonomous navigation subsystem based on the image processing becomes the important element.

In the space, a change of the temperature and the influence of the radiation are big. Furthermore, a lander of the 400kg-class is assumed in the SLIM project, therefore it is difficult to equip and use high-performance computers which is usually usable on ground. A method to solve this problem is to use a small-scale computer with an exclusive hardware such as FPGA (Field Programmable Gate Array), and to adopt the algorithm that parallel computation is possible.

In this paper, a crater detection using Haar-Like feature[2,3] is proposed to realize a navigation subsystem. The Haar-Like feature detects a local light and shade pattern. By using plural feature detections, various object recognition can be realized.

Besides, various methods for detecting the crater from the surface image of moon have been proposed[4-6]. In the conventional method, the edge based method has been applied to the crater detection, high rate of correct detection is shown, however, much erroneous detection also occur. In the technique with Haar-Like features, the crater detection system can learn based on both the positive and negative images photographed by various spacecrafts beforehand, so the erroneous detection can be reduced in comparison with the conventional methods. For the learning method, AdaBoost[2,3,7] learning algorithm that is one of the supervised machine learning method is adopted.

On the other hand, methods using boosting algorithm have been proposed[5,6], however, the detection rate for unlearned images provided by various spacecrafts is not evaluated.

In this paper, we report the crater detection using Haar-Like features and AdaBoost learning algorithm, and examine an important matter in the learning processing using images provided by various spacecrafts.

2. Haar-Like Features

Fig. 1 shows the examples of the Haar-Like features. Each feature shows the shape of the detection window that detects local light and shade properties in the image. Based on the characteristics of the object should be detected, the appropriate features are chosen and used.

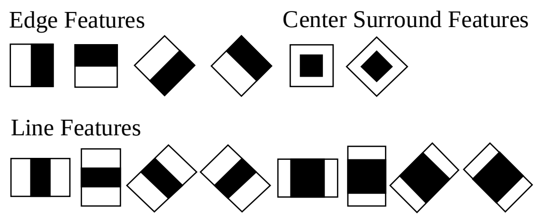

Fig. 1. Examples of the Haar-Like features.

On the calculation of the Haar-Like feature, the sum of the brightness value of the pixels included in the white rectangle is subtracted from the sum of the brightness value in the black rectangle. Finally the calculated results are judged by the machine learning.

In a object detection, a detection window is scanned by the whole image, therefore, a lot of addition of the brightness value is required. To carry out this calculation rapidly, an integral image is usually calculated beforehand.

$$I(i,j)=\sum_{x=0}^{i}\sum_{y=0}^{j}v(x,y)\,, \tag{1}$$

where $v(x,y)$ is the brightness value of the pixel and $I(i,j)$ is the integral value of the image. By using the method, the sum of the detection window can be obtained by Eq. (2) rapidly without depending on the rectangular size.

$$\sum_{x=x_1}^{x_2}\sum_{y=y_1}^{y_2}v(x,y)$$
$$=I(x_2,y_2)-I(x_1-1,y_2)-I(x_2,y_1-1)+I(x_1-1,y_1-1) \tag{2}$$

3. AdaBoost Learning Algorithm

The detector using one detection window is called "Weak Detector", the detection rate using one detection window is low. However, when the weak detectors are connected to the cascade structure[8], a strong detector can be realized. As a method to constitute a strong detector by determining a kind and the number of the weak detectors to connect to cascade, AdaBoost learning algorithm[2,3,7] is used.

AdaBoost learning algorithm is a kind of supervised machine learning algorithm, and is used for training the classifier using weak detectors. For the learning, both "Positive Images" and "Negative Images" are used. The positive images are the images that should be detected, and the negative images are the images that should not be detected. Needless to say, the positive images in this study are crater images, however, the negative image can adopt any image besides a crater image.

Besides, the number of positive and negative images are set to 7000 and 3000, respectively. Therefore, the learning time by AdaBoost learning algorithm is needed the above for a several days when the personal computer is used. However, the additional learning of images obtained newly is not required, so the long learning time does not become a problem on the detection process.

Moreover, the improvement methods of this boosting technology are already proposed[9], we are going to examine the more suitable learning method as needed.

4. Learning of the Images

As the learning of the crater images using AdaBoost learning algorithm, the images that are provided by "Apollo" are first used in this study. The examples of the positive images used in this study are shown in Fig. 2. In the learning, the oval-shaped crater is not learned because the direction of camera is revised by controlling the posture of spacecraft and is kept toward just below.

These images are the crater images clipped out by big photographs. The size of the clipped crater image varies, however, the size of image is all resized and unified to 24x24 pixels for learning.

In the images shown in Fig. 2, the direction of the shadow in the crater is all the same. When only these images are used for learning, only craters having the

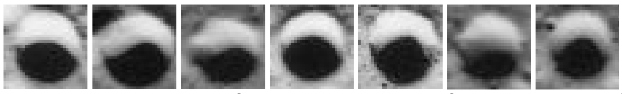

Fig. 2. The examples of the positive images for the learning of the crater detector. These are the clipped images from big photographs. The images are resized to 24x24 pixels, and the direction of shadow is unified.

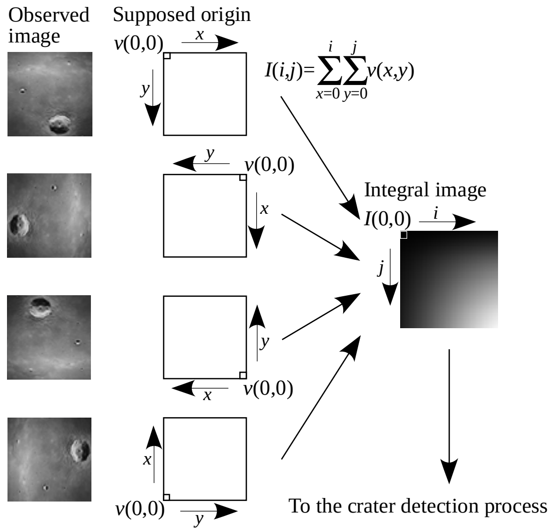

Fig. 3. Modification of the origin of the image and the direction of axis for corresponding to the direction of shadow in the crater. The appropriate origin and the direction of axis are generally chosen based on the flight plan of spacecraft. If a trouble occurred to the spacecraft, all directions are tried.

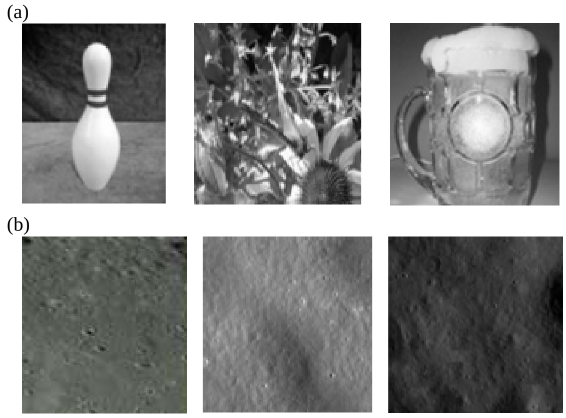

Fig. 4. The examples of the negative images. (a) is the samples of the random images that are well used for face detection, and (b) is the samples of the surface images of moon that does not include a crater should be detected.

shadow with the same course can be detected. To correspond the direction of the shadow flexibly, the crater images are rotated, and are added to the positive images.

However, when the crater images are rotated at π[rad], and used for learning, the mountain should be misrecognized as the crater based on the direction of the shadow. Furthermore, if the origin of the observed image and the calculation direction of the integral image are changed as shown in Fig. 3, the range of rotation angle of image that should be learned beforehand becomes

Table 1. Condition of the positive and negative images for learning the crater detector.

Name	Rotation range of the positive image	Kind of the negative image
Detector A	+0.5π ~ -0.5π	Fig. 4(b)
Detector B	+0.3π ~ -0.3π	Fig. 4(a) and (b)
Detector C	+0.3π ~ -0.3π	Fig. 4(b)

+0.25π[rad] ~ -0.25π[rad] at least. In this study, two kinds of range shown in Table 1 are tried to adopt to the learning.

Next, the images shown in Fig. 4(a), (b) are used for the negative images. Fig. 4(a) shows the random images that are well used as the negative images for face detection, and Fig. 4(b) shows the surface image of moon that does not include a crater should be detected. In this study, (1) the case that both Fig. 4(a) and (b) are used for the negative images, and (2) the case that only Fig. 4(b) is used for the negative image are tried, respectively. Namely, the detection experiments are performed by the combination of the condition shown in Table 1.

5. Experimental Examples of the Crater Detection

In this chapter, the implemented crater detector is evaluated versatilely.

5.1 Detection Rate

First, the detection rate of the proposed crater detector is evaluated. On the learning of the crater detector, the images provided by "Apollo" are used, and the unlearned images by "Apollo" is used for the crater detection. Furthermore, the conditions shown in Table 1 are used for learning of the positive and negative images. The experimental examples are shown in Table 2.

As the table shows, Detector C shows the best result. In the case of Detector A, the range of rotation angle of image is too wide, as the result, the detection of the crater is confused with a mountain. Moreover, in the case of Detector B, it seems that the random images are inappropriate as the negative images. Namely, the use only for the negative images that should be rejected directly derives a good result. Fig. 5 shows a sample image of the crater detection using Detector C. As the figure shows, a desirable detection result is provided.

5.2 Computational Time

In this section, the computational time is evaluated by changing the analysis condition variously. The conditions should be changed here are the minimum size of the crater detection and the enlarged rate of the detection window. The combination of setting and the experimental results are shown in Table 3. The Detector C is adopted as the learning condition, and the image shown in Fig. 5 is analyzed.

As the table shows, the computational time is improved by a change of the condition. If the only characteristic crater should be found as the landmark, the condition that shows highest speed can be adopted.

6. Discussion

When the images provided by "Apollo" are adopted to learn the detector, a good detection result is obtained if the crater detection is carried out for the unlearned images by "Apollo". The crater detection using Haar-Like feature can improve the ability by learning using AdaBoost, so it is thought that the detection for an unlearned image is possible to some extent.

However, we have confirmed that the detection rate turns worse when the unlearned images provided by the other spacecrafts, such as "Kaguya" and "Lunar Orbiter",

Table 2. Experimental examples. The crater detector is learned by the images provided by "Apollo", and the unlearned images by "Apollo" is analyzed. The minimum size of crater detection and the enlarged rate of detection window are set to 24x24[pixels] and 1.05[times], respectively.

Name	Rate of the correct detection	Rate of the false detection
Detector A	35.0%	11.4%
Detector B	67.8%	6.3%
Detector C	89.3%	8.6%

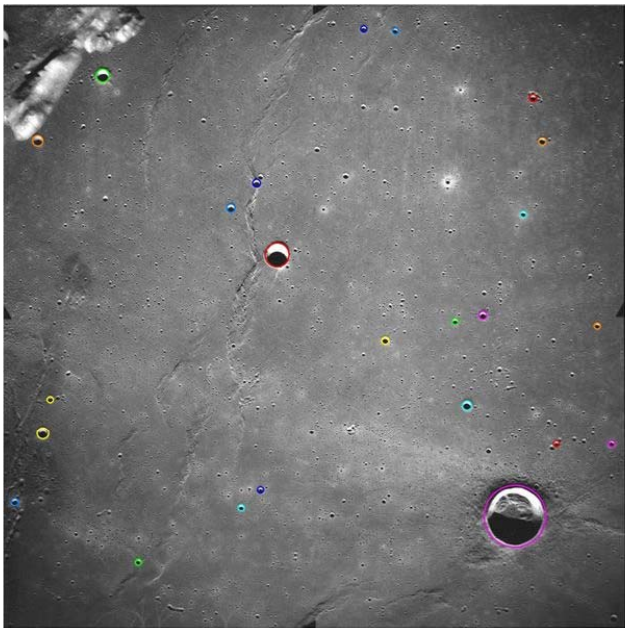

Fig. 5. Experimental example of the crater detection. This figure shows an example using the condition of the Detector C. The size of the whole image is 2400x2440 pixels.

Table 3. Relation between the condition for the crater detection and the processing time on the computer simulation. The image shown in Fig. 5 is analyzed. The condition of Detector C shown in Table 1 is adopted for learning.

Enlarged rate of the detection window [times]	Minimum size of the crater detection [pixels]	Processing time [ms]
1.05	24x24	417.4
1.05	30x30	292.6
1.05	40x40	189.7
1.10	24x24	223.5
1.10	30x30	137.8
1.20	40x40	61.9

Table 4. Rates of correct and false detection. Detector C is learned by the images provided by "Apollo". Detector Ca is learned by the images provided by "Apollo" and "Kaguya". The unlearned images provided by "Kaguya" and "L. O. (Lunar Orbiter)" are analyzed.

Name	Rate of the correct detection		Rate of the false detection	
	Kaguya	L. O.	Kaguya	L. O.
Detector C	4.0%	45.5%	42.0%	22.7%
Detector Ca	37.8%	56.1%	55.0%	23.5%

because the characteristics of the images are different greatly(Table 4). Of course, the improvement of the detection rate can be expected by additional learning of the images by the other spacecrafts more, however, it is not guaranteed whether the system can support an image got by the actual spacecraft. Therefore the some kind of normalization method of image is finally required.

Then, we are going to adopt the PCA(Principle Component Analysis) and ICA(Independent Component Analysis)[10] as the preprocessing of the observed image. PCA is the method that calculates the chief component of image based on the eigenvalue and eigenvector of the covariance matrix of the images. By extracting a chief component, the object recognition that is not influenced by the brightness of image is possible[10].

Besides, ICA is the method to disintegrate to an independent component each other by calculating the inverse system of the mixed process of components. In the study that applied the method to the face recognition, the parts of eyes and a nose can be broken down from a target image[10]. If this technique is applied to the crater detection, the main body of crater and the shade are separated, and a more robust detection system may be realized.

7. Conclusion

In this paper, we have confirmed that a rapid and practical crater detection can be implemented by using Haar-Like features and AdaBoost learning algorithm. Moreover, the suitable setting of the positive and negative images for realizing a crater detector with high detection rate has been shown based on the experimental results.

Besides, the obtained crater detector can correspond to the unlearned images provided by the various spacecrafts to some extent, however, the ability of the crater detector may become insufficient when the properties of the unlearned images are extremely different. Therefore, it is thought that the normalization of image properties is necessary.

We are going to examine the normalization of image using PCA and ICA method as mentioned in Chapter 6. However, the computational costs of these methods are high, so the device of both hardware and software for image processer is necessary to perform a real-time operation. We will report the suitable method for the moon landing system using PCA and ICA in future.

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