Crater Detection Robust to Illumination and Shape Changes using Convolutional Neural Network*

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As a vast amount of data with respect to the moon and Mars is collected, exploration missions are shifting to the next step, the aim of which is a precise landing on a predetermined target. A promising technology for precision landing is terrain relative navigation (TRN), which collates landmarks detected from images and maps of landmarks. Crater detection is one of the essential technologies for TRN. A problem in detecting craters is the apparent change in craters due to illumination conditions. Another problem is the change in shape due to crater degradation. We propose a novel crater detection method based on combining a support vector machine (SVM) and a convolutional neural network (CNN) to make detection performance robust against apparent change. In the linear SVM, gradient images of a crater image dataset are learned. The learned classifier is then used to calculate the objectness score for region proposal. Next, the CNN identifies the image of the proposed region as to whether or not it is a crater. Our results show that the proposed method can detect craters in a wide range of illumination and shape conditions, and has better average precision than traditional crater detectors.

Key Words: Crater Detection, Terrain Relative Navigation, Support Vector Machine, Convolutional Neural Network

Nomenclature

\( FN \): false negative  
\( FP \): false positive  
\( g \): image gradient  
\( O \): objectness  
\( s \): weighting factor  
\( TN \): true negative  
\( TP \): true positive  
\( w \): trained coefficient of linear SVM

Subscripts

\( i, j \): position in image  
\( k \): layer in image pyramid

1. Introduction

Accumulated scientific knowledge of interplanetary bodies collected by past science missions has led to current exploration missions being planned for in-situ observation and landing at a predetermined site. The landing site needs to be highly valuable to satisfy science requirements and also be safe enough to meet engineering requirements simultaneously. Current landers do not have the capability to land precisely on the surface of interplanetary bodies with gravity because of current landing technology limitations. Therefore, improving landing accuracy is required to expand the possible areas to explore, as well as realizing highly valuable exploration missions. Precise landing missions where autonomously landing on a planetary surface within 100 m of a predetermined site require a novel approach for the entry, descent and landing (EDL) technique. One of the solutions for precision landing is terrain relative navigation (TRN) technology. TRN is an essential technology for pinpoint landing and consists of two main phases: feature detection and feature matching. Firstly, we need to know the precise position of the spacecraft. In general, internal sensors and ranging from the Earth are used to determine the position of the spacecraft, but this does not meet the accuracy required for pinpoint landing. Therefore, the spacecraft needs to extract features of the surface of the target body using data obtained by sensors, and estimate its own precise position by matching it with a map. From this point of view, crater detection, which is the subject of this paper, is the first part of TRN. Then, following the crater detection process, the crater matching process\(^1,2\) is performed to obtain the precise position of the spacecraft and to realize a pinpoint landing.

A representative method of TRN is optical navigation using extracted terrain features from images captured by a navigation camera.\(^1–6\) Craters distributed throughout the lunar surface are salient features, and their locations and sizes are observable in scientific data collected by lunar orbiters. Crater maps can be generated in advance from the data, and the position of the lander can be estimated by collating the crater maps with processing results of images captured during the powered descent phase. High-contrast terrain is also used as terrain features in TRN on Mars.\(^7\) Such TRN technologies using captured images are called vision-based navigation. In the field of cruise missiles, terrain can be di-
rectly observed using active sensors such as an altimeter and flash lidar for localization. However, using these technologies is currently difficult for landing missions because of constraints such as sensor power consumption and usable altitude limitations.

Apparent changes in landmarks such as craters are an important problem when it comes to vision-based navigation during landing missions. Craters are used as terrain landmarks in many vision-based navigation methods for lunar precision landing, but their appearance can change significantly based on surrounding conditions. Illumination condition is one of the causes of apparent changes, as shown in Fig. 1. The appearance of a crater changes significantly due to illumination conditions. When the incident angle is extremely high or low, it may be hard to detect craters in images. This creates a limitation in the time range for landing missions using vision-based navigation. Another problem is the difference in shapes of craters, as shown in Fig. 2. The reasons for the difference in crater shape include degradation and differences in the crater-formation process. Generally, new craters often have a clear appearance, while degraded craters often have an unclear shape. In addition, large craters generally form complex craters with a shallow bottom in contrast with diameter. Unlike simple craters, such craters are less likely to form clear shadows, making crater detection difficult. It is easy for humans to identify them even if there are these kinds of craters, but it becomes a problem if landers need to detect these craters autonomously.

Many studies have been conducted in the fields of precision landing and crater counting such as techniques for detecting salient topography features such as craters on the surface of the moon and Mars. Cheng et al.⁸ proposed a crater detection method using edge detection and edge grouping with elliptical fitting for precision landing on Mars. Okada et al.⁹ used principal component analysis based on the crater images obtained by various moon orbiters, and the first principal component is used as a template to detect craters in a captured image. All of these methods mainly target craters with clear edges and shadows. Emami et al.¹⁰ used convex crater shadows obtained from edge information, and proposed regions are processed using a convolutional neural network (CNN) to identify craters and non-craters. This method is resistant to variations in crater surface characteristics since it is trained on CNN. However, it is difficult to use when there are large crater shape changes because of assumption of shadow shape. Li et al.,¹¹ Silburt et al.,¹² and Roy et al.¹³ proposed crater detection based on deep learning, but computational cost is too high to implement these methods in onboard computers because they use a large-scale neural network for the purpose of crater counting.

The crater detection method proposed in this paper is based on CNN and a support vector machine (SVM), which are generally used for object detection in machine learning and deep learning in order to understand the apparent change in landmarks. First, candidate regions of craters are proposed from images captured using the linear SVM learned from a crater dataset. The proposed regions are input to the network using CNN, which identifies whether or not the regions are crater or non-crater. The computational cost for linear SVM is small because it is used as a filter to calculate the objectness in a captured image. Additionally, region proposals greatly reduce the amount of input data to CNN, which requires higher computational cost.

A generated crater dataset is given in Section 2. Details of our proposed crater detection method are described in Section 3. Results for crater detection are given in Section 4. The results show that our approach has high crater detection performance under a wider range of conditions compared to the conventional method. Our conclusion is given in Section 5.

2. Crater Image Dataset

To learn the robust features of craters through supervised learning with SVM and CNN, a large training dataset of crater images and negative images with a wide range of illumination and shape conditions is required. Trained SVM is then used for region proposal, and CNN is used to identify whether or not the proposed region is crater or non-crater. Training crater images are extracted from the Kaguya (SELENE) High-Definition Camera System (HDTV) Data Archive.¹⁴ The crater dataset created for supervised learning of SVM and CNN includes about 30,000 training images. Data augmentation methods such as horizontal flip are used to generate a large dataset. The craters in this dataset include various shapes under various illumination conditions to make it robust to these kinds of variations. For example, the sun elevation of some crater images in the dataset is high so that the shape of the shadow is indistinct, as well as some crater images are taken with low sun elevation and only the crater rim is visible. Another dataset includes new craters with clear rims and craters with indistinct rims due to degra-
Crater images for the training dataset were captured at perpendicular angles and slanted angles, and were selected from the original HDTV image data to detect craters from images captured under various attitude conditions. Figure 3 shows examples of the crater dataset created. A negative dataset was cropped randomly from HDTV images and regions containing space or craters were deleted. As shown in Fig. 3, the positive dataset includes craters with shallow bottoms and indistinct edges, clear rims and shadows, low sun elevation with only the rims visible, and high sun elevation with indistinct shadows. Crater datasets including a large number of crater images under such wide conditions are essential for supervised learning. In other words, it is possible to obtain robust features against a wide range of conditions using this type of dataset.

3. Crater Detection

This section describes the proposed crater detection method that combines a region proposal using SVM and crater classification using a neural network with CNN. First, we describe the overall system of our crater detection method. The region proposal and crater classification are then explained.

3.1. Crater detection system

In general object detection methods such as R-CNN, \(^{15}\) region proposal is the first step and a candidate region image including a potential area for an object is input for object classification, such as CNN. Simple sliding window and selective search \(^{16}\) are general approaches for region proposal. Since the computational cost of CNN is relatively high, it is desirable that the proposed regions for objects that are input to the CNN are as small as possible while covering all objects. Although the sliding window is the simplest approach, the amount of inputs for the proposed region could be very large. Selective search is a better approach to reduce the amount of input data, but is not suitable for images of the lunar surface that have change little in color. Our method uses linear SVM for region proposal, and candidate regions for objects are input to CNN, thereby achieving robust crater detection against illumination conditions and shape changes while reducing computational cost.

Figure 4 shows the proposed crater detection architecture. Coarse crater detection is performed using the input lunar surface image obtained using linear SVM. Trained coefficients of linear SVM are then used as an image filter to calculate the objectness score from an image of the surface. Proposed regions based on the objectness score, which means the possibility of being a crater, are input to the subsequent CNN to classify if it is a crater or not. Finally, non-maximum suppression is applied to the classification results.

3.2. Region proposal using linear SVM

The computational cost for a region proposal using lunar surface images needs to be as low as possible because the spacecraft onboard processor has minimal computational resources, and it is difficult to process a large number of data. The simplest approach to obtain a candidate region for an ob-
ject is the sliding window, but using this approach for crater detection is not realistic since a large number of candidate regions could be input to CNN. Calculating objectness of the regions obtained using the sliding window is a better approach to reduce the amount of data input for image processing in CNN. The variance of intensity information and difference between the maximum and minimum value of intensity are possible approaches to calculate the objectness in each window, but it is difficult to distinguish craters and the unevenness of the lunar surface. In this section, we describe our region proposal scheme.

3.2.1. Linear SVM training

In recent research on object detection, a method to calculate its objectness from normalized gradient images is proposed.17) Our research targets detection of craters where it is not possible to obtain edges as clear as artifacts. However, it appears that some edge information can be obtained from normalized gradient images of craters. Figure 5 shows normalized gradient images of a crater dataset. The figure shows that craters have a high gradient that is circular in contour due to the change in intensity value at the crater rim and in its shadow. On the other hand, a negative dataset has random values since the negative images are randomly cropped from images of the lunar surface. Therefore, in our approach, normalized gradient images obtained from captured lunar surface images are trained to linear SVM, and CNN classifies input regions extracted based on their objectness, which is calculated using gradient images and trained SVM. This approach results in low computational cost and highly precise crater detection. The size of the gradient image to be trained in linear SVM is 15 × 15 px taking into account both the computational resources of the spacecraft and classification accuracy results under several SVM sizes.

Figure 5 shows the coefficients of linear SVM trained with normalized gradient images generated from a crater dataset. As a result of training, we found that trained SVM has the feature of providing crater contours. This linear classifier constructed using linear SVM can be used as an image processing filter to calculate the objectness score for a region proposal. Since the linear classifier has a low computational cost, candidate regions for craters can be extracted from a whole lunar surface image in a short processing time.

3.2.2. Region proposal scheme

The flow of region proposal using the trained linear SVM model is as follows. First, image pyramids are generated from the captured 512 × 512 px lunar surface image. The image pyramids include sizes of 512 × 512, 256 × 256, 128 × 128, 64 × 64 and 32 × 32 in order to detect multiscale craters. A gradient image is generated applying the Sobel filter to generated image pyramids. Coefficients of linear SVM trained using normalized gradient images are collated with the gradient image of the whole lunar surface image to obtain the objectness map. However, proposed regions that are extracted simply using the objectness score may not be properly represented as large, degraded craters have small gradients and low objectness scores. This results in only small, distinctive craters being detected. Small craters are not included in crater maps when used at high altitude because small craters cannot be observed from high altitudes. From this point of view, it is more advantageous in the later stage of the crater matching process to detect a large number of large craters. Therefore, we corrected the objectness score according to the size of the proposed region to detect large craters precisely. Since objectness scores tend to be smaller when crater size is large since most large craters have indistinctive rims, the score is corrected with a coefficient proportional to the crater size. This reduces the variation in the crater detection results depending on the crater size. The corrected objectness score is given using the following equation.

\[ O_{ij}^c = \left( w \cdot g_{ij}^c \right) s^c, \]  

(1)

The correction factor \( s^c \) is set to 1 for the largest crater, and for the other craters it is set to be inversely proportional to the crater size. Therefore, a large crater with indistinctive shape also has a high objectness score, and can be detected as a candidate region of craters in the region proposal process.

Candidate regions for craters are extracted as local maxima of objectness maps. The top 500 local maxima are selected to extract a sufficient number of candidate crater regions. The gradient images of the lunar surface images and
objectness maps calculated by filtering with trained linear SVM. Figure 7 shows the gradient images and objectness maps of each scale. A large gradient image has objectness peaks for small craters, while a small gradient image has objectness peaks for large craters. The candidate regions of multi-scale craters can be extracted by calculating the objectness from gradient images of multiples sizes with the same linear SVM.

3.2.3. Performance evaluation of region proposal

Figure 8 shows the receiver operating characteristic (ROC) curve of the classification results for the crater dataset. We compared the classification performance of our proposed method, linear SVM with intensity information of the original image instead of the gradient image, and other basic objectness scores. “Variance” in Fig. 8 is intensity variance in the local window, and “Max-Min” is the difference between maximum and minimum intensities in the local window. The ROC curve shows how the false positive rate and true positive rate change when the threshold value is changed with respect to a score such as objectness and the other index. The closer the area under the curve (AUC) is to 1, the higher the classification performance. The false positive rate and true positive rate are given as follows.

\[
\text{False Positive Rate} = \frac{FP}{FP + TN} \quad (2)
\]

\[
\text{True Positive Rate} = \frac{TP}{TP + FN} \quad (3)
\]

In a crater detection problem, \(TP\) represents the number of samples that correctly identified a crater as a crater, \(FP\) represents the number of samples that incorrectly identified negative data as a crater, \(FN\) represents the number of samples that incorrectly identified a crater as negative, and \(TN\) represents the number of samples that correctly identified negative as negative.
Figure 8 shows that linear SVM with gradient images can distinguish craters more precisely than the other methods. Linear SVM trained from gradient images has the highest classification performance, as opposed to the low performance by other indexes such as variance in a sliding window.

From these results, we found that using gradient images for objectness calculation is appropriate for crater classification. Classifying craters from original intensity images is difficult because the appearance varies greatly depending on illumination conditions and the shape of the craters. On the other hand, contour information, which is a common feature of craters, is extracted from gradient images.

3.3. Crater classification using CNN

The proposed regions of craters extracted using SVM are input into a neural network that classifies input image as crater or non-crater. Although the amount of input image data for crater classification using CNN is significantly reduced when applying region proposal using SVM, a neural network generally requires high computational cost. Especially, it is not realistic to use a deep neural network such as AlexNet, which is mainly used for deep learning in terms of onboard memory and processing time, if we consider implementation using onboard computers in the spacecraft. In our approach, the neural network to classify craters consists of one convolution layer, one max pooling layer, one fully connected layer, and one softmax layer as shown in Fig. 4, which can be implemented with limited resources. The number of training parameters in AlexNet is about 60 million, while our network has about 6000 parameters, so it is possible to calculate using a limited memory. We used the ReLU layer as the activation function. The image corresponding to the candidate region proposed using linear SVM is unified to 28 × 28 px and used as data input into the neural network. Since the moon surface has little color information, the capture image is assumed to be monochrome, so the number of channels of the input layer is one. The output layer is two-class classification because the neural network needs to classify whether the input image belongs to crater or non-crater. The image dataset shown in Fig. 3 is used for training the neural network, and dataset is divided into 3:1 for training and validation. The neural network is trained with 50 epochs, a learning rate of 0.0001, and validation accuracy of 99.73%.

4. Simulation Results

This section describes the simulation results of our crater detection method.

4.1. Validation dataset

In order to verify robustness against changes in illumination conditions and crater shapes, we prepared a validation dataset of lunar surface images from the SELENE data archive, which includes craters under ideal illumination conditions, poor illumination conditions, and craters that have ideal shapes and degraded shapes. Ground truth craters were extracted manually from 512 × 512 px images.

The targeted crater size for detection is 10 px or more. General TRN technologies using craters as landmarks require an adequate number of craters for crater matching with a map. Therefore, craters that are too small are not essential for crater matching using a map.

To compare crater detection performance in an object detection scheme, we used detected bounding box region accuracy as the performance index, not the center position of craters.

4.2. Conventional method

In this simulation, our method was compared with the crater detection method developed during the Smart Lander for Investigating Moon (SLIM) project at Japan Aerospace Exploration Agency (JAXA). The vision-based navigation developed in the SLIM project applies principal component analysis (PCA) to a large number of crater images extracted from past lunar orbiters, and the first principal component is used as a template image to detect craters from a captured lunar surface image. Since intensity images are used to extract the principal component, the template image is rotated depending on the sun azimuth, which is known in advance to obtain invariance against the azimuth. This method does not target the detection of multi-scale craters, but craters with a size of about 15 × 15 px. Therefore, in this simulation, the same template image was used to image pyramids to detect multi-scale craters from lunar surface images.

Since our method uses image datasets that include craters under a wide range of sun azimuths and elevations, it has higher robustness against illumination changes than the conventional method. In addition, our method does not need information about illumination conditions to detect craters because contour features are extracted using gradient images in the first step.

4.3. Crater detection results

The proposed method and the conventional method were compared for crater detection performance using the validation dataset described in Section 4.1. Figure 9 shows the results for crater detection. The green squares in the figure indicate craters that were detected correctly, and the red squares indicate craters that were misrecognized. We divided performance results according to illumination conditions and shape changes, which means sun elevation and crater size, respectively, and then we compared the average precision (AP) of each method. Table 1 shows the comparison of AP for each method. AP is an object detection performance index expressed by precision and recall, which are given using the following equations.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (4)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} = \text{True Positive Rate} \quad (5)
\]

Precision represents the probability that the input data is positive when it is classified as positive, which means input data is recognized as an object. In crater detection, it represents the probability that a crater is identified correctly when the input data is classified as a crater. Recall represents the probability that the detection system detected ground truth
craters correctly. The AUC of the precision-recall curve, in which precision is the vertical axis and recall is the horizontal axis when plotting from the detected crater with highest score, represents AP. AP close to 1 means higher performance in crater detection.

As shown in Fig. 9 and Table 1, both methods have similar performance in the case of good conditions such as appropriate sun elevation (approximately 30 deg) and small-sized craters. On the other hand, when large-sized craters that are not targeted in the conventional method are included as crater detection targets, the AP is 0.483 for the conventional method, whereas it is 0.713 for our method. This means better crater detection performance is achieved under a wide range of shapes. This is because training the neural network with crater datasets including various craters enables robust detection, from small-sized and clear-shaped craters to large-sized, complex-shaped and indistinctive craters. Furthermore, comparing the AP under a wide range of sun elevation conditions, the conventional method is 0.138 and our method is 0.530. From these results, we found that our approach achieves better performance under a wider range of conditions than the conventional method.

5. Conclusion

We proposed a novel crater detection method that combines region proposals with linear SVM and crater classification with CNN to realize robustness against changes in illumination conditions and the shape of craters. Craters are salient landmarks on the lunar surface, and crater detection is a key technology for terrain relative navigation to realize precision landing on planetary bodies. The SELENE HDTV data archive was used to create crater image datasets to train the SVM and neural network. Simulation results using real images captured of the moon shows our method can detect craters under a wide range of illumination conditions and
various crater sizes, and has better crater detection performance than the conventional method. Crater detection is the prior stage performed before crater matching, and we showed crater-based optical navigation has the possibility of being used, even in severe areas where the sun elevation is very low, such as polar regions, by combining it with the crater matching method.

However, the overall computational cost increases when using a neural network. Although our method applies a very small network using only one convolution layer, one max pooling layer, and one fully connected layer, it is necessary to evaluate the mountability on edge devices such as FPGA and the processing time as issues for future work.

In addition, crater detection results show false detection at crater rims. This is because the crater datasets created in this study do not include hard negative data such as images including crater rims. Hard negative mining is another issue for future work to improve crater detection accuracy. Furthermore, crater matching, which is the latter part of TRN, requires the crater center position, not only the bounding box position. To further improve the accuracy of crater detection, additional network such as bounding-box regression\(^{1(5)}\) should be added to the latter stage of the proposed network to estimate the precise position of the crater center.

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