Intelligent Detection and Classification of Craters on Terrestrial Planets Based on YOLOv5 Postprint

Authors: Xutong Yuan, Li Xizhi

Date: 2026-04-08T11:05:47+00:00

Abstract

This study proposes an improved intelligent crater detection model based on YOLOv5 and constructs a dedicated crater dataset for training. To meet the detection requirements for craters of different scales, the study improves the model' s network structure by adding a small-scale feature extraction module and optimizing the feature fusion method. Experimental results demonstrate that the mean Average Precision (mAP@50) of the improved model on the crater dataset increased from 79.2% to 81.2%. This result is equivalent to a precision improvement of nearly 2% brought by adding approximately 100 training images, enhancing the recognition rate of small-target craters while providing crater classification functionality. It holds significant application value in few-shot detection tasks where the volume of training data is small. Compared with the current mainstream open-world object detection foundation model DINO-X, the improved model shows a significant advantage in crater recognition accuracy and exhibits good robustness for recognition under different lighting conditions. This research provides an important reference for real-time crater detection and related tasks, demonstrating its potential application value in deep space exploration missions.

Full Text

Intelligent Detection and Classification of Terrestrial Planetary Craters Using YOLOv5

Yuan Xutong[1,2], Li Xizhi[1] 1. Shanghai Astronomical Observatory, Chinese Academy of Sciences, Shanghai 200030, China 2. School of Astronomy and Space Science, University of Chinese Academy of Sciences, Beijing 100049, China

Abstract

Impact craters are among the most significant geomorphological features on the surfaces of terrestrial planets. The statistical analysis of their number, size, and distribution is of great importance for determining the age of planetary surfaces, analyzing geological evolution, and selecting landing sites for deep space exploration missions. This paper proposes an improved intelligent detection and classification method for terrestrial planetary craters based on the YOLOv5 (You Only Look Once version 5) deep learning framework. By constructing a multi-source planetary crater dataset and optimizing the network architecture —specifically by incorporating small-scale feature extraction modules and optimizing feature fusion mechanisms—we achieve rapid and accurate identification of craters across varying scales. Experimental results demonstrate that the improved model increases the mean Average Precision (mAP) from 79.2% to 81.2%, a performance gain equivalent to adding approximately 2,000 training images. The model significantly enhances the recognition rate for small-scale craters and provides robust classification capabilities. Compared to mainstream general-purpose models like DINO-X, our model exhibits superior accuracy and maintains strong robustness under varying lighting conditions, providing an efficient technical tool for automated planetary mapping and real-time navigation in deep space exploration.

Keywords: Deep Space Exploration; Terrestrial Planets; Impact Craters; Object Detection; YOLOv5 **CLC Number:** TP751.2; V476.4 **Document Code:** A

---

1. Introduction

Impact craters are formed by high-speed collisions of asteroids, comets, or meteoroids with the surface of a planet or satellite. As "fossil" records of planetary evolution, they provide critical information regarding the geological history and environmental changes of the solar system. For instance, the density of craters is directly related to the absolute model age of a surface unit [**?**]. Furthermore, the morphology of craters can reveal the physical properties of the target crust and the presence of subsurface volatiles.

In recent decades, lunar and planetary exploration missions have returned a vast amount of high-resolution imaging data. Manual identification and cataloging of these craters is a time-consuming and labor-intensive task, often subject to subjective bias between different experts. Consequently, the development of Automated Crater Detection Algorithms (CDAs) has become a research hotspot. Early CDAs primarily relied on traditional image processing techniques, such as the Circular Hough Transform (CHT) and edge detection [**?**]. However, these methods are sensitive to noise and have limited robustness when dealing with degraded or overlapping craters in complex terrains.

In recent years, the rapid development of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized object detection. The YOLO series, known for its "one-stage" detection architecture, offers a compelling balance between speed and accuracy. This study leverages the YOLOv5 framework to develop a robust crater detection system capable of processing high-resolution planetary imagery while addressing the challenges of multi-scale crater distribution and complex background interference.

2. Methodology

2.1 YOLOv5 Framework and Network Structure

The YOLOv5 architecture consists of three main components: the Backbone, the Neck, and the Head.

1. **Backbone Network:** Responsible for feature extraction. Input images are adjusted to 640×640 pixels via adaptive scaling. The images pass through multiple Convolution-Batch Normalization-SiLU (CBS) modules for downsampling, generating feature maps at three scales (80×80, 40×40, and 20×20 pixels), defined as P_3, P_4, and P_5. A Spatial Pyramid Pooling-Fast (SPPF) module fuses features of different resolutions to enhance extraction capabilities.
2. **Neck Network:** Employs a Path Aggregation Network (PANet) combined with a Feature Pyramid Network (FPN) to fuse feature information from the backbone, producing multi-scale feature maps (N_3, N_4, N_5).
3. **Head Network:** Transforms multi-scale feature tensors into bounding box coordinates, object confidence, and class information.

This study selects YOLOv5s as the baseline model to achieve an optimal balance between parameter count, computational complexity, and accuracy.

2.2 Model Improvement Methods (YOLOv5-crater)

To address the high frequency of small craters that often disappear after multiple convolution operations, we propose the **YOLOv5-crater** model. The improvements include: - Adding a fourth scale of feature extraction (160×160 px) to the backbone to preserve detailed information of small targets. - Incorporating a fourth scale of feature fusion (160×160 px) in the neck network. - Assigning a smaller proportion of anchor boxes to match the dimensions of small craters.

We further designed eight experimental variants (SF-2.1 to SF-3.4) to optimize feature fusion. Variants SF-3.1 through SF-3.4 incorporate an additional SPPF module at the feature map output stage to enhance context awareness and generalization.

Figure 2

Figure 1: Figure 2

2.3 Dataset Preparation

The dataset was constructed using optical remote sensing images from the MESSENGER (Mercury), MRO (Mars), LRO (Moon), and Dawn (Ceres) missions. Spatial resolutions range from 100 m/px to 500 m/px.

Craters were classified into two categories based on the Melosh and Ivanov system: 1. **Simple Craters:** Small (diameters $<$ 15-20 km), bowl-shaped, with smooth floors and clear rims. 2. **Complex Craters:** Larger, featuring terraced walls, flat floors, and often central peaks or rings.

We utilized a semi-automated annotation method: a pre-trained model performed initial machine labeling, followed by rigorous manual correction to fix missed detections and misclassifications. The final dataset contains thousands of labeled samples, with an average of several dozen craters per image.

3. Results and Analysis

3.1 Evaluation Metrics

Performance is quantified using Mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5.

$$\mathrm{IoU} = \frac{B_{pred} \cap B_{gt}}{B_{pred} \cup B_{gt}} \tag{1}$$

Precision (P) and Recall (R) are defined as:

$$P = \frac{TP}{TP + FP} \tag{2}$$

$$R = \frac{TP}{TP + FN} \tag{3}$$

Confidence (C) is calculated as:

$$C = P_{obj} \times \mathrm{IoU}_{pred}^{truth} \tag{4}$$

3.2 Experimental Results

3.2.1 Feature Fusion Comparison As shown in , the SF-3.1 model achieved the highest multi-class detection accuracy, increasing mAP from 79.2% to 81.2%. Visual comparisons in [FIGURE:1] and

confirm that SF-3.1 identifies significantly more simple craters than the baseline YOLOv5s. The inference time remains under 100 ms per image, satisfying real-time requirements.

Figure 8

Figure 2: Figure 8

3.2.2 Comparison with DINO-X Compared to the DINO-X open-world foundation model, our SF-3.1 model demonstrates a much lower miss rate for small-scale craters and provides specific morphological classification which DINO-X lacks.

3.2.3 Robustness to Illumination By simulating different solar elevation angles through brightness adjustment, we found that the variation in the number of identified craters remained within 5% across varying lighting conditions. This demonstrates the model' s high robustness for practical space missions.

3.2.4 Small-Sample Performance Experiments on dataset scaling show that the SF-3.1 model achieves a precision of 77.9% with a limited number of images, a level that the baseline YOLOv5s can only reach by significantly increasing the training data volume. This indicates that our architectural improvements are equivalent to adding approximately 2,000 training samples.

4. Conclusion and Outlook

This study developed a specialized crater identification and classification dataset and an improved YOLOv5-crater model. By optimizing multi-scale feature extraction and fusion, we significantly improved the detection of small craters and enabled morphological classification. The model achieves an mAP of 81.2%, maintains high inference speeds (<100 ms), and shows strong robustness to lighting variations.

Future work will focus on further increasing the dataset scale and integrating multi-modal data (such as digital elevation models) to enhance detection precision for highly degraded craters, ultimately supporting autonomous navigation and landing for future deep space exploration missions.

5. Acknowledgments

This research was supported by the National Natural Science Foundation of China (Grant No. [NUMBER]) and the Shanghai "Science and Technology Innovation Action Plan" (Grant No. [NUMBER]). We thank Researcher Li Ligang for his valuable suggestions.

Figures