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Safe Lunar Surface Navigation: Leveraging U-Net and Semantic Segmentation for Obstacle Detection

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ABSTRACT—

Obstacle detection on the lunar surface is crucial for safe navigation during lunar missions. This abstract focuses on the utilization of U-Net architecture, combined with semantic segmentation, as an effective technology for obstacle detection. U-Net, a deep learning architecture, is adept at capturing intricate spatial features and has been successfully employed for image segmentation tasks. By training the U-Net model on annotated lunar surface images, it can accurately identify and classify obstacles such as rocks, craters, and boulders. The integration of semantic segmentation allows for precise mapping and enables astronauts and autonomous vehicles to navigate the lunar surface more safely and efficiently. The continued advancement of U-Net architecture and the availability of high-resolution lunar imagery will further enhance obstacle detection capabilities in future lunar exploration missions.

Keywords— **U-Net architecture, semantic segmentation, deep learning, image segmentation, safe navigation, lunar missions, rocks.**

Introduction

Safe exploration of the lunar surface is of paramount importance for successful lunar missions and the well-being of astronauts. The presence of various obstacles, such as rocks, craters, and boulders, poses significant challenges to navigation and necessitates the development of robust obstacle detection techniques. In this context, semantic segmentation, combined with advanced deep learning techniques, emerges as a promising technology to enhance the safety and efficiency of lunar surface exploration. By employing semantic segmentation algorithms, high-resolution lunar surface images can be analyzed and segmented into distinct obstacle classes, enabling precise mapping and identification of potential hazards. This paper focuses on the integration of semantic segmentation techniques to aid in safe lunar surface exploration, ensuring accurate obstacle detection.

Motivation

The motivation behind incorporating semantic segmentation for obstacle detection on the lunar surface lies in the need to ensure the safety and success of lunar missions, providing astronauts with reliable navigation information and enabling autonomous vehicles to maneuver effectively in hazardous terrain. The application of semantic segmentation in obstacle detection on the lunar surface holds the potential to revolutionize lunar exploration by enabling real-time identification and mapping of obstacles, aiding in decision-making processes, and paving the way for future scientific discoveries.

Problem Definition

The challenge lies in developing an accurate and efficient obstacle detection system using semantic segmentation techniques that can handle the complexities of the lunar terrain, to minimize the risk of collisions and mission failures.

Literature survey

Various methods have been implemented for obstacle detection. Various algorithms and hardware equipments were used for the same. This section provides a comprehensive information about such findings.

1. Wu, F., Vibhute, A., Soh, G. S., Wood, K. L., & Foong, S. (2017)[1]

Enhancing Travel Efficiency and Security in Dangerous Territories using the "Virgo" Spherical Robot. This study presents a magnetic proximity sensor-based spherical robot that utilizes the pure-pursuit algorithm for trajectory tracking. By calculating the distance between the current location and the designated waypoint, the system adjusts the wheel speed accordingly. Components such as sensor data acquisition, waypoint commander, trajectory controller, and drivetrain controller are integrated to query and store readings, calculate trajectories, and navigate while considering detected obstacles.

2. Kuang, B., Wisniewski, M., Rana, Z. A., & Zhao, Y. (2021)[2]

A Framework for Rock Segmentation in Rover Automation using Synthetic Image Generation and Transfer Learning. This paper proposes a framework that employs a rock segmentation network called NI-U-Net++ for automating the challenging task of rock segmentation. The framework involves a two-stage process, including pre-training with synthetic images generated through a synthetic algorithm, followed by transfer learning. The system generates segmented images by leveraging the capabilities of the pre-trained network, aiding in efficient rock segmentation.

3. Matsumoto, K., Sasa, S., Katayama, Y., & Ninomiy, T. (2003)[3]

Integration of Optical Sensors and Algorithms for Obstacle Detection: A Study on Stereo, Topography from Brightness, and Shade Methods. This study focuses on the integration of optical sensors with three algorithms: stereo, topography from brightness, and shade methods for obstacle detection. The stereo method calculates land depth, while the topography from brightness utilizes mean and variance of brightness to identify steep slopes and rough terrain patterns. These optical sensor algorithms provide valuable information for robust obstacle detection.

4. Ronneberger, O., Fischer, P., & Brox, T. (2015)[4]

U-Net Architecture for Image Segmentation: Extracting Important Features and Creating Skip Connections. This paper introduces the U-Net architecture, which effectively reduces the spatial dimensions of an input image while extracting crucial features through unpadded convolutions in the encoder part. In the decoder part, the number of filters in convolutional layers gradually decreases, accompanied by upsampling. The use of skip connections allows comprehensive information exchange between encoder and decoder blocks, resulting in accurate segmentation of images.

5. Ma, L., Xie, W., & Huang, H. (2019)[5]

Hybrid Network Architecture for Autonomous Navigation of Unmanned Surface Vehicles: Leveraging ResNet and Improved DesNet. This study proposes a hybrid network architecture that combines ResNet and improved DesNet to develop a feature pyramid method known as bidirectional feature pyramid networks. The proposed method, based on convolutional neural networks (CNN), enhances autonomous navigation and obstacle detection capabilities for unmanned surface vehicles, making them suitable for operations such as search, rescue, and territory observation.

6. Ulrich, I., & Nourbakhsh, I. (2000)[6]

Appearance-based Obstacle Detection System: Utilizing Color Filtering and Histogram Comparison. This paper presents an appearance-based obstacle detection system that analyzes the differences in pixel appearance from the ground. The system applies color filtering, transforms the input image into the HSI color space, performs histogramming of reference areas, and compares them with reference histograms. These techniques contribute to the accurate identification of obstacles.

Methods

The whole system is divided into two parts, first part consists of Graphical User Interface and second part is Model.

1. Graphical User Interface –

The web interface will be available for the user to prompt or upload an image. After successfully uploading image it will be forwarded by Django framework which acts as a connectivity between web interface and model to the ML model.

2. Model –

The model incorporates supervised learning approach where inputs and outputs are passed in the training process.

The Dataset contains the images of lunar surface which consists of regions amalgamated by rocks. The dataset contains such images of rocks which can be used for training to detect rocks as an obstacles by the model.

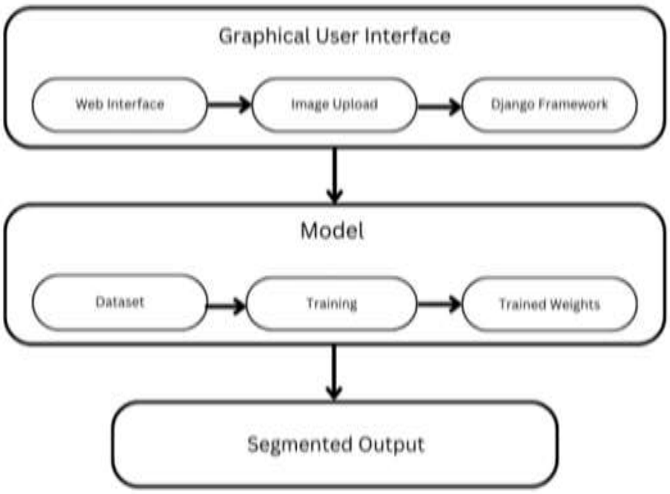


Figure 1. The pipeline consists of proposed system that detects obstacles on the lunar surface.

Model Implementation

1. The Artificial Lunar Landscape Dataset :

The dataset contains 9766 realistic images of regions combined with rocks it was created by Roman Pessia , Genya Ishigami and Quentin Jodelet of the Space Robotics Group, Keio University in Japan. They used NASA's LRO LOLA Elevation Model as a source of large scale terrain data. The dataset focuses on four classes i.e. is larger rocks, smaller rocks, the sky and lunar surface. This classes are the target class for the multiclass classification.

2. Network Implementation

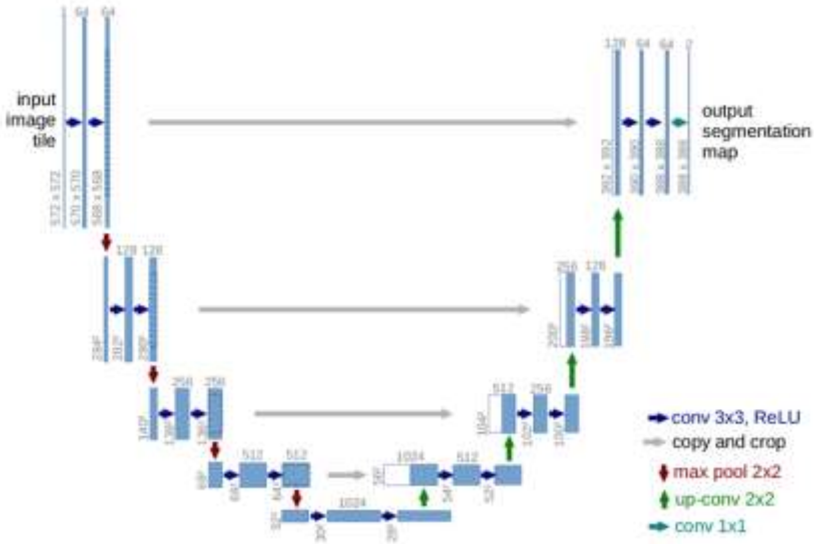


Figure 2. The U-Net Architecture

The U-Net Architecture [4] was created by Olaf Ronneberger, Philipp Fischer, Thomas Brox in 2015. It was mainly used for the purpose of Bio-medical image segmentation. U-Net Architecture mainly consists of three parts Encoder, Decoder and Skip connections. Encoder is applied to reduce the spatial dimensions of image and the decoder network is used to take the abstract representation and generate a semantic segmentation mask. During the encoder path image features are saved and passed to the decoder part. This is done in order to save the original features which were loss during the encoding part. This job is done by skip connections.

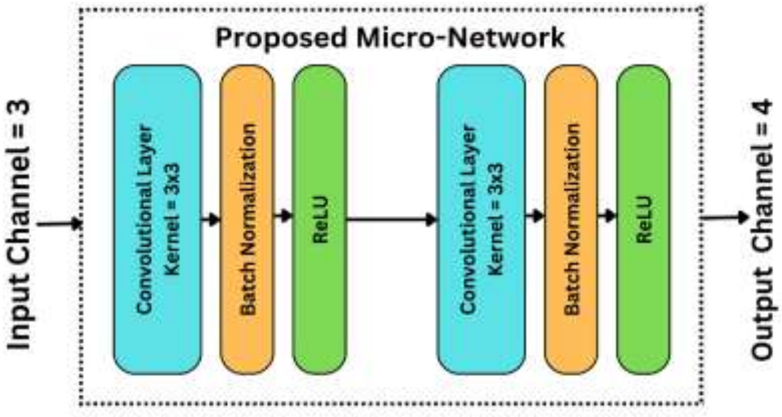


Figure 3. The Layer configuration where light blue, orange and green refers to convolutional layer with 3×3 kernel size, batch normalization layer and ReLU activation layer.

The model incorporates this network for the U-Net implementation. The convolution layer contains a kernel with 3×3 channel size. Its main job is to extract the meaningful features from the image. The next layer is of batch normalization which boosts the training of network by standardizing the inputs to the network. The next layer is the ReLU activation layer adds non-linearity to the network and prevents from the vanishing gradient situations. This micro-network is used repeatedly before each max-pooling layer and after each upscaling layer. This micro-network makes successful implementation of U-Net. After the last up-convolution in the U-Net the micro-network the model outputs a segmented image with specified channels.

3. Training Process

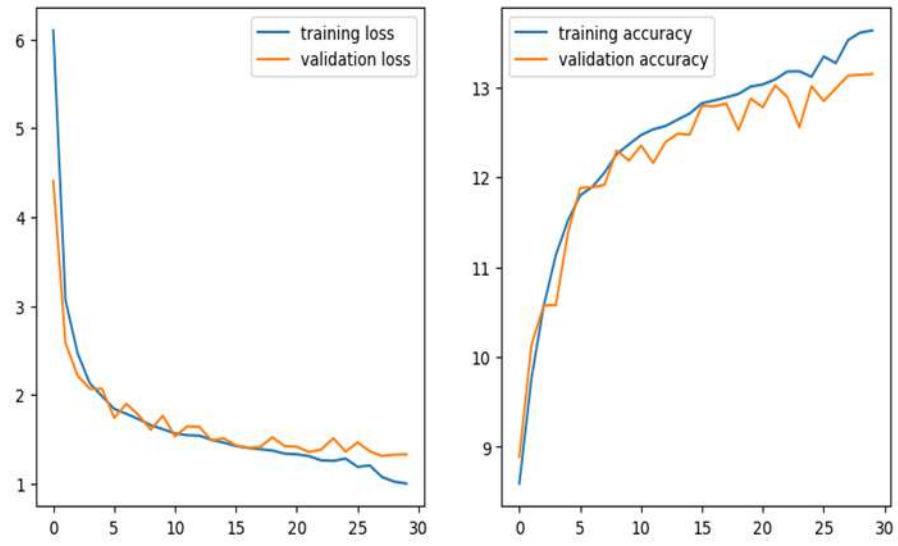
Training process incorporates the cross validation technique which divides the dataset into training and validation part. The main components which play important part in training a machine learning model known as Hyperparameters are listed in the below table. The number of epochs is set to 30, the batch size is 458 samples per batch, the learning rate is set to 0.0001, to control learning rate, the scheduler is incorporated that is ReduceLROnPlateau, the optimizer adopts the Adam (Adaptive momentum) and the cross entropy loss is chosen as loss function. For accuracy calculation Intersection over Union (IoU) is chosen.

Hyperparameters	Values
Epoch	30
Batch Size	16
Learning Rate	0.0001
Optimizer	Adam
Scheduler	ReduceLROnPlateau
Accuracy	IoU
Loss Function	Cross Entropy Loss

4. Results and Discussion

The training process and implementation of the model were conducted on the online deep learning platforms like Kaggle, programming languages like Python 3.10, CUDA, PyTorch and OpenCV were leveraged in the implementation process.

4.1 The results from the model:



(a) (b)

Figure 4. (a) refers to epoch wise loss in the training and validation sets. (b) refers to epoch wise accuracy in the training and validation sets.

Original Image

Prediction

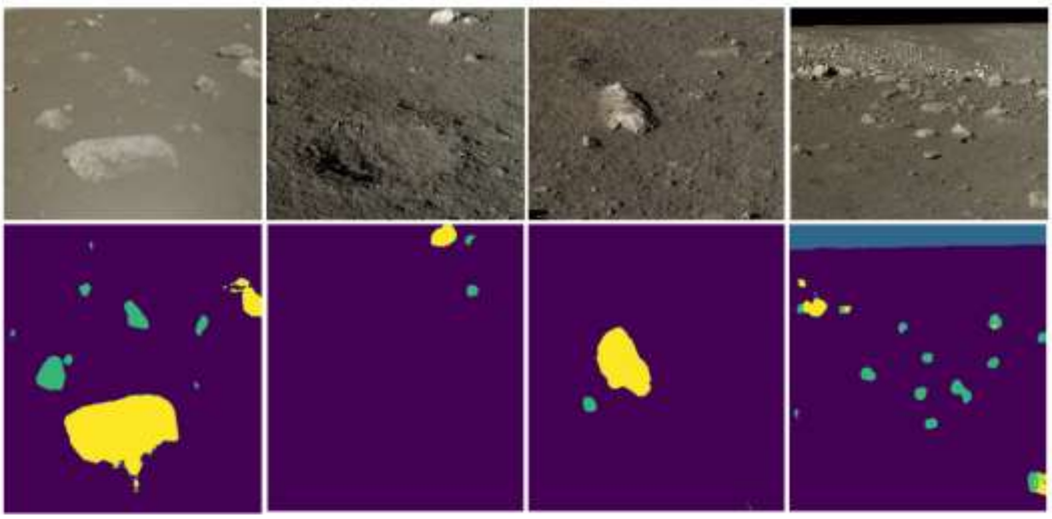


Figure 5. Results from proposed system

Conclusion

In conclusion, semantic segmentation, as a computer vision task, plays a crucial role in grouping together similar parts of lunar surface images into distinct obstacle classes, enabling safe navigation during lunar exploration missions. The integration of U-Net architecture further enhances the accuracy and efficiency of obstacle detection, ensuring the rover's safe operation and mitigating potential risks. By employing these advanced techniques, minimizes the risk of collisions and mission failures.

Future work

- Efficiency can be increase in darker areas.
- Integration of functionality that detects obstacles using bounding boxes.
- Integration of functionality that supports real-time object detection.
- This project can be integrated into the visual navigation system to further assist various advanced functions, such as path planning, localization, scene matching.

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