Detecting Lunar Wrinkle Ridges Through Deep Learning Based on DEM and Aspect Data (Postprint)

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Abstract

Lunar wrinkle ridges are an important stress geological structure on the Moon, which reflect the stress state and geological activity on the Moon. They provide important insights into the evolution of the Moon and are key factors influencing future lunar activity, such as the choice of landing sites. However, automatic extraction of lunar wrinkle ridges is a challenging task due to their complex morphology and ambiguous features. Traditional manual extraction methods are time-consuming and labor-intensive. To achieve automated and detailed detection of lunar wrinkle ridges, we have constructed a lunar wrinkle ridge data set, incorporating previously unused aspect data to provide edge information, and proposed a Dual-Branch Ridge Detection Network (DBR-Net) based on deep learning technology. This method employs a dual-branch architecture and an Attention Complementary Feature Fusion module to address the issue of insufficient lunar wrinkle ridge features. Through comparisons with the results of various deep learning approaches, it is demonstrated that the proposed method exhibits superior detection performance. Furthermore, the trained model was applied to lunar mare regions, generating a distribution map of lunar mare wrinkle ridges; a significant linear relationship between the length and area of the lunar wrinkle ridges was obtained through statistical analysis, and six previously unrecorded potential lunar wrinkle ridges were detected. The proposed method upgrades the automated extraction of lunar wrinkle ridges to a pixel-level precision and verifies the effectiveness of DBR-Net in lunar wrinkle ridge detection.

Full Text

Preamble

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Abstract

Lunar wrinkle ridges are important tectonic structures on the Moon that reflect its internal stress state and geological activity. They provide crucial insights into lunar evolution and represent key factors influencing future lunar exploration activities, such as landing site selection. However, automatic extraction of lunar wrinkle ridges remains challenging due to their complex morphology and ambiguous features, while traditional manual extraction methods are time-consuming and labor-intensive. To achieve automated and detailed detection of lunar wrinkle ridges, we constructed a comprehensive lunar wrinkle ridge dataset that incorporates previously unused aspect data to provide edge information, and proposed a Dual-Branch Ridge Detection Network (DBR-Net) based on deep learning technology. This method employs a dual-branch architecture and an Attention Complementary Feature Fusion module to address the issue of insufficient feature representation for lunar wrinkle ridges. Comparative experiments with various deep learning approaches demonstrate that the proposed method exhibits superior detection performance. Furthermore, the trained model was applied to lunar mare regions to generate a distribution map of lunar mare wrinkle ridges. Statistical analysis revealed a significant linear relationship between the length and area of lunar wrinkle ridges, and six previously unrecorded potential lunar wrinkle ridges were detected. The proposed method advances automated extraction of lunar wrinkle ridges to pixel-level precision and verifies the effectiveness of DBR-Net for lunar wrinkle ridge detection.

Key words: Moon -methods: data analysis -planets and satellites: surfaces -techniques: image processing

1. Introduction

Lunar geological structures can be broadly classified into linear or circular structures according to their geometric characteristics (Lu et al. 2022). Lunar wrinkle ridges are among the most common linear structures on the lunar surface, formed by compressional stresses within the Moon (Schultz 2000) and closely related to its internal stress state. Studying lunar wrinkle ridges is essential for understanding the lunar stress field and evolution history.

Previous studies have employed two main approaches for detecting lunar wrinkle ridges: manual visual interpretation and automated methods. Yue et al. (2015) used optical data and manual visual methods to extract lunar wrinkle ridges, while Yao & Chen (2018) visually identified them on Digital Elevation Model (DEM) data. These studies were pioneering in determining the orientation and distribution of lunar wrinkle ridges. However, manual extraction methods are inefficient and labor-intensive, limiting their applicability for large-scale identification. To address these limitations, automated extraction methods based on traditional image processing techniques have been developed. Lou & Kang (2018) utilized the characteristic elevation profiles of lunar linear structures and applied multiple average filtering to DEM data for linear structure extraction. Micheal et al. (2014) calculated phase symmetry from slope information to extract lunar wrinkle ridges based on DEM data. Jiang et al. (2015) employed a block clustering algorithm based on image features for terrain classification of Chang' e-1 Charge Coupled Device (CCD) Stereo Camera images. While these traditional image processing methods improve extraction efficiency and are straightforward to implement, they primarily identify ridge lines that indicate only the general trend, failing to capture the complete shape or edges of lunar wrinkle ridges. Additionally, their effectiveness is highly dependent on appropriate threshold selection.

While the general orientation of lunar wrinkle ridges can be determined, considerable potential exists for enhanced precision in their identification. From a morphological perspective, lunar wrinkle ridges exhibit complex and varied topography, complicating accurate delineation of their boundaries and fine details based solely on elevation data. Moreover, conventional image processing techniques are substantially threshold-dependent, which impedes their efficacy in identifying the intricately undulating features characteristic of lunar wrinkle ridges. Consequently, it is imperative to address these limitations to improve the accuracy and reliability of lunar wrinkle ridge identification, requiring the development of advanced methods that can effectively capture nuanced topography while reducing threshold dependency.

In planetary image processing, many researchers have successfully applied deep learning methods to achieve excellent results in image segmentation and classification. For instance, Silburt et al. (2019) applied U-Net to automatically detect craters, while Zhang et al. (2024) utilized an improved Deeplabv3+ model to identify lunar sinuous rilles. Peng et al. (2023) employed deep learning methods based on Convolutional Neural Networks (CNNs) and transformers for fine structure segmentation of magnetic bright point images. Li et al. (2024) integrated CNNs and Support Vector Machines (SVMs) to identify contaminated images in light curve data preprocessing. These studies collectively underscore the substantial potential of deep learning in astronomical image processing, highlighting its capability to enhance analysis accuracy and efficiency.

Inspired by these successes, this study addresses the challenges of insufficient detail and low efficiency in lunar wrinkle ridge recognition by constructing a deep learning dataset for lunar wrinkle ridge detection through manual annotation. This dataset encompasses DEM data, aspect data, and corresponding label data, with aspect data identified as a significant feature for delineating ridge edges. We propose a Dual-Branch Ridge Detection Network (DBR-Net) to address the complexities of lunar wrinkle ridge morphology and edge detection. The DBR-Net architecture consists of a dual-branch encoder that separately extracts body features from DEM data and edge features from aspect data. To effectively fuse these multi-source features, an Attention Complementary Feature Fusion (ACFF) module is incorporated, ensuring robust and complementary integration of body and edge features that enables accurate delineation of both the shape and edges of lunar wrinkle ridges. The proposed DBR-Net achieves significant improvement in ridge extraction resolution, refining the representation from coarse ridge lines to precise pixel-level edge delineation. Experimental results validate the method’ s efficacy, demonstrating superior performance in lunar wrinkle ridge detection. As a direct outcome, we generated a detailed distribution map of wrinkle ridges within the lunar mare and identified six previously unrecorded lunar wrinkle ridges, highlighting the potential for new scientific discoveries in lunar morphology.

2. Data

Developing a high-quality dataset for lunar wrinkle ridge detection is a critical prerequisite for training and validating deep learning models in this domain. Previous work has been constrained by limited dataset availability, impeding progress. To address this issue, this study constructs a comprehensive deep learning dataset specifically designed for lunar wrinkle ridge detection, integrating DEM data and aspect data that are essential for capturing topographic and morphological characteristics. This dataset serves as a foundational resource for model training, evaluation, and benchmarking, facilitating more accurate and reliable detection of lunar wrinkle ridges in future research.

2.1. Study Area

Lunar wrinkle ridges are predominantly found in lunar mare regions. Therefore, our study area is specifically selected within the lunar mare. The dataset was created using data from a region spanning longitudes 90°W–45°W and latitudes 0–60°N, chosen for its rich distribution of lunar wrinkle ridges and availability of DEM and aspect data. The trained model was subsequently applied to detect lunar wrinkle ridges in a broader area covering longitudes 90°W–45°E and latitudes 30°S–60°N, encompassing nearly the entire lunar mare. This extended coverage allows comprehensive evaluation of model performance and identification of potential unrecorded lunar wrinkle ridges. The study area is illustrated in Figure 1 [Figure 1: see original paper].

2.2. Data Type

Lunar terrain recognition primarily relies on two data types: optical imagery and DEM data. While optical imagery offers high resolution, accurate identification of lunar wrinkle ridges is often hindered by illumination variations. Qiao et al. (2021) demonstrated that different illumination conditions significantly impact terrain recognition accuracy in optical imagery, leading to potential extraction errors. In contrast, DEM data are inherently independent of illumination conditions and provide rich structural information, making them more robust for morphological feature analysis. DEM data not only circumvent illumination limitations but also capture critical topographic details such as elevation profiles and ridge geometries essential for precise identification. Given these advantages, this study employs DEM data acquired from the Lunar Orbiter Laser Altimeter (LOLA) instrument onboard the Lunar Reconnaissance Orbiter for lunar wrinkle ridge identification.

However, both optical imagery and DEM data have limitations in representing lunar wrinkle ridges, specifically regarding edge features. The characteristic gentle-to-steep slopes of lunar wrinkle ridges result in blurry boundaries between ridges and surrounding landforms, significantly increasing identification complexity. Both data types face notable difficulties distinguishing ridge edges from surrounding terrain, causing previous studies to identify only ridge lines without achieving accurate depiction of overall structure. Therefore, exploring new data types with edge representation capabilities is crucial for accurate lunar wrinkle ridge recognition.

To capture ridge edges, we introduced aspect data. Slope is the first derivative of a surface with both magnitude and direction, where aspect represents the bearing (or azimuth) of the slope direction—defined as the compass direction of steepest downhill slope with an angular range from 0° to 360°. Aspect data identify the downslope direction of maximum rate of change from each pixel to its neighbors. In aspect data, downslope values at ridge edges exhibit similarity, making aspect data sensitive to ridge edges and complementary to the body features represented by DEM data. Given these advantages, this study employs both DEM data and aspect data for lunar wrinkle ridge identification.

2.3. Data Source and Processing

The DEM data used in this study were presented by Barker et al. (2016), in which the DEM co-registered Terrain Camera data with LOLA instrument geodetic accuracy data called SLDEM2015. Figure 2 shows the DEM data. The horizontal resolution is 512 pixels/degree (59 m/pixel) with typical vertical accuracy of 3–4 m. These data are archived in the Planetary Data System (PDS) and accessible via https://pds-geosciences.wustl.edu/lro/lro-l-lola-3-rdr-v1/lrolol_{1xxx}/data/sldem2015/tiles/float_{img}.

Aspect data are derived from DEM data using the Geospatial Data Abstraction Library (GDAL), a translator library for raster and vector geospatial data formats. We utilize its Python version to generate aspect data by invoking the gdal.DEMProcessing command. The calculation process for aspect data (Burrough et al. 2011) is as follows: Suppose the surface function is f(x, y), where z is altitude and x and y are coordinate axes. Slope is defined such that Slopex and Slopey are slopes in the row (x) and column (y) directions respectively. The aspect is given by:

$\text{Aspect} = \arctan(\text{Slopey} / \text{Slopex})$

Aspect values represent compass directions (0°–360°). Figure 3 shows the aspect data.

In digital terrain modeling, aspect data are derived from DEM data using simple local operations. The aspect value of each pixel is typically calculated from data in a continuously moving 3 × 3 sliding window, illustrated in Figure 4. The slopes of pixel e5 in row (x) and column (y) directions can be expressed as:

$\text{Slopex} = (e3 + 2e6 + e9 - e1 - 2e4 - e7) / 8$ $\text{Slopey} = (e7 + 2e8 + e9 - e1 - 2e2 - e3) / 8$

The aspect value of pixel e5 can then be obtained from the aspect equation.

Additionally, variance filtering is applied to process aspect data. This technique uses the sliding window shown in Figure 4 with the following calculation formula:

$S(e5) = (1/9)\ \Sigma(ei - \bar{e})^2$ for $i = 1$ to 9

where $\bar{e}$ represents the average value of the sliding window and S(e5) is the pixel value after variance filtering. This process produces consistently lower values for downhill areas of lunar wrinkle ridges and highlights slopes with similar directions, differentiating them from surrounding terrain and enhancing edge characterization. The filtered aspect data are depicted in Figure 5.

2.4. Dataset

The dataset is constructed by manually labeling lunar wrinkle ridges based on DEM data and variance-filtered aspect data. During manual labeling, Yue et al. (2015) provided some previously explored lunar wrinkle ridge position coordinates. To facilitate deep learning applications, the sliding window clipping method divides images into 1069 blocks of 512 × 512 pixels, partitioned into training and testing sets at an 8:2 ratio.

3. Methods

3.1. Overview

A dual-branch lunar wrinkle ridge detection network was utilized to detect lunar wrinkle ridges, as illustrated in Figure 6 [Figure 6: see original paper]. The model integrates semantic segmentation, an attention mechanism, and feature-level fusion (Feng et al. 2020). Building on DeepLabV3+'s excellent performance in remote sensing and the effectiveness of its Atrous Spatial Pyramid Pooling (ASPP) module (Chen et al. 2017) for multi-scale target detection, we developed DBR-Net as an improvement upon DeepLabV3+. The network takes DEM data and aspect data as input, with a dual-branch feature encoder that extracts multi-level features independently. Semantic information from dual-branch high-level features is fused using the ACFF module, while rich spatial details from low-level features are merged with high-level features through skip connections. Finally, the decoder transforms the combined feature map into segmentation results.

3.1.1. Dual-branch Feature Encoder The dual-branch feature encoder consists of residual blocks and initially utilizes a dual-branch architecture to extract features independently before fusing both branches to enhance feature representations. Two ResNet-34 models, pre-trained on ImageNet, serve as backbone networks for feature extraction with identical branch structures. ResNet-34 incorporates residual modules designed to facilitate efficient learning and address vanishing gradient problems. Compared to ResNet-18 and ResNet-50 variants, ResNet-34 achieves optimal balance between network performance and computational efficiency, providing sufficient feature representation capacity to capture contextual information while maintaining reduced computational and memory requirements. As proposed in ResNet (He et al. 2016), we set 3, 4, 6, 3 residual blocks at each stage. The dual-branch encoder extracts features separately from DEM and aspect data, producing two distinct multi-level feature types that effectively capture body features from DEM data and edge features from aspect data.

Numerous studies have demonstrated that fusing different feature information enhances results and advances research in complex visual tasks (Ebel et al. 2020; Ye et al. 2024). The multi-type, multi-level features extracted by the dual-branch encoder provide a foundation for flexible feature fusion methods. Low-level features contain rich spatial information while high-level features contain semantic information. Based on these characteristics, this study developed distinct fusion strategies: an additive approach for low-level features to augment spatial dimension information, and an ACFF module based on attention mechanisms for high-level features.

3.1.2. Backbone of Dual-branch Feature Encoder To fully extract and integrate different features, the encoder module employs a dual-branch architecture with ResNet-34 as each branch’ s backbone. ResNet-34 incorporates residual modules that facilitate efficient learning and address vanishing gradient problems. Its relatively shallow architecture effectively captures contextual information while reducing computational and memory demands. To tackle training challenges in deep networks, ResNet introduced the pivotal residual block, with architecture described by He et al. (2016). The residual block structure is illustrated in Figure 7 [Figure 7: see original paper]. The core concept introduces a residual connection that allows input to be directly passed to subsequent layers and summed with output after convolutional operations. The residual block adds a shortcut connection before the second ReLU activation function, transforming the activation function input from the original $H(X) = F(X)$ to $H(X) = F(X) + X$. This design enables residual blocks to learn identity mapping more easily, avoiding information loss in deep networks and achieving significant success in image classification and computer vision tasks. In this study, we imported modules such as ResNet and BasicBlock from torchvision.models.resnet to construct ResNet-34, reconstructing the encoder architecture to build the dual-branch feature encoder.

3.1.3. Attention Complementary Feature Fusion Module The ACFF module, based on attention mechanisms, is designed to effectively fuse high-level semantic information and enhance the model’ s ability to distinguish lunar wrinkle ridges from backgrounds. The module structure is shown in Figure 8 [Figure 8: see original paper]. First, a maximization method combines the most significant features from DEM and aspect branch feature maps. Point-wise convolution serves as a local channel context aggregator, exploiting point-wise channel interactions at each spatial position. Significant features obtained after maximization emphasize the entire lunar wrinkle ridge structure through feature mapping via point-wise convolution and channel attention based on local context information.

The local channel context L(X) is calculated as:

$$L(X) = \beta(\gamma(\text{Conv}(\text{Max}(X\_\{DEM\}, X\_\{Aspect\}))))$$

where γ denotes ReLU activation, β denotes batch normalization, Max denotes maximization, and Conv represents 1×1 convolution blocks.

Finally, fused features are computed as:

$$F\_\{fused\} = \text{Concat}(L(X), \sigma(L(X)) \quad X\_\{DEM\}, \sigma(L(X)) \quad X\_\{Aspect\})$$

where Concat denotes concatenation, denotes element-wise multiplication, and σ denotes the sigmoid function. Element-wise multiplication weights the input feature map. At deeper model levels, increased feature diversity enables more effective capture of relationships among different features. Therefore, we apply concatenation with weighted features to enhance feature type diversity.

4. Experiments and Results

4.1. Implementation Details

All experiments were conducted using the PyTorch deep learning framework with binary cross-entropy loss function and stochastic gradient descent (SGD) optimizer. The initial learning rate is 1×10^{-3} with a decay strategy reducing the rate to 0.1 times its original value every 20 epochs. The complete training cycle comprises 60 epochs. All experiments were performed on a computer equipped with an NVIDIA RTX A5000 GPU and Intel Xeon Gold 6126 CPU. Table 1 presents the hyperparameter settings and hardware environment.

4.2. Evaluation Metrics

To comprehensively assess model performance, we employed the confusion matrix as the primary evaluation tool. This tabular layout visually represents correspondence between model predictions and actual classes, particularly suitable for binary classification tasks. In this study, the binary classification task involved categorizing pixels into "Class A" (lunar wrinkle ridges) and "Class B" (background). The confusion matrix form is shown in Table 2 .

True Positives (TP) represent correctly predicted Class A samples. False Negatives (FN) represent Class A samples incorrectly predicted as Class B. False Positives (FP) represent Class B samples incorrectly predicted as Class A. True Negatives (TN) represent correctly predicted Class B samples.

From the confusion matrix, we derive standard semantic segmentation metrics: precision, recall, F1-score, and IoU, which serve as objective evaluation metrics for lunar wrinkle ridge detection ability.

Precision = TP / (TP + FP)

Precision is the proportion of actual lunar wrinkle ridge samples among all samples predicted as ridges, reflecting model accuracy in predicting the positive class.

Recall = TP / (TP + FN)

Recall is the proportion of actual lunar wrinkle ridge samples correctly predicted as ridges, measuring the model' s ability to identify positive class samples.

F1-score = 2 × (precision × recall) / (precision + recall)

F1-score is the harmonic mean of precision and recall, providing a comprehensive metric that balances both.

IoU = TP / (TP + FP + FN)

IoU (Intersection over Union) measures the overlap between predictions and ground truth, commonly used to assess segmentation effectiveness.

4.3. Comparison Experiments

This section verifies the proposed model' s performance and evaluates aspect data' s contribution to detection results. Since our method yields pixel-level extraction results that cannot be compared with traditional methods extracting only ridge lines, we selected several mainstream deep learning-based semantic segmentation methods for comparison. Performance comparisons using different data explore aspect data contributions, while method comparisons verify the proposed approach' s effectiveness. DBR-Net is compared with FCN, RefineNet, PSPNet, and DeepLabV3+, using both DEM-only and combined DEM+aspect data inputs. All models were trained and tested using our manually annotated dataset under identical environmental and hardware conditions. Performance indicators are presented in Table 3 .

4.3.1. Performance Comparison of Different Data To assess aspect data effectiveness, we used both DEM-only and DEM+aspect combination inputs. Four comparison methods use concatenation to merge data types into dual-channel single-branch input, while DBR-Net processes both data types through a dual-branch architecture. Results show that all models' comprehensive metrics (F1-score and IoU) improved when using combined DEM+aspect data versus DEM-only data. This enhancement primarily attributes to aspect data providing ridge edge features absent in DEM data. Compared to DEM-only data, the combined approach demonstrates significant advantages. Ridge edges and surrounding terrains exhibit minimal elevation differences, rendering elevation features relatively inconspicuous. While DEM data effectively represent ridges with significant elevation differences, they lack edge characterization capability. Aspect data leverage continuous terrain change rate information to represent gradually changing ridge edges, capturing more terrain information than DEM data alone. Combining both data types integrates body and edge features, providing more valuable spatial information for lunar wrinkle ridge extraction.

4.3.2. Performance Comparison with Different Methods Compared to traditional image processing methods, deep learning approaches enhance extraction from coarse ridge line representations to pixel-level edge representations. Figure 9 [Figure 9: see original paper] qualitatively shows extraction results across multiple scenarios using combined DEM+aspect data. While all methods capture primary ridge structure and orientation, DBR-Net demonstrates superior effectiveness in detailing ridge intricacies and edges, preserving smaller ridges and providing more accurate contours. DBR-Net achieves the highest precision (89.20%), recall (78.42%), F1-score (83.46%), and IoU (71.61%). Compared to original DeepLabV3+, DBR-Net shows improvements of 0.5% in precision, 4.27% in recall, 2.71% in F1-score, and 3.89% in IoU. These improvements attribute to the dual-branch structure and ACFF module, which enhance flexibility in addressing complementary features and enable more effective fusion through attention mechanisms, improving overall performance.

4.4. Ablation Study

We performed ablation studies to verify component functions in DBR-Net, as shown in Table 4 . The baseline model is unmodified DeepLabV3+. Compared to single-branch models, dual-branch models using Add/Concat fusion methods demonstrate partial improvement by simultaneously processing body and edge features but fail to effectively integrate their differentiated characteristics. The ACFF module successfully integrates both feature types, enhancing ridge contour capture and significantly improving recall and overall metrics. Results demonstrate the necessity of using both dual-branch structure and ACFF module together.

4.5. Transfer Learning Experiment

Mars exhibits wrinkle ridges similar to those on the Moon. Although Mars and the Moon differ in environmental and geological contexts, their wrinkle ridges share fundamental morphological characteristics such as linear structures and central elevated crests. This similarity provides model transferability motivation, using manually labeled Martian wrinkle ridges to evaluate DBR-Net' s generalization capability.

Martian DEM data were sourced from the Mars HRSC MOLA Blended DEM Global 200 m v2 (Fergason et al. 2018), combining data from the Mars Orbiter Laser Altimeter (MOLA) and High-Resolution Stereo Camera (HRSC) at 200 m/pixel resolution. Images were normalized to reduce domain shift, and wrinkle ridges at multiple Martian sites were manually annotated as a validation dataset, cropped to 512 × 512 pixels (110 images total). DBR-Net' s prediction results for selected regions are shown in Figure 10 [Figure 10: see original paper]. Quantitative evaluation metrics for test images are IoU = 62.3% and F1 = 77.1%. This transfer experiment demonstrates that despite interplanetary geological differences, certain features remain transferable, confirming DBR-Net' s generalization ability and capacity to learn ridge morphology across planetary bodies.

5. Discussion

The trained DBR-Net was applied to detect ridges in the lunar mare within latitudes 30°S-60°N and longitudes 90°W-45°E. For optimal visualization clarity and resolution, main text results focus on a representative sector spanning 30°N-60°N latitude and 90°W-0° longitude, as shown in Figure 11 [Figure 11:

see original paper]. Complete large-scale extraction results are provided as supplementary materials at https://zenodo.org/records/15365723.

This map delineates lunar wrinkle ridge edges, supplementing existing ridge line maps from previous studies. It provides information on ridge length, width, and area, revealing a significant linear relationship between ridge length and area. Furthermore, comparative analysis with manually labeled datasets and existing catalogs detected six previously unrecorded potential lunar wrinkle ridges. Morphological analysis and three-dimensional (3D) visualizations were conducted to validate and demonstrate the method' s effectiveness.

5.1. Lunar Wrinkle Ridge Detection

Based on manually labeled lunar wrinkle ridges from Yue et al. (2015), we developed a lunar wrinkle ridge dataset. Using trained DBR-Net, we performed inference on each image to obtain refined ridge extractions. Figure 11 displays morphological delineation and distribution of wrinkle ridges in lunar mare regions identified in this study. Red pixels represent detected lunar wrinkle ridges, while yellow numbers identify newly detected potential ridges. We speculate these newly detected ridges may have degraded over time due to their advanced age, resulting in textural features similar to surrounding terrain in optical images that make conventional manual interpretation difficult. By utilizing DEM and aspect data, we successfully detected these potential ridges based on terrain variation information.

5.2. Morphological Analysis of Potential Lunar Wrinkle Ridges

Table 5 provides latitude/longitude coordinates, length, width, and height for six newly detected potential lunar wrinkle ridges. Compared with established ridges, these features' morphological parameters fall within reasonable ranges. We reconstructed 3D models using DEM data, with visualizations presented in Figure 12 [Figure 12: see original paper]. The potential ridges exhibit morphological characteristics similar to established lunar wrinkle ridges. Results demonstrate deep learning techniques' effectiveness for lunar wrinkle ridge identification, validating DBR-Net performance and highlighting significant potential for other terrain recognition domains.

5.3. Statistical Analysis of Lunar Wrinkle Ridges

Based on pixel-level identification, we conducted systematic parametric statistical analysis of over 3000 lunar wrinkle ridge segments across the entire lunar mare, revealing a significant linear relationship between ridge length and area, as illustrated in Figure 13 [Figure 13: see original paper].

This quantitative relationship provides a new scaling reference for lunar tectonic evolution studies. The linear correlation sheds new light on wrinkle ridge formation mechanisms, suggesting development under a unified lunar stress field. This finding supports dynamic models capable of explaining ridge formation processes and aligns with Yue et al. (2015) conclusions that lunar wrinkle ridges form mainly through tectonic activity, not solely from volcanic origins or pre-mare buried structures. Previous formation mechanism studies could not analyze area parameters due to lack of detailed characterization basis. Our pixel-level extraction enables this linear relationship, explaining the scientific value of detailed extraction results and providing new foundations for studying lunar wrinkle ridge dynamics.

6. Conclusions

This study addressed challenges in detecting lunar wrinkle ridges by developing a comprehensive deep learning dataset and proposing DBR-Net, a semantic segmentation model specifically designed to leverage DEM and aspect data. DBR-Net incorporates a dual-branch structure with a complementary feature fusion module integrating attention mechanisms, enabling enhanced flexible feature extraction and efficient multi-source feature fusion.

In DBR-Net, body features from DEM data are combined with edge features from aspect data, enabling more precise ridge contour capture and elevating extraction from coarse ridge lines to pixel-level edge representation. Comparative experiments with various mainstream semantic segmentation models validated DBR-Net' s efficacy, confirming aspect data' s positive impact and demonstrating superior performance with precision of 89.20%, recall of 78.42%, F1-score of 83.46%, and IoU of 71.61% on the lunar wrinkle ridge dataset.

The method was applied to lunar mare regions, creating a detailed distribution map of lunar mare wrinkle ridges. Pixel-level identification enabled systematic parametric statistical analysis of over 3000 ridge segments, revealing a significant linear length-area relationship that provides new foundations for studying lunar wrinkle ridge dynamics. Additionally, six new potential lunar wrinkle ridges were identified and their morphological characteristics analyzed and visualized. Overall, this study introduces DBR-Net as an effective model for lunar wrinkle ridge detection, significantly advancing efficiency and accuracy in lunar terrain analysis.

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