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Computer Vision for Terrain Mapping and 3D Printing In-situ of Extra/-terrestrial Habitats

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Abstract. This paper addresses the complexities inherent in constructing sustainable extraterrestrial habitats within lava tubes that are envisioned as promising locations for human habitation and scientific inquiry. These environments are characterized by various challenges, which are addressed in this case by integrating computer vision (CV) techniques and 3D printing in-situ. The CV component generates a detailed depth map from synthetic imagery to combine this depth map with an adaptive 3D printing process, which is proposed to ensure level surfaces at various depths, facilitating precise foundation and habitat placement within the demanding context of lava tubes. Significantly, synthetic imagery is employed due to the absence of real lava tube photos at this early stage of the current exploration. The focal point lies in utilizing advanced deep learning (DL) algorithms and convolutional neural networks (CNN) to generate depth maps for extra/-terrestrial environments. This research represents a platform for further knowledge development in the fields of CV and its application to 3D printing in-situ, hence opening new avenues for sustainable extraterrestrial habitats.

Keywords: Lava tube habitats · Computer vision · 3D printing · Depth map · Robotic construction · Adaptive filling · Real-time mapping · Surface irregularities · Habitability

1 Introduction

The exploration and colonization of celestial bodies have long been envisioned by humankind. One of the significant challenges faced in this endeavor is the construction of habitable spaces in extraterrestrial environments, particularly within the irregular and treacherous confines of lava tubes [1]. These natural underground spaces, prevalent on the Moon, Mars, and Earth [2], offer a unique opportunity for safe habitation and scientific research due to their protective nature against radiation and extreme temperatures [3, 4].

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Fig. 1. Rhizome 1.0[1] prototypes using TU Delft rovers (left) and Vertico's cement-based concrete and robotic system (right)

However, harnessing the potential of lava tubes requires innovative approaches to overcome their inherent irregularities and hazards [5, 6]. This paper presents an innovative approach relying on knowledge developed in the European Space Agency (ESA) funded project, Rhizome 1.0 (see Fig. 1), aiming to revolutionize extraterrestrial construction methodologies by synergizing computer vision (CV) techniques and advanced 3D printing towards transforming lava tubes into viable multi-functional habitats.

This exploration, as part of the ESA and Vertico funded project, Rhizome 2.0,[2] begins with a deep understanding of the complexities within these natural formations. Lava tubes, shaped by ancient volcanic activities, present uneven surfaces riddled with cracks, crevices, and rocky formations [7]. Traditional construction methods prove inadequate, demanding a paradigm shift towards autonomous, adaptive systems capable of navigating unpredictable terrains.

3D printing is becoming increasingly acknowledged as a technology with great potential for extra-/terrestrial construction due to its versatility and efficiency [17]. In-situ 3D printing, guided by artificial intelligence (AI), enables the on-site production of extra-/terrestrial habitats using locally available information and materials. Hence, in this research, a robotic AI-supported 3D printing construction system is envisaged that maps the irregularities of lava tube surfaces. Specifically, the synergy between real-time mapping, machine learning (ML) i.e., deep learning (DL), CV, and depth sensing technologies is aimed at optimizing the efficiency, precision, and adaptability of the construction process, facilitating the on-site production of extra-/terrestrial habitats with a high degree of autonomy and resource utilization. This precise mapping acts as the cornerstone upon which the adaptive filling i.e., terrain leveling mechanisms operate, ensuring a stable and regularized surface for subsequent construction of habitats.

The paper presents the intricacies of the proposed methodology, emphasizing the integration of CV for dynamic terrain analysis and 3D printing for on-site, customized construction. While both CV and LiDAR play pivotal roles, this work explores the capabilities of CV, especially when compared to the well-established LiDAR scanning, in enhancing real-time terrain analysis and adaptive 3D printing for in-situ habitats.

[1] Link to CS-wiki: http://www.roboticbuilding.eu/project/rhizome-development-of-an-autarkic-design-to-robotic-production-and-operation-system-for-building-off-earth-habitats/.

[2] Link to CS-wiki: http://www.roboticbuilding.eu/project/rhizome-2-0/.

2 Related Work

The pursuit of constructing habitable spaces in extraterrestrial environments has spurred diverse research endeavors. The integration of CV techniques and 3D printing for in-situ construction, as explored in this study, aligns with and builds upon several existing threads of research.

In the realm of 3D printing for extraterrestrial habitats, Bier et al. (2021) introduced significant advancements in the design, production, and operation of subterranean off-Earth infrastructure. Von Ehrenfried (2022) delved into the concept of living in caves on Earth, Moon, and Mars, providing insights into potential subterranean living spaces to reduce exposure to radiation.

Considering the safety aspects of lunar habitats, de Angelis et al. (2006) conducted a comprehensive radiation safety analysis specifically tailored for lunar lava tubes, exploring their viability as protective shelters. Meanwhile, Ehresmann et al. (2021) focused on Mars, presenting findings on natural radiation levels measured with the MSL/RAD instrument, contributing valuable data for future Martian habitat designs.

Expanding the discussion to geological features, Sauro et al. (2020) offered a comprehensive review of lava tubes on Earth, Moon, and Mars, shedding light on their varied sizes and morphologies through comparative planetology. Furthermore, Perkins (2020) delved into the intriguing prospect of lava tubes serving as havens for ancient alien life and potential shelters for future human explorers.

Beyond planetary exploration, the literature includes a wealth of information on computer vision and LiDAR technologies. Porr et al. (2002) presented a VLSI-compatible computer vision algorithm for real-time stereoscopic depth estimation. In the realm of LiDAR technology, Zhao et al. (2019) discussed recent developments and industry trends.

This diverse array of research forms the foundation for the current study, weaving together insights from space exploration, habitat design, and advanced sensing technologies. While these studies contribute valuable insights to the broader field of space exploration and construction, the present research uniquely focuses on the fusion of CV and 3D printing technology, offering an innovative approach to address the complexities of lava tube environments.

3 Problem Statement

The prospect of utilizing lava tubes as potential habitation sites on celestial bodies like Mars and the Moon has sparked ambitious efforts in space colonization [8]. These subterranean chambers offer natural shielding against cosmic radiation and extreme temperature fluctuations, making them promising candidates for secure and sustainable living spaces [2–6]. However, the uneven and rugged terrains within lava tubes pose significant challenges for construction.

Integrating CV techniques with advanced 3D printing technology offers a transformative approach to address the challenges posed by complex landscapes. It brings about real-time adaptability and efficiency, making it a promising solution for construction projects in challenging terrains. Terrain analysis is a complex undertaking in a lava tube, primarily due to numerous surface irregularities to traverse in varying lighting conditions. To overcome the difficulties associated with real-time mapping, comprehensive terrain analysis requires the use of proper cameras and sophisticated CV techniques. By utilizing advanced CV algorithms, precise insights into the topography are achieved, enabling 3D printing that dynamically responds to identified irregularities in real-time. This capability not only streamlines the construction process but also ensures structural stability while leveling surfaces with accuracy. Utilizing advanced CV algorithms is essential for precisely deciphering the irregularities, as they have the potential to provide exact insights into the terrain [13, 14]. These algorithms are included in the category of depth detection algorithms that map and decipher the irregularities of lava tube surfaces, ranging from smaller surface irregularities to substantial hills and valleys.

4 Implications

The core objective of employing CV in lava tubes transcends mere technical challenges; it fundamentally impacts the habitability of the constructed spaces. By precisely mapping irregularities, the construction system ensures not only structural stability but also facilitates the seamless attachment of habitable structures against the lava tube walls and ground surfaces where necessary.

The understanding of the terrain's irregularities is crucial for the adaptive filling approach. The pixel-wise classification provided by the model is the cornerstone of the adaptive filling technique. By accurately identifying irregularities, the subsequent construction processes are finely tuned to the specific challenges posed by the lava tube environment.

This CV-supported technology developed on Earth for off-Earth applications will be transferred to on-Earth applications in remote, challenging terrains like mountainous regions or extreme possibly disaster-stricken environments where rapid, stable infrastructure deployment is crucial.

From disaster-prone regions needing resilient structures to ecologically sensitive areas requiring eco-friendly solutions, CV driven innovation bridges the gap between space exploration and terrestrial needs by minimizing environmental impact and heralding a sustainable future for construction practices worldwide.

5 CV vs. LiDAR Scanning

While LiDAR scanning utilizes laser pulses to measure distances, creating precise 3D representations of surfaces, there are advantages of using CV, making the process of depth estimation possibly more effective and efficient especially in scenarios where LiDAR scanning might encounter limitations:

(a) Real-time Analysis: CV operates instantaneously, allowing for swift analysis of dynamic environments [9, 10]. In lava tubes, where conditions can change rapidly, the ability to make immediate decisions based on real-time data is crucial. CV systems swiftly process visual data, enabling adaptive responses to unforeseen challenges in the construction process.

(b) Cost Efficiency: Unlike LiDAR technology, which can be expensive [11, 12], CV systems utilize off-the-shelf cameras and sensors, making them more cost-effective and accessible. This affordability renders CV a practical choice, especially in scenarios with limited budgets.
(c) Redundancy: Employing both LiDAR and CV creates redundancy in data collection methods. In situations where LiDAR scanning might fail due to technical issues or environmental constraints, such as extreme dust or low visibility, CV can serve as a reliable backup. Redundancy ensures a continuous flow of data, essential for uninterrupted construction operations.
(d) Low Power Consumption: Cameras generally consume less power compared to LiDAR systems.
(e) Color and Texture Information: Cameras provide additional color and texture information, enhancing the richness of data.
(f) Wider Field of View: Cameras may have a wider field of view, contributing to a more comprehensive understanding of the surroundings.

The real-time analysis offered by CV enables swift responses to dynamic environments, crucial for unpredictable conditions like those in lava tubes. The cost efficiency of CV, using available cameras and sensors, makes it practical, especially in budget-constrained scenarios. LiDAR does have also several advantages such as night vision, no use of complex algorithms, consistency and reliability in all weather conditions.

Ideally incorporating both LiDAR and CV in the endeavor ensures redundancy in data collection, providing a reliable backup in situations where technical issues or environmental constraints might impede the effectiveness of one system.

6 Methodology

In this research, an incremental solution approach is adopted where the methodology involves breaking down the overarching problem into manageable stages, proposing and implementing solutions one step at a time. Each phase is designed to build upon the preceding steps from synthetic depth map generation to the utilization of the U-Net deep learning framework for image segmentation. By doing so, the approach is systematically refined and optimized, ensuring the effectiveness of the proposed solutions. To demonstrate the impact of each step, comprehensive results, including quantitative data and qualitative insights are presented, showcasing the tangible outcomes achieved at each stage. This approach not only enhances the transparency of the employed methodology but also allows for a thorough evaluation of the efficacy of proposed solutions.

Depth Map and U-Net. The explored CV-supported methodology employs a Grasshopper script crafted to extract details from a 3D surface model, going beyond mere visual representation. Due to the very limited lava tube imagery, the advanced capabilities of Perlin noise algorithms[3] [15] are leveraged to create synthetic depth maps that unveil the irregularities of the surfaces. A depth map, in this work, is represented as a compact integer-valued grayscale image where each pixel represents the distance from the camera

[3] In depth estimation, the Perlin noise script was employed to generate synthetic depth maps or surfaces that mimic real-world textures and help train depth estimation models more effectively.

to the corresponding point in the scene. Lighter pixels indicate closer objects, and darker pixels represent farther objects. Depth maps are vital for tasks like 3D modeling and understanding the spatial layout of a scene from 2D images. The depth maps (see Fig. 2) serve as the foundational bedrock for the in-depth analysis, providing an understanding of the intricacies inherent to lava tubes.

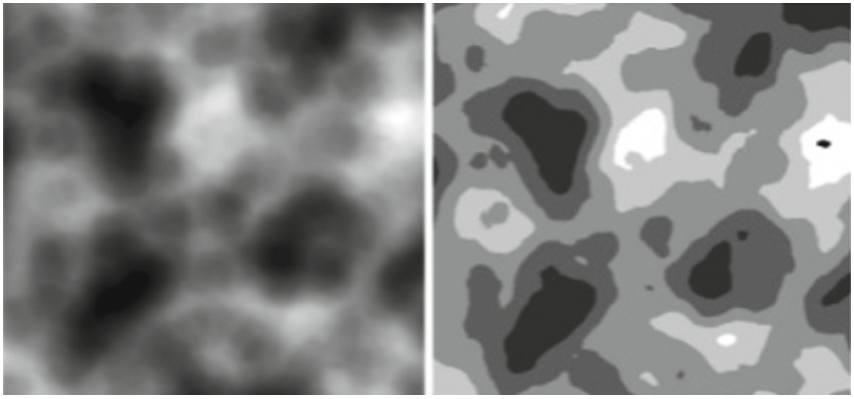

Fig. 2. Depth maps. Original input (left) and simplified depth map (right). The image underwent a thresholding operation, classifying pixels into five distinct intensity levels. This segmentation technique provides nuanced distinctions in visual features by categorizing the image into five layers based on intensity values. The choice of five layers strikes a balance between computational efficiency and the need to capture both coarse- and finer-grained structures in the lava tube. While optimizing computational resources, future adaptations may consider adding layers to enhance representation, acknowledging the trade-off between simplicity and the depth required for a more detailed analysis.

At the core of the method lies a robust data generation process to capture the raw essence of surface irregularities. The resulting black-and-white depth maps form the initial dataset; offer a glimpse into the diverse topography of the lava tube environment (see Fig. 3).

Python is used to process the imagery generated in the Grasshopper software further. The script processes the initial depth maps, transforming them into a spectrum of color-coded masks. Each hue on these masks signifies a distinct depth level, creating a representation of the lava tube's irregularities. The color-coded dataset forms the cornerstone of the training process, enabling the model to comprehend the interplay of depth within the lava tube environment. Each lava tube cavity is classified based on these data-rich depth maps. The depth understanding forms the foundation of the adaptive filling approach. With precision, irregularities are filled, hence ensuring a stable, level surface on the surface of choice.

A U-Net [16] i.e., DL framework specifically developed for image segmentation, is employed in this study to associate depth maps with the intricate features of terrain imagery within the challenging lava tube environment. Renowned for its prowess in capturing fine details, U-Net plays a pivotal role in this approach. Following the architecture of the original U-Net implementation, convolutional layers for both down- and

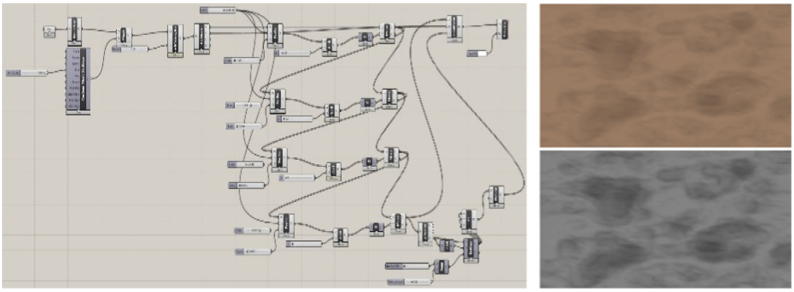

Fig. 3. Generation of the depth maps. Left: Grasshopper software script for synthetic image generation via Perlin noise algorithms. Right: Depth maps output in colour and black/white produced by Rhino's ZBuffer. Training models on both grayscale and color images enhance the model's robustness allowing it to learn features and patterns that are invariant to color variations, making it more adaptable to different scenarios.

up-sampling are utilized, ensuring adaptability to the unique characteristics of the lava tube surfaces. Notably, the U-Net model takes a grayscale image of the terrain (single-channel) as input and produces a depth map (multi-channel) as output, providing a comprehensive representation of the terrain's spatial intricacies.

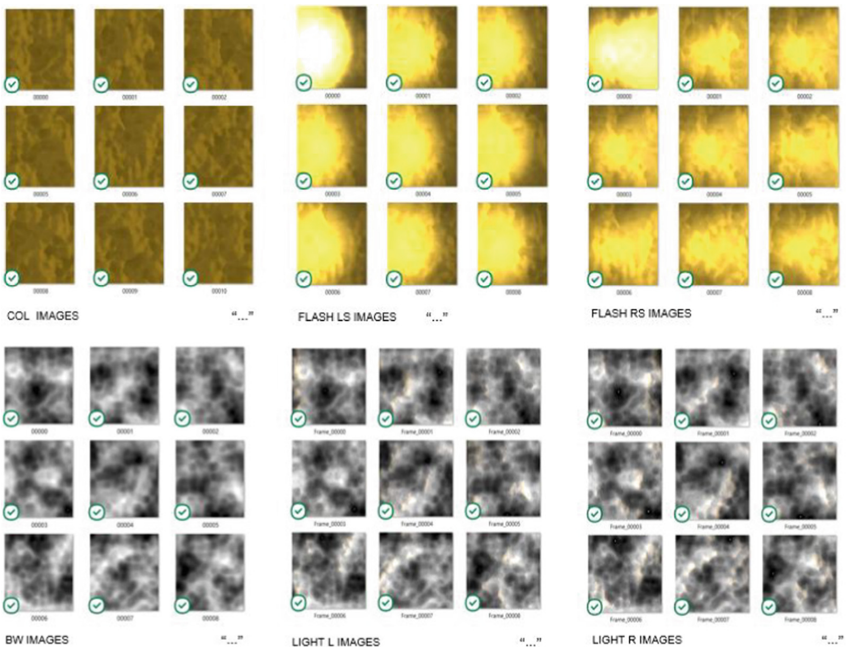

Fig. 4. Training data batch sample

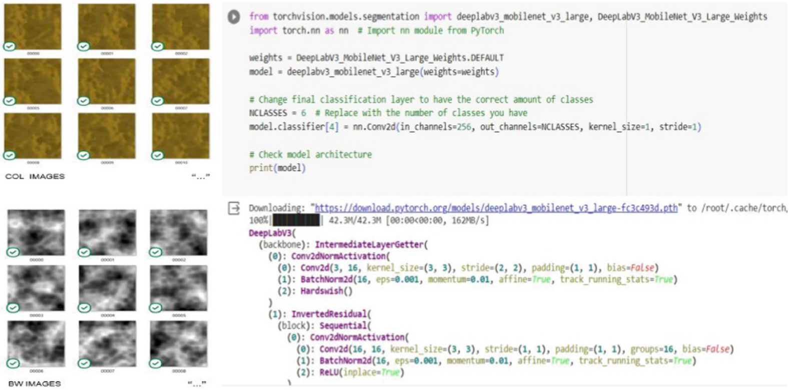

Fig. 5. Python Pseudocode. Extract from the model training, segmentation and classification models. DeepLabV3 assigns semantic labels to every pixel in an image, effectively segmenting the image into meaningful parts [19, 20].

Training Curves. The objective is to minimize the disparity between the predicted outputs and the actual labels in the training dataset. The U-Net was optimized using the Adam optimizer, a cross-entropy loss, and dropout for regularization. The Adam optimizer is a stochastic gradient descent method incorporating an adaptive estimation of the learning rate based on the mean and variance of the gradients of the model weights [18]. The training data consisted of six batches, each containing 100 images categorized into various scenarios, including color, black/white, left light source, right light source, left flash of light, and right flash of light (see Figs. 4 and 5).

The training process involved 20 epochs, and the learning rate was set to 0.001. Note that a decrease in the loss correlates with an increase in performance.

The training curves (see Fig. 7) illustrate the model's learning progress, demonstrating a reasonable proficiency in handling the tasks. Notably, the training accuracy exhibit steady improvement over time. However, it's observed that the validation accuracy shows only marginal enhancement, suggesting a potential risk of overfitting on the training data. This discrepancy hints at the need for additional data to enhance generalization and fine-tune the model's performance on unseen examples.

The training curves indicate consistent improvement in training accuracy indicating that the model improves at predicting the depth maps in the training set. It is crucial to balance high training accuracy with good validation performance to ensure that the model generalizes well to unseen data. If validation accuracy rises during training, it signifies the model is improving in making accurate predictions on new data, fulfilling the main purpose of validation. Initially high validation loss suggests the model struggles to fit data, but a decreasing trend over time shows that the model is learning and adapting through training. The training and validation metrics provide insights into how well the model is learning and generalizing from the data, from the learning curves it can be extrapolated:

Training Accuracy (0.8). The training accuracy of 0.8 indicates that, on the training data, the model correctly predicts the desired outcomes 80% of the time. This suggests

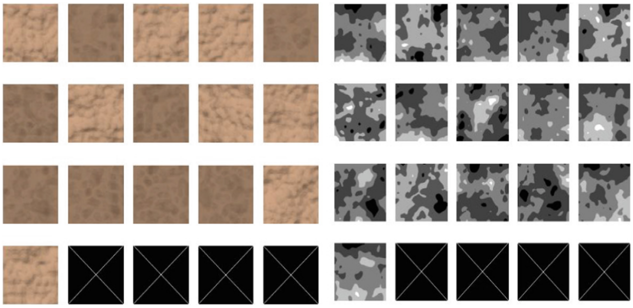

Fig. 6. Example predictions. Test samples are shown on the left. The predictions of the train U-Net are visualized on the right. A threshold of 5 is chosen, hence the 5 grayscale levels in the predictions.

a reasonable level of proficiency in capturing patterns within the training set, quite sufficient for the task.

Validation Curves. Validation curves are visual tools in ml that illustrate how a model performs during training by plotting a chosen metric, like accuracy or loss. These curves aid in determining optimal settings, avoiding overfitting or underfitting. Analyzing the curve's shape provides valuable insights into the model's behavior, assisting in the refinement of parameters for enhanced predictive accuracy and robustness.

Validation Accuracy (0.5). The lower validation accuracy of 0.5 suggests that the model's performance on new, unseen data is not as successful. It could indicate a potential issue with overfitting, where the model may be too specialized to the training data and does not generalize well. This indicates that more training data is required to omit overfitting.

In summary, while the model is learning well on the training data (as indicated by the high training accuracy and low training loss), the challenge lies in ensuring good generalization to new data (reflected in the lower validation accuracy and higher validation loss). Figure 6 shows example predictions. It would be worth to consider regularization techniques, or acquiring additional diverse data to address the observed overfitting and enhance the model's overall performance (Fig. 7).

In the context of this study, understanding the implications of these numerical values is crucial. To illustrate, a score of 0.8 signifies that 80% of pixels are correctly classified, but 20% are misclassified. Assessing precision for irregular surfaces with intricate details, this level may fall short of expectations. While it indicates a promising beginning, it raises concerns, suggesting, for example, that part of the image could be inaccurately predicted.

In summary, the experiments yield a satisfactory outcome, indicating that the applied methodologies are effective to a certain extent. However, there is room for improvement in refining and optimizing the approaches employed. The results suggest a promising foundation, yet opportunities for enhancing precision, efficiency, or addressing specific limitations are apparent, presenting avenues for future enhancements in the experimental design or implementation strategies.

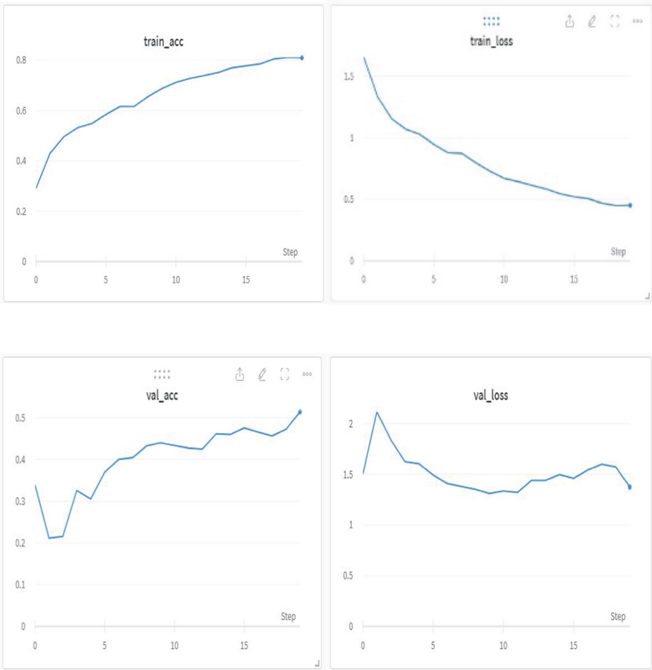

Fig. 7. Training curves indicating the training process. From left to right, the training accuracy, training loss, the validation accuracy, validation loss.

7 Conclusion

In conclusion, this research represents a fusion of technological innovation and adaptability, envisaging a new era in construction methodologies. Through the integration of CV techniques and 3D printing technology, the complex challenges posed by lava tube irregularities are addressed. The result is a comprehensive system capable of autonomously analyzing real-time surface data which dynamically adapts the 3D printing construction process to these intricate features of the surface. This procedure provides the necessary prerequisites for leveling surfaces as well as constructing the habitats requiring positioning and maneuvering of the printer robot.

The model, following training and validation, has demonstrated promising potential. The augmentation of the dataset with diverse examples would enhance the model's understanding, paving the way for more effective generalization in future applications. Simultaneously, ongoing meticulous evaluations of the model's architecture would ensure its capability to handle increasingly intricate irregularities.

In a future experimental setup in a lava tube in Sicily to be implemented in collaboration with the University of Palermo and the I NEBRODI Naturalistic Association, a camera placed at the extremity of a robotic arm of a rover would capture the essence of the lava tube environment, yielding a wealth of images that intricately document the irregularities of the surfaces. These images, showcasing the nature of the terrain, would serve as the foundational elements for the training dataset.

For further advancement of the study, a proposed strategy involves capturing real photographs of a lava tube and coupling them with LIDAR results to ascertain the depth in each image. This approach aims to provide a tangible dataset for validation, laying the groundwork for refining and fine-tuning the pre-trained model on image and depth map pairs. While the specifics of this process remain a challenge for future exploration, it stands as a crucial step in ensuring the model's accuracy and applicability in real-world scenarios.

Reflecting on the significance of these findings, it becomes evident that the successful development and implementation of an integrated construction methodology with CV represents a pivotal moment in the trajectory of space exploration. The adaptability showcased in addressing the challenges of extraterrestrial environments positions this approach as a cornerstone for future sustainable habitats beyond Earth.

This research not only marks a significant leap forward in construction but also sets the stage for a continuous journey of innovation and refinement, with the ultimate goal of establishing sustainable habitats in extra-/terrestrial environments.

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