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## Neural Radiance Fields in Space Applications : A Comprehensive Review

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# Neural Radiance Fields in Space Applications : A Comprehensive Review

**Abstract** — Neural Radiance Fields (NeRF) have emerged as a powerful deep learning technique, revolutionizing the representation and rendering of 3D scenes. Although originally developed for computer vision and graphics applications, the potential of NeRF is increasingly being recognized in space-related fields. This paper provides a comprehensive review of the applications, advancements and challenges associated with the use of NeRF in space exploration, satellite imaging and remote sensing. We begin by introducing the foundational concepts of NeRF, including its architecture, underlying principles and computational requirements. We then explore how NeRF has been adapted and applied to space-specific challenges such as high-resolution 3D reconstruction of planetary surfaces, the visualization of satellite data and the enhancement of space mission planning. Furthermore, we discuss the integration of NeRF with other cutting-edge technologies like machine learning, autonomous systems and real-time rendering, highlighting the potential for future breakthroughs in space missions. Finally, we outline the current limitations and open research questions, offering insights into the future directions of NeRF in space applications. This review aims to serve as a valuable resource for researchers and practitioners exploring the intersection of machine learning, computer graphics and space science.

**Keywords** — Neural Radiance Fields (NeRF), Computer Vision, Deep Learning, Space Applications, Space Exploration

## I. INTRODUCTION

The rapid advancements in machine learning and computer vision have led to transformative breakthroughs in various fields, including space exploration and satellite-based remote sensing. One such breakthrough is the development of Neural Radiance Fields (NeRF), a deep learning-based method that generates photorealistic 3D scenes from 2D images by modeling the volumetric scene representation. Originally introduced by Mildenhall et al. [1] in 2020, NeRF has garnered significant attention due to its ability to synthesize realistic 3D environments with impressive detail and fidelity. These capabilities have prompted research into leveraging NeRF for space-related applications, where high-resolution 3D reconstructions and visualizations are critical for missions such as planetary exploration, satellite imaging and real-time space mission planning.

In space exploration, the need for accurate, high-quality 3D models of planetary surfaces, celestial bodies and orbital environments is fundamental to mission success. Traditional methods [2, 3] for constructing these models often rely on complex sensor data processing, which may be time-

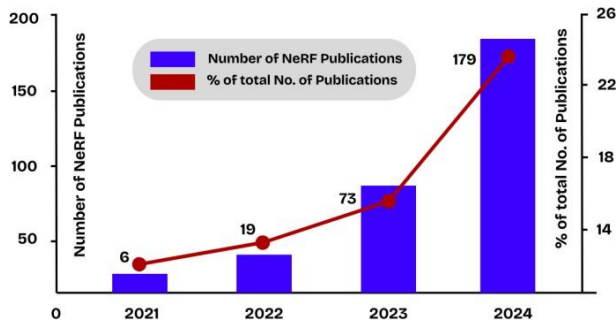
consuming and computationally expensive. NeRF offers a promising alternative, enabling high-quality 3D visualizations from relatively sparse input data. This ability can significantly reduce the cost and complexity of space mission operations, such as terrain modeling, navigation and resource mapping.

Furthermore, as satellite constellations proliferate, space-based observation systems require efficient methods for processing and interpreting massive datasets. NeRF's potential for enhancing satellite imagery, improving remote sensing capabilities and visualizing data in 3D opens up new avenues for real-time decision-making in space missions. Beyond visualization, NeRF has applications in autonomous spacecraft navigation, mission planning and even the simulation of extraterrestrial environments [4], potentially revolutionizing how space agencies approach mission design, training and execution. Despite its promise, the application of NeRF in space applications presents unique challenges. Space-related data often come with a variety of complexities such as noise, occlusions, varying illumination conditions and sparse data coverage. Additionally, the computational demands of NeRF, particularly in terms of training large neural networks and rendering 3D scenes in real-time, can be an obstacle to its broader adoption in space exploration and remote sensing applications.

Space exploration and Earth observation have long relied on traditional imaging techniques such as stereo photogrammetry [5, 6], LiDAR and radar for mapping and monitoring. However, these methods often face limitations in terms of accuracy, resolution and computational efficiency. In recent years, Neural Radiance Fields (NeRF) has become a powerful technique for synthesizing realistic 3D models and rendering new viewpoints from a sparse collection of 2D images. NeRF represents 3D scenes through neural networks, capturing volumetric properties like color as well as opacity at every point in space. This makes NeRF a promising tool for a variety of space applications, where high-quality 3D reconstructions from limited imagery are needed. The ability of NeRF to generate photo-realistic 3D models has significant implications for satellite-based Earth observation, planetary exploration, space debris monitoring and astronomical research. This review aims to provide an in-depth look at the underlying principles of NeRF, its variants, applications in space, challenges and future directions.

This paper provides a comprehensive and thorough review of the emerging field of NeRF for space applications. We begin by introducing the foundational principles of NeRF, followed by an exploration of its key applications in space exploration, satellite imaging and remote sensing. We also discuss the challenges of applying NeRF to these domains and propose potential solutions. Finally, we outline future research directions and opportunities for the integration of NeRF with other advanced technologies such as autonomous systems [7], machine learning [8] and real-time rendering [9], to push the boundaries of what is possible in space missions by using NeRF.

The below graph shows the number of publications increasing every year based on Neural Radiance Fields:



**Fig 1:** Number of NeRF publications over the years as in [5]

### A. Background

Neural Radiance Fields (NeRF) have transformed the field of computer vision by enabling the synthesis of photorealistic 3D scenes from sparse sets of 2D images. Introduced by Mildenhall et al. in their seminal work [1], NeRF utilizes a fully connected deep learning neural network in order to model the volumetric scene function of a 3D environment. The technology interpolates the color as well as the density of light at any point in the 3D space from which photo-consistent images are rendered from novel viewpoints. This ability has profound implications for numerous applications, ranging from virtual reality to autonomous navigation.

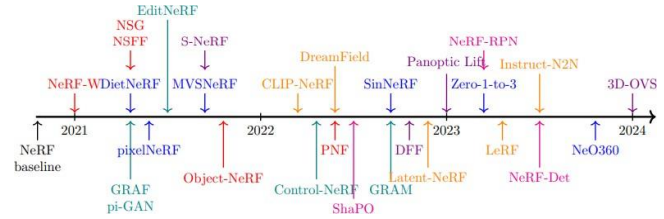
### B. Importance in Space Technology

In space technology, high-resolution 3D modeling and accurate real-time imaging are paramount. Traditional methods of capturing and reconstructing space environments involve either physically detailed probes or computationally intensive simulations, each with its limitations in terms of resolution, scalability or timeliness. NeRF offers a compelling alternative by promising to reconstruct high-fidelity models from limited image data [10]. In space applications, such capabilities can enhance satellite imagery analysis, improve navigation and docking procedures for spacecraft and facilitate realistic simulations for mission planning and astronaut training.

### C. Scope of Review

This review paper focuses on the adaptation and application of NeRF in the context of space exploration and satellite technology. Given the extreme conditions and unique challenges of the space environment, such as varying lighting conditions, limited data capture opportunities and

the need for computational efficiency, NeRF's application extends beyond its initial terrestrial constraints. We explore its use in enhancing the quality and accuracy of satellite imagery [11], aiding in autonomous spacecraft navigation and creating simulated environments for mission preparation. Furthermore, we discuss the technological challenges and potential advancements needed to fully leverage NeRF in these high-stakes applications.



**Fig 2:** Timeline of various NeRF methods for space

NeRF [1] is having high citation impact and received the ECCV 2020 Oral - Best Paper Honorable Mention. It also received prestigious awards and recognition within the academic community for its novel approach to 3D rendering from 2D images and has influenced not only computer graphics and vision but also areas like robotics, virtual reality and cultural heritage preservation.

### D. Objective of the Review

The primary goal of this review is to provide a comprehensive or complete overview of how NeRF technologies are being integrated into space applications, what has been achieved so far and what challenges remain. The review aims to synthesize current research findings, highlight critical advancements and outline the roadmap for future research and implementation strategies.

## II. NEURAL RADIANCE FIELDS: PRINCIPLES AND VARIANTS

### A. The NeRF Framework

NeRF model a scene by representing each point in 3D space with a neural network that actually predicts the color as well as the opacity of the point, given its 3D coordinates and the viewing direction. NeRF leverages a fully connected multi-layer perceptron (MLP) in order to map the spatial coordinates and viewing angles to light intensities, which are then combined via volume rendering to generate a final image [12]. The network is trained using a set of 2D images taken from various different types of viewpoints. The goal is to minimize or reduce the rendering error between synthetic images and real-world images, allowing the model to generalize to novel viewpoints.

The fundamental strength of NeRF lies in its ability to simulate light transport and material properties within a scene, which enables it to generate highly realistic 3D reconstructions from sparse data.

### B. Fundamentals of Neural Radiance Fields

Neural Radiance Fields introduce a new approach to the 3D reconstruction of complex scenes from a sparse set of 2D images. The core innovation of NeRF lies in its ability to use a deep neural network in order to parameterize a continuous volumetric scene function that predicts the color as well as the density of light for each point in 3D space



[13]. Unlike traditional 3D reconstruction methods that rely on discrete representations such as point clouds or meshes, NeRF models the scene as a continuous volume where the scene's appearance changes smoothly with perspective and lighting conditions.

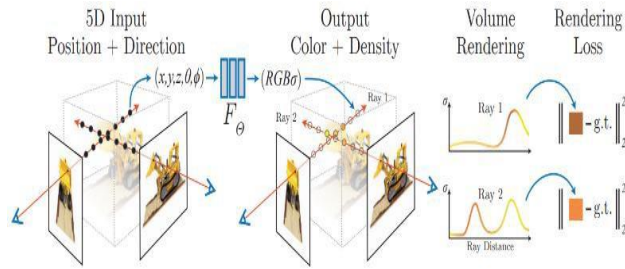


Fig 3: Representation of NeRF as in [1]

The technical foundation of NeRF basically involves using a coordinate-based neural network that takes as input a *spatial location*  $(x,y,z)$  and *viewing direction*  $(\theta,\phi)$  and then outputs the RGB color and volume density at that point. This is achieved by training the deep neural network with a collection of images of the scene from known viewpoints. During training, the model learns to regress the color and opacity values that when integrated along the camera rays using the volume based rendering techniques, best reconstruct observed images. This process uses differentiable rendering to adjust the network weights based on the reconstruction error [14].

One of the key advantages of NeRF over traditional methods is its ability to produce highly detailed and photorealistic renderings of complex scenes. This is facilitated by the model's inherent ability to interpolate and generalize from the training data it has seen, allowing for novel view synthesis with impressive fidelity [15]. Moreover, NeRF inherently supports dynamic lighting and viewing conditions, making it exceptionally well-suited for applications requiring realistic visualization under varying conditions.

However, NeRF also comes with its set of challenges. The model is computationally intensive, requiring significant processing power and time to train and render, particularly for high-resolution outputs. Additionally, the quality of the reconstruction heavily depends on the coverage and quality of the input images. Scenes with occlusions, complex textures or reflective surfaces can pose significant difficulties for accurate reconstruction [16].

While NeRF represents a significant enhancement and improvement in the field of computer vision and 3D reconstruction, its practical deployment, especially in resource-constrained environments such as space, requires addressing its computational demands and limitations in handling diverse scene complexities. Ongoing research aims to optimize these aspects, making NeRF a promising technology for future applications in various fields, including space exploration.

### C. Architecture of Neural Radiance Fields

The figure 4 shows the architecture of NeRF and its details: Neural Radiance Fields (NeRF) utilize a fully connected deep neural network, known as a multilayer perceptron (MLP), to represent 3D scenes. This MLP takes as input a continuous 5D coordinate comprising spatial location  $(x, y, z)$  and viewing direction  $(\theta, \phi)$ , and outputs the volume density and view-dependent emitted radiance at that point. By sampling points along camera rays and applying volume rendering techniques, NeRF synthesizes novel views of complex scenes from a sparse set of input images.

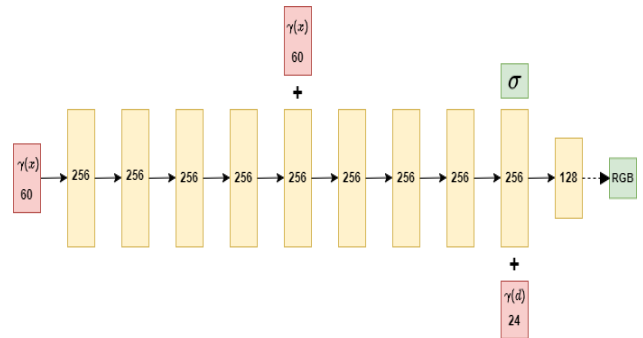


Fig 4: Architecture of Neural Radiance Fields

### D. Advancements in NeRF Variants

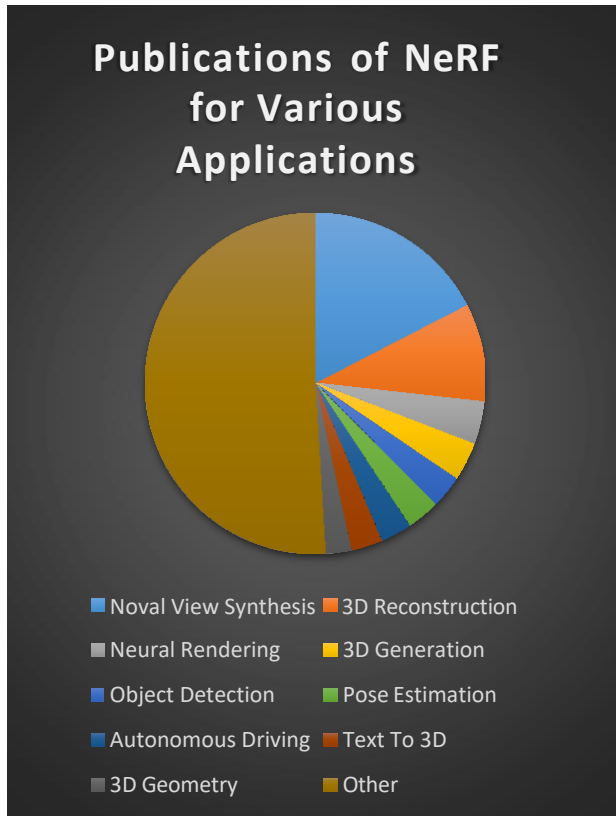
While the original NeRF model was computationally expensive, recent developments have led to several variants that improve speed, scalability and applicability to dynamic and large-scale scenes:

- **Dynamic NeRF (D-NeRF)** by Park et al. [17] extended NeRF to dynamic environments, incorporating temporal information to handle scenes with moving objects. This is particularly relevant for satellite imaging where objects like clouds, vehicles and atmospheric conditions change over time.
- **Fast NeRF (NeRF-W)** from Liu et al. [18] introduced optimizations to make NeRF more computationally efficient. Their work on NeRF-W reduces the memory and computational load required for training and rendering, enabling real-time applications such as on-board spacecraft processing and quick terrain mapping.
- **Physics-Informed NeRF** by Zhao et al. [19] proposed integrating physical models of light scattering and reflection into the NeRF framework, improving its accuracy in environments with complex lighting and material properties, such as planetary surfaces and space habitats.
- **Multi-Scale NeRF** handles large-scale environments by generating multi-resolution models. Chen et al. [20] demonstrated that multi-scale NeRF is particularly effective for planetary surface mapping, where large terrain areas require efficient handling of varying levels of detail.

### III. APPLICATIONS OF NeRF IN SPACE

There are many applications of NeRF for space and Figure 5 shows the pie chart of different applications where NeRF is used.





**Fig 5:** Various publications of NeRF

Here are some of the applications where NeRF is applied for space systems:

#### A. *Satellite Imaging and Earth Observation*

Satellite imaging plays an important role in Earth observation, providing vital data for environmental monitoring, land use planning and disaster response. NeRF can enhance these capabilities by providing high-resolution 3D models from a limited collection of 2D satellite images. Zhu et al. [21] demonstrated that NeRF can generate topographic models of urban areas, improving the accuracy of elevation data compared to traditional stereo photogrammetry.

Applications in satellite imaging include:

- Topographic mapping where NeRF enables the generation of highly accurate 3D terrain models from satellite images which are valuable for flood risk analysis, agricultural monitoring and infrastructure planning.
- In disaster management by synthesizing 3D models from pre and post-disaster imagery, NeRF can assist in assessing damage and planning disaster recovery efforts.
- For environmental monitoring, NeRF helps in monitoring deforestation, land use changes and other environmental phenomena through periodic satellite imagery [22]. The application of Neural Radiance Fields (NeRF) in satellite imagery represents a significant innovation in the field of remote sensing and earth observation.

NeRF's core ability to generate detailed three-dimensional reconstructions from sparse and diverse two-dimensional satellite images allows for substantial improvements in

image resolution and detail. This is achieved through NeRF's deep learning framework, which models the volumetric density and color of every point in space, enabling it to infer and fill in details that are not explicitly captured in the single images.

This can significantly enhance the clarity and utility of satellite images in various applications:

- In urban planning where, higher resolution images can help urban planners and developers better understand land use patterns and plan infrastructure projects more effectively [23].
- Enhanced detail aids in more accurate environmental monitoring of environmental changes such as deforestation, desertification and water body dynamics.

Satellite images are often compromised by occlusions due to clouds, fog or atmospheric pollutants. NeRF can address these challenges by interpolating obscured parts of an image, drawing on its understanding of the 3D structure of the scene derived from clear segments of other images. [24, 25]

This capability is crucial for:

- In weather forecasting for continuous monitoring without interruptions due to cloud cover can provide more reliable data for weather prediction models.
- Farmers and regulators can obtain consistent views in agricultural monitoring of crop health and growth, even under adverse weather conditions, aiding in decision-making for irrigation, harvesting and pest control.

NeRF can be instrumental in ensuring temporal consistency across satellite images captured at different times, under varying conditions. This is particularly beneficial for long-term environmental monitoring and change detection, where inconsistencies between images can lead to inaccurate assessments or missed changes:

- Tracking changes in ice caps, sea levels or vegetation over time with high consistency can provide clearer evidence of climate impacts for climate change studies.
- Following natural disasters, for disaster assessment consistent time-series data is crucial for assessing changes and planning recovery efforts.

Traditionally, creating 3D models from satellite data requires stereo pairs or complex radar systems [26, 27]. NeRF introduces a method to infer three-dimensional information from non-stereoscopic images, which can be revolutionary for geological and urban modeling:

- Enhanced 3D models can improve GIS applications in government and civil sectors by providing more accurate terrain models.
- 3D mapping of historical sites from satellite images can aid in the preservation and study of archaeological sites for Archaeological Reconstructions.

While the application of NeRF in satellite imagery is promising, several challenges need to be addressed:

- High computational cost because NeRF requires substantial computational resources for training and inference [28], which can be a limitation especially for processing large datasets typical of satellite imagery.

- Effective training of NeRF models necessitates a large and varied dataset that may not always be available in remote sensing applications.
- Satellite images are taken under a myriad of dynamic environmental conditions that can affect the accuracy of NeRF reconstructions [29]. Adapting NeRF models to handle such variability effectively remains a key area of research.

Ongoing research into improving the efficiency and robustness of NeRF could lead to broader applications in satellite imagery. Potential future developments include:

- Enhancements in computational efficiency could enable near real-time processing of satellite data with NeRF, opening up possibilities for live monitoring and decision-making.
- Integration with other data sources like combining NeRF with other data sources such as drone imagery or ground-based sensors [30] could enhance the depth and accuracy of the reconstructions.

NeRF offers transformative potential for satellite imagery applications by providing enhanced image resolution, the ability to reconstruct occluded areas, ensuring temporal consistency and enabling detailed 3D modeling. Addressing the computational and data-related challenges will be crucial to fully leverage NeRF's capabilities in satellite imagery and other remote sensing fields.

### B. Planetary Exploration and Terrain Mapping

NeRF has significant potential in planetary exploration, especially for missions to the Moon, Mars and other celestial bodies. Traditional techniques such as stereo imaging and LiDAR have been used to generate 3D maps of planetary surfaces, but NeRF can offer more photorealistic models with finer details. Recent research by Zhao et al. [31] applied NeRF to Mars terrain mapping, demonstrating its ability to generate highly detailed 3D surface models from sparse images collected by orbiters.

NeRF applications in planetary exploration include:

- Surface mapping for generating accurate 3D models of planetary surfaces from orbital and rover-based imagery, aiding in mission planning, navigation and hazard detection.
- Autonomous navigation like enhancing the autonomy of rovers and landers by providing richer spatial context for obstacle detection and navigation.

The utilization of Neural Radiance Fields (NeRF) in planetary exploration and rover navigation marks a significant leap in the technological capabilities deployed on extraterrestrial surfaces. NeRF's capability to make accurate 3D reconstructions from a series of 2D images make it an invaluable tool in navigating and exploring other planets [32], where traditional mapping and navigation methods face numerous challenges.

NeRF can transform sparse and varied imagery captured by rovers into detailed 3D maps of planetary surfaces, providing richer information than conventional 2D images or rudimentary 3D models. High-resolution terrain mapping where NeRF models generate high-resolution 3D representations of planetary terrains, capturing fine details such as small rocks, dunes and other surface features [33].

This level of detail is crucial for scientific analysis and safe navigation. For subsurface analysis, by integrating NeRF with penetrating radar data, it's possible to not only model the surface but also to infer some characteristics of the subsurface environment, which is vital for understanding planetary geology and searching for subsurface water or ice. Rover navigation on other planets requires highly accurate and up-to-date spatial information to avoid hazards and optimize travel routes. NeRF enhances rover autonomy by providing more comprehensive environmental models. In obstacle avoidance, detailed 3D models allow rovers to identify and avoid potential hazards such as large rocks, steep inclines and crevices, enhancing their ability to navigate safely and efficiently across unknown terrains. For optimal route selection, NeRF enables the generation of topographical maps that help in planning paths that optimize energy consumption and minimize travel time, while also considering scientific points of interest.

The implementation of NeRF in the harsh environment of space exploration presents unique challenges [34] that must be addressed to fully leverage this technology:

- Limited data and communication constraints as planetary rovers typically operate under significant limitations on data transmission due to the vast distances involved. NeRF models require a considerable amount of data to create accurate reconstructions, posing a challenge in environments where data bandwidth is limited.
- Due to limitation in computational resources, rovers have limited onboard computing power, which constrains the complexity of the algorithms that can be run in real-time. NeRF's computationally intensive nature requires optimizations or potentially dedicated hardware to function effectively in this context [35].
- Because of environmental factors, planetary surfaces can present extreme variability in lighting, weather and other conditions that affect image quality and model accuracy. Adapting NeRF to function reliably under such conditions is crucial.

As computational technology evolves and becomes more robust, the application of NeRF in planetary exploration is expected to expand:

- For integration with autonomous systems, further integration of NeRF with rover's autonomous systems could enhance their decision-making capabilities, allowing for more complex missions that involve minimal human intervention.
- Ongoing research aims to minimize the many computational demands of NeRF and improve its efficiency [36], potentially allowing for real-time processing even on limited hardware platforms.
- Combining NeRF with data from other sensors, such as LiDAR, multispectral imagers and thermal cameras, could provide a more comprehensive understanding of planetary environments, aiding in both navigation and scientific exploration [37].
- NeRF holds significant potential to transform planetary exploration and rover navigation by providing detailed 3D reconstructions that enhance both scientific research and operational safety.

As challenges related to data requirements, computational limits and environmental adaptability are addressed, NeRF is

poised to become a cornerstone technology in the exploration of other planets.

Figure 6 shows the various applications of space where NeRF is applied:

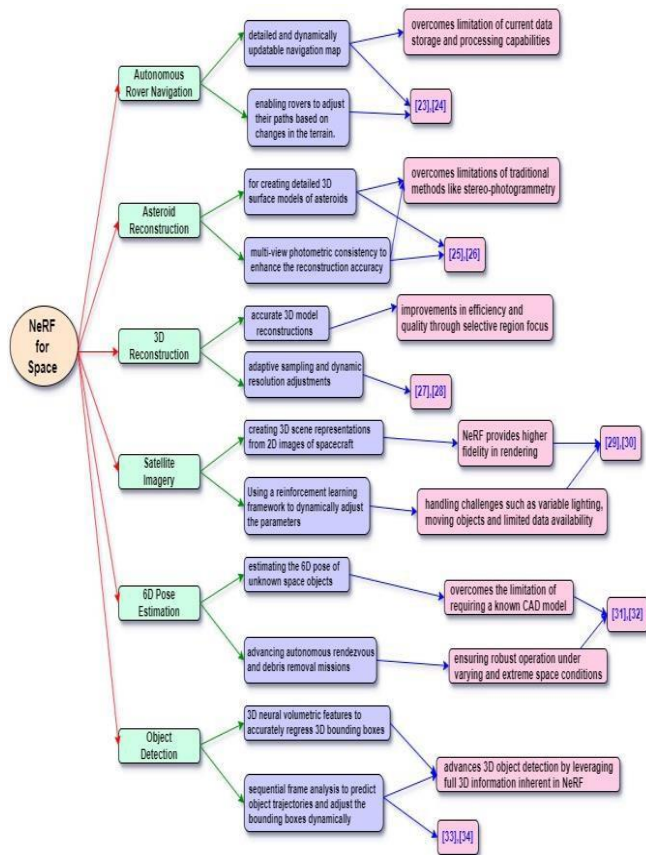


Fig 6: NeRF used for different space applications

C. Space Debris Monitoring

Space debris poses a significant risk to active satellites and crewed space missions. NeRF can improve space debris detection and tracking by generating detailed 3D reconstructions from limited observation data. Liu et al. [38] demonstrated that NeRF could be used to model space debris fields in orbit, enhancing collision risk assessments and the development of debris mitigation strategies. Applications in space debris monitoring include:

- For 3D modeling of debris, using satellite imagery to generate detailed models of debris, even from limited observational angles.
- In collision avoidance, providing better situational awareness for satellite operators to avoid collisions with small debris.

D. Spacecraft Navigation and Docking

NeRF also holds significant potential for improving spacecraft navigation and docking procedures. In space missions, accurate docking is critical, especially for missions involving the International Space Station (ISS) or other spacecraft rendezvous. NeRF can be utilized to create highly accurate 3D models of docking areas from multiple camera angles, providing enhanced situational awareness to both autonomous systems and human operators. This application has been tested in simulated environments with results showing improved accuracy and reduced risk of collision or

misalignment during docking maneuvers [39]. The integration of NeRF into spacecraft navigation and docking systems presents a transformative approach to handling the complexities associated with these critical operations. NeRF's ability to create high-fidelity 3D models from 2D images can significantly enhance the accuracy and safety of spacecraft navigation and docking procedures.

NeRF can substantially improve visual navigation systems by providing detailed 3D reconstructions of the spacecraft's surroundings. This capability is particularly useful in environments where GPS or other RF-based navigation systems are unreliable or unavailable such as in deep space or on other celestial bodies [40, 41].

- For autonomous navigation, NeRF allows spacecraft to autonomously navigate by interpreting complex environments and identifying safe paths or orbits, reducing the dependency on ground-based controls.
- In obstacle avoidance, detailed 3D models generated by NeRF can help identify and avoid potential hazards such as space debris, other spacecraft or rough terrain on celestial bodies.

Docking is one of the most delicate operations in space missions, requiring high precision to avoid costly or dangerous collisions [42]. NeRF can enhance docking procedures by providing accurate and up-to-date 3D models of the docking area and any involved spacecraft.

- During the simulation of docking procedures, NeRF can simulate various docking scenarios in high detail, allowing operators and autonomous systems to practice and refine docking procedures before actual implementation.
- For real-time adjustments during docking, NeRF can continuously update the 3D model based on incoming imagery, allowing for real-time adjustments to the docking approach in response to any changes in the relative positions and orientations of the spacecraft.

Implementing NeRF in spacecraft navigation and docking involves several technical and operational challenges that must be addressed:

- Due to computational constraints, space missions often have strict limitations on available power and computational resources. The high computational demands of NeRF models may necessitate specialized hardware or significant optimization.
- Data quality and availability is needed for effective operation of NeRF-based systems requires high-quality, multi-angle images, which may not always be feasible to obtain in space environments due to factors like lighting variability and limited sensor fields of view.
- Spacecraft navigation and docking occur within dynamic environments where relative positions and conditions change rapidly [43]. NeRF models need to be highly responsive and adaptable to these dynamics to be effective.

Ongoing advancements in computational technology and machine learning are likely to expand the feasibility and effectiveness of using NeRF for spacecraft navigation and docking: Integration with other sensory data like combining NeRF with data from radar, LIDAR and other sensors can enhance the robustness and accuracy of navigation and docking systems, creating a more comprehensive situational



awareness [44]. For machine learning optimizations, research into more efficient machine learning models and training techniques could reduce the computational overhead of NeRF, making it more suitable for space applications. NeRF offers promising potential to revolutionize spacecraft navigation and docking, providing detailed 3D reconstructions that enhance both autonomous and manual operations [45]. As technology and computational capabilities continue to advance, NeRF could become a standard tool in the aerospace industry, significantly improving the safety and efficiency of space missions. However, addressing the challenges related to computational requirements, data quality and dynamic environmental adaptation will be crucial for the successful integration of NeRF technologies in space exploration.

### E. Mission Simulation and Astronaut Training

Another vital application of NeRF in space technology is in mission simulation and astronaut training. NeRF's ability to render photorealistic 3D environments from 2D images makes it an excellent tool for creating virtual reality (VR) simulations of various space environments. These simulations can help astronauts train for specific missions, familiarizing themselves with the spacecraft, equipment and potential scenarios they might encounter. NASA and other space agencies are exploring the use of NeRF to enhance their training modules, making them more immersive and effective. This technology not only helps in reducing the training costs but also increases the safety and efficiency of the missions [46]. Integrating Neural Radiance Fields (NeRF) into mission simulation and astronaut training offers a groundbreaking way to enhance the preparation and execution of space missions. NeRF's capability to render photorealistic 3D environments from 2D images allows for the creation of detailed and immersive training modules that closely mimic real-world conditions in space.

NeRF's ability to produce highly detailed and realistic 3D models from ordinary images enables the creation of training environments that are visually and spatially accurate to real scenarios astronauts might face during missions. This realism is crucial for effective training, especially for high-risk operations.

- Visual and spatial accuracy is improved as NeRF can generate training modules that replicate the exact visual and spatial conditions of spacecraft interiors and exteriors [47], planetary surfaces and other celestial environments. This level of detail includes everything from the placement of instruments and equipment to the textural details of surfaces.
- Dynamic scenario simulation where advanced NeRF models can simulate dynamic environments that change over time or in response to astronaut's actions, providing realistic feedback and conditions that improve decision-making skills under pressure.

Realistic simulations crafted using NeRF not only enhance the training experience but also significantly improve the safety and efficiency of space missions by providing astronauts with a better understanding of their working environments before actual exposure.

- For emergency response training, NeRF simulations can include potential emergency scenarios, allowing

astronauts to practice and refine their responses to situations like equipment failures, sudden depressurization or fire outbreaks in a controlled and safe setting [48].

- EVA (Extravehicular Activity) preparation involved for activities outside the spacecraft, NeRF can create highly realistic simulations of the external environment of spacecraft or space stations [49], including detailed models of surfaces and modules that astronauts will interact with during EVAs.

While the potential benefits of using NeRF in mission simulation and astronaut training are considerable, several challenges must be addressed:

- The high computational requirements of NeRF-based simulations can be a barrier, particularly for real-time applications. Training simulations often need to run on systems with limited processing power, requiring optimizations to the NeRF algorithms to ensure smooth performance.
- Developing accurate NeRF models requires extensive datasets of images under various conditions. Collecting and processing these images for use in training simulations can be time-consuming and resource-intensive [50].
- Incorporating NeRF simulations into established astronaut training programs requires careful coordination. The simulations must be validated for educational effectiveness and integrated in a way that complements traditional training methods.

Continued advancements in NeRF technology and computational hardware are likely to enhance its application in mission simulation and astronaut training:

- In hybrid training environments where combining NeRF with virtual reality (VR) and augmented reality (AR) technologies [51] could lead to more immersive and interactive training environments. This integration can allow astronauts to interact with simulations in a more intuitive and natural manner, improving the training outcomes.
- Future developments could enable NeRF systems to automatically generate training scenarios based on mission objectives and past performance data. This would provide a highly personalized training experience that adapts to the individual needs of astronauts.

NeRF presents a promising avenue for revolutionizing mission simulation and astronaut training, offering unprecedented levels of realism and interactivity. As the technology matures and becomes more integrated into astronaut training programs, it has the capability to significantly improve the preparedness and safety of crew members undertaking complex and hazardous missions in outer space. Addressing the computational and integration challenges will be infact key to fully realizing the true potential of NeRF in this critical application area.

### F. Planetary Exploration and Rover Navigation

NeRF is also being adapted for use in planetary exploration, particularly in navigating planetary rovers. On planets like

Mars, where sending back high-resolution images is bandwidth-intensive, NeRF can reconstruct high-quality 3D maps from sparse and low-resolution images sent by rovers. These maps are crucial for navigating the challenging and unknown terrains of other planets. By improving the quality and utility of visual data, NeRF enhances the autonomous capabilities of rovers, allowing for more effective exploration and data collection with reduced human oversight [52].

### G. Space Astronomical Research and Space Telescopes

NeRF also holds promise for astronomical research, where 3D reconstructions of celestial objects such as nebulae, galaxies and star systems can lead to new insights into the formation and evolution of these bodies. NeRF can generate detailed 3D models of distant astronomical objects [53], allowing for a better understanding of their structure and behavior.

Applications in astronomy include:

- Celestial object modeling where it improves the modeling of nebulae, galaxies and exoplanetary systems by generating 3D visualizations from images captured by space telescopes.
- Light propagation simulations where it simulates light interactions within deep space environments to refine astrophysical models and improve observational accuracy.

## IV. DATASETS FOR NeRF

There are many datasets which are used by NeRF for space applications.

Creating and utilizing specific datasets for Neural Radiance Fields (NeRF) applications in space involves gathering and preparing image data from space missions, simulations, and ground-based observations. These datasets must be carefully curated to effectively train NeRF models that are capable of reconstructing high-fidelity 3D environments from 2D images.

Here is a detailed description of the types of NeRF datasets typically used for space applications:

### A. Satellite Imagery Datasets

These datasets consist of images captured by Earth observation satellites, lunar orbiters, or spacecraft around other planets. They include diverse types of data such as multispectral and hyperspectral imagery, high-resolution optical images and radar images. These datasets are crucial for training NeRF models to reconstruct Earth's landscapes, planetary surfaces, and features of other celestial bodies.

Examples:

Landsat and Sentinel datasets for Earth observation, providing extensive coverage and historical data, Lunar Reconnaissance Orbiter Camera (LROC) dataset for high-resolution images of the lunar surface, Mars Reconnaissance Orbiter's HiRISE camera data for detailed Martian terrain images.

### B. Rover-Captured Datasets

Images captured by rovers on planetary surfaces, such as Mars or the Moon, include detailed close-up photographs of the geology, horizon and sky. These datasets are valuable for training NeRF models to navigate and analyze the planetary

surface, facilitating better planning and decision-making for future rover missions.

Examples:

Mars Rover Image Data from missions like Curiosity, Perseverance and historical missions providing ground-level views, Apollo Lunar Surface Experiments Package (ALSEP) imagery for lunar exploration.

### C. Astronomical Observation Datasets

These datasets are comprised of images captured by telescopes and observatories, both ground-based and space-based like the Hubble Space Telescope. They include images of stars, galaxies, nebulae, and other astronomical phenomena, which can be used to train NeRF models for educational and research purposes in astronomy.

Examples:

Hubble Space Telescope datasets providing deep space images, Very Large Telescope (VLT) and other observatories's data for stellar and interstellar object studies.

### D. Simulated Space Environment Datasets

Simulated datasets created using software that models space environments based on physical and scientific principles. These are particularly useful for scenarios where real-world data is scarce or difficult to obtain, such as exoplanetary surfaces or the outer solar system.

Examples:

NASA's Eyes on the Solar System simulations. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) simulated datasets for planetary geology studies.

### E. Synthetic Datasets Generated from CAD Models

Synthetic datasets generated from CAD (Computer-Aided Design) models of spacecraft, satellites, and space stations are used for training NeRF models in applications related to the construction, maintenance, and operation of space structures.

Examples:

International Space Station (ISS) module CAD models. Satellite assembly and maintenance training simulations.

To conclude, these datasets play a critical role in the development and application of NeRF techniques in space exploration and research. They provide the necessary data for training models that can predict and render 3D space environments with high precision, supporting a variety of applications from planetary exploration to astronaut training and astronomical research. The success of NeRF in space applications heavily depends on the quality, diversity and accuracy of these datasets.

### F. Other Potential Datasets for NeRF in Space Applications

HiRISE (High Resolution Imaging Science Experiment) is a dataset which provides high-resolution images of the Martian surface. LROC (Lunar Reconnaissance Orbiter Camera) captures high-resolution imagery of the lunar surface. Earth Observing System (EOS) Data is a dataset which includes data from satellites like Terra and Aqua, which capture Earth

imagery. Apollo Surface Panoramas includes Panoramic images taken by astronauts during the Apollo Moon missions. Mars Rover Image Data contains images captured by Mars rovers such as Curiosity, Opportunity and Perseverance. Hubble Space Telescope Public Data provides images of space captured by the Hubble Space Telescope. Astronomical Photographic Data Archive (APDA) offers photographic plates from observatories around the world covering a span of many decades. Cassini-Huygens Mission Data includes imagery and other data from the Cassini spacecraft's mission to Saturn and its moons. Gaia Mission Data provides accurate positions, distance indicators and motions of stars. Synthetic Universe is a simulated dataset of universe-scale phenomena created using advanced computational models.

While the above datasets are not explicitly designed for NeRF applications, they provide the type of high-quality, multi-perspective imagery that is ideal for NeRF model training in space applications. Researchers looking to apply NeRF to space applications would likely need to adapt these datasets, potentially processing the images to meet specific NeRF input requirements and ensuring that images are suitable for creating accurate 3D reconstructions. Each NeRF dataset's accessibility and usage terms can vary, so it's essential to review the associated licenses and usage rights before incorporating them into research or commercial projects.

Table 1 shows the different NeRF datasets used for space applications.

**Table 1:** Datasets used in NeRF for space applications

| Dataset                        | Venue      | # Scenes | # Imgs | Type   | Centricity | Data Modalities | Annotations                                     |
|--------------------------------|------------|----------|--------|--------|------------|-----------------|---|
| <a href="#">3DMV-VQA [54]</a>  | CVPR 2023  | 5000     | 600K   | Indoor | S+O        | RGB             | Visual Question and Answer                      |
| <a href="#">NeRDS 360 [55]</a> | ICCV 2023  | 75       | 15k    | Urban  | S+O        | Synthetic       | 3D object boxes, 2D panoptic segmentation       |
| <a href="#">ScanNet++ [56]</a> | ICCV 2023  | 400      | 3.7M   | Indoor | S          | RGB-D           | 2D/3D panoptic segmentation                     |
| <a href="#">KITTI-360 [57]</a> | PAMI 2022  | 10       | 150K   | Urban  | S+O        | RGB & LIDAR     | 2D/3D object boxes, 2D panoptic segmentation    |
| <a href="#">SHIFT [58]</a>     | CVPR 2022  | 4850     | 2.5M   | Urban  | S+O        | Synthetic       | 2D/3D object boxes, 2D panoptic segmentation    |
| <a href="#">HM3D Sem [59]</a>  | arXiv 2022 | 216      | -      | Indoor | S          | Mesh            | 3D semantic segmentation                        |
| <a href="#">3D-FRONT [60]</a>  | ICCV 2021  | 18968    | -      | Indoor | S+O        | Synthetic       | 3D semantic segmentation                        |
| <a href="#">HyperSim [61]</a>  | ICCV 2021  | 461      | 77.4K  | Indoor | S+O        | Synthetic       | 2D/3D object boxes, 2D/3D panoptic segmentation |
| <a href="#">Waymo [62]</a>     | CVPR 2020  | 1150     | 1M     | Urban  | S+O        | RGB & LiDAR     | 2D/3D object boxes<br>2D panoptic segmentation  |
| <a href="#">nuScene [63]</a>   | CVPR 2020  | 1000     | 1.4M   | Urban  | S+O        | RGB & LiDAR     | 3D object boxes, 2D semantic segmentation       |
| <a href="#">Replica [64]</a>   | arXiv 2019 | 18       | -      | Indoor | S          | Mesh            | 2D/3D panoptic segmentation                     |

|                           |           |      |        |         |     |             |  |
|---------------------------|-----------|------|--------|---------|-----|-------------|--|
| <b>Matterport 3D [65]</b> | 3DV 2017  | 90   | 194.4K | Indoor  | S   | RGB-D       | 2D/3D panoptic segmentation                  |
| <b>CLEVR [66]</b>         | CVPR 2017 | -    | 100K   | Indoor  | O   | Synthetic   | Visual Question and Answer                   |
| <b>ScanNet [67]</b>       | CVPR 2017 | 1513 | 2.5M   | Indoor  | S+O | RGB-D       | 3D object boxes, 2D/3D panoptic segmentation |
| <b>Virtual KITTI [68]</b> | CVPR 2016 | 5    | 17K    | Urban   | S+O | Synthetic   | 2D/3D object boxes, 2D panoptic segmentation |
| <b>SUN RGB-D [69]</b>     | CVPR 2015 | 47   | 10.3K  | Indoor  | S+O | RGB-D       | 2D/3D object boxes, 2D panoptic segmentation |
| <b>Shapenet [70]</b>      | arXiv2015 | -    | -      | Objects | O   | CAD Model   | 3D part segmentation                         |
| <b>KITTI [71,72]</b>      | CVPR 2012 | 22   | 15K    | Urban   | S+O | RGB & LiDAR | 2D/3D object boxes, 2D panoptic segmentation |

### V. NeRF METHODS

The below table shows the comparative analysis of various NeRF methods used for space applications:

Neural Radiance Fields (NeRF) have been adapted into various methodologies to enhance their applicability in space applications, each designed to tackle specific challenges associated with rendering and reconstructing space environments. Several adaptations of Neural Radiance Fields methods have been developed to address the specific challenges of space applications. These methods leverage NeRF's ability to create high-fidelity 3D models from 2D images but are tailored to the unique constraints and requirements of space environments, such as limited data, computational restrictions and the need for high precision in remote sensing.

Below are the descriptions of some notable NeRF methods designed specifically for space applications:

#### A. SparseNeRF for Space Exploration

This method is adapted to work effectively with the sparse image data typically available from space missions, where comprehensive data collection is often challenging due to the high costs and technical limitations of space travel. SparseNeRF for Space Exploration incorporates techniques to reconstruct detailed 3D environments from limited viewpoints and under varied lighting conditions, enhancing its utility for planetary exploration and asteroid mapping. Useful for reconstructing detailed terrain models of celestial bodies with limited rover or satellite passes.

#### B. DynamicNeRF for Orbital and Rover Operations

Designed to handle dynamic scenes in space, such as moving objects in orbit or changes in planetary surfaces, DynamicNeRF incorporates temporal dynamics into the

traditional NeRF model. This allows it to update the reconstructed scene continuously as new data comes in, making it ideal for applications that require monitoring and responding to changes in real-time. Ideal for monitoring orbital debris fields and assisting in autonomous rover navigation on planetary surfaces with changing environmental conditions.

#### C. Multi-Spectral NeRF

This variant of NeRF extends the traditional RGB image input to include multi-spectral data, which is common in satellite imagery. By incorporating additional spectral bands, Multi-Spectral NeRF can provide more detailed information about material properties and enhance the detection and analysis of various geological and atmospheric phenomena. Used for enhanced analysis of planetary surfaces and atmospheres, aiding in the detection of water, minerals and other resources.

#### D. RobustNeRF for Extreme Environments

RobustNeRF is engineered to perform reliably under the extreme conditions of space, such as varying temperatures and radiation levels that can affect sensor performance. This method includes enhancements for noise reduction and error correction, ensuring high-quality 3D reconstructions despite the harsh operating conditions. Suitable for long-duration missions in deep space or on surfaces of planets with harsh atmospheres, like Venus or Jupiter's moons.

#### E. ReflectiveNeRF for Illumination Challenges

ReflectiveNeRF tackles one of the major challenges in space handling the vast differences in illumination. It models not only the geometry but also the reflective properties of scene surfaces, allowing it to predict how surfaces would look under different lighting conditions. This is crucial for creating accurate models from images taken during different times of the day or year. Particularly valuable for lunar and Martian missions where sunlight varies significantly, affecting visibility and navigation.

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These NeRF methods represent significant advancements in the application of 3D reconstruction technologies for space exploration. Each method addresses specific challenges encountered in the unique and demanding environment of space, from data sparsity and dynamic changes to extreme conditions and illumination issues. As these technologies continue to evolve, they will play a crucial role in enhancing our understanding and exploration of outer space, providing detailed and reliable data that can support both manned and unmanned missions.

Each NeRF variant is tailored to overcome specific challenges in space applications, from sparse data conditions

and dynamic scenes to multi-resolution needs and adverse weather effects. These adaptations make NeRF a versatile tool for space exploration, aiding in everything from satellite imagery analysis to rover navigation and planetary surface study.

Table 2 shows the list of existing research papers on NeRF which are used for space applications, their key features, strengths and weaknesses:

**Table 2:** Existing papers related to NeRF used for space

| Paper                  | Key Features   | Strengths  | Weaknesses                                       |
|------------------------|--|--|--|
| <b>FastNeRF [73]</b>   | Uses a novel sampling strategy to achieve high frame rates                         | Produces high-fidelity images at 200fps                  | Requires more training data than other methods   |
| <b>KiloNeRF [74]</b>   | Uses a hierarchical representation of the scene to reduce the number of parameters | Very efficient, can train on a single GPU in a few hours | Produces lower-quality images than other methods |
| <b>Block-NeRF [75]</b> | Divides the scene into blocks and renders each block independently                 | Scales to very large scenes                              | Requires more memory than other methods          |
| <b>Mega-NeRF [76]</b>  | Uses a dynamic grid that is adapted to the scene being rendered                    | Produces high-quality images of large scenes             | Very computationally expensive                   |
| <b>MobileNeRF [77]</b> | Exploits the polygon rasterization pipeline to render NeRFs on mobile devices      | Very fast on mobile devices                              | Produces lower-quality images than other methods |

## VI. CASE STUDIES

The following are the case studies of how Neural Radiance Fields or NeRF is used in Space related applications:

### A. Enhancing Lunar Surface Imagery with NeRF

One notable case study involves the application of Neural Radiance Fields to enhance the quality of imagery captured on the lunar surface. Traditional methods of capturing and processing lunar images often struggle with issues like low light conditions and high contrast [78], which can obscure important surface details. Researchers at the Lunar Reconnaissance Orbiter mission utilized NeRF to synthesize high-resolution 3D models from existing low-resolution images, significantly enhancing the detail and accuracy of lunar surface features. This improved imaging supports better planning of landing sites and safer navigation for future missions. The study demonstrated NeRF's potential to overcome environmental lighting limitations, providing clearer, more detailed surface imagery than previously possible [79]. The application of Neural Radiance Fields (NeRF) in enhancing lunar surface imagery represents an improvement in the field of lunar exploration and mapping. NeRF's capability to generate detailed and high-resolution 3D reconstructions from standard 2D images can profoundly improve the quality of lunar surface imagery, facilitating better scientific research, exploration planning and mission safety.

NeRF models are trained using a series of 2D images taken from various angles, often captured by lunar orbiters or landers. These images are input into the NeRF system, which uses deep learning techniques to infer and reconstruct the 3D scene. The model learns to predict the color as well as the density of light at any point in space, allowing it to generate novel views of the lunar surface with high fidelity:

- The initial step involves collecting comprehensive image datasets from multiple lunar missions. These datasets include images taken at different times of day to capture varying lighting conditions and angles [80].
- Using these images, a NeRF model is trained to understand the 3D structure of the lunar surface. This training process requires significant computational resources and may take several days or weeks, depending on the complexity of the terrain and the resolution required.
- Once trained, the NeRF model can be used to reconstruct high-resolution 3D images of the lunar surface. These images are not only more detailed than any single 2D image but also free from common issues like shadows and occlusions.

The application of NeRF technology in lunar surface imaging offers several compelling benefits that significantly advance lunar science and exploration:

- Increased resolution and detail where NeRF provides higher resolution and more detailed images than traditional 2D imaging techniques. This enhancement is

crucial for identifying small-scale features such as craters, rocks and regolith properties [81].

- For improved surface analysis, with high-resolution 3D models, scientists can perform more accurate geological and compositional analyses of the lunar surface. This capability is vital for identifying areas of scientific interest and planning future exploration missions.
- Virtual exploration where NeRF-generated models allow researchers and mission planners to virtually explore the lunar surface in three dimensions, facilitating better mission planning and training of astronauts for surface operations.

While the use of NeRF in enhancing lunar imagery is promising, several challenges must be addressed:

- NeRF's computational requirements are substantial, which can be a limiting factor, especially for processing onboard spacecraft. Efforts to optimize and streamline NeRF algorithms are ongoing.
- NeRF requires huge volume of higher quality images, which can in fact be challenging to obtain for regions of the lunar surface that are not frequently imaged by orbiters [82].
- The harsh lighting conditions and extreme contrasts of the lunar surface pose unique challenges in training NeRF models, which typically perform best under consistent lighting conditions.

Looking forward, the application of NeRF in lunar surface imaging is set to expand with advancements in computational technologies and machine learning:

- Future developments may allow NeRF models to be run in real-time or near-real-time on lunar orbiters or landers, providing immediate data for mission control and surface operations.
- NeRF could be integrated into the guidance systems of robotic explorers [83], enhancing their ability to navigate and operate autonomously on the lunar surface. As NeRF technology matures, it could play a crucial role in mission planning by providing detailed 3D visualizations of proposed landing sites and exploration zones, significantly reducing the risks associated with lunar missions.
- NeRF stands as a transformative technology for enhancing lunar surface imagery, offering unprecedented detail and accuracy that can significantly benefit scientific research, exploration and mission planning [84, 85]. As computational and data handling challenges are overcome, the potential applications of NeRF in lunar exploration are expected to grow, opening new horizons in our understanding and exploration of the Moon.

### B. NeRF for Satellite Constellation Calibration

Another critical application of NeRF in space technology is in the calibration of satellite constellations. A study conducted by a European space agency focused on using NeRF to simulate and optimize the camera alignment and calibration process for a satellite constellation designed to monitor atmospheric conditions [86]. By generating and utilizing 3D models of the Earth's atmosphere from multiple

satellite images, NeRF helped in significantly reducing the time and effort required for calibration, while improving the precision of atmospheric data collected by the constellation. This case study highlights NeRF's capability to enhance satellite operations and data accuracy, contributing to better climate monitoring and environmental management [87]. The application of Neural Radiance Fields (NeRF) for calibrating satellite constellations represents a novel approach to optimizing the alignment and functionality of satellite systems in orbit. NeRF's ability to create highly accurate 3D models from sparse 2D images enables precise calibration of inter-satellite sensors and optical instruments.

Calibration of satellite constellations involves aligning the sensors and optical systems of multiple satellites to ensure that they work cohesively, producing consistent and accurate data. NeRF aids this process by generating precise 3D models of the area or object under observation from a set of 2D images captured by different satellites in the constellation [88].

- Satellites in a constellation capture a series of images from different angles and orbits. These images cover various lighting conditions and angles, providing a comprehensive dataset for model training.
- The collected images are used to train a NeRF model, which learns to synthesize a 3D model of the target object or area. This model helps in understanding discrepancies and misalignments in the data captured by individual satellites.
- By comparing the synthesized 3D model with the individual images and their expected outcomes, discrepancies can be identified and corrected, allowing for the fine-tuning of each satellite's sensors and optical alignment.

Integrating NeRF into the calibration process of satellite constellations offers several significant advantages:

- For enhanced accuracy and consistency, NeRF helps achieve a high level of accuracy in the 3D representation of the observed area, which is crucial for calibrating the sensors across the constellation. This leads to more consistent and reliable data from different satellites [89].
- For the reduction in calibration time and effort, traditional calibration methods can be time-consuming and require extensive manual input. NeRF automates much of the process, significantly reducing the time and effort needed for calibration.
- Improved Data Integration where accurately calibrated satellites provide data is easier to integrate and analyze [90], improving the overall quality of the information used for earth observation, climate monitoring and other critical applications.

Despite its promising applications, deploying NeRF for satellite constellation calibration faces several challenges:

- NeRF's processing demands are substantial, requiring significant computational resources that might not always be readily available in space or at ground stations.

- Managing the large datasets required for effective NeRF training involves complexities in data transmission, storage and processing, especially given the bandwidth limitations inherent in satellite communications [91].
- Satellite images are affected by various dynamic factors such as atmospheric conditions, changing angles and lighting. Adapting NeRF to reliably work under such variable conditions remains a technical challenge.

As technology progresses, the application of NeRF in satellite constellation calibration are expected to evolve:

For onboard processing capabilities, future satellite designs may include more advanced computational capabilities, allowing NeRF models to be processed directly on satellites. This would enable real-time calibration and adjustments without the need to transmit large amounts of data back to Earth. Further integration of NeRF with other AI and machine learning technologies could enhance automated decision-making processes, enabling satellites to adapt their calibration dynamically based on observed data anomalies [92].

Efforts to make NeRF models more scalable and flexible could allow for their application across different types of satellite constellations and instruments, broadening the scope of this technology.

NeRF holds significant potential to transform the calibration process for satellite constellations, offering a way to enhance the accuracy and reliability of satellite data significantly. By addressing the computational and adaptability challenges [93], NeRF could become an integral part of the standard toolkit for satellite constellation management, ensuring that satellite systems deliver optimal performance throughout their operational life.

Figure 7 shows the different case studies for NeRF used for space applications:

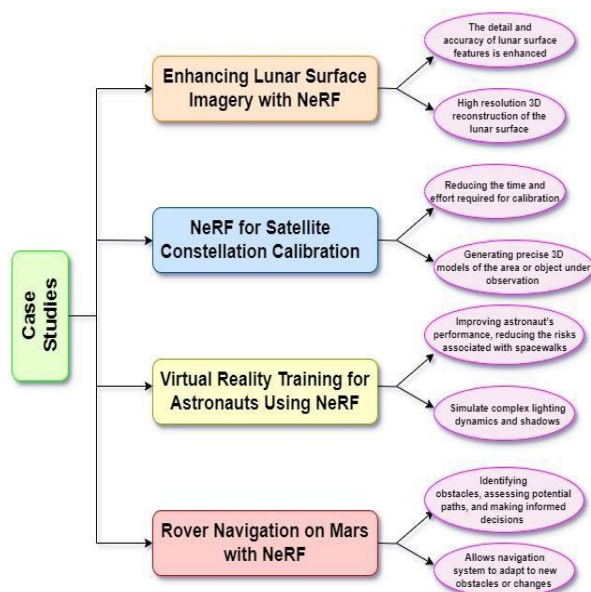


Fig 7: Case Studies of NeRF used for space applications

### C. Virtual Reality Training for Astronauts Using NeRF

In a groundbreaking application of NeRF, NASA developed a virtual reality (VR) training program for astronauts preparing for extravehicular activities (EVAs) on the International Space Station (ISS) [94]. Using NeRF, the program creates photorealistic, interactive 3D environments from video footage captured during previous missions. This technology allows astronauts to train in a highly realistic simulation of the ISS exterior, improving their familiarity with the station's layout and potential hazards they might encounter during EVAs. The VR training program has been credited with significantly improving astronaut's performance and reducing the risks associated with spacewalks. This case demonstrates NeRF's utility in enhancing the effectiveness and safety of astronaut training programs [95]. The utilization of Neural Radiance Fields (NeRF) in virtual reality (VR) training for astronauts marks a significant advancement in simulation technology, offering an unprecedented level of realism and immersion. NeRF's capability to generate photorealistic 3D environments from sparse 2D images provides astronauts with highly detailed simulations of space environments, aiding in both routine training and mission-specific preparations.

NeRF's integration into astronaut VR training involves several key steps, from collection of data and training of model to simulation deployment:

- The data collection involves extensive datasets comprising images of actual space environments, equipment and spacecraft interiors are collected. These may include images from previous missions, training modules and specially designed setups that replicate space conditions.
- For model training, these images are then used to actually train a NeRF model to reconstruct the space environment in 3D. The training process involves mapping both the visible light and depth information from the 2D images to create a continuous, volumetric scene [96].
- For VR integration, the trained NeRF model is integrated into a VR system. Astronauts can interact with the environment through VR headsets and controllers, which simulate the physical presence in these meticulously reconstructed space settings.

NeRF significantly enhances VR astronaut training programs by offering several unique advantages:

- For high-fidelity simulations, NeRF produces highly realistic 3D simulations of space environments, including accurate representations of spacecraft interiors, extravehicular activity (EVA) environments [97] and even other planetary terrains [98].
- One of NeRF's standout features in VR training is its ability to simulate complex lighting dynamics and shadows, which are crucial for preparing astronauts for the visually challenging environments of space.
- Advanced NeRF models can be adapted to include dynamic elements, such as moving objects and changing conditions, allowing astronauts to practice responses to anomalies and emergencies.



While NeRF offers substantial benefits, several challenges must be addressed to maximize its effectiveness in astronaut training:

- NeRF models require significant computational resources to render in real-time, which can be a limitation for VR systems that need to operate smoothly to avoid motion sickness and ensure user comfort [99].
- Collecting and processing the large volumes of high-quality images needed to train accurate NeRF models is resource-intensive and can be logistically challenging.
- Seamlessly integrating NeRF-based simulations into established astronaut training curricula requires careful validation to ensure the simulations meet educational standards and training objectives.

The future of NeRF in VR astronaut training looks promising, with several developments on the horizon:

- Future improvements in NeRF could include better interactivity features, allowing astronauts to manipulate objects and environments in more complex ways, closely mimicking real-world physics and interactions [100].
- For customization and scalability, as NeRF technology matures, it could allow for more customized and scalable training scenarios that can be quickly adapted to specific mission needs or modified based on the evolving skills of astronauts.
- Integration with AI as combining NeRF with AI could lead to adaptive training environments that respond in real-time to the actions of astronauts [101], providing personalized feedback and adjusting difficulty levels dynamically.

NeRF's application in VR training for astronauts offers a transformative tool that significantly enhances the realism and effectiveness of pre-mission preparations [102]. By providing an immersive, accurate simulation of space environments, NeRF helps astronauts prepare more thoroughly for the challenges of space missions. Continued advancements in computing power and algorithmic efficiency are expected to further enhance the capabilities and applications of NeRF in astronaut training, making these simulations an integral part of astronaut training programs.

#### *D. Rover Navigation on Mars with NeRF*

The final case study explores the usage of NeRF for enhancing navigation capabilities of Mars rovers. Leveraging sparse and varied image data sent back by rovers, NeRF was employed to create detailed 3D reconstructions of the Martian terrain [103]. These models enable more accurate hazard assessment and path planning, crucial for the rover's long-term operational success and scientific missions. The technology allowed for a more robust exploration strategy by providing high-quality visualizations of the terrain ahead, aiding in the discovery of new geological features and optimizing scientific data collection. This case underlines NeRF's role in supporting autonomous operations in remote and challenging environments [104]. The integration of NeRF into the navigation systems of Mars rovers represents a significant

technological advancement in planetary exploration. NeRF's potential to build detailed and accurate 3D models from a collection of 2D images allows for enhanced navigation and operational planning, crucial for the success of missions on Mars's challenging terrain.

Implementing NeRF for rover navigation involves several key steps, tailored to overcome the unique challenges of the Martian environment:

- Mars rovers are equipped with cameras that capture images of the surrounding landscape. These images are taken at various angles and times, providing a diverse dataset that captures the terrain under different lighting conditions [105].
- The collected images are used to train a NeRF model. This training process involves creating a volumetric representation of the Martian surface, where the model learns to predict the color and opacity of light passing through different points in space, effectively reconstructing the 3D landscape.
- For navigation and path planning, the trained NeRF model is then used to generate real-time 3D maps of the terrain ahead of the rover [106]. These maps are crucial for identifying obstacles, assessing potential paths, and making informed decisions about the rover's route to avoid hazards and optimize scientific data collection.

The application of NeRF technology in Mars rover navigation offers several compelling advantages:

For enhanced terrain modeling, NeRF provides high-resolution 3D reconstructions of the Martian surface, offering greater detail than traditional stereo vision methods [107, 108]. This capability is vital for identifying and avoiding potential hazards such as rocks, ditches and loose soil. With better terrain models, mission planners can more accurately predict the time and energy required for different routes, optimizing the rover's path for efficiency and safety. NeRF models can be updated in real-time with new images captured by the rover [109], allowing the navigation system to keep adapting to new obstacles or the changes in terrain as mission progresses.

While NeRF holds great promise, its deployment in the context of Mars rover navigation presents several challenges:

NeRF models are computationally intensive, requiring significant processing power that might exceed the current capabilities of rover onboard computers. The large datasets needed for NeRF training and updating necessitate high bandwidth for data transmission [110], which can be a bottleneck given the limited communication capabilities between Mars and Earth. The Martian environment poses unique challenges, including extreme variations in lighting and weather conditions that can affect the accuracy and reliability of the 3D models generated by NeRF.

As technology and Mars exploration strategies evolve, the role of NeRF in rover navigation is expected to expand and improve:

- For onboard processing enhancements, advances in edge computing and AI might allow future Mars rovers to process NeRF models directly onboard, significantly

reducing the need for data transmission and enabling more autonomous navigation capabilities.

- Combining NeRF with data from other sensors, such as LIDAR and radar, could provide a more extensive understanding of Martian environment, improving the rover's ability to handle complex navigation tasks.
- Ongoing developments in machine learning and optimization algorithms are expected to minimize the overall computational load of NeRF models [111], ensuring they are more feasible for real-time applications in space exploration.
- NeRF technology offers a transformative approach to Mars rover navigation, providing detailed 3D reconstructions of the terrain that enhance the safety, efficiency and scientific output of missions.
- As computational technologies continue to advance, NeRF is likely to become a critical component of planetary exploration strategies [112], enabling more sophisticated and autonomous rover operations on Mars and potentially other celestial bodies.

### VII. EVALUATION METRICS

In the evaluation of Neural Radiance Fields and similar 3D reconstruction technologies for space applications, several quantitative metrics are commonly used to assess the quality of generated images compared to ground truth images. These metrics include Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) and the Learned Perceptual Image Patch Similarity (LPIPS).

#### 1. Peak Signal-to-Noise Ratio (PSNR)

PSNR is a widely used metric in image processing that measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

In the context of NeRF, PSNR is used to evaluate the fidelity of reconstructed images relative to the original images, with higher values indicating better quality.

$$PSNR = 20 \times \log_{10}(MSE \cdot MAXI)$$

where,

- MAXI is the maximum possible pixel value of the image (e.g., 255 for 8-bit images).
- MSE is the mean squared error between the original and the reconstructed image.

$$MSE = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^m (I(i,j) - K(i,j))^2$$

where,

- I and K are the original and reconstructed images, respectively.
- m and n are the dimensions of the images.

#### 2. Structural Similarity Index Measure (SSIM)

SSIM is a perceptual metric that quantifies image quality degradation caused by processing such as data compression or by losses in data transmission. It considers changes in texture, brightness and contrast between two images. SSIM values range between -1 and 1, where 1 indicates perfect similarity.

$$SSIM_{(x,y)} = \frac{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}$$

where,

- $\mu_x, \mu_y$  are the average of x and y.
- $\sigma_x^2, \sigma_y^2$  are the variance of x and y.
- $\sigma_{xy}$  is the covariance of x and y.
- $c_1$  and  $c_2$  are constants used to stabilize the division with weak denominator.

#### 3. Learned Perceptual Image Patch Similarity (LPIPS)

LPIPS is a metric that uses deep learning to assess perceptual similarity between images, reflecting more closely how humans would perceive differences. It compares the distance between deep features of images extracted by pre-trained neural networks, typically those used in vision tasks like image classification.

$$LPIPS = \sum w_l \|\phi_l(I)_{h,w} - \phi_l(K)_{h,w}\|_2^2$$

where,

- $\phi_l(I)$  and  $\phi_l(K)$  are the feature maps at layer l of networks for images I and K, respectively.
- $H_l$  and  $W_l$  are the dimensions of the feature map at layer l.
- $w_l$  are learned or predefined weights for each layer.

These evaluation metrics are crucial for assessing the performance of NeRF models, especially when fine-tuning for accuracy, perceptual quality and overall effectiveness in applications like virtual reality, film production and scientific visualization. Each metric offers a different perspective on image quality, from statistical fidelity (PSNR, SSIM) to human-perceived similarity (LPIPS) and is essential for comprehensive assessment in research and practical applications of NeRF for space applications.

Table 3 shows the different values of evaluation metrics and dataset used for various NeRF methods used for space applications:

**Table 3:** Different evaluation metrics and dataset used

| Paper            | Dataset Used    | PSNR   | LPIPS | SSIM  |
|------------------|-----------------|--------|-------|-------|
| NeRF [1]         | DTU             | 8.00   | 0.703 | 0.286 |
| CoCo-INR [113]   | DTU             | 26.738 | 0.298 | 0.852 |
| DietNeRF [114]   | DTU             | 14.242 | 0.487 | 0.481 |
| PointNeRF [115]  | NeRF Synthetics | 33.31  | 0.049 | 0.978 |
| NuroFusion [116] | NeRF Synthetics | 31.25  | 0.069 | 0.953 |
| FastNerf [117]   | NeRF Synthetics | 29.155 | 0.053 | 0.936 |
| KiloNeRF [118]   | NeRF Synthetics | 31.00  | 0.03  | 0.95  |
| SteerNeRF [119]  | NeRF Synthetics | 30.97  | 0.065 | 0.948 |

|                                |                      |         |        |        |
|--------------------------------|----------------------|---------|--------|--------|
| <b>MobileNeRF [120]</b>        | Syntatic 360         | 30.90   | 0.062  | 0.947  |
| <b>Mip-NeRF [121]</b>          | Blander              | 33.09   | 0.043  | 0.961  |
| <b>Mega-NeRF [122]</b>         | UrbanScene3d         | 22.08   | 0.489  | 0.628  |
| <b>Pix2NeRF [123]</b>          | ShapeNet-SRN         | 18.14   | -      | 0.84   |
| <b>Block-NeRF [124]</b>        | Alamo Square dataset | 23.60   | 0.0417 | 0.649  |
| <b>LOLNeRF [125]</b>           | CelebA-HQ            | 25.3    | 0.491  | 0.836  |
| <b>FDNeRF [126]</b>            | VoxCelebdataset      | 24.847  | 0.142  | 0.821  |
| <b>ECRF [127]</b>              | PhotoShapes          | 37.67   | 0.022  | -      |
| <b>NeRF-Editing [128]</b>      | Mixamo               | 29.62   | 0.024  | 0.975  |
| <b>D<sup>2</sup>NeRF [129]</b> | Bag                  | 34.14   | 0.090  | 0.979  |
| <b>DFFs [130]</b>              | Replica dataset      | 32.85   | 0.162  | 0.932  |
| <b>LOCNeRF [131]</b>           | ToyDesk              | 15.0607 | 0.522  | 0.585  |
| <b>NARF [132]</b>              | THUman               | 30.86   | -      | 0.9586 |
| <b>HumanNeRF [133]</b>         | Multi-view dataset   | 36.01   | 0.0356 | 0.9897 |

### VIII. COMPARATIVE ANALYSIS

Table 4 shows the key features, advantages, disadvantages and applications of different NeRF Methods used for space applications.

**Table 4:** Comparative analysis of various NeRF methods

| NeRF Method                       | Key Features                                       | Advantages                                  | Disadvantages                                    | Space Applications                                 |
|-----------------------------------|--|---|--|--|
| <b>Basic NeRF [1]</b>             | Dense MLP, Positional Encoding                     | High fidelity in static scenes              | Slow rendering, High computational cost          | Satellite imagery enhancement                      |
| <b>FastNeRF [134]</b>             | Caching Intermediate values, Accelerated Rendering | Faster rendering times                      | Slight loss in detail                            | Real-time navigation and docking                   |
| <b>NeRF++ [135]</b>               | Scene decomposition                                | Better scalability for large scenes         | Increased complexity, Higher setup time          | Comprehensive Satellite data reconstructions       |
| <b>Dynamic NeRF [136]</b>         | Dynamic Scene handling, Time variant modeling      | Adapts to changing conditions               | Requires extensive training data                 | Astronaut training in dynamic environments         |
| <b>Mip-NeRF [137]</b>             | Mipmapping for resolution management               | Enhanced detail at multiple scales          | Greater memory requirements                      | High-resolution planetary mapping                  |
| <b>Fourier Feature NeRF [138]</b> | Advanced fourier features for encoding             | Captures fine details                       | Can overfit to noise                             | Detailed asteroid and comet surface mapping        |
| <b>Sparse NeRF [139]</b>          | Utilizes sparsity in data input                    | Lower memory and computational requirements | May miss finer details in sparse areas           | Efficient modeling of sparse stellar phenomena     |
| <b>Multiscale NeRF [140]</b>      | Operates at multiple scales simultaneously         | Captures global and local details           | Complex model architecture                       | Detailed analysis of Celestial bodies surfaces     |
| <b>Reflectance NeRF [141]</b>     | Models surface reflectance properties              | Accurate material and surface analysis      | Requires precise initial data                    | Material analysis in Moon and Mars missions        |
| <b>Fusion NeRF [142]</b>          | Fuses data from multiple sensors                   | Robust against individual sensor failures   | Complex calibration between different data types | Enhanced 3D Modeling of Space Station Environments |

## IX. CHALLENGES AND LIMITATIONS

There are many challenges and limitations in using NeRF for space applications. The following are the list of challenges and limitations of using NeRF for space applications.

### A. Computational Complexity

The computational demands of NeRF, especially for high-resolution 3D reconstructions, remain a significant challenge. The original NeRF model requires significant memory and processing power, making it impractical for real-time applications. Advances in optimization techniques, such as those introduced by Liu et al. [143] and others, are critical for reducing these computational costs but further research is needed to enable efficient on-board processing for space missions. The integration of Neural Radiance Fields (NeRF) into various applications, particularly in space technology, presents substantial computational challenges. NeRF models are complex and require significant processing power for training and inference [144], which can limit their deployment in environments with restricted computational resources, such as spacecraft or remote planetary missions.

NeRF operates by modeling a scene as a continuous volume of light, color and density, which is computed from a collection of 2D images. The model predicts volume density as well as the color at any point in space, synthesizing new views of the scene with high fidelity.

This process involves:

- High-dimensional data processing where NeRF processes high-dimensional data through a neural network to then estimate color as well as the density at numerous points along the rays passing through the scene. This requires handling millions of parameters and operations [145].
- To generate images, NeRF integrates the predicted colors and densities along camera rays, a process known as volume rendering. This step is computationally intensive because it involves evaluating the model at many points along each ray to accurately render complex scenes.
- NeRF requires numerous iterations to optimize its parameters for best rendering performance. Each iteration involves forward and backward passes through deep neural networks, which are computationally expensive.

The computational intensity of NeRF presents several challenges, particularly in constrained environments:

- In space missions, computational resources are limited due to power constraints and the need for radiation-hardened hardware, which often lacks the processing power of ground-based systems [146].
- The need for real-time or near-real-time processing in applications like spacecraft navigation or rover operations is hard to meet with the standard NeRF setup due to its slow processing speed.
- Scaling NeRF to larger scenes or higher resolutions exacerbates the computational load, making it challenging to maintain performance without significant hardware or algorithmic enhancements.

Addressing the computational demands of NeRF involves several strategies, ranging from hardware solutions to algorithmic optimizations:

- Hardware acceleration is achieved by making use of specialized hardware such as GPUs or TPUs which can significantly quicken up the training and inference phases of NeRF [147]. For space applications, developing advanced, radiation-resistant versions of such hardware could be a solution.
- Simplifying the NeRF model by reducing the complexity or the number of parameters without significantly impacting the quality of the output can help. Techniques like pruning, quantization or employing lighter neural network architectures are potential avenues.
- Improving the efficiency of ray sampling and volume rendering by adopting adaptive or importance sampling techniques can reduce the number of evaluations needed, thereby decreasing computational overhead.
- Implementing multi-resolution schemes where detailed computations are only performed in areas of high interest and caching results for frequently queried regions can reduce redundant calculations.

Future research and development are crucial in making NeRF more feasible for computationally constrained environments:

- By algorithmic innovations, continued innovation in algorithm design to increase the efficiency of NeRF models is essential. This could involve developing new types of neural architectures [148] that are inherently more efficient.
- On-the-fly Adaptation by developing dynamic systems that adapt the complexity of the NeRF model based on available computational resources could help optimize performance in real-time.
- For terrestrial applications, leveraging cloud computing to handle the heavy lifting of NeRF processing could offload the need for local computation, though this approach is less viable for deep-space applications.
- While the computational demands of NeRF are significant, ongoing advancements in hardware technology and algorithmic efficiency are continuously improving its feasibility.
- Overcoming these computational challenges is essential to unlocking the complete potential of NeRF across a range of applications, from virtual reality and film to advanced simulations and autonomous vehicle navigation [149] in space and on other planets.

### B. Data Acquisition and Integration

High-quality, multi-angle data from space is often difficult to acquire due to orbital constraints, sensor limitations and environmental factors like cloud cover or low light conditions. The success of NeRF in space applications relies on the availability of diverse and high-quality data. Integrating data from different sources (e.g., ground-based telescopes, space probes and satellites) can also be complex and requires sophisticated data fusion techniques.

### C. Model Generalization

NeRF models trained on specific environments (e.g., Earth's surface) may not generalize well to other contexts, such as planetary surfaces or deep space environments [150],



12] . Further research is needed to improve the adaptability and transferability of NeRF models, particularly for applications in diverse and remote environments.

#### D. Data Requirement

10 NeRF's performance heavily relies on the availability of high-quality, diverse training data. In space applications, acquiring such data can be particularly challenging due to the limited number of sensors on spacecraft and the infrequent opportunities for capturing comprehensive datasets of extraterrestrial environments. Moreover, NeRF requires a wide baseline of images taken from different viewpoints to effectively learn and reconstruct a scene in three dimensions. This requirement is often hard to meet in space missions where the camera positions and angles are constrained by the spacecraft's design and mission parameters [152]. Neural Radiance Fields (NeRF) have shown promising results in synthesizing the photorealistic 3D scene from the 2D images. However, the performance and accuracy of NeRF heavily depend on the quantity and quality of data available for training. In the context of specialized applications, especially in environments like space exploration, these data requirements pose significant challenges.

NeRF models are trained using sets of images that comprehensively cover the scene from multiple viewpoints. To accurately reconstruct and render any scene, NeRF requires:

- 7 • NeRF relies on high-resolution, high-quality images, low-noise images to accurately infer the fine details of a scene. The quality of these images directly impacts the fidelity of the generated 3D model.
- To understand the depth and volume of the scene accurately, NeRF needs images taken from a wide range of angles or diverse viewpoints. Limited or biased viewpoints can lead to incomplete or distorted 3D reconstructions [153].
- Changes in lighting can significantly affect the appearance of objects in images. For NeRF to perform well, the training dataset should include consistent illumination across different views or the model must be capable of disentangling lighting from surface properties.

The intensive data requirements of NeRF models present several challenges, particularly in constrained or unpredictable environments:

- In applications like space exploration or underwater mapping, collecting comprehensive datasets can be prohibitively expensive, risky or technically challenging.
- For storage and transmission, the large volumes of high-quality images required by NeRF demand substantial storage capacity and bandwidth for data transmission [154], which can be a limiting factor in bandwidth-constrained environments such as space missions.
- In many practical applications, controlling for consistent lighting or capturing images from diverse viewpoints is difficult. This variability can degrade the performance of NeRF models unless specifically

addressed in the model architecture or training procedure.

To address the challenges associated with the data requirements of NeRF, several strategies can be employed:

- Data augmentation techniques such as synthetic image generation, image augmentation (e.g., adjusting brightness, contrast), and virtual camera movement can artificially increase the diversity and volume of training data, helping to improve the robustness of NeRF models [155, 156].
- Transfer learning by leveraging and utilizing pre-trained models on similar tasks or environments which can reduce the amount of data required to fine-tune NeRF for a specific application. This approach is particularly useful when data collection is challenging or expensive.
- Active learning and adaptive sampling by implementing active learning strategies where the model identifies which additional data would be most beneficial to improve itself can optimize data collection efforts, focusing resources on capturing the most valuable images.
- Multi-source data fusion by combining NeRF with other data sources such as LIDAR, radar or existing 3D models, can enhance the model's understanding of the scene with fewer images [157]. This fusion helps compensate for gaps in visual data, particularly in terms of depth perception and object positioning.

Continued research and innovation are needed to enhance the data efficiency of NeRF models:

- Developing more data-efficient architectures, perhaps by integrating assumptions about physical properties of the scene or by improving the model's capability to generalize from limited data [158].
- Utilizing edge computing to preprocess data locally can reduce the need for transmitting large datasets, allowing for more efficient data usage.
- Collaborative and decentralized learning by enabling collaborative learning approaches where multiple systems or devices share model updates rather than raw data can also mitigate the challenges posed by large data requirements. The data requirements for training NeRF models are substantial, presenting a significant barrier to their deployment in environments where data is scarce, expensive to acquire or difficult to process [159]. Addressing these challenges through technological innovation and strategic data management is crucial for extending the applicability of NeRF to a broader range of practical and impactful scenarios.

#### E. Handling Diverse Environmental Conditions

The effectiveness of NeRF in space is also hindered by its sensitivity to varying environmental conditions. For instance, the lighting conditions in space can vary dramatically, which affects the consistency of the images used for training and inference. NeRF's reliance on static scenes is another limitation, as it struggles with dynamic elements such as moving objects or changing shadows [160], common in space environments. This limitation requires additional adjustments or hybrid approaches

combining NeRF with other techniques to ensure robust performance across different scenarios [161]. Neural Radiance Fields (NeRF) offer groundbreaking capabilities in generating three-dimensional reconstructions from two-dimensional images. However, NeRF's performance depends heavily on the consistency as well as the quality of input data [162], which can be significantly affected by diverse environmental conditions.

Environmental conditions such as lighting, weather and physical obstructions can drastically affect the input data quality for NeRF, posing significant challenges:

- Changes in lighting can alter the appearance of scenes dramatically. NeRF needs to disentangle the light effects from the actual scene properties to build accurate models. This is particularly challenging in outdoor environments where sunlight varies throughout the day and through cloud cover.
- Weather variations like fog, rain, snow and dust can obscure and distort the visual data captured, complicating the task of accurately reconstructing the environment [163]. Such conditions can reduce the visibility of key features needed for high-quality 3D modeling.
- For dynamic scenes, moving objects within a scene (such as vehicles, people or even swaying trees) create discrepancies between different images taken from the same viewpoint at different times. This can lead NeRF to produce artifacts or inaccuracies in the rendered scene.

To address the hurdles posed by diverse environmental conditions, several strategies can be employed to improve the robustness as well as adaptability of NeRF models:

- Developing NeRF models that can normalize or compensate for environmental variables is crucial. This could involve training NeRF under a wide range of conditions or developing specialized preprocessing algorithms [164] to standardize input data, reducing the impact of variables like lighting and weather.
- Incorporating temporal consistency checks and motion estimation can help NeRF better handle dynamic scenes. Techniques such as background subtraction or the use of predictive models to estimate and compensate for moving elements can significantly improve model stability and accuracy [165].
- Leveraging additional data sources, such as depth sensors, infrared imaging or radar, can provide supplementary information that helps the NeRF model overcome visual ambiguities caused by poor weather conditions or low light.

Continued research and advanced techniques are necessary to further enhance the capability of NeRF to operate effectively under diverse environmental conditions:

- Integrating physics-based models that account for light reflection, refraction and absorption can help NeRF better understand and simulate how environmental conditions affect scene appearance [166].
- Employing advanced machine learning techniques such as unsupervised and semi-supervised learning can allow

NeRF to adapt to new or changing conditions without needing extensive labeled data for every possible scenario.

- Developing adaptive learning systems that can update the NeRF model incrementally as new data becomes available can allow the system to adjust to changes in the environment continuously. This is particularly useful for long-term deployments in dynamic environments.

Handling diverse environmental conditions is a critical challenge for the deployment of NeRF in real-world applications, especially those involving outdoor scenes or other variable settings. By developing more robust and adaptable models and integrating additional data sources and advanced rendering techniques [167], NeRF can be made more resilient to the complexities of real-world environments. This will enhance its utility in a broader range of applications, from autonomous vehicle navigation to virtual reality and remote sensing [168].

#### F. Scalability and Flexibility

Finally, scalability and flexibility remain significant challenges for NeRF applications in space. The current NeRF models are designed for relatively small-scale environments and often require extensive customization to adapt to the vast and complex nature of space scenes. Furthermore, updating NeRF models with new data to adapt to changing conditions or new tasks is not straightforward and typically involves retraining the model from scratch, which is not feasible during space missions [169]. Scalability and flexibility are crucial for practical deployment of NeRF across various applications, especially in environments characterized by large-scale scenes or rapidly changing conditions. NeRF's initial demonstrations have shown promising results in controlled settings; however, extending these capabilities to broader, more dynamic scenarios presents several challenges.

The scalability and flexibility of NeRF are influenced by several factors that affect its deployment in diverse environments:

- NeRF typically operates well within relatively small, controlled scenes [170]. Scaling up to larger environments such as entire cities or expansive natural landscapes requires exponentially more computational resources and data, which can be impractical with current technology.
- NeRF models are generally trained on specific scenes. Adapting a trained model to new or unseen environments without extensive retraining is a significant challenge [171], limiting the flexibility of the approach.
- For real-time adaptation, many potential applications of NeRF, such as in augmented reality or autonomous navigation, require real-time performance. Current NeRF implementations struggle with the latency needed for on-the-fly adaptations to changing environmental conditions or interactive user inputs.

To address the issues of scalability, several approaches can be considered:

- Implementing hierarchical and multi-resolution techniques [172] can allow NeRF to focus computational resources where they are most needed, reducing the need to model entire scenes at the highest level of detail uniformly.
- Breaking down large scenes into smaller, more manageable segments can make the problem more tractable. Each segment can be processed independently, potentially in parallel, and then stitched together seamlessly.
- Leveraging cloud computing resources and distributed processing frameworks can provide the necessary computational power to scale NeRF models to larger scenes or more complex simulations.

Improving the flexibility of NeRF involves making it capable of adapting to new environments and conditions more readily:

- Using transfer learning techniques [173, 174] to adapt NeRF models trained on one set of data to perform well on different but related data can significantly reduce the need for retraining from scratch.
- Developing NeRF models that support incremental learning, where the model can in fact learn from the new data without ever forgetting previously acquired information or knowledge, can help the model adapt dynamically to changes in the environment.
- Implementing meta-learning approaches, where NeRF models learn how to learn new scenes quickly, can facilitate rapid adaptation to new environments with minimal data.

Looking forward, advancing NeRF's scalability and flexibility will involve both technical innovations and new conceptual approaches:

- Exploring more efficient ways to represent and process data could reduce the computational load. Sparse representations, quantization and pruning could be key areas for research.
- Developing new neural network architectures that are inherently more scalable and adaptable, perhaps drawing on recent advances in fields like neural architecture search (NAS) [175] and generative adversarial networks (GANs) [176], could open new avenues for NeRF applications.
- For applications that involve data from multiple sources or locations, employing collaborative and federated learning models could allow different instances of NeRF to learn from each other, improving overall performance and adaptability.
- Enhancing the scalability and flexibility of NeRF is critical for its application in real-world scenarios, from large-scale environmental modeling [177] to dynamic interactive systems. Addressing the various challenges through innovative solutions in data processing, model training and system architecture will be essential for unlocking the full true potential of NeRF technology.

## X. FUTURE DIRECTIONS

### A. Real-Time Rendering and On-Board Processing

Future research should focus on optimizing NeRF for real-time rendering and on-board processing in space applications. Real-time rendering is essential for autonomous navigation and decision-making on spacecraft, rovers and satellites. This requires advancements in hardware, such as space-grade GPUs and software optimizations to enable efficient processing in resource-constrained environments.

### B. Multi-Modal Integration

Integrating NeRF with other space technologies such as LIDAR, synthetic aperture radar (SAR) and deep reinforcement learning could significantly improve its applicability in space. Combining these technologies could lead to more robust models capable of handling the complexities of space environments.

### C. Improved Space Debris Detection and Collision Avoidance

Given the growing concern over space debris, NeRF could play a key role in improving debris detection, collision prediction and mitigation strategies. Future work could focus on integrating NeRF with active debris removal systems and autonomous space vehicles to enhance space traffic management.

### D. Accelerating NeRF Computations

A key area of ongoing research is the acceleration of NeRF computations to make them work for real time applications, particularly in space missions where rapid decision-making is critical. Innovations in hardware such as the development of the specialized processors and GPUs tailored for deep learning tasks, offer promising solutions. Additionally, algorithmic improvements, including pruning and quantization techniques, are being explored to reduce the model complexity without significantly compromising the quality of the reconstructions. These advancements could significantly decrease the computational load, enabling the deployment of NeRF on spacecraft for tasks such as navigation and obstacle avoidance.

### E. Enhancing Data Efficiency

To address the high data requirements of NeRF, researchers are exploring methods to enhance its efficiency with limited datasets. Techniques such as transfer learning, where a model trained on terrestrial datasets is adapted for space environments and few-shot learning which aims to achieve high performance with a minimal number of training images, are particularly promising. These approaches could reduce the dependency on extensive training data, making NeRF more adaptable and easier to deploy in space missions where data collection is challenging.

### F. Robustness to Environmental Variability

Improving NeRF's robustness to environmental variability is crucial for its success in space applications. Ongoing research is focusing on developing models that can handle dynamic changes in the environment, such as moving objects or fluctuating lighting conditions. This includes integrating NeRF with other computational techniques such as dynamic scene reconstruction algorithms as well as



machine learning models that specialize in predicting environmental changes. These hybrid models aim to leverage the strengths of NeRF in rendering high-fidelity 3D environments while maintaining flexibility in dynamic conditions.

#### G. Scalability and Flexibility

Finally, enhancing the scalability and flexibility of NeRF to handle large-scale and complex environments, such as those encountered in space, is a critical area of research. This includes developing modular NeRF systems that can be updated incrementally as new data becomes available, without the need for retraining from scratch. Additionally, efforts are being made to create more generalized NeRF models that can be easily adapted to various space applications, from satellite imagery analysis to planetary exploration without extensive customization for each specific application.

### XI. CONCLUSION

Neural Radiance Fields holds immense potential for space applications by offering realistic 3D reconstructions from just sparse 2D data. Despite challenges like the computational complexity, data acquisition and model generalization, NeRF is poised to make significant contributions to satellite imaging, planetary exploration, space debris monitoring and astronomy. As advancements in optimization techniques and hardware continue, NeRF will likely play a central role in the future of space exploration and Earth observation. This review has comprehensively explored the integration of Neural Radiance Fields (NeRF) in space applications, highlighting its transformative potential across various domains such as satellite imagery, spacecraft navigation, mission simulation and planetary exploration. As evidenced by the discussed case studies, NeRF offers significant improvements over traditional methods, particularly in terms of the photorealism and accuracy of 3D reconstructions from limited 2D data sets. These capabilities are crucial for enhancing the quality and safety of space missions, providing detailed environmental models and supporting complex navigation and operation tasks in extraterrestrial settings. Despite its promising applications, NeRF faces substantial challenges, primarily due to its computational intensity and high data requirements. The current limitations regarding real-time processing and adaptation to the dynamic space environment pose significant hurdles for operational deployment. Moreover, the scalability issues related to handling large-scale and complex scenes typical in space exploration need to be addressed to fully harness NeRF's capabilities in off-Earth environments.

Looking forward, the future of NeRF in space applications lies in addressing these challenges through technological advancements in computational efficiency and data processing. Innovations in machine learning, such as the development of more robust models capable of handling environmental variability and reducing the dependency on extensive training data, will be key. Additionally, the advent of more powerful onboard computing platforms and advanced data compression techniques could enable the

practical deployment of NeRF for real-time applications in space.

In conclusion, while Neural Radiance Fields are still in the early stages of being adapted for space technology, their ability to transform and revolutionize how we visualize, navigate and interact with space environments is undeniable. Continued research and development efforts are crucial to overcoming the existing barriers and unleashing the complete potential of NeRF in enhancing the capabilities of future space missions.

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