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Evaluation of 3D Reconstruction of Non-collaborative Surfaces using Neural Radiance Fields

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Abstract – This paper investigates the effectiveness of Neural Radiance Fields (NeRF) in reconstructing the three-dimensional models of non-collaborative surfaces, with a specific focus on transparent and reflective materials. These surfaces often pose significant challenges to traditional photogrammetric methods due to their optical complexity. The study compares the accuracy of NeRF with that of conventional photogrammetric techniques based on Multi-View Stereo (MVS). Two objects, a plastic and an aluminium water bottle, were photographed with a smartphone and processed in both Agisoft Metashape and NefStudio to generate 3D models. The reconstructed models were evaluated against reference point clouds obtained through laser scanning. Accuracy assessment was conducted using the M3C2 analysis in CloudCompare, in which NeRF achieved mean distance errors of 0.650 mm and 0.153 mm for transparent and reflective surfaces, respectively. These values were lower than those obtained from MVS, which recorded 0.833 mm and 0.088 mm, respectively. The results indicate that while photogrammetry yields reliable outcomes for textured surfaces, NeRF demonstrates improved performance in modelling complex reflective and transparent geometries. These findings support the potential of NeRF as a practical alternative or complementary approach to traditional photogrammetry in scenarios involving challenging surface characteristics.

Keywords *– 3D reconstruction, neural radiance fields, multi-view stereo, laser scanning, non-collaborative surface*

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1.0 Introduction

Three-dimensional (3D) reconstruction is an essential technique for replicating real-world objects as digital 3D models, allowing in-depth analysis, reproduction, and systematic documentation. There are two common techniques in the 3D reconstruction domain: image-based and range-based methods. Among image-based techniques, photogrammetry is widely adopted as an indirect measurement method to reconstruct 3D geometry from 2D images through mathematical computation. The typical workflow consists of Structure from Motion (SfM), which estimates camera poses and generates sparse point clouds, followed by Multi-View Stereo (MVS) to produce dense depth maps from overlapping images (Zhou et al., 2024).

SfM-MVS is particularly effective when applied to textured surfaces, as variations in appearance assist with feature matching across images. However, its performance deteriorates significantly when dealing with transparent or reflective materials. The challenges mainly arise from difficulties in accurately estimating depth due to reflection-induced artefacts, such as ghosting and occlusion (Luo et al., 2024; Fu et al., 2023). Moreover, the non-linear light paths within transparent materials distort depth information, compromising the geometric fidelity of the reconstructed model (Daffara et al., 2020).

Range-based methods, such as laser scanning, utilise active sensing by emitting laser beams and measuring the time taken for them to return after striking an object's surface. These techniques offer high precision and can capture detailed models of complex structures (Cai et al., 2020; Mazzacca et al., 2023). However, their efficacy is markedly diminished when utilised on translucent or highly reflecting substances. Reflective surfaces can cause the laser signal to scatter or deflect, leading to data loss and partial reconstructions (Hoshi et al., 2022; Mazzacca et al., 2023).

Transparent objects further complicate laser scanning by failing to reflect laser beams adequately, resulting in insufficient geometric information (Yang et al., 2021). To mitigate these constraints, preprocessing strategies or hybrid approaches are frequently utilised to improve surface detectability.

Recent advancements in 3D reconstruction have integrated deep learning techniques to overcome these challenges. Neural Radiance Fields (NeRF), introduced by Mildenhall et al. (2020), represent a digital 3D scene as a continuous five-dimensional (5D) volumetric function of spatial position and viewing direction. NeRF generates a photorealistic 3D scene by predicting colour and density at any given point in space from a set of oriented 2D images (Murtiyoso et al., 2023). The model uses a fully connected Multi-Layer Perceptron (MLP) network trained to minimise rendering loss, thereby producing synthetic views that closely match the actual input images (Mazzacca et al., 2023).

This foundation enables NeRF to effectively capture complex visual effects, such as reflections and refractions, making it particularly suitable for reconstructing non-collaborative surfaces. In contrast to conventional methods, NeRF does not rely on discrete geometry or explicit feature matching but instead reconstructs scenes through learnt volumetric representation. Consequently, it offers benefits for handling optically complex materials, where traditional photogrammetry and laser scanning underperform.

This study explores NeRF's ability to reconstruct transparent and reflective surfaces and evaluates its performance against conventional photogrammetry and laser-scanning methods. Two types of water bottles, one transparent and one reflective, were selected for the analysis. The study contributes to ongoing efforts to refine 3D reconstruction techniques by highlighting NeRF's potential to address challenges posed by non-collaborative surface properties. Most previous studies on NeRF reconstruction focused on visual fidelity or synthetic datasets, with minimal empirical evaluation using real-world objects. However, only a limited number of studies have directly tested NeRF on actual non-collaborative materials in practical settings, particularly in comparison with established photogrammetric approaches.

This lack of experimental benchmarking constitutes a clear research gap that this study aims to fill. While existing literature discusses the theoretical capabilities of NeRF, direct experimental comparisons with traditional methods on such materials remain limited. This study specifically addresses this gap by experimentally evaluating NeRF's performance against photogrammetry for reflective and transparent surfaces, using laser scanning as the reference benchmark.

2.0 Methodology

The methodology in this study consists of four main phases: material preparation, data acquisition, processing, and evaluation of visual and geometric accuracy. These phases were implemented to compare the effectiveness of the NeRF and photogrammetric approaches in reconstructing non-collaborative objects. Ground-truth models were acquired via laser scanning for quantitative comparison.

2.1 Materials and Data Acquisition

Two types of objects were selected to represent non-collaborative surfaces. A plastic water bottle was used to examine the limitations of reconstruction methods for transparent surfaces, while an aluminium water bottle was used to examine the handling of reflective materials (Figure 1). These objects were selected due to their relevance in industrial and engineering contexts, where optical complexity often affects data acquisition quality.

Figure 1. Plastic and aluminium water bottles were used as test objects for reconstructing transparent and reflective surfaces

Images were captured using a Xiaomi Redmi Note 10 Pro smartphone, which features a 108-megapixel camera. This high-resolution sensor enabled the capture of detailed textures and surface characteristics necessary for photogrammetric processing. Photographs were taken by manually circling each object and capturing it from multiple angles to ensure adequate image overlap. For each object, between 42 and 87 images were recorded, depending on the geometric complexity of the surface. Camera position, distance, and focal length were kept consistent throughout the capture process to minimise variability.

On the other hand, laser-scanning data were collected using the EinStar handheld 3D scanner (Figure 2), which is equipped with three infrared projectors, two stereo depth cameras, and one colour camera. This device enables the rapid acquisition of dense point clouds with a resolution of up to 0.1 millimetres. Built-in features such as smart tracking, automatic alignment, and noise filtering contributed to the accurate capture of object geometry. The scanner was used to document each object from multiple viewpoints, after which the scans were aligned and merged using proprietary software to generate a clean and complete reference point cloud.

Figure 2. EinStar handheld 3D scanner used to capture ground-truth point clouds

2.2 3D Reconstruction

3D reconstruction for MVS was performed using Agisoft Metashape. The process began with image alignment via Structure-from-Motion (SfM), which estimated both internal and external camera parameters via image matching and produced a sparse point cloud. In this study, the alignment accuracy parameter in Metashape was set to 'High' for all datasets to ensure consistent and accurate estimation of camera poses. The SfM input was then used in MVS reconstruction to generate a dense point cloud. The process was followed by the generation of a mesh model with its respective texture.

On the other hand, the 3D reconstruction for NeRF was performed using Nerfstudio. NeRF itself does not support an image alignment procedure; hence, the camera parameters estimated from Metashape were converted to the Nerfstudio format to train a neural network to model radiance and density across 3D space. The training was performed by rendering synthetic views and comparing them to the original images. The NeRF training itself ran for about 30,000 steps and was completed in approximately 30 minutes per dataset. NeRF's neural representation, as shown in Figure 3, enabled it to interpolate complex view-dependent effects and reconstruct challenging surfaces that traditional image-based methods struggled with. Once convergence was achieved, the trained model was transformed into point cloud and mesh formats. All NeRF processing was carried out on a computer powered by an Intel Core i7 processor and an NVIDIA Dual RTX 4060 graphics card.

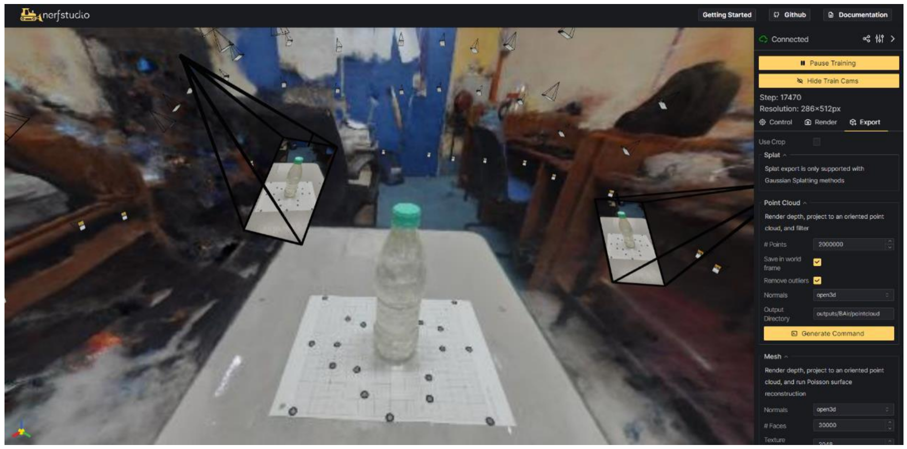

Figure 3. NeRF processing pipeline in Nerfstudio, illustrating volumetric training using multi-view images

Since transparent and reflective surfaces pose challenges for both photogrammetry and laser scanning, each object was coated with a thin layer of yellow fluorescent paint, as shown in Figure 4. This treatment was applied to facilitate the geometric analysis of the 3D model generated by the NeRF technique.

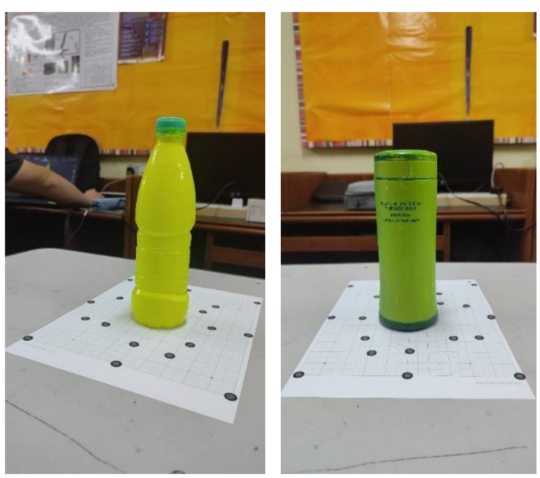

Figure 4. Transparent and reflective bottles coated with yellow, fluorescent paint to improve surface detectability

2.3 Accuracy Evaluation

To evaluate the accuracy of the reconstructed models, all point clouds were aligned with the corresponding ground truth data in CloudCompare. The alignment was performed using rigid transformation techniques to ensure proper spatial registration. The M3C2 plugin was used to compute cloud-to-cloud distances between the test models and the reference scans. The evaluation was based on two quantitative metrics, standard deviation and mean distance error, where the values were extracted from the generated Gaussian distribution graph. These metrics were used to assess both the geometric accuracy and consistency of each reconstruction method across different surface types.

3.0 Results and Discussion

Figure 5 shows the reconstruction results of the transparent and reflective water bottles in their original condition. NeRF outperformed MVS in handling transparent objects. Its volumetric representation allowed it to reconstruct the general shape of the clear surface. However, distortions persisted in areas with strong refraction. Meanwhile, MVS struggled to reconstruct the same object, resulting in an incomplete, noisy point cloud. The laser scanner was unable to reconstruct the clear surfaces due to signal loss during measurement. Only the bottle cap, being opaque, was successfully reconstructed.

A similar pattern was observed for the reflective aluminium bottle. The point cloud generated by NeRF provided a more complete and detailed representation, demonstrated efficiency in handling reflective areas, and offered a coherent model of the object. In contrast, MVS reconstructed the bottle's overall shape but failed to resolve high-gloss areas, resulting in surface gaps and distortions. Meanwhile, the laser scanner produced the most accurate and detailed point cloud, successfully capturing the full geometry and surface details of the aluminium bottle without significant interference from its reflective nature.

Geometric accuracy was analyzed using the Multiscale Model-to-Model Cloud Comparison (M3C2) in CloudCompare. M3C2 computes distances between corresponding 3D points in the reconstructed dataset and the ground truth model. In this study, the laser-scanning output was used as ground truth to evaluate 3D models from both NeRF and MVS. However, since MVS and laser scanning failed to reconstruct the transparent and reflective surfaces in their uncoated state, the objects were coated with a solid colour to improve surface detectability, as shown in Figure 6.

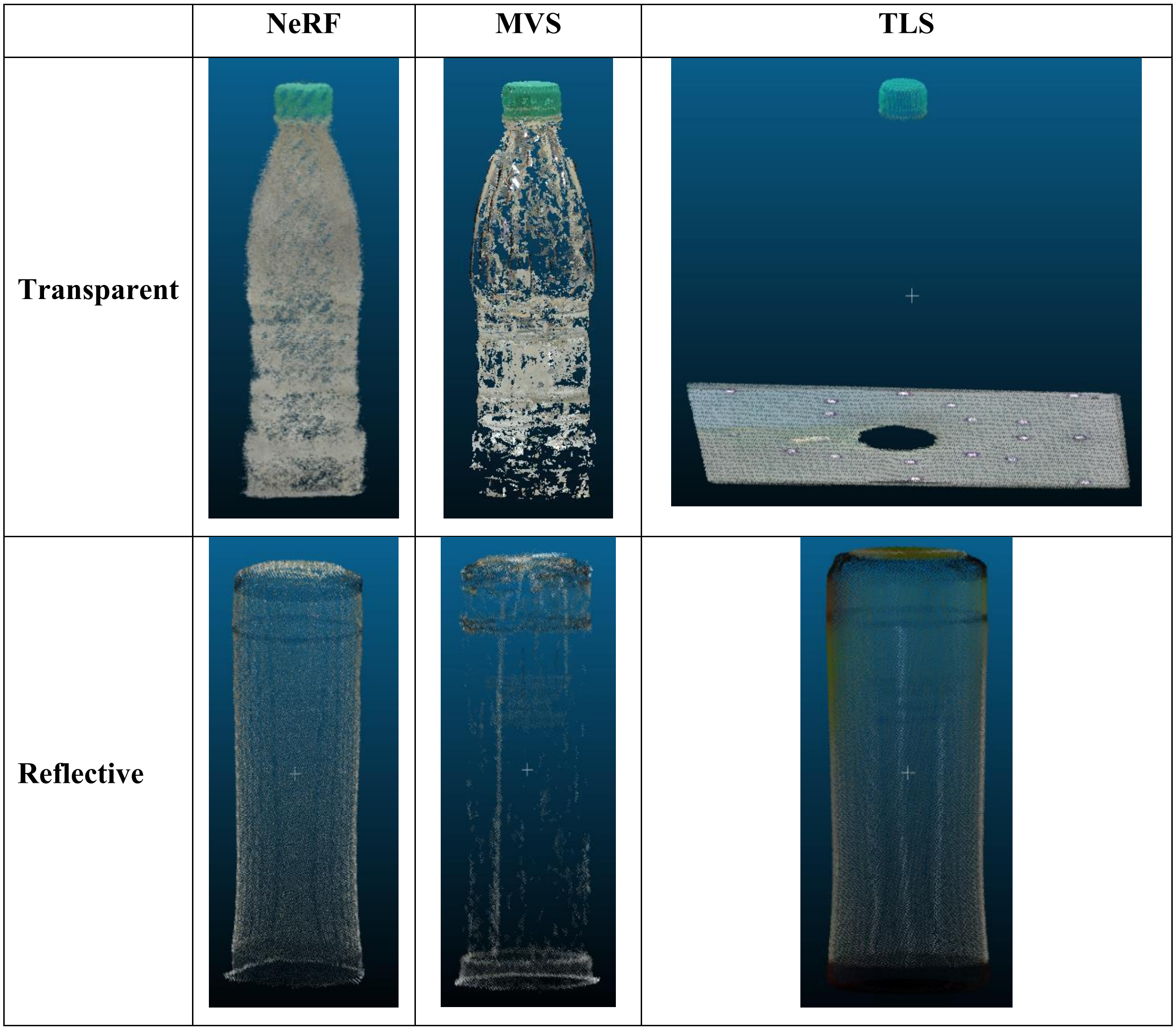

Figure 5. Reconstructed 3D point clouds of original uncoated objects using NeRF, MVS, and laser scanning

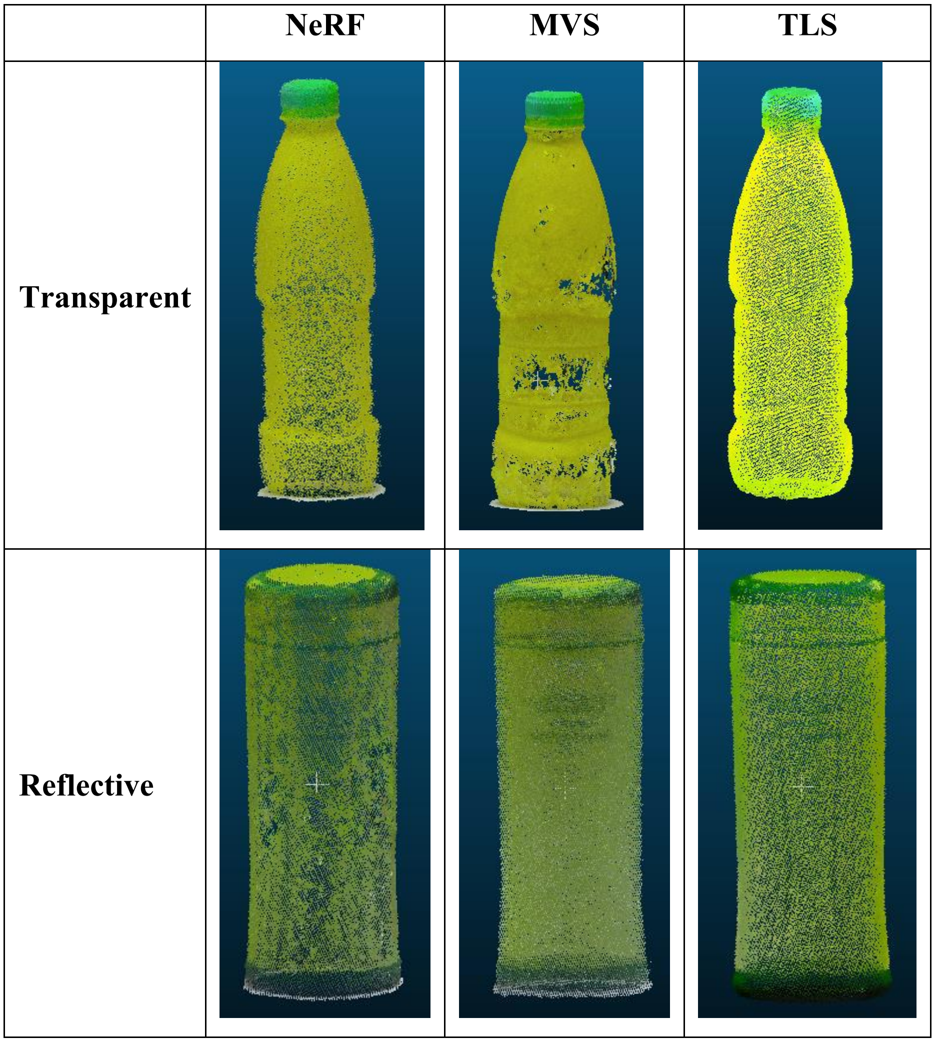

Figure 6. Reconstructed 3D point clouds of coated objects to enable accurate comparison with laser scan ground truth

Figure 7 shows that the MVS-generated histogram exhibits a Gaussian distribution, with most distance values concentrated near the mean. However, there were noticeable deviations in the tails, suggesting variability in reconstruction accuracy. The mean distance was 0.833 mm, indicating that the MVS point cloud was generally well-aligned with the ground truth. The standard deviation was 2.846 mm, showing the spread of distance errors around the mean. These deviations can be attributed to variations in image quality or insufficient coverage, leading to errors in the generated point cloud, especially in hard-to-capture areas due to lighting or angles. MVS accuracy relies on feature matching between images, and reflective surfaces can cause mismatches or distortions, leading to noise in the data.

In contrast, NeRF exhibited a broader, slightly bimodal distribution with two peaks. This indicates the presence of two distinct groups of error distances in the NeRF-generated point cloud. The first peak, closer to zero, may represent areas where the NeRF technique closely matched the laser-scanned ground truth. The second peak, farther from zero, suggests areas where NeRF struggled to accurately capture the geometry or surface details, possibly due to complex material properties such as transparency or reflection, insufficient training data, or occlusions. The mean distance for NeRF was 0.650 mm, indicating good overall alignment with the ground truth. However, the standard deviation was higher at 3.890 mm, suggesting a broader range of error distances compared to the MVS data. NeRF relies on dense sampling of views to accurately model surfaces, and variations in data density or coverage gaps can lead to higher errors, resulting in the observed bimodal distribution.

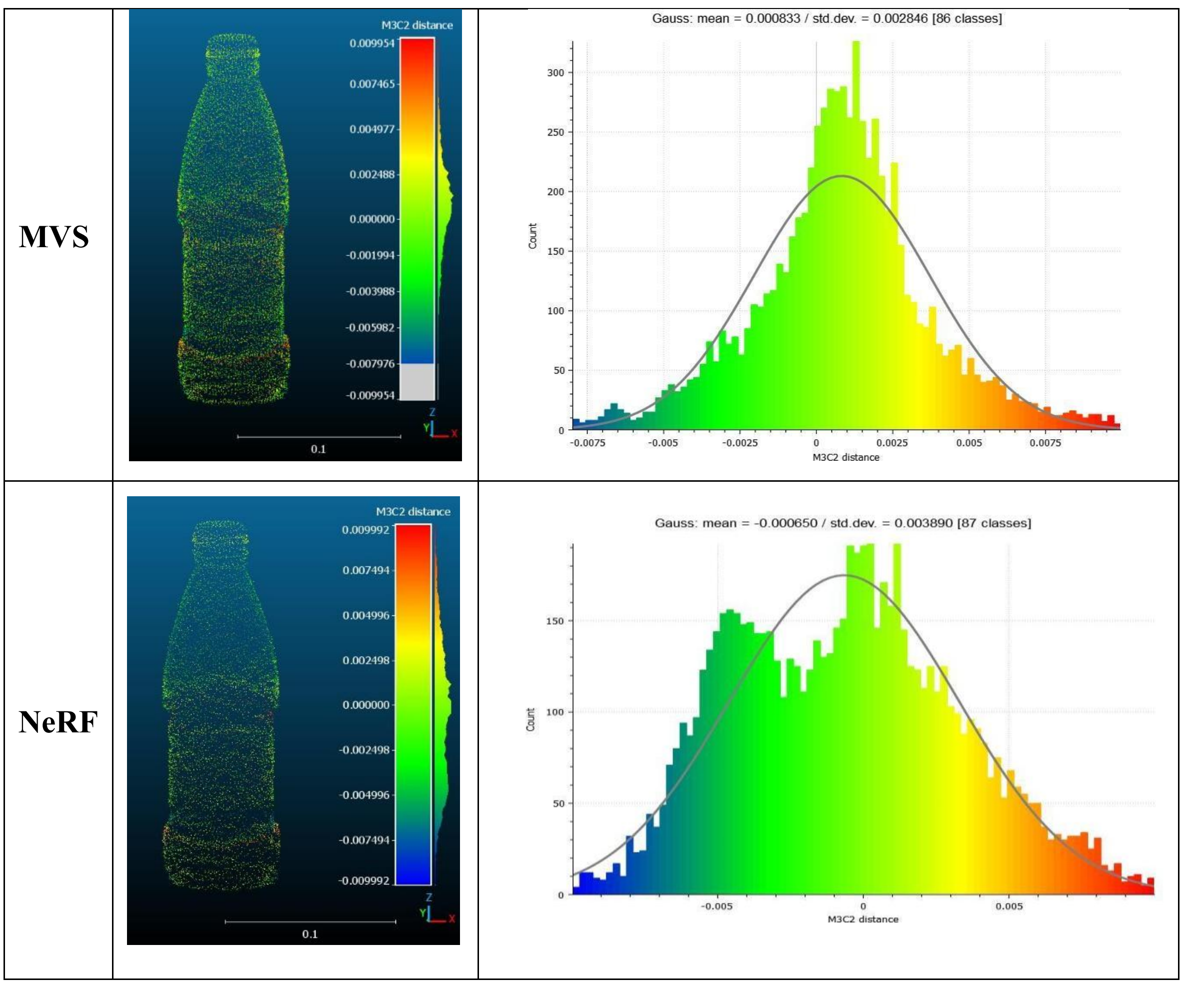

Figure 7. M3C2 histogram comparison of transparent object reconstruction: NeRF vs MVS against laser-scanned ground truth

Figure 8 shows a sharp peak around the mean, indicating that most points in the MVS point cloud were close to their corresponding points in the laser scanner point cloud. The standard deviation of 2.916 mm measures the spread of these distances around the mean; a lower standard deviation indicates higher precision. Despite some variations, the majority of points were tightly clustered around the mean distance of 0.088 mm, suggesting minimal bias. Factors such as poor image quality or inadequate coverage may contribute to the observed standard deviation.

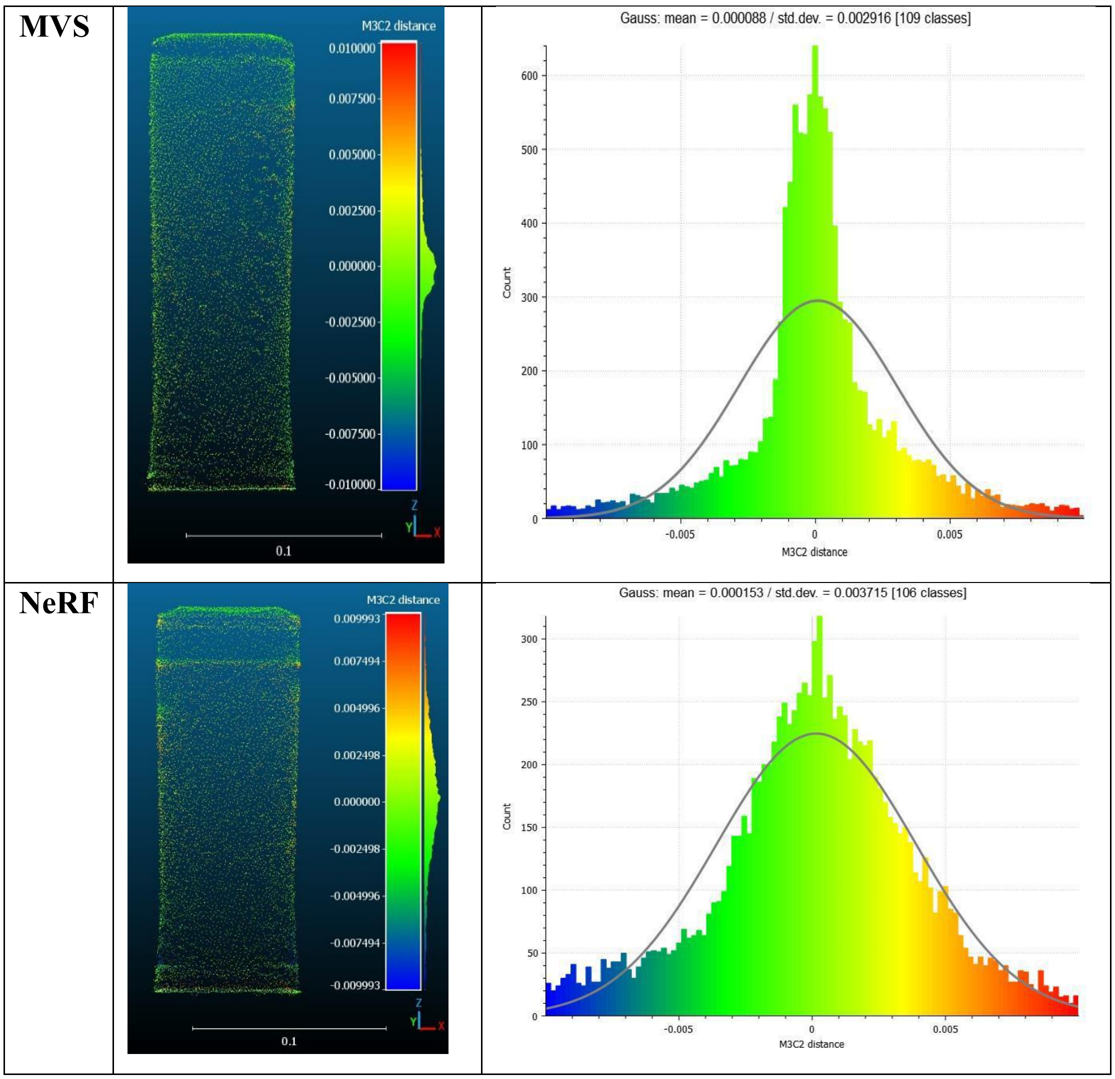

Figure 8. M3C2 histogram comparison of reflective object reconstruction: NeRF vs MVS against laser-scanned ground truth

The NeRF histogram also shows a peak around the mean, but with a broader spread, indicating more variability. The standard deviation of 3.715 mm, slightly higher than that of MVS, suggests greater variability in the NeRF point cloud. The mean distance of 0.153 mm indicates that, on average, the NeRF point cloud was very close to the ground truth, with minimal bias. The performance of NeRF depends on the quality and quantity of input images and the neural network's ability to generalise from the training data. Variability in data quality can lead to inconsistencies, reflected in the higher standard deviation.

Both techniques exhibited minimal bias, with means close to zero, indicating that, on average, the point clouds aligned well with the laser-scanner ground truth. However, MVS had a lower standard deviation, suggesting higher precision, while NeRF showed slightly more variability. MVS might have benefited from colour variations on the aluminium bottle, improving feature detection and matching accuracy, which could explain the smaller standard deviation compared to NeRF.

These findings offer practical implications for industries such as industrial design and digital heritage preservation. Engineers and researchers can utilize these results to determine the most suitable reconstruction technique based on surface characteristics. In contexts where high precision is critical, such as quality control for metallic manufactured parts, MVS remains the superior choice when surface textures or coatings are present, as they facilitate feature matching. On the contrary, NeRF offers rapid visualization when shape accuracy is prioritized.

However, several limitations must be acknowledged. Although MVS demonstrated higher precision on the aluminium surface, its dependency on distinct visual features remains a bottleneck. MVS performance would likely degrade on perfectly uniform or highly specular surfaces without a coat. On the other hand, the higher variability in NeRF suggests that its current geometric reconstruction optimization remains sensitive to noise, which could limit its reliability for high-tolerance engineering applications without further refinement.

4.0 Conclusion

This study has demonstrated the comparative strengths and weaknesses of photogrammetry and Neural Radiance Fields (NeRF) for reconstructing non-collaborative surfaces. Transparent and reflective objects have traditionally posed a significant challenge for image-based 3D reconstruction techniques, primarily because of their unpredictable light interactions and the lack of consistent visual features. While mature and widely adopted, photogrammetry struggled to produce usable reconstructions of transparent and reflective surfaces. Its dependence on texturerich, diffuse surfaces renders it ineffective in scenarios involving optical complexity. Conversely, NeRF offered a compelling alternative, successfully reconstructing the object geometry in all test cases, including those where photogrammetry failed. Its volumetric synthesis from multi-view image inputs effectively addresses several limitations of traditional techniques. Quantitative assessments confirmed NeRF's superiority across key metrics, including mean distance and standard deviation, while qualitative observations further highlighted its resilience in maintaining surface integrity. These findings suggest that NeRF may serve as a practical and accurate solution for 3D digitisation tasks involving challenging surface materials.

Overall, the study contributes to a growing body of evidence supporting the integration of deep learning approaches for accurate geometric 3D modelling, particularly when traditional photogrammetric techniques prove inadequate. As tools such as NeRF continue to evolve, they are likely to play an increasingly prominent role in domains requiring accurate digital representations of real-world objects, regardless of surface complexity. Future research should expand on these findings by exploring a wider range of materials, including large glass structures. Additionally, exploring uncontrolled outdoor lighting conditions would be beneficial. Further studies could also focus on other methods, such as 3D Gaussian Splatting (3DGS).

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Reference

Cai, Y., Cao, M., Li, L., & Liu, X. (2020). An end-to-end approach to reconstructing 3D model from image set. *IEEE Access, 8*, 193268–193284. https://doi.org/10.1109/ACCESS.2020.3032169

Daffara, C., Muradore, R., Piccinelli, N., Gaburro, N., Rubeis, T., & Ambrosini, D. (2020). A cost-effective system for aerial 3D thermography of buildings. *Journal of Imaging, 6*(8), 76. https://doi.org/10.3390/jimaging6080076

Fu, C., Huang, N., Huang, Z., Liao, Y., Xiong, X., Zhang, X., & Cai, S. (2023). Confidence-guided planar-recovering multiview stereo for weakly textured plane of high-resolution image scenes. *Remote Sensing, 15*(9), 2474. https://doi.org/10.3390/rs15092474

Hoshi, S., Ito, K., & Aoki, T. (2022). Accurate and robust image correspondence for structure-from-motion and its application to multi-view stereo. *2022 IEEE International Conference on Image Processing (ICIP)*, 2626–2630. https://doi.org/10.1109/ICIP46576.2022.9897304

Luo, W., Lu, Z., & Liao, Q. (2024). LNMVSNet: A low-noise multi-view stereo depth inference method for 3D reconstruction. *Sensors, 24*(8), 2400. https://doi.org/10.3390/s24082400

Mazzacca, G., Karami, A., Rigon, S., Farella, E. M., Trybala, P., and Remondino, F.: NERF For Heritage 3D Reconstruction, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLVIII-M-2-2023, 1051–1058, https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-1051-2023.

Mildenhall, B., Srinivasan, P. P., Tancik, M., Barron, J. T., Ramamoorthi, R., & Ng, R. (2020). NeRF: Representing scenes as neural radiance fields for view synthesis. In *ECCV* (pp. 405–421). https://doi.org/10.1007/978-3-030-58452-8_24

Murtiyoso, A., Markiewicz, J., Karwel, A., & Kot, P. (2023). Investigation on the use of NeRF for heritage 3D dense reconstruction for interior spaces. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-1/W3-2023*, 115–121. https://doi.org/10.5194/isprs-archives-XLVIII-1-W3-2023-115-2023

Yang, Y., Zhang, J., Wu, K., Zhang, X., Sun, J., Peng, S., & Wang, M. (2021). 3D point cloud on semantic information for wheat reconstruction. *Agriculture, 11*(5), 450. https://doi.org/10.3390/agriculture11050450

Zhou, L., Wu, G., Zuo, Y., Chen, X., & Hu, H. (2024). A Comprehensive Review of Vision-Based 3D Reconstruction Methods. Sensors, 24(7), 2314–2314.
https://doi.org/10.3390/s24072314