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EVALUATION OF NERF 3D RECONSTRUCTION FOR ROCK ART DOCUMENTATION

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ABSTRACT:

Digital documentation of rock art traditionally relies on a point cloud captured by a terrestrial laser scanner (TLS) or derived from an oriented image obtained using photogrammetry. In modern photogrammetry, the dense point cloud is generated using multi-view stereo (MVS) and subsequently used to generate a photorealistic 3D model. A recent method to reconstruct 3D models from images is Neural Radiance Fields (NeRF), which uses volume density to render the scenes through neural networks. The advantage of NeRF is that it can construct 3D models faster without using high computer processors and memory. NeRF has been studied in various applications, including cultural heritage, but not specifically for rock art documentation. Therefore, this paper evaluates three-dimensional (3D) reconstruction techniques using NeRF on Nerfstudio platform on two rock art datasets and compares them with the point cloud and 3D mesh models obtained from TLS and photogrammetry/MVS. The results have shown that NeRF does not match MVS in achieving geometric precision and texture quality. However, its learning-based approach accelerates reconstruction and offers potential enhancements to complement photogrammetric workflow.

1. INTRODUCTION

The precise digital geometric documentation of rock art paintings has become increasingly essential for preservation. Various methods exist for documenting their geometry in the digital documentation era, as traditional manual tracing or rubbing poses risks of damaging the paintings due to pressure applied during recording. Besides, manual tracing encounters distortion issues due to representing three-dimensional (3D) surfaces as two-dimensional (2D) plane paper records (Sanz, 2014). Moreover, managing large-scale motifs in manual documentation projects presents challenges in storage mediums (Sanz, 2014). Within digital techniques, the geometric elements of rock art painting and their shelter can be precisely recorded and documented in the form of a 3D model.

Over the past two decades, the use of terrestrial laser scanners (TLS) in the digital recording of heritage objects has become preferable in cultural heritage studies because of their capability to capture objects' geometry precisely. TLS measures and records the object's geometry through a laser beam and presents the result as the point cloud (Peña-Villasenín et al., 2019). The advantage of TLS for geometric recording is that it can mitigate distortion issues and enable more efficient data storage. However, TLS is expensive and not always practical when considering the cost of rock art recording and documentation projects (Davis et al., 2017).

The photogrammetry technique is one of the alternatives to recording and documenting the geometric elements of rock art painting at a cheaper cost. The photogrammetry technique has been available longer than TLS. However, it historically demands in-depth knowledge and rigorous analytical principles, making it challenging for non-photogrammetrists to transform 2D imagery into 3D models (Remondino et al., 2017). The photogrammetry technique has regained popularity in the last decade thanks to advancements in automated image orientation and 3D reconstruction processes. This resurgence has revived interest in photogrammetric 3D modelling as a practical and accessible approach for documenting rock art for non-experts (Jalandoni et al., 2018).

The process of generating a 3D model from 2D images through photogrammetry begins with image orientation. Modern photogrammetry employs the Structure-from-Motion (SfM) method, which simultaneously calculates the camera pose and object structure through image matching to create a tie point cloud and finalise the output through bundle adjustment. The primary output from SfM is the exterior orientation parameters, which are then used as input for generating a dense point cloud based on the Multi-View Stereo (MVS) approach. MVS conducts dense matching to generate a dense point cloud (Furukawa & Ponce, 2010), and the density of the points can be built up to the pixel-to-pixel level, depending on the resolution of the input image.

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The resultant dense point cloud resembles that measured from TLS, but it is derived based on the mathematical model of light rays of viewing angles from overlapped images. The geometric documentation of rock art paintings is not limited to the presentation of point clouds but also in the form of photorealistic 3D models (Bendicho et al., 2017; Davis et al., 2017; Peña-Villasenín et al., 2019). It requires the process of triangulating the point cloud to create the surface of the 3D model. The oriented pixels on the image calculated during the SfM are placed into respective triangulated polygons to generate a photorealistic 3D model (Nocerino et al., 2020). However, the MVS process is time-consuming and requires high computational capabilities to accelerate computing the dense point clouds and textured 3D models.

A recent innovation in 3D reconstruction, Neural Radiance Fields (NeRF), has attracted interest in 3D modelling studies. Initially introduced by Mildenhall et al. (2020), NeRF has revolutionised the synthesis of novel views. NeRF is a specialised technique that puts the trained image into artificial neural networks, a segment within the domain of artificial intelligence (AI) utilised in computer vision and graphics (Mazzacca et al., 2023). Advantageously, NeRF efficiently renders 3D scenes from 2D images without high computing power and memory (Mildenhall et al., 2020; Tancik et al., 2023).

NeRF does not generate point clouds or 3D meshes as its outputs, as photogrammetry and TLS do. Instead, it renders the 3D scene as a volumetric density representation (Mildenhall et al., 2020). NeRF renders a 3D scene by firstly querying the recovered camera pose coordinate consisting of 3D positions (x,y,z) and 2D viewing direction (θ, Φ) along the camera rays. Subsequently, it learns and synthesises the viewing by predicting volume density (α) and colour (RGB) outputs for specific viewpoints using the classic volume rendering technique (Mildenhall et al., 2020). This unique capability facilitates the creation of new perspectives on a scene and demonstrates considerable potential in generating high-quality, photorealistic scene images, virtual reality, augmented reality, and computer graphics (Deng et al., 2022; Tewari et al., 2022).

NeRF has gained significant attention for its ability to create detailed and realistic 3D reconstructions in cultural heritage documentation. An early concept has been demonstrated by Sun et al. (2022) using collections of Internet photos, and the potential of NeRF for digital cultural heritage has been reviewed by Croce et al. (2023). Remondino et al. (2023) demonstrate the advantages of NeRF reconstruction on non-collaborative objects, which are usually not able to be generated by photogrammetry, while Croce et al. (2023) demonstrate the ability to use a limited number of images and resolution on NeRF reconstruction.

The evaluation of NeRF output quality mostly assesses the accuracy of the 3D model generated by NeRF by comparing it with the photogrammetry/MVS method. The evaluation involves analysing discrepancies of NeRF-generated point cloud through distance error analysis, point cloud density and completeness (Croce et al. 2023; Mazzacca et al. 2023; Murtiyoso and Grussenmeyer 2023; Pepe, Alfio, and Costantino 2023; Remondino et al. 2023). Among the previously mentioned studies, there is limited literature that discusses its potential for the digital documentation of rock art. Therefore, this paper aims to assess the quality of 3D models rendered using NeRF for rock art documentation and quantify their geometric accuracy and texture quality compared with 3D models constructed using the MVS technique in photogrammetry.

2. METHODOLOGY

In this study, NeRF 3D reconstruction was performed using two datasets acquired at Gua Tambun's rock art site. The first dataset contains 58 images captured by DJI Phantom 4 Pro with a resolution of 16.8 megapixels (5472 x 3078). The second dataset includes 111 images captured by the DJI Phantom 4, producing 12-megapixel (4000 x 3000) images. Both datasets were processed using Agisoft Metashape for photogrammetry/MVS workflow (Figure 1).

Image orientation based on Structure-from-Motion (SfM) with the "High" preset for alignment accuracy was initiated. SfM calculates the image orientation parameters by matching the homogonous features on the overlapping images and projecting these features to the model space to create tie points. After registering the control point to correct the model scale and orientation, the tie points were reprojected back to their original images through bundle adjustment to estimate the final image orientation parameters. Following the orientation output from the SfM, a dense point cloud was then generated based on MVS using the "Medium" quality setting, followed by meshing and texturing to generate a coloured 3D model in the photogrammetry workflow of this study. The reported ground sample distances (GSDs) are 2.03 mm (Dataset 1) and 3.72 mm (Dataset 2).

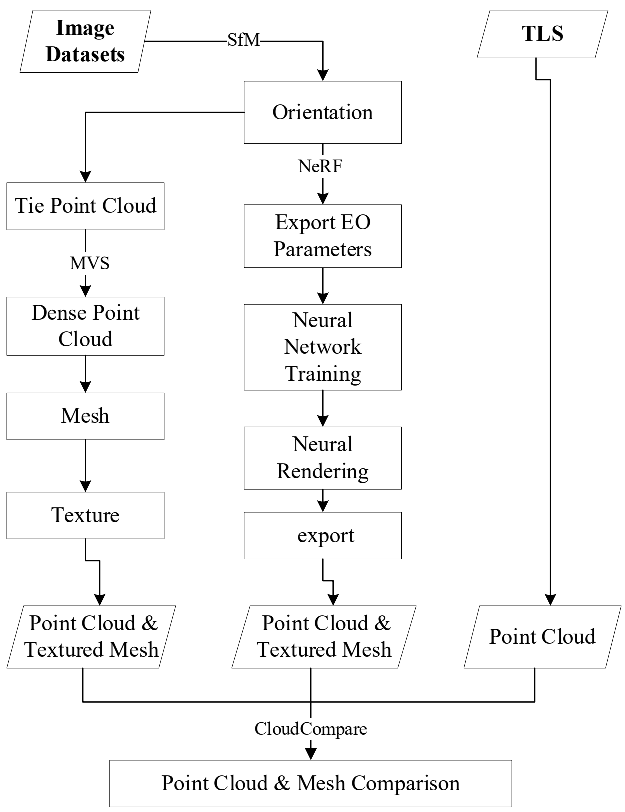


Figure 1. Methodology.

On the other hand, the 3D scene reconstruction using NeRF was performed using Nerfstudio (Tancik et al., 2023). As NeRF does not directly handle image orientation but requires pre-oriented input, the orientation parameters estimated in Metashape were converted and exported to Nerfstudio format to train and render the rock art site. The 'balance' speed rendering setting was used during the process. While NeRF was not originally designed to generate 3D models based on point clouds, the recreated neural radiance fields can be exported into a point cloud and a 3D textured mesh for analysis. Both MVS and NeRF techniques were executed on a laptop powered by a 9th-generation i5 9300H CPU running at 2.40GHz, with NVIDIA GeForce GTX 1650 and 24 gigabytes of memory.

The TLS point cloud served as a reference (ground truth) for comparison in this study to quantify the quality of the point clouds generated using NeRF and photogrammetry. CloudCompare software was used to analyse the geometric accuracy of MVS and NeRF-generated point cloud and 3D mesh models in terms of mean error and standard deviation. The point clouds and 3D models exported from Nerfstudio were rescaled and oriented to match the shape and position of both TLS and MVS in CloudCompare.

The point cloud density between NeRF and MVS was also analysed, as both NeRF and MVS were expected to produce the same density since the number of points exported from Nerfstudio corresponded to Metashape results. The texture quality from NeRF was also compared with that of the 3D model derived using the MVS approach.

3. RESULTS AND DISCUSSION

The training process in Nerfstudio took about two hours to complete for both datasets, half the time compared to photogrammetry. Conversion from volume density to point cloud was instantaneous, but conversion into 3D mesh took approximately one hour. For a fair comparison, the number of converted points and faces were set to be close to the number on point cloud and mesh generated using MVS in Metashape, respectively.

Figure 2 displays the point cloud generated from both datasets. Dataset 1, produced using photogrammetry, contains approximately 10 million points, while Dataset 2 comprises 4.5 million points. Despite Dataset 1 only covering half of the rock art panel using fewer images compared to Dataset 2, it exhibits a higher number of points in the dense cloud, likely due to the utilisation of larger image resolutions.

On the other hand, the number of point clouds converted from Nerfstudio appears quite similar to those from MVS for both datasets. Upon closer inspection, NeRF demonstrates the ability to generate point clouds of vegetation areas situated at the centre-lower part of the 3D model, which MVS does not. However, noticeable noise is observed at the surrounding edge of the 3D point cloud.

The geometric accuracies of all point clouds from both NeRF and MVS were analysed by measuring the error and standard deviation of signed distance calculated against TLS using M3C2 in CloudCompare. Based on Figure 3, the point cloud derived from Dataset 1 from MVS exhibited an error of 0.25cm with a standard deviation of 10cm. In contrast, the point cloud generated by NeRF exhibited an error of 3.9cm with a standard deviation of 37cm. Referring to Dataset 2, the point cloud obtained from MVS resulted in an error of 0.47cm and a standard deviation of 11cm. However, the point cloud generated by NeRF showed an error of 0.97cm and a standard deviation of 27cm.

The analysis conducted using M3C2 indicates the consistent performance of the point cloud generated by the MVS method across both datasets, showcasing an error approximately 1.2 times higher than the GSD. Conversely, errors derived from NeRF showed significantly higher values, reaching approximately 19 and 26 times the GSD for Dataset 1 and Dataset 2, respectively. The substantial standard deviation observed in the NeRF-generated point clouds indicates significant noise presented in both datasets.

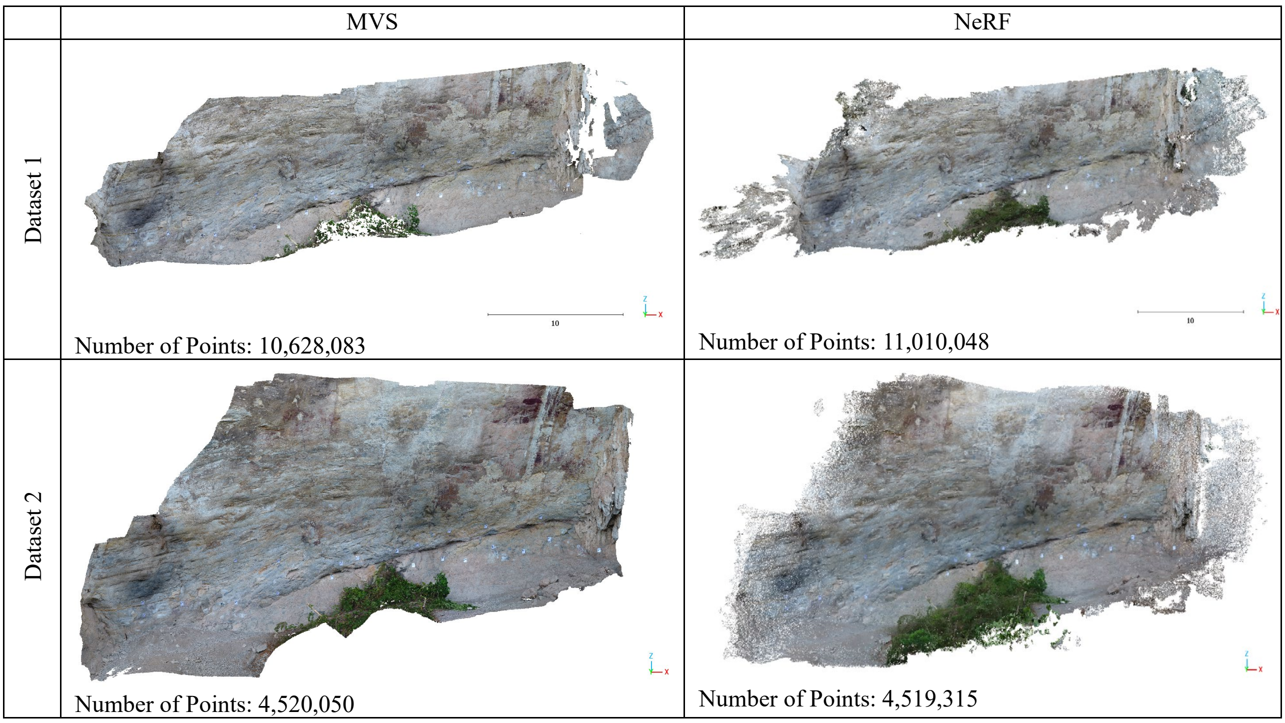


Figure 2: Point cloud output from MVS and NeRF.

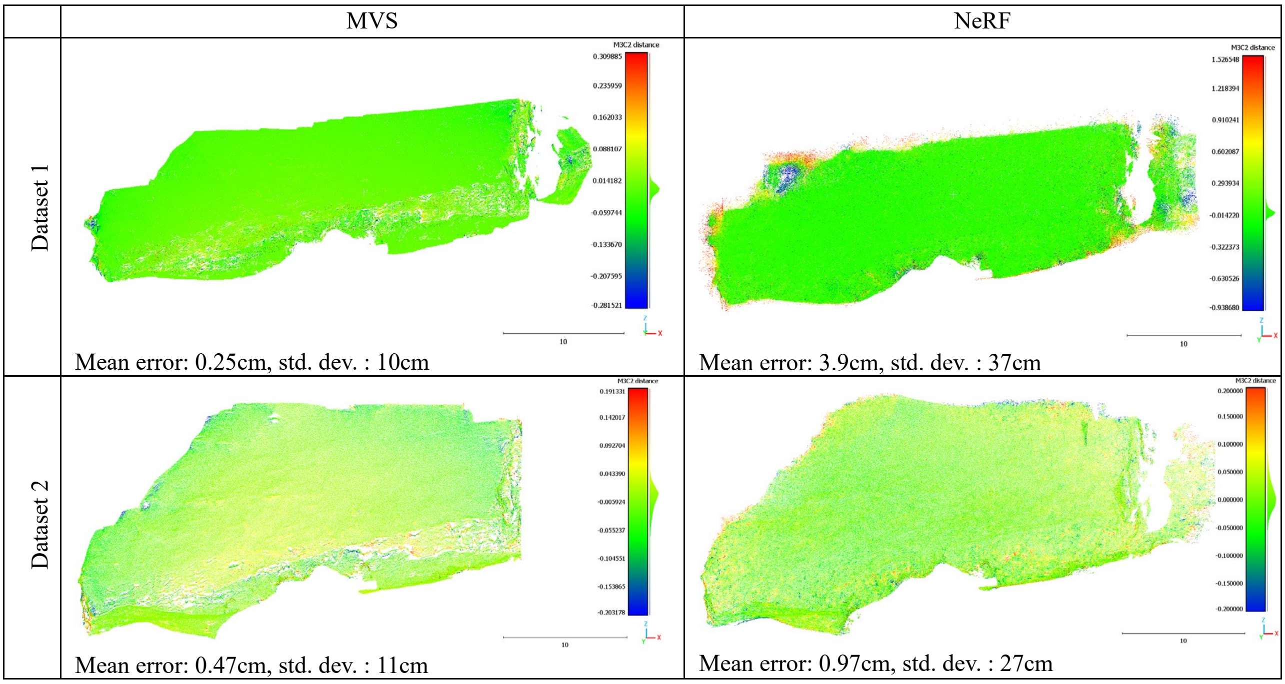


Figure 3. M3C2 analyses of MVS and NeRF point clouds. The cooler colours represent a small error between the observed 3D model with ground truth (TLS), and warmer colours indicate high errors.

The second analysis evaluates the quality of the generated point cloud in terms of point density by calculating the number of neighbours within a 5cm radius sphere for each point using CloudCompare. Since the number of points exported from Nerfstudio was set to match the number of points generated by Metashape, both NeRF and MVS exhibit the same average number of neighbours in both datasets, as expected, as depicted in Figure 4.

The point cloud derived using MVS is distributed homogenously across the entire object for both datasets. On the other hand, the density of the point cloud generated by NeRF appeared heterogeneously, more concentrated at the centre of the objects. The result may be explained by the denser area resulting from multiple overlapping images acquired to follow photogrammetric principles.

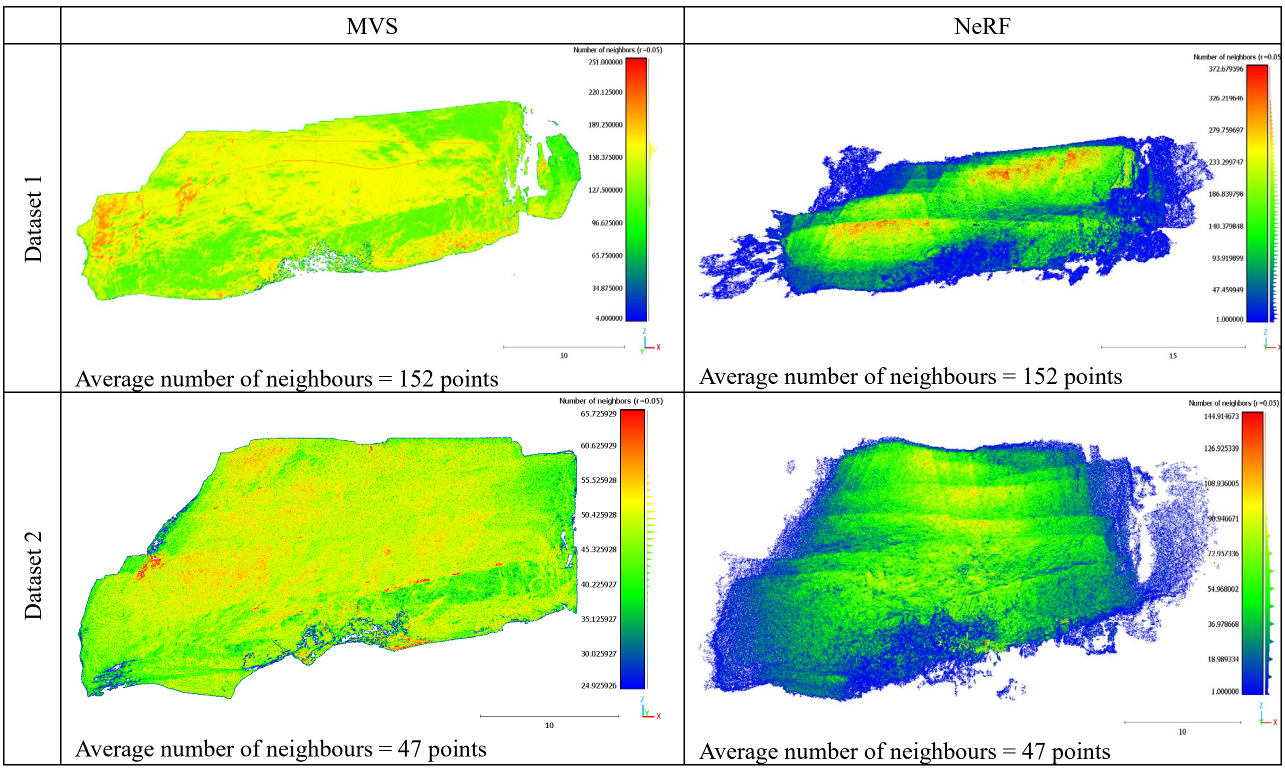


Figure 4. Analyses of point density in CloudCompare based on a 5cm radius sphere for each point. The warmer colours represent a dense number of neighbouring points. In contrast, cooler colours represent sparse neighbouring points.

The third analysis evaluates the geometric accuracy of the 3D mesh model from NeRF. As NeRF recreates the 3D scene using input images from photogrammetry, the geometric of the mesh model should be identical in theory. In this study, the number of mesh faces exported from Nerfstudio is almost similar to the 3D model generated using Metashape, as shown in Figure 5. The geometric accuracy of 3D mesh was then analysed using cloud-to-model (C2M) comparison by measuring the signed distance of each vertex of NeRF's mesh relative to the polygon of 3D mesh from Metashape. After subset the model to fit the same area on both 3D models of each dataset, the discrepancies between NeRF and MVS is 0.5cm with a standard deviation of 12cm for Dataset 1 and 0.8cm error with a 10cm standard deviation for Dataset 2 (Figure 6). The small errors produced have shown the ability of NeRF to generate an accurate 3D mesh model, suggesting the potential for an alternative or complement of the 3D modelling technique on standard photogrammetric workflow.

However, the texture quality exported from Nerfstudio does not meet the resolution produced by Metashape. As the assessment yields the same quality from both datasets, only output from Dataset 1 is reported in this paper, as shown in Figure 7. The texture of rock art on the 3D model generated from the photogrammetry method using Metashape has sharp, clean, and precise details. On the contrary, the texture of the painting viewed on the Nerfstudio web viewer and exported 3D mesh are blurry, and it is hard to identify the pattern of the paintings. Moreover, some faces on the 3D mesh were flipped after being converted from NeRF.

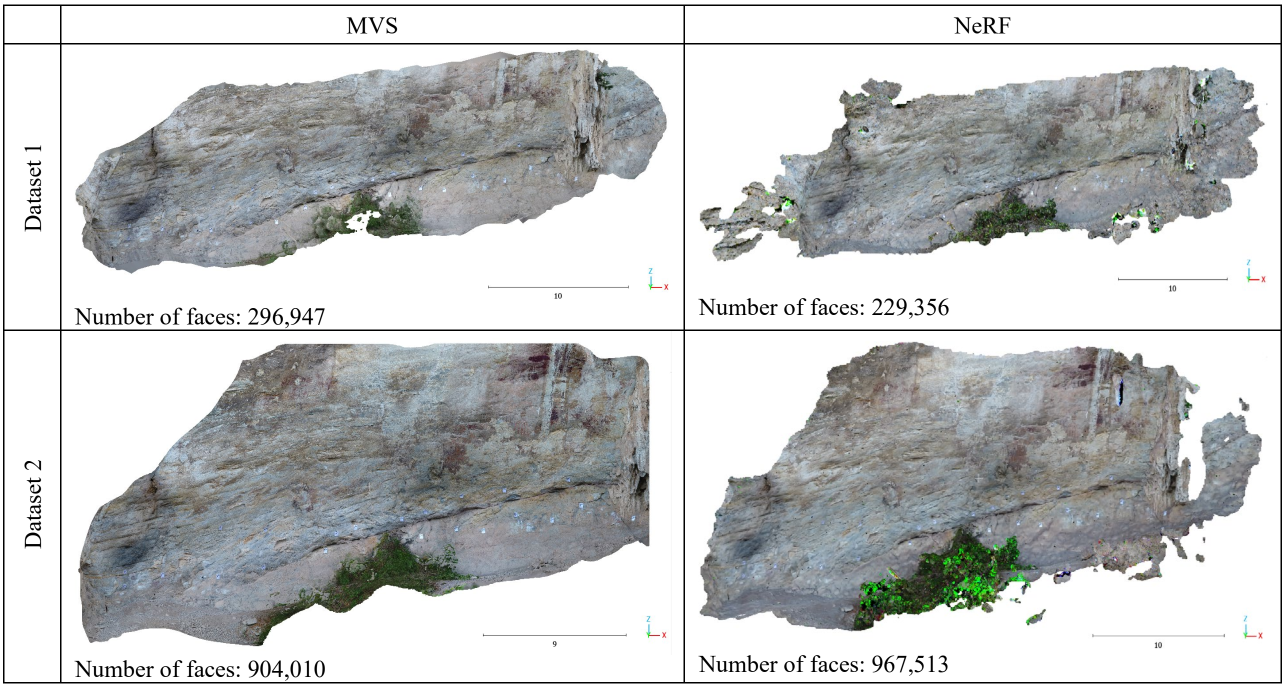


Figure 5. 3D mesh model generated using MVS and NeRF.

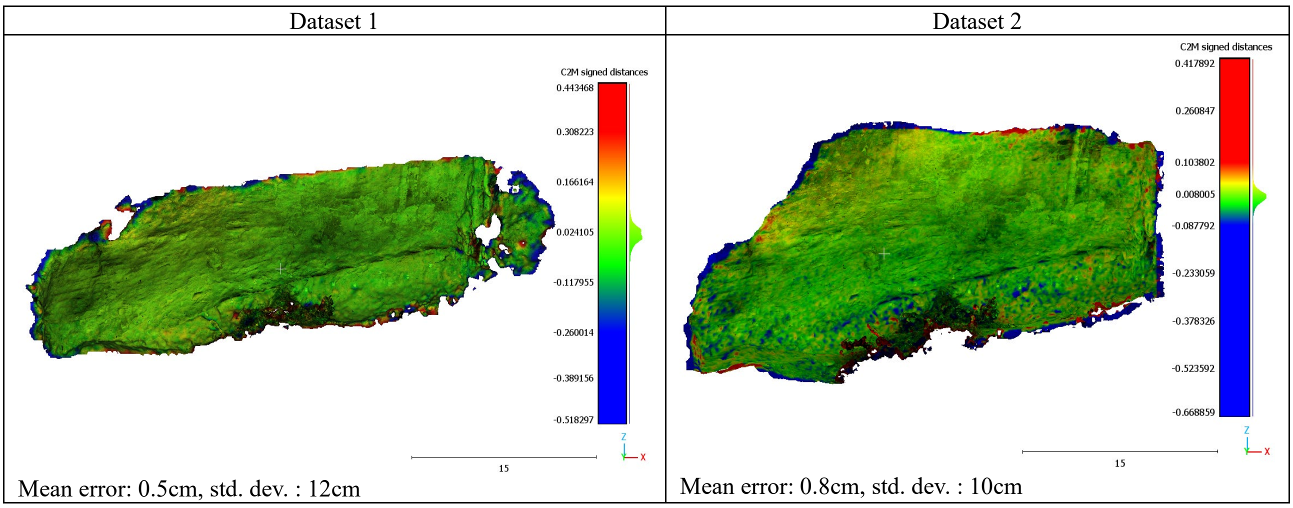
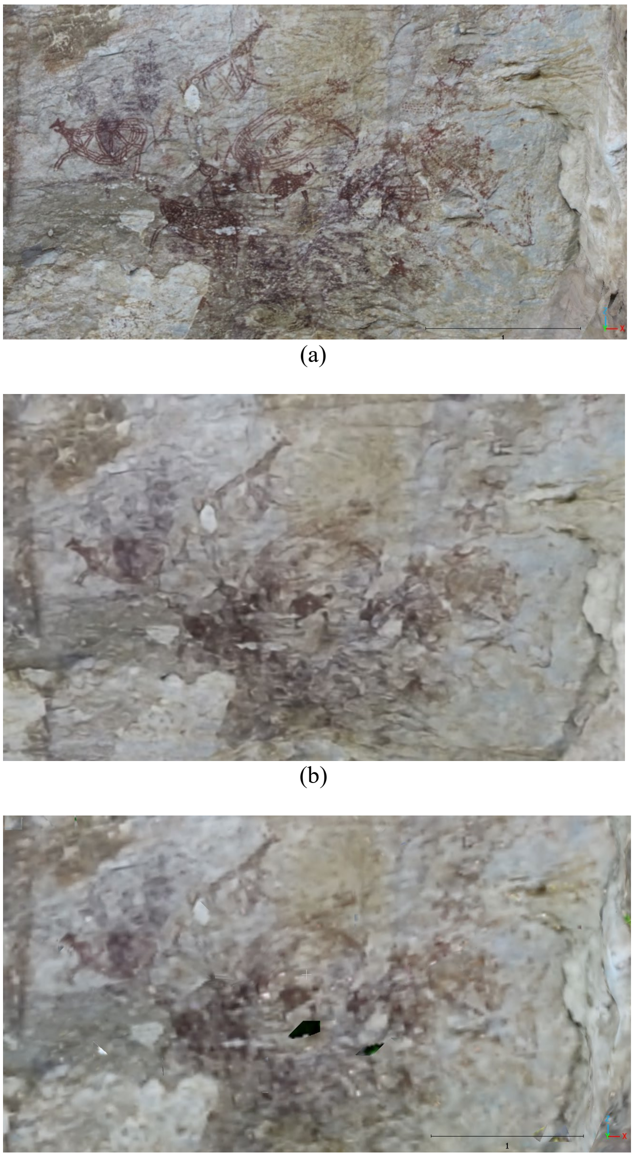


Figure 6. Comparison of NeRF-generated 3D model and MVS. The cooler colours represent small distance errors, and the warmer colours indicate high errors.



(a)

(b)

(c)

Figure 7. Quality of texture on the 3D model derived using (a) Metashape, (b) Nerfstudio rendering, and (c) NeRF export.

4. CONCLUSION

This study investigates the potential of the NeRF 3D reconstruction for the digital documentation of rock art painting applications on two datasets of the same site. The initial assessment has shown that 3D reconstruction using NeRF could accelerate the 3D modelling process, even using medium-spec computers with limited memory. This capability is advantageous for rapidly processing large amounts of data.

However, notable noise is observed in the rendered scene inside Nerfstudio's web viewer, necessitating a post-training noise filtering method if the rendered scene needs to be used for virtual reality applications directly. Besides, NeRF is developed mainly for rendering the 3D scene. Hence, no measurement tools are currently available to measure the painting directly on the web viewer.

NeRF processing requires input from recovered images processed outside of its workflow. In this context, the image orientation needs to be processed using SfM first. Hence, the data collection must follow the photogrammetric principle. NeRF will likely be unable to reconstruct the 3D model if the SfM fails to orient the images accurately. This argument is supported by a small error reported from the 3D mesh model comparison of MVS and NeRF, as both 3D reconstructions used the same recovered input images.

Other quantitative assessments have compared point cloud converted from NeRF with dense cloud of MVS and TLS, where the accuracy of NeRF does not match the MVS. While MVS achieves millimetre accuracy, the error from NeRF can be up to the centimetre level. Moreover, the density of the point cloud converted from NeRF is not homogonous like MVS and perhaps can be improved in future for robust documentation.

Finally, the qualitative assessment of the rendered texture using NeRF and the exported 3D model does not match the resolution produced by photogrammetry. Hence, it can be concluded that NeRF, at the current stage, is able to generate a reasonable geometry of objects but produces low-resolution texture. Nevertheless, the current limitations of 3D modelling techniques using NeRF provide opportunities for further research to improve the quality of rendered scenes as well as generated point cloud and texture of 3D models to be used in digital rock art recording or incorporate this state-of-the-art 3D reconstruction method into the current photogrammetric workflow.

Further studies will test different NeRF platforms, such as Instant-NGP (Müller et al., 2022) and Luma AI, using different images, such as those acquired using a spherical lens camera and low-resolution multispectral images (Zainuddin et al., 2019) and apply it on the development of virtual reality of rock art sites for digital documentations.

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