Challenges and Capabilities of 3DGS in Detecting Tiny Details for Cultural Heritage

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Abstract

3D reality-based techniques are well-known in Cultural Heritage documentation and exploitation. Recently, Neural radiance Field (NeRF) and 3D Gaussian Splatting (3DGS) have been arose as a possible new technique for 3D modelling reality, if not even substitutes of photogrammetry. NeRF is a neural field used to build a three-dimensional depiction of a scene using photographs. Gaussian splatting provides for an efficient and precise representation of geometry and appearance characteristics by modelling things and surfaces as a set of Gaussians. This paper presents a comparison of the models derived from two different techniques (Structure from Motion – SfM, 3DGS) for the acquisition and detection of cracks and tiny details in the bathroom of the Royal Palace of Caserta. The idea is to analyse the resultant data to understand if 3DGS is mature enough to be utilised for the accurate reconstruction of this type of objects, to provide data useful for structural analysis. The Postshot AI tool by Jawset was tested using the different parameters for the training of the AI and using the same set of data. The results are promising in terms of speed and graphical results but not so satisfactory as for real data accuracy needed for deepen analysis.

1. Introduction

Three-dimensional survey for Cultural Heritage documentation and conservation is based on a well-known methodology, and the integration of techniques is, by now, an established procedure. Photogrammetry is a passive technique that allows to obtain a 3D textured point cloud, is cheaper and more versatile than terrestrial Laser scanner (TLS), but, as opposed to the latter, is not metric, is sensitive to environmental lights and requires a grade of experience. TLS, on the contrary, can be challenging when acquiring small details.

In the domain of computer graphics, and especially in the context of 3D rendering, Neural Radiance Field (NeRF) and 3D Gaussian Splatting (3DGS) have become a well-known method. NeRFs (Mildenhall et al., 2021) is a recent technology that creates 3D models from 2D images using deep learning deriving the scene's reflectance characteristics and reconstructing its geometry. NeRF follow the acquisition steps of SfM (Structure form Motion), so the acquisition of overlapping images and calculation of external and internal parameters.

Gaussian splatting (Fei et al, 2025) is the most recent technique that involves projecting data points into a visualization space and smoothing them using a Gaussian function. As per its specifications, it is mostly useful for rendering indistinct objects or semi-transparent materials where the visualization of density or intensity within a volume are needed.

Both NeRF and 3DGS are techniques that work with volumes, but there are some differences between them. NeRF recreates the scene as a continuous volumetric function. 3DGS represents it as a group of discrete “splats” – point clouds with gaussian profiles. It is faster than NeRF because it reduces all the computational requirements, but it is said to be less accurate for modelling intricate lighting scenes hence accurate. This makes GS more suitable for real time applications and for modelling large environments. The two main differences between NeRF and GS are that (i) NeRF converts opacity values, while 3DGS models them directly; (ii) NeRF requires dense sampling across the 3D space, whereas 3DGS uses rasterization-based rendering.

This paper presents a comparison of the results derived from two different techniques (SfM, 3DGS) for the acquisition and detection of cracks and tiny details in the bathroom of the Royal Palace of Caserta (Figure1).

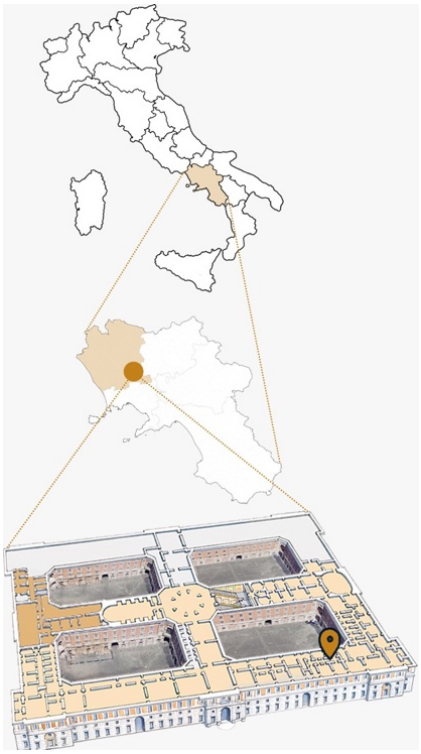


Figure 1. The Royal palace of Caserta with the placement of the bathroom alongside the Royal Apartments, located on the first floor of the Place.

The purpose is to analyse the results of 3DGS with challenging artefacts and objects, to investigate if the results can be used for further analysis as structural and mechanical with Finite Element Methods (FEM). It was decided to test only 3DGS using Jawset Postshot platform.
The work is done in the frame of the PRIN PNRR SINERGY funded project and is intended to combine 3D models and thermography for prediction of damages in ancient furniture and buildings. The idea of this paper is to analyse the accuracy of the data collected for the identification of tiny details.

2. State of the Art

The evaluation of Gaussian Splatting for 3D reconstruction is starting to be investigated applied to different test objects. Yang et al. (2024) presented a benchmark to investigate the quality of the results obtained with GS considering laboratory data and compression. For industrial components and settings, Sun et al. (2025) presented a 3D reconstruction using adaptive methods and a robust scaling to increase the accuracy of the results compared to a ground truth. Sambugaro et al. (2024) did a comparative analysis considering results from Colmap, NeRF and 3DGS in outside environment.
When it comes to indoor 3D reconstruction, the importance to have accurate data span from object detection to virtual reconstruction to BIM.
Fang et al. (2025) propose a qualitative and quantitative comparison of data obtained with Colmap software (SfM), NeRF and 3DGS. Results obtained through the same tool have been also compared to Simultaneous Localization and Mapping (SLAM) systems, calculating the accuracy using tracking data, mapping fidelity and view synthesis (Zhou et al., 2024). For the detection of fine details, Ye et al. (2024) proposed a homo directional view-space positional gradient for densification, that helps recovering fine details by splitting.
There have also been studies (Fang and Wang, 2024) that have investigated the possibility to optimise the 3D reconstruction with Gaussian Splatting, setting a constrained number of gaussians, hence reaching improvements in rendering quality. In the Cultural Heritage and Architectural field, Clini et al. (2024) investigated the representation of data considering NeRF, 3DGS and SfM-MVS.
Murtiyoso and Macher (2025) have investigated the accuracy of 3D GS for the creation of orthophotos in Cultural Heritage digitization and analysis comparing the results with Terrestrial Laser Scanner (TLS) and MVS (Multi-View stereo). Comparisons of 3D data from these tools have been done also in the field of underwater data, as in Tanduo et al. (2025), in which Neural Radiance Fields (NeRF), SeaThru-NeRF, and 3D Gaussian Splatting (3DGS) are compared to SfM workflows.

3. Materials and Methods

3.1 Test objects

The objects selected for the comparison and analysis are from the bathroom of the Royal Apartments of the Palace in Caserta (Figure2a,b). The first one is a crack on the wall that have been measured with a calliper in some parts to have a ground truth (Figure2a) and a perfume holder (Figure2b).
These objects have been selected because (i) the crack needs a really high accuracy in the reconstruction because needs to be investigated further with Finite Element software for structural analysis and (ii) the holder is made of thin metal parts that are challenging in the reconstruction phase.

a

b

Figure 2. The two test objects: (a) the crack on the wall and (b) the perfume holder.

3.2 Methodology

The photogrammetric survey has been carried out with a Canon 5D Mark IV full frame camera coupled with a 20 mm lens setting ISO at 800 and aperture at 4 with a GSD of 0.2 mm. The distance from the object was kept constant using a tripod.
The point clouds have been scaled using both markers and laser scanner data. No particular problems have been faced during the survey: the wall whit the crack is well illuminated and with specific details and decoration that made the acquisition of the images, the proper overlapping and the post processing easy. The perfume holder is a little trickier because is in a corner where the illumination is lower and is sustained by a dark wooden table. The survey was however straightforward. The only part trickier than the others during the reconstruction phase were the metal parts that are ruined and can be easily confused with the wall behind.
The images were processed with Agisoft Metashape to provide a ground truth, and then with Colmap, using the standard process:

1. Feature detection/extraction
2. Feature matching and geometric verification
3. Sparse Reconstruction
4. Bundle Adjustment refinement
5. Dense Reconstruction

The *.ply of the dense reconstruction and the camera parameters calculated in Colmap have been exported and the latest have been used in PostShot platform (https://www.jawset.com) to test the 3DGS result so that all the resultant data have the same internal and external orientation.

PostShot can compute the camera poses from the images (Camera Tracking) but importing an existing alignment usually increases the quality of the generated splats and makes it possible to create metrically scaled scenes without much computational effort. On the other hand, since the aim of the paper is to compare the results to investigate the possibility to use 3DGS for accurate 3D data analysis, using the same camera poses allows to start from the same data.
After the import of images and camera poses, there are few settings to be defined. The descriptions are taken from the official website of the tool:

1. Radiance Field Profile consists in the reconstruction part.
   a. the best option is supposed to be Splat3 that can best reconstruct fine details in both the foreground and background. Compared to the other profiles, it can also better utilize the details of higher resolution images.
   b. Splat3 MCMC uses a more randomized sampling of the scene than the other models. As a result, it may not produce as many fine details.
   c. Splat3 ADC it densifies the scene during training. Unlike the Splat3 and Splat MCMC profiles, the Splat ADC profile does not allow specifying the maximum number of Splats created. Instead, the Splat Density parameter controls the growth rate of the model size.
2. Max Splat Count: this parameter is only available when the Splat3 or Splat MCMC profile is selected. It sets a limit on the total number of Gaussian Splatting primitives that the training process will generate
3. Anti-Aliasing: checking this option improves the model quality and prevents artefacts when zooming away from the original camera positions.

For the tests on the objects, all the three different Radiance Fields representation have been used. Then the splats have been exported and compared to the Metashape ones and for the crack, the measurements of the thickness done with a calliper were also used as ground truth.

4. Results

All the data gained through the different techniques have been compared to understand the level of detail obtained. For the first test object, it was considered the actual thickness of the crack measured with a calliper in two different positions: 4mm and 14mm. The software used for comparing the data was CloudCompare using the plugin M3C2 that allows to obtain more precise and robust comparisons. This tool provides a Folded Normal distribution: it calculates signed distances and provides robust, noise-aware, and multi-scale comparisons. In contrast to simple unsigned distance methods, M3C2 is designed to compute the distance between clouds along the normal direction, reducing errors on steep surfaces. The parameter set for the comparison were:

1. Selection of "core point" – whole cloud.
2. normal scale – identified by the software.
3. projection scale – identified by the software.
4. max depth – identified by the software.

The normals have been calculated from Metashape point cloud. First comparison was between the point cloud from Metashape, taken as reference, and the others (Figure3a-d): as expected, Colmap gave a good result while the 3DGS was not equally accurate. The worst was Splat3 ADC probably because of the algorithm and the purpose of working on density of data. Probably, for small objects, this process is not sufficient. Splat 3 MCMC gave a little better result in term of standard deviation possibly because the randomised sampling does not work well with fine details, while Splat3 was the best, as expected considering the properties of the algorithm. The results are summarized in Table 1.

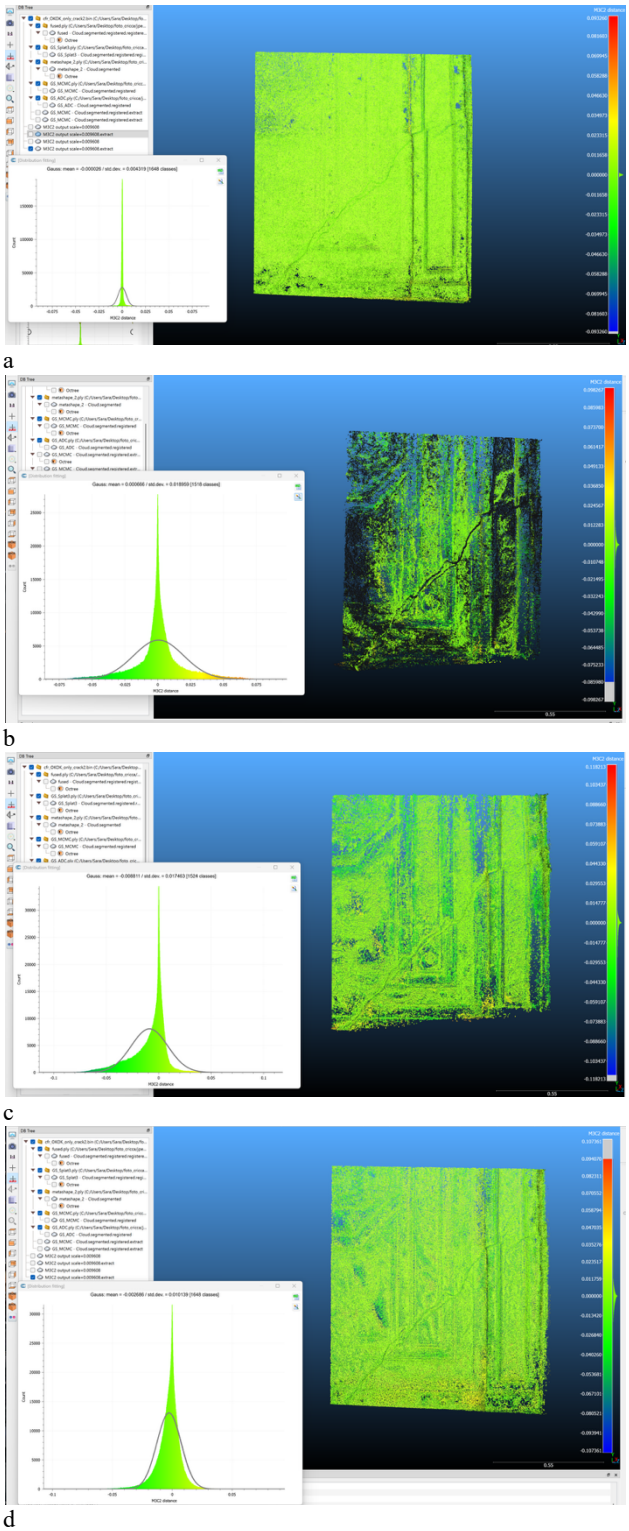


Figure 3. Comparison between Metashape result and (a) Colmap; (b) Postshot with Splat3 ADC setting; (c) Postshot with Splat3 MCMC setting; (d) Postshot with Splat3 setting.

Tool	Mean (mm)	Std deviation (mm)
Colmap	-0.03	0.4
Splat3 ADC	0.7	19
Splat3 MCMC	0.9	17
Splat3	0.3	10

Table 1. Mean and standard deviation of the comparison between the point cloud obtained with Metashape and the other point clouds.

However, the standard deviation is too high for each parameter tested considering that the minimum thickness of the crack is 4mm. Furthermore, the GS obtained with Postshot resulted in some truly noisy results (Figure4) that needed to be cleaned both manually and with a denoising algorithm (Gonizzi et al 2024).

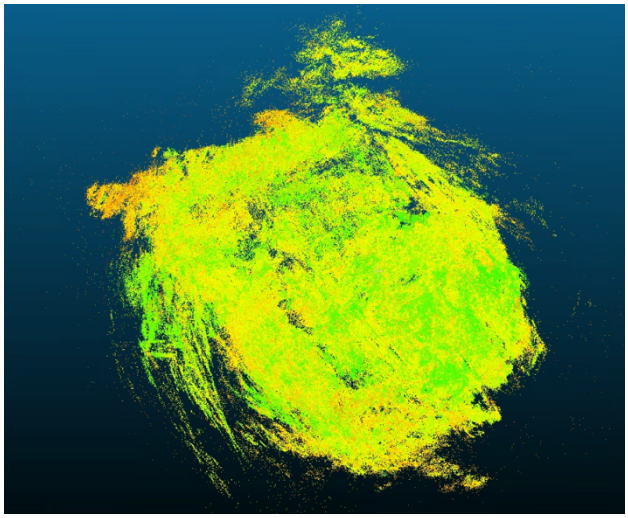
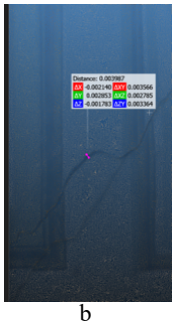


Figure 4. The reconstruction of the perfume holder done with Postshot Spalt3 parameters. At least half the spalts are noise and have to be removed.

This noise can also influence the visualization of data and the results of the comparisons and made also difficult to visualise the profiles and the characteristics of the crack and the metal holder. Nevertheless, with the manual and denoising process, the 3DGS point clouds resulted to be cleaned enough to provide reliable data, even if a more robust automatic cleaning should be applied to have a better result.
The reconstruction of the crack was also compared with manual measurements taken on the crack using a calliper. Results are shown in Figure 5 and Table 2.

a



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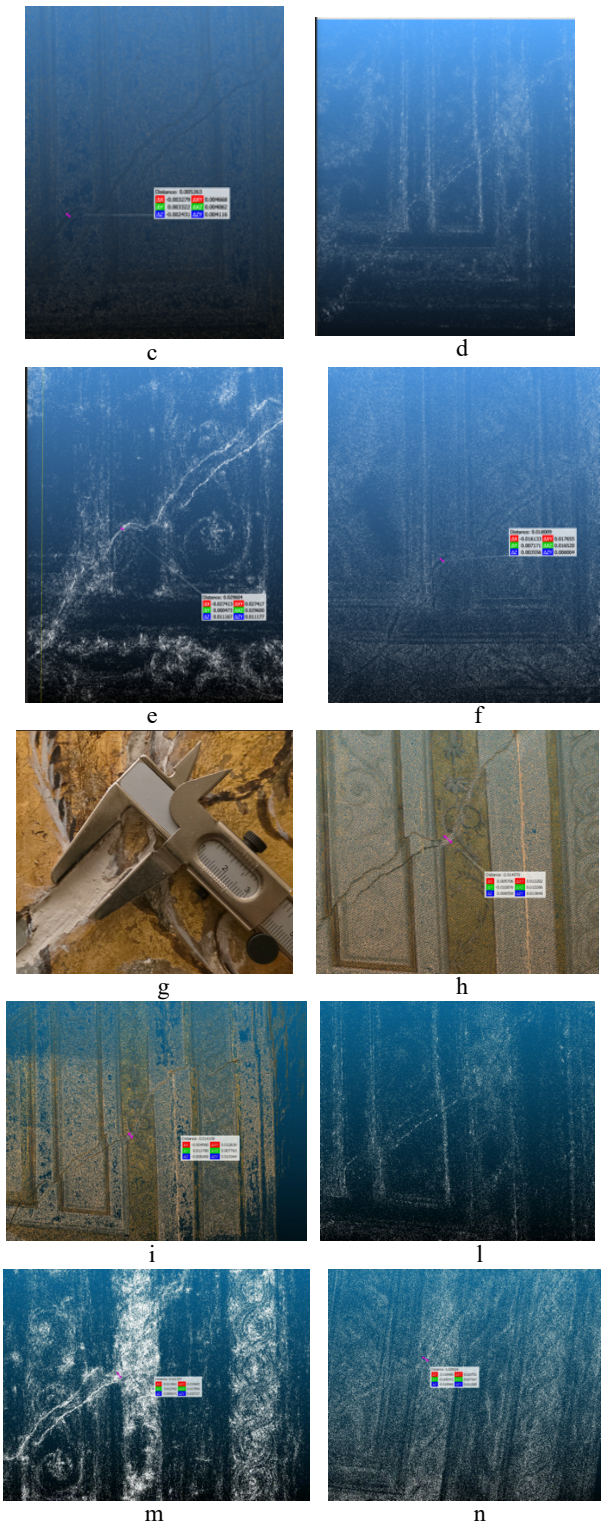


c d e f g h i l m n

Figure 5. Comparison between the two measurements (a, g) taken with the calliper and the results of the different software: (b,h) Agisoft Metashape; (c,i) Colmap; (d, l) Postshot Splat3 ADC; (e,m) Postshot Slat3 MCMC; (f,n) Postshot Splat3.

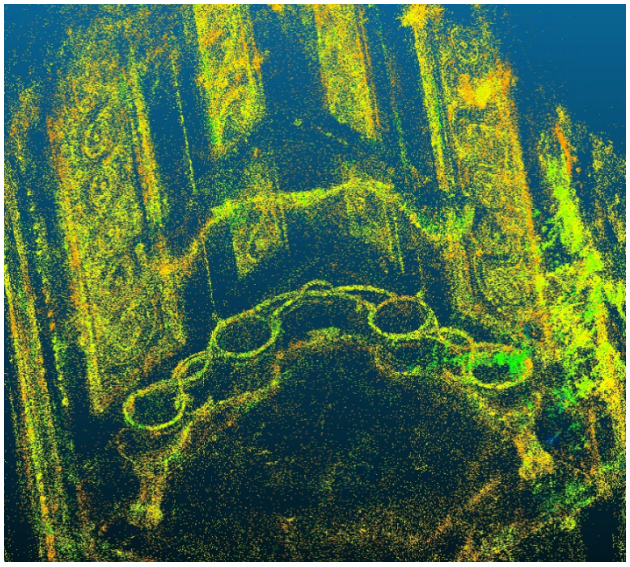
The comparisons need to consider two factors that can influence the uncertainty of the process: the manual measurement with the calliper is quite accurate but the point selected on the point clouds are not at the same level of accuracy.

The aspects that influenced this matter were several: (i) a point cloud not dense enough; (ii) noisy points that can make the selection more difficult considering that they can be easily selected instead of the correct ones; (iii) difficulties in the identification of the shape of the crack, especially for GS results.

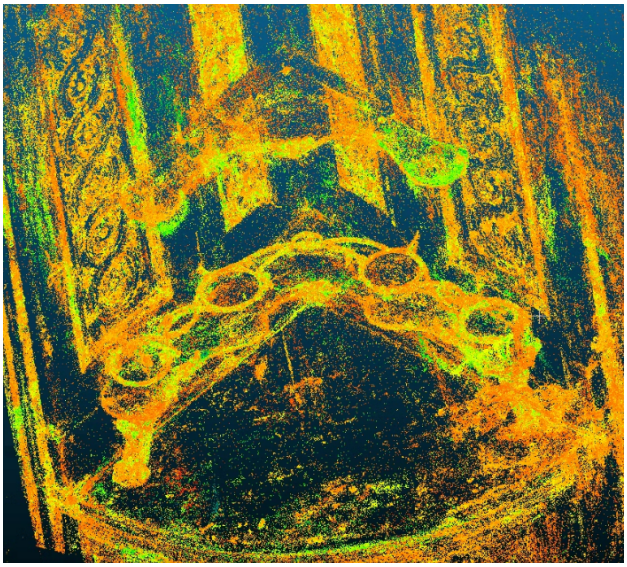
	1st measure mm	2nd measure mm
Reference	4 mm	14 mm
Metashape	3.9	15
Colmap	5	14
Splat3 ADC	/	/
Splat3 MCMC	3	22
Splat3	5	21

Table 2. Mean and standard deviation of the comparison between the point cloud obtained with Metashape and the other point clouds.

Again, Metashape (Figure5b,h) gave the best results with both the samples chosen for the comparison. Colmap (Figure5c,i) gave good measurement for the second sample while the first the result is 1 mm higher than the real ones. Considering the thickness of the crack in that part and the reason why the 3D reconstruction is needed, 1 mm larger is not a satisfactory result.
The Splat3 ADC (Figure5d,l) gave a result too sparse and too noisy to permit even to understand the shape and the profiles of the crack. In the Splat3 MCMC and Splat3 (Figure5e,m; f,n), the shape of the crack was slightly identifiable but still was quite difficult to see properly the exact profile. This is the reason why, especially the second measurement gave a large difference, 8mm and 7mm respectively.
These results are probably a sum of a not accurate reconstruction and difficulties in identifying the side of the crack to be selected. It is hence questionable if such results can be utilised for structural analysis or for defects detection.
For the second test object, the results of 3DGS are even only visually not dense enough to permit a proper accurate reconstruction of the object (Figure6a-c; Table 3). Some parts are completely missing, and the level of noise is also influencing the identification of geometries.



a



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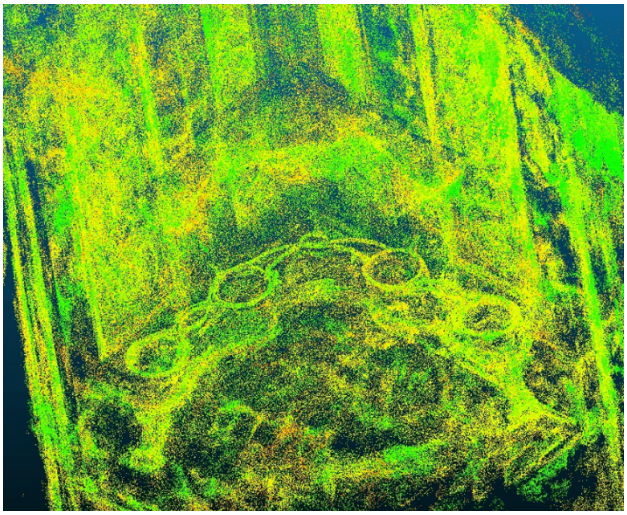
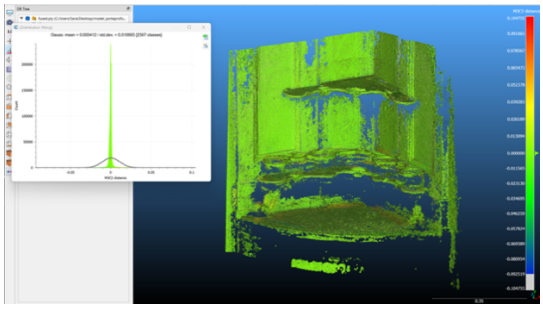


c

Figure 6. Reconstruction of the perfume holder made with Postshot: (a) Splat3 ADC; (b) Splat3 MCMC, (c) Splat3.

Tool	Mean (mm)	Std deviation (mm)
Colmap	0.4	10
Splat3 ADC	3	24
Splat3 MCMC	5	25
Splat3	2.5	22

Table 3. Mean and standard deviation of the comparison between the point cloud obtained with Metashape and the other point clouds for the perfume holder.



a

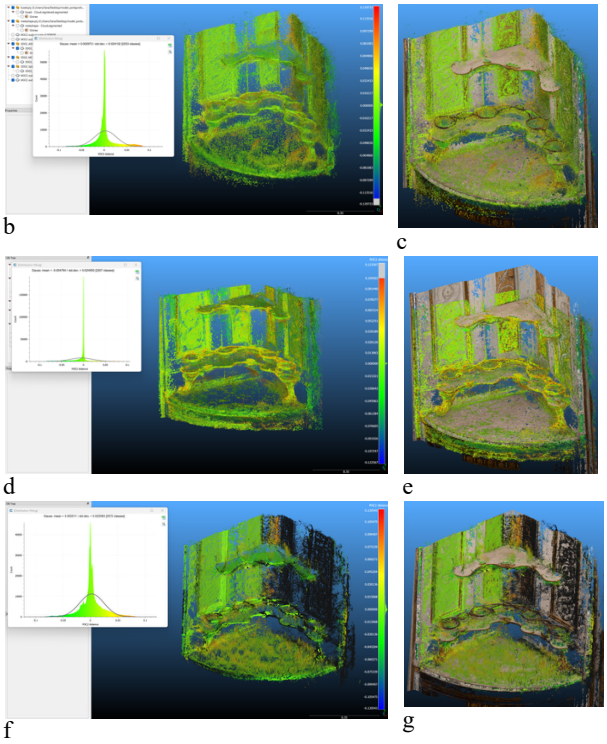


Figure 7. Comparison between the point cloud of the perfume holder by Metashape and (a) Colmap; (b,c) Postshot Splat3 ADC; (d,e) Postshot Slat3 MCMC; (f,g) Postshot Splat3.

The comparison among 3D data (Figure7a-g) provides a clear understanding of a not sufficient 3D reconstruction derived from 3DGS. The screenshots of the raw results have been coupled with the visualization of splats superimposed on the point cloud from Metashape (Figure 7 c,e,g) to underline the sparse reconstruction of 3DGS in some parts of the object (aka the first shell and the base of the table).
The comparison gave approximatively the same results as for the crack. The Colmap point cloud, however, gave a slightly worse standard deviation probably because the parameters have been left as default. It is possible that for this kind of object and for the number of images used, the Density Trade-off parameter needed to be changed or other parameters as the StereoFusion and the StereoWindow radius need to be taken into consideration.
3DGS, along with the incompleteness of the data, gave worse results both in terms of mean and standard deviation.
It is interesting noting that the main deviations are gathered around the metal parts that are the smallest details of the object (Figure8).

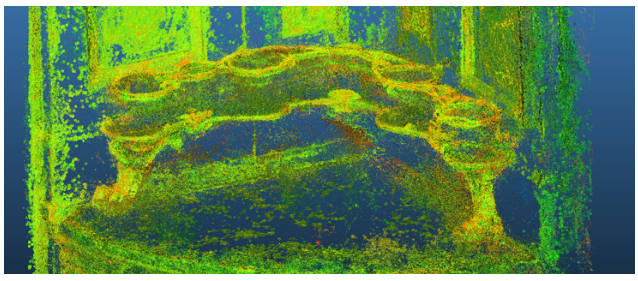


Figure 8. A detail of the comparison between Metashape point cloud and the Postshot Splat3 MCMC tool's result. It is clearly visible that the maximum standard deviation is assembled around the metal part that are also the thicker ones.

5. Conclusions

In this paper, we presented a first attempt of 3D reconstruction using Gaussian Splatting. The idea was not to create something new but test an existing tool with peculiar test objects and arose because, in the frame of the PRIN PNRR project, some different necessities emerged.
The first test object, a worrying crack on the wall of the bathroom, was not initially considered since the purpose of the project regards wooden furniture. But while surveying the area, the need to investigate this artefact in deepen considering maybe some Finite Element Analysis (FEA) to understand the structural stability and behaviour, occurred.
Photogrammetry and laser scanning are well-know, deeply used techniques and the results obtained with the first one regarding the reconstruction of the crack are satisfactory. The differences among real distances and reconstructed ones, calculated on the point cloud, gave a deviation acceptable in terms of uncertainty of the calculations. So, it was decided to test other 3D reconstruction tools to investigate their usefulness. NeRF and 3DGS are the ultimate research trends in 3D modelling, so the choice was obvious. By now, only Gaussian Splatting was tested.
For thin objects such as the crack, the tool evaluated gave bad results both in terms of mean and standard deviation, compared to the SfM results. This is more evident when dealing with details that need to be reconstructed to be used for analyses that require the higher accuracy possible. Since the FEA process add itself some uncertainty, it is mandatory to have the most accurate models to start with.
Then it was decided to test the algorithm on a different object, less thick than the crack but with different characteristic and bottlenecks. The perfume holder is placed in a corner of the room, with less illumination and is made of wood, stoney material and metal part. The most difficult part was the metal circles that specifically held the bottles and containers for perfumes and creams. The part is deteriorated and is not easily identifiable in the matching phase, because in some pictures, the colour is like other details in the background.
The results of the Gaussian Splatting were not satisfactory since the deviation is too high even for an object bigger than the crack, but that still needs a higher accuracy in the reconstruction, because of its geometry, its details and specifics.
Future work will consider the test on different Gaussian Splatting tools/algorithms, and also tests on NeRF ones, using as samples different type of objects in terms of overall dimensions, details' dimension and shape, geometry and materials. Other tests will be done with metallic specimens with coded dimensions to have a proper ground truth to which compare the results of the 3D reconstruction. This passage could possibly give an even more accurate comparison's result.

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References

Clini, P., Nespeca, R., Angeloni, R., Coppetta, L., 2024: 3D representation of Architectural Heritage: a comparative analysis of NeRF, Gaussian Splatting, and SfM-MVS reconstructions

using low-cost sensors, *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLVIII-2/W8-2024*, 93–99, https://doi.org/10.5194/isprs-archives-XLVIII-2-W8-2024-93-2024.

Fan, C., Lin, Y., 2024: Pseudo-hyperdimensional optical remote sensing: assessment and challenge, *Proc. SPIE 13496, AOPC 2024: Optical Sensing, Imaging Technology, and Applications*, 134960F https://doi.org/10.1117/12.3046273

Fan, L., Yang, Y., Li, M., Li, H. Zhang, Z., 2024. *Trim 3D gaussian splatting for accurate geometry representation*. arXiv preprint arXiv:2406.07499

Fang, G., Wang, B. 2024: Mini-Splatting: Representing Scenes with a Constrained Number of Gaussians. In: Leonardis, A., Ricci, E., Roth, S., Russakovsky, O., Sattler, T., Varol, G. (eds) *Computer Vision – ECCV 2024. Lecture Notes in Computer Science,* vol 15135. Springer, Cham. https://doi.org/10.1007/978-3-031-72980-5_10

Fang, X., Zhang, Y., Tan, H., Liu, C., Yang, X., 2025: Performance Evaluation and Optimization of 3D Gaussian Splatting in Indoor Scene Generation and Rendering, *ISPRS International Journal of Geo-Information* 14, no. 1: 21. https://doi.org/10.3390/ijgi14010021

Fei, B., Xu, J., Zhang, R., Zhou, Q., Yang, W., He, Y., 2025: 3D Gaussian Splatting as a New Era: A Survey, in *IEEE Transactions on Visualization and Computer Graphics*, vol. 31, no. 8, pp. 4429-4449, doi:10.1109/TVCG.2024.3397828

Gonizzi Barsanti, S., Marini, M.R., Malatasta, S.G., Rossi, A. 2024: A Study of Denoising Algorithm on Point Clouds: Geometrical Effectiveness in Cultural Heritage Analysis. In: Takenouchi, K. (eds) *Proceedings of the 21st International Conference on Geometry and Graphics. ICGG 2024*. Lecture Notes on Data Engineering and Communications Technologies, vol 218. Springer, Cham. https://doi.org/10.1007/978-3-031-71013-1_10

Sun, G., Liu, D., Yang, Z., An, S., Zhang, Y., 2025: 3D reconstruction and precision evaluation of industrial components via Gaussian Splatting, *Computers & Graphics,* Volume 132, 104422, ISSN 0097-8493, doi.org/10.1016/j.cag.2025.104422.

Jung, J., Kim, T., Min, H., Kim, S., Jung, Y.H., 2024: Intricacies of Opening Geometry Detection in Terrestrial Laser Scanning: An Analysis Using Point Cloud Data from BLK360. *Remote Sens*. *16*, 759. https://doi.org/10.3390/rs16050759

Mildenhall, B., Srinivasan, P.P., Tancik, M., Barron, J.T., Ramamoorthi, R. Ng, R., 2021: Nerf: Representing scenes as neural radiance fields for view synthesis. *Communications of the ACM*, 65(1), pp.99-106.

Murtiyoso, A., Macher, H., 2025: Gaussian Splatting for Facade Orthophoto Generation – Comparison with MVS and TLS, *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.,* XLVIII-M-9-2025, 1059–1064, https://doi.org/10.5194/isprs-archives-XLVIII-M-9-2025-1059-2025.

Sambugaro, Z., Orlandi, L., Conci, N., 2024: 3D reconstruction methods in industrial settings: a comparative study for COLMAP, NeRF and 3D Gaussian Splatting, *CEUR WORKSHOP PROCEEDINGS,* volume 3762, pages 212--217.

Tanduo, B., Matrone, F., and Murtiyoso, A., 2025: Initial Experiments on the Use of Radiance Fields for Underwater 3D Reconstruction, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLVIII-M-9-2025, 1475–1481, https://doi.org/10.5194/isprs-archives-XLVIII-M-9-2025-1475-2025

Yang, Q., Yang, K., Xing, Y., Xu, Y., Li. Z., 2024: A Benchmark for Gaussian Splatting Compression and Quality Assessment Study. In P*roceedings of the 6th ACM International Conference on Multimedia in Asia (MMAsia '24). Association for Computing Machinery,* New York, NY, USA, Article 12, 1–8. https://doi.org/10.1145/3696409.3700172

Ye, Z., Li, W., Liu, S., Qiao, P., Dou, Y., 2024: AbsGS: Recovering Fine Details in 3D Gaussian Splatting. In *Proceedings of the 32nd ACM International Conference on Multimedia (MM '24). Association for Computing Machinery,* New York, NY, USA, 1053–1061. https://doi.org/10.1145/3664647.3681361

Zhou, Y., Zeng, Z., Chen, A., Zhou, X., Ni, H., Zhang, S., Li, P., Liu, I., Zheng, M., Chen, X., 2024: Evaluating Modern Approaches in 3D Scene Reconstruction: NeRF vs Gaussian-Based Methods, *2024 6th International Conference on Data-driven Optimization of Complex Systems (DOCS)*, Hangzhou, China, pp. 926-931, doi: 10.1109/DOCS63458.2024.10704527