Gaussian Splatting vs. Classical Photogrammetry: A Comparison for Virtual Backdrops

Philipp Haslbauer, Mike Pullen, Carolin Reichherzer, Aljosa Smolic
Lucerne University of Applied Sciences and Arts, Switzerland
philipp.haslbauer@hslu.ch, mike.pullen@hslu.ch, carolin.reichherzer@hslu.ch, aljosa.smolic@hslu.ch

***Abstract*—This paper describes and evaluates three end-to-end workflows from capture to reconstruction including photogrammetry, 3D Gaussian splatting (GS), and extraction of textured meshes from splats with the explicit aim of individuals unfamiliar with 3D reconstruction creating backdrops for virtual production with a central presenter by using a smartphone as capture device. We show that GS significantly outperforms the alternatives in our experiments.**

***Index Terms*—Gaussian Splats, 3D Reconstruction, Photogrammetry**

I. Introduction

Recently, the importance of 3D Gaussian Splatting (GS) in the space of 3D reconstruction has risen dramatically. The highly realistic rendering quality, real-time rendering capability as well as ease of creation of GS lends itself well for various use cases where high fidelity and realistic depictions of reality are important. One such market is virtual production which has been targeted by a variety of companies specializing in novel radiance field technologies [3], [27].

However, there is still a severe lack of quality comparisons to existing technology, namely photogrammetry which is established in many software implementations. We present a pilot study which focuses on accessible workflows for the creation of static 3D reconstructions by non-professional end-users for the use in home virtual production and compares novel 3D reconstruction technology with established photogrammetry methods.

This paper makes the following contributions:

- Visual and preference-backed comparisons of established photogrammetry and novel methods with respect to capture of rooms.
- Guidance instructions on the capture of rooms.
- A summary of issues that continue to plague previous and novel methods.

II. Related Work

Digital photogrammetry is the recreation of 3D scenes from 2D measurements, namely photographs. Besides the novel GS, several existing methods fall under the umbrella term of photogrammetry [2]. One such photogrammetry method that is still relevant even in novel photogrammetric techniques is Structure from Motion (SfM) [24].

Gaussian Splatting (GS) has been employed in computer graphics for decades as an enhanced form of point-cloud representation that encodes richer geometric and appearance information (e.g., [40]). Conceptually, it sits between traditional point clouds and full volumetric techniques, linking it to both volume rendering [30] and modern radiance-field methods [16]. Despite these merits, GS long remained a niche choice within mainstream graphics pipelines.

That changed in 2023, when a landmark study [12] demonstrated that, combined with contemporary machine-learning, GS can dramatically improve 3D reconstruction and novel-view synthesis-much as Neural Radiance Fields (NeRF) had done earlier [16]. By optimizing Gaussians directly from multi-view images, the method produces photorealistic renderings of real-world scenes that frequently surpass classical techniques. The surge of interest has sparked a wave of extensions, refinements, and applications [4]. The output format of GS is commonly abbreviated as ”splat”.

As 3D meshes are still the standard in the modern graphics pipeline, several studies have sought to address these shortcomings of GS. 2D Gaussian Splatting (2DGS) [9] enforces surface modeling of GS using surfels, resulting in smooth surfaces which enables high quality mesh extractions which was previously not possible with GS.

III. Methodology

We selected three main reconstruction methods and two output formats for the scene reconstruction workflows, an overview of which can be seen in Fig. 1.

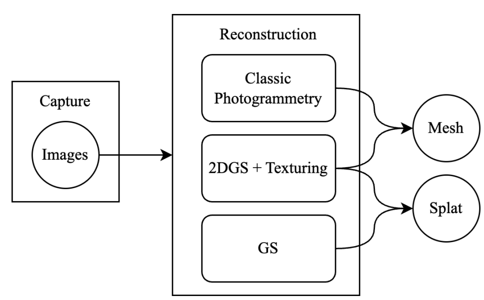

Fig. 1: The tested workflows rely on RGB images as input material and result in either splats or meshes as outputs.

A. Capture

In preparation of the specialized room capture, guidance instructions were created through experimental capture and reconstruction of room scenes. The devices were smartphones (iPhone 14 Pro) as this device type is the most likely to be in end-users' hands. For smartphone captures, two lenses/sensors (1: $24mm$, $f1.78$, 2: $13mm$, $f2.2$[1]) were used and one capture was created for each.

For the final captures, seven different scenes were selected, one of which was a complete room, whereas others were captured as backdrops (one side of room). The rooms can be seen in the evaluation, see Fig.2.

B. Reconstruction

As our focus is on workflows that are accessible for end users, we selected corresponding methods in each category, and optimized their results in a best-effort manner. While this is not using the exactly same input data, it gives a good performance indication from a user perspective. The following methods were selected:

1) GS: Postshot (PS) [19] is one of the leading software products for GS techniques. Unlike most high-level end-to-end platforms that use GS, PS allows the adjustment of GS parameters. For the reconstruction in PS, we set $30,000$ steps of optimization and targeted $1000k$ Gaussians. We kept the default image size limit of 1600 pixels. In PS, this setting applies to the longer image side. We also kept the default Radiance Profile SplatMCMC, likely based on 3DGS-mcmc [13].

2) 2DGS: Mesh and Texture Reconstruction via GS (2DGS + TSDF Meshing + MVS Texturing). Abbrev.: 2DGS.

We used 2DGS over alternative methods [6], [38] because it performed best in our preliminary tests. We extend the workflow of 2DGS by a texturing stage that we saw in use in Gaustudio [35]. For the SfM stage we use Colmap's Automatic Reconstruction with mostly default settings. We set "Shared Intrinsics" and use the smallest pretrained vocabulary tree [25]. For the GS optimization stage, default settings were used. In our case, all images are captured in portrait, so the shorter side is resized to 1600 pixels. We added a texturing stage that relies on the texrecon tool from mvs-texturing [17]. We prepared our SfM dataset for texturing by resizing all images to a maximum of 2000 pixels on the shorter side and exporting the camera data to .cam format via Colmap's model_converter tool.

3) Photogrammetry: RealityCapture (RC) [20].

For the photogrammetry workflow RC was used end-to-end. RC is an established software specialized on reconstruction of scenes from RGB images. We mostly used default settings to create the reconstructions. We only changed:

- sfmMaxFeaturesPerImage: 40000 → 80000
- sfmMaxFeaturesPerMpx: 10000 → 20000
- sfmBackgroundDetectThreadPriority: Low → Normal
- sfmImagesOverlap: Medium → Low
- sfmBackgroundDetectFeatures: False → True

IV. Evaluation

For evaluation, each scene was rendered using a GS reconstruction of a person as a stand-in for a virtual presenter, with videos generated on a consistent camera trajectory circling around the presenter. See Fig. 2, all videos and 3D reconstructions are available online [8].

In preparation, we rated the renderings (see Table I) using a 5-point quality scale. The ratings of the wider lens captures were generally higher with reconstructions from the narrower lens captures having more issues with missing parts.

Photogrammetry with RC achieves an average scene rating of 1.5, meshing and texturing achieves a rating of 1.786 and GS attains a much higher average rating of 3.21 across all scenes (Tab. I).

Scene	Rating (GS)	Rating (2DGS)	Rating (RC)
Chapel	3.5	1	2
Lecture Room	3.5	2	1
Lecture Hall	3.5	2.5	2.5
Meeting Room	2	2	1
Office Space	3	2	1
Outdoor Scene	4	1	1
Cluttered Space	3	2.5	2
Mean Values	3.21	1.86	1.50

TABLE I: Scene-specific ratings colour-coded from red (low) to green (high) of reconstructions from avg. of $23mm$ and $13mm$ lens captures.

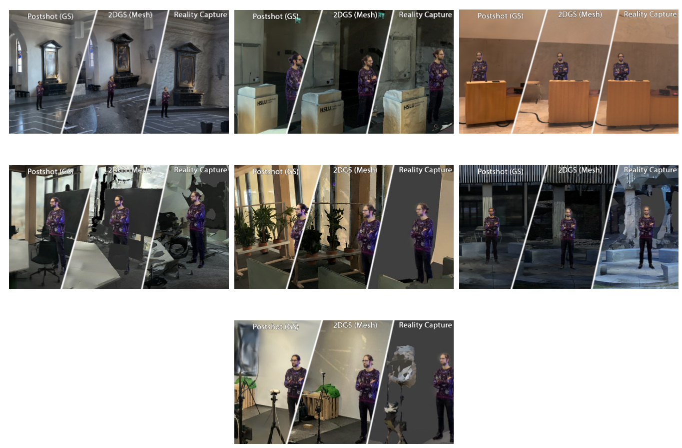

Fig. 2: Visual comparisons, order as in TABLE I.

The videos were further used in an two-alternative forced-choice (2AFC) task, which was distributed as an online survey to members of the University and the public. Participants were presented with two videos using two different reconstruction methods and had to select which video they prefer in terms of visual quality. The test featured the same environments as described in Fig. 2 with three pairwise comparisons for each scene: GS vs. Photogrammetry with RealityCapture (RC), GS vs. 2DGS, and RC vs. 2DGS. Only videos with the better preliminary rating (wide lens vs. narrow lens) were selected for this task. We used exact binomial tests to compare method preferences ($N = 203$ choices per comparison, 29 participants. See Table II.). GS was significantly preferred over RC (96.6%,

[1]Focal length is full-frame equivalent, not real focal length.

$p < 0.001$) and 2DGS (98.0%, $p < 0.001$). 2DGS was also significantly preferred over RC (80.3%, $p < 0.001$).

Comparison	Preferred Method (%)	p-Value
GS vs. RC	GS (96.6%)	< 0.001
GS vs. 2DGS	GS (98.0%)	< 0.001
RC vs. 2DGS	2DGS (80.3%)	< 0.001

TABLE II: Results of the pairwise comparisons between Gaussian Splats (GS), Photogrammetry with RealityCapture (RC), and 2DGS.

V. Discussion

In this paper we evaluated three accessible end-to-end workflows and evaluated them in pairwise comparisons under our specific experimental conditions. We found that GS was consistently preferred in terms of visual quality. We found many issues that still plague the technology and make captures more difficult.

The capture guidelines secure high image match ratios except for RC where the achieved image overlap seems to be insufficient. RC delivers excellent textures but its strict matching yields low match ratios that cause holes, missing fine details and occasional catastrophic reconstructions, though importing Colmap SfM data could alleviate these issues. RC struggles with some reflective surfaces and transparencies but copes well with others (see videos on webpage [8]), such as the chapel floor. PS (GS) captures small details, reflections and semi-transparent objects with superior fidelity yet often introduces floaters and view-dependent colour flicker on uniform walls under dynamic lighting. 2DGS meshes exhibit voxel-related surface waviness, distorted or misplaced textures and reflection-induced indentations or holes. Although GS by far achieves the best visual quality, meshes are still relevant. They are well-established and the standard in CGI and compatible with physics simulation, whereas GS is still lacking and mostly a visual feat.

We have identified several recurring problems and present possible pathways for resolution.

1) Guidance: Capturing complete, high-quality image sets is physically exhausting. A brief shooting guide helps, but user skill still matters and even skilled users can have issues with incomplete scene capture. App-level live previews as in Scaniverse [23] or other software-based guidance mechanisms, see [3], [21], ease the task. Robotics work that fuses SLAM with GS [11], [18], [29], [37] could offer on-device previews. Route-planning systems could automate coverage [15], [26]. Active-view selection and uncertainty quantification [10] could help making training more efficient and make informed training data selections. Without more advanced automated guidance, the capture of input material is more akin to analogue photography than to any modern digital process.

2) Small Rooms: Tight spaces demand many shots because close walls add little context and blank areas dominate; swapping to a wider lens often helps but can introduce distortions which are not problematic for some newer changes to GS [31].

3) Reconstructions of Rooms (2DGS, GS): Indoor scenes quality could be improved; GaussianRoom [32] and GSDF [36] jointly optimise signed-distance fields and splats to boost accuracy.

4) Matching: Sparse image overlap impedes matching. Deep models [5], [14] could align even low-overlap photos.

5) Dynamic Lighting: Lengthy captures under changing sunlight skew colour and exposure. Bilateral-guided radiance fields [28] and Splatfacto-w [33] both deal with this in their own ways.

6) Background Modeling: Distant scenery can turn into blobs; PS creates a GS globe around the scene which works outdoors but may crash indoors. Masking far backgrounds and reconstructing them separately could help both splat-to-mesh and photogrammetry.

7) Reflections (2DGS, RC): Mirrors and glass create holes; 2DGS could mitigate them via directional-light factorisation [39].

8) Dynamic Objects: These can sabotage static reconstructions, and should be masked manually or automatically [7], [34]. Persistent intrusions may need masking plus 3D-guided inpainting.

9) Floaters (GS): “Floaters” are stray Gaussians in empty space. 3DGS-MCMC [13] (already in Postshot) reduces them; 3dgsconverter’s outlier removal [1] cleans finished splats

10) Level of Detail (GS): GS outputs a single heavy splat. Producing multiple LoD versions—or introducing established LoD concepts to GS [22]—lets large scenes render smoothly on modest hardware.

VI. Conclusion

We evaluated 3 accessible photogrammetric workflows for the reconstruction of rooms by user hand and showed that GS consistently comes out on top with regards to visual quality under our specific experimental conditions. In addition, we presented potential resolutions to address current shortcomings in photogrammetric workflows.

We also showed that the field of 3D reconstruction, although progressing at break-neck pace, still has many areas where improvements are necessary. One major issue common to all methods and where we see the greatest potential is capture guidance. If automated, it could make GS a more user-friendly technology, paving the way to proper 3D digital photography enriching immersive technology.

Acknowledgment

This work was supported by the Swiss Innovation Agency Innosuisse (108.779 INT-ICT, FaVoRe) and through the European Commission Horizon Europe program (grant agreement 101070109, TRANSMIXR https://transmixr.eu/). It was executed in partnership with Nimagna AG (Christoph Niederberger).

References

[1] GitHub - francescofugazzi/3dgsconverter: 3D Gaussian Splatting Converter: A tool to seamlessly convert 3DGS .ply files to a Cloud Compare-friendly format and vice-versa. Features include RGB coloring, density filtering, and flyer removal for enhanced point cloud editing. — github.com. https://github.com/francescofugazzi/3dgsconverter. [Accessed 13-05-2025].

[2] J. S. Aber, I. Marzolff, and J. B. Ries. Chapter 3 - photogrammetry. In J. S. Aber, I. Marzolff, and J. B. Ries, editors, *Small-Format Aerial Photography*, pages 23–39. Elsevier, Amsterdam, 2010.

[3] L. AI. Luma AI - Interactive Scenes — lumalabs.ai. https://lumalabs.ai/interactive-scenes. [Accessed 21-05-2025].

[4] A. Dalal, D. Hagen, K. G. Robbersmyr, and K. M. Knausgård. Gaussian splatting: 3d reconstruction and novel view synthesis: A review. *IEEE Access*, 12:96797–96820, 2024.

[5] B. Duisterhof, L. Zust, P. Weinzaepfel, V. Leroy, Y. Cabon, and J. Revaud. Mast3r-sfm: a fully-integrated solution for unconstrained structure-from-motion. *arXiv preprint arXiv:2409.19152*, 2024.

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

[7] GitHub - IDEA-Research/Grounded-SAM-2: Grounded SAM 2: Ground and Track Anything in Videos with Grounding DINO, Florence-2 and SAM 2 — github.com. https://github.com/IDEA-Research/Grounded-SAM-2.git. [Accessed 13-05-2025].

[8] P. Haslbauer, M. Pullen, C. Reichherzer, and A. Smolic. Gaussian Splatting vs. Classical Photogrammetry — Immersive Realities Center — irc-hslu.github.io. https://irc-hslu.github.io/GSvsPhotogrammetry/, 2025. [Accessed 15-07-2025].

[9] B. Huang, Z. Yu, A. Chen, A. Geiger, and S. Gao. 2d gaussian splatting for geometrically accurate radiance fields. In *ACM SIGGRAPH 2024 conference papers*, pages 1–11, 2024.

[10] W. Jiang, B. Lei, and K. Daniilidis. Fisherrf: Active view selection and uncertainty quantification for radiance fields using fisher information. *arXiv preprint arXiv:2311.17874*, 2023.

[11] N. Keetha, J. Karhade, K. M. Jatavallabhula, G. Yang, S. Scherer, D. Ramanan, and J. Luiten. Splatam: Splat track & map 3d gaussians for dense rgb-d slam. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21357–21366, 2024.

[12] B. Kerbl, G. Kopanas, T. Leimkuehler, and G. Drettakis. 3d gaussian splatting for real-time radiance field rendering. *ACM Trans. Graph.*, 42(4), July 2023.

[13] S. Kheradmand, D. Rebain, G. Sharma, W. Sun, Y.-C. Tseng, H. Isack, A. Kar, A. Tagliasacchi, and K. M. Yi. 3d gaussian splatting as markov chain monte carlo. *Advances in Neural Information Processing Systems*, 37:80965–80986, 2024.

[14] V. Leroy, Y. Cabon, and J. Revaud. Grounding image matching in 3d with mast3r. In *European Conference on Computer Vision*, pages 71–91. Springer, 2024.

[15] Y. Li, Z. Kuang, T. Li, G. Zhou, S. Zhang, and Z. Yan. Activesplat: High-fidelity scene reconstruction through active gaussian splatting. *arXiv preprint arXiv:2410.21955*, 2024.

[16] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng. Nerf: representing scenes as neural radiance fields for view synthesis. *Commun. ACM*, 65(1):99–106, Dec. 2021.

[17] GitHub - nmoehrle/mvs-texturing: Algorithm to texture 3D reconstructions from multi-view stereo images — github.com. https://github.com/nmoehrle/mvs-texturing. [Accessed 13-05-2025].

[18] Z. Peng, T. Shao, Y. Liu, J. Zhou, Y. Yang, J. Wang, and K. Zhou. Rtg-slam: Real-time 3d reconstruction at scale using gaussian splatting. In *ACM SIGGRAPH 2024 Conference Papers*, pages 1–11, 2024.

[19] Jawset Postshot — jawset.com. https://www.jawset.com/. [Accessed 21-05-2025].

[20] RealityCapture - 3D Models from Photos and/or Laser Scans — capturingreality.com. https://www.capturingreality.com/. [Accessed 13-05-2025].

[21] RealityScan — Free to download 3D scanning app for mobile — unrealengine.com. https://www.unrealengine.com/en-US/realityscan. [Accessed 21-05-2025].

[22] K. Ren, L. Jiang, T. Lu, M. Yu, L. Xu, Z. Ni, and B. Dai. Octree-gs: Towards consistent real-time rendering with lod-structured 3d gaussians. *arXiv preprint arXiv:2403.17898*, 2024.

[23] Scaniverse — Free 3D scanner — Capture & explore with Gaussian Splatting — scaniverse.com. https://scaniverse.com/. [Accessed 21-05-2025].

[24] J. L. Schönberger and J.-M. Frahm. Structure-from-motion revisited. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[25] J. L. Schönberger, T. Price, T. Sattler, J.-M. Frahm, and M. Pollefeys. A vote-and-verify strategy for fast spatial verification in image retrieval. In *Computer Vision–ACCV 2016: 13th Asian Conference on Computer Vision, Taipei, Taiwan, November 20-24, 2016, Revised Selected Papers, Part I 13*, pages 321–337. Springer, 2017.

[26] B. Sun, H. Chen, S. Leutenegger, C. Cadena, M. Pollefeys, and H. Blum. Frontiernet: Learning visual cues to explore. *arXiv preprint arXiv:2501.04597*, 2025.

[27] Volinga - Making 3D Real - Volinga offers professional 3DGS pipeline solutions for the media and entertainment industry. Create and edit 3DGS content with our standalone software, then bring it to life on screen with our Unreal Engine plugin. — web.volinga.ai. https://web.volinga.ai/. [Accessed 21-05-2025].

[28] Y. Wang, C. Wang, B. Gong, and T. Xue. Bilateral guided radiance field processing. *ACM Transactions on Graphics (TOG)*, 43(4):1–13, 2024.

[29] J. Wei and S. Leutenegger. Gsfusion: Online rgb-d mapping where gaussian splatting meets tsdf fusion. *IEEE Robotics and Automation Letters*, 2024.

[30] L. A. Westover. *Splatting: a parallel, feed-forward volume rendering algorithm*. The University of North Carolina at Chapel Hill, 1991.

[31] Q. Wu, J. M. Esturo, A. Mirzaei, N. Moenne-Loccoz, and Z. Gojcic. 3dgut: Enabling distorted cameras and secondary rays in gaussian splatting. *arXiv preprint arXiv:2412.12507*, 2024.

[32] H. Xiang, X. Li, K. Cheng, X. Lai, W. Zhang, Z. Liao, L. Zeng, and X. Liu. Gaussianroom: Improving 3d gaussian splatting with sdf guidance and monocular cues for indoor scene reconstruction. *arXiv preprint arXiv:2405.19671*, 2024.

[33] C. Xu, J. Kerr, and A. Kanazawa. Splatfacto-w: A nerfstudio implementation of gaussian splatting for unconstrained photo collections. *arXiv preprint arXiv:2407.12306*, 2024.

[34] K. Xu, T. H. E. Tse, J. Peng, and A. Yao. Das3r: Dynamics-aware gaussian splatting for static scene reconstruction. *arXiv preprint arXiv:2412.19584*, 2024.

[35] C. Ye, Y. Nie, J. Chang, Y. Chen, Y. Zhi, and X. Han. Gaustudio: A modular framework for 3d gaussian splatting and beyond. *arXiv preprint arXiv:2403.19632*, 2024.

[36] M. Yu, T. Lu, L. Xu, L. Jiang, Y. Xiangli, and B. Dai. Gsdf: 3dgs meets sdf for improved rendering and reconstruction. *arXiv preprint arXiv:2403.16964*, 2024.

[37] S. Yu, C. Cheng, Y. Zhou, X. Yang, and H. Wang. Rgb-only gaussian splatting slam for unbounded outdoor scenes. *arXiv preprint arXiv:2502.15633*, 2025.

[38] Z. Yu, T. Sattler, and A. Geiger. Gaussian opacity fields: Efficient adaptive surface reconstruction in unbounded scenes. *ACM Transactions on Graphics (TOG)*, 43(6):1–13, 2024.

[39] Y. Zhang, A. Chen, Y. Wan, Z. Song, J. Yu, Y. Luo, and W. Yang. Ref-gs: Directional factorization for 2d gaussian splatting. *arXiv preprint arXiv:2412.00905*, 2024.

[40] M. Zwicker, H. Pfister, J. van Baar, and M. Gross. Surface splatting. In *Proceedings of the 28th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '01, page 371–378, New York, NY, USA, 2001. Association for Computing Machinery.