Exploring the Potential of Gaussian Splatting Environment for Indoor Wayfinding Simulation

Adibah Nurul Yunisya[1], Edward Verbree[1], and Peter Van Oosterom[1]

[1] Affiliation 1: Architectural Engineering and Technology, Delft University of Technology, Delft, the Netherlands

Correspondence: Adibah Nurul Yunisya (a.n.yunisya@tudelft.nl)

Abstract. Many wayfinding studies have adopted virtual reality (VR) as a simulation method due to its ability to provide a safe and flexible process in the simulation. Meanwhile, the wayfinding mechanism includes enriching spatial memory, collected from a great detail of the environment, which is essential in wayfinding decision-making. Nonetheless, many VR digital environments aren't necessarily able to portray great detail of a real environment. Recently, Gaussian Splatting is emerging as a state-of-the-art digital model that can accommodate a photorealistic environment for indoor wayfinding simulation by examining how well it can represent key indoor wayfinding variables with greater visual accuracy and realism. Therefore, this study aims at exploring Gaussian Splatting's potential for accommodating indoor wayfinding VR simulation. The study was conducted by identifying the clarity of the Gaussian Splatting environment in accordance with the indoor wayfinding variables (architectural differentiation, plan configuration, signage and room number, and visual access). The findings suggest that Gaussian splatting could provide richer sensory stimulation, which is an essential factor in recognising and analysing wayfinding behaviour, even with the lowest level of detail.

BoK Concepts. [CV4-7] Virtual and immersive environments [TA14-2-1-1] Point clouds, [GC2] Spatial simulation modelling

Keywords. gaussian splatting, virtual reality, indoor wayfinding

1 Introduction

Recently, wayfinding studies have used VR as a simulation method more frequently due to its ability to offer safe and flexible simulation scenarios, which often can't be done in conventional simulation, such as emergency evacuation and fire-induced simulation (Dong et al., 2022; Feng et al., 2022; Meng and Zhang, 2014; Zhiming et al., 2020). However, many VR simulation environments do not capture many real-world details, such as lighting effects, material reflections, and surface textures.

Meanwhile, the human eye captures subtle variations in lighting and shadow, which enhance depth perception and help individuals interpret spatial relationships, which are key factors influencing wayfinding decisions. These uses are closely linked to environmental legibility (EL), which refers to how easily an environment can potentially be learnt and understood by individuals (Li and Klippel, 2016). EL in the indoor environment can be broken down into architectural differentiation, plan configuration, signage and room numbers, and visual access (Weisman, 1981). Architectural differentiation identifies areas and features that are visually distinct. Plan configuration explores spatial layout and geometry clarity and readability. Signage and room numbers evaluate the visibility and legibility of graphical wayfinding aids. While visual access, which investigates the ability to see into nearby rooms or down hallways, helps people understand how spaces are connected and decide where to go next.

These elements play a great role in path identification, area differentiation, signage recognition, and spatial transition of wayfinding. Therefore, analysing EL will require careful attention to visual parameters such as geometry, occlusion, lighting, and texture. Without these elements, the virtual environment risks disconnecting users from the spatial logic of the real world, weakening the accuracy of wayfinding behaviour observed in the simulation.

Gaussian Splatting (GS) recently emerged as an advanced rendering technology that enables photorealistic 3D reconstruction from multi-view images using volumetric splatting, capturing lighting, depth, and material texture with greater realism. GS are rendered using a forward-splatting process that blends them directly onto the image plane, resulting in a smooth and continuous surface representation. Every splat represents a 3D anisotropic Gaussian in the form of an ellipsoid collected from multiview data. This technique allows subtle visual cues to be preserved with high fidelity.

One of the strengths of GS is its ability to improve construction quality through dynamic optimisation. Figure 1 illustrates how the system is able to respond under reconstruction areas by cloning so that the gap areas are well-filled. While the constructed area is responded to by splitting and refining to produce sharper detail. This way, GS is able to provide a high-accuracy real environment representation through the lighting, text, and shape, which are essential elements for spatial understanding in wayfinding.

Prior study of GS had mentioned various advancements, such as 4DGS offering real-time dynamic scene rendering (Wu et al., 2024), GaussianPro providing advancements in large-scale scene GS processing, and GS implementation in visual navigation (Lei et al., 2025). Following the rapid advancement and detail GS can offer, this study aims to explore the potential of GS in fulfilling the visual wayfinding criteria in VR simulation.

2 Methodology

The GS environment will be processed through 3 stages, which are environment scan, environment training, and environment post-processing (Figure 2). In the environment scan stage, the image will be collected using 2 different scanning tools, which are the XGRIDS Lixel L2 Pro and iPhone 13. After collecting all the image datasets, the images are then trained in Lixel Cyber Colour (LCC) and Postshot to create the raw GS model.

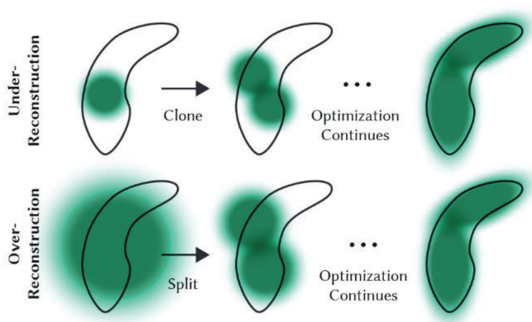

Figure 1. Adaptive Gaussian densification scheme
Source: (Kerbl et al., 2023)

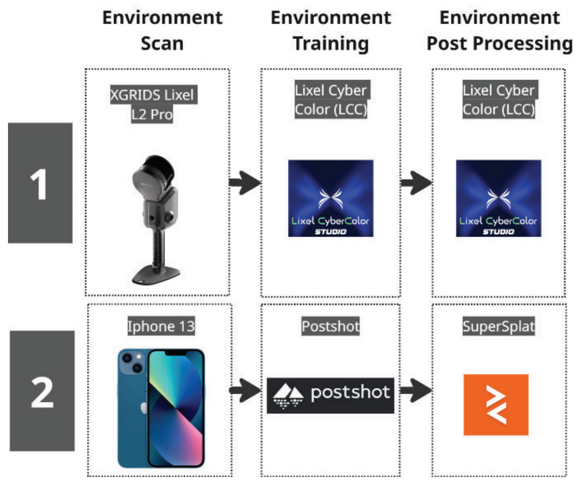

Figure 2. Gaussian Splatting model processing tools and stages

After being trained in postshot, the GS model was then processed in SuperSplat to provide a clearer model that could expose all the spatial traits.

To evaluate the potential of the Gaussian Splatting (GS) environment for wayfinding study, it will be conceptually compared with its ability to support the identification of four indoor wayfinding variables by Weisman (1981): architectural differentiation, plan configuration, signage and room numbers, and visual access. These variables will be compared with visual parameters such as geometric fidelity, lighting, occlusion, texture realism, and legibility, which affect spatial awareness and decision-making. This method theoretically assesses how well each environment type supports spatial cognition through visual realism.

3 Results and Discussion

The wayfinding process involves several processes, beginning with cognitive mapping, decision-making, and finally, decision execution (Chen and Stanney, 1999). In cognitive mapping, the first process of wayfinding, the mental image is created by duplicating the real world into our brain, which is kept as a memory. This process involves capturing environmental images through our senses (Figure 3). Therefore, providing a sensory-stimulated environment in a wayfinding study is essential. Meanwhile, in the VR study, the only sensory stimulation provided during the simulation was presented through visual stimulation. Consequently, a photorealistic digital environment is required to trigger accurate wayfinding behaviour. As Schwering et al. (2017) emphasise, wayfinding is not simply the execution of sequential

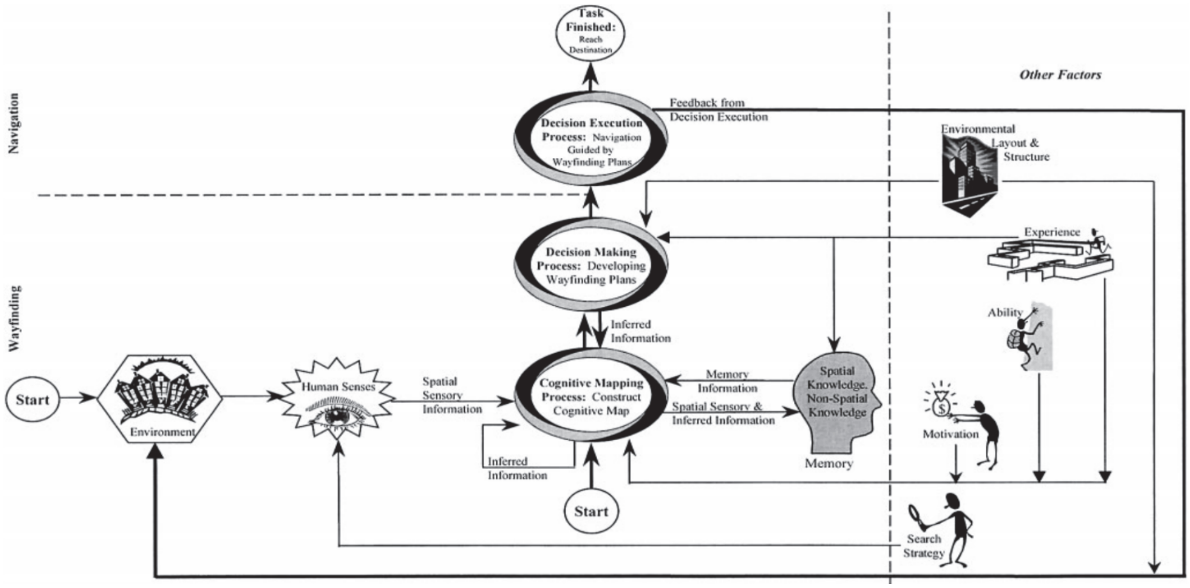

Figure 3. Wayfinding process involving sensory stimuli and memory acquisition

Source: (Chen & Stanney, 1999)

instructions but a process of integrating spatial information, forming mental representations, and learning the structure of an environment. This strengthens the importance of visual fidelity in VR in supporting natural orientation and cognitive engagement.

A study of VR wayfinding by Mortensen (2020) was conducted to compare movement behaviour between high and low levels of detail (LOD) environments. The result indicated a lower level of task completion error in a high LOD VR environment, indicating the important role of environmental detail in building an accurate cognitive map. Additionally, Alyahya & McLean (2022) also mentioned the importance of multiple involvements of sensory cues, which would stimulate a better sense of presence through greater development of mental imagery. With a good sense of place, there will be a better attitude towards the destination and an inducement of the visit intention, especially in the tourism sector (Figure 4).

In various recent studies, it has been indicated that Gaussian splatting could provide a highly detailed photorealistic environment that replicates the real environment through photogrammetry. Figure 5 shows a Gaussian Splatting model of a cactus, which was

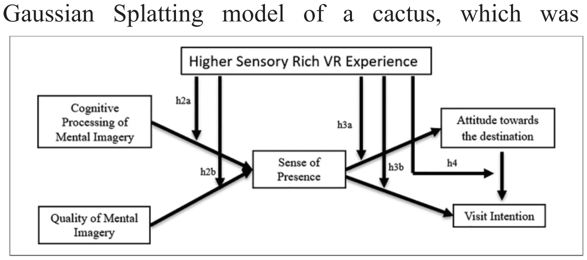

Figure 4. Sensory rich VR experience in wayfinding tourism behaviour

Source: (Alyahya & McLean, 2022)

processed using Polycam. The Gaussian splatting scan result showed its ability to visualise the details of the cactus pricks, which are often hard to capture in other model processing methods, despite some missing parts on the cactus table. This result indicates the lowest LOD of GS (LOD 0), which provides a high detail in some parts but still shows missing or incomplete geometry in other areas (Figure 6), indicating that while the model excels at capturing fine textures, it may require further refinement or denser input data to improve completeness.

Upon further analysis this study evaluates the visual clarity for wayfinding through image sequence capture from the LCC viewer (Figure 7). The model captures a series of hallways of the East Side Faculty of Architecture and Built Environment at TU Delft. In identifying this sequence, it indicated high fidelity of visual connectivity, surface realism, spatial geometry, recognisable corridors

Figure 5. A Gaussian Splatting model of cactus showed high detail in capturing prick shapes

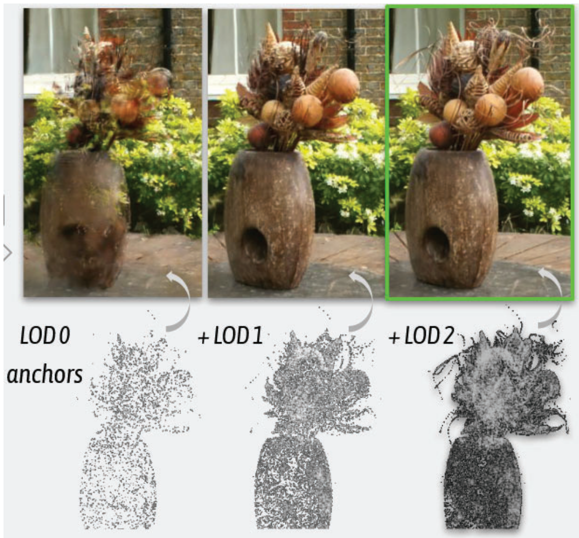

Figure 6. Varying LOD levels of Gaussian Splatting
Source: (Ren et al., 2024)

and junctions, identifiable near and far space, and clear visual connectivity.

Nonetheless, in close inspection of the room number and signages illustrated in Figure 8, there are slight differences in results between the LCC XGRIDS and the Postshot processing technique. The LCC XGRIDS processing technique showed sufficient readability of signages, although the level of clarity can still be further improved. In thePostshot processing technique, images were concentrated on signages and significant landmarks such as fire escape routes and fire hoses. The image collecting process enables a high-fidelity GS environment, which could optimise the wayfinding cognitive mapping process.

The result shown in LCC XGRIDS and Postshot GS training indicated different LOD on different parts of the environment. In LCC XGRIDS the scanning process was

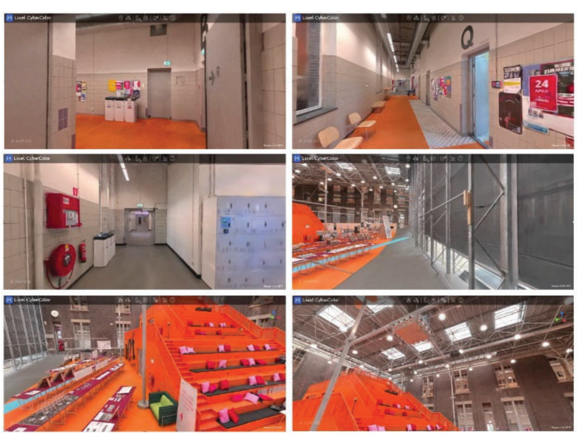

Figure 7. Visual sequence of the TU Delft Faculty of Architecture and the Built Environment hallway generated using Gaussian Splatting

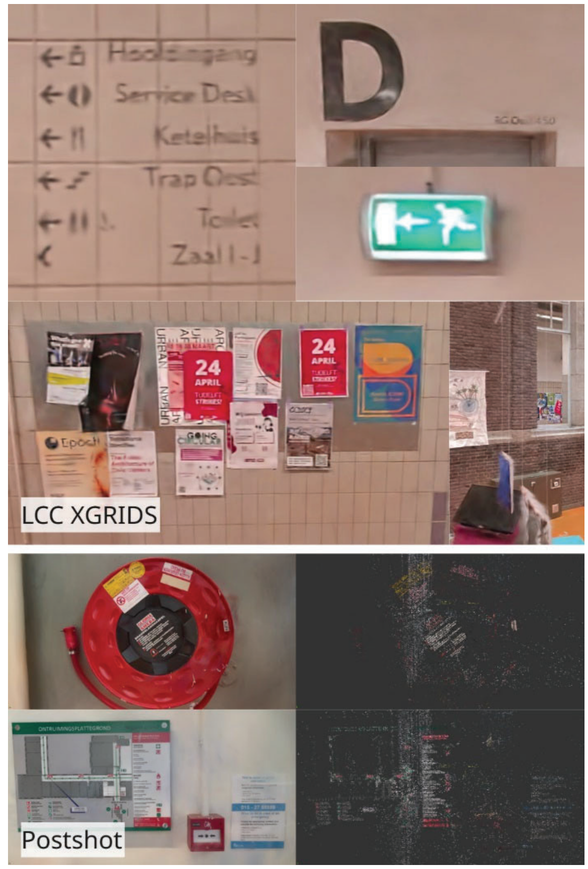

Figure 8. Signage and room number training result using LCC XGIRDS (top) and Postshot (bottom)

focusing on geometric development, thus creating high surface realism in corridor areas. Meanwhile, in the postshot environment (Figure 9), camera positioning was not evenly spread, resulting in different LOD on different parts. The camera well captured signages, providing an LOD 2 model, but on some parts, such as the wall and floor, projecting LOD 0.

Table 1 shows the indoor wayfinding variable and its required visual parameters. Architectural differentiation in indoor wayfinding is interpreted through architectural features such as material texture and spatial clarity between walls and doors. Thus, visual parameters in these variables include the ability to identify distinct material texture, surface realism, and shadow contrast between elements. Meanwhile, the plan configuration relates to the spatial layout of the building. Therefore, the visual parameter includes accurately identifying geometry and spatial relationships, recognising corridors and junctions, and near and far spaces. The signage and room number variable indicates the identification of graphical spatial information presented through signage and room numbers. Accordingly, some visual parameters are text clarity, clear contrast in lighting and shadow, and scale consistency. The visual access variable indicates visual connectivity between spaces, which is interpreted in the

Figure 9. Postshot GS training result and camera positioning

visual parameters as the ability to have continuous visibility across spaces and a clear visual of openings.

Table 1. Required Visual Fidelity and Parameters for Key Indoor Wayfinding Variables

Indoor wayfinding Variable	Required Visual Parameters	GS
Architectural Differentiation	• Distinct material textures • Surface realism (walls vs. floors) • Shadow contrast between elements	High
Plan Configuration	• Accurate geometry and spatial relationships • Recognizable corridors and junctions • Clear separation between near and far spaces	High
Signage and Room Numbers	• Easy-to-read signs and numbers • Scale consistency	High

All the results indicated the potential of GS to provide a more realistic environment, which would provide better sensory stimuli for VR wayfinding stimulation. A better cognitive map will be built by providing higher resolution in the VR environment and providing a more accurate wayfinding behaviour.

4 Conclusion

This study explored the potential of GS as a higher-resolution VR wayfinding environment in accordance with the indoor wayfinding variables by Weisman (1981): architectural differentiation, plan configuration, signage and room numbers, and visual access. The exploration showed that GS offers great potential in preserving visual characteristics that are essential for wayfinding, specifically lighting, texture fidelity, spatial depth, and cue visibility, even with LOD 0. This capability highlights the potential of GS to support wayfinding simulation on lower-specification devices, reducing the reliance on high-end equipment.

GS can capture the real environment accurately without missing its realism, allowing a more immersive representation of the real world. These findings highlight the potential of GS in providing a more accurate spatial representation in a virtual simulation of spatial cognitive and wayfinding research. In the future, this study plans to involve human participants to validate the depth perception and spatial understanding in wayfinding simulation. This future study will help assess how well GS replicates real-world visual cues critical for wayfinding and further inform its application in cognitive navigation research.

Declaration of Generative AI in writing

The authors declare that they have not used generative AI tools to prepare this manuscript. Specifically, the AI tools were utilised for language editing and improving grammar and sentence structure but not for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

Acknowledgements.

This research project is made possible with funding from the Indonesia Endowment Fund for Education (LPDP) and institutional support from Delft University of Technology (TU Delft), where the research is hosted.

References

Alyahya, M. and McLean, G.: Examining Tourism Consumers' Attitudes and the Role of Sensory Information in Virtual Reality Experiences of a Tourist Destination, J. Travel Res., 61, 1666–1681, https://doi.org/10.1177/00472875211037745, 2022.

Chen, J. L. and Stanney, K. M.: A Theoretical Model of Wayfinding in Virtual Environments: Proposed

Strategies for Navigational Aiding, Presence, 8, 671–685, https://doi.org/10.1162/105474699566558, 1999.

Dong, W., Qin, T., Yang, T., Liao, H., Liu, B., Meng, L., and Liu, Y.: Wayfinding Behavior and Spatial Knowledge Acquisition: Are They the Same in Virtual Reality and in Real-World Environments?, Ann. Am. Assoc. Geogr., 112, 226–246, https://doi.org/10.1080/24694452.2021.1894088, 2022.

Feng, Y., Duives, D. C., and Hoogendoorn, S. P.: Wayfinding behaviour in a multi-level building: A comparative study of HMD VR and Desktop VR, Adv. Eng. Inform., 51, 101475, https://doi.org/10.1016/j.aei.2021.101475, 2022.

Lei, X., Wang, M., Zhou, W., and Li, H.: GaussNav: Gaussian Splatting for Visual Navigation, IEEE Trans. Pattern Anal. Mach. Intell., 47, 4108–4121, https://doi.org/10.1109/TPAMI.2025.3538496, 2025.

Li, R. and Klippel, A.: Wayfinding Behaviors in Complex Buildings: The Impact of Environmental Legibility and Familiarity, Environ. Behav., 48, 482–510, https://doi.org/10.1177/0013916514550243, 2016.

Meng, F. and Zhang, W.: Way-finding during a fire emergency: an experimental study in a virtual environment, Ergonomics, 57, 816–827, https://doi.org/10.1080/00140139.2014.904006, 2014.

Mortensen, J.: Wayfinding in Virtual Environments, Master thesis, NTNU, 2020.

Ren, K., Jiang, L., Lu, T., Yu, M., Xu, L., Ni, Z., and Dai, B.: Octree-GS: Towards Consistent Real-time Rendering with LOD-Structured 3D Gaussians, https://doi.org/10.48550/arXiv.2403.17898, 17 October 2024.

Schwering, A., Krukar ,Jakub, Li ,Rui, Anacta ,Vanessa Joy, and and Fuest, S.: Wayfinding Through Orientation, Spat. Cogn. Comput., 17, 273–303, https://doi.org/10.1080/13875868.2017.1322597, 2017.

Weisman, J.: Evaluating Architectural Legibility: Way-Finding in the Built Environment, Environ. Behav., 13, 189–204, https://doi.org/10.1177/0013916581132004, 1981.

Wu, G., Yi, T., Fang, J., Xie, L., Zhang, X., Wei, W., Liu, W., Tian, Q., and Wang, X.: 4D Gaussian Splatting for Real-Time Dynamic Scene Rendering, https://doi.org/10.48550/arXiv.2310.08528, 15 July 2024.

Zhiming, F., Huisheng, G., Lixue, J., Xiaolian, L., and Wei, L.: Human movement characteristics during emergency evacuations in a virtual environment, Fire Saf. J., 115, 103147, https://doi.org/10.1016/j.firesaf.2020.103147, 2020.