Comparative Analysis of Dense RGB-D SLAM Systems Using 3D Gaussians Versus Neural Implicit Methods on Embedded Platforms

Assignee Research

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Abstract

Simultaneous localization and mapping is essential for position tracking and scene understanding. 3D Gaussian-based map representations enable photorealistic reconstruction and real-time rendering of scenes using multiple posed cameras. We show for the first time that using 3D Gaussians for map representation with unposed camera images and inertial measurements can enable accurate SLAM. Our method, MM3DGS, addresses the limitations of prior neural radiance field-based representations by enabling faster rendering, scale awareness, and improved trajectory tracking. Our framework enables keyframe

1 Introduction

This paper examines: MM3DGS SLAM: Multi-modal 3D Gaussian Splatting for SLAM Using Vision, Depth, and Inertial Measurements. Research question: How do dense RGB-D SLAM systems utilizing 3D Gaussian representations compare to neural implicit methods in terms of memory consumption and frame rate on embedded platforms using the ScanNet benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.6/10.

3 Results

12 papers retrieved. 15 claims extracted; 15 independently verified. Quality review score: 8.6/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
MM3DGS achieves a 3$\times$ improvement in tracking compared to the current 3DGS SLAM state-of-the-art.	✓	0.21
MM3DGS achieves a 5% improvement in photometric rendering quality compared to the current 3DGS SLAM state-of-the-art.	✓	0.30
MM3DGS allows real-time rendering of a high-resolution dense 3D map.	✓	0.23
SLAM approaches using sparse point clouds yield state-of-the-art tracking accuracy.	✓	0.21
Maps generated by SLAM approaches using sparse point clouds are disjoint due to sparsity.	✓	0.17
NeRF-based SLAM approaches yield output maps that are spatially and photorealistically dense.	✓	0.23
NeRF-based SLAM approaches are computationally expensive at inference time.	✓	0.18
NeRF-based SLAM approaches are not capable of accurately tracking in real-time.	✓	0.18
Most 3DGS approaches use depth inputs from relatively expensive sensors such as LiDARs.	✓	0.23
Relying solely on RGB-D cameras may lead to erroneous depth, especially as the distance from the camera increases.	✓	0.24
MM3DGS is the first real-time visual-inertial SLAM framework using 3D Gaussians.	✓	0.23
The MM3DGS SLAM framework consists of four main stages: pose optimization (tracking), keyframe selection, Gaussian initi	✓	0.26
In the MM3DGS framework, the ith 3D Gaussian is defined by position μi, shape Σi, opacity oi, and color ci.	✓	0.24
The covariance matrix Σ of a 3D Gaussian can be decomposed into Σ = RSSTRT, where R is an orthonormal rotation matrix an	✓	0.23
The 2D view-space covariance matrix Σ' is computed as Σ' = JWΣ(JW)T, where J is the Jacobian of the affine approximation	✓	0.31

References

- http://arxiv.org/abs/2403.16095v1
- http://arxiv.org/abs/2404.00923v1
- http://arxiv.org/abs/2503.20786v1