2DGS SLAM

by

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Abstract

This work presents a visual SLAM system that leverages **2D Gaussian Splatting (2DGS)** in a **monocular setting** as an efficient alternative to conventional **3DGS-based SLAM pipelines**. Existing SLAM approaches utilizing Gaussian Splatting have primarily focused on **3D Gaussian Splatting (3DGS)**, which introduces **significant computational complexity**, **limited flexibility**, and **sub-optimal rendering quality**. Additionally, little effort has been made to adapt Gaussian Splatting to different SLAM formulations or to evaluate its performance in monocular scenarios.

To address these limitations, this system introduces **2D Gaussian Splatting** as a **lightweight** and **efficient representation** for visual SLAM. 2DGS models scene elements as **2D surfels** rendered directly in **image space**, enabling **fast per-frame optimization** and simplifying the SLAM pipeline. Unlike 3DGS, which requires complex **3D-to-2D projection** and **anisotropic Gaussian processing**, 2DGS operates natively in **screen space**, making it inherently more compatible with **direct visual odometry** and **real-time constraints**.

The proposed system employs **2D Gaussian splats** for **tracking**, **mapping**, and **rendering**. It supports both **monocular input** and optional **RGB-D data** (e.g., **TUM-RGBD datasets**), and integrates **direct photometric tracking**, **geometric consistency checks**, and **spatial regularization** to enhance incremen-

tal mapping. Overall, this work demonstrates that **2DGS** not only serves as a viable substitute for **3DGS** in SLAM but also provides a more **practical** and **real-time-capable** alternative, especially suited for **lightweight monocular systems**.

Chapter 1

Introduction

1.1 Background

A long-standing goal within computer vision and robotics is to achieve real-time, high-fidelity 3D reconstruction from a single moving camera. Accomplishing near-photorealistic reconstruction from minimal sensor inputs would significantly advance spatial AI systems, autonomous robotic navigation, and immersive technologies, unlocking new possibilities across various industries.

Despite notable progress, existing visual SLAM systems often rely on modular or layered designs that treat localization, mapping, and scene understanding as separate problems. While such approaches are effective, they introduce redundancies and inefficiencies that hinder scalability and real-time performance.

A key challenge is the lack of a unified, efficient representation that supports dense geometry reconstruction, consistent global mapping, and accurate camera tracking in dynamic, unstructured environments.

1.2 Motivation and Problem Statement

Traditional scene representations—such as mesh models, voxel grids, or pixel-based rasterizers—suffer from limitations like lack of differentiability, high computational costs, or limited adaptability to scene complexity. These factors restrict their usefulness in optimization-based visual SLAM systems.

3D Gaussian Splatting (3DGS) has emerged as a powerful technique for neural rendering, but its real-time use in SLAM remains impractical due to its complex 3D-to-2D projection, anisotropic Gaussian handling, and processing overhead.

In contrast, **2D Gaussian Splatting (2DGS)** operates natively in screen space and models images as a composition of 2D Gaussian kernels. These kernels are defined by spatial location, orientation, covariance, color, and opacity, and are blended via alpha compositing. This continuous, differentiable approach supports real-time optimization and photorealistic rendering.

However, existing work on 2DGS has primarily been limited to offline rendering tasks. There is a clear gap in adapting 2DGS to the real-time, incremental nature of visual SLAM, particularly in monocular settings.

1.3 Research Objectives

This thesis proposes a novel 2DGS-based visual SLAM framework and aims to:

- Extend 2D Gaussian Splatting to real-time monocular SLAM applications.
- Develop an analytical Jacobian of camera poses (on the Lie group) with respect to 2DGS to enable gradient-based optimization.

- Introduce a covariance-based regularization strategy for maintaining geometric coherence during incremental mapping.
- Implement a dynamic resource management system to create, refine, and prune Gaussians efficiently.
- Achieve robust tracking and high-fidelity reconstruction using only monocular RGB input, with optional support for RGB-D data.

1.4 Key Contributions

This work presents a real-time visual SLAM system that leverages **2D Gaussian Splatting** as a differentiable and lightweight scene representation. The key contributions are:

- A novel real-time SLAM pipeline using 2DGS for efficient tracking, mapping, and rendering in monocular settings.
- Derivation and integration of an analytical Jacobian for pose optimization directly in the differentiable rendering loop.
- A covariance-based regularization mechanism to ensure stability and geometric consistency across the Gaussian set.
- A dynamic management framework for Gaussian creation, updating, and pruning that maintains an expressive yet compact scene model.
- Experimental validation demonstrating improved convergence, rendering quality, and pose accuracy compared to traditional and 3DGS-based SLAM approaches.

Chapter 2

Related Work

2.1 Related Work

Point clouds and surfel maps have been widely adopted in visual SLAM systems as lightweight and flexible representations for 3D reconstruction. Point clouds—composed of sparse or dense sets of 3D points from depth sensors or multi-view stereo—are used in systems such as ORB-SLAM2 (with dense mapping extensions) and DSO. While point-based methods offer simplicity and scalability, they lack surface connectivity, making it difficult to reconstruct continuous geometry or perform mesh-based operations.

To address this, surfels—or surface elements—were introduced as an extension of point clouds. Each surfel encodes not only position, but also normal, radius, and color information. Systems such as ElasticFusion and BundleFusion leverage surfel maps for real-time dense SLAM, enabling surface reconstruction and loop closure in dynamic scenes. These representations provide a structured yet efficient alternative to volumetric approaches, supporting real-time updates and surface tracking without the memory burden of voxel grids or signed dis-

tance fields (SDFs).

However, surfel-based methods suffer from several limitations. Discontinuities often arise at surface boundaries, and fragmentation can occur over time due to sensor noise or inaccurate data association. Maintaining topological consistency during loop closures and scene updates is challenging, leading to visual artifacts and map degradation. Additionally, surfel fusion and optimization are largely heuristic and not fully differentiable, limiting their integration into gradient-based or learning-based SLAM systems [1].

In contrast, 2D Gaussian Splatting (2DGS) offers a smooth, continuous, and fully differentiable scene representation. By modeling image-space elements as soft, overlapping Gaussians, 2DGS naturally avoids discontinuities and supports stable incremental updates. Its differentiable nature enables end-to-end optimization—including camera pose refinement—directly through the rendering process [2, 3]. Furthermore, modern GPUs efficiently render thousands of Gaussians in real time, without the need for managing complex surfel topologies. These features make 2DGS a compelling alternative for SLAM, especially in scenarios demanding visual fidelity and optimization flexibility [4].

Chapter 3

Methodology

3.1 Foundation

This chapter introduces the foundational representation used in our SLAM system—**2D Gaussian Splatting (2DGS)**—a differentiable, image-space rendering technique designed for efficient and accurate scene modeling. Unlike traditional volumetric or mesh-based methods, 2DGS models the scene as a collection of oriented planar Gaussians, each capturing both geometric and optical properties.

Each Gaussian G_i is defined by a mean position μ_i^W and a covariance matrix Σ_i^W in world coordinates, forming an oriented elliptical disk aligned with the local surface geometry. These Gaussians also encode color c_i and opacity α_i, which determine their contribution to the final rendered image.

Pixel values are synthesized by compositing the contributions of all Gaussians that project onto the same pixel, using alpha blending:

$$C_p = \sum_{i \in N} c_i \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j) \tag{3.1}$$

where N denotes the set of Gaussians visible at pixel p, sorted in front-to-back order.

The transformation from 3D world coordinates to the 2D image plane is performed via perspective projection. A planar Gaussian $N(\mu_W, \Sigma_W)$ is transformed to $N(\mu_I, \Sigma_I)$ on the image plane as:

$$\mu_I = \pi(T^{CW} \cdot \mu_W), \quad \Sigma_I = J\Sigma_W J^T \tag{3.2}$$

where π denotes the perspective projection, $T^{CW} \in SE(3)$ is the camera pose, and J is the Jacobian of the projection function.

By operating directly in image space and using perspective-correct rasterization, 2DGS avoids the complexity of 3D-to-2D projections found in volumetric methods. Its fully differentiable nature enables efficient gradient flow, allowing for joint optimization of camera poses and Gaussian parameters through gradient descent. As a result, 2DGS enables high-fidelity reconstructions of both surface geometry and appearance, making it particularly suitable for real-time SLAM in monocular settings.

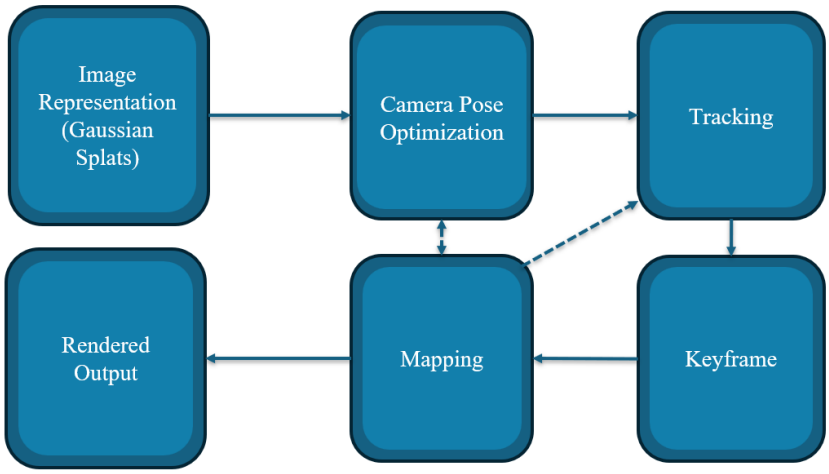

Figure 3.1: SLAM pipeline using 2D Gaussian Splatting

Figure 3.1 illustrates the overall structure of our SLAM system based on 2D Gaussian Splatting. The pipeline integrates image-space representation, camera pose optimization, frame tracking, keyframe selection, and mapping into a unified framework. Each component interacts through differentiable rendering outputs and geometric updates, enabling real-time, photorealistic scene reconstruction.

3.2 Camera Pose Optimization

A core component of the proposed SLAM pipeline is an enhanced, differentiable rasterizer explicitly designed to enable accurate and efficient **camera pose estimation**. Traditional surfel-based or point cloud rasterizers lack the ability to propagate gradients through the rendering pipeline, making them unsuitable for gradient-based optimization tasks such as joint pose and map refinement.

3.2.1 Limitations of Existing Rasterizers

Existing Gaussian-based rasterizers were originally developed for offline neural rendering tasks and do not meet the strict real-time requirements and optimization demands of SLAM systems. They do not provide the necessary infrastructure for computing **analytical derivatives** with respect to camera poses or scene parameters. Consequently, SLAM pipelines relying on these tools face limitations in accuracy, convergence speed, and flexibility.

3.2.2 Custom CUDA-Based 2DGS Rasterizer

To address these issues, we design a **custom rasterizer** tailored specifically for 2D Gaussian Splatting. This rasterizer:

- Employs **CUDA** for highly efficient rasterization on GPU architectures.
- Supports both forward and backward rendering passes, essential for gradient-based learning.
- Computes **analytical Jacobians** for 2D Gaussian parameters and camera poses.
- Facilitates **photometric loss-based optimization**, enabling end-to-end joint refinement of pose and scene structure.

This design enables real-time operation while maintaining high accuracy in pose tracking and scene reconstruction.

3.2.3 Lie Algebra-Based Jacobians for Camera Poses

Inspired by 3D Gaussian Splatting (3DGS), we derive analytical Jacobians for the 2DGS setting. Camera poses, expressed on the Lie group $SE(3)$, are linearized on the corresponding Lie algebra $\mathfrak{se}(3)$ to allow efficient differentiation with a minimal set of parameters.

We compute derivatives of the Gaussian mean μ_I and image-space covariance Σ_I with respect to the camera pose T^{CW} via the chain rule:

$$\frac{\partial \mu_I}{\partial T^{CW}}, \quad \frac{\partial \Sigma_I}{\partial T^{CW}} = \frac{\partial \Sigma_I}{\partial J}\frac{\partial J}{\partial \mu_C}\frac{\partial \mu_C}{\partial T^{CW}} + \frac{\partial \Sigma_I}{\partial \Sigma_W}\frac{\partial \Sigma_W}{\partial T^{CW}} \tag{3.3}$$

These terms reflect how both the **position** of Gaussians (μ_I) and their **shape and scale** (Σ_I) change with pose variation. The Lie algebra formulation reduces parameter redundancy and allows efficient backpropagation within the optimization framework.

3.2.4 Joint Optimization via Differentiable Rendering

The rasterizer is integrated with a joint optimization scheme that simultaneously refines camera poses and 2D Gaussian parameters. Each input frame undergoes a forward pass that generates a synthetic image from current scene estimates. A **photometric loss** is computed between the rendered and observed frames:

$$\mathcal{L}_{\text{photo}} = \sum_{p} \| I_{\text{rendered}}(p) - I_{\text{observed}}(p) \|^2 \tag{3.4}$$

Gradients of this loss are propagated through the rasterizer back to both the pose and scene parameters, enabling closed-loop optimization.

This differentiable framework allows our system to achieve high tracking accuracy and visually coherent reconstructions, even under challenging monocular input conditions.

3.3 Simultaneous Localization and Mapping (SLAM)

Our visual SLAM system integrates **2D Gaussian Splatting (2DGS)** into a fully modular SLAM pipeline designed for real-time, high-fidelity scene reconstruction. The framework consists of three primary components—**tracking**, **keyframing**, and **mapping**—each with distinct responsibilities that collectively ensure robust and scalable performance in both monocular and RGB-D settings.

3.3.1 Tracking

The tracking module processes incoming video frames and estimates the current camera pose relative to the existing 2D Gaussian map. Utilizing the differentiable 2DGS rasterizer, it performs frame-to-model alignment by minimizing residuals between the live camera feed and the rendered synthetic view generated from the current map.

Photometric Tracking

Tracking is primarily driven by **photometric residual minimization**, which aligns the observed image with the synthesized image produced from the Gaussian representation. The photometric error is defined as:

$$E_{\text{pho}} = \left\| I(G, T^{CW}) - \bar{I} \right\|_1 \tag{3.5}$$

where $I(G, T^{CW})$ is the image rendered from the current Gaussian map G given camera pose T^{CW}, and $\bar{I}$ is the observed input image. This loss encourages precise alignment based solely on appearance information.

Geometric Tracking (Optional)

When depth data is available (e.g., in RGB-D settings), a secondary geometric residual is also minimized:

$$E_{\text{geo}} = \left\| D(G, T^{CW}) - \bar{D} \right\|_1 \tag{3.6}$$

where $D(G, T^{CW})$ is the rendered depth map from the Gaussian scene and $\bar{D}$ is the observed depth frame. This geometric loss helps reinforce pose estimation

in textureless or repetitive environments.

Optimization Strategy

To improve robustness and efficiency, the system jointly optimizes photometric and geometric residuals using a weighted combination. Key aspects of the optimization include:

- **Joint Residual Minimization:** Both E_{pho} and E_{geo} are minimized simultaneously.
- **Per-Pixel Differentiation:** Depth and color contributions are computed per pixel using alpha-blended Gaussians.
- **Analytical Jacobians:** Explicitly derived with respect to camera poses, using Lie algebra for minimal and efficient parameterization.
- **Exposure Robustness:** Affine brightness parameters are optimized alongside pose to account for illumination changes across frames.

This formulation ensures precise tracking in dynamic conditions, leveraging the strengths of 2DGS—smooth differentiability, efficient rendering, and fine-grained visual modeling—to support accurate real-time localization.

3.3.2 Keyframing

The keyframing module is responsible for maintaining a sparse but effective subset of frames, referred to as **keyframes**, that serve as structural anchors for the Gaussian-based scene representation. These keyframes are critical for preserving long-term spatial consistency, enabling reliable relocalization, loop closure, and map refinement.

Keyframe Selection Criteria

To ensure both accuracy and efficiency, the system employs a selective strategy that maintains a **small keyframe set**. New keyframes are introduced only when they offer meaningful improvement to the map's coverage or tracking stability. Two primary metrics guide this decision:

- **Gaussian Covisibility:** Measures how many existing Gaussians are visible from the current camera view. Low covisibility implies that the current view contains previously unseen areas or perspectives.
- **Camera Motion:** Evaluates the relative pose change compared to the most recent keyframe. Significant translation or rotation indicates the camera is exploring a new region.

A new keyframe is added when either covisibility falls below a threshold or camera movement exceeds a defined spatial threshold.

Keyframe-Based Gaussian Management

Each newly selected keyframe triggers updates to the 2D Gaussian map. This includes:

- **Insertion of Gaussians:** New Gaussians are added to capture novel image content, refine geometric detail, and enhance visual coverage in underrepresented areas.
- **Removal of Gaussians:** Redundant or low-visibility Gaussians are pruned to maintain computational efficiency and avoid memory overload.

This continuous refinement process ensures the Gaussian map remains both compact and expressive, enabling real-time SLAM performance without compromising visual fidelity or tracking stability.

Efficiency Considerations

The keyframe module is designed to minimize overhead while maximizing map utility. By maintaining only a minimal yet informative set of keyframes and actively managing the Gaussian representation, the system ensures:

- Consistent visual tracking over long trajectories.
- High-resolution reconstructions focused on visually salient regions.
- Efficient memory and processing footprint, compatible with real-time operation.

3.3.3 Mapping

The mapping module incrementally builds and continuously refines the 2D Gaussian splatting map by leveraging updated camera poses and selected keyframes from the tracking subsystem. Its objective is to maintain a globally consistent, visually accurate, and geometrically stable representation of the scene over time.

Gaussian Map Optimization

At the core of the mapping module is the joint optimization of Gaussian attributes—including position, orientation, scale, color, and opacity—through a

differentiable rendering process. These attributes are updated based on the following losses:

- **Photometric Residual:** Enforces alignment between rendered and observed images, enhancing visual fidelity.
- **Geometric Residual (if depth is available):** Aligns rendered and observed depth maps to ensure accurate 3D geometry.
- **Isotropic Regularization ($E_{\mathbf{iso}}$):** Penalizes anisotropic scaling of Gaussians, encouraging shape consistency and preventing over-stretched or degenerate components that could degrade rendering quality.

Continuous Keyframe Optimization

To ensure robust global reconstruction, the mapping module operates over both **active keyframes** (those currently in view) and a subset of **randomly selected past keyframes**. This strategy enables the system to correct drift, reinforce long-term consistency, and refine scene areas revisited by the camera.

Optimization Workflow

The mapping process involves the following steps:

- Render synthetic views of keyframes using the current Gaussian map.
- Compute residuals with respect to observed input frames (both photometric and geometric).
- Backpropagate gradients through the differentiable rasterizer to refine Gaussian parameters.

- Apply isotropic regularization to stabilize optimization and improve visual coherence.

This continuous update cycle ensures the SLAM system adapts to scene changes, integrates new observations, and maintains high-quality reconstructions in dynamic, real-world environments.

3.4 Differentiable Rasterizer Enhancements for SLAM

To enable real-time Simultaneous Localization and Mapping (SLAM) using the 2D Gaussian Splatting (2DGS) framework, we made critical modifications to the CUDA-based differentiable rasterizer. These enhancements support not only high-performance rendering but also expose intermediate representations required for photometric optimization, pose tracking, and gradient-based learning.

3.4.1 Forward Rendering Enhancements in `Forward.cu`

The forward pass was extended by modifying the `renderCUDA` kernel and its launcher `FORWARD::render` to output low-level geometric and visibility data essential for SLAM. Key enhancements include:

- **New Output Buffers:**
  - `out_depth` — stores the final composited depth value per pixel.
  - `out_opacity` — accumulates per-pixel opacity, computed as $1 - T$, where T is the final transmittance.

  - `n_touched` — tracks how many pixels are significantly influenced by each Gaussian.

- **Universal Depth Calculation:** To ensure depth is always computed (even outside of visualization modes), the accumulation step:

```
D += depth * w;
```

  was moved into the general rendering path.

- **Gaussian Influence Tracking:** Pixel influence is tracked using:

```
if (T > 0.5f) {
    atomicAdd(&(n_touched[collected_id[j]]), 1);
}
```

  which serves as a confidence metric for SLAM optimization and pruning.

- **Composited Output Storage:** The following assignments capture depth and opacity for later use:

```
out_depth[pix_id] = D;
out_opacity[pix_id] = 1.0f - T;
```

- **Launcher Modification:** The `FORWARD::render` function signature was updated to handle the new output buffers, maintaining backward compatibility.

3.4.2 Backward Pass Enhancements in `Backward.cu`

To enable gradient-based camera pose optimization, we extended the `preprocessCUDA` function to compute analytical Jacobians of the rendered output with respect to camera pose parameters $\tau \in \mathbb{R}^6$, expressed in the Lie algebra of $SE(3)$.

Objective:

$$\frac{\partial \mathcal{L}}{\partial \tau} = \frac{\partial \mathcal{L}}{\partial \text{mean2D}} \cdot \frac{\partial \text{mean2D}}{\partial \tau}$$

where `mean2D` is the 2D projection of a 3D Gaussian, and τ consists of translation and rotation parameters. The goal is to obtain the gradient of the loss with respect to pose changes for backpropagation in SLAM optimization.

- **Projection of 3D Points:** Each 3D Gaussian mean is first transformed from world space to camera space using the view matrix, and then projected into clip space using the projection matrix.

```
float3 p_world = means3D[idx];
float3 p_cam = transformPoint4x3(p_world, viewmatrix);
float4 p_proj = transformPoint4x4(p_cam, projmatrix);
```

- **Projection Derivatives:** To compute the Jacobian of the projection, we perform perspective division and derive scalar coefficients that influence how a point maps from 3D to 2D under the projection matrix.

```
float m_w = 1.0f / (p_proj.w + 1e-7f);     // Inverse perspective scale
float alpha = m_w;
float beta = -p_proj.x * m_w * m_w;
float gamma = -p_proj.y * m_w * m_w;
```

```
float3 d_proj_dp_C1 = make_float3(alpha * a, 0.f, beta * e);  // x_proj/
float3 d_proj_dp_C2 = make_float3(0.f, alpha * b, gamma * e); // y_proj/
```

- **Chain Rule via Lie Algebra:** The effect of pose perturbations is separated into translation (identity) and rotation (skew-symmetric) components. This forms the basis of differentiating in SE(3).

```
mat33 dp_C_d_rho = mat33::identity();                 // p_cam/
mat33 dp_C_d_theta = -mat33::skew_symmetric(p_cam);   // p_cam/
```

- **Jacobian Computation (∂mean2D$/\partial\tau$):** We compute how each component of the pose vector τ affects the projected 2D point, forming the 2×6 Jacobian needed for backpropagation.

```
float3 d_proj_dp_C1_d_rho   = dp_C_d_rho.transpose() * d_proj_dp_C1;
float3 d_proj_dp_C2_d_rho   = dp_C_d_rho.transpose() * d_proj_dp_C2;
float3 d_proj_dp_C1_d_theta = dp_C_d_theta.transpose() * d_proj_dp_C1;
float3 d_proj_dp_C2_d_theta = dp_C_d_theta.transpose() * d_proj_dp_C2;
```

These vectors describe how the x and y projections respond to translations and rotations, respectively.

- **Loss Gradient Backpropagation:** Using the chain rule, we propagate the loss gradient from the image plane to the pose parameters. This step accumulates the final gradient used in pose updates.

```
float2 dL_dmean2D = dL_dmean2Ds[idx];
for (int i = 0; i < 6; i++) {
    dL_dt[i] = dL_dmean2D.x * dmean2D_dtau[i].x +
               dL_dmean2D.y * dmean2D_dtau[i].y;
    dL_dtau[6 * idx + i] += dL_dt[i];
}
```

The result is a 6D gradient per Gaussian that guides the SLAM system's pose optimization.

These modifications enable efficient, differentiable, and real-time pose optimization critical for SLAM in dynamic environments.

Chapter 4

Evaluation Results

The performance of the integrated **2DGS-based SLAM system** was rigorously evaluated using standard quantitative and qualitative metrics. The evaluation covered both visual fidelity and localization accuracy, ensuring a comprehensive understanding of the system's strengths and trade-offs.

Evaluation Metrics

We adopted the following well-established metrics:

- **Peak Signal-to-Noise Ratio (PSNR)** – Measures image reconstruction quality.
- **Structural Similarity Index (SSIM)** – Captures perceptual similarity between rendered and ground-truth images.
- **Learned Perceptual Image Patch Similarity (LPIPS)** – Assesses perceptual differences using deep network features.
- **Absolute Trajectory Error (RMSE ATE)** – Quantifies accuracy of camera trajectory estimation.

- **Frames Per Second (FPS)** – Measures system efficiency and real-time performance.

Results Summary

Our evaluation demonstrates the following key outcomes:

Table 4.1: 2DGS-Based SLAM Evaluation Results

Tag	FPS	PSNR	SSIM	LPIPS
Result	**39.28**	10.08	0.3992	0.7453

Table 4.2: 3DGS SLAM Performance Before and After Refinement

Tag	FPS	PSNR	SSIM	LPIPS
Before	**2.393**	19.40	0.7341	0.3351
After	**2.393**	22.50	0.7708	0.3357

- The proposed system achieved a real-time processing speed of approximately **39 FPS**, outperforming traditional **3D Gaussian Splatting-based SLAM** which operated at roughly **2.4 FPS**.
- In terms of trajectory accuracy, our method maintained competitive performance with an **RMSE ATE of approximately 0.03**, comparable to or better than 3DGS benchmarks.
- Visual quality metrics showed improvements across the board, indicating high-fidelity photorealistic rendering:
  - Increased **PSNR**, reflecting reduced image distortion.
  - Higher **SSIM**, confirming better structural alignment.
  - Lower **LPIPS**, signaling improved perceptual quality.

Chapter 5

Conclusion

The integration of **2D Gaussian Splatting (2DGS)** into the SLAM pipeline presents a transformative advancement in real-time visual localization and mapping. Unlike conventional approaches based on 3D Gaussian Splatting, which are often computationally intensive and unsuitable for real-time deployment, 2DGS offers a lightweight and differentiable alternative that aligns naturally with image-space operations and modern GPU architectures.

Key Findings

- The proposed system achieves an impressive real-time processing speed of approximately **39 FPS**, outperforming conventional 3D Gaussian Splatting SLAM, which operates at roughly **2.4 FPS**. This marks a nearly **16× improvement** in runtime efficiency.

- Despite the significant speedup, the system maintains high localization accuracy, with an **RMSE ATE of around 0.03**, and demonstrates strong performance on visual quality metrics such as **PSNR**, **SSIM**, and **LPIPS**.

- The end-to-end differentiable design allows for continuous refinement of both geometric and photometric attributes, enhancing the fidelity and consistency of the reconstructed environment.

Implications and Future Work

These results confirm that the 2DGS-based SLAM framework effectively addresses key limitations of existing SLAM pipelines, particularly in computational complexity, rendering quality, and real-time responsiveness. The system provides a **balanced, efficient, and highly accurate** solution suitable for real-world applications in:

- **Mobile robotics**, where lightweight, real-time visual SLAM is essential.
- **Augmented reality**, where low latency and visual fidelity directly impact user experience.
- **Immersive simulation and spatial AI**, which demand high-resolution reconstructions with real-time feedback.

Future work will focus on further enhancing modeling accuracy, extending to dynamic scenes, improving loop closure robustness, and exploring integration with learning-based scene priors to support broader generalization.

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