GSORB-SLAM: Gaussian Splatting SLAM benefits from ORB features and Transmittance information

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Abstract—The emergence of 3D Gaussian Splatting (3DGS) has recently sparked a renewed wave of dense visual SLAM research. However, current methods face challenges such as sensitivity to artifacts and noise, sub-optimal selection of training viewpoints, and a lack of light global optimization. In this paper, we propose a dense SLAM system that tightly couples 3DGS with ORB features. We design a joint optimization approach for robust tracking and effectively reducing the impact of noise and artifacts. This involves combining novel geometric observations, derived from accumulated transmittance, with ORB features extracted from pixel data. Furthermore, to improve mapping quality, we propose an adaptive Gaussian expansion and regularization method that enables Gaussian primitives to represent the scene compactly. This is coupled with a viewpoint selection strategy based on the hybrid graph to mitigate over-fitting effects and enhance convergence quality. Finally, our approach achieves compact and high-quality scene representations and accurate localization. GSORB-SLAM has been evaluated on different datasets, demonstrating outstanding performance. The code will be available.

I. INTRODUCTION

Over the past two decades years, Simultaneous Localization and Mapping (SLAM) has remained a hot research topic, evolving from traditional SLAM, which focuses on improving localization accuracy, to neural radiance field (NeRF) SLAM, which provides rich scene representations. As one of the key points in fields like autonomous driving, virtual reality (VR), and embodied artificial intelligence [15], SLAM has gained increasing importance in map representation, which plays a crucial role in downstream tasks. Visual SLAM has introduced various map representations, such as point/surfel clouds [8]–[10], mesh representations [11], [12], and voxels [13], [14].

In recent years, NeRF-based novel view synthesis [16] has gained widespread popularity among researchers due to its high-fidelity construction and led to the development of numerous advanced dense neural SLAM methods. These methods have achieved impressive progress. However, because volumetric rendering expensive samples along rays in the optimization of NeRF, it cannot render full-resolution images, so the rendering results are still far from the photorealism we aspire to achieve.

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Excitingly, the 3D Gaussian splatting (3DGS) technique [4] has enabled high-quality, full-pixel novel view synthesis and real-time scene rendering under the standard GPU-accelerated frameworks. Consequently, several SLAM methods based on 3DGS [19]–[21] have been developed. These methods significantly improve rendering quality and achieve rendering speeds up to 100x faster compared to NeRF-based SLAM. However, pressing issues still need to be addressed, such as the Bundle Adjustment (BA) problem and sensitivity to artifacts, which leads to degraded tracking accuracy. Additionally, the lack of multi-view constraints and strong anisotropy causes Gaussians to overfit to the current viewpoint.

To address these issues, we propose a tightly coupled 3DGS and ORB feature SLAM system, called GSORB-SLAM, in the paper. For mapping, we design an adaptive extended Gaussian method that effectively identifies uninitialized Gaussian regions by combining accumulated transmittance and geometric information. This allows the system to represent the scene compactly while improving real-time performance. Additionally, to reduce overfitting caused by the lack of multi-view constraints and enhance convergence quality, we propose a viewpoint selection strategy for rendering frame (RF) that combines the overlap graph with the co-visibility graph, forming a hybrid graph. During the tracking process, we develop sparse feature points for frame-to-frame tracking, which provide an initial pose for the joint optimization of photometric and reprojection errors. In joint optimization tracking, a frame-to-model tracking method based on surface Gaussians is proposed to enhance tracking robustness by reducing the impact of artifacts and noise. Finally, we retain sparse feature point clouds for backend BA to reduce accumulated errors and lighten the computational burden on the device. Our main contributions are summarized as follows:

- We design an adaptive extended differentiable Gaussian method and rendering frame selection strategy based on a hybrid graph to achieve high-fidelity and compact scene representations.
- For tracking, we propose a joint optimization method based on surface Gaussians and sparse feature points to ensure accurate and robust frame-to-model tracking.
- We conducted experiments on different datasets, and the results demonstrate that our method outperforms the baseline in both tracking and mapping.

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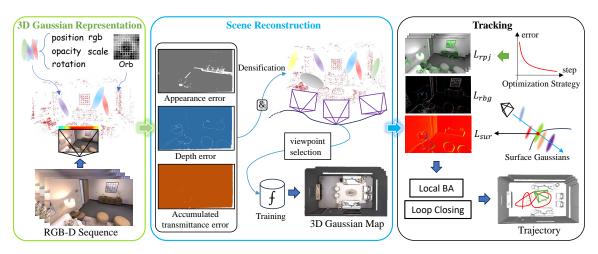


Fig. 1. In 3D Gaussian representation, RGB-D sequences are used as input. Gaussians are spawned to the scene based on the re-rendering of color, depth, and transmittance. A viewpoint selection strategy is used to choose the rendering frames for map training. Additionally, we not only tightly couple feature points and surface Gaussians but also perform lightweight global optimization through sparse point clouds, ultimately achieving accurate and robust tracking.

II. RELATED WORK

A. NeRF SLAM

NeRF [16] achieves realistic image rendering by performing pixel-ray sampling on 2D images. Utilizing multi-layer perceptron and volumetric differentiable rendering, NeRF can novel view synthesis of unobserved regions. iMAP [29] is the first to integrate NeRF into SLAM to achieve implicit neural representation. Since then, many excellent NeRFbased SLAM methods [33]-[35] have emerged. NICE-SLAM [30] proposes a hierarchical multi-feature grid to achieve high-quality scene reconstruction. Unlike iMAP, it updates only the visible grid features at each step. Orbeeze-SLAM [31] uses ORB features for triangulation to implement monocular tracking with a depth-free estimator and employs NeRF for implicit scene representation. Point-SLAM [32] distributes point clouds onto object surfaces, which exhibits improved reconstruction quality through neural point cloud representation. However, NeRF ray sampling for individual pixels incurs high computational costs, leading to slow rendering speeds (below 15 FPS).

B. 3DGS SLAM

Recently, 3D Gaussian Splatting (3DGS), which employs tile-based rasterization to render high-resolution images, has achieved significantly faster rendering speeds, reaching up to 300 FPS. Many researchers have attempted to integrate this advanced technology into SLAM [17], [18], [22], [23]. Splat-TAM [5] optimizes camera poses by minimizing photometric error through differentiable Gaussians guided by silhouettes and adds 3DGS to unobserved areas based on the geometric median depth error. Nevertheless, this methodology may result in an excessive number of Gaussian primitives, thereby markedly increasing the memory requirements and computational burden. Gaussian-SLAM [6] explores the limitations of 3DGS in SLAM and utilizes the submap to seed and optimize Gaussians, ultimately achieving camera pose tracking and map rendering. GS-SLAM [19] derives an analytical formula for backward optimization with re-rendering RGB-D loss

and uses depth filtering to remove unstable Gaussians during tracking. However, setting the appropriate depth filtering threshold is difficult, as it must account for noise and convergence levels. Photo-SLAM [20] employs feature points to determine camera poses and proposes a Gaussian-Pyramid-based training approach to construct scenes. Jiang [21] designs a method that connects ORB-SLAM3 with 3DGS, enabling a combination of those techniques. Although both Photo-SLAM [20] and Jiang [21] utilize feature points, they do not fully exploit the potential performance benefits of feature points. Through our analysis of 3DGS, we have found that feature points can significantly enhance 3DGS-SLAM in multiple aspects.

C. Traditional SLAM

Traditional visual SLAM methods have evolved into two major categories: direct methods and feature methods. Direct methods [24], [25] estimate camera poses by minimizing photometric error and comparing pixel differences between two adjacent frames. This requires a strong assumption of photometric consistency. Feature methods [26], [27] use image features such as corners and lines. These methods minimize pixel errors between corresponding features across frames using reprojection error. The ORB-SLAM series [1], [10], [28] achieves real-time accurate localization based on ORB features and performs global optimization of sparse landmarks and poses through graph optimization. Although these methods excel in real-time performance and localization accuracy compared to advanced scene representation techniques (e.g., NeRF, 3DGS), their limited environment representation capabilities constrain their applicability to more advanced tasks.

III. METHOD

The overview of our propose GSORB-SLAM system is shown in Fig. 1. Given a set of RGB-D sequences as input, we first introduce a 3D Gaussian field **G** (III-A). Secondly, we propose a method to use Gaussians for incremental

mapping efficiently and how to select RF for training (III-B). Finally, we design the acquisition of surface Gaussians and how to achieve accurate and robust pose tracking by jointly using the ORB feature, along with lightweight global optimization based on sparse landmarks (III-C).

A. 3D Gaussian field

Gaussian map representation. Our scene of SLAM is represented by a collection of anisotropic 3D Gaussian with opacity attributes:

$$\mathbf{G} = \{G_i : (X_i^w, \Sigma_i, o_i, c_i) | i = 1, ..., N\}.$$
 (1)

Similar to [4], each Gaussian contains a group of parameters: the position $X_i^w \in \mathbb{R}^3$ in the world coordinate system, the opacity $o_i \in [0,1]$, the trichromatic vector $c_i \in \mathbb{R}^3$ representing the color of each Gaussian and the 3D covariance matrix $\Sigma_i \in \mathbb{R}^{3\times 3}$ is a combination of a rotation matrix $R \in SO(3)$, and a scale diagonal matrix $S \in \mathbb{R}^{3\times 3}$.

$$\Sigma_i = RSS^T R^T. (2)$$

Differentiable rendering. 3DGS renders colors by blending Gaussians along rays, from near to far, and splatting them onto the pixel screen.

$$\tilde{C} = \sum_{i=1}^{n} c_i \alpha_i T_i, T_i = \prod_{i=1}^{i-1} (1 - \alpha_i),$$
 (3)

where the density α_i denotes the opacity contribution of the Gaussian to the pixel, which is determined by both the Gaussian function and the opacity. T_i is the accumulated transmittance, which decays as the ray passes through the number of Gaussians. Meanwhile, to obtain geometric information, depth z in the camera coordinate system are used instead of color c for rendering:

$$\tilde{D} = \sum_{i=1}^{n} z_i \alpha_i T_i. \tag{4}$$

Inspired by [3], we impose constraints on T_i to obtain the surface depth:

$$\tilde{D}_s = \max\{z_i | T_i > 0.5\}.$$
 (5)

Since the surface depth is selected based on the median of the accumulated transmittance, if the transmittance remains less than full transmittance (set to 1) even in a converged state, the surface depth will be uncertain. Therefore, we need to estimate the accumulated transmittance of the pixel to ensure that the obtained surface depth is stable.

$$\tilde{T} = \sum_{i=1}^{n} \alpha_i T_i. \tag{6}$$

B. Mapping

Initialization. In SLAM, large-scale Gaussian primitives may occupy spatial regions, affecting the addition of new initialized Gaussian in under-reconstructed. To address this, it is advisable to initialize the Gaussian scale to be roughly the size of a single pixel [5], [6]. For the *i*-th Gaussian

initialization, the position X_i^w is determined by the 3D points X_i^c in the camera coordinate system and the extrinsic matrix W_{wc} , which represents the camera-to-world transformation. The color c_i is extracted from the RGB image, opacity is initialized to 1, and the R_i rotation matrix is initialized to the unit quaternion $q \in SE(3)$. The scale is initialized to the three-dimensional vector $s_i \in \mathbb{R}^3$ as follows:

$$s_i = \frac{(KW_{wc}X_i^c)_z}{d_f}, d_f = \left| \frac{f_x + f_y}{2} \right|,$$
 (7)

K is the camera intrinsic matrix, $(\cdot)_z$ takes the third dimension, which corresponds to depth. f is the camera focal length.

Adaptive densification. To improve the convergence speed of differentiable Gaussians and obtain high-fidelity results, it is important to spawn new Gaussians to model the geometry and appearance of newly observed areas. We design an appearance mask M_c , which is generated based on the grayscale values of the re-rendering image, and a reconstructed geometric mask $M_d = (|D - \tilde{D}| < 0.05)(\tilde{D} > 0)$.

Since the geometric accuracy of rendering is influenced by the convergence of differentiable Gaussians, we design an adaptive depth error threshold σ_d to prevent redundant additions:

$$\sigma_d = \mu\{E_d\} + 40\eta\{E_d\}$$
 (8)

$$E_d = \left| D(x, y) - \tilde{D}(x, y) \right|_{(x, y) \in M_d} \tag{9}$$

- $\mu\{\cdot\}$ is the mean operation, $\eta\{\cdot\}$ is the median operation. Spawning new Gaussians needs to meet the following requirements:
- (1) Based on accumulated transmittance: $\tilde{T}(x,y) < 0.8$. This helps to improve areas where gradient descent is slow due to a lack of supervision by re-initializing them. In SLAM, it is unfeasible to set a enough number of iterations for training. Another reason is to ensure tracking accuracy, a new Gaussian needs to be spawned if the accumulated transmittance has not reached 80% of the full transmittance.
- (2) Based on geometry: $(M_c < 50)(E_d < \sigma_d)(\tilde{T}(x, y) < 0.99)$. The $(M_c < 50)(E_d < \sigma_d)$ is to identify under-reconstructed areas by using errors in geometry and ap-

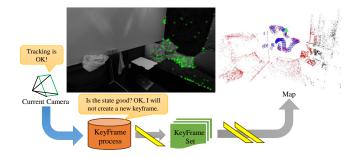


Fig. 2. The green points represent feature points. At this moment, a keyframe should be generated, but in this case, since the tracking requirements are met, a keyframe is not generated and inserted into the map. As a result, observations of this region will be lost during subsequent training.

pearance, while $(\tilde{T}(x, y) < 0.99)$ is to prevent continuously adding Gaussians due to significant geometric errors at the edges. As illustrated in Fig. 1, the accumulated transmittance proves to be more robust against edge errors.

The new Gaussians will be spawned to regions that meet at least one of the above criteria:

$$Add(G_i)$$
, if (1) or (2). (10)

Keyframe generation. Feature-based SLAM [1] focuses only on the number of feature points and does not consider their distribution, shown in Fig. 2. Therefore, an overlap graph method is designed to generate keyframes based on the degree of overlap:

$$OG(i,j) = \frac{\pi(W_{ij}, \mathcal{K}_j)}{\mathcal{K}_i},\tag{11}$$

where $\pi_{ij}(\cdot)$ represents the projection of the *j*-th frame onto the *i*-th frame, and \mathcal{K}_i indicates the number of random points in the *i* frame.

Rendering frame selection strategy. The RF are selected from keyframes, and a good selection strategy can greatly improve rendering quality. The TAMBRIDGE [21] achieves excellent reconstruction results by selecting a keyframe based on the co-visibility graph [1]. However, we found that relying solely on the set of rendering frames selected from the co-visibility graph might lead to limitations in training perspectives, potentially only covering a small portion of the main object. These factors can lead to a decline in reconstruction quality. To address this, we propose a novel rendering frame selection strategy based on a hybrid graph.

First, we select the adjacency n_a frames and the optimized n_b frames to add to RF set \mathcal{R} . The adjacency frames increase the probability of the current viewpoint being selected, as the current viewpoint requires more optimization for tracking. Additionally, the optimized frames are included due to the presence of the backend pose optimization thread.

Secondly, a window W is initialized with the current frame f_1 . To improve the efficiency and quality of selection, candidate frames F_c are prioritized from the co-visibility graph. If $OG(f_{top(W)}, f_j) < \beta_1$, then f_j ($j \in F_c$) will be added to the window and also to \mathcal{R} , until F_c has been fully traversed. The $top(\cdot)$ is the index of the newly added frame. The window W can prevent approximately identical viewpoints from the co-visibility graph from being repeatedly added, as weak tracking continuously generates new keyframes. Additionally, since some keyframes are not present in the co-visibility graph, candidate frames F_k will be selected by sorting the keyframes based on their timestamps. These F_k will then be added to \mathcal{R} according to the overlap graph $OG(f_1, f_j)_{j \in F_k} > \beta_2$. It is worth noting that the number of frames added in this part does not exceed n_s .

Finally, n_r frames are randomly selected and added to \mathcal{R} . This is done to prevent catastrophic forgetting of the global map due to continuous learning.

Map optimization. In frame-to-model tracking mode, map optimization is crucial. In continuous SLAM, we design a isotropic regularization loss to overcome anisotropic

influence (strip-shaped Gaussian primitives):

$$\mathcal{L}_{iso} = \frac{1}{N} \sum_{i=0}^{N} (\max\{s_i\} - \min\{s_i\} | s_i > \gamma), \quad (12)$$

and a scalar regularization:

$$\mathcal{L}_{s} = \sum_{i=0}^{N} (s_{i} - \gamma | s_{i} > \gamma), \gamma = 0.03 * \max\{(\mathbf{G})_{z}\}.$$
 (13)

To make the media Gaussian fit the surface better, we design a surface depth loss:

$$\mathcal{L}_{sur} = \left| \tilde{D}_s - D \right|_1. \tag{14}$$

Meanwhile, the surface depth requires geometric depth for maintenance, so we add geometry supervision:

$$\mathcal{L}_d = \left| \tilde{D} - D \right|_1. \tag{15}$$

For color supervision, we combine L1 and SSIM [7] losses:

$$\mathcal{L}_{rgb} = \lambda |\tilde{C} - C|_1 + (1 - \lambda)(1 - SSIM(\tilde{C}, C)). \tag{16}$$

Final map optimization loss:

$$\mathcal{L}_{mapping} = \omega_1^m \mathcal{L}_{rgb} + \omega_2^m \mathcal{L}_d + \omega_3^m \mathcal{L}_{sur} + \omega_4^m (\mathcal{L}_{iso} + 2\mathcal{L}_s), \tag{17}$$

where ω^m is a set of weights for mapping.

C. Tracking

Frame-to-model tracking. We jointly optimize the photometric error based on 3DGS re-rendering and ground truth, as well as the reprojection error based on feature points, to obtain accurate poses. The reprojection loss:

$$\mathcal{L}_{rep} = \sum_{i \in \mathcal{M}} \sum_{i \in \mathcal{P}} \varphi(\|p_i - \pi(W_{cj}, P_i^j)\|_2), \tag{18}$$

where \mathcal{M} is the set of local keyframes, \mathcal{P} represents the matched features, p_i is the pixel observation in the image, W_{cj} is the pose of the j-th camera relative to the current camera and P_i^j is i-th 3D point of j-th camera, and φ represents the information matrix.

During the optimization process, to prevent incorrect feature point matches from impacting the reduction of total loss, we will remove outliers in advance, allowing the re-rendering loss item to become the primary component.

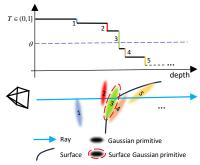


Fig. 3. Surface Gaussian analysis: The coordinate system represents the extent to which transmittance decreases after the ray passes through the Gaussian, along with a visualization of the corresponding position of the Gaussian. The value θ is a predefined threshold, and the Gaussian where T drops to θ indicates the depth value closest to the surface.

Since the re-rendering depth relies on accumulation from rays passing through Gaussians, it can exhibit instability. When a ray passes through a Gaussian with special opacity, the case represented by the index 1 in Fig. 3 or artifacts, this contribution will also be added to the final rendering result. Therefore, we propose surface depth instead of re-rendering depth to enhance the robustness of the tracking. Additionally, we only adopt Gaussian surfaces that are close to full transmittance as geometric features. Further, the optimize the combined loss using the Adam optimizer:

$$\mathcal{L}_{tracking} = (\tilde{T} > 0.99)(\omega_1^t \mathcal{L}_{rgb} + \omega_2^t \mathcal{L}_{sur}) + \omega_3^t \mathcal{L}_{rpj}.$$
(19)

Bundle adjustment. In the backend thread, we use graph optimization to jointly optimize map points and camera poses based on sparse feature points, similar to [1]. The backend operates as an independent thread, unaffected by the training. Therefore, once the camera poses are optimized, they can promptly provide more accurate camera poses for reconstruction, enhancing the reconstruction quality.

IV. EXPERIMENT

A. Experiment Setup

Dataset. To thoroughly evaluate the performance of the method presented in this paper, following [5], [30], [32], we select three sequences from the real-world TUM dataset [40] and eight sequences from the synthetic Replica [39] dataset for comprehensive evaluation.

Baesline. We select the state-of-the-art NeRF SLAM methods: NICE-SLAM [30] and Point-SLAM [32]. In addition, we include 3DGS-based SLAM methods: Splat-TAM [5], GS-SLAM [19], MonoGS [18], Sun [37] and methods combining feature points and 3DGS: Photo-SLAM [20] and TAMBRIDGE [21]. We also incorporated the traditional SLAM method: ORB-SLAM2 [1].

Metrics. For measuring RGB rendering performance we use PSNR(dB), SSIM and LPIPS. For camera pose estimation tracking we use the average absolute trajectory error (ATE RMSE [cm]) [38]. The **best** results will be highlighted in red, while the **second-best** will be highlighted in blue. The result is the average of six times data.

Implementation details. We fully compile our SLAM in C++ and CUDA. Additionally, the SLAM runs on a desktop

TABLE I TRACKING RESULTS ON RGB-D TUM DATASET (ATE RMSE \downarrow [cm]). "-" INDICATES UNAVAILABLE DATA BECAUSE THE RELATED WORK IS

NOT OPEN.								
Method	Fr1/desk1	Fr2/xyz	Fr3/office	Avg.				
ORB-SLAM2	1.60	0.40	1.00	1.00				
Point-SLAM	4.34	1.31	3.48	3.04				
NICE-SLAM	4.26	31.73	3.87	13.28				
MonoGS(RGB-D)	1.52	1.58	1.65	1.58				
GS-SLAM	3.30	1.30	6.60	3.73				
SplatTAM	3.35	1.24	5.16	3.25				
Sun	3.38	_	5.12	-				
Photo-SLAM	2.60	0.35	1.00	1.31				
TANBRIDGE	1.75	0.32	1.42	1.16				
Ours	1.48	0.39	0.88	0.91				
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TABLE II $\label{table ii} Tracking \ Results \ on \ the \ Replica \ Dataset \ (ATE \ RMSE \downarrow \ [cm]).$ The Lost indicates tracking lost.

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Method	R0	R1	R2	Of0	Of1	Of2	Of3	Of4
ORB-SLAM2	0.45	0.29	Lost	0.47	0.28	0.75	0.69	0.59
Point-SLAM	0.61	0.41	0.37	0.38	0.48	0.54	0.69	0.72
NICE-SLAM	0.97	1.31	1.07	0.88	1.00	1.06	1.10	1.13
MonoGS(RGB-D)	0.47	0.43	0.31	0.70	0.57	0.31	0.31	3.20
GS-SLAM	0.48	0.53	0.33	0.52	0.41	0.59	0.46	0.70
SplatTAM	0.31	0.40	0.29	0.47	0.27	0.29	0.32	0.55
Ours	0.35	0.22	0.33	0.33	0.19	0.54	0.63	0.45

equipped with Intel i7-12700KF and an NVIDIA RTX 4060ti GPU. We set parameters $\omega^m = \{1.0, 0.7, 0.1, 5\}, \lambda = 0.8$ $\{\beta_1, \beta_2\} = \{0.07, 0.3\}, \{n_a, n_b, n_s, n_r\} = \{5, 5, 13, 7\}.$ For the TUM datasets, we set weight $\omega^t = \{1.0, 0.7, 0.1\}$, and we set weight $\omega^t = \{0.7, 1.0, 0.1\}$ for the Replica datasets.

B. Localization and Rendering Quality Evaluation

Localization. Table I shows the tracking results on the TUM RGB-D dataset. Our method outperforms other baseline methods, even surpassing the state-of-the-art ORB-SLAM2. In comparison, both TANBRIDGE and Photo-SLAM, which are based on ORBSLAM3 [10], exhibit general localization performance, while ours demonstrates superior localization accuracy. This is not only because we jointly optimize feature points and 3DGS, but also because we propose a novel surface geometry-based tracking method, which better handles noise in real-world environments. Table II reports results on the synthetic Replica dataset. The feature-based ORB-SLAM2 loses track in sequence R2, which contains a weakly textured wall. In contrast, our method not only achieves tracking across all sequences better than ORB-SLAM2, but it also outperforms other 3DGSbased SLAM methods.

Rendering quality. We quantitatively evaluate the rendering quality on the Replica and TUM RGB-D datasets, with the results shown in Table IV and Table V, respectively. It is evident that our method achieves superior rendering quality compared to others. The visualization results in Fig. 4 show that our method is capable of generating higher-quality realistic images.

C. Ablation Study

To demonstrate the role of our component within the GSORB-SLAM, we conducted a series of ablation experiments, with the results presented in Table III and Table VI. In Table VI, we analyse two typical sequences, but this does not mean that our method is ineffective on other sequences.

Surface Depth vs. Depth. We choose the TUM dataset because it contains noise from real-world environments, which strongly demonstrates the advantages of our method. As

TABLE III $TRACKING \ RESULTS \ AT \ DIFFERENT \ DEPTHS \ ON \ THE \ TUM \ DATASETS.$ $(ATE \ RMSE \downarrow \ [CM])$

	*			
Method	Fr1/desk1	Fr2/xyz	Fr3/office	Tracking/Iter.(ms)
Depth	2.46	0.41	0.94	16
Surface depth (Ours)	1.48	0.39	0.88	11

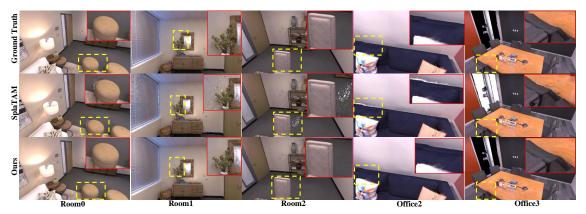


Fig. 4. The render visualization results on the Replica dataset.

TABLE IV RENDERING PERFORMANCE COMPARISON OF RGB-D SLAM METHODS ON REPLICA.

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Sequence	Metric	R0	R1	R2	Of0	Of1	Of2	Of3	Of4
	PSNR↑	32.40	34.80	35.50	38.26	39.16	33.99	33.48	33.49
Point-SLAM	SSIM↑	0.97	0.98	0.98	0.98	0.99	0.96	0.96	0.98
	LPIPS↓	0.11	0.12	0.11	0.10	0.12	0.16	0.13	0.14
	PSNR↑	22.12	22.47	24.52	29.07	30.34	19.66	22.23	24.49
NICE-SLAM	SSIM↑	0.69	0.76	0.81	0.87	0.89	0.80	0.80	0.86
	LPIPS↓	0.33	0.27	0.21	0.23	0.18	0.24	0.21	0.20
	PSNR↑	32.86	33.89	35.25	38.26	39.17	31.97	29.70	31.81
SplatTAM	SSIM↑	0.98	0.97	0.98	0.98	0.98	0.97	0.95	0.95
	LPIPS↓	0.07	0.10	0.08	0.09	0.09	0.10	0.12	0.15
	PSNR↑	31.56	32.86	32.59	38.70	41.17	32.36	32.03	32.92
GS-SLAM	SSIM↑	0.968	0.973	0.971	0.986	0.993	0.978	0.970	0.968
	LPIPS↓	0.094	0.075	0.093	0.050	0.033	0.094	0.110	0.112
	PSNR↑	34.83	36.43	37.49	39.95	42.09	36.24	36.70	36.07
MonoGS(RGB-D)	SSIM↑	0.954	0.959	0.965	0.971	0.977	0.964	0.963	0.957
	LPIPS↓	0.068	0.076	0.075	0.072	0.055	0.078	0.065	0.099
	PSNR↑	35.58	38.07	38.60	42.09	42.49	36.63	36.06	37.89
Ours	SSIM↑	0.986	0.990	0.992	0.993	0.993	0.988	0.989	0.989
	LPIPS↓	0.037	0.039	0.038	0.034	0.030	0.050	0.041	0.053

shown in Table III, it is obvious that our method outperforms the tracking method based on re-rendering depth. This is because our method reduces the impact of artifacts and noise on tracking. In addition, our surface-based method is approximately 10ms faster than the re-rendering-based method.

RF selection strategy. To ensure meaningful comparisons, we reference the frame selection method used in TAN-BRIDGE, which is based on a co-visibility selection strategy. As shown in Table VI, our method not only improves rendering quality but also enhances localization accuracy.

Keyframe generation. To demonstrate that generating keyframes based on sparse feature points has deficiencies in constructing 3D Gaussian fields, similar to what is proposed in TANBRIDGE, we compare original keyframes generated [1] from feature points with our method. In Table VI, our method shows improvements in both PSNR 3 dB and ATE 0.29 cm. Especially in the Of1 sequence, the presence of mostly weak textures prevents keyframes generation, affecting the sampling during training.

TABLE V

RENDERING PERFORMANCE COMPARISON OF RGB-D SLAM METHODS ON TUM DATASETS. "-" INDICATES UNAVAILABLE DATA BECAUSE THE

RELATED	WORK IS NOT	OPEN.
Metric	Fr1/desk1	Fr2

Sequence	Metric	Fr1/desk1	Fr2/xyz	Fr3/office
	PSNR↑	13.87	17.56	18.43
Point-SLAM	SSIM↑	0.63	0.71	0.75
	LPIPS↓	0.54	0.59	0.45
	PSNR↑	12.00	18.20	16.34
NICE-SLAM	SSIM↑	0.42	0.60	0.55
	LPIPS↓	0.51	0.31	0.39
-	PSNR↑	21.22	23.44	20.15
TANBRIDGE	SSIM↑	0.88	0.90	0.82
	LPIPS↓	0.19	0.10	0.25
	PSNR↑	20.870	22.094	22.744
Photo-SLAM	SSIM↑	0.743	0.765	0.780
	LPIPS↓	0.239	0.169	0.154
	PSNR↑	22.60	_	22.30
Sun	SSIM↑	0.91	_	0.89
	LPIPS↓	0.15	_	0.16
	PSNR↑	22.00	24.50	21.90
SplatTAM	SSIM↑	0.86	0.95	0.88
	LPIPS↓	0.19	0.10	0.20
	PSNR↑	23.10	24.70	24.38
Ours	SSIM↑	0.886	0.936	0.911
	LPIPS↓	0.176	0.114	0.171

TABLE VI

THE ABLATION ANALYSIS ON REPLICA RO AND OF1 SEQUENCES.

Variable]	R0	Of1		
RF Stra.	KF Gen.	Reg.	ATE ↓	PSNR ↑	ATE ↓	PSNR↑	
$\overline{}$	√	√	0.35	35.58	0.19	42.49	
X	\checkmark	\checkmark	0.35	34.24	0.24	41.51	
\checkmark	X	✓	0.38	35.21	0.76	35.43	
	✓	Х	0.37	35.52	0.20	42.10	

Regularization. In Table VI, the regularization plays a certain role. This is because the regularization suppresses the Gaussian from forming elongated shapes, thereby reducing its impact on localization.

V. CONCLUSION

We proposed GSORB-SLAM, a tightly coupled system integrating 3DGS and ORB features. Experimental results demonstrated that our joint optimization method, based on geometric surfaces and feature points, reduced the sensitivity of the system to noise. The viewpoint selection strategy, based on a hybrid graph, and the adaptive Gaussian expansion method were designed to improve the rendering quality of dense SLAM. Through experiments, our approach showed impressive performance.

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