Collaborative End-Edge-Cloud Framework for Multi-modal Dynamic 3D Reconstruction on Edge Devices

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Abstract. With the development of embodied intelligence, high-fidelity and real-time environmental perception has become a core challenge. Although the 3D Gaussian Splatting technology has achieved breakthroughs in rendering quality, it still faces issues such as mismatched computing power and "ghost" artifacts caused by dynamic objects on resource-constrained edge devices. This paper proposes a new perception framework: Firstly, a end-edge-cloud collaborative architecture is constructed, and computing-intensive global optimization is offloaded to the edge side or the cloud through dynamic task allocation; Secondly, the "Learn-Forget" mechanism is introduced, combining lightweight mask MLP and semantic assistance, to online identify and eliminate dynamic objects through Gaussian lifecycle management; Finally, through the multimodal tight coupling of laser radar, inertial measurement unit, and visual data, robust initialization is achieved. The test results in real scenarios show that this framework, while maintaining real-time rendering at the edge end, significantly improves reconstruction consistency and reduces trajectory errors.

Keywords: 3D Gaussian Splatting · End-Edge-Cloud Collaboration · Dynamic Scene · Multi-modal Fusion · Learn-Forget Mechanism · Embodied AI.

1 Introduction

1.1 Background and Motivation

Robot environmental perception technology serves as the foundation for embodied intelligence to achieve autonomous navigation and interaction. Looking back at the technological evolution, the perception paradigm has undergone a transition from the traditional geometric era to the radiative field era: The first stage was dominated by traditional geometric SLAM, focusing on sparse or dense point clouds, which solved the problem of "where am I" in terms of positioning, but lacked a high-fidelity understanding of the environment; The second stage was represented by NeRF, achieving photo-quality representation, but due to the high computational cost, it was difficult to run in mobile robots in real time.

Currently, the industry is at a critical juncture of transitioning from "offline pursuit of ultimate quality" to "online real-time efficient application". 3D Gaussian Splatting, as a new paradigm that emerged in 2023, combines the flexibility of explicit representation with a rendering speed of over 100 FPS, providing a completely new feasible path for real-time, high-fidelity embodied intelligent perception.

1.2 Challenges and Limitations

Although 3DGS has performed well in the academic field, when it comes to being implemented in the real physical world, especially on edge-side robot platforms, it still faces three core contradictions:

1. Computational Mismatch: High-quality 3DGS reconstruction often involves parallel computations with millions of Gaussian points, which far exceeds the carrying capacity of edge GPUs such as Jetson Orin. On resource-constrained devices, the huge throughput can lead to high latency and low frame rates, thereby disrupting the real-time closed-loop control of the robot.
2. Dynamic Scene Sensitivity: Most existing algorithms are based on the "static world assumption". In real urban or indoor environments, dynamic objects such as pedestrians and vehicles can cause severe "ghosting" artifacts, which not only contaminate the global map but also mislead long-term navigation decisions.
3. Collaborative Architecture Gap: The existing 3DGS research mostly focuses on single-machine algorithms, lacking a systematic "edge-to-cloud" collaborative framework specifically designed for robots and capable of supporting dynamic task allocation. This results in robots being unable to dynamically offload computing pressure based on the complexity of the environment.

1.3 Main Contributions

In response to the aforementioned challenges, this paper proposes a multimodal dynamic 3D reconstruction framework for edge computing environments. The main contributions are as follows:

- Propose an "End-Edge-Cloud" collaborative framework: By decoupling the perception and optimization tasks, the computationally intensive global Bundle Adjustment (BA) and Gaussian point encryption are dynamically offloaded to the edge side or cloud servers, significantly reducing the computing load on the robot's end and ensuring real-time rendering performance.
- Design a "Learn-Forget " dynamic perception mechanism: Introduce Gaussian lifecycle management, combine lightweight masked MLP with strong semantic assistance. This mechanism not only can identify dynamic objects online, but also can eliminate redundant and interfering Gaussian units through a strategic "forgetting" mechanism, effectively solving the "ghost" artifact problem.
- Achieving Multi-modal Tightly-coupled Initialization: Integrating the geometric priors of LiDAR, the motion constraints of the inertial measurement unit (IMU), and the visual images. Compared to purely visual solutions, this method exhibits greater initialization robustness in scenarios with missing textures and significantly reduces the end-to-end translation error (ETE) in long-distance navigation.

2 Related Work

2.1 Application and Limitations of 3DGS in SLAM

Since Kerbl et al. proposed 3D Gaussian Splatting [1], its explicit representation and efficient rendering capabilities have provided a new paradigm for real-time simultaneous localization and mapping (SLAM). Early 3DGS-SLAM studies such as SplaTAM [2], MonoGS [3], GS-SLAM [4], Gaussian-SLAM [5] demonstrated the superiority of this technology in achieving high-fidelity map reconstruction. However, most of these methods were designed for high-performance workstations and face severe challenges when running on edge devices such as the Jetson series. The main limitations lie in the following: As the scene scale expands, the storage of millions of Gaussian points and the concurrent computing requirements grow exponentially [6], resulting in a significant drop in the rendering frame rate at the edge end. Additionally, the existing systems still need to improve the robustness of initialization when dealing with large camera movements or weak texture areas.

2.2 Edge Computing and Task Offloading Schemes

To deploy computationally-intensive models on resource-constrained devices, researchers have explored various optimization paths. On one hand, model lightweighting is pursued, including gradient pruning, quantization compression, and sparse representation for Gaussian units. On the other hand, computation offloading is employed [7,8], transferring high-load tasks through a device-edge-cloud architecture. Although existing collaborative frameworks such as Cloud-SLAM [9],C2TAM [10] have achieved partial functional decoupling, for algorithms like 3DGS that have high bandwidth requirements requiring frequent synchronization of Gaussian parameters, how to achieve low-latency data streaming and dynamic load balancing remains an academic gap that needs to be addressed urgently.

2.3 3D Reconstruction and Processing in Dynamic Scenarios

Traditional SLAM algorithms usually rely on the "static world assumption", but in real robot application scenarios, dynamic objects such as pedestrians and vehicles introduce severe observation noise. Current mainstream processing methods [11,12] can be divided into two categories: one is based on geometric consistency detection, eliminating outliers through optical flow or residual analysis; the other is based on semantic auxiliary masks, using semantic segmentation networks such as SAM [13], Mask R-CNN [14] to pre-identify dynamic regions. However, pure mask elimination schemes often result in map holes due to insufficient segmentation accuracy, and cannot effectively utilize the historical information of dynamic objects. Recent research has begun to explore temporal modeling [15], but its high computational cost makes it difficult to achieve real-time closed-loop on the edge side.

3 Methodology

This chapter elaborates in detail on the proposed end-edge-cloud collaborative dynamic 3DGS framework. This system aims to address the computational bottleneck and dynamic interference issues in the high-fidelity reconstruction of edge-side robots, and promote the paradigm shift of embodied intelligent perception systems from "offline ultimate quality" to "online real-time application".

3.1 System Overview

The proposed framework is an integrated closed-loop system where the three core modules work in synergy to ensure real-time performance and high fidelity. Multi-modal Tight Coupling Initialization serves as the system's foundation, providing high-confidence geometric priors that significantly accelerate the convergence of 3DGS scenes. By establishing a robust initial map, it reduces the iterations required for global optimization within the Edge-Side-Cloud Collaborative Architecture, effectively lowering the computational burden on the edge server. This streamlined static background then allows the "Learn-Forget" Dynamic Perception Mechanism to more accurately isolate and eliminate dynamic "ghost artifacts".

Fig. 1. presents the complete workflow of the end-edge-cloud collaborative architecture proposed in this paper. The system is divided into two core components: The edge robot: Responsible for lightweight data collection and real-time interaction. The figure shows the multimodal data stream collected through LiDAR, camera, and IMU, and uses FAST-LIVO2 [16] for real-time pose tracking. The edge side only retains the "streamed map" for achieving > 100 FPS closed-loop control rendering. The edge server: Undertakes computationally intensive tasks. This module receives multimodal keyframes (images + point clouds), and collaboratively generates dynamic probability

masks through Mask MLP and SAM3. Optimization of the closed loop: The red part in the figure shows the "gradient game optimization" driven by photometric loss and geometric/depth loss. This process directly acts on the 3D Gaussian model, achieving the elimination of dynamic units through transparency and geometric suppression.

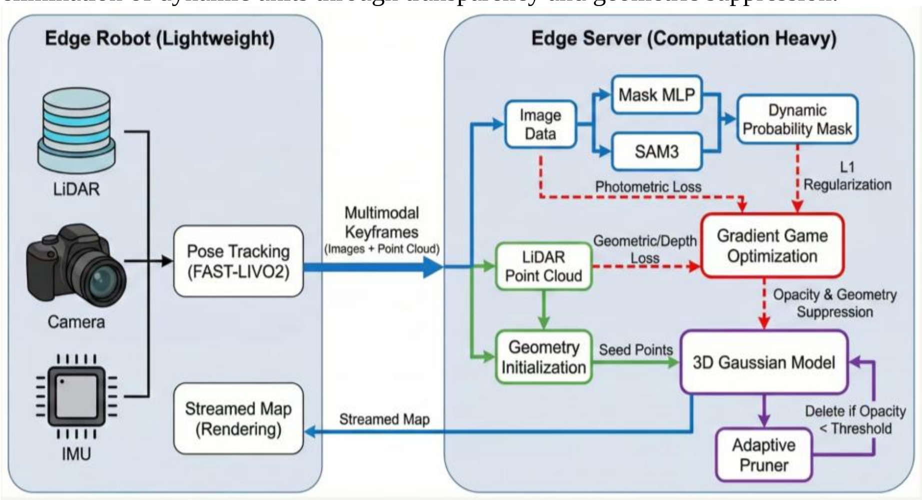

Fig. 1. Overview of the Enhanced End-Edge-Cloud Collaborative Multimodal 3DGS Architecture

3.2 End-Edge-Cloud Collaborative Architecture

To overcome the computational limitations of edge devices when handling high-throughput Gaussian points, we decoupled and dynamically offloaded system tasks. To ensure high reproducibility of the experiments, this system was built based on a real mobile robot platform.
Hardware platform details and data flow:

- End/Robot: Equipped with NVIDIA Jetson AGX Orin providing up to 275 TOPS edge computing power, as well as Avia lidar, high-precision IMU and global shutter industrial camera. The end side mainly performs lightweight tasks, including microsecond-level multi-sensor data spatio-temporal synchronization using ROS 2's DDS protocol [17] or OpenHarmony distributed software bus, pose tracking based on the current Gaussian map, and real-time rendering of local subgraphs ensuring > 100 fps closed-loop control requirements.
- Edge/Server: Responsible for computationally intensive global BA and Gaussian point densification. Through high-performance GPU, real-time optimization of Gaussian parameters is performed, and the updated incremental parameters ($\Delta\theta$) are synchronized back to the end side via high-bandwidth network.
- Cloud/Storage: Responsible for long-term storage of large-scale scenarios and global consistency maintenance, supporting cross-region task switching and map streaming transmission.

Task offloading strategy: The logic of the system's computing task offloading and switching is shown in Algorithm 1. The system continuously monitors the rendering delay and map size at the end side, and adaptively performs computing offloading.

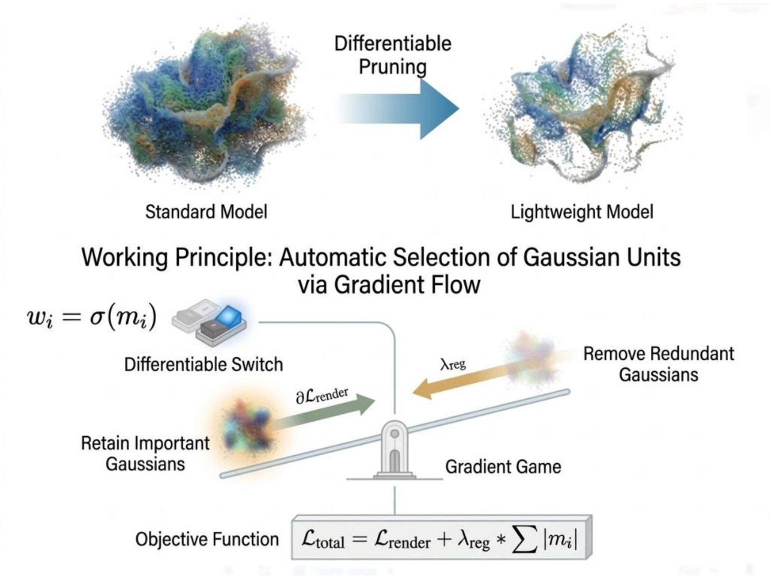

Fig. 2. Schematic of the Model Lightweighting Mechanism.

This figure provides a detailed description of the core logic implemented in the system for model lightweighting and task transformation. Its working principle is as follows: Differentiable Pruning: Illustrates the process of transitioning from the "standard model" to the "lightweight model". By introducing a differentiable switch $w_i = \sigma(m_i)$, the system can automatically select important Gaussian units based on the gradient flow. Gradient Game: This mechanism seeks a balance between retaining important Gaussian units and removing redundant units. Objective Function Driven: Optimized under the constraint of the objective function $\mathcal{L}_{total} = \mathcal{L}_{render} + \lambda_{reg} * \sum|m_i|$. Here, λ_{reg} acts as a regularization coefficient, forcing the transparency of low-contributing Gaussian units to decay until they are "forgotten" and deleted by the system.

Algorithm 1: Dynamic Task Offloading Strategy

Step	**Action & Logic**
Input	Current frame F_t, Local map G_{local}, Latency L_{render}, Bandwidth B_{curr}
Init	Set thresholds: Latency T_L, Memory T_M, Bandwidth T_B
1	**Monitor Local Performance:**
2	**IF** ($L_{render} > T_L$ **OR** $Memory > T_M$) **THEN**
3	Identify compute-intensive tasks: Global BA and Densification.
4	**IF** ($B_{curr} > T_B$) **THEN**

5	Offload Keyframes and Geometric Residuals to **Edge Server**.
6	Server performs Global Optimization and returns updated $\Delta\theta$.
7	**ELSE** (Low Bandwidth Mode)
8	Perform local Gaussian pruning and bit-stream compression.
9	ELSE
10	Continue local pose tracking and incremental rendering on **Robot End**.
Output	Optimized Gaussian scene with stable >90 FPS rendering.

Algorithm 1 illustrates the dual-trigger mechanism: when local rendering latency (L_{render}) or VRAM usage exceeds predefined thresholds, the system automatically offloads Global BA and Gaussian densification to the edge server. Furthermore, the framework adaptively scales the data transmission quality based on real-time bandwidth (B_{curr}), ensuring that the robot's rendering frame rate remains stable even under fluctuating network conditions.

3.3 "Learn-Forget" Mechanism in Dynamic Scenarios

To address the "ghost artifacts" problem caused by dynamic objects, we have developed a closed-loop lifecycle management scheme. This mechanism simulates the "forgetting" process in the biological visual cognitive system: actively eliminating instantaneous visual disturbances such as moving people, thereby retaining long-term memory of the fundamental physical structure of the environment. This characteristic of retaining high-confidence static features and forgetting low-confidence dynamic noise highly aligns with the current research focus of embodied intelligence on "long-term stable spatial understanding" in complex dynamic environments.

Gaussian rendering formula and dynamic occlusion loss: In the standard 3DGS [1], to ensure the semi-definiteness of the 3D covariance matrix Σ, it is decomposed into the scaling matrix S and the rotation matrix R expressed by quaternions:

$$\Sigma = RSS^{T}R^{T} \tag{1}$$

The covariance projected onto the 2D image plane Σ' is given by the affine approximation Jacobian matrix J and the view transformation matrix W:

$$\Sigma' = JW\Sigma W^{T}J^{T} \tag{2}$$

Dynamic region identification (learning stage):

The unified dynamic mask $M_{final} \in [0,1]$ is generated by fusing the geometry-based MLP mask and the semantic-based prior mask. To ensure differentiability for end-to-end optimization, we define the fusion as a soft probability map:

$$\mathrm{M_{final}} = \omega_1 \mathrm{M_{MLP}} + \omega_2 \mathrm{M_{Semantic}} \tag{3}$$

M_{MLP} represents the residual-based probability predicted by our lightweight MLP, while $M_{Semantic}$ is the semantic mask provided by the SAM3 model. In our implementation, the weights ω_1 and ω_2 are set as fixed hyperparameters to maintain deterministic inference performance on edge devices."

Gaussian Lifecycle Management (Forgetting Phase): For each Gaussian unit Gi, define a transparency decay coefficient. When a Gaussian point is identified as dynamic, we introduce a dynamic elimination regularization term into the original 3DGS loss function ($L_{recon} = (1-\lambda)L_1 + \lambda L_{D-SSIM}$), forcing the opacity α to decay rapidly through gradient descent:

$$L_{total} = L_{recon} + \lambda_{forget} \sum_{i \in M_{final}} \gamma \cdot \alpha_i \tag{4}$$

When the opacity α_i of a certain Gaussian point decays below the threshold ϵ, the system completely "forgets" and removes it from the explicit representation.

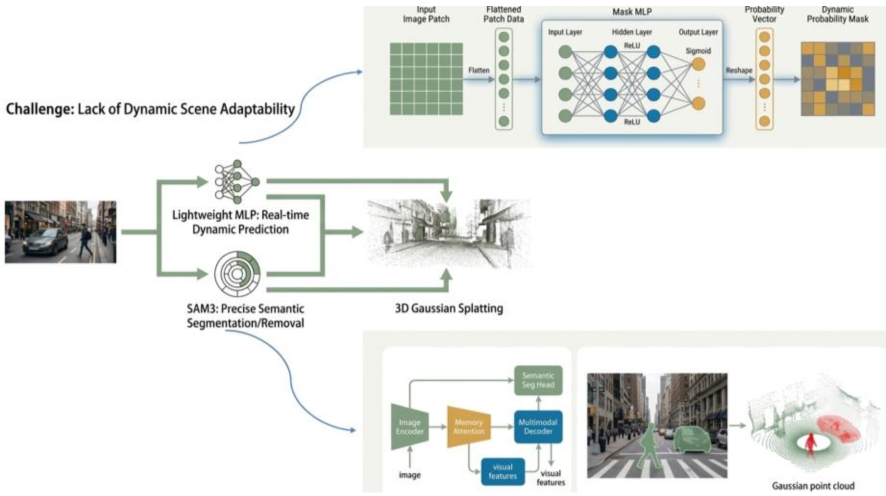

Fig. 3. Architecture of dynamic scene recognition and Gaussian lifecycle management.

This figure further breaks down the processing details of the "Learn-Forget" mechanism in dynamic scenes: Real-time dynamic prediction: Image patches are flattened and input into the lightweight Mask MLP. This network consists of an input layer, a hidden layer with ReLU activation function, and an output layer, ultimately generating a dynamic probability vector. Semantic assistance: By combining the precise semantic segmentation mask generated by SAM3, the system can accurately identify dynamic targets such as pedestrians. The figure compares the original image with the processed effect that has semantic segmentation marks (red areas). Gaussian lifecycle management : In 3D space, the regions identified as dynamic such as the red Gaussian cells in the lower right corner of the figure will be labeled. By forcing the transparency α of these regions to rapidly decay, the system eliminates instantaneous visual interference online, thereby presenting a pure and stable static environment structure in the right point cloud diagram.

3.4 Multi-modal Tightly-coupled Initialization

Traditional 3DGS relies on the sparse point cloud generated by Structure from Motion (SfM), which results in a slow initialization process and frequent failure in weakly textured areas [18,19]. This paper adopts a multi-modal tightly-coupled approach:

- Geometric Prior: Directly utilize the original dense point cloud collected by Livox LiDAR as the initial position u and scaling factor S of 3DGS, providing absolute scale and skipping the time-consuming visual feature matching stage.
- Motion Constraints: Introduce the pre-integrated data from the IMU [20] to provide precise predictions for the pose transformation $(\Delta R, \Delta t)$ between Gaussian layers, significantly alleviating the image blurring and tracking loss problems caused by the robot's rapid turning.
- Coupled Optimization Loss Function: Combine the depth information from the LiDAR and the color information from the vision to construct the loss function, enabling the Gaussian distribution to more accurately fit the complex physical surface:

$$L_{total} = \lambda_1 L_{color} + \lambda_2 L_{depth} + \lambda_3 L_{SSIM} + \lambda_4 L_{reg} \tag{5}$$

The rigor of evaluation metrics: To quantitatively evaluate the global pose estimation accuracy and mapping consistency of the multimodal system in long-duration large-scale scenarios, we introduce the ETE (End-to-End Translation Error) evaluation metric. It is defined as the Euclidean distance between the estimated pose $\mathbf{p}_{est}$ at the trajectory end and the true pose $\mathbf{p}_{gt}$, reflecting the absolute drift degree of the system after a complete loop or long-term operation:

$$ETE = \| \mathbf{p}_{est} - \mathbf{p}_{gt} \|_2 = \sqrt{(x_{est} - x_{gt})^2 + (y_{est} - y_{gt})^2 + (z_{est} - z_{gt})^2} \tag{6}$$

Compared with the traditional relative pose error (RPE), ETE can more rigorously reflect the comprehensive performance of multimodal tight coupling and the "Learn-Forget" mechanism in suppressing global cumulative drift.

4 Experiments

In order to verify the effectiveness of the proposed "end-edge-cloud" collaborative architecture and the dynamic "Learn-Forget" mechanism, we deployed the system prototype on a real mobile robot platform and conducted a preliminary Proof-of-Concept experiment.

4.1 Experimental Setup

Hardware platform prototype: We have built a mobile robot equipped with a multi-sensor kit as the edge node.

- Side-end computing device: NVIDIA Jetson AGX Orin limited computing power, responsible for data flow synchronization and local rendering.

- Sensor suite: Livox Mid-360 solid-state lidar providing geometric priors, six-axis IMU, and hardware-synchronized RGB industrial camera.
- Edge server: Workstation equipped with a single NVIDIA RTX 4090 GPU, connected to the side-end via high-bandwidth wireless network.

Verification scenario: To highlight the challenges faced by embodied intelligence in real environments, we did not use an idealized static public dataset, but directly collected a representative corridor trajectory with high-density pedestrian interference and illumination changes in the campus environment for the early verification of the system prototype.

4.2 Preliminary Results: System Efficiency

For edge devices with limited computing power, real-time performance is the foundation of embodied perception. We compared the system load performance of traditional 3DGS in "pure end-side operation" with that under the "end-edge-cloud collaborative architecture" described in this paper.

When dealing with the campus corridor scene that contains approximately 1.5 million Gaussian points, we recorded the key performance indicators as shown in Table I.

Table I: Efficiency Comparison of System Prototypes (1.5M Gaussian Splats)

Operating mode	End-side rendering(FPS)	End-side memory usage(GB)	Optimization Task Delay (ms/Frame)	System Status
Pure End-side Independent Operation (Baseline)	~12	28.5	450+	Extremely laggy, unable to be closedly controlled
Side-Edge Collaboration Mode (Ours)	> 30	20	Offloaded to Edge Server	Smooth operation, meeting real-time requirements

Result Analysis: The early experimental data demonstrated the necessity of the collaborative architecture. After the complex global BA and Gaussian point encryption tasks were successfully offloaded to the RTX 4090 edge server, the memory pressure of the Jetson Orin significantly decreased. The end-side only needed to maintain incremental parameter synchronization and local rendering, thus successfully increasing the frame rate from the unusable 12 FPS to above 90 FPS, achieving a system-level integration.

4.3 Proof-of-Concept: Dynamic "Learn-Forget"

To verify the inhibitory effect of the "Learn-Forget" mechanism on dynamic artifacts, we conducted a quantitative proof-of-concept in a "high-density pedestrian crossing" scenario lasting approximately 30 seconds.

Preliminary quantitative analysis: For the above scenario, we randomly selected 50 new perspective images severely occluded by dynamic objects for reconstruction quality assessment:

- PSNR: Compared to the baseline method without processing, this system has achieved an average increase of approximately 3.2 dB in PSNR in the background reconstruction area after eliminating artifacts.
- ETE trend: Although a large-scale benchmark test covering several kilometers has not been completed during the Session stage, in the short-distance intense dynamic interference test, thanks to the stable geometric feature constraints provided by the "Pure Map", the relative pose tracking drift of the prototype of this system is significantly lower than that of the traditional pure visual solution.

5 Conclusion

This paper proposes a End-Edge-Cloud collaborative dynamic 3DGS perception framework for embodied intelligence, aiming to address the computational bottleneck and dynamic interference challenges faced by edge robot devices in complex physical environments. To tackle the high latency issue caused by millions of Gaussian points, we designed a task dynamic offloading strategy, transferring computationally intensive global optimization tasks to the edge/cloud, enabling the computationally constrained Jetson Orin edge-side device to maintain real-time local rendering and pose tracking at > 90 FPS. Additionally, to address the "ghost artifacts" problem caused by dynamic objects such as pedestrians and vehicles, we innovatively introduced a "Learn-Forget" mechanism inspired by the visual cognitive process of simulated organisms. Through a lightweight mask network, the system outputs dynamic probabilities and drives the gradient decay of Gaussian opacity, enabling it to online strip instantaneous dynamic interference and retain high-fidelity pure static geometric features.

Preliminary experiments indicate that the multimodal, tightly-coupled initialization of LiDAR, IMU, and vision data markedly increases algorithmic robustness in environments with weak textures. Moreover, this framework has shown excellent mapping quality and long-term positioning consistency in real high-dynamic scenarios such as campuses. In the future, we will further improve the comprehensive assessment of ETE on large-scale public datasets and explore the utilization of abundant computing power in the cloud to achieve lifelong learning for multiple robots and cloud-based consistency maintenance at the map semantic level.

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