

MM3DGS SLAM: Multi-modal 3D Gaussian Splatting for SLAM Using Vision, Depth, and Inertial Measurements

Photorealistic Scene Reconstruction for SLAM Using 3D Gaussian Splatting



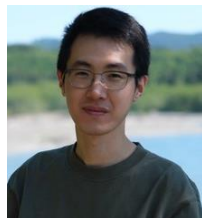
Lisong C. Sun



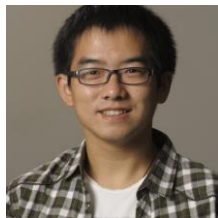
Neel P. Bhatt



**Jonathan C.
Liu**



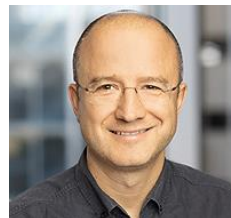
Zhiwen Fan



**Zhangyang
Wang**



**Todd E.
Humphreys**



Ufuk Topcu



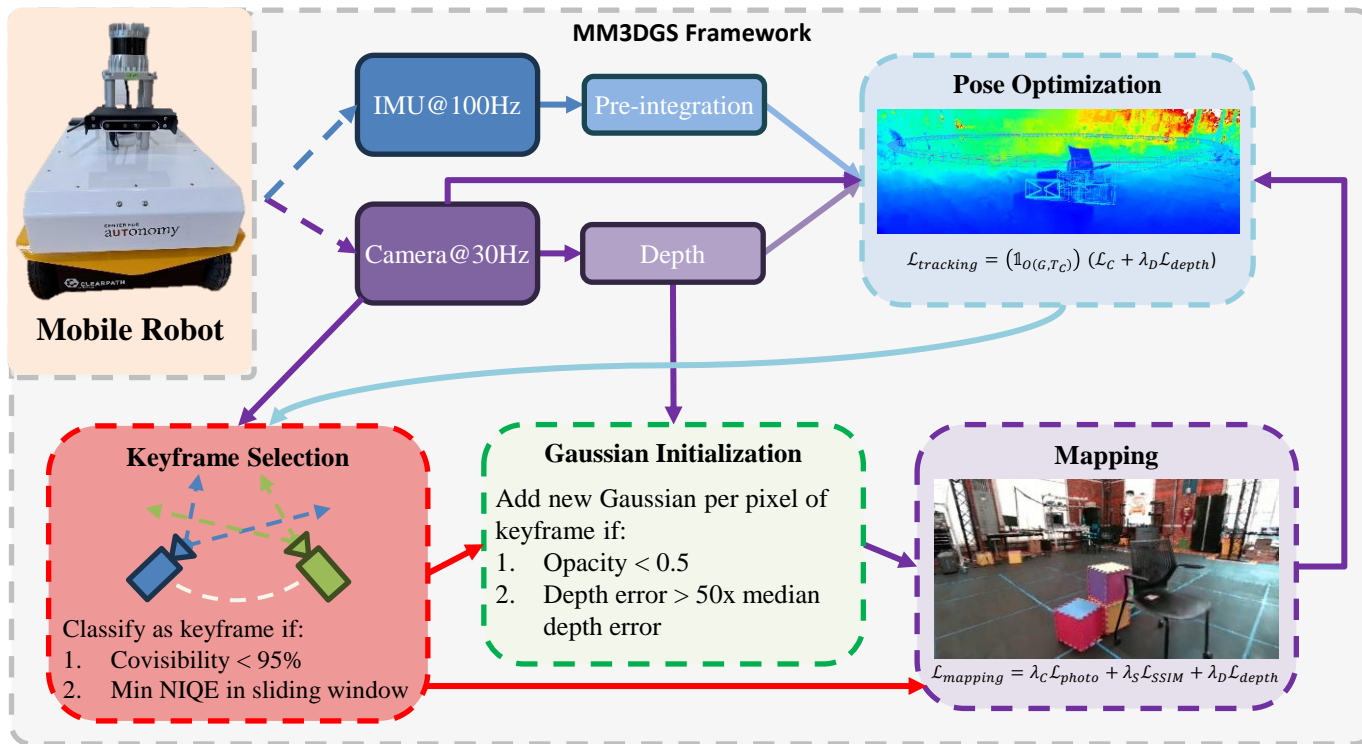
Motivation

- SLAM is essential for **position tracking** and **scene reconstruction**
- Photorealistic reconstruction in real-time is a desired feature for many applications
- How do we enable real-time photorealistic SLAM?

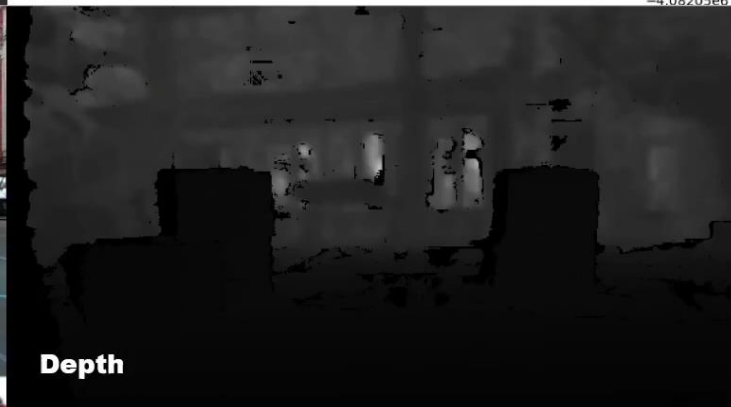
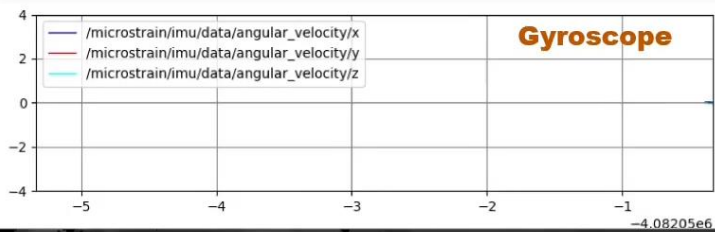
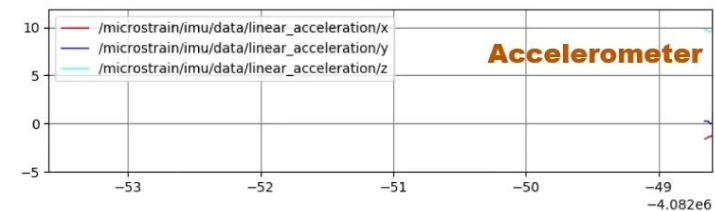
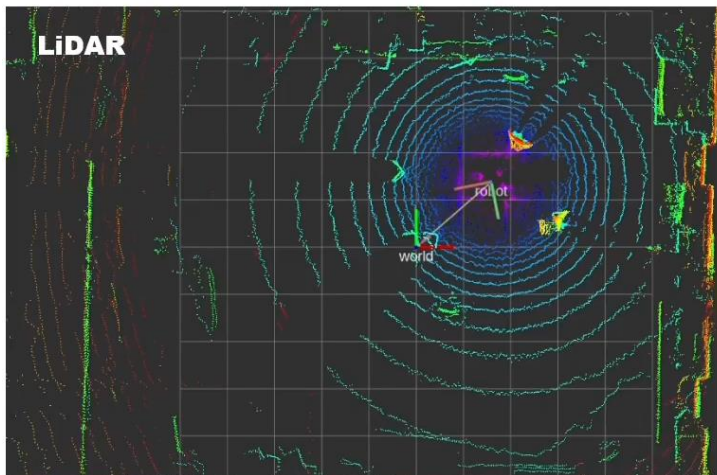
Our Contributions:

- We show for the **first time** that a SLAM framework utilizing a 3D Gaussian map and integrating inertial measurements and depth with unposed RGB images enables **(1)** superior rendering quality, **(2)** superior tracking, and **(3)** scale awareness.
- We release a multi-modal **dataset** consisting of various scenes collected using a mobile robot equipped with these sensing modalities

Overview of the MM3DGS SLAM Framework

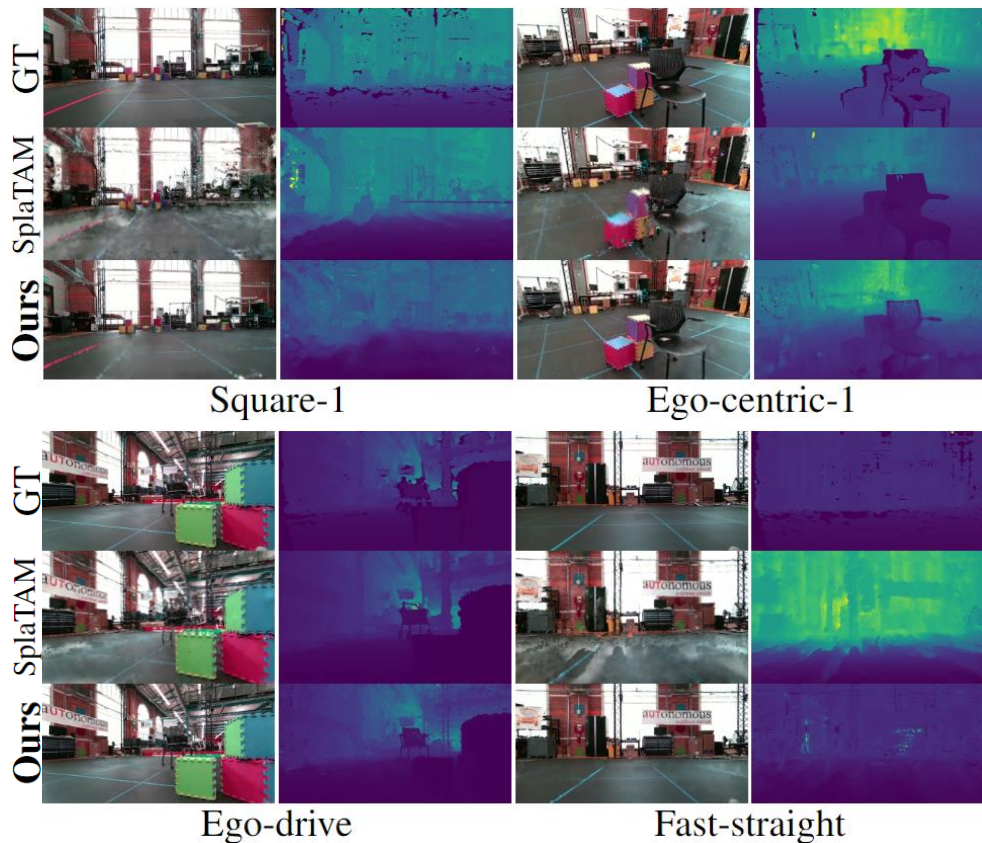


A Scene From Our UT-MM Dataset (RGB-D+LiDAR+IMU+GT)

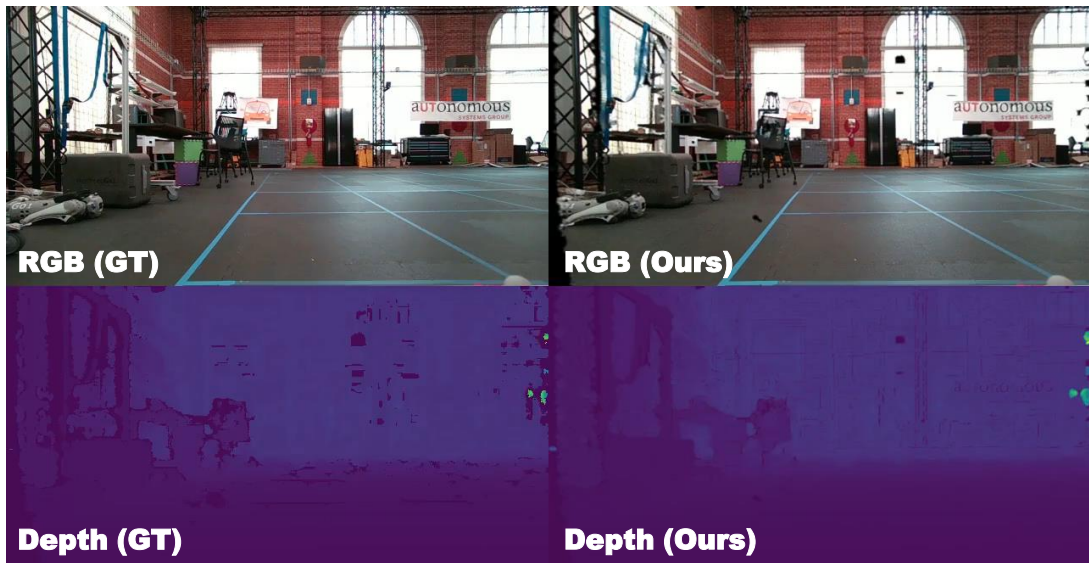


Qualitative Results – Rendering

- We present our results on 4 scenes from our dataset:
 - **Square:** Robot moves along a trajectory outlining a square loop
 - **Ego-centric:** Robot moves around objects of interest while keeping them in the center of the view
 - **Ego-drive:** Robot moves around objects of interest without keeping them in the center of the view
 - **Straight:** Robot moves roughly along a straight path

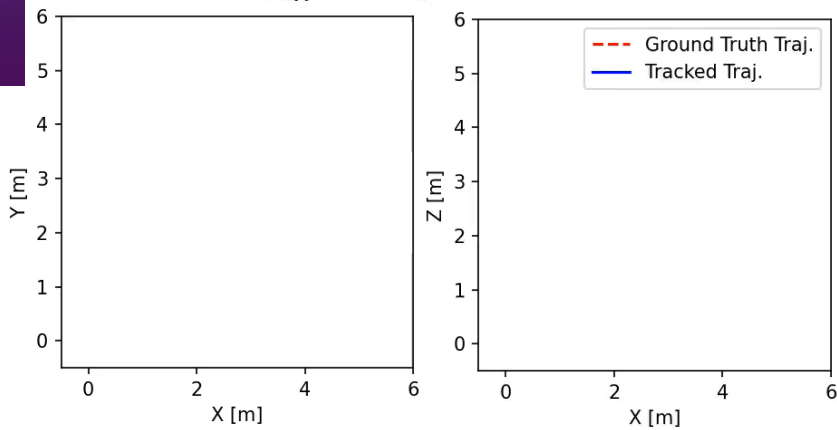
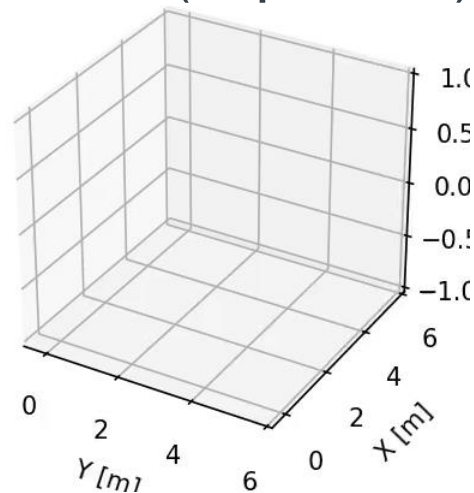


Tracking+Rendering Performance on UT-MM (Square-1)



Online map generation

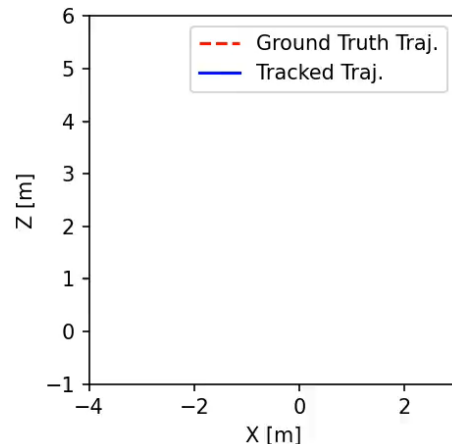
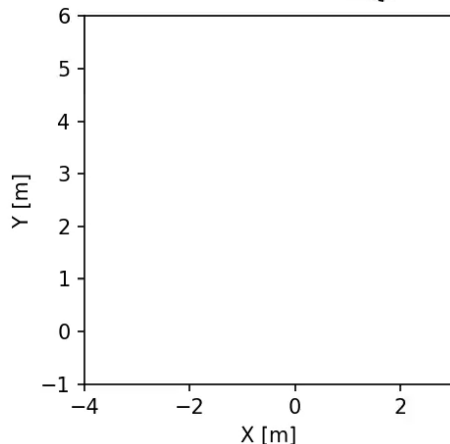
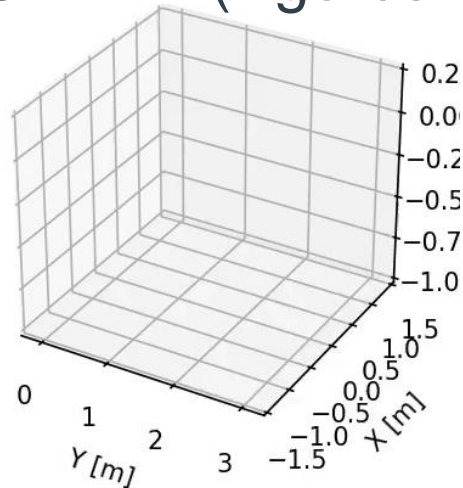
- Our framework integrates RGB-D+IMU with keyframing along with a depth loss based on the Pearson correlation coefficient and can render at **90fps**
- We achieve **3x** better tracking and **5%** increase in rendering quality compared to the state-of-the-art baseline (SpliTAM)



Tracking+Rendering Performance on UT-MM (Ego-centric-1)

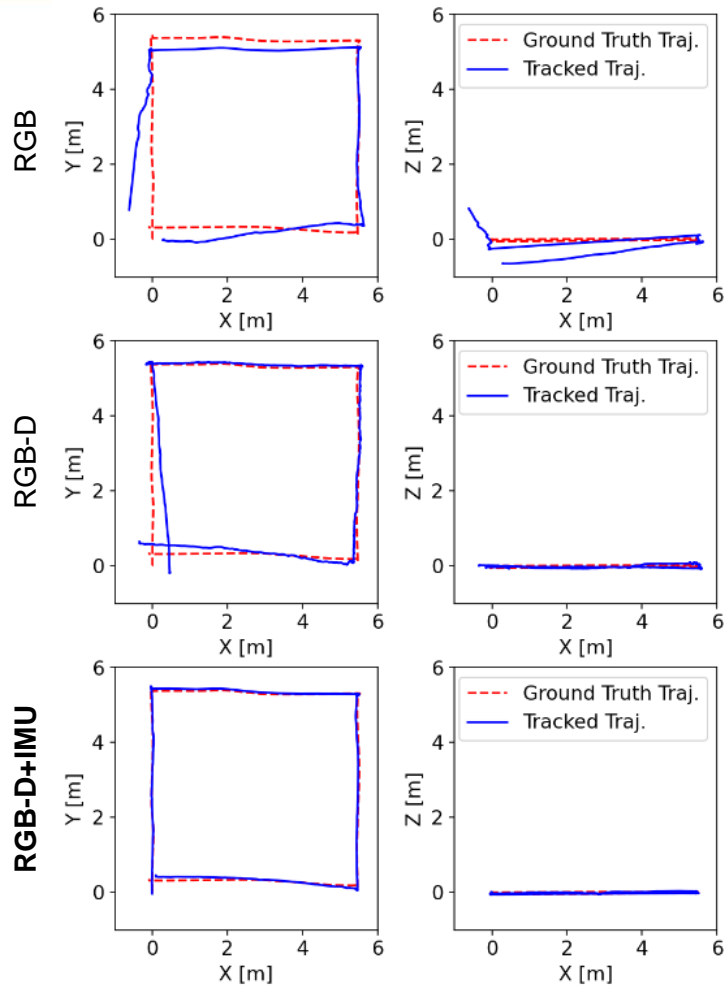


Rendered map (post generation)



Qualitative Results – Tracking

- Depth measurements help correct drift in the vertical direction (z)
- IMU measurements help correct drift in the longitudinal and lateral directions (x and y)
- IMU and depth measurements together help address drift related errors in all directions



Quantitative Results

- SplaTAM uses RGB-D data (does not integrate IMU) without keyframing and an L1 loss for depth
- Our framework integrates RGB-D+IMU with keyframing and depth loss is based on the Pearson correlation coefficient
- We achieve **3x** better tracking and **5%** increase in rendering quality

TABLE I: Multi-modal SLAM results on the UT-MM dataset: ATE RMSE \downarrow is in cm and PSNR \uparrow is in dB, with SplaTAM is used as a baseline. Best results are in **bold**. Both depth and inertial measurements benefit tracking and image quality.

Method	Avg		Square-1		Ego-centric-1		Ego-drive		Fast-straight	
	ATE	PSNR	ATE	PSNR	ATE	PSNR	ATE	PSNR	ATE	PSNR
SplaTAM (RGB-D)	12.06	22.03	32.86	18.67	4.40	22.78	4.20	20.61	6.78	26.07
Ours (RGB)	39.14	19.73	59.48	16.54	4.09	23.151	67.20	17.51	25.78	21.71
Ours (RGB+IMU)	33.23	19.58	44.26	17.01	3.41	22.96	68.50	17.12	16.78	21.24
Ours (RGB-D)	8.75	22.20	20.38	16.55	6.86	22.24	4.25	23.58	3.52	26.42
Ours (RGB-D+IMU)	3.98	23.30	7.11	18.59	1.15	24.95	4.54	23.61	3.13	26.05

Conclusion

Our Contributions:

- We develop MM3DGS: the **first SLAM framework** utilizing a 3D Gaussian map and integrating inertial measurements and depth with unposed RGB images
- We achieve **3x** superior tracking and **5%** increase in rendering quality along with enhanced scale awareness
- We release a multi-modal dataset collected using a mobile robot equipped with these sensing modalities where we showcase these results



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Thank you!

