

SLAM for Robotics: Towards Lifelong Spatial Memory and Navigation in Unstructured Worlds

Jianhao Jiao

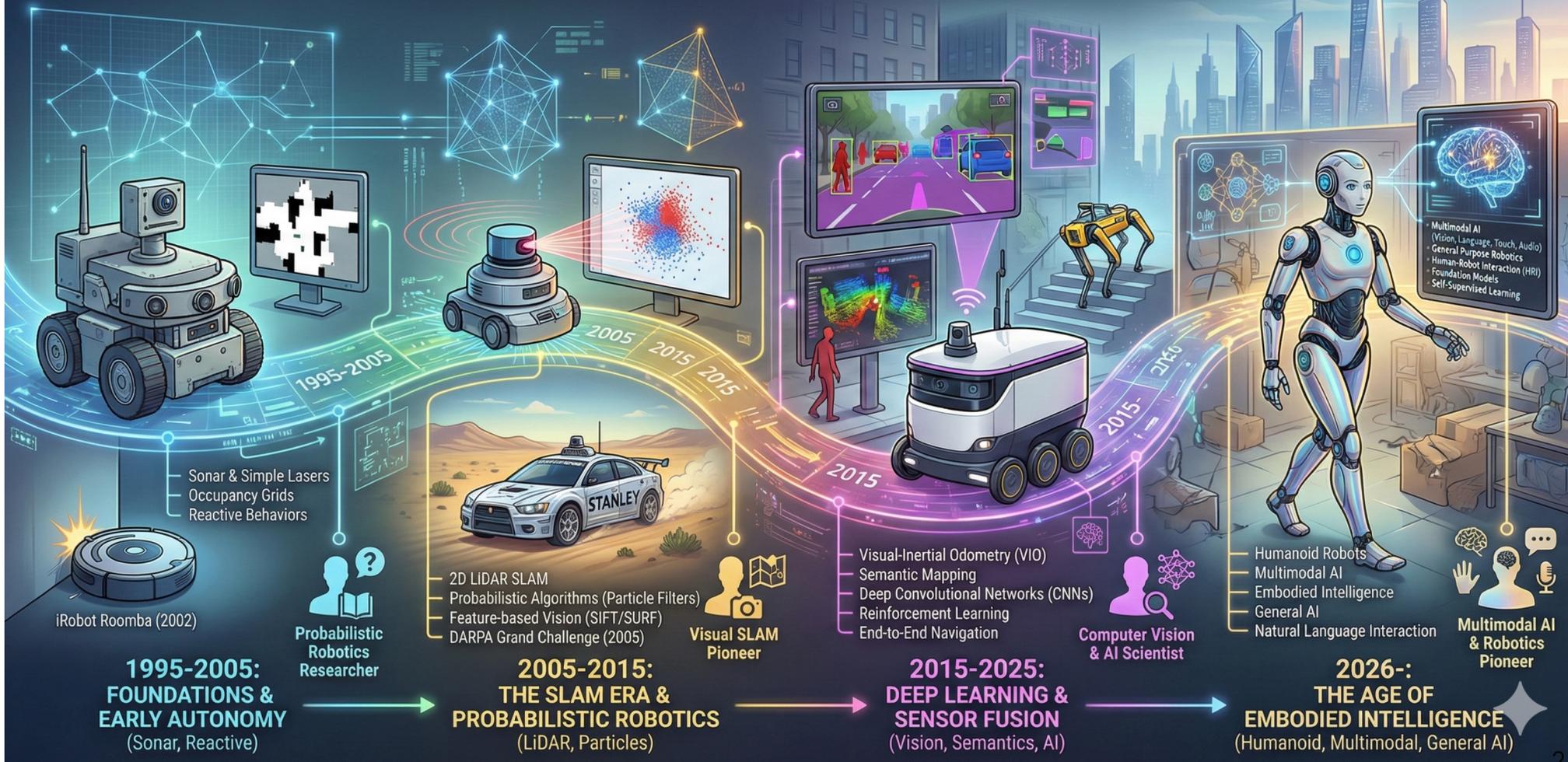
Senior Research Fellow
University College London

Email: jiaojh1994@gmail.com | Website: <https://gogojjh.github.io>

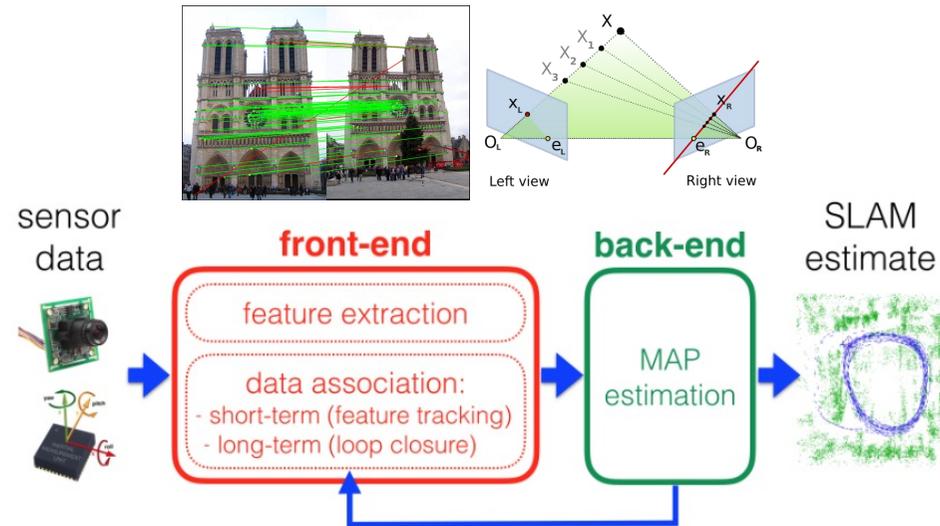


Invited by Prof.Hong Zhang, SUST
2026-03-05

30-YEAR EVOLUTION OF MOBILE ROBOT NAVIGATION & THE FUTURE OF EMBODIED INTELLIGENCE (1995-2026+)



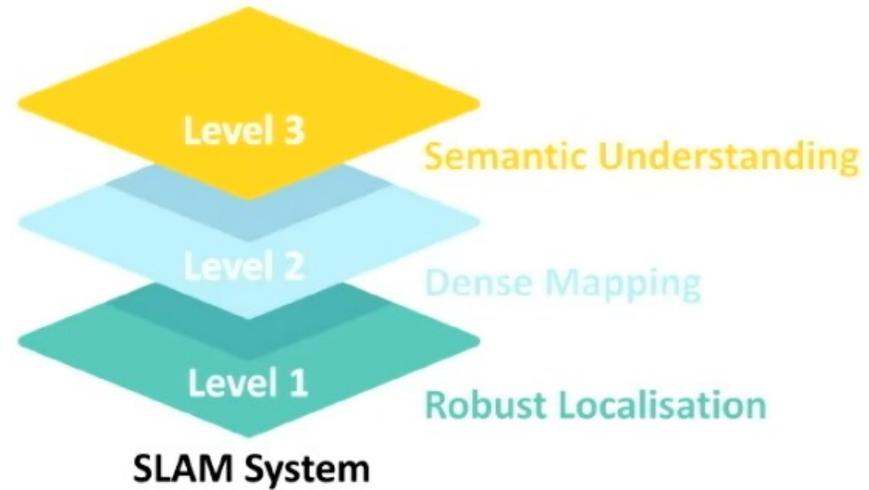
What is SLAM?



➤ SLAM comprises the simultaneous estimation of the **state** of a robot equipped with on-board sensors, and the construction of a model (the **map**) of the environment that these sensors are perceiving.

--- *Past, present, and future of SLAM: Toward the robust-perception age, T-RO2017*

What is SLAM?



- **Spatial AI** is the online problem where vision is to be used, usually alongside other sensors, as part of the AI which permits an embodied device to interact usefully with its environment.
- **SLAM**, a continuously evolving and broadening field with progress marked by real-time system-building, demos and open source, is the basis for working towards Spatial AI.

--- Prof. Andrew Davison, talk at MIT 2025

SLAM Examples



Gaussian Splatting SLAM [Matsuki2024CVPR]

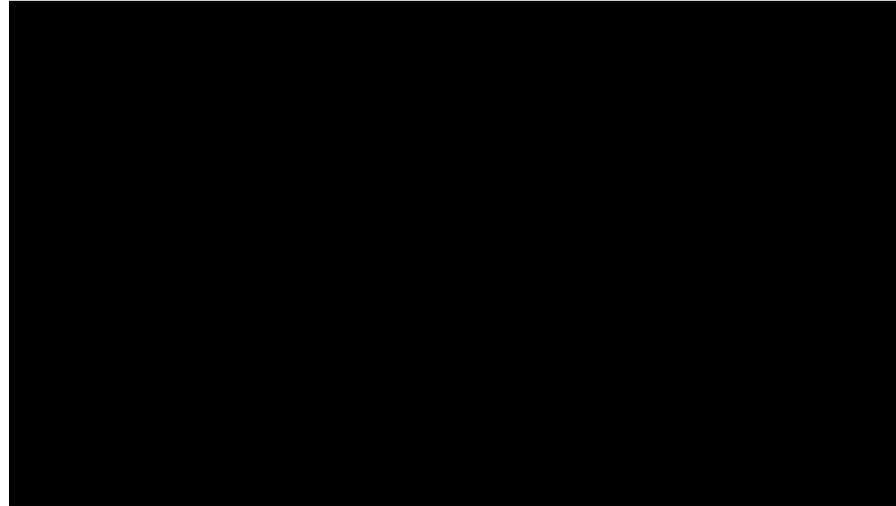


Scene Graph Reconstruction [Hughes2022RSS]

SLAM for Robotics: Mobile Autonomy Outside the Lab

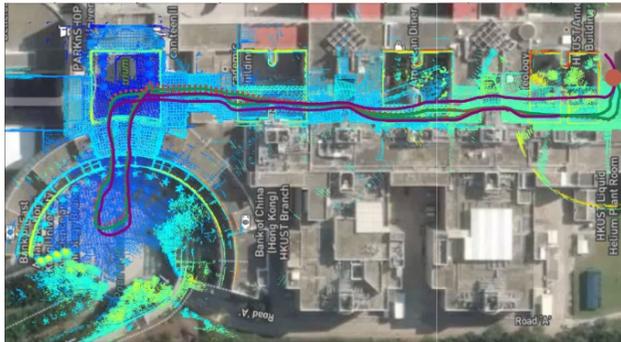


Vision-Language Navigation [Zantout2025IROS]

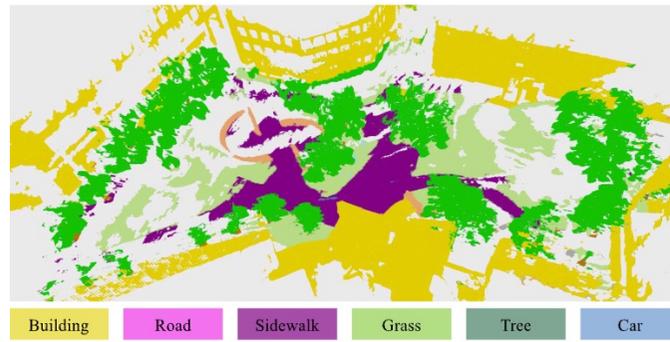
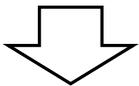


High-Speed Navigation [Ren2025SR]

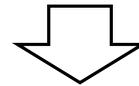
From Classic SLAM to Lifelong Navigation



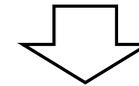
LiDAR SLAM [Jiao2021TRO]



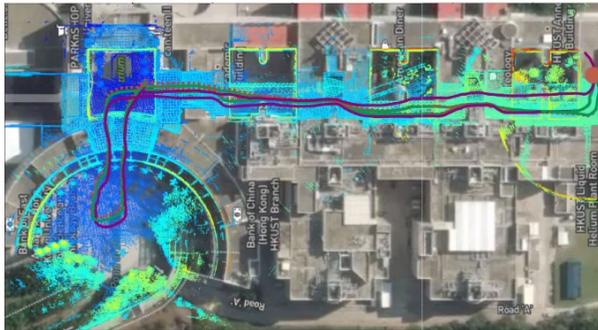
Metric-Semantic Mapping [Jiao2024TASE]



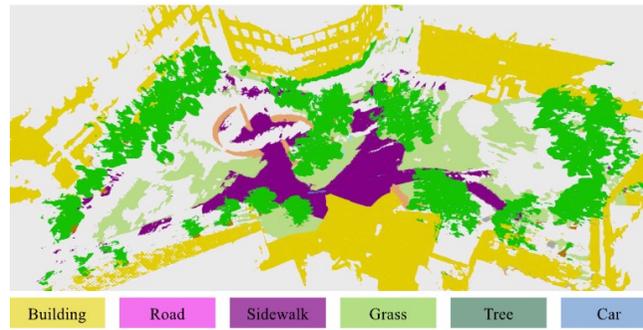
Lifelong Navigation [Under Review]



From Classic SLAM to Lifelong Navigation



LiDAR SLAM [Jiao2021TRO]



Metric-Semantic Mapping [Jiao2024TASE]

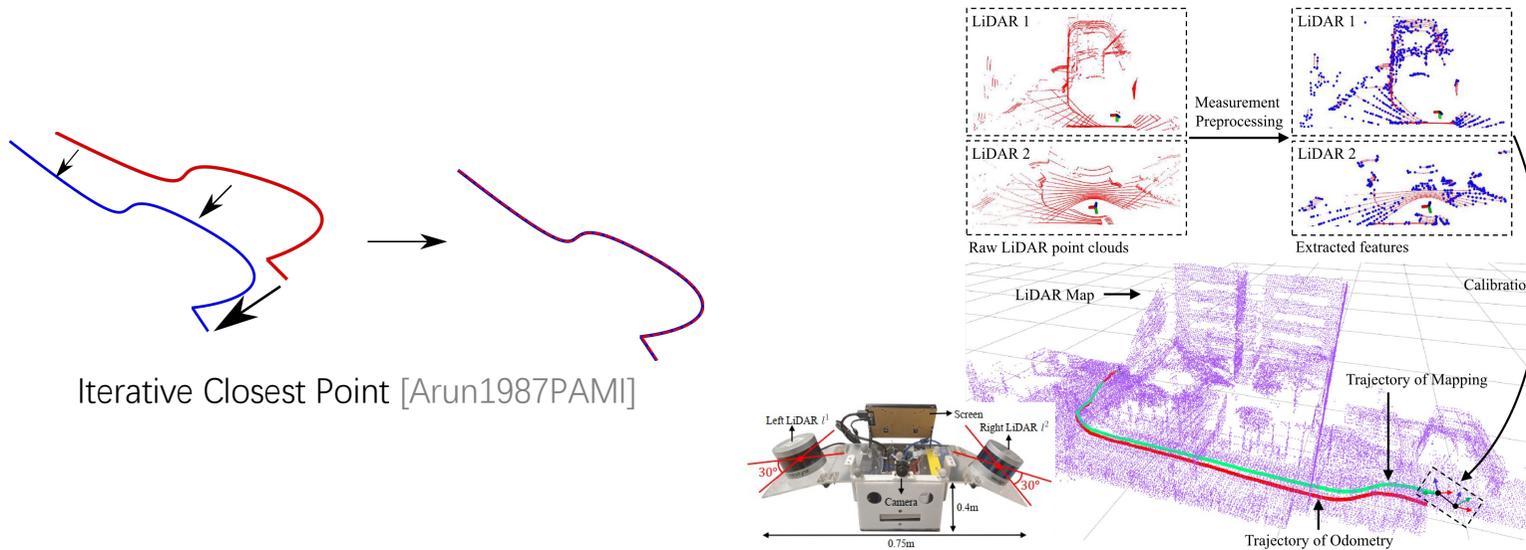


Lifelong Navigation [Under Review]

Some questions:

- Why does this transition happen?
- What are the new focus in lifelong navigation?
- What are the best candidates for scene representations?

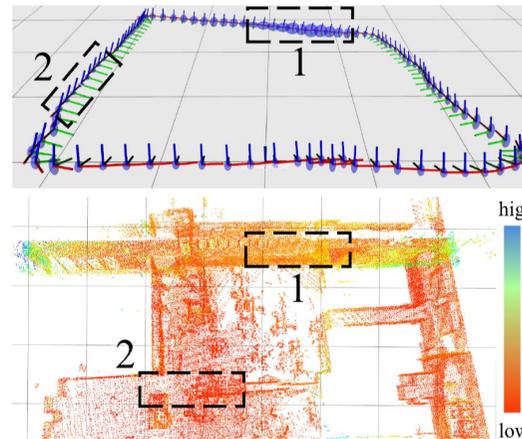
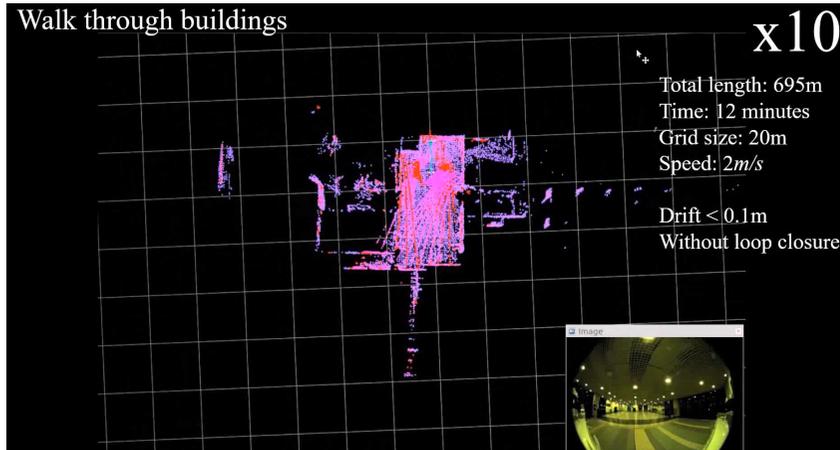
Classic LiDAR SLAM



M-LOAM: Multi-LiDAR SLAM with uncertainty-aware mapping [Jiao2021TRO]

- Extrinsic as one of estimated states
- Propagate errors (noise, extrinsic error, degeneracy) into map

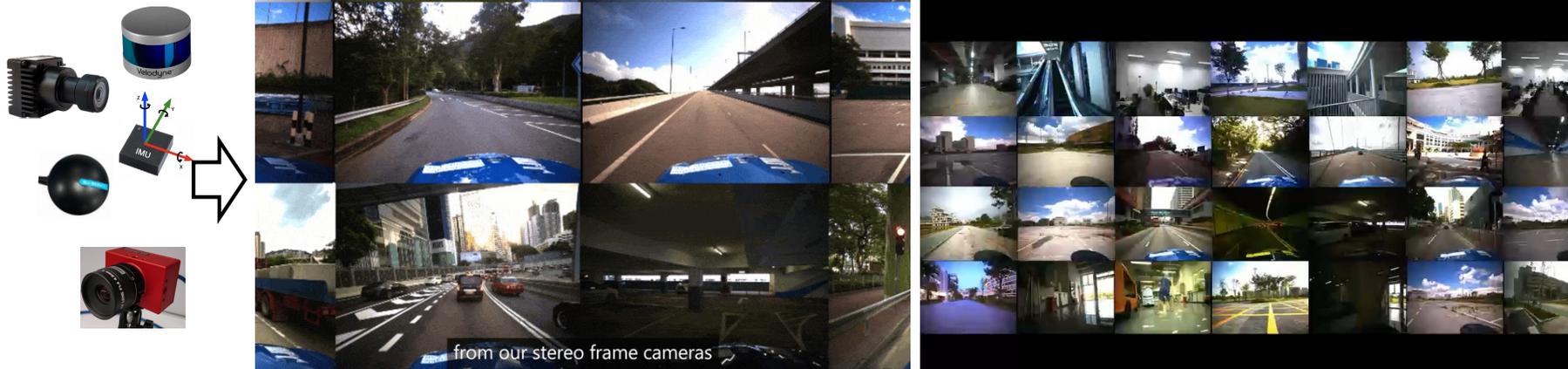
Classic LiDAR SLAM (2018-2021)



M-LOAM: Multi-LiDAR SLAM with uncertainty-aware mapping [Jiao2021TRO]

- Extrinsic as one of estimated states
- Propagate errors (noise, extrinsic error, degeneracy) into map

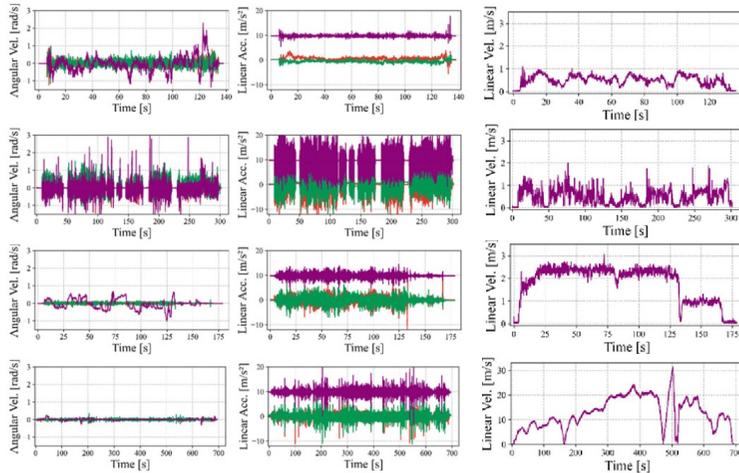
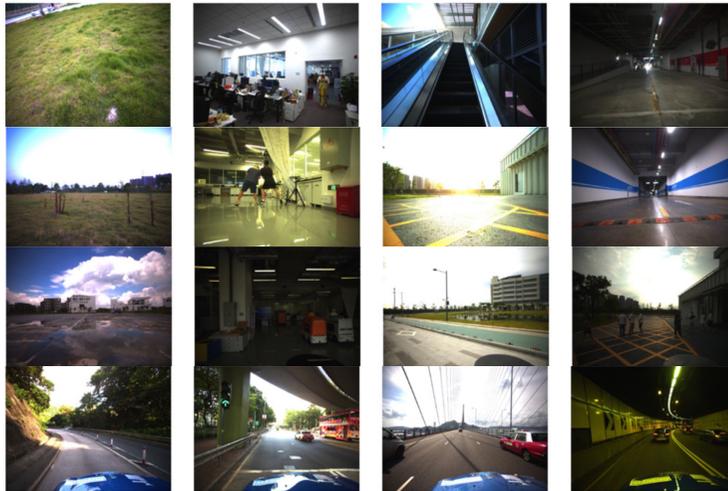
Challenging SLAM Datasets (2021-2023)



FusionPortable Dataset for SLAM Evaluation [Jiao2022IROS] [Wei2025IJRR]

- **Open question:** is it possible to use one SLAM for all platforms and all environments?
- **Data:** 42km trajectories on 4 platforms, covering 10 challenging scenarios
- Motion patterns for different types of robots vary significantly

Challenging SLAM Datasets (2021-2023)



fusionportable.github.io/dataset/fusionportable_v2/

FusionPortable Research Dashboard

- Home
- Calibration
- Localization & Mapping
- Perception
- Datasets
- Search
- Previous
- Next

FusionPortable V2

From Campus to Highway: A Unified Multi-Sensor Dataset for Generalized SLAM Across Diverse Platforms and Scalable Environments

News

- (2025-09-28) The list of [Related Works](#) that have utilized the FusionPortable dataset has been updated.
- (20250410) Some rosbags are extracted as individual files and converted into the KITTI format. Click here to try.
- (20240629) The tutorial of sensor calibration (intrinsic and extrinsic) is provided. Click here to try.
- (20240508) Groundtruth poses of all vehicle-related sequences are postprocessed: eliminate poses characterized by high uncertainty.
- (20240422) Data can be downloaded from [Baidu Wang Pan](#) with the code `bjj8`.
- (20240414) All sequences, ground-truth trajectories, and ground-truth maps have been publicly released. If you find issues of GT trajectories and maps, please contact us or report here.
- (20240413) A small simulated navigation environment is provided.
- (20240408) The development tool has been initially released.
- (20240407) Data can be downloaded from [Google Drive](#).

Overview

Usage Steps

- Read through the overview of the FusionPortableV2 dataset: *sensors*, *coordinate frames*, and *definitions of ROS topics and message*.
- Download data from this [link](#).
- Check examples of using the dataset from this [link](#).

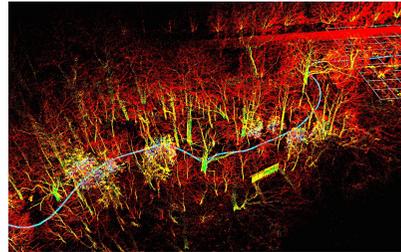
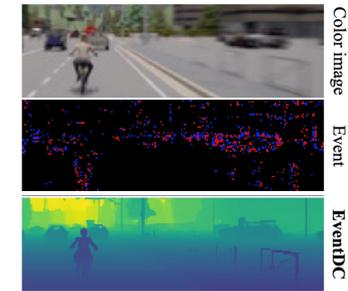
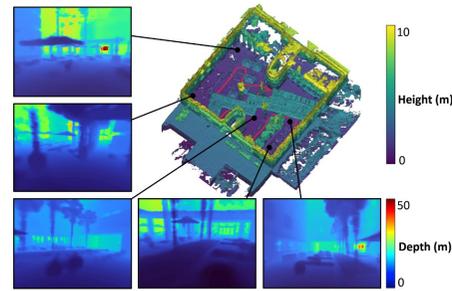
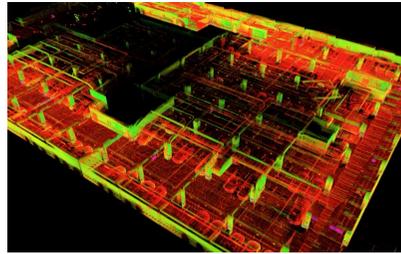
Sensors

- Handheld Sensor:**
 - 128-beam Ouster LIDAR (OS1, 120m range);
 - Stereo FLIR BFS-U3-3154C cameras;
 - Stereo DAVIS346 cameras;
 - STM300 IMU;
 - 3DM-GQ7-GNSS/INS
- UGV Sensor:** Omron E6B2-CW26C wheel encoder
- Legged Robot Sensor:** Built-in joint encoders, contact sensors, and IMU of the Uniree A1

Sensor	Characteristics	ROS Topic	ROS Message Type	Rate (Hz)
3D LIDAR	Ouster OS1-128, 83°vert. × 360°horiz. FOV DME: ICN20048, 9-axis MEMS Range: near-ir, reflectivity, signal images	/os1cloud/points /os2cloud/imu /os_image_node/range, nearir, ..._image	sensor_msgs/PointCloud2 sensor_msgs/Imu sensor_msgs/Image	10 100 10
Frame Camera	Stereo FLIR BFS-U3-3154C, global shutter 66.2°vert. × 42.0°horiz. FOV 1024 × 768 resolution	/stereo/frame_(left, right)/image_raw	sensor_msgs/CompressedImage	20
Event Camera	Stereo DAVIS346, 67°vert. × 83°horiz. FOV 346 × 240 resolution Images that capture color data	/stereo/davis_(left, right)/events /stereo/davis_(left, right)/image_raw	dds_msgs/EventArray sensor_msgs/CompressedImage	30 20
IMU	IMU: MPU6150, 6-axis MEMS STM300, 6-axis MEMS	/stereo/davis_(left, right)/imu /stm300/imu	sensor_msgs/Imu	1000 200
INS	3DM-GQ7-GNSS/INS Dual antenna, RTK-enabled INS	/3dm/ins/raw/odom /3dm/ins/gps_(left, right)/fix /3dm/ins/ins	nav_msgs/Odometry sensor_msgs/NavSatFix sensor_msgs/Imu	10 10 200
Wheel Encoder	Omron E6B2-CW26C, 1000PR	/mini_hercules/encoder	sensor_msgs/Float32	100
Legged Sensor	Built-in joint encoders and contact sensors Built-in DMU	/uniree/joint_state /uniree/imu	sensor_msgs/JointState sensor_msgs/Imu	50 50
	Out-of-the-box kinematic-inertial odometry	/uniree/body-odom	nav_msgs/Odometry	50

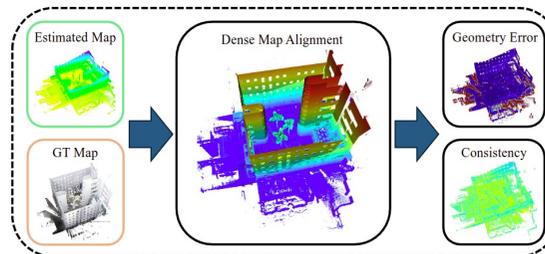


Impact of the FusionPortable Dataset

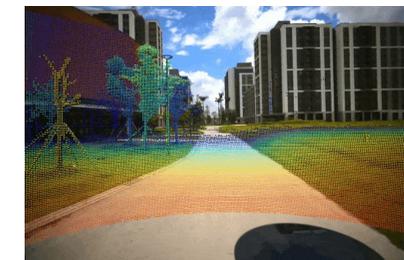


LONER [RAL2023]

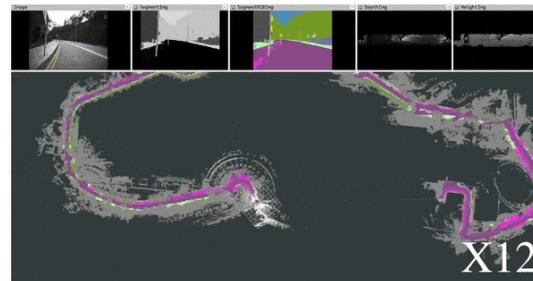
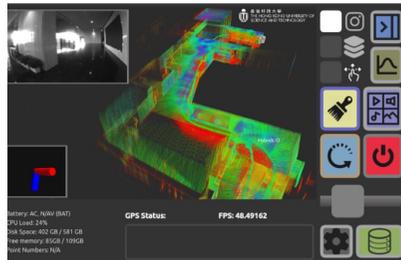
Event-based Depth Completion [NeurIPS2025]



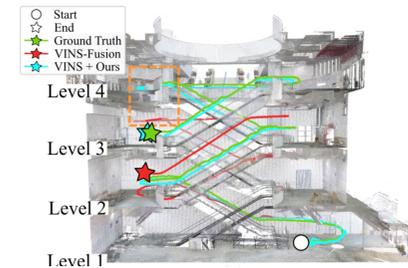
Mapping Evaluation [RAL2025]



LCE-Calib [T-MECH2022]



Metric-Semantic Mapping [TASE2024]



Verification of Loop Closure [Under Review]



SLAM-Enabled Products and Systems



Drones



AR Glasses



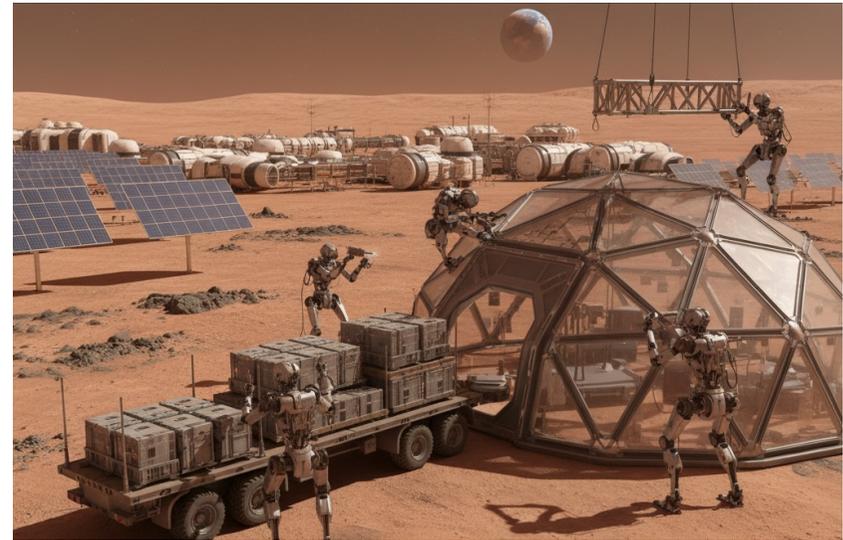
Sweeping Robots

- **Mature Geometric Perception:** Localization and sparse/semi-dense serve as foundational technologies for many real-world products.
- **But Autonomy Gap:** systems remain fragile and lack context as well as interaction, requiring human intervention for long-term operation or recovery.

Next-Gen SLAM: Spatial Memory for Embodied Navigation



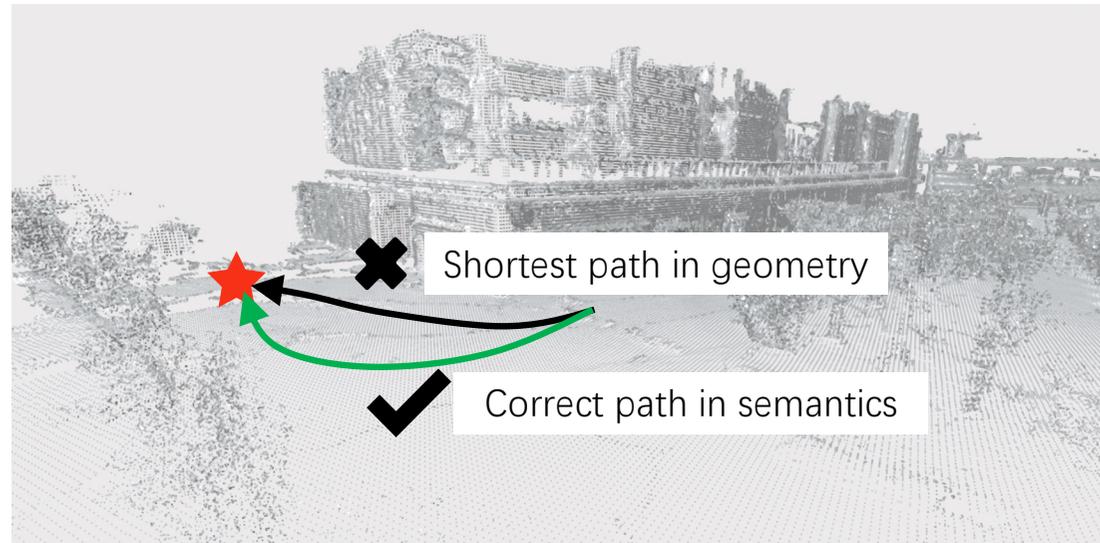
Semantic Understanding



Task Versatility and Learning

Lifelong Autonomy

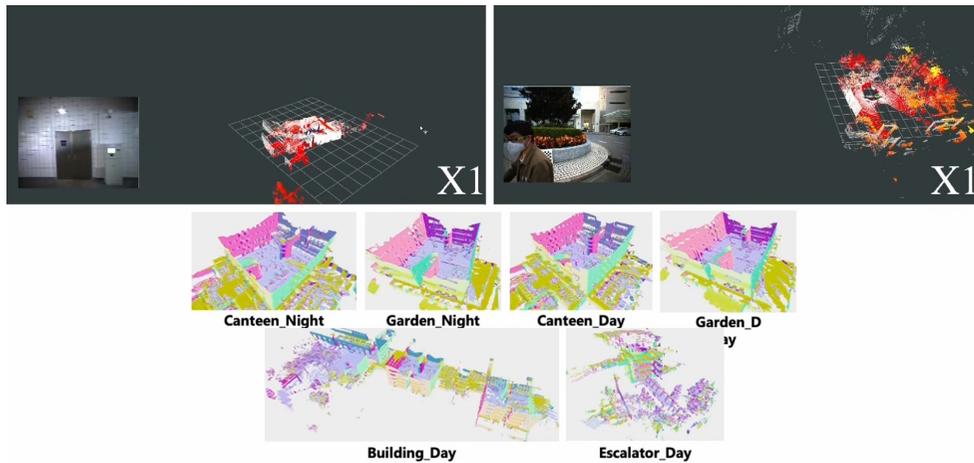
Large-Scale Semantic Mapping



Real-time metric-semantic mapping [Jiao2024TASE]

- GPU-accelerated volumetric mapping
- Bayesian update for noisy semantic labels
- Enhance the safety of robot navigation in unstructured environments

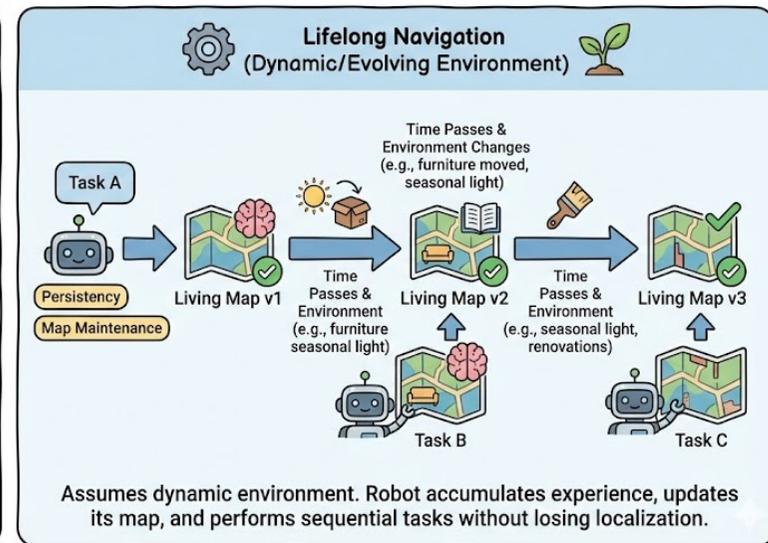
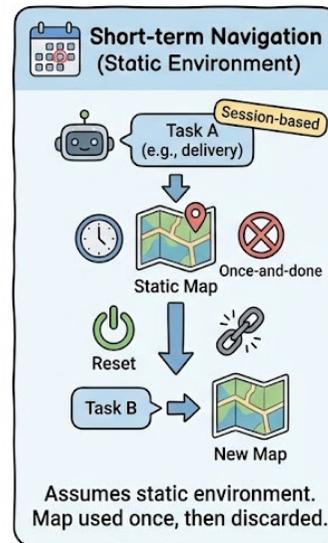
Large-Scale Semantic Mapping



Real-time metric-semantic mapping [Jiao2024TASE]

- GPU-accelerated volumetric mapping
- Bayesian update for noisy semantic labels
- Enhance the safety of robot navigation in unstructured environments

New Focus: Lifelong Navigation



What lifelong navigation focuses:

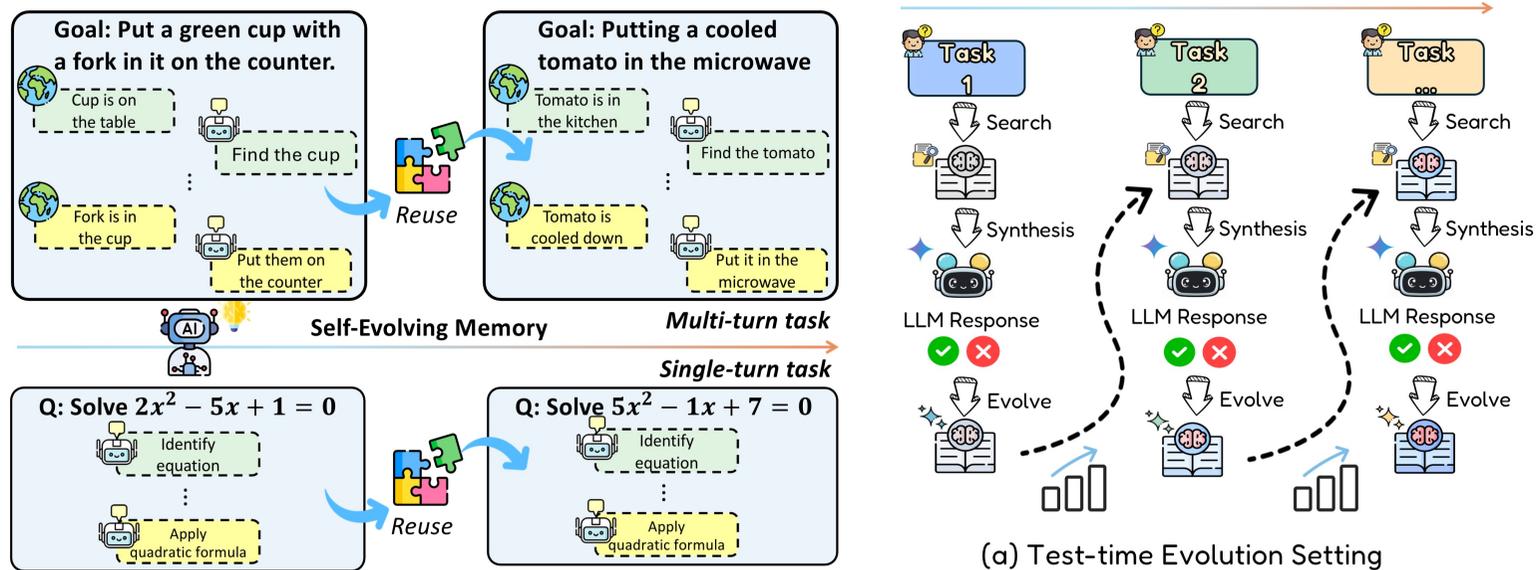
- **Working** in highly dynamic real-world scenarios
- **Problems:** long-term localization, semantic understanding, dynamic mapping, etc.
- **Beyond accuracy evaluation:** success rate, memory growth rate, etc.

Coincidence vs. Inevitability: Map as a type of Memory

Evo-Memory: Benchmarking LLM Agent Test-time Learning with Self-Evolving Memory

Tianxin Wei^{†,1}, Noveen Sachdeva², Benjamin Coleman², Zhankui He², Yuanchen Bei¹, Xuying Ning¹, Mengting Ai¹, Yunzhe Li^{†,1}, Jingrui He¹, Ed H. Chi², Chi Wang², Shuo Chen², Fernando Pereira², Wang-Cheng Kang² and Derek Zhiyuan Cheng²

[†]Work done while at Google DeepMind, ¹University of Illinois Urbana-Champaign, ²Google DeepMind



Existing Solutions: Dense Mapping and Graph Extraction

i. Scan the environment



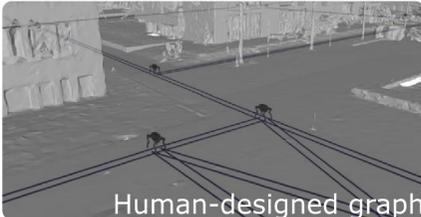
Laser scanner

ii. Process point cloud



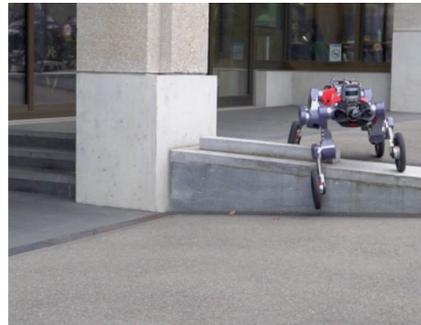
Collection time: ~ 90 min.

iii. Create navigation graph



Human-designed graph

iv. Path planning & Follow



[Lee2024Science Robotics]

- ✓ Accurate results
- ✓ Well-defined pipeline

- ✗ Carefully data capture
- ✗ High storage overload
- ✗ Time-consuming reconstruction

Existing Solutions: Teach and Repeat



[Qiao2025ICRA]

- **Teach:** user drives a robot which stores sparse visual information in a relative pose graph
- **Repeat:** robot localizes by matching live visual data to map and steers to stay on path

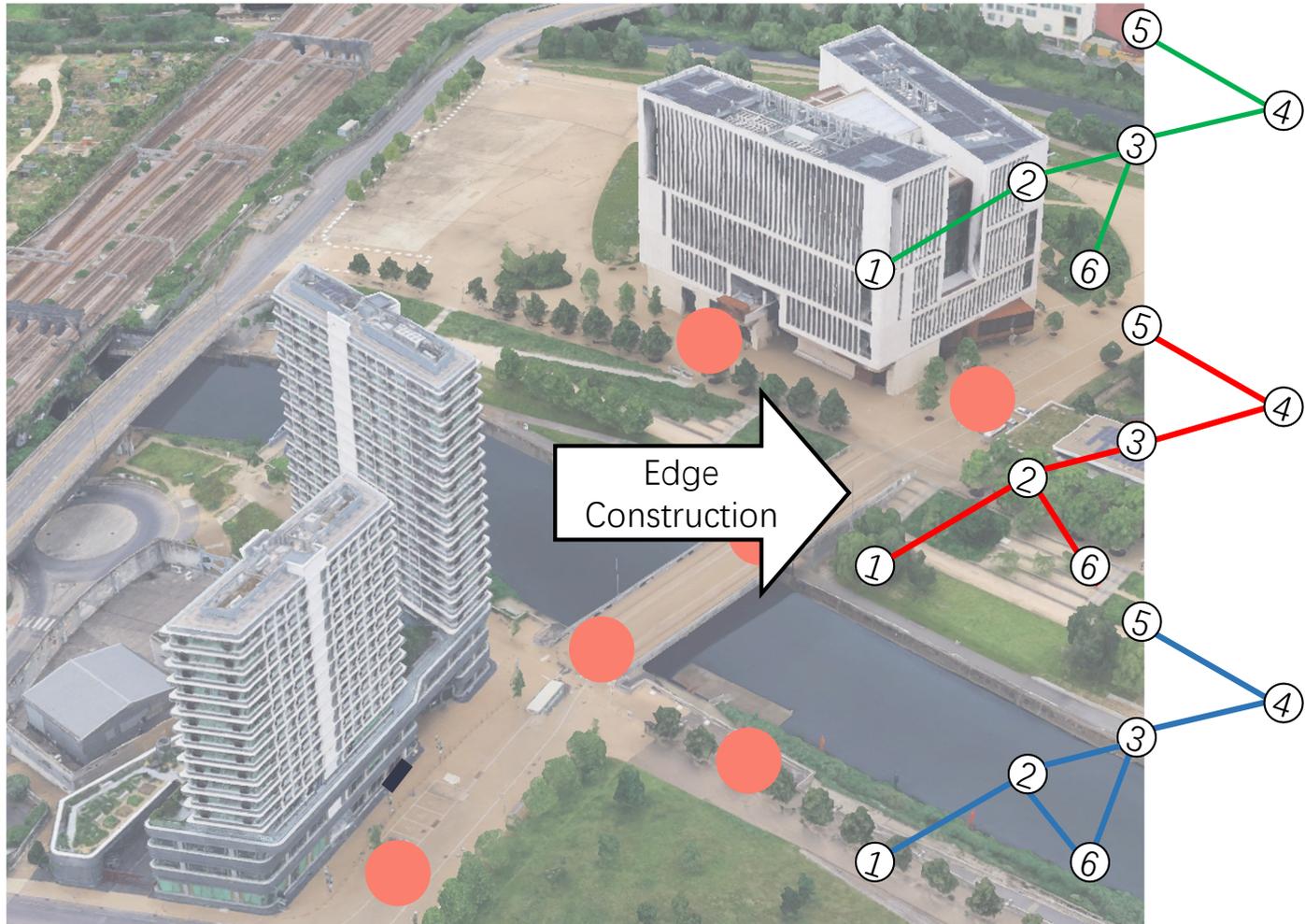
✓ Well-defined pipeline
✓ Relaxing global consistency

✗ Limited to the teach path
✗ Time-consuming data collection

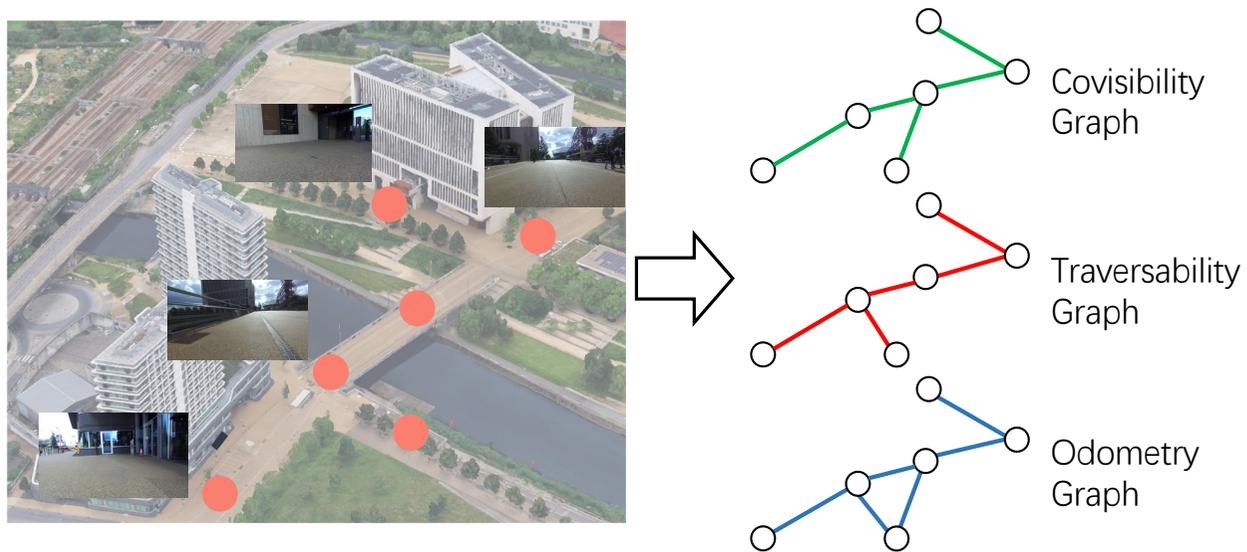
Our Solution: Sparse Map Representation



Our Solution: Sparse Map Representation



Our Solution: Sparse Map Representation



- **Map** is represented as a three-layer topometric map.
- **Submap** is constructed by individual mobile devices integrated with odometry.
- **Collaborative localization** with 3D geometric foundation model

How to Extend the Mapping Scale?



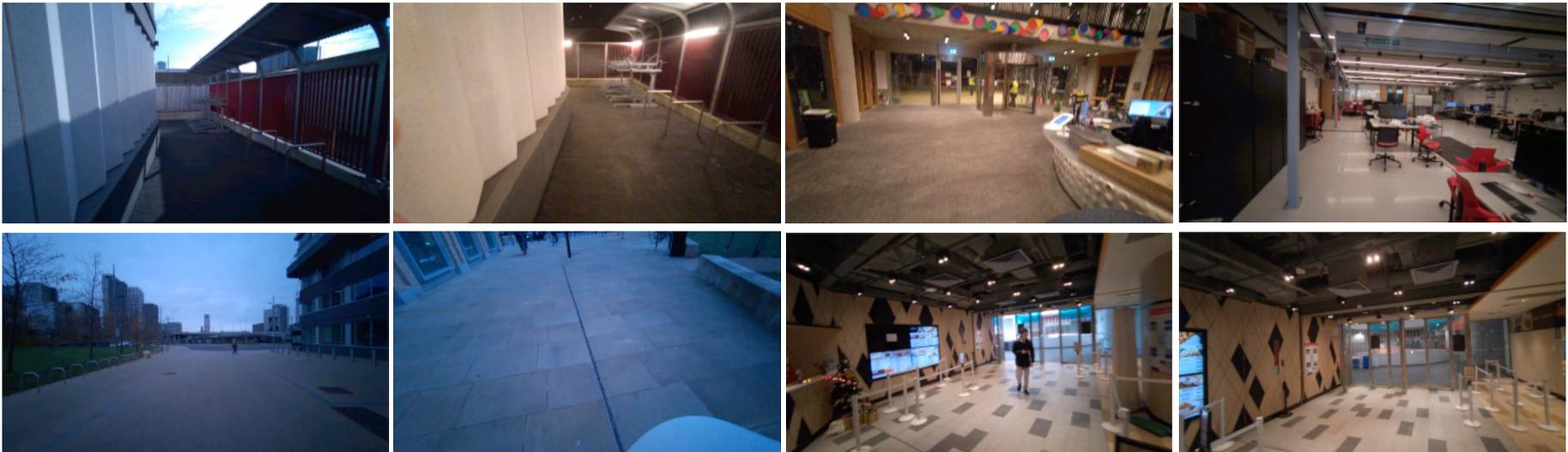
Our Solution: Crowdsourcing Mapping



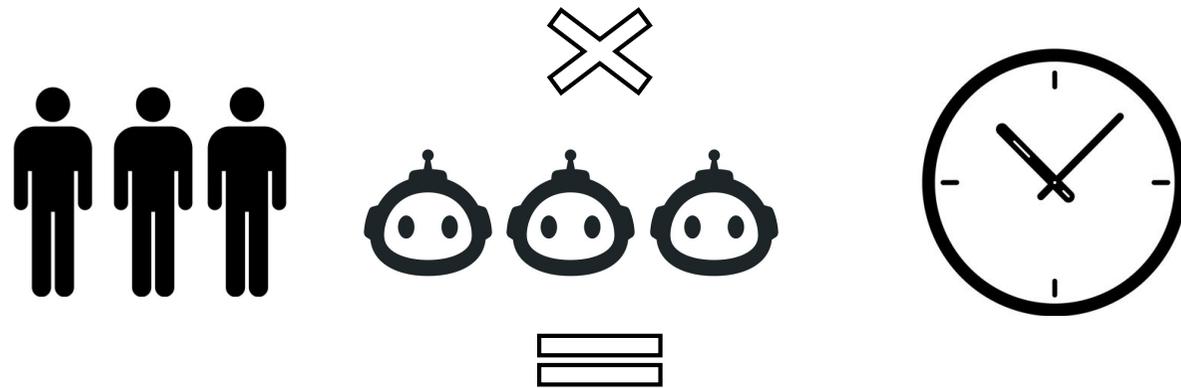
Relax



Our Solution: Crowdsourcing Mapping

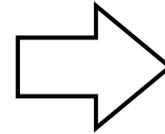


Our Solution: Crowdsourcing Mapping

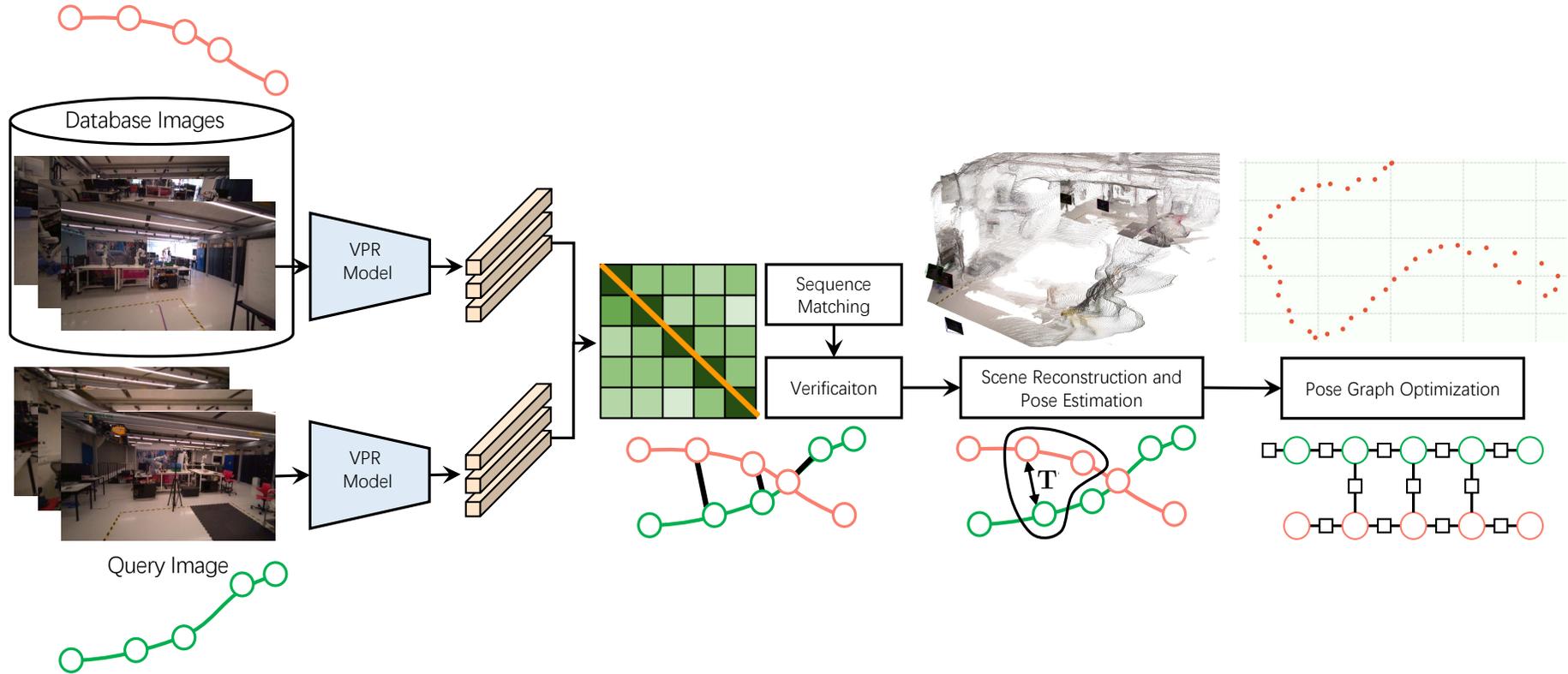


Large amount of **Fresh** mapping data from **Public Users**

Our Solution: Crowdsourcing Mapping



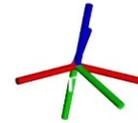
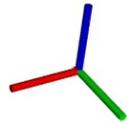
OpenNavMap System: Open Navigation Map



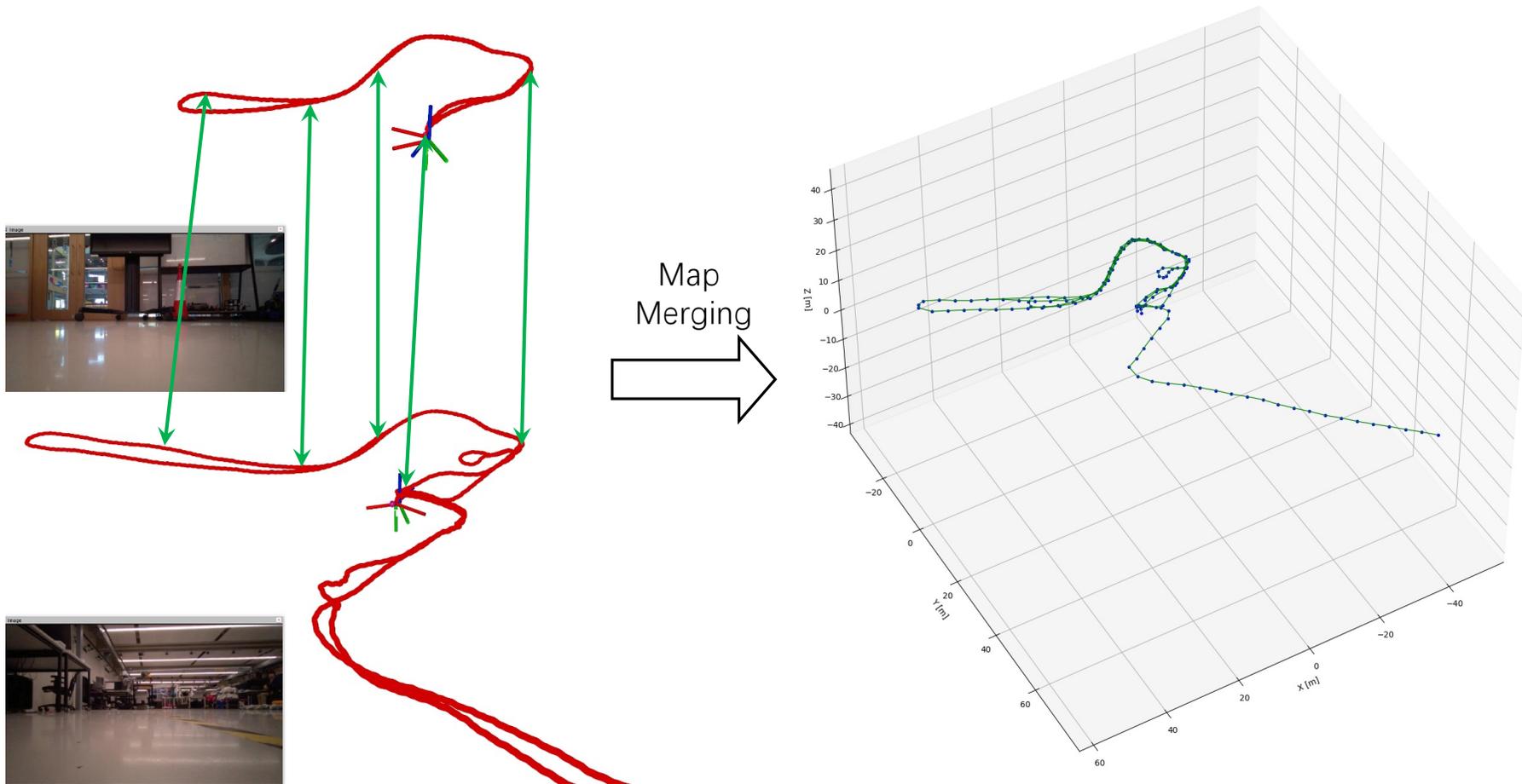
Collaborative localization Pipeline by Gathering Multi-Source Submaps

IROS2025 OWN Workshop Best Paper

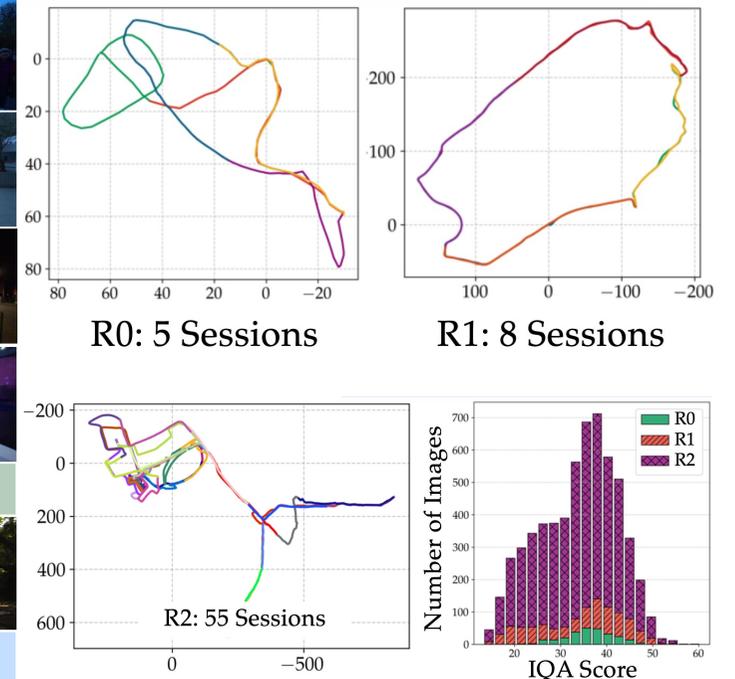
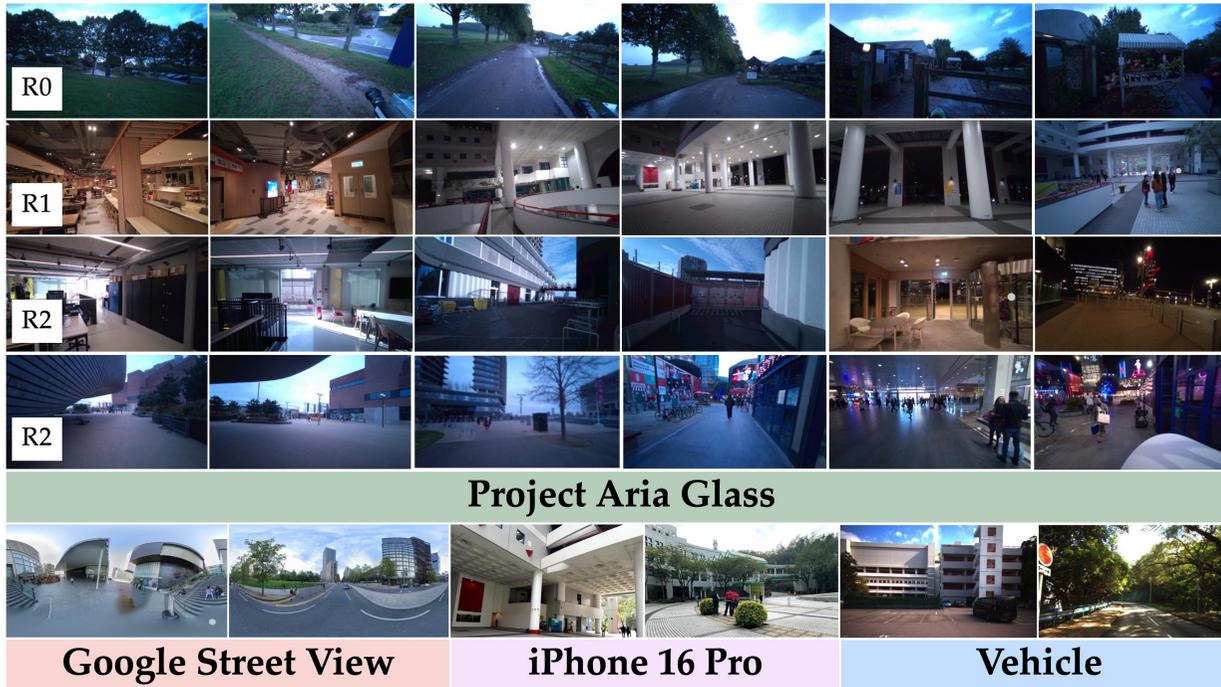
Submap Construction



Collaborative Localization and Map Merging

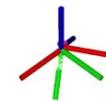
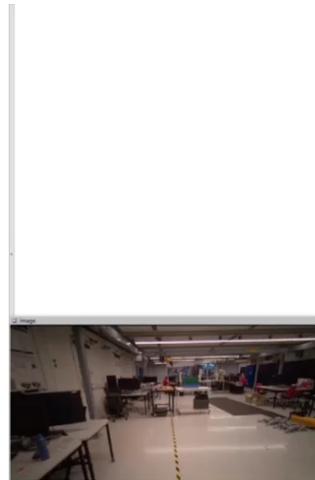
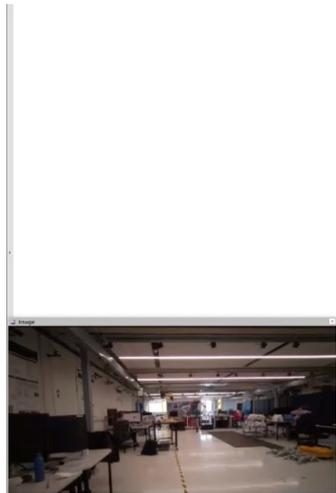


Experiments

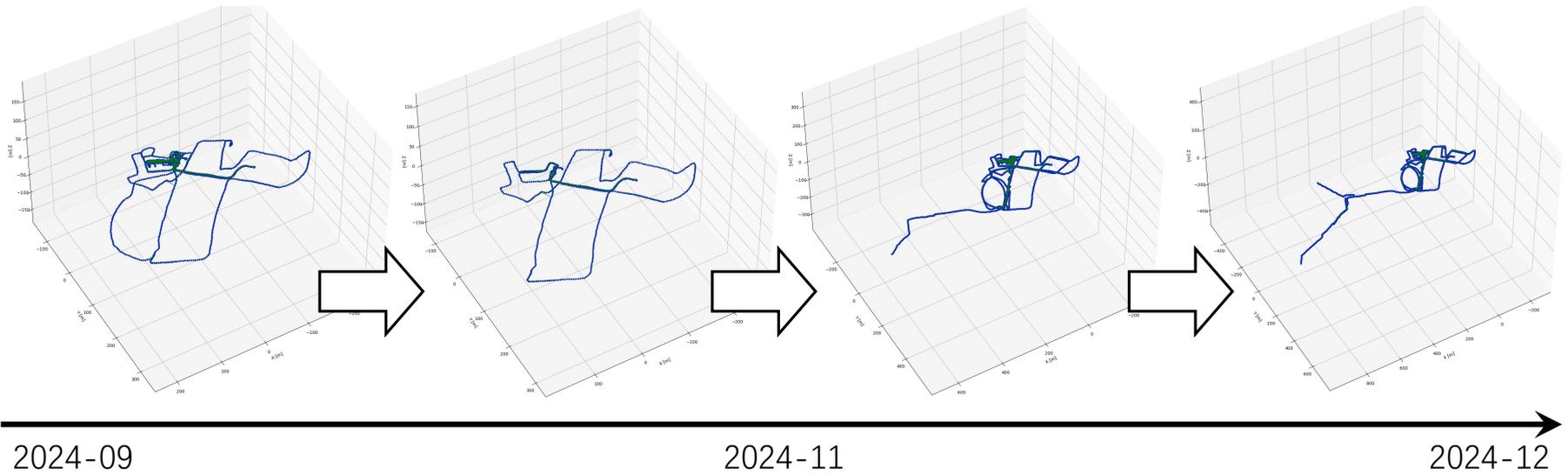


Dataset evaluation: 9 months, 37 sequences, 19km trajectories

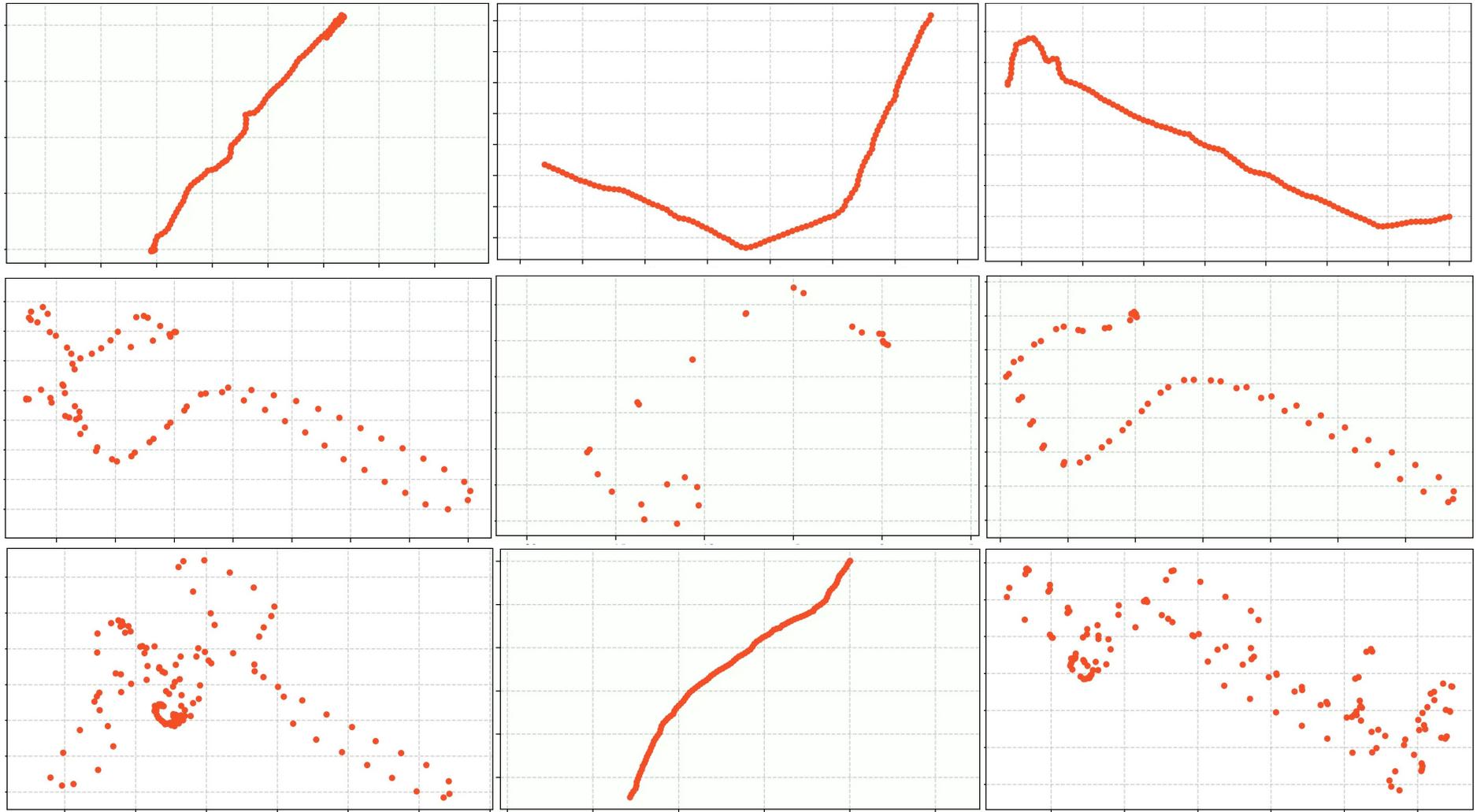
Map Merging with More Submaps



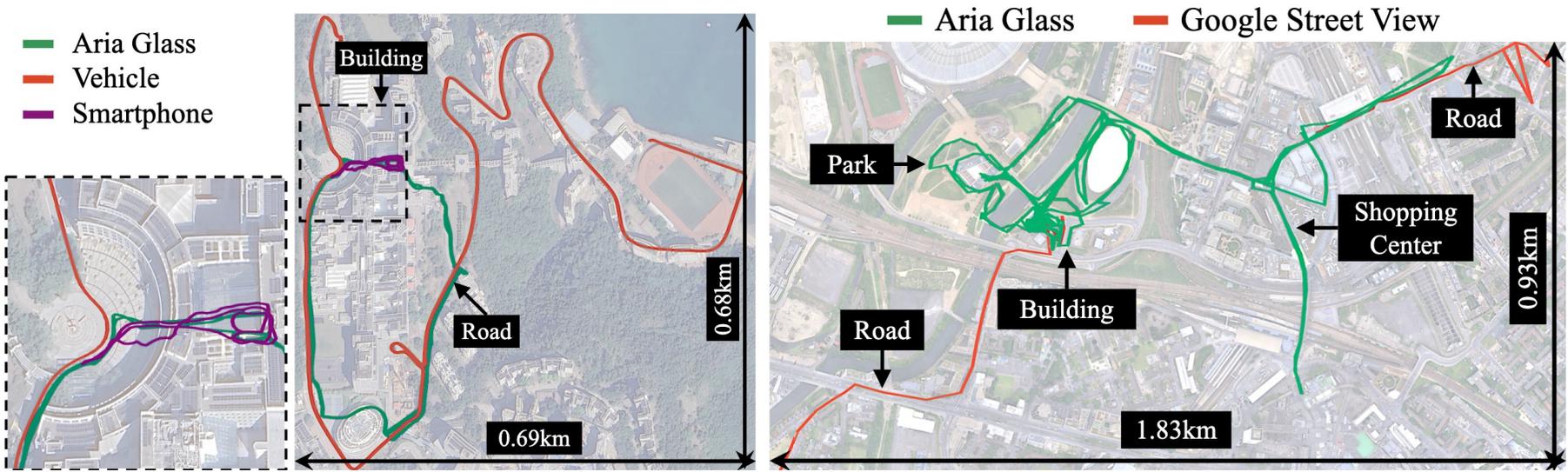
Map Merging with More Submaps



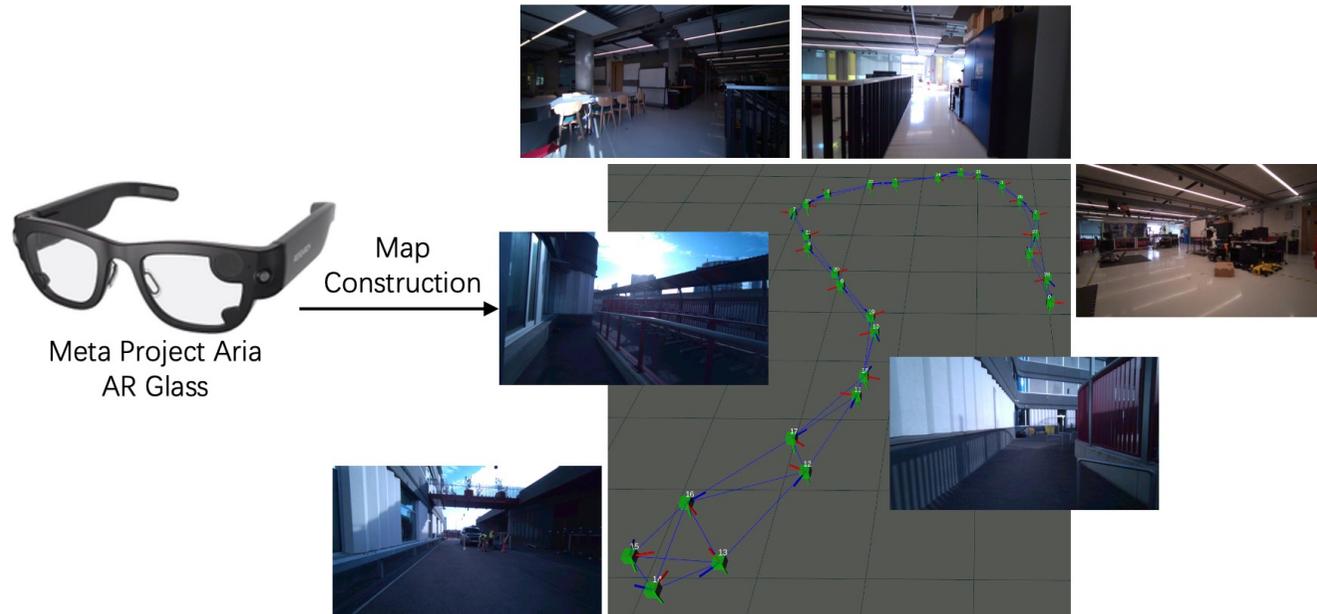
Map Merging with Shuffle Submap Orders



Final Map Construction



LiteVloc: Visual Navigation with the OpenNavMap



Map-Lite Visual Localization for Image Goal Navigation [Jiao2025ICRA]

- **Map:** sparse and discrete map eliminates the dense, metrically-precise map construction.
- **Hierarchical Vloc:** first retrieve place, then estimate the relative pose.

LiteVloc: Visual Navigation with the OpenNavMap

Introduction

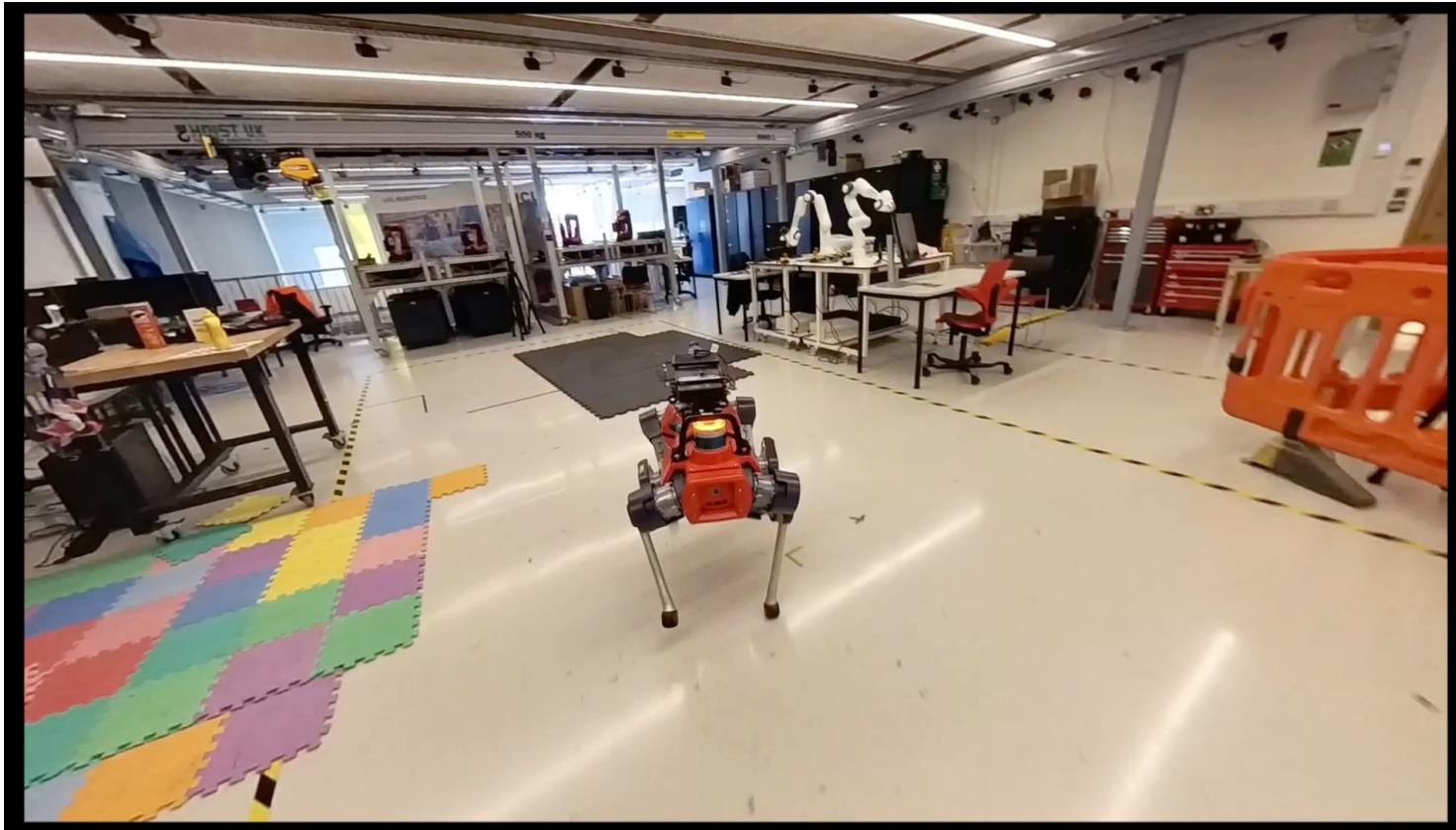


Goal image



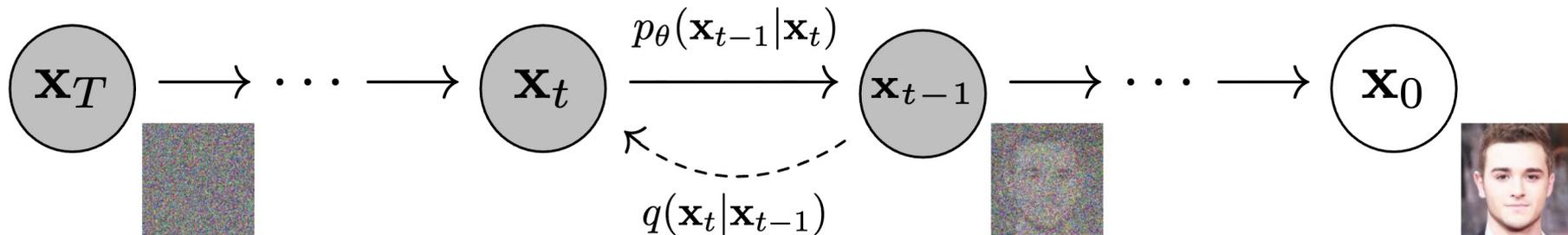
Imagine the robot is navigating its usual route

Demonstration of Visual Navigation



Zero-shot deployment

Generative Model for Visual Planner



Algorithm 1 Training

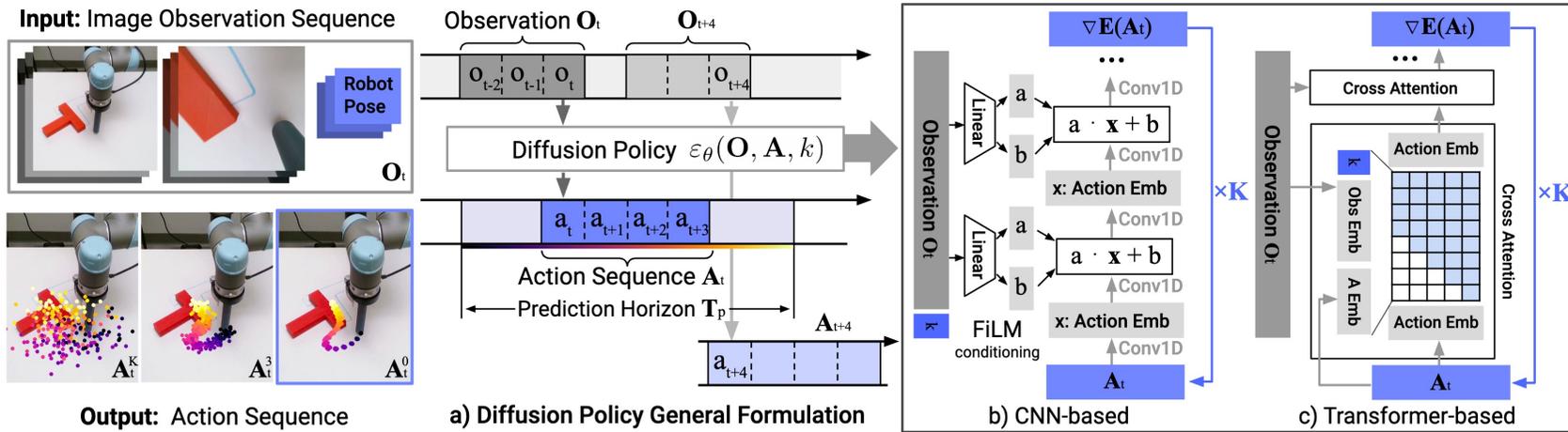
- 1: **repeat**
- 2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
- 3: $t \sim \text{Uniform}(\{1, \dots, T\})$
- 4: $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- 5: Take gradient descent step on $\nabla_\theta \|\epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, t)\|^2$
- 6: **until** converged

Algorithm 2 Sampling

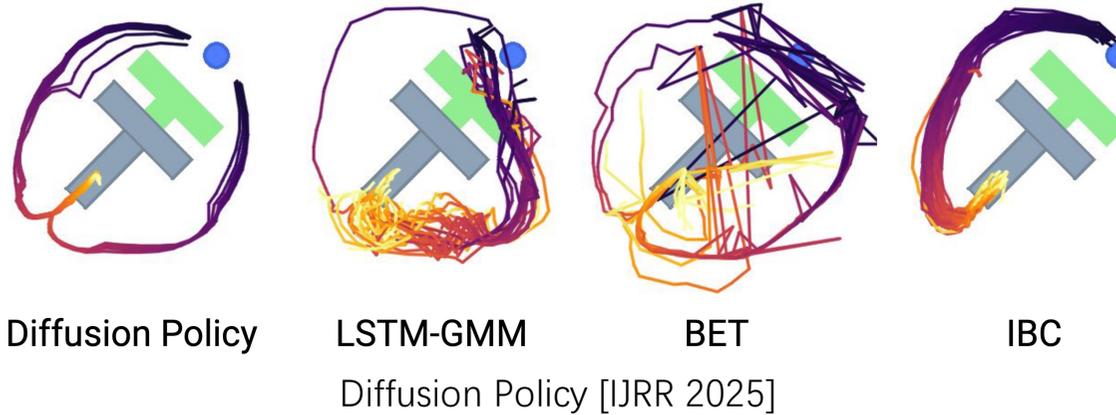
- 1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- 2: **for** $t = T, \dots, 1$ **do**
- 3: $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
- 4: $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
- 5: **end for**
- 6: **return** \mathbf{x}_0

DDPM [NeurIPS 2020]

Generative Model for Visual Planner



$$\mathbf{A}_t^{k-1} = \alpha(\mathbf{A}_t^k - \gamma \varepsilon_\theta(\mathbf{O}_t, \mathbf{A}_t^k, k) + \mathcal{N}(0, \sigma^2 I))$$



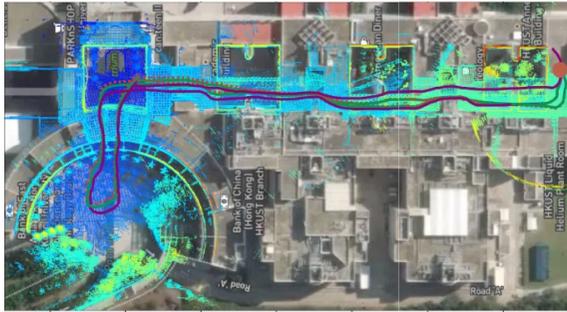
Diffusion Policy in B-Spline Space



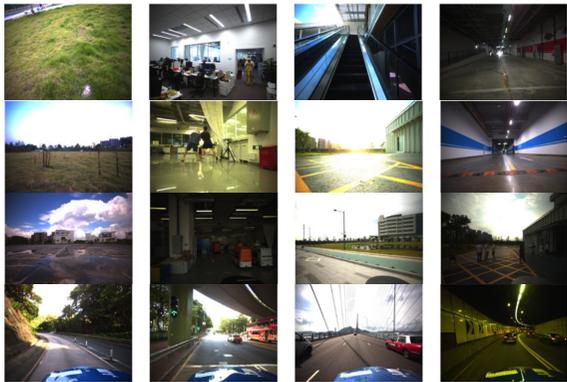
B-Splines as a strong inductive bias for policy learning [under review]

Next-Gen SLAM: Spatial Memory for Embodied AI

Geometric Representation

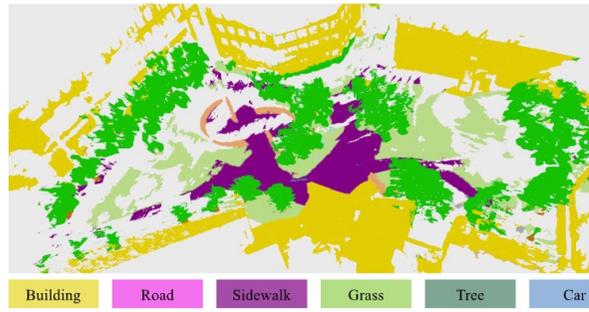


M-LOAM: multi-LiDAR SLAM



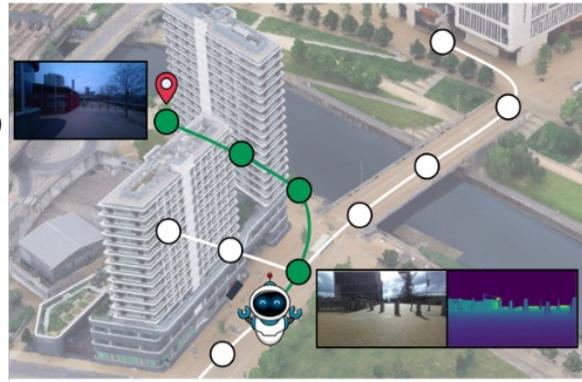
FusionPortable Dataset

Semantic



Metric-Semantic Mapping

Lifelong

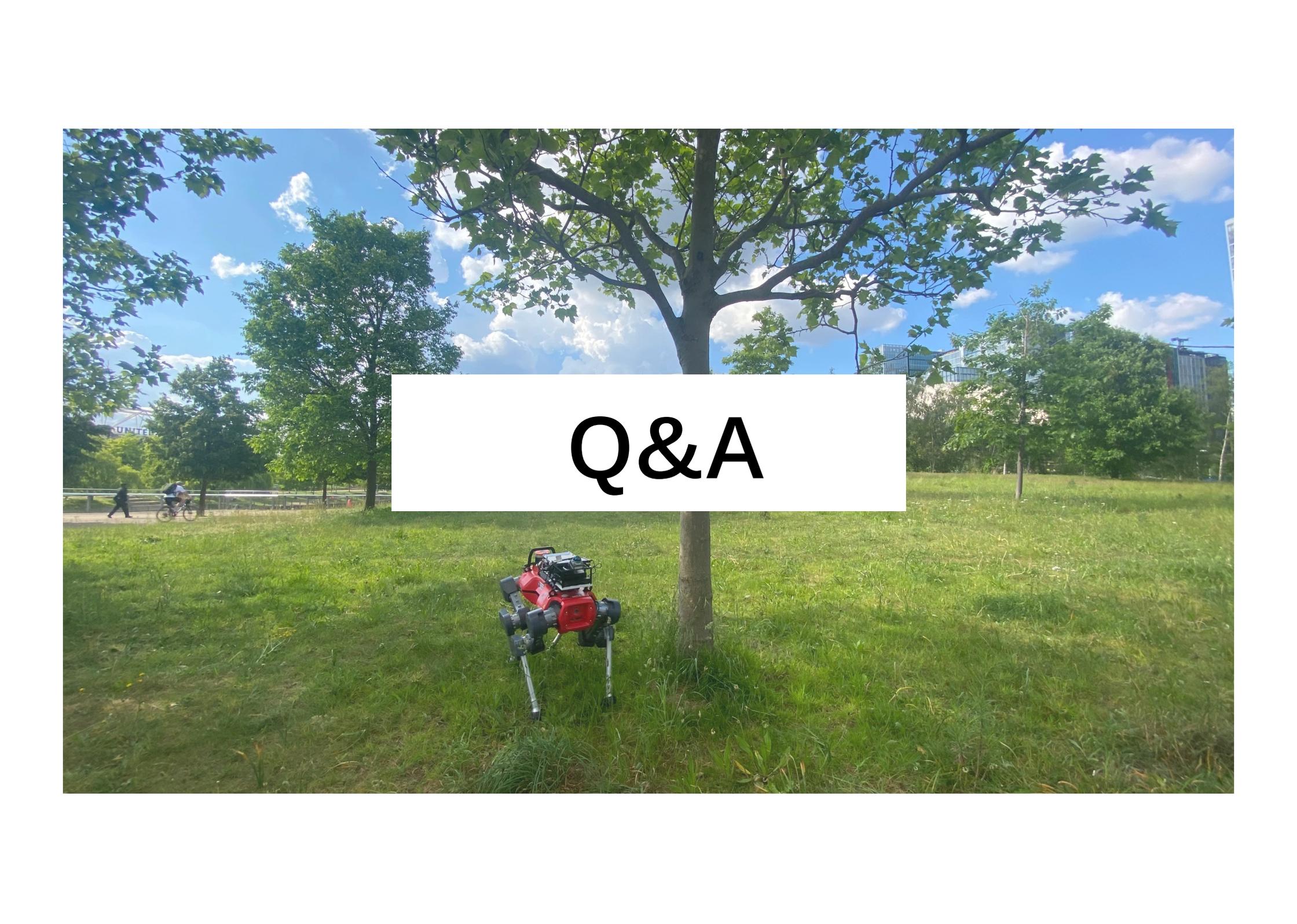


OpenNavMap and LiteVLoc

Lifelong Field Autonomy



Goal

A red quadruped robot is positioned in a grassy field. A large tree with green leaves is in the center. A white rectangular box with the text 'Q&A' is overlaid on the image. In the background, there are other trees, a blue sky with clouds, and a building with 'UMTEL' visible. A person is walking and a person is riding a bicycle on a path to the left.

Q&A