MRCD - Mobile Robot Campus Dataset for Evaluating SLAM Algorithms on Wheeled Robots

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***Abstract*—The Mobile Robot Campus Dataset (MRCD) is a valuable resource to evaluate advanced localization, mapping, and navigation algorithms. It comprises a collection of data sequences recorded in a campus environment using a mobile wheeled robot, which present diverse outdoor scenery and challenges for robot algorithm development and benchmarking. MRCD features key high-quality sensor modalities of our robot, a highly accurate Ground Truth (GT) reference based on continuous-time registration, and a point cloud of the campus with centimeter range resolution. To demonstrate the capabilities of MRCD, we benchmark several state-of-the-art Simultaneous Localization and Mapping (SLAM) algorithms. The results reveal a performance gap between vision- and lidar-based algorithms, highlighting the need for further development of vision-based techniques to enable cost-efficient sensor setups. MRCD offers a robust platform for testing and benchmarking, aimed at contributing to autonomous robot research.**

***Index Terms*—ROS2, Dataset, Robotics, Outdoor, SLAM, LISLAM, VISLAM, Continuous Ground Truth**

I. Introduction

SIDEWALK autonomous delivery robots (SADR) are an emerging solution to the challenge of last-mile delivery, promising to improve efficiency, safety, and sustainability in urban logistics for increasingly congested urban areas [1]. Accurate localization is a core requirement for their operation, typically achieved using SLAM, which enables robots to map their environment while estimating their position. SLAM has several variations, including Light Detection and Ranging (LiDAR)-based, visual, visual-inertial and LiDAR-inertial approaches. Developing and benchmarking SLAM algorithms requires diverse datasets with GT data in the form of maps or trajectories for evaluating algorithms. Although there are several datasets (e.g. [2], [3], [4]), few focus on the point of view and the unique challenges faced by SADR in pedestrian environments.

This paper presents MRCD, a multimodal dataset for SLAM research in public sidewalk settings. It includes eight sequences collected in three distinct areas of a university campus using a SADR-prototype (see Figure 1) equipped with 3D LiDAR, stereo cameras, Inertial Measurement Unit (IMU), wheel encoder (WE) and Real-Time Kinematic (RTK) Global Navigation Satellite System (GNSS). Accessible for the Robot Operating System 2 (ROS2), MRCD provides continuous-time GT and a Terrestrial Laser Scanner (TLS)-scanned 3D point cloud covering $138.073\,\mathrm{m}^2$ across varied sceneries and weather conditions. In addition, a benchmark of state-of-the-art (SOTA) LiDAR-Inertial SLAM (LI-SLAM), Visual-Inertial SLAM (VI-SLAM), and Visual SLAM (V-SLAM) algorithms highlighting the dataset's unique challenges is provided.

MRCD aims to contribute significantly to the research community by providing a realistic and comprehensive foundation for developing SLAM algorithms, pushing the boundaries of autonomous robot navigation in semi-structured urban environments.

Fig. 1. Transport robot *Laura* used for recording the dataset.

II. Related Work

MRCD adds to the growing number of datasets designed for autonomous systems. They can be categorized by their sensor platform: handheld, road-bound vehicle, robot, and aerial.

As MRCD was recorded using a SADR, related work focuses on ground-based platforms. Road-bound vehicle datasets are excluded here due to their road-centric perspective, which is less relevant for SADRs. Object Detection (OD) datasets are

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Our dataset is available at https://sm20598.github.io/MRCD/
Please find our Supplementary Material at LINK

also disregarded due to MRCD's primarily targeting SLAM-application. However for completeness, OD-related and road-centric datasets are summarized in the Supplementary Material. Table I highlights handheld and robot datasets, including details on sensor types, environment scale and GT generation, following the characterization of [4].

Handheld datasets typically include IMU and camera recordings, with LiDAR only available in TUM RGB-D [5], NCD [10], VECTor [11], Hilti 2022 [12], Hilti-Oxford [13] and MCD [2]. Among these MCD is the only one that also provides GNSS data. Naturally, none of them include WE data. With respect to scale, only TUM VI [8], UMA-VI [9], Hilti 2022, Hilti-Oxford and MCD feature environments larger than $500\,\mathrm{m}^2$. Outdoor sequences which are relevant for SADR are found in UZH-Event [6], NCD, PennCOSYVIO [7], TUM VI, Hilti-Oxford and MCD. Most of the indoor handheld datasets use Motion Capture Systems (MoCap) for providing GT poses. The 2022 Hilti dataset offers GT poses for outdoor sequences received from a Robotic Total Station (RTS), while VECTor applies Scan Matching (SM) techniques, UMA-VI focuses on a Structure-from-Motion (SfM) approach and PennCOSYVIO relies on AprilTag detection. NCD and Hilti-Oxford generate GT solely via SM. MCD provides both GT poses and maps using Survey-grade prior Map Continuous-Time Registration (SMCTR) and TLS for map generation, the same techniques as applied in MRCD. Besides MCD, handheld datasets providing a TLS-generated GT map are NCD, VECTor and Hilti-Oxford.

Robot-based datasets typically offer a wider range of sensor modalities, often combining LiDAR, GNSS, and IMU data, along with camera recordings. Unlike handheld datasets, robot-mounted sensors provide a distinct point of view, which is closer to the ground level and captures motion dynamics reflecting the real-world conditions, such as IMU disturbances from uneven terrain or vibrations from turns. Datasets like NCLT [14], Rosario [15], Nebula [17], and FusionPortableV2 [4] also include WE, allowing accurate motion capture from mobile robot platforms. While many robot datasets are limited to small environments ($<500\,\mathrm{m}^2$), some, such as M3ED [19], Hilti 2024 [3] and FusionPortableV2 cover large-scale areas, making them suitable for advanced navigation and mapping research.

GT pose generation varies across datasets. NCLT and M3ED use RTK-GNSS and SLAM-based methods, while M2DGR [16] combines RTK-GNSS, MoCap, and a Laser Tracker (LT). FusionPortable datasets (V1 [18], V2) use MoCap and RTK-GNSS, enhanced by SM. Nebula relies entirely on SLAM-based techniques. M3ED distinguishes with its SLAM- instead of TLS-based GT map generation. Similarly, FusionPortableV2 combines MoCap, RTK-GNSS, and SM to generate GT maps. Only M2DGR, FusionPortable and FusionPortable2 feature 4-wheeled robots operating in pedestrian spaces, but only FusionPortable2 includes WE. M3ED and Hilti 2024 are based on legged or tracked robots, other focus on non-urban settings (Rosario, Nebula).

This highlights the lack of datasets tailored to SADRs. MRCD addresses this by capturing realistic robot motion, including turning-induced vibrations using a robot with considerable extrinsics between sensors for SADRs in diverse outdoor settings. It combines an extensive set of sensor modalities with SMCTR for GT poses and TLS for GT maps [21]. MRCD is also the first dataset to provide a native ROS2 Humble benchmark for evaluating SLAM algorithms, commonly used in modern robotics, making it a comprehensive resource for large-scale mobile robot research.

III. Robot

MRCD is collected using the wheeled robot *Laura*, shown in Figure 1, which has been developed for the TaBuLa-LOG project [22]. *Laura* combines both high-fidelity LiDAR and cameras, making it a multi-sensor platform particularly suitable for dataset recording. The robot's basis is a Clearpath Jackal enhanced with an Nvidia Jetson Orin, an upgraded Onbot-PC (i9-13900T, 64 GB DDR5 RAM), high-end sensors, and a transport box. Due to sidewalk traffic regulations, the robot's maximum speed is limited to $6\,\frac{\mathrm{km}}{\mathrm{h}}$. The robot is equipped with WEs, a 3D LiDAR on top, several stereo cameras, an IMU and an RTK-GNSS module. The LiDAR, a Velodyne VLP-16, provides a 3D point cloud with a frequency of $10\,\mathrm{Hz}$. The forward-facing passive stereo camera is a Stereolabs ZED 2, which offers two $30\,\mathrm{Hz}$ video streams, a $200\,\mathrm{Hz}$ IMU data stream, and a $10\,\mathrm{Hz}$ point cloud. Additionally, a ground-facing active stereo camera, the Intel RealSense D435, provides a $15\,\mathrm{Hz}$ point cloud and two $30\,\mathrm{Hz}$ video streams. LiDAR and cameras are placed in locations to assist in localization, obstacle detection, and velocity control based on ground conditions. The RTK-GNSS, an EMLID Reach M2, enables accurate global localization. LiDAR and stereo cameras were externally calibrated using the atom calibration framework [23]. Camera data is anonymized to comply with European data protection regulation. Details on the calibration and anonymization process, the ROS2 topics included in the dataset, and additional sensor information can be found in the Supplementary Material.

IV. Dataset Analysis

The dataset was recorded in winter 2025 on the campus of the Hamburg University of Technology (TUHH), using the robot's manual driving mode. It covers an area of $559\,\mathrm{m}\times247\,\mathrm{m}$ ($137.073\,\mathrm{m}^2$). It includes a variety of public pedestrian spaces featuring diverse terrains, such as uneven surfaces (e.g. cobblestones, bumpy walkways), vegetation, buildings, and slopes. A total of eight sequences were recorded across three main areas: A I & A II in *Alley*, G I & G II in *Grove*, and T I - T IV in *Town*. The sequences vary in length from $202\,\mathrm{m}$ to $787\,\mathrm{m}$ and cover a total of $2895\,\mathrm{m}$, adding up to $1\,\mathrm{h}$ recording time. An overview of the routes is provided in Figure 2.

Alley – spans from the northern part to the center of the campus. Two sequences were recorded. The first, featuring an average pace of $6\,\frac{\mathrm{km}}{\mathrm{h}}$ (walking speed), includes a steep ramp and navigation within a wide courtyard, bordered by tall buildings. The second, recorded at a pace of $2\,\frac{\mathrm{km}}{\mathrm{h}}$, crosses additional narrow vegetation-lined corridors and forms a looped back-and-forth track where most locations are passed twice.

TABLE I
DATASET COMPARISON ACROSS SENSOR MODALITY, ENVIRONMENT SCALE (SMALL ($< 500\,\mathrm{m}^2$), AND LARGE ($> 500\,\mathrm{m}^2$)) AND GT FORM.

	Dataset	Sensors Modality					Environment Scale		GT Pose	GT Map
		IMU	Camera	LiDAR	GNSS	WE	Small	Large		
Handheld Setups	2012 TUM RGB-D [5]	✓	✓	✓	0	0	✓	0	MoCap	0
	2017 UZH-Event [6]	✓	✓	0	0	0	✓	0	MoCap	0
	2017 PennCOSYVIO [7]	✓	✓	0	0	0	✓	0	Apriltag	0
	2018 TUM VI [8]	✓	✓	0	0	0	✓	✓	MoCap	0
	2020 UMA-VI [9]	✓	✓	0	0	0	✓	✓	SfM	0
	2020 NCD [10]	✓	✓	✓	0	0	✓	0	SM	TLS
	2022 VECTor [11]	✓	✓	✓	0	0	✓	0	MoCap, SM	TLS
	2022 Hilti [12]	✓	✓	✓	0	0	✓	✓	MoCap, RTS	0
	2023 Hilti-Oxford [13]	✓	✓	✓	0	0	✓	✓	SM	TLS
	2024 MCD [2]	✓	✓	✓	✓	0	0	✓	SMCTR	TLS
Robot Setups	2016 NCLT [14]	✓	✓	✓	✓	✓	✓	0	RTK-GNSS, SLAM	0
	2019 Rosario [15]	✓	✓	0	✓	✓	✓	0	RTK-GNSS	0
	2022 M2DGR [16]	✓	✓	✓	✓	0	✓	0	RTK-GNSS, MoCap, LT	0
	2022 Nebula [17]	✓	0	✓	✓	✓	✓	0	SLAM	TLS
	2022 FusionPortable [18]	✓	✓	✓	✓	0	✓	0	MoCap, RTK-GNSS, SM	TLS
	2023 M3ED [19]	✓	✓	✓	✓	0	✓	✓	RTK-GNSS, SLAM	SLAM
	2024 Hilti [3]	✓	✓	✓	0	0	✓	✓	SM	TLS
	2024 FusionPortableV2 [4]	✓	✓	✓	✓	✓	✓	✓	MoCap, RTK-GNSS, SM	TLS
	2025 MRCD [20] (Ours)	✓	✓	✓	✓	✓	0	✓	SMCTR	TLS

Grove – covers the southern campus and is characterized by dense vegetation and a central pond. Two looped sequences, in both clockwise and counterclockwise directions, follow mostly flat paths bordered by grass, bushes and trees.

Town – is located in the northern part of the campus, featuring tall buildings and cobblestone paths that challenge sensor perception. It includes 2 unidirectional loops around 4 buildings, a short sequence through courtyards with narrow corridors and slalom course in between flower beds, and a sequences among large trees on cobblestone terrain.

MRCD offers a diverse and realistic set of environmental conditions, suitable for evaluating navigation, mapping, and perception algorithms in outdoor pedestrian zones.

V. SURVEY MAP CONTINUOUS-TIME REGISTRATION

For the development and evaluation of SLAM algorithms, an accurate GT is needed. We use the method presented in [2]. It aligns raw LiDAR point cloud data with a pre-existing map through a continuous optimization process that explicitly models the deskewing process. The preexisting map is a 3D point cloud of the TUHH campus premises. It was collected in 125 scans using a Faro Focus S70 and Faro Focus Premium TLS. The point cloud used to generate the GT has $5\,\mathrm{cm}$ resolution. Optimization takes into account factors such as initial pose estimates, LiDAR data alignment, and IMU sensor readings, using a B-spline-based continuous path estimate and correcting for any biases in the IMU. All of these elements are optimized with respect to measurement uncertainty.

VI. BENCHMARK ON SLAM ALGORITHMS

MRCD includes a benchmark of SOTA SLAM algorithms on each sequence, comparing pose estimates with GT using the

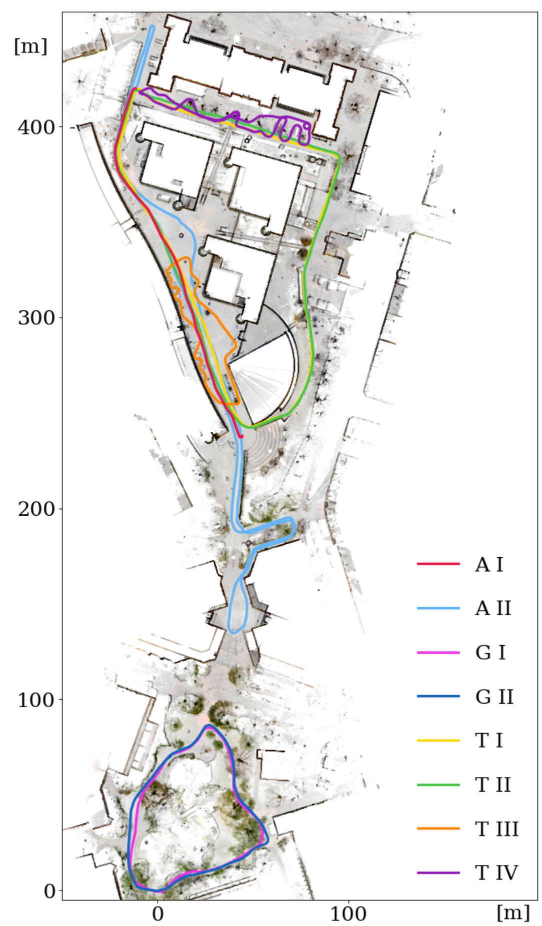

Fig. 2. GT trajectories of recorded routes on TUHH campus.

evo-package [24]. As our robot operates on ROS2 Humble, we focus on algorithms natively supported in this environment and exclude those requiring bag file conversion or implementations for other ROS versions. All algorithms are evaluated on a workstation equipped with a 24 core Intel i9 13900K, 128 GB RAM, and two NVIDIA RTX 4090 GPUs.

LI-SLAM – We evaluate 3 open-source LI-SLAM algorithms: Fast-LIO (FL) [25], 2D & 3D Google's Cartographer (GC) [26], and NAV2 SLAM Toolbox (ST) [27]. FL uses Kalman Filtering with direct feature association and parallel KD-Tree search. GC relies on submap-based matching and loop closure via a branch-and-bound approach. ST applies sparse graph optimization with loop closure detection and scan matching, tightly integrated with the ROS2 navigation stack.

V-SLAM – We benchmark NVIDIA's Isaac ROS Visual SLAM (NIR) [28], OPEN-VINS (OV) [29], RTAB-MAP (RTM) [30], and ORB-SLAM 3 (ORB3) [31]. NIR is a GPU-accelerated graph-based stereo-inertial VI-SLAM method with loop closure for drift correction. OV uses a filter-based visual-inertial approach. RTM offers real-time stereo-inertial mapping based on an incremental appearance-based loop closure detector. ORB3 provides stereo visual-inertial SLAM together with multi-map fusion, but due to a persisting issue with pose jumps, only the visual stereo mapping was evaluated.

Table II lists the Absolute Trajectory Error (ATE) of all algorithms with the best performance highlighted in bold and the second-best underlined for each LiDAR- and visual-based method. We consider an algorithm to have failed a sequence, denoted by –, if it consistently aborts at a particular location over several runs before progressing halfway through the trajectory. For all algorithms, we only adjust but do not optimize input parameters. For RTM, we additionally reduce playback speed to 0.7 due to significantly poor real-time performance, which would prevent any comparison. For further insights on the algorithm performance, the results of the benchmarks for LI-SLAM and V-SLAM compared to GT are plotted and provided in the Supplementary Material.

All LI-SLAM algorithms demonstrate stable performances with an average ATE of 0.685 m. As expected, 2D algorithms show higher ATE in sequences with greater changes in altitude (A I, A II). On average, ST performs worse compared to all other LI-SLAM algorithms, though outperforming GC2D in some sequences (A I, G I). Noticeable, although sequence T II follows approximately the same trajectory as T I but in opposite direction, the results on T II are overall worse. In T II, the trajectory initially traverses an open space with few distinctive geometric features, which does have a small but detrimental impact on performance. On sequences T III and T IV, which provide strong serpentine and shaky motions, the geometric robustness of LI-SLAM is clearly exhibited.

In contrast, V-SLAM are significantly less accurate with an average ATE of 26.24 m. NIR performs best overall, especially in 2D, where accumulated altitude drift can be avoided, leading to more stable and accurate results, even in sequences with large differences in altitude. OV demonstrated overall stable performance, with only T VI's characteristic curves causing recurring crashes. In all sequences, RTM aborts mapping when losing visual odometry, but its memory-based design enabled sequential progress. However, navigation in featureless environments, such as the open areas of T I and T II, and visual monotony when driving down a ramp in A I and A II, prevented continuation. RTM's trajectories on T III and T IV exemplify half-processed sequences that aborted early. ORB3 demonstrates stability, but also shows a significant drop-off in sequences with open areas.

Despite higher computational demand, the results confirm LI-SLAM's robustness and V-SLAM's sensitivity to scene structure and lighting as in [2]. It should be noted that a strong variation in the performance of V-SLAM over multiple runs affected the reproducibility of the results. One reason for the fluctuation could be the playback approach of ROS2 bags which prioritizes realistic performance over reliable communication, causing message drops at runtime. Hence, the already sparse visual features and strong dynamic motion, which cause distortion and motion blur, hamper feature extraction and image stitching.

TABLE II
ATE IN m OF LI-SLAM AND V-SLAM ALGORITHMS PER SEQUENCE.

	A I	A II	G I	G II	T I	T II	T III	T IV
				LI-SLAM				
ST	0.77	1.76	0.33	0.55	1.05	2.93	0.27	0.43
GC2D	3.08	1.47	0.43	0.41	0.83	**0.87**	<u>0.13</u>	0.14
GC3D	<u>0.43</u>	<u>0.70</u>	<u>0.10</u>	**0.16**	**0.46**	1.65	**0.10**	**0.11**
FL	**0.20**	**0.34**	**0.09**	<u>0.20</u>	<u>0.59</u>	<u>1.03</u>	0.15	<u>0.13</u>
				V-SLAM				
NIR2D	<u>14.04</u>	**40.75**	17.49	19.49	**16.32**	**22.85**	<u>5.67</u>	**6.53**
NIR3D	15.70	<u>50.93</u>	16.25	19.84	<u>19.72</u>	28.54	**5.66**	<u>9.24</u>
OV	30.48	58.36	<u>9.27</u>	**9.04**	24.99	39.57	8.53	–
RTM	–	–	27.15	24.74	–	–	12.63	16.81
ORB3	**6.97**	<u>46.21</u>	**5.97**	<u>11.75</u>	30.11	<u>25.41</u>	15.19	20.99

VII. CONCLUSION

This paper presents MRCD, a dataset for outdoor mobile robotics. It features various high-resolution sensor recordings, continuous-time GT, and characteristic sequences captured with a wheeled robot. Benchmarking a range of SLAM algorithms on MRCD reveals sequence-specific challenges and underscores the dataset's relevance for SLAM algorithm development. MRCD aims to support the development of localization and mapping algorithms by exposing current limitations. Especially in V-SLAM, low computational effort carries great potential for lightweight mobile platforms, yet remains hindered by sensitivity to visual disturbances. Researchers and practitioners are invited to leverage MRCD to tackle real-world challenges in outdoor mobile robotics. Currently, MRCD only features daytime single-season recordings, which will be extended with nighttime sequences and seasonal variations. In future work, the present low IMU-frequency will be addressed while additional segmentation annotations will be included.

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TABLE III
OVERVIEW OF SUPPLEMENTARY MATERIAL

Type of Data	**Content (Filename/Location)**	**Description**
Supplementary Material Text	PDF	Supplemental information complementing the paper by providing further info on Related Work, Sensor Calibration, Anonymization.
Git Hub	`Git Hub`	MRCD's official Github page providing detailed information on complete content, all relevant links, docker images, user guide, SLAM-tutorials, and more.
Dataset Full	https://doi.org/10.15480/882.15125	8 Sequences with all topics recorded in ROS2 bag format.
Dataset Full compressed	https://doi.org/10.15480/882.15125	8 Sequences including all topics in ROS2 bag compressed format.
Dataset without camera topics	https://doi.org/10.15480/882.15125	8 Sequences without camera topics in ROS2 bag format.
Dataset without camera topics compressed	https://doi.org/10.15480/882.15125	8 Sequences without camera topics in ROS2 bag compressed format.
GT	https://doi.org/10.15480/882.15125	Ground Truth Data for all 8 sequences in .csv files in continuous format as well as sampled with 10 Hz.
GT Map	https://doi.org/10.15480/336.5041	Ground Truth Point Cloud of TUHH-Campus in .e57 format.