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MapsHD: A benchmark suite for LiDAR odometry frameworks

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ABSTRACT

This paper describes a software toolbox for LiDAR (Light Detection and Ranging) and LiDAR-Inertial Odometry qualitative and quantitative evaluation. We provide software as https://github.com/MapsHD organization with all necessary information at https://github.com/MapsHD/HDMapping. Our software contributions are a) ground truth data processing tool, b) dockerized state-of-the-art LO and LIO algorithms, c) multi-session data registration to common coordinate system, d) Absolute Pose Error (APE) and Relative Pose Error (RPE) metrics,

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e) import/export tools for easier 3D data handling and visualizing, e.g., in Cloud Compare software. This software is compatible with ROS1 (Robot Operating System) and ROS2 data formats. We show an example benchmark of LeGO-LOAM, LIO-SAM, FAST-LIO, DLO, VoxelMap, Faster-LIO, KISS-ICP, CT-ICP, SLICT, DLIO, GLIM, iG-LIO, LIO-EKF, I2EKF-LO, GenZ-ICP, RESPLE, odometry_ros_wrapper, Point-LIO, and LOAM-Livox algorithms. For all experiments we provide movies. The contribution of the paper is software-oriented LO/LIO algorithm benchmark suite. The novelty lies in the integration of multiple benchmarking steps into a unified framework, thus overall effort needed for qualitative and quantitative evaluation is reduced.

Metadata

Table 1
HDMapping software code metadata.

Nr.	Code metadata description	Metadata
C1	Current code version	v1.00
C2	Permanent link to code/repository used for this code version	https://github.com/MapsHD/HDMapping/releases/tag/v0.98
C3	Permanent link to reproducible capsule	https://github.com/MapsHD/HDMapping/releases/tag/v0.98
C4	Legal code license	MIT License
C5	Code versioning system used	git
C6	Software code languages, tools, and services used	C++, python
C7	Compilation requirements, operating environments & dependencies	Ubuntu 24.04, Windows 11, macOS, cmake >= 4.0.0
C8	If available Link to developer documentation/manual	https://github.com/MapsHD/HDMapping/blob/main/README.md
C9	Support email for questions	januszbedkowski@gmail.com

1. Introduction

This paper describes a software toolbox for LO: LiDAR odometry (Light Detection and Ranging) and LIO: LiDAR-Inertial Odometry qualitative and quantitative evaluation. LiDAR and LiDAR-Inertial Odometry estimate trajectory based on LiDAR measurements and optionally fused with IMU (Inertial Measurement Unit). Inertial Measurement Unit enables estimating rotations based on measured accelerations and rotational velocities. LiDAR measures distances and optionally intensity. These algorithms can be used by mobile robots and autonomous cars to estimate trajectory. Moreover, mobile mapping systems (hand-held, backpack) also use these algorithms for initial trajectory estimation. This estimation is affected by incremental error; thus another technique (back end of SLAM: Simultaneous Localization and Mapping) can reduce it by the so-called loop closure [1]. In our open source project HDMapping ,[1] we provide all the necessary tools for evaluating the current state-of-the-art LiDAR odometry algorithms. Our goal is to facilitate multidisciplinary audiences with software tools enabling automated LiDAR odometry evaluation. We target following disciplines, audiences, and end-users: caving, speleology, surveying, cultural heritage, environmental management, geology, urban search and rescue, urban mapping, ground truth for AGV (Automated Guided Vehicle), mobile robot navigation, precision forestry, agricultural robotics, underground mining, education, entertainment, forensics, critical infrastructure inspection, space exploration, protection systems, digital twin content generation, automation in construction etc.… The benefit from this software is an orchestrated benchmark workflow that is easy to extend with other algorithms. Our software enables:

- organising datasets,
- automated downloading of all repositories in a single step in the form of Docker images,
- automated run of all LiDAR odometry algorithms,
- exporting to HDMapping format for easy qualitative inspection (visualizing all registered point clouds),
- automated quantitative evaluation using state-of-the-art RPE (Relative Pose Error) and APE (Absolute Pose Error).

We designed this software to enable LiDAR odometry evaluation [2] for a larger audience. We hope many multidisciplinary disciplines can benefit from it. This is a response to the research and development needs related to the proper choice of LiDAR odometry algorithm for a specific application. For example, mobile robotics requires online calculations, in contrary precision forestry can calculate off-line but it requires highest accuracy and precision as it is possible.

2. Motivation and significance

Benchmarking of LiDAR odometry algorithms is essential to provide qualitative and quantitative prerequisites for further scientific evaluation. This provides evidence of the performance, thus we can justify witch algorithm perform best/worse/average. The contribution of our paper is as follows:

- We provide end-to-end LiDAR odometry benchmark tools.
- It solves the problem of qualitative and quantitative benchmark of recent LiDAR odometry algorithms.
- We provided novel tools for ground truth data processing.
- Our goal is to unify the LiDAR odometry benchmark, thus research community can benefit from it by reducing an effort required to build such end-to-end solution.
- We designed software to be as simple to use as it is possible. The core functionality is derived as Windows based GUI (Graphical User Interface) applications, thus programming effort is not required. Other software components are partially dockerized, moreover we provide an orchestration to run experiments in semi automated way (this work is still in constant progress). Our goal is to minimize programming effort and make LiDAR odometry benchmark available for larger audiences such as students/researchers from Geodesy and Cartography, Earth Sciences, Transport, Speleology, Precise Forestry, Agriculture etc.
- We support following algorithms in our framework: LeGO-LOAM [3](2018), LIO-SAM [4](2020), FAST-LIO [5](2021), DLO [6](2022), VoxelMap [7](2022), Faster-LIO [8](2022), KISS-ICP [9](2022), CT-ICP [10](2022), SLICT [11](2022), DLIO [12](2023), GLIM [13](2024), MAD-ICP [14](2024), ig-lio [15](2024), LIO-EKF [16](2024), I2EKF-LO [17](2024), Genz-ICP [18](2024), LIO-GVM [19](2024), RESPLE [20](2025). Summary of supported frameworks presented in Table 2.

[1] https://github.com/MapsHD/HDMapping.

Table 2
Benchmarked frameworks' software code metadata. We provide LIO → HDMapping converters for easier data analysis, visualization and qualitative/quantitative evaluation.

Framework with repo	Approach	License	Commercial Use	Year
LeGO-LOAM	LO/LIO*	BSD-3	Yes	2018
LoamLivox	LO	GPL-2	No	2019
FAST-LIO	LIO	GPL-2	No	2020
LIO-SAM	LIO	BSD-3	Yes	2020
CT-ICP	LO	MIT	Yes	2022
DLO	LO	MIT	Yes	2022
VoxelMap	LO	GPL-2	No	2022
Faster-LIO	LIO	GPL-2	No	2022
KISS-ICP	LO	MIT	Yes	2022
SLICT	LIO	GPL-2	No	2023
DLIO	LIO	MIT	Yes	2023
Point-LIO	LIO	BSD-3	Yes	2023
GLIM	LIO/LVIO**	MIT	Yes	2024
MAD-ICP	LO	BSD-3	Yes	2024
IGLIO	LIO	GPL-2	No	2024
LIO-EKF	LIO	MIT	Yes	2024
I2EKF-LO	LO	GPL-2	No	2024
GenZ-ICP	LO	MIT	Yes	2025
RESPLE	LO/LIO*	GPL-3	No	2025

* LO/LIO → IMU is optional.
** LIO/LVIO → Visual odometry is optional.

Table 3
Algorithm families and corresponding frameworks.

Algorithm family	References
LiDAR Odometry (LO)	[3,9,10,21–23]
LiDAR-Inertial Odometry (LIO)	[16,24–26,26–31]
Multiple LiDAR (L)	[32–36]

Table 4
Coupling strategies in LiDAR–inertial odometry.

Coupling type	References
Loosely-Coupled	[24]
Tightly-Coupled	[4,15,37–40]

2.1. Novelty and contribution

The contribution of the paper is software-oriented LO/LIO algorithm benchmark suite. The novelty lies in the integration of multiple benchmarking steps into a unified framework, thus overall effort needed for qualitative and quantitative evaluation is reduced thanks to:

- input data conversion,
- ground-truth processing,
- dockerized execution of multiple state-of-the-art methods,
- multi-session registration,
- qualitative visualization,
- quantitative evaluation with standardized outputs (Table 3).

3. Related work

The family of LiDAR Odometry algorithms is rapidly growing since a) decreased cost of LiDAR, b) more open-source reference solutions, c) advantages of LiDAR over other sensing technologies, d) integrated IMU and e) decreased weight of the LiDAR. We distinguish LO (LiDAR Odometry), LIO (LiDAR Inertial Odometry) and multiple LiDARs approaches - summary of frameworks is presented in Table 2.

In LIO we distinguish Loosely-Coupled and Tightly-Coupled solutions as presented in Table 4.

We classify implementations into feature-based methods (extracting edges or plane elements), point to plane methods, methods assuming a ground plane, ground, facade, pillar, beam, sphere etc. and feature-less methods using e.g., Gaussians or meshes. Summary is presented in Table 5.

Table 5
Classification of LIO implementations by feature representation.

Method category	References
Feature-based (edges, planes)	[3,24,41–43]
Point-to-plane	[21,44–46]
Ground-plane assumption	[3,41]
Ground, facade, pillar, beam	[47]
Sphere features	[48]
Feature-less (Gaussians, mesh)	[49–51]

Table 6
Taxonomy of LiDAR odometry and LiDAR–inertial odometry methods.

Category	Subcategory	References
Sensor information	LiDAR intensity	[52–54]
Optimization framework	Single-pose estimation	[24]
	Fixed-lag smoothing	[55,56]
	Factor-graph optimization	[57]
Time formulation	Continuous-Time	[57–59]
	Discrete-Time	[60,61]

Table 7
Novelty table. **DT**: discrete time, **CT**: continuous time, **LC**: loosely-coupled, **TC**: tightly-coupled, **FLS**: fixed-lag smoothing, **(G)VM**: (Gaussian) voxel map.

Method	DT	CT	LC	TC	FLS	(G)VM
LeGO-LOAM [3] 2018	•					
LIO-SAM [4] 2020	•			•	•	
FAST-LIO [5] 2021	•			•	•	
DLO [6] 2022	•		•			
VoxelMap [7] 2022	•			•		• (point with covariance)
Faster-LIO [8] 2022	•			•		• (no Gaussian)
KISS-ICP [9] 2022	•					
CT-ICP [10] 2022		•			•	• (no Gaussian)
SLICT [11] 2022		•		•	•	• (no Gaussian, Surfels)
DLIO [12] 2023		•		•	•	
GLIM [13] 2024	•			•	•	•
MAD-ICP [14] 2024	•		•			
ig-lio [15] 2024	•			•	•	•
LIO-EKF [16] 2024	•			•		
I2EKF-LO [17] 2024	•					
Genz-ICP [18] 2024	•					
LIO-GVM [19] 2024	•			•	•	•
RESPLE [20] 2025		•		•		

LiDAR also provides intensity which can be used in LO. Looking from the optimization framework point of view, we have single pose transformation estimation and fixed-lag smoothing within a factor-graph optimization framework. Finally we have Continuous-Time and Discrete-Time solutions. Table 6 summarizes LO and LIO methods by sensor usage, optimization approach, and temporal formulation.

3.1. LiDAR odometry

Instead of x, y, z coordinates (or horizontal, vertical angle, distance) LiDAR can provide intensity values for each measurement point. Information about intensity can improve pose estimation. We can distinguish repetitive and non-repetitive scanning patterns[62]. The main advantage of non-repetitiveness is that we cover almost the entire surrounding space with 3D measurements without the need to move. For both scanning patterns, we should consider the 3D scan distortion. Most state-of-the-art LiDAR-only methods include a point cloud deskewing algorithm based on a constant velocity model like KISS-ICP [9] and VoxelMap [7](2022).

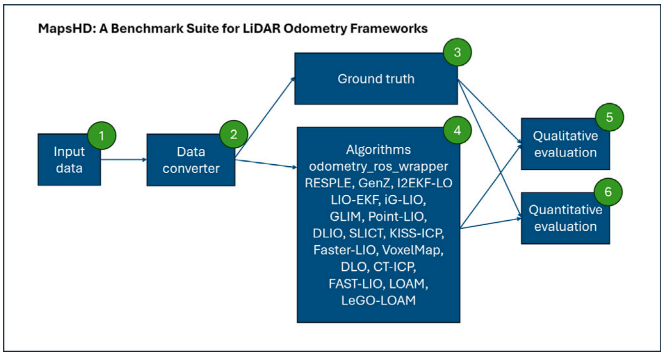

Fig. 1. “MapsHD: A Benchmark Suite for LiDAR Odometry Frameworks” software architecture composed of 1. Input data, 2. Data converter, 3. Ground truth, 4. Algorithms, 5. Qualitative evaluation, 6. Quantitative evaluation.

Table 8
List of other state-of-the-art (SOTA) algorithms with justification for why we did not include them in the proposed benchmark suite. This is considered future work because it requires additional effort and contact with the original authors to resolve significant programming or compatibility issues. (*) 2nd place in the ICRA HILTI 2023 SLAM challenge; 1st place in the ICCV 2023 SLAM Challenge.

Index	Work	Reason for not being in our benchmark suite
1	UA-MPC [78]	Our benchmark does not address rotary LiDARs
2	HCTO [79]	Source code is not publicly available
3	AEOS [80]	Source code is not publicly available
4	R-VoxelMap [81]	Source code is not publicly available
5	DUFOMap [82]	Crowded scenes were not within the scope of our benchmark
6	A Dynamic-Aware LIO [84]	Dynamic scenes were not within the scope of our benchmark
7	MAD-ICP [85]	Compatibility issue (only trajectory is output)
8	LIO-SAM [86]	Uses loop closures
9	D-LIO [88]	Future work
10	KISS-SLAM [87]	Building issue
11	[96]	Future work
12	2FAST-2LAMAA [97]	Future work
13	MM-LINS [98]	Future work
14	VOX-LIO [89]	Source code is not publicly available
15	SS-LIO [90]	Source code is not publicly available
16	LIO-GVM [19]	Unresolved programming issues
17	SR-LIO [99]	Future work
18	Light-LOAM [100]	Future work
19	LOG-LIO2 [31]	Future work
20	NV-LIOM [101]	Future work
21	Voxel-SLAM [102]	Future work (*)
22	LIO-SEGMOT [103]	Future work
23	GLIO [104]	Future work
24	LOG-LIO [105]	Future work
25	F-LOAM [106]	Future work
26	A-LOAM (no publication)	Future work
27	RC-Vox [91]	Source code is not publicly available
28	STATIC-LIO [92]	Source code is not publicly available
29	SC-F-LOAM [107]	Future work
30	SC-LeGO-LOAM [108]	Future work
31	LINS [109]	Future work
32	PIN-SLAM [110]	Future work
33	SPS-LIO [93]	Source code is not publicly available
34	[94]	Source code is not publicly available
35	Universal [95]	Source code is not publicly available
36	MFS-LO [117]	Model (deep learning) not publicly available
37	UnMinkLO-Net [113]	Model (deep learning) not publicly available
38	TransLO [114]	Future work (deep learning)
39	LIO-Livox [111]	Future work
40	DALI-SLAM [112]	Future work
41	PWCLO-Net [116]	Future work (deep learning)
42	DSLO [115]	Model (deep learning) not publicly available

Table 9
Links to the movies for each algorithm from our framework.

Algorithm	Movie
lidar odometry ros wrapper	https://www.youtube.com/watch?v=w233P_MZMWk
RESPLE	https://www.youtube.com/watch?v=5PAB4xJmMoo
GenZ-ICP	https://www.youtube.com/watch?v=vgGku-cOBVg4&feature=youtu.be
I2EKF LO	https://www.youtube.com/watch?v=B2358Gn62Ho
iG LIO	https://www.youtube.com/watch?v=KlZf7nHeVmI
GLIM	https://www.youtube.com/watch?v=zyZDJECqOG0
Point LIO	https://www.youtube.com/watch?v=JlD1hDJHcrs
DLIO	https://www.youtube.com/watch?v=xFLqFcoAtk8
SLICT	https://www.youtube.com/watch?v=TUaJN7FJOFU
KISS ICP	https://www.youtube.com/watch?v=GyB8UuQN0Io
FASTER LIO	https://www.youtube.com/watch?v=bV1jgF_m-Zo
VoxelMap	https://www.youtube.com/watch?v=oRiuvJRNl-c
DLO	https://www.youtube.com/watch?v=-UH81mNLw8Q
CT ICP	https://www.youtube.com/watch?v=swEsJHwtE50
FAST LIO	https://www.youtube.com/watch?v=ENlaQTtOXEM&feature=youtu.be
LOAM Livox	https://www.youtube.com/watch?v=MbKHTmUcI2w
LeGO LOAM	https://www.youtube.com/watch?v=WpFBXe1zKto
Ground Truth	https://www.youtube.com/watch?v=8sHyUNC3mZs
Qualitative evaluation	https://www.youtube.com/watch?v=C0CcG9vAokY
Quantitative evaluation	https://www.youtube.com/watch?v=PsJaXpWFAis

3.2. LiDAR inertial odometry

Introducing Inertial Measurement Unit (IMU) measurements, typically derived from accelerometers, gyroscopes and magnetometers, improves LiDAR odometry by providing prior orientation and rough estimation of the local displacement. Jointly minimising the cost derived from LiDAR and IMU measurements, the LiDAR-Inertial Odometry (LIO) can perform well with acceptable drift during large-scale experiments. There are abundant research results that demonstrate that this method can estimate the poses of the sensor pair at the IMU update rate with high precision, even under fast motion conditions or with insufficient features [37].

3.3. Loosely-coupled versus tightly-coupled LIO

Tightly-coupled methods estimate the state jointly using LiDAR measurement residuals together with the IMU measurement model in a single estimator, whereas loosely-coupled methods fuse subsystem outputs. In [63], the authors apply the IMU preintegration method proposed in [64] to obtain the initial pose of the current keyframe $k+1$ from the previous keyframe k. The advantage of loosely-coupled LIO is that it works with reduced computational expense[65].

3.4. Residuals

The original approach is Iterative Closest Point [66], and it introduces a point-to-point residual. It is called a dense method that works with a large subset of LiDAR-scan points. It is potentially expensive for real-time operation. The Generalised Iterative Closest Point (GICP) [67] is a common dense point-based scan matching method, where local surface normal information is used to better address the measurement noise in scan matching by using both point-to-point and point-to-plane matching, with planes being evaluated in local neighbourhoods.

Some algorithms, after point selection, perform feature extraction to extract features from the ‘good points’. They extract plane and edge features by computing the local smoothness of the point candidate [24,42]. Thus, they construct point-to-edge residuals and point-to-plane residuals. The advantage of this approach is its great performance, accuracy and precision in structured environments with plenty of planar

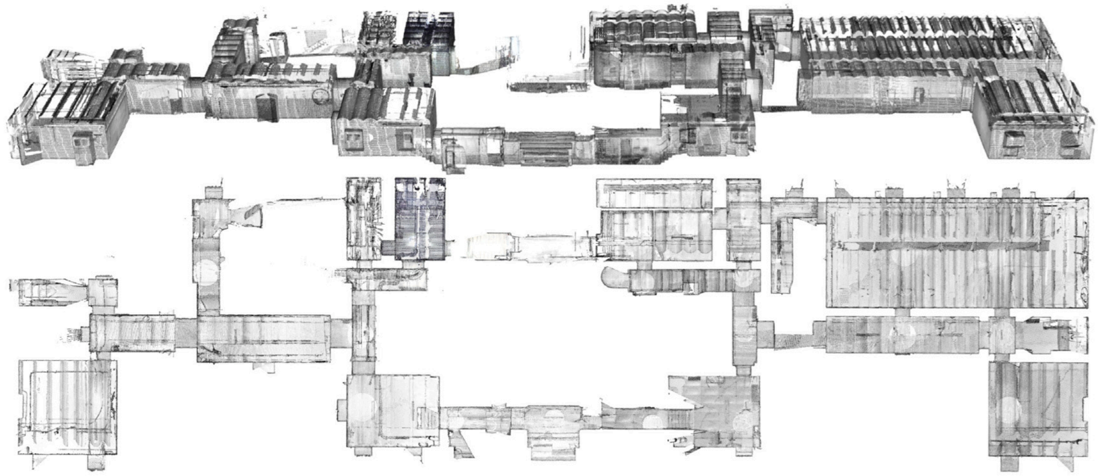

Fig. 2. Ground truth data from Hamesse et al. [118] available at https://charleshamesse.github.io/bunker-dvi-dataset/ processed with software from https://github.com/MapsHD/benchmark-HDMapping-ground-truth/tree/Bunker-DVI-Dataset-reg-1.

shapes. Also, ellipsoidal surfels [68] and ground features [3] can be incorporated. Features can be matched by proximity [69], type [24], or descriptor [68], depending on the algorithm and feature type.

Another approach is the grid-based method: Probability grid methods map LiDAR scans into grids and compute the occupancy probability densities that can later be matched using Newton's method [70]. This approach, also called Gaussian Voxel Map[39] or Normal Distributions Transform [71] is used in this letter. The residual metric can be a weighted distribution-to-distribution (D2D) distance and is similar to the D2D residual in GICP [67] and D2D-NDT (Normal Distributions Transform) [71]. An interesting approach[39] is the Mahalanobis distance, which is weighted by the similarity of the matched correspondences, ensuring that the pairs with higher similarity and closer distance contribute more to the estimation process. For the correspondence evaluation, authors extract the similarity term from the squared Hellinger distance [72]. The advantage of this approach is a rather small computational complexity (no need to classify LiDAR data) and robustness against noisy LiDAR data acquired in a structured environment. The disadvantage is the discretisation of 3D space into buckets.

3.5. Fixed-lag smoothing within a factor-graph optimization framework

The temporal sliding-window optimization (fixed-lag smoothing) makes full use of all measurements within the sliding window [57]. To bound the computational complexity of the fixed-lag smoother, it is necessary to maintain temporal sliding windows with constant size. The advantage is that such an approach can be a basis for real-time systems. In [56] a hierarchical estimation-based LiDAR odometry is presented. Low-level scan-to-map matching estimates pose of each frame by aligning associated features in the frame and corresponding surrounding map with high efficiency. High-level fixed-lag smoothing further optimizes keyframe poses in a sliding window by matching associated features among multiple frames with high accuracy. The advantage is a fast and accurate pose estimation.

3.6. Continuous versus discrete time solutions

Continuous-time state estimation for solving SLAM problem is first systematically derived in [73]. In [74,75] the Authors proposed a continuous SLAM solution with a spinning 2D laser scanner, which is relatively dense and friendly for surfel-based registration. In [59], the Authors proposed a continuous-time trajectory estimator, which now supports the fusion of 3D LiDAR points and inertial data, and it is easy to expand and fuse data from other asynchronous sensors at arbitrary frequencies. In [57], the Authors employ a B-spline to parameterise a continuous-time trajectory as it has the good properties of locality and closed-form analytic time derivatives, C^{k-1} smoothness for a spline of order k (degree $k-1$). Specifically, they parameterise the continuous-time 6-DoF trajectory with uniform cumulative B-splines in a split representation format [76]. The advantage of the continuous method is that it outperforms the discrete-time methods in terms of accuracy, especially when aggressive motion occurs. An interesting approach can be found in [58] where the Authors to account for a rapid motion, divide the temporal window into K equidistant small-resolution segments. In each segment, the movement is still parameterised with two control poses. They represent the continuous-time trajectory over this segment as a continuous function.

3.7. Novelties in state of the art

We collected novelties (**DT**: Discrete Time, **CT**: Continuous Time, **LC**: Loosely-Coupled, **TC**: Tightly-Coupled, **FLS**: Fixed-Lag Smoothing, **(G)VM**: (Gaussian) Voxel Map) of state-of-the-art LiDAR odometry algorithms in Table 7.

4. Software description

Fig. 1 shows "MapsHD: A Benchmark Suite for LiDAR Odometry Frameworks" software architecture. It is composed of 6 components. **Input data** stores data from mobile mapping systems (LiDAR and IMU) in folder. **Data converter** https://github.com/MapsHD/mandeye_to_bag provides all necessary data conversion between our framework and ROS 1 and ROS 2 (Robot Operating System). **Ground truth** https://github.com/MapsHD/benchmark-HDMapping-ground-truth provides software for creating ground truth trajectories. **Algorithms** block provides Docker images for the LiDAR odometry algorithms integrated from the HDMapping project (Table 1); the source-code repository for each algorithm is listed in Table 2, together with a generic ROS odometry wrapper.[2]

All above mentioned algorithms produce a trajectory that can be qualitatively and quantitatively evaluated. **Qualitative evaluation** can be done with tool "multi_session_registration_step_3" from **HDMapping**. We encourage watching this movie: https://www.youtube.com/watch?v=C0CcG9vAokY. **Quantitative evaluation** can be done with tool "multi_session_registration_step_3" from **HDMapping** and any of TUM compatible evaluation framework [77] and e.g., https://github.com/MichaelGrupp/evo. We show

[2] https://github.com/MapsHD/benchmark-lidar_odometry_ros_wrapper-to-HDMapping.

an example in this movie: https://www.youtube.com/watch?v=PsJaXpWFAis. We have provided a tutorial for quantitative evaluation at https://github.com/MapsHD/benchmark-HDMapping-evaluation-of-odometry-and-SLAM. Hyper-parameters belong to the integrated third-party methods rather than to the benchmark framework itself. Thus, we encourage end-users to modify them for further investigation. Our framework is intended to standardize as much of the benchmarking pipeline as possible through common data conversion, unified output handling, and standardized evaluation procedures. At the same time, because the framework integrates many independent third-party algorithms, some implementation specific settings remain method dependent.

5. State of the art ToDo list (Future work)

In this section we elaborated on other SOTA (State of The Art) LIO approaches with justification as to why we have not yet added these contributions to proposed benchmark suite. The challenge is huge and it is worth researching since a demand is significant. All issues are collected in Table 8. Our benchmark does not address a rotary LiDARs [78], where UA-MPC efficiently optimizes motor speed control according to different scenes. An interesting HCTO algorithm [79] utilizes LiDAR inertial odometry with hybrid continuous time optimization for compact wearable mapping system. Active Environment-aware Optimal Scanning Control for UAV LiDAR-Inertial Odometry in Complex Scenes is elaborated in [80]. It demonstrates an approach for emerging challenge of close range remote sensing—navigation in complex environments. Recent approach R-VoxelMap [81] utilized a novel voxel mapping method that constructs accurate voxel maps using a geometry-driven recursive plane fitting strategy to enhance the localization accuracy of online LiDAR odometry, unfortunately source code is unavailable. An emerging challenge for LIO algorithms is crowded scenes. It is addressed in [82] and the benchmark addressing crowded scenes is available in [83]. Similar challenge is addressed in [84]. An interesting work MAD-ICP [85] unfortunately provides only trajectory, thus making it difficult to integrate with our benchmark. LiDAR odometry with loop closures is elaborated in [86,87]. Great candidate for further investigation is 6DoF Direct LiDAR-Inertial Odometry Based on Simultaneous Truncated Distance Field Mapping [88]. We found several interesting approaches without code [89–95]. The following contributions we consider for future work investigation [31,96–112]. Some projects have unsolved programming issues [19]. DNN models are not available for [113–115]. We consider following DNN models for future work [114,116]. We found A-LOAM at https://github.com/HKUST-Aerial-Robotics/A-LOAM without publication.

6. Illustrative example

We provided an end-to-end tutorial on how to use our framework to conduct benchmark of several LiDAR odometry algorithms. Input data comes from Bunker dataset [118] available at https://charleshamesse.github.io/bunker-dvi-dataset/. For each step of the example benchmark we provide a movie (see Table 9). The goal of this example is to show end-to-end workflow from data shown in Fig. 2 to qualitative evaluation of trajectories shown in Figs. 3 and 4 and quantitative results shown in Table 10 (APE - absolute pose error) and in Table 11 (RPE - relative pose error), calculated using the benchmark.[3] We provide flexible approach to quantitative evaluation since our trajectories are exported in TUM format.

7. Impact

This open source open hardware project has already had a significant impact. It is designed to be as easy as possible to use across different domains e.g., Robotics, Informatics, Geodesy and Cartography, Earth Sciences, Transport, Speleology, Precise Forestry, Agriculture etc. We identified new opportunities as follows:

- *New research questions that can be pursued as a result of our software. For example it can boost the LiDAR odometry investigations and mobile mapping applications in general.*
- *Our software improves the pursuit of existing mobile mapping research, as it provides an end-to-end framework for LiDAR odometry benchmarking.*
- *We have encouraged plenty of end-users to use our mobile mapping system for ground truth data collection. Our affordable solution and Windows based applications have spread throughout research and professional community.*
- *Our software is popular in many domains. We have more than 330 stars on GitHub. We have already collected 20 publications in our knowledge base—HDMapping framework.[4] Our software has already helped more than ten universities to build mobile mapping laboratories. Our free software is appreciated by practitioners, teachers and students.*

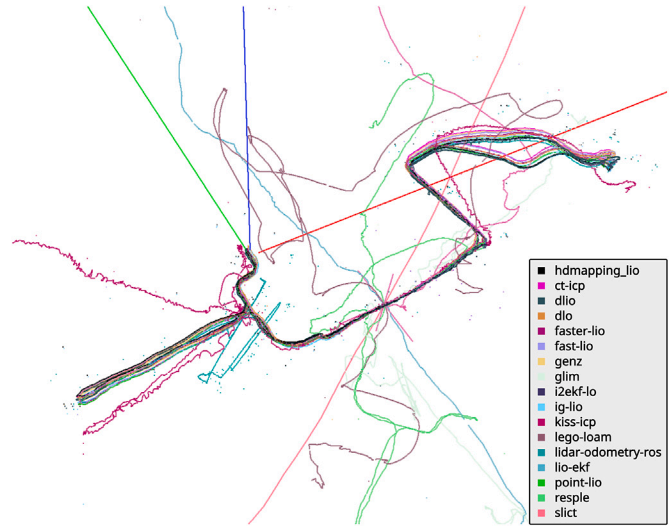

Fig. 3. All trajectories processed with our framework using the tool "multi_session_registration_step_3" from **HDMapping**. Our software enables visual inspection of the trajectories in 3D view. It is an added value to SOTA. Different colors correspond to different algorithms. All data is registered to ground truth.

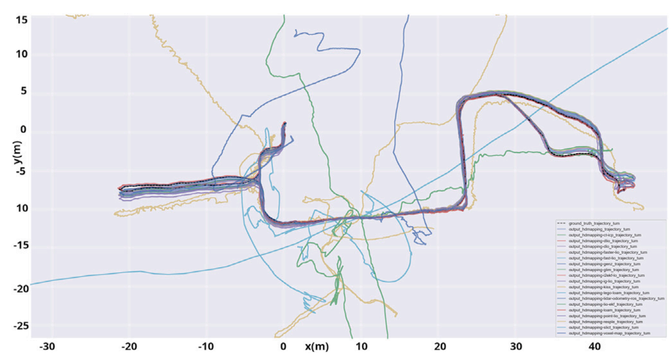

Fig. 4. All trajectories are plotted. Different colors of trajectories correspond to different algorithms, and the legend enumerates all algorithms.

[3] https://github.com/MapsHD/benchmark-HDMapping-evaluation-of-odometry-and-SLAM/tree/Bunker-DVI-Dataset-reg-1.

[4] https://github.com/MapsHD/HDMapping.

Table 10
APE – absolute pose error.

	max	mean	median	min	rmse	sse	std
hdmapping_lio	0.302556	**0.053789**	**0.051380**	**0.000633**	**0.062583**	256.53924	**0.031990**
ct-icp	0.666496	0.211218	0.174998	0.041055	0.242838	193.00931	0.119821
dlio	1.203014	0.195927	0.180943	0.014603	0.212762	1482.2399	0.082945
dlo	1.017893	0.327377	0.285013	0.127095	0.366897	440.72542	0.165645
faster-lio	0.347235	0.127601	0.105748	0.010635	0.151864	75.507115	0.082344
fast-lio	0.357433	0.131987	0.124529	0.000690	0.145813	69.610126	0.061974
genz	0.488600	0.169859	0.119617	0.004529	0.209698	123.08170	0.122969
glim	53.31329	24.89923	22.24682	8.054237	26.91718	2,372,127.7	10.22561
i2ekf-lo	**0.299496**	0.089043	0.084234	0.004999	0.098937	**11.971344**	0.043126
ig-lio	0.635094	0.259547	0.229687	0.010365	0.288841	273.14620	0.126744
kiss-icp	57.23357	21.27990	17.94439	6.451049	25.04907	2,053,663.7	13.21445
lego-loam	45.38227	19.31593	16.35771	4.025432	22.07724	392,848.28	10.69109
lidar-odometry-ros	36.09209	13.96986	12.36597	2.147020	16.29795	869,120.02	8.394422
lio-ekf	361.0541	174.1565	179.7231	15.12114	194.9721	124,268,234	87.65638
point-lio	0.389449	0.151193	0.128220	0.006296	0.170734	95.437209	0.079314
resple	22.00656	6.931513	5.190022	1.623168	8.480002	229,681.91	4.885136
slict	1270.128	563.9430	473.4318	74.99585	658.1596	471,726,602	339.3262

Table 11
RPE – relative pose error.

	max	mean	median	min	rmse	sse	std
hdmapping_lio	**0.026669**	**0.001612**	**0.001426**	**0.000000**	**0.002018**	0.266823	**0.001215**
ct-icp	0.170148	0.023061	0.020382	0.001367	0.026755	2.342112	0.013565
dlio	1.093084	0.021576	0.012364	**0.000000**	0.038824	49.35438	0.032277
dlo	0.183737	0.015045	0.011616	0.000439	0.019664	1.265524	0.012661
faster-lio	0.166162	0.005490	0.004920	0.000518	0.007506	**0.184422**	0.005119
fast-lio	0.154157	0.006580	0.005684	0.000405	0.008558	0.239704	0.005472
genz	0.162090	0.009768	0.008770	0.000160	0.011779	0.388194	0.006583
glim	0.989137	0.051066	0.030066	0.001327	0.091262	27.25978	0.075637
i2ekf-lo	0.153804	0.009901	0.008268	0.000481	0.013135	0.210836	0.008632
ig-lio	0.154341	0.012851	0.010856	0.000778	0.015633	0.799884	0.008902
kiss-icp	0.760740	0.102368	0.086851	0.005766	0.123726	50.08825	0.069491
lego-loam	5.699232	0.321794	0.321513	0.003122	0.399876	128.7203	0.237381
lidar-odometry-ros	0.984388	0.009174	0.007499	0.000424	0.020608	1.389191	0.018454
lio-ekf	1.125873	0.233184	0.188362	0.004624	0.278770	253.9659	0.152768
point-lio	0.158866	0.010723	0.009878	0.000534	0.012579	0.517904	0.006576
resple	0.218377	0.062758	0.062635	**0.000000**	0.069234	15.30499	0.029236
slict	5.427715	2.860021	3.026210	0.341203	2.965140	9565.756	0.782519

- *This software is under MIT license, thus everyone can benefit from it. It has helped some start-ups build more sophisticated mobile mapping portfolios on top of our software.*
- *Our rapidly growing community is composed of more than 200 people.*

8. Conclusions

This paper describes a software toolbox for LiDAR and LiDAR-Inertial Odometry qualitative and quantitative evaluation. We provide software for building ground truth trajectories. The purpose of our framework is LiDAR odometry qualitative and quantitative evaluation. We provide software as https://github.com/MapsHD organization with all necessary information at https://github.com/MapsHD/HDMapping. Our software contributions are a) ground truth data processing, b) dockerized state-of-the-art LO and LIO algorithms, c) multi-session data registration to common coordinate system, d) APE (Absolute Pose Error) and RPE (Relative Pose Error) metrics, e) import/export tools for easier 3D data handling and visualizing, e.g., in Cloud Compare software. This software is compatible with ROS1 (Robot Operating System) and ROS2 data formats. We show an example benchmark of LeGO-LOAM, LIO-SAM, FAST-LIO, DLO, VoxelMap, Faster-LIO, KISS-ICP, CT-ICP, SLICT, DLIO, GLIM, iG-LIO, LIO-EKF, I2EKF-LO, GenZ-ICP, RESPLE, odometry_ros_wrapper, Point-LIO, and LOAM-Livox algorithms. For all experiments we provide movies. Our framework is easy to use since for most software components we provide dockers and instructional movies.

The contribution of the paper is software-oriented LO/LIO algorithm benchmark suite. The novelty lies in the integration of multiple benchmarking steps into a unified framework, thus overall effort needed for qualitative and quantitative evaluation is reduced.

CRediT authorship contribution statement

Janusz Będkowski: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Michał Pełka:** Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Karol Majek:** Software. **Marcin Matecki:** Software. **Adrian Radulescu:** Software. **Charles Hamesse:** Resources, Data curation. **Ethan Decleyn:** Resources, Data curation. **Przemysław Lekston:** Software. **Tomasz Owerko:** Validation, Resources. **Artur Adamek:** Data curation. **Przemysław Kuras:** Validation, Resources. **Michał Ciszewski:** Validation, Resources. **Jakub Kolecki:** Validation, Resources. **Karolina Tomaszkiewicz:** Validation, Resources. **Łukasz Ambroziński:** Validation, Resources. **Joanna Koszyk:** Validation, Resources. **Bartosz Hyla:** Validation, Resources. **Karolina Pargieła:** Validation, Resources. **Anna Malczewska:** Validation, Resources. **Tomasz Lipecki:** Validation, Resources, Methodology. **Bartosz Mitka:** Validation, Resources, Methodology, Investigation. **Klapa Przemysław:** Validation, Resources. **Pelagia Gawronek:** Validation, Resources. **Martin Mokros:** Data curation, Conceptualization. **Jozef Výbošťok:** Resources, Methodology, Investigation. **Juliána Chudá:** Validation, Resources. **Michal Skladan:** Validation, Resources. **Carlos Cabo:** Validation, Resources, Investigation. **Kim André**

Anstensen: Validation, Resources, Methodology. **Craciun Daniel-Marian:** Validation, Resources, Investigation, Conceptualization. **Antun Jakopec:** Validation, Resources, Investigation. **Michal Wlasiuk:** Software, Resources, Investigation, Data curation. **Kornel Mrozowski:** Validation. **Maksymilian Kulicki:** Validation, Resources. **Krzysztof Stereńczak:** Resources. **Oskar Bartosz:** Validation, Software, Resources, Methodology. **Jakub Markiewicz:** Validation, Resources. **Sławomir Łapiński:** Validation, Resources. **Adam Kostrzewa:** Validation, Resources. **Mariana Campos:** Validation, Resources. **Machi Zawidzki:** Validation, Resources. **Jacek Szklarski:** Validation, Resources. **Rami Faraj:** Resources, Investigation. **Loris Redovniković:** Validation, Resources, Methodology, Investigation. **Jurica Jagetić:** Validation, Resources. **Samer Karam:** Validation, Resources, Investigation. **Răzvan Dumbravă:** Resources, Investigation. **Milosz Mielcarek:** Validation, Resources. **Grzegorz Krok:** Validation, Resources. **Michal Laszkowski:** Validation, Resources. **Jaroslaw Wajs:** Validation, Resources, Investigation, Data curation. **Jakub Chudziński:** Validation, Resources.

Declaration of generative AI and AI-assisted Technologies in the Writing Process

Authors declare that during preparation of this work no AI-assisted tools were used.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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