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FLYBO: A Unified Benchmark Environment for Autonomous Flying Robots

Anthony Brunel^{1,2}, Amine Bourki², Olivier Strauss¹ and Cédric Demonceaux³

¹LIRMM, Univ. Montpellier, CNRS, 860 rue de St Priest, 34095 Montpellier, France.

²Gambi-M R&D, Champs-sur-Marne, France.

³ImViA, Université Bourgogne Franche-Comté (UBFC), Le Creusot, France.

{anthony.brunel, olivier.strauss}@lirmm.fr, amine.bourki@gmail.com,

cedric.demonceaux@u-bourgogne.fr

www.flybo.org

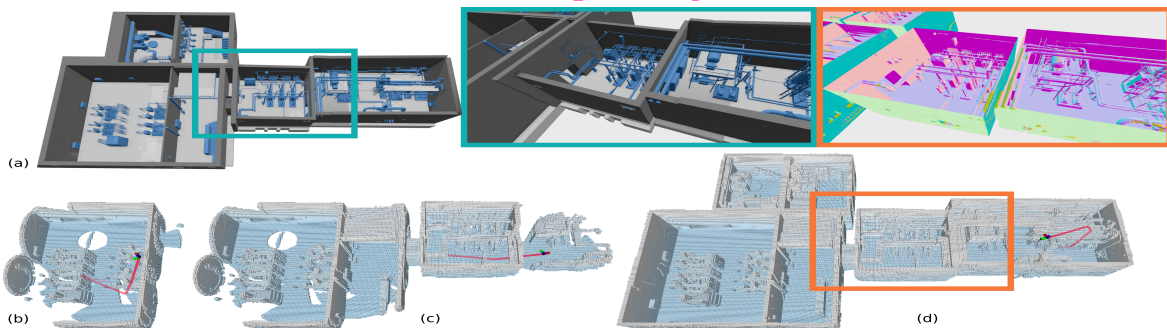


Figure 1: An MAV equipped with odometry- and active depth sensors autonomously explores a complex synthetic area from FLYBO (a) while gradually mapping the scene throughout different exploration stages and planning trajectories online (b–d). Simultaneously, the perceived surfaces are also reconstructed online (close-up views). FLYBO provides datasets, references and a framework to benchmark such systems w.r.t their volumetric exploration and online surface reconstruction capabilities.

Abstract

The use of Micro-Aerial Vehicles (MAVs) equipped with odometry- and depth sensors has become predominant for a wide variety of challenging industrial applications such as the autonomous exploration (i.e., digital mapping), and inspection (i.e., online surface reconstruction) of unknown facilities. However, despite the ongoing attention these topics receive, autonomous exploration systems still lack common evaluation grounds to assess their relative performance in terms of data and experimental tools. We address this deficit by introducing FLYBO, the first unified benchmark environment that focuses on the performance of such flying robots in terms of autonomous exploration and online surface reconstruction. It includes (i) 11 challenging realistic indoor- and outdoor datasets of increasing complexity and size, with ground-truth, (ii) a comprehensive benchmark of 7 of the top-performing autonomous exploration algorithms including methods without publicly available code. (iii) A unified experimental system factorizes the routines shared by autonomous planners in order to fairly and accurately assess their exploration performance in a controlled environment.

1. Introduction

Over the past decade, Micro-Aerial Vehicles (MAVs) have considerably gained in popularity and commercial maturity, giving birth to even consumer-grade products at an affordable price. In particular, MAVs equipped with depth- and odometry sensors have become a staple equipment to help map, digitize, locate and reconstruct relatively intricate facilities, even in absence of prior knowledge about their structure, or comprising objects [1]. As a result, the ability of such autonomous flying robots to *efficiently explore* unknown environments [8, 6, 65] while *accurately reconstructing surfaces* [63] that are perceived therein has become critical to help minimize risks and operational costs.

Autonomous exploration planning has been a long-standing problem for over two decades [78, 79] and has received an ongoing attention within the scientific communities of Computer Vision [33], Robotics [6, 14] and Computer Graphics [23, 77]. Despite this activity, state-of-the-art autonomous planning systems (commonly referred-to as “planners”) are evaluated on disparate data, in sometimes drastically diverse experimental conditions [65, 19], and overall, lack a unifying public benchmark.

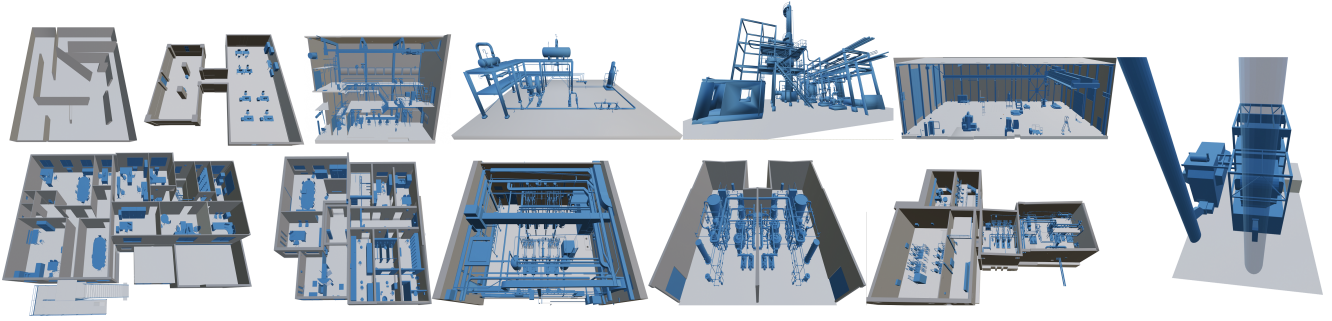


Figure 2: Overview of the 11 areas we consider in FLYBO, through a few selected views and levels.

In terms of datasets, the evaluation of autonomous exploration and their online surface reconstruction capabilities requires 3D models that are (i) watertight (to avoid aberrant flight behaviors, especially indoors) and (ii) realistic in terms of their structural complexity, size and geometry. CAD-derived data in particular are a gold-standard w.r.t these criteria and are favored when available as a benchmarking reference in a controlled, simulated-environment for autonomous exploration [8, 19], and surface reconstruction [47, 43].

We address the aforementioned challenges by making the following main contributions:

- *System:* We present FLYBO, the first unified benchmark environment specifically tailored for the evaluation of autonomous flying MAVs for the tasks of volumetric exploration and online surface reconstruction.
- *Datasets:* The package includes 11 challenging CAD-derived datasets with ground-truth, that represent realistic indoor- and outdoor areas of varying nature, size and structural complexity.
- *Benchmark:* We evaluate 7 of the leading state-of-the-art autonomous exploration planners, including methods with no public code using our own re-implementations.
- *Tools:* In order to fairly and accurately assess the pure exploration planning part of existing systems, we provide an experimental framework that factorizes the common routines that are shared by all planners. Our system also allows to generate the quantitative and qualitative results seamlessly and on the fly.
- A project website with a leaderboard will be published upon acceptance along the datasets, our re-implementations, and unified evaluation system.

2. Related Work

Autonomous Exploration Planning. Autonomous exploration planning algorithms are commonly categorized into frontier-based, sampling-based or hybrid strategies. Frontier-based methods rely on the concept of frontier voxels that separate *empty* and *unknown* spaces in the explored

environment. The first method to introduce this paradigm was Classic [78] and has originally done so in 2D exploration planning. The method proceeds by visiting the nearest available frontier at each algorithm iteration, until all achievable frontiers are visited. Despite its apparent simplicity, the method also performs very well in 3D and is still considered relevant as a baseline system in terms of 3D exploration efficiency [8, 82]. The seminal work of Yamauchi et al. [78] has led to numerous extensions including multi-agent exploration [79], and more sophisticated strategies to extract frontiers using stochastic differential equations [67], information theory and a multi-objective utility function [21], or more generally, in a Next-Best View (NBV) fashion, i.e., by maximizing a given utility function greedily [24]. Another trend in frontier-based planning is to enhance its main original drawbacks of speed and efficiency. Rapid [14] addresses these shortcomings by alternating between the original behavior of Classic [78] and minimizing the deviation angle between the current trajectory of the MAV and its incidence with frontier candidates. This simple heuristic has led to impressive gains in terms of volumetric efficiency and is still considered a strong-performing planner w.r.t current state-of-the-art [82, 14]. The current main difficulty to assess the performance of Classic [78] and Rapid [14] outside the scope of their originally documented performances lies in the absence of their public implementations. We address this by providing common, efficient implementations of their systems.

Sampling-based solutions are the second dominant trend in autonomous exploration. They are based on sampling sparse viewpoint candidates to visit in order to limit the size of the search space, and ultimately, the volumetric efficiency of the process altogether. Such approaches often rely on tree data structures that connect the sampled positions and allow to produce feasible trajectories through queries [42, 49]. The top-performing sampling strategies are based on Rapidly-exploring Random Trees (RRT*) [49] and develop one [63] or multiple tree structures [6, 65] from randomly sampled seed positions. The motivating theoretic

	MAZE	OFFICES A	OFFICES B	OFFICES C	FACILITY A	FACILITY B	FACILITY C	WAREHOUSE	PLATFORM A	PLATFORM B	POWERPLANT
Area (m^2)	400	470	120	534	115	323	478	800	384	480	1000
Volume (m^3)	1000	1410	1443	1602	690	1450	2868	9600	3456	12000	26598
Bounding volume (m)	$20 \times 20 \times 2.5$	$22 \times 28 \times 3.4$	$8 \times 20 \times 12$	$30 \times 16 \times 7.4$	$12 \times 14 \times 6$	$19 \times 17 \times 4.6$	$38 \times 22 \times 6$	$40 \times 20 \times 12$	$16 \times 24 \times 9$	$24 \times 20 \times 25$	$33 \times 31 \times 26$
#Rooms	-	2	4	23	1	2	5	1	-	-	-
#Levels	1	1	4	2	1	1	2	2	3	3	1
#CAD mesh faces	130	6910	227k	857k	373k	1120k	1072k	793k	149k	470k	2000
Structural complexity	Low	Low	Intermediate	High	High	High	High	High	Intermediate	High	Low
Scale	Small	Intermediate	Intermediate	Large	Intermediate	Small	Large	Large	Large	Large	Large
Indoor / outdoor	Indoor	Indoor	Indoor	Indoor	Indoor	Indoor	Indoor	Indoor	Outdoor	Outdoor	Outdoor

Table 1: Statistics of the 11 Areas that comprise the dataset part of FLYBO.

cal purpose behind this paradigm lies in the scalability and ease of convergence although the early strong-performing methods of the kind such as NBVP [6] tend to get stuck in local exploration. In contrast, AEP [65] combines the NBVP [6] strategy with the storage of previously-explored node positions and re-assessing their information gain as well as considering frontiers, leading to a hybrid strategy that has a sparing effect regarding globally-exploring views. More recently, SplatPlanner [8] proposed a hybrid scheme that combines the flexibility of RRT* with frontiers that are sampled based on their spatial density using highly-efficient bilateral filtering operations, leading to impressive performance in terms of volumetric efficiency and coverage.

The task of autonomous exploration is inherently tied to the one of autonomous inspection, or online surface reconstruction in assessing the accuracy of the geometry that is produced by autonomous planners [37]. Several works jointly consider criteria for online surface reconstruction in a mono-agent scenario [37, 77, 63] or even as multi-agent solutions [23]. Despite the existence of a rich but much more specialized literature on reconstruction in general [5, 43] and online surface reconstruction in particular [68, 37], our proposed benchmark strictly focuses on the online surface reconstruction of general autonomous exploration systems in order to provide new insights regarding their performance beyond the traditional volumetric criteria, as a *trade-off* between their volumetric efficiency and the accuracy of their reconstructed surfaces in a controlled environment. This is made possible thanks to the unified nature of our FLYBO benchmarking framework.

Datasets and Benchmarks for Autonomous Flying Robots. Current state-of-the-art autonomous planners commonly evaluate their performance either on a handful of disparate, non-public CAD datasets [8, 82], or by resorting to borrowing datasets from other tasks [23, 69]. Such datasets are RGBD-derived [9, 17, 3, 69, 76], which can suffice to evaluate autonomous planners embedded on non-flying robots [77, 23], but are however impractical for simulating flying robots that can fly through unscanned regions and are also far from ideal to evaluate surface reconstruction in presence of sometimes severe structural artifacts and missing parts, that can also bias frontier-based explorations.

In contrast, FLYBO proposes watertight and highly-structured CAD-derived environments, comprising the first public dataset and benchmark focusing on MAV-based autonomous exploration systems.

3. Flying through FLYBO

3.1. Dataset and Acquisition

Our proposed benchmark is comprised of **11 areas**, as detailed in Table 1 and illustrated in Figure 2. They consist of CAD models that were manually designed by human experts and directly serve our experimental framework to evaluate state-of-the-art methods for the considered tasks.

- **MAZE.** This is the most structurally simple area of our dataset. It allows to isolate exploration behaviors on the simplest form of indoor scenes, i.e., consisting of one ground level and flat walls. The performance on this area also serves as a baseline to assess the robustness to increasing levels of structural complexity and scene size.
- **OFFICES A.** Incrementally more complex than MAZE, it depicts two interconnected furnished office areas of moderately-sized open-spaces with few objects.
- **OFFICES B.** Another set of interconnected office areas with more geometric complexity spanning multiple levels and that contain an important number of present objects.
- **OFFICES C.** Similarly, area C is much more challenging in terms of structural complexity, amount of objects and details as well as in terms of overall scale.
- **FACILITY A, B AND C.** These facilities depict complex industrial indoor environments, comprising piping, ducts, complex equipments and very challenging intricate spaces to move through. FACILITY A–C are of high structural complexity and of increasing sizes and scales. They span the plausible usecases that autonomous exploration algorithms would typically have to deal with in a real-life inspection scenario, ranging from moderate difficulty to highly-challenging overall.
- **WAREHOUSE** is a large-scale area that contains a large central empty space that is surrounded by many complex equipments that span two interconnected levels.

- **PLATFORM A AND B** represent large industrial outdoors with increasing amounts of cluttering objects and complex equipments. They present numerous intricate spaces that are difficult to maneuver through for an MAV.
- **POWERPLANT** was originally available as an open-source model and used by several state-of-the-art planners to evaluate performance [8, 20, 14]. The area represents a very large-scale powerplant for which the exact crop considered for evaluation was undisclosed and potentially different. We address this by providing one fixed crop to this model with its corresponding experimental settings.

3.2. Tasks and Metrics

The proposed benchmark is specifically tailored for autonomous exploration planning systems, a.k.a planners. However, given that the most common cause of failure in MAV-based inspection campaigns generally is poorly reconstructed geometry provided by the offline, *a posteriori* assessment of the mapped 3D data, we consider both the tasks of (i) pure autonomous exploration planning per se, and (ii) online surface reconstruction to evaluate such systems. In practice, the online surface reconstruction may often constitute the deciding factor of whether an MAV exploration campaign is deemed successful in a production-ready scenario, sometimes regardless of the efficiency and speed of the exploration process.

Autonomous Exploration Planning. Given $\mathcal{V} \subset \mathbb{R}^3$ a voxel-grid that represents the occupancy states of voxels initially labeled as ‘unknown’, the objective is to re-label such entities as ‘free’ or ‘occupied’ while computing collision-free trajectories online. The standard metrics [23, 8, 19, 65, 14] we consider are defined as follows:

- The volumetric efficiency of the explorations in m^3/s ,
- The volumetric coverage that we define as a fraction of the covered volume at a fixed exploration plateau relative to the top score, for simplification.

Online Surface Reconstruction. We adopt the standard metrics in the field for general-purpose surface reconstruction [23, 46, 43], namely:

- The surface coverage, expressed as the recall over time,
- The accuracy of the produced meshes as F-score and RMSE w.r.t ground-truth references [23, 46].

All of the aforementioned metrics are averaged over multiple runs (5 throughout our experiments) to account for the inherently stochastic nature of the task. This is also a common practice in the field [8, 19, 65, 14].

3.3. Ground-truth Generation

To evaluate autonomous planners according to the aforementioned tasks, we consider the following data:

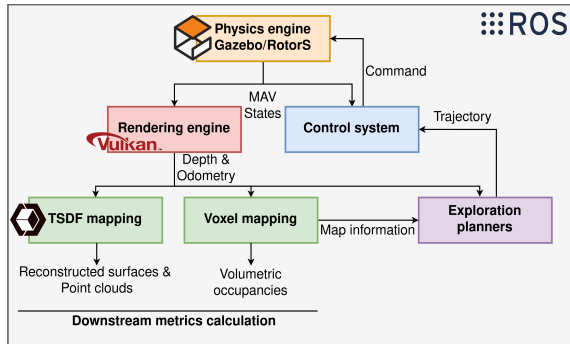


Figure 3: Schematic workflow and components of our proposed unified experimental framework.

Autonomous Exploration Planning. For all the considered metrics, the reference data are the input CAD models.

Online Surface Reconstruction. In this particular case, the direct use of CAD models is not adequate because the surface-based metrics such as recall and F-score account for the amount of geometric surfaces that can be reconstructed, hence perceived in a scene. To avoid introducing significant biases in our evaluation, we run an interactive exploration mapping mode without simulated noise that is manually controlled. This allows to recover only the exterior, perceivable parts of the CAD scenes and to store them as highly accurate and dense point clouds to compute the considered metrics w.r.t surface reconstruction.

3.4. Unified Simulation Framework

We propose the first unified experimental simulation framework tailored for MAV-based autonomous exploration planners (Figure 3). It factorizes the common simulation routines shared by all systems, and the generation of intermediate data outputs and the computation of downstream metrics in a seamless, unified way.

The proposed simulation framework builds upon the Robot Operating System (ROS Kinetic) library [61]. It simulates a Hummingbird quadrotors MAV model from Ascending Technologies and its physics are modeled by the popular Gazebo-based RotorS simulator [29]. The control is insured by a flying robots control framework [27]. Traditional collision-checking is ensured within a sphere centered at the position of the MAV. The computed trajectories are typically piecewise-linear and are smoothed out with a polynomial trajectory optimization [62] to send graceful paths to the control system. The rendering engine uses the Vulkan API¹, assuming perfect poses from RotorS. It simulates a 20Hz DepthVision camera synchronized with the odometry. We take into account depth and odometry controlled noise, similar to ESM [63] we use a gaussian depth error with quadratic scaling modeling recent depth

¹<https://www.khronos.org/vulkan/>

camera [44]. The system simulates noise in positions and depthmaps for realism. TSDF [38] and point clouds are continuously generated as well as the final meshes.

3.5. Featured Autonomous Exploration Systems

Our benchmark experiments consider 7 methods from state-of-the-art featuring the following systems: Classic [78], Rapid [14], NBVP [6], AEP [65], ESM_{IPP} [63], ESM_{Recon} [63] and SplatPlanner [8]. We have re-implemented Classic [78], Rapid [14] and SplatPlanner [8] in absence of public implementations for these methods. NBVP [6], ESM_{IPP} [63], ESM_{Recon} [63] and AEP [65] are used based on their public implementations. Finally, we integrate all of the considered systems in our evaluation framework. NBVP [6] and AEP [65] are inherently dependent on Octomap [35] and thus, they can not benefit from our continuous voxel mapping component (Figure 3).

4. Results

4.1. Autonomous Exploration

Figure 4 and Table 2 respectively summarize the benchmark results in terms of volumetric exploration efficiency averaged over 5 runs with min-max performance and volumetric coverage also averaged over the 5 same runs.

Volumetric efficiency. The first general trend that emerges from the reported data is that certain methods maintain a steady performance throughout the dataset areas. This is the case for SplatPlanner [8], AEP [65], NBVP [6], ESM_{IPP} [63] and ESM_{Recon} [63].

In contrast, Classic [78] and Rapid [14] seem to have sometimes severe performance drops on specific area types. Classic [78] seems to struggle on all the larger scenes (e.g., FACILITY C, WAREHOUSE, PLATFORM A–B, POWERPLANT). This can be explained by the fact that its exhaustive visit of nearest frontiers is linearly correlated to the increased input scale, hence the efficiency drops.

Rapid [14] on the other hand tends to suffer in presence of higher levels of structural complexity, such as indoor scenes with narrow, intricate spaces such as OFFICE C and FACILITY B. On such scenes, the planner tends to oscillate between the traditional Classic [78] heuristic, and its characteristic maximization of the MAV velocity. In particular, while geometric complexity increases, many frontiers are unfavorably oriented w.r.t to the current MAV trajectory.

Volumetric coverage. ESM_{IPP} [63] is a clear winner per the average relative scene coverage, followed by SplatPlanner [8] and ESM_{Recon} [63]. NBVP [6] and AEP [65] perform the worst among the considered planners and Classic [78] shows competitive performance rank-wise, despite its algorithmic simplicity, and performs especially well on smaller areas like MAZE, OFFICES A–C and FACILITY A–C. Rapid [14] shows competitive performance throughout.

4.2. Online Surface Reconstruction

Figure 5 and Table 3 respectively summarize the results regarding the surface coverages and accuracies of the final produced meshes. Both of these scores are also averaged over the same 5 runs and Figure 5 also shows the min-max scores per planner (as colored intervals).

Coverage. Regarding this metric, Classic [78] performs unexpectedly well throughout the areas, except for larger ones similarly to the reported performance drop in volumetric efficiency in such environments. NBVP [6] performs the worse overall, and Rapid [14] performs reasonably well throughout. The top-performing systems are ESM_{IPP} [63] and SplatPlanner [8].

Accuracy of the produced meshes. The reported scores for this metric are the most surprising ones. ESM_{IPP} [63] claims the first place in terms of RMSE while ESM_{Recon} [63] is the better one w.r.t F-scores, closely followed by Rapid [14] and SplatPlanner [8]. It is also worth mentioning that AEP [65] performs worse than the original NBVP [6] method in terms of RMSE and is almost as bad w.r.t F-score. This can be explained by the fact that AEP [65] induces a trade-off between local (NBVP [6] - like) and global (frontier-like) exploration behaviors, which seems to disserve it, accuracy-wise.

4.3. Volumetric Exploration vs. Surface Reconstruction

The Pareto-optimal planners on FLYBO are ESM_{IPP} [63], ESM_{Recon} [63] and SplatPlanner [8] that are the respective leaders w.r.t volumetric exploration (coverage) and surface reconstruction (F-score), while SplatPlanner [8] emerges as the best compromise between the two task-representative metrics (Figure 6).

4.4. Additional Statistics

Table 4 provides indicative timings and statistics.

5. Discussion and Perspectives

The impact of the present work can potentially lead to several avenues of extensions and future work, a few of which are specified in the following discussion.

Given the structured, unified nature of FLYBO, the proposed data and framework can be used to support the development of Reinforcement-Learning (RL) based approaches to autonomous exploration. Methods that build on RL typically require a moderate amount of training data [13] and an efficient means of scaling the number of experiments which could naturally benefit from the flexibility of our system.

An important component of autonomous planning lies in the generation of efficient, continuous, graceful trajectories [22, 55, 80]. Such methods as well as replanning strategies [55, 81, 82] could also directly benefit from our frame-

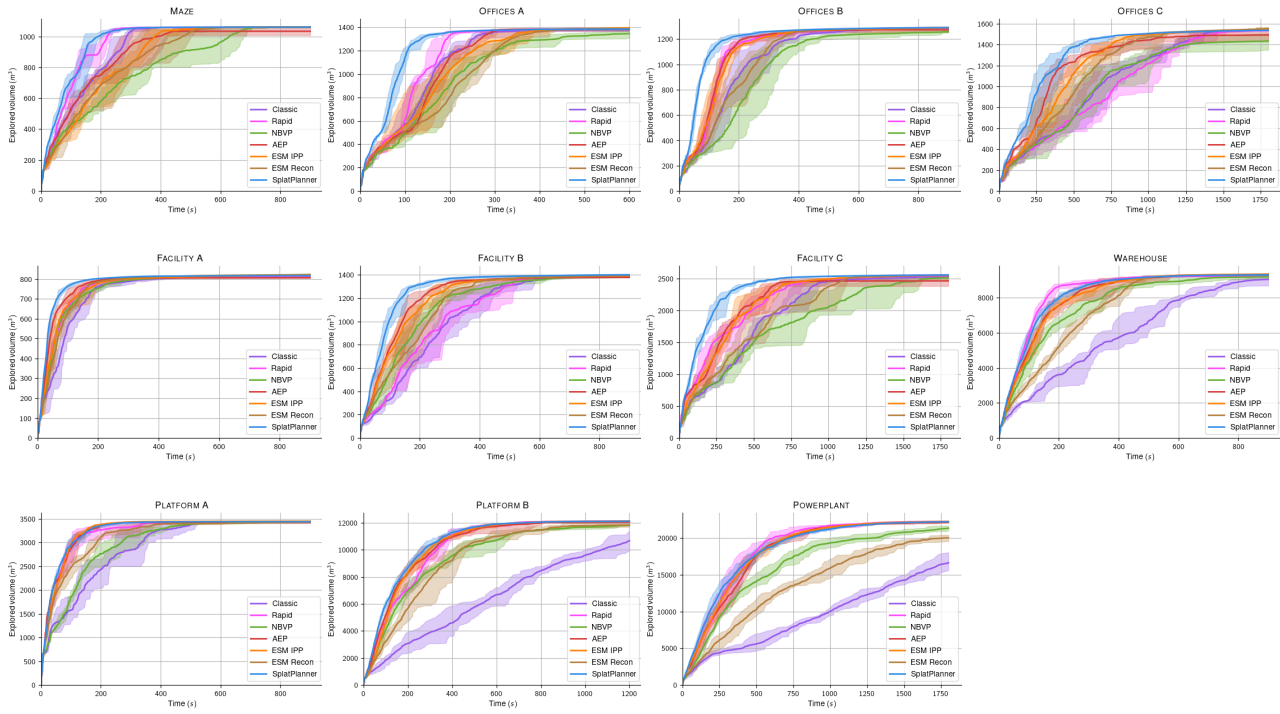


Figure 4: **Autonomous Exploration: Volumetric Efficiency** – Explored volumes over time, averaged over 5 runs.

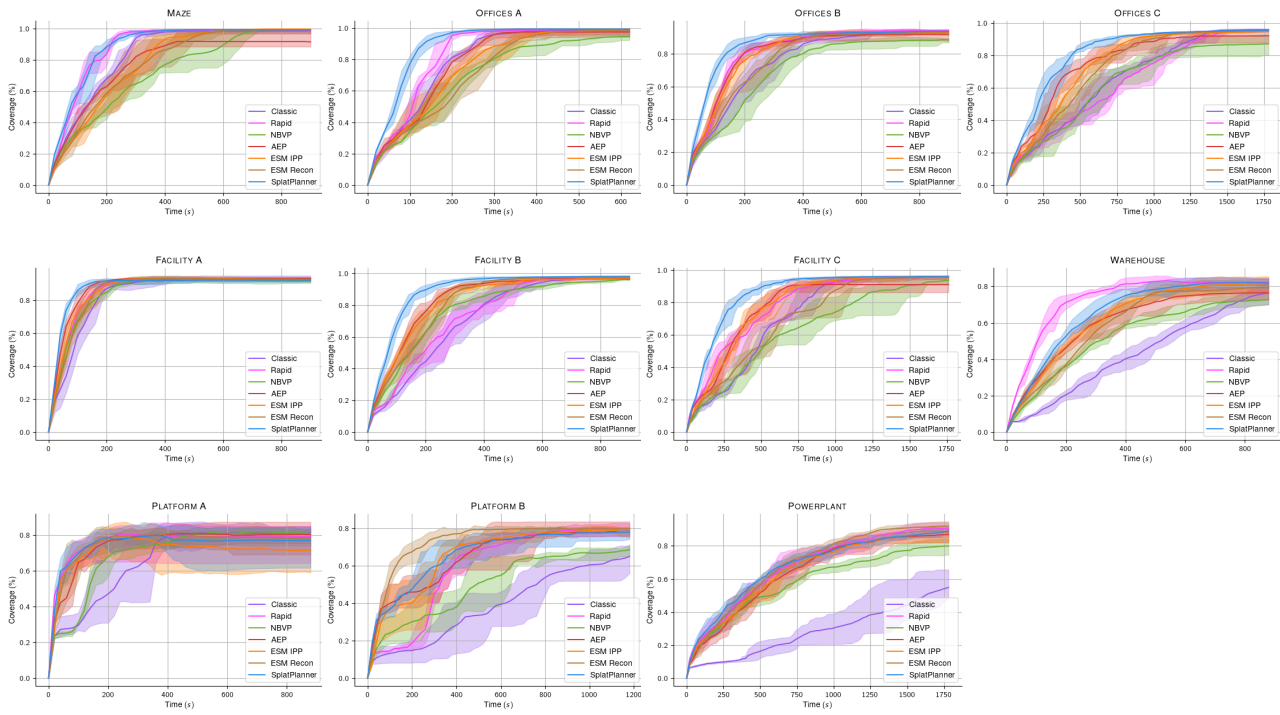


Figure 5: **Online Surface Reconstruction: Coverage** – Scene surface recall over exploration time, averaged over 5 runs.

	MAZE	OFFICES A	OFFICES B	OFFICES C	FACILITY A	FACILITY B	FACILITY C	WAREHOUSE	PLATFORM A	PLATFORM B	POWERPLANT	Mean	Rank
Classic [78]	0.9992	0.9945	0.9957	0.9926	0.9868	0.9911	0.9883	0.9681	0.9933	0.8795	0.7484	0.9579	5.3
Rapid [14]	0.9988	0.994	0.9987	0.9912	0.99	0.9932	0.995	0.9861	0.9934	0.9995	0.9999	0.9945	3.7
NBVP [6]	0.9925	0.9648	0.9685	0.9258	0.9973	0.9866	0.9774	0.9834	0.9887	0.9748	0.9587	0.9744	5.8
AEP [65]	0.975	0.9911	0.9882	0.9656	0.9836	0.9863	0.9642	0.9962	0.9939	0.993	0.9945	0.9847	5.5
ESM _{IPP} [63]	0.9997	1.0	0.9962	0.9976	0.9961	0.9925	0.9971	1.0	1.0	1.0	1.0	0.9981	2.2
ESM _{Recon} [63]	1.0	0.9953	0.9988	1.0	1.0	0.9927	0.9974	0.9974	0.9863	0.9758	0.9001	0.9858	2.9
SplatPlanner [8]	0.9998	0.9923	1.0	0.9935	0.9959	1.0	1.0	0.9952	0.9976	0.999	0.9984	0.9974	2.6
Plateau Time (s)	700	600	750	1650	700	750	1650	900	550	1200	1800		

Table 2: **Autonomous Exploration: Volumetric Coverage** – Scores at plateau, relative to the best value (5 run average).

	MAZE	OFFICES A	OFFICES B	OFFICES C	FACILITY A	FACILITY B	FACILITY C	WAREHOUSE	PLATFORM A	PLATFORM B	POWERPLANT	Mean	Rank
Classic [78]	0.9807	0.9792	0.9371	0.9661	0.9266	0.9459	0.9629	0.7781	0.8111	0.6738	0.6694	0.8755	3.9
Rapid [14]	0.9831	0.9905	0.9435	0.962	0.9257	0.9477	0.9574	0.8097	0.7912	0.7597	0.8673	0.9034	2.8
NBVP [6]	0.9888	0.9609	0.9086	0.916	0.9257	0.9351	0.9416	0.7289	0.778	0.7009	0.8251	0.8736	5.8
AEP [65]	0.9362	0.9687	0.9182	0.9385	0.9132	0.9353	0.9214	0.7581	0.7647	0.7616	0.8484	0.8786	5.8
ESM _{IPP} [63]	0.9944	0.982	0.9344	0.9575	0.9338	0.9429	0.9613	0.8077	0.7028	0.768	0.8513	0.8942	3.6
ESM _{Recon} [63]	0.9862	0.9831	0.9355	0.9603	0.9355	0.9468	0.9538	0.7927	0.7965	0.7986	0.8809	0.9064	2.7
SplatPlanner [8]	0.9848	0.9891	0.9391	0.9597	0.9201	0.9527	0.9602	0.8118	0.7576	0.7575	0.8674	0.9	3.3
Classic [78]	0.018 ± 0.014	0.019 ± 0.025	0.021 ± 0.02	0.015 ± 0.015	0.021 ± 0.021	0.02 ± 0.019	0.02 ± 0.019	0.03 ± 0.034	0.03 ± 0.032	0.046 ± 0.046	0.032 ± 0.028	-	2.6
Rapid [14]	0.021 ± 0.014	0.018 ± 0.014	0.021 ± 0.019	0.016 ± 0.015	0.022 ± 0.021	0.02 ± 0.021	0.02 ± 0.018	0.029 ± 0.033	0.032 ± 0.034	0.043 ± 0.046	0.034 ± 0.03	-	2.7
NBVP [6]	0.018 ± 0.013	0.019 ± 0.016	0.023 ± 0.022	0.017 ± 0.016	0.021 ± 0.02	0.021 ± 0.019	0.022 ± 0.02	0.031 ± 0.032	0.037 ± 0.035	0.044 ± 0.045	0.034 ± 0.027	-	5.
AEP [65]	0.023 ± 0.015	0.021 ± 0.016	0.024 ± 0.022	0.017 ± 0.017	0.026 ± 0.026	0.021 ± 0.02	0.025 ± 0.022	0.032 ± 0.033	0.037 ± 0.037	0.043 ± 0.046	0.034 ± 0.028	-	6.1
ESM _{IPP} [63]	0.016 ± 0.012	0.018 ± 0.015	0.021 ± 0.019	0.016 ± 0.016	0.019 ± 0.017	0.02 ± 0.019	0.02 ± 0.018	0.029 ± 0.032	0.036 ± 0.03	0.042 ± 0.045	0.036 ± 0.03	-	2.3
ESM _{Recon} [63]	0.018 ± 0.013	0.019 ± 0.015	0.022 ± 0.019	0.016 ± 0.015	0.02 ± 0.018	0.02 ± 0.019	0.021 ± 0.019	0.029 ± 0.031	0.031 ± 0.029	0.038 ± 0.044	0.031 ± 0.027	-	2.5
SplatPlanner [8]	0.02 ± 0.014	0.018 ± 0.015	0.021 ± 0.02	0.016 ± 0.016	0.022 ± 0.022	0.018 ± 0.017	0.021 ± 0.018	0.028 ± 0.032	0.033 ± 0.03	0.043 ± 0.045	0.033 ± 0.028	-	2.7

Table 3: **Online Surface Reconstruction: Mesh Accuracy** – Comparative evaluation of the produced meshes by means of F-score and RMSE, averaged over 5 runs.

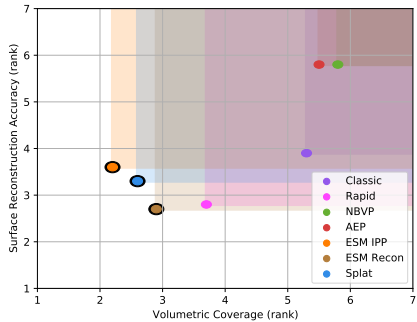


Figure 6: Summary of our benchmark results showing the *state-of-the-art*, Pareto-optimal planners (circled in black) w.r.t their joint Autonomous Exploration Coverage vs. Online Reconstruction Accuracy ranks on FLYBO.

work, planning implementations and data in order to improve existing planners with alternatives to their commonly supported piecewise-linear trajectories.

Future work includes the addition of state-of-the-art planners that are not yet published or available in our benchmark. Other exciting lines of work include the addition of data modalities such as LiDAR scans to the proposed indoor scenes within the realm of autonomous flying robots, to serve downstream applications such as online scene completion [20, 18], or by considering online shape recognition to speed up explorations by using the volumetric occupancy

	#Iterations	Per-iter. avg time (ms)	Tot. Path length (m)
Classic [78]	147 ± 7	35 ± 19	292 ± 21
Rapid [14]	52 ± 6	85 ± 110	442 ± 15
NBVP [6]	196 ± 2	858 ± 83	554 ± 8
AEP [65]	173 ± 5	37 ± 9	500 ± 15
ESM _{IPP} [63]	251 ± 1	N/A	673 ± 1
ESM _{Recon} [63]	246.9 ± 1	N/A	679 ± 2
SplatPlanner [8]	61 ± 2	236 ± 69	641 ± 31

Table 4: Comparative breakdown of exploration planning timings and statistics on the WAREHOUSE (at $t = 900s$).

of objects in a TSDF representation [36, 4].

6. Conclusion

We have presented FLYBO, the first unified benchmark environment that is specifically tailored for autonomous exploration using MAVs. It provides common material in terms of datasets, implementation of state-of-the-art methods, and a unified, exploration-centric, evaluation framework. In particular, our system allows to evaluate a planner according to all of the presented criteria and datasets in merely 17h30 of computation, which is a fraction of the time required to produce and package our framework and experiments. We hope that this significant speed-up will stimulate new contributions to the field in the near future.

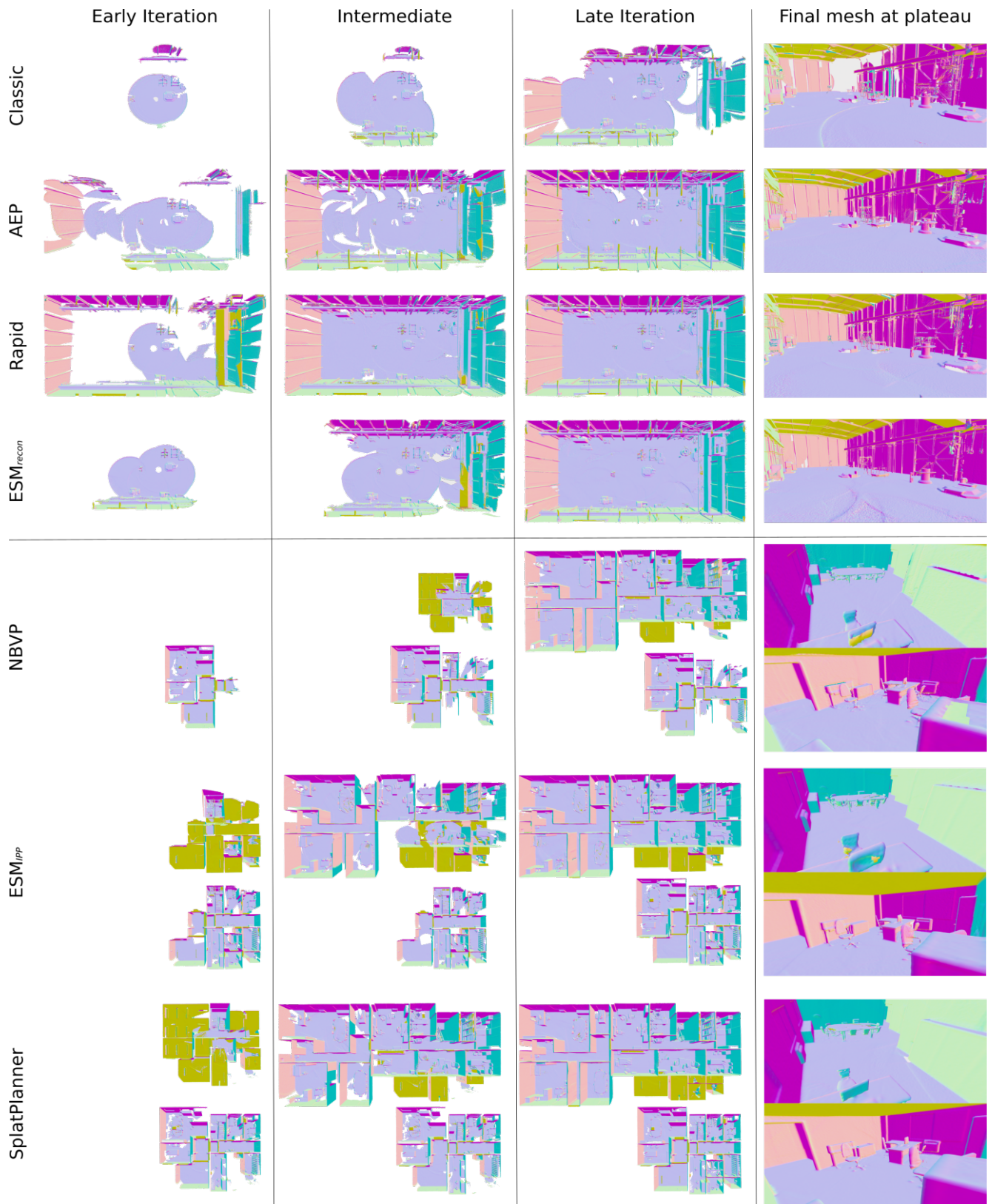


Figure 7: A few selected qualitative results – The top four rows show results on the WAREHOUSE area, while the bottom three rows show the two-story OFFICES C at different exploration stages, running different methods.

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