# Datasets and Benchmarking of a path planning pipeline for planetary rovers

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***Abstract*— We present datasets of 2.5D elevation maps of planetary environment that were collected on Mt. Etna during the space-analogous ARCHES mission [1]. In addition to the raw elevation maps, we provide cost maps that encode the traversibility of the terrain. We demonstrate how these cost maps are used during our development of mapping and planning algorithms for ground based robots in the context of the planetary rover navigation. More specifically, we use the benchmarking pipeline to evaluate the parameters and choice of methods that are used for the 2.5D cost map generation, which in turn affects the path planning behavior. Finally, we showcase how the provided maps can be supplied as a test environment in Bench-MR, which is a framework for benchmarking of motion planning algorithms for wheeled robots.**

## I. INTRODUCTION

Given the amount of available path/motion planning algorithms, selecting the right one for a given robot, environment, and application is a tough problem. In this work, we focus on benchmarking the path planning pipeline used for geometric planning on a planetary rover prototype called LRU (Lightweight Rover Unit) [2]. LRU is developed at the Robotics and Mechatronics Center, DLR. We use the benchmarking tools not only to evaluate the path planning algorithms but also to evaluate the parameters and choice of methods that are used for the 2.5D cost map generation, which are the input to the path planning algorithms. In this paper, we demonstrate the usage of benchmarking datasets and tools to evaluate the parameters and choice of methods that are used for the 2.5D cost map generation. However, as a next step, we plan to also evaluate different path planning algorithms and are currently working in that direction.

This work focuses on using benchmarking tools, to best-decide the parameters and methods, used for both the cost-map generation and path planning as part of the navigation pipeline running on the LRU.

**Contributions:**

- datasets for evaluation of path planning algorithms in planetary representative environments. Provided are 2.5D elevation maps and 2.5D cost maps.
- evaluate the parameters and choice of methods that are used for the 2.5D cost map generation in our navigation pipeline

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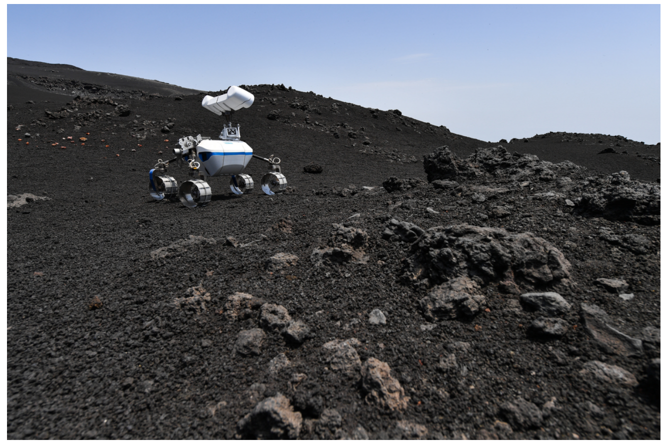


Fig. 1: LRU on Mt.Etna, Italy at the ARCHES demo-mission site where the mapping data was collected.

## II. RELATED WORK

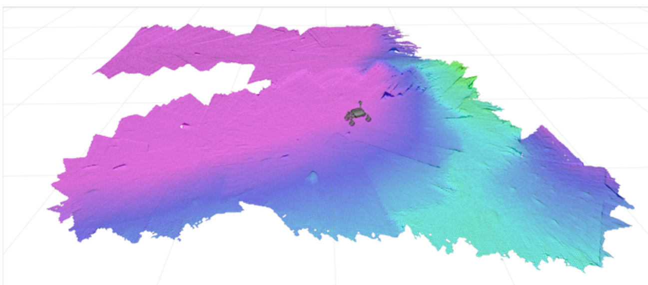
Path planning is an important component of mobile-robotics. There exist a variety of algorithms to perform path planning. They can be broadly classified into different categories like search-based algorithms, sampling-based algorithms, potential field algorithms, trajectory-optimization algorithms and learning-based algorithms [3], [4]. This categorization is also by no means exhaustive and is subjective. Off-late, there has been interest in the robotics community to benchmark path planning algorithms. As a result of this, we can see the release of some platforms and tools to help benchmark path planning/motion planning algorithms. One such recent benchmarking platform is PathBench [4] which facilitated benchmarking of both classical and learning-based path planning algorithms. Most of these platforms also have some readily available datasets to evaluate/benchmark path planning and motion planning algorithms. For example, in Bench-MR [5], there are predefined grid-based and polygon-based environments as well as feature to custom generate grid-based environment. BARN (Benchmark for Autonomous Robot Navigation) [6] dataset provides simulated cluttered environment models with varying levels of difficulty to evaluate navigation pipelines of mobile robots. However, they poorly represent the unstructured outdoor planetary environment that we are interested in. We hope, the datasets we provide, complement well existing ones and can be used in existing benchmarking platforms to better test the performance of path planning algorithms in an unstructured outdoor planetary analogue environment.

## III. Datasets

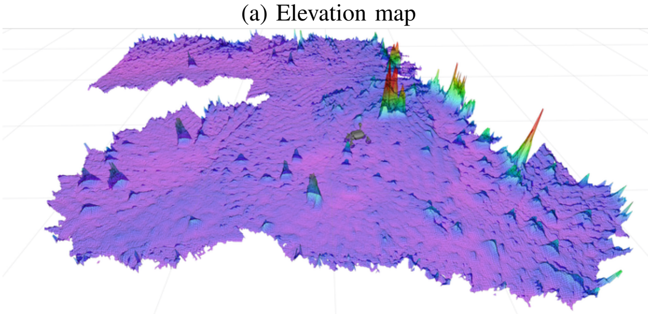
We provide world-models of real outdoor planetary-analogue terrain in the form of 2.5D cost grid-maps. In addition, we provide the 2.5D elevation maps as the cost maps were computed based on the locomotion capabilities of LRU rover and one can compute different cost maps if needed. We provide both the elevation and cost maps in PFM (Portable FloatMap) image format. In addition, we also provide the 2.5D cost maps in PNG image format. The datasets can be obtained under: `https://rmc.dlr.de/benchmark_maps_2022`.

## IV. Navigation in Unstructured Environments

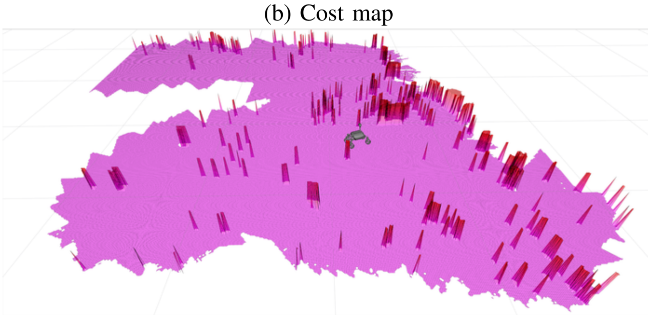
We develop navigation for robots in unstructured environments. The cost of moving in unstructured environments is given by the traversibility of the underlying terrain. Generation of cost and obstacle maps from elevation data is given in 1 and shown in Fig. 2.



(a) Elevation map



(b) Cost map



(c) Obstacle map

Fig. 2: Representation of 2.5D elevation, cost, and 2D obstacle map. Cost and obstacle maps are computed from the underlying elevation.

Our objective of geometric path planning in unstructured environments is to minimize the cost accumulated along the path. This differs from moving in structured environments with binary obstacle maps, where cells are either blocked or free and therefore all free cells have the same cost for traversing. Planning in structured environments typically aims to optimize path length and does not respect the cost of the terrain.

The input to the path planner is a 2.5D cost map which is representative of the environment around the rover and is computed as: Depth-Image $\rightarrow$ 3D Point Cloud $\rightarrow$ 2.5D Elevation Map $\rightarrow$ 2.5D Cost Map. We aggregate such 2.5D cost maps computed form single depth images and build a bigger 2.5D cost map centered around the robot to perform path planning. The size of this map can be chosen and is set to 40 meters for the generation of the benchmark datasets. The resolution of the grid in the maps is set as 5 cm.

Using this as an input, the path planner computes a 2D path connecting start and goal pose. For more details on the generation of 2.5D cost maps that are used as input for path planning, refer to [7].

**Cost Map Generation for Path Planning:**

We store the knowledge of the traversibility in a 2.5D cost map. The values in this 2D array take continuous values $> 0$. The cost map $\mathbf{C}_{pla}$ used for planning is computed as

$$\mathbf{C}_{pla} = \mathbf{f}_{obs}\big(\mathbf{f}_{aug}\big(\mathbf{C}_{ele}(\mathbf{E})\big),\ \mathbf{C}_{ele}(\mathbf{E})\big) \tag{1}$$

where $\mathbf{C}_{ele}$ is the cost map associated by the underlying elevation map $\mathbf{E}$ and computed as in [7]. Obstacle detection is performed by $\mathbf{f}_{obs}$ and purely based on $\mathbf{C}_{ele}$. A cell is marked as obstacle in $\mathbf{C}_{pla}$ if its value $c_{ele}$ exceeds a given obstacle detection constant $c_{obs}$. $\mathbf{f}_{aug}$ augments $\mathbf{C}_{ele}$ and is used to change the ratio $r = max(\mathbf{C}_{pla})/min(\mathbf{C}_{pla})$ between cost of traversable cells. Changing this ratio controls the behavior of the cost-minimizing path planner. Large $r$ prefer longer paths along low costs and small $r$ result in shorter paths through high cost regions. We demonstrate three methods that can be used for $\mathbf{f}_{aug}$.

*Thresholding* values in $\mathbf{C}_{ele}$ that are below $c_{thr}$ to a constant $c_{flat}$. This will create regions of flat cost values of $c_{flat}$ and regions with continuous values $> c_{thr}$. Depending on the settings of $c_{flat}$, $c_{thr}$, and $c_{obs}$ this augmentation can either increase or decrease the ratio $r$. The corner case $c_{thr} = c_{obs}$ sets $r = 1$ and results in binary obstacle maps as cost map.

$$c_{aug} = \begin{cases} c_{flat} & \text{if } c_{ele} <= c_{thr} \\ c_{ele} & \text{otherwise} \end{cases} \tag{2}$$

*Adding a constant* $c_{cst} > 0$ to all costs will reduce the $r$ but will maintain information of the unstructured cost. In the case of large $c_{cst}$ values compared to the costs in $\mathbf{C}_{ele}$, the planning behavior is similar to a binary cost map.

$$c_{aug} = c_{ele} + c_{cst} \tag{3}$$

*No augmentation* and thus a straight mapping from $\mathbf{C}_{ele}$:

$$c_{aug} = c_{ele} \ . \tag{4}$$

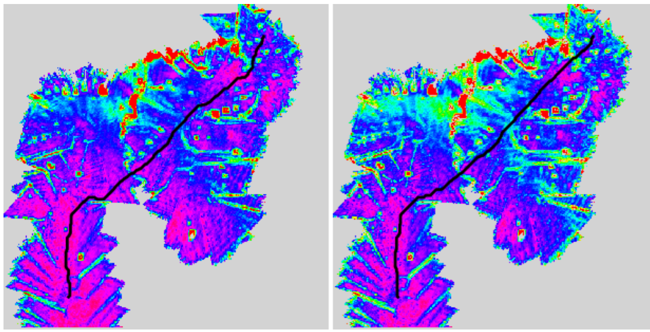


Fig. 3: Augmenting the cost map (left) by adding a small constant (right) leads to smoother and shorter paths. Paths are black lines, obstacles are red, unknown cells are gray, and costs from small to large are pink to green.

## V. Benchmarking

### A. Evaluation Criteria

For our purpose of autonomous navigation in planetary environments, we are concerned about safety, effort and maintaining a valid state estimation. We use the following metrics on the paths found by an A* planner to compare options for $\mathbf{f}_{aug}$.

**normalized average clearing distance** Distance to obstacles is the main safety metric. We normalize by the average over all path for a given test case.

**normalized path length** Metric for effort and time of reaching the goal. We normalize by the average over all path for a given test case.

**Angle over length (aol)** This metric describes the smoothness of paths. Path with less curvature are beneficial for reliable vision based state estimation.

### B. Experiments

We define a set of methods and parameters for $\mathbf{f}_{aug}$ and use these to augment cost maps of three test cases. A test case consists of $\mathbf{C}_{ele}$, start, and goal. The obstacle detection is $c_{obs} = 0.75$ for all test cases.

| pararms # | Option | parameters |
|---|---|---|
| 1 | none | |
| 2 | thresholding | $c_{flat} > 0$<br>$c_{thr} = 0.75$ |
| 3 | thresholding | $c_{flat} = 0.05$<br>$c_{thr} = 0.5$ |
| 4 | thresholding | $c_{flat} = 0.05$<br>$c_{thr} = 0.35$ |
| 5 | adding constant | $c_{cst} = 0.7$ |
| 6 | adding constant | $c_{cst} = 0.1$ |

TABLE I: Set of methods and parameters for cost map augmentation used in experiments.

Take note that parameter set 2 results in a binary obstacle map since $c_{thr} = c_{obs}$. Any value $c_{flat} > 0$ will result in the same planned path.

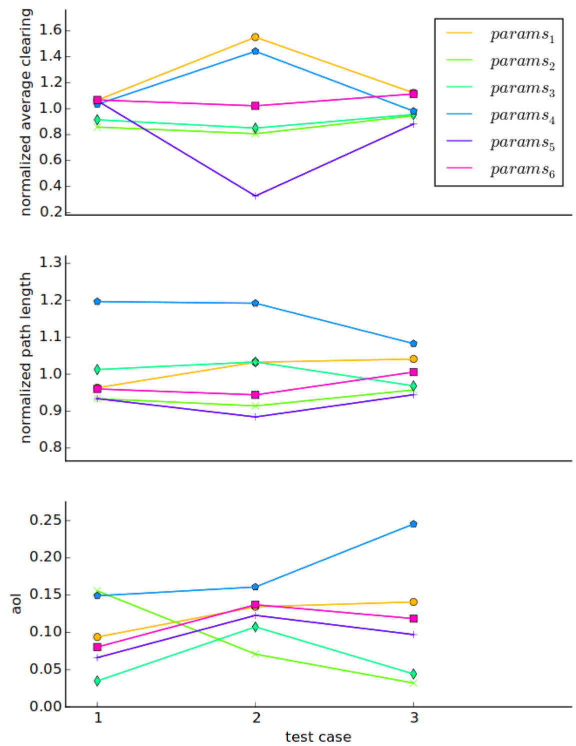



Fig. 4: Augmenting the cost map of unstructured environments can be used to implicitly control the behavior of the planner. Methods can be used to smooth paths (smaller aol), emphasize path optimality more on path length. Obstacles, unlike in structured environments, are often surrounded by regions of high traversibility cost. Augmenting the cost map may lead to changes in clearing to obstacles.

The metrics show that adding a large constant ($params_5$) to the map reduces the path length but also reduces the average distance to obstacles. The reduction in distance to obstacles is a result of the cost of the unstructured environment, see fig. 4. A similar observation is done for the case of binary maps ($params_2$). This is as expected, since both adding a large constant or setting all cost to a constant reduce the ratio $r$.

Augmenting with a threshold ($params_3$ and $params_4$) segregates the map into regions of constant small traversibility cost and regions of large cost. This results in longer paths, as regions with high cost are circumvented.

Adding a small constant ($params_6$) result in shorter paths and smaller aol when compared to not augmenting the cost but at smaller average distance to obstacles.

### C. Benchmarking in Bench-MR using the datasets

We also used the provided datasets to benchmark some of the path planning algorithms in Bench-MR to verify the usability of the data in other benchmarking platforms. Though, we had to make minor modifications to the input data to meet the input requirements of Bench-MR like inverting the cost as in Bench-MR lower cost is associated to obstacles. Also, in Bench-MR, the environment is internally converted to an obstacle map represented as occupancy-grid based on a user-defined threshold. Therefore, we could not use the continuous cost-space we provide in our datasets. Shown in fig. 5 and fig. 6 are some of the plots resulting from running the benchmarking of some of the sampling-based path planners in Bench-MR.

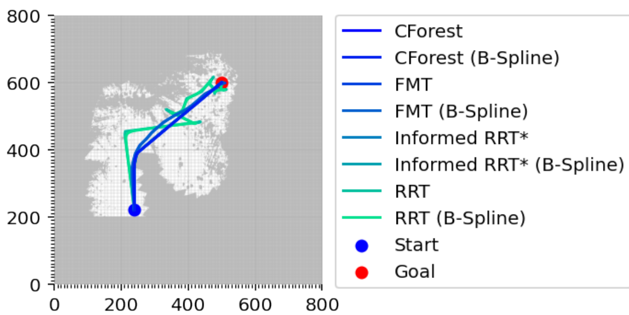



Fig. 5: Paths computed using some of the different planners in Bench-MR. Darker regions represent obstacles.

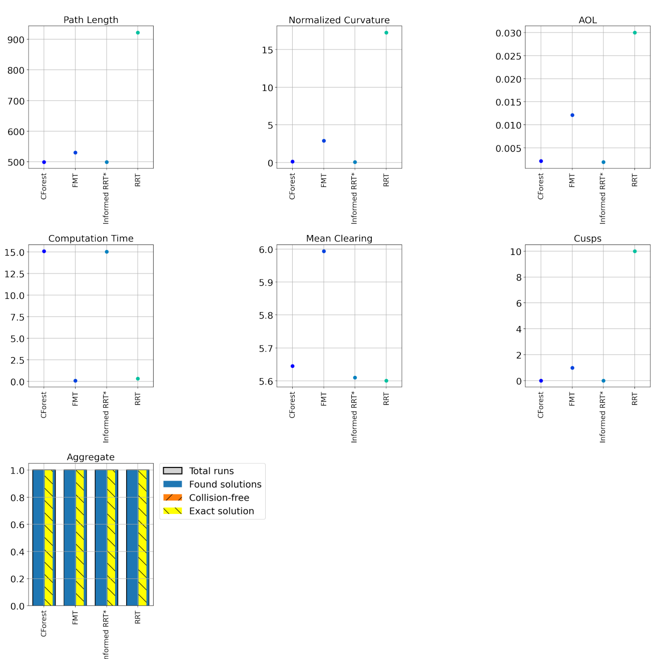



Fig. 6: Benchmarking results of some of the different planners in Bench-MR.

## VI. CONCLUSIONS

We provide benchmarking datasets for the evaluation of path planning of mobile robots in a planetary analogue environment. As an environment representation for input to the path planning algorithms, we provide 2.5D cost maps which encode the cost of traversability for our planetary rover prototype LRU. In addition, we also provide the 2.5D elevation maps from which one can compute different cost maps as they desire to meet the needs of their mobile robot locomotion capabilities or to generate 2.5D cost maps of different complexity. One can also generate binary occupancy maps by applying a threshold to define which cost value is to be treated as an obstacle. More importantly, we show that benchmarking tools can also be used, to not only find the right path planning algorithms, but also to tune the parameters and decide on the best methods that are involved in the generation of environment representations, which are the input to the path planning algorithms. We showed this with an experiment, in which we compare augmentation methods in our 2.5D cost map generation process. As a next step, we are in the process of evaluating also different path planning algorithms.

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