Visual SLAM on a Lunar Testbed for Polarization Cameras Under Challenging Lighting Conditions

Clayder Gonzalez, Edward Vanderfeen, Michael Milford, Thierry Peynot and Alejandro Fontan

***Abstract*— Visual SLAM systems struggle in scenarios with strong lighting variations and/or significant perceptual aliasing, which is common in off-Earth environments. Polarization cameras offer an alternative to conventional cameras, providing additional information about light reflection from objects and surfaces. In this paper, we present a proof-of-concept lunar dataset, recorded in the QUT Lunar Testbed under varying lighting conditions. We describe our current vision-based robot-mounted setup, the capabilities of the facility, and the next steps for dataset recording. Our experiments include three sequences with varying lighting conditions, evaluated using four state-of-the-art VSLAM systems, highlighting the limitations of current approaches under challenging lighting and perceptual aliasing scenarios.**

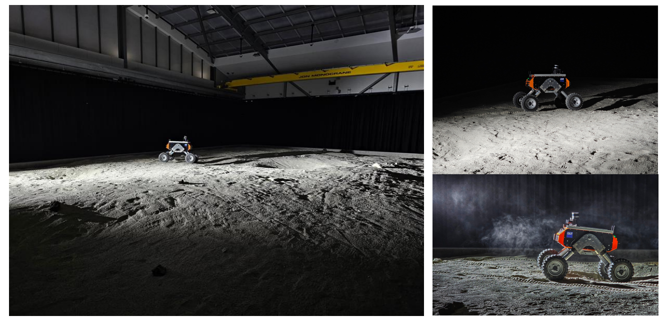

Fig. 1: Yandiwamba Lunar Testbed

I. INTRODUCTION

In January of 2024, Ingenuity, the helicopter sent to Mars alongside the rover Perseverance, was compromised due to a fault in its autonomous navigation system [1]. According to Håvard Grip, the pilot of Ingenuity, this problem could have been the result of incorrectly detected features on the terrain the helicopter was flying over. Outer-world terrains are unstructured environments where robust and accurate localisation is critical. Despite substantial progress in the development of visual Simultaneous Localisation and Mapping (SLAM) systems, their performance remains brittle under adverse conditions [2] [3], for example, those involving challenging lighting such as image glare and overexposure that can appear suddenly. These conditions frequently cause feature association failures in visual localisation pipelines, which can lead to tracking loss, degraded trajectory estimates, or full system failure. Yet, most benchmarking datasets underrepresent these environments, leaving the limitations of current systems underexplored and often unquantified [4].

Polarization cameras are devices that incorporate micropolarizer arrays over each pixel of the image sensor. These arrays contain tiny polarization filters, typically oriented at 0°, 45°, 90°, and 135°, aligned with specific pixels. For each orientation, four images can be obtained: $\mathbf{I}_0$, $\mathbf{I}_{45}$, $\mathbf{I}_{90}$, and $\mathbf{I}_{135}$. Additionally, an intensity image, $\mathbf{I}$ (equivalent to an image captured without polarizing filters), can be computed from these four orientation images. On the Moon, polarization image sensors can provide a passive means to mitigate harsh lighting and unfiltered solar reflections on dust-covered surfaces, which can otherwise impair visual perception and autonomous navigation. Traditionally, polarization images have been used in SLAM to estimate surface normals; more recently, additional information from these sensors is being leveraged to improve performance under challenging conditions [5] [6].

In this work, we propose a proof-of-concept dataset composed of three sequences recorded with a polarization camera on an indoor Lunar Testbed (see Figure 1). We evaluate four state-of-the-art visual SLAM systems, highlighting their limitations. Our future work will build upon this dataset to provide a comprehensive multi-sensor vision-based benchmark, including a polarization camera, an event camera, and an RGB-D camera, for testing localization pipelines in lunar scenarios.

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II. RELATED WORK

The number of datasets released to evaluate VSLAM has grown rapidly in recent years [7]. Traditional datasets include the EuRoC MAV Dataset [8], which provides stereo images and IMU data recorded from a micro aerial vehicle in indoor environments for visual–inertial SLAM evaluation. The KITTI [9] Visual Odometry Dataset contains stereo imagery collected from a car in outdoor urban and highway scenes. The TUM Mono Dataset [10] is designed for monocular SLAM, providing sequences captured with a single camera. Finally, synthetic datasets, such as the TartanAir Dataset [11], offer large-scale data with error-free ground-truth trajectories.

Datasets for planetary exploration. The ROBEX Dataset, ARCHES Dataset [12], MADMAX Dataset [13], and, more recently, the S3LI-Vulcano Dataset [14] are large-scale datasets collected in rocky, feature-poor terrains analogous to those present on the martian and lunar surfaces. They include a combination of stereo images, IMU data, LiDAR, and ground-truth information to evaluate SLAM systems. These datasets are valuable for understanding SLAM performance under challenging conditions; however, incorporating additional sensors, such as polarization cameras, could provide further insights.

Datasets for Lunar exploration from NASA. The NASA's Polar Stereo dataset [15] and Polar Traverse dataset [16] are examples similar to what is presented in this article because they were recorded on a lunar testbed. One important characteristic of these datasets is that they support our claim that the lunar surface has factors such as "oblique sunlight, regolith reflectance, and the absence of atmospheric scattering", which make these datasets important to test SLAM systems. Although these datasets are important sources of information, they differ from our dataset in the use of polarization cameras. We believe that polarization cameras can leverage the different properties of regolith reflectance to benefit SLAM systems.

Datasets for polarization cameras. Most datasets containing polarization camera images consist of objects captured in indoor scenarios. However, some examples also include outdoor scenes, such as [17] and [18]. A limitation of these datasets is that the images are not provided as sequences, which makes them unsuitable for use in localization systems. To the best of our knowledge, the only dataset with polarization camera images that can be used with a localization system is the work of [19].

Datasets for varying lighting conditions. The UMA-VI dataset is a visual–inertial benchmark designed to evaluate odometry and SLAM methods under challenging conditions such as low-textured environments and dynamic illumination. The ETH-Illumination dataset evaluates illumination-robust direct visual SLAM methods using both real and synthetic data. The latter is also used in [4], where it is applied to SLAM systems beyond direct methods. These datasets provide insight into how SLAM systems perform under illumination changes; however, most sequences are recorded in indoor and structured environments, and therefore still lack unstructured outdoor scenarios.

III. Methodology

Yandiwanba (Yan-dee-wan-ba) means 'to go from below to above', 'from the ground to a higher place, or way way above', in the Yagarabul language. The Yandiwanba Lunar Testbed is Australia's largest covered lunar testing facility and is designed to support planetary robotics experiments in realistic analogue conditions. The testbed consists of a $19\,\mathrm{m} \times 11.4\,\mathrm{m}$ regolith-filled area whose particle distribution, soil composition, and optical properties approximate lunar terrain while remaining safe for operation. The facility provides multiple overhead cameras covering the entire testbed area, enabling vision-based experiments and ground-truth monitoring. Experiments can be conducted under both natural sunlight and controlled illumination using artificial point-source lighting that mimics low-incidence solar conditions similar to those at the lunar South Pole. This capability enables the acquisition of datasets with varying and challenging lighting conditions relevant for evaluating visual localization systems.

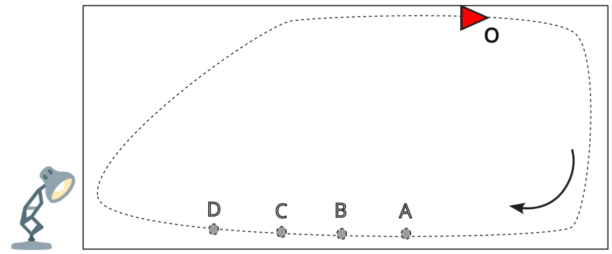


Fig. 2: Designated path for the mobile robot's navigation.

TABLE I: Light changes per segment on each sequence

Segment	Sequence 0	Sequence 1	Sequence 2
OA	OFF	OFF	OFF
AB	OFF	ON 60%	ON 100%
BC	OFF	OFF	OFF
CD	OFF	ON 60%	ON 100%
DO	OFF	OFF	OFF

Setup. For our data capture platform, we mounted a Lucid Triton TRI050S monochromatic polarization camera on an AgileX Bunker Mini mobile robot. The camera was operated in auto gain–exposure mode and calibrated using Kalibr [20]. The AgileX Bunker Mini employs a skid-steering locomotion system suitable for rough-terrain navigation. The platform can reach speeds of $\approx 1\,\mathrm{m/s}$ and climb slopes of $\approx 30°$.

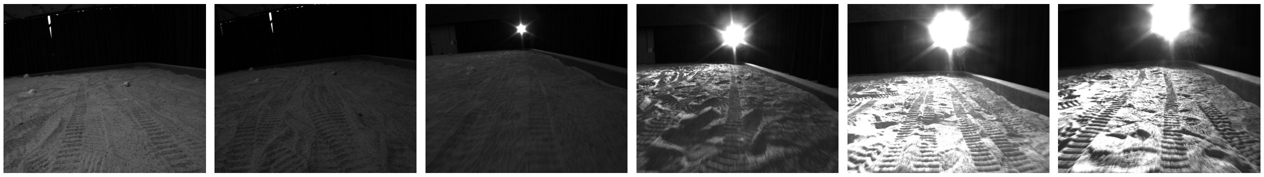
Dataset taxonomy. The robot follows a trajectory that covers the full area of the lunar testbed, as depicted in Figure 2. The unambiguous shape of the trajectory allows us to align trajectories using ICP, since at this stage full sensor synchronization is not yet provided. The trajectory was repeated three times under varying levels of lighting changes (see Table I).

Evaluation. For these preliminary tests, we ran the structure-from-motion system GLOMAP [21] on images recorded with a backward-facing GoPro camera to obtain a reference trajectory for comparison with the estimated trajectories. We then perform ICP alignment between the GLOMAP trajectory and the trajectories estimated by the VSLAM systems. The final 3D error is reported as a percentage of the total trajectory length, since monocular approaches do not recover the true scale.

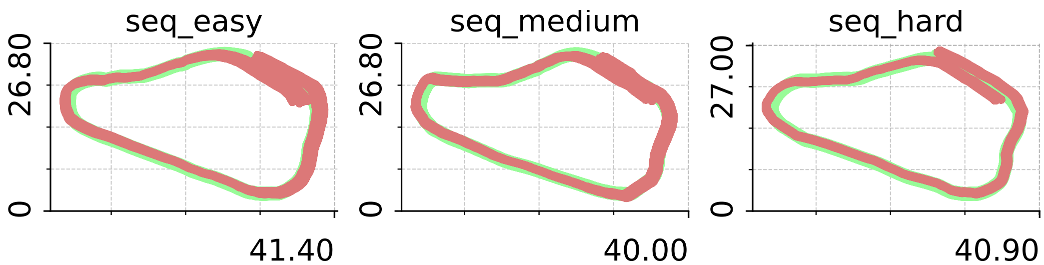
IV. Experiments

We evaluate four state-of-the-art VSLAM approaches, namely ORB-SLAM3 [22], DROID-SLAM [23], MASt3R-SLAM [24], and DPVO [25], on the three sequences [7]. Representative images and trajectories from the sequences are shown in Figure 3.

Interestingly, each baseline exhibits failure modes arising from different sources. ORB-SLAM3 frequently loses tracking due to degraded ORB feature matching in the visually aliased regolith. DROID-SLAM experiences catastrophic failure from the beginning, most likely due to the characteristics of the polarization data. Interestingly, although



(a) No light changes (b) Medium Changes (c) Difficult Changes



(d)

Fig. 3: **Upper row:** thumbnails from the polarization camera depicting different lighting conditions. **Lower row:** trajectories of DPVO on polarization camera images and GLOMAP on the GoPro stream.

DPVO builds on the foundations of DROID-SLAM, it is able to reconstruct all three trajectories, albeit with substantial drift. Finally, MASt3R-SLAM suffers from visual aliasing by attempting to create loop closures with incorrect candidates.

Even though we attempted to introduce strong lighting variations, we were unable to observe any significant impact on the performance of the VSLAM systems (see Table II) as a direct result. This was likely due to the dominance of other failure modes across all evaluated systems and the fact that the lighting changes were not sufficiently extreme. In future experiments, we plan to implement more extreme and realistic lighting conditions to better evaluate system performance and guide improvements.

TABLE II: 3D errors expressed as a percentage (%) of the total trajectory length for each sequence.

	DPVO				
Sequence	$\mathbf{I}_0$	$\mathbf{I}_{45}$	$\mathbf{I}_{90}$	$\mathbf{I}_{135}$	$\mathbf{I}$
0 Easy	0.8	0.8	0.8	1.1	1.3
1 Medium	0.7	0.5	0.7	1.0	0.9
2 Difficult	0.9	0.7	0.9	0.7	0.9

V. CONCLUSIONS

We present a proof-of-concept lunar dataset, recorded with a polarization camera on a mobile robot navigating the QUT Lunar Testbed under varying lighting conditions. The dataset comprises three sequences that capture challenging illumination scenarios, intended to evaluate the performance of visual SLAM systems.

Preliminary experiments with four state-of-the-art VSLAM systems reveal distinct failure modes related to perceptual aliasing caused by the regolith, lighting variations, and polarization camera images. This diversity of failure modes highlights the need for a comprehensive dataset to explore multiple sensor modalities in lunar-like scenarios.

In future work, we plan to develop a new extensive dataset that provides a full set of vision sensors including RGB-D, event-based and polarization cameras, to create a richer multi-sensor benchmark for lunar and planetary robotics scenarios. We will ensure accurate localization ground truth using a Topcon PS103A robotic total station and map ground truth using a Hovermap LiDAR scanner. We will cover a comprehensive variety of failure modes, such as light conditions or changes in the terrain, to foster scientific and technical research in the space domain.

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