

Navigating the Underground: Tackling Localization Challenges for UAVs in Tunnels

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Abstract—In this work a survey of the issues and difficulties for Unmanned Aerial Vehicles (UAVs) in underground environments, in particular tunnels, will be carried out. In addition to not having Global Navigation Satellite System (GNSS) signal or any other type of external positioning, this kind of environment will present a number of unique constraints that make a wide range of visual-inertial (VIO), or LiDAR-inertial (LIO), localization algorithms unusable. In addition, state-of-the-art algorithms will be validated with real flight data in a tunnel and possible solutions will be offered for achieving robust and reliable localization using only the on-board. In this way, the deployment of autonomous navigation tasks in these degraded environments will be pushed.

I. INTRODUCTION AND RELATED WORK

Unmanned Aerial Vehicles (UAVs) have become increasingly valuable tools for several applications, including inspection, search and rescue, or mapping. However, their deployment in underground environments, particularly tunnels, presents unique challenges that push the boundaries of current aerial robotic localization and navigation technologies [1]. The absence of Global Navigation Satellite System (GNSS) signals, limited visual features, and symmetrical structures in tunnels create a complex environment for UAV autonomous operation, which requires innovative solutions to ensure accurate and reliable navigation [2], since state-of-the-art navigation algorithms often struggle in such environments due to environmental constraints and sensor limitations.

To overcome these challenges, researchers have been exploring various approaches, including visual-inertial odometry (VIO), LiDAR-based techniques, and sensor fusion methods [2] [3]. These solutions aim to provide robust localization and navigation capabilities for UAVs operating in the visually challenging environment of underground tunnels, which pose the following difficulties:

- **GNSS Denial:** the most fundamental challenge in underground navigation is the lack of GNSS signals, which are crucial for conventional UAV localization techniques. In the absence of GNSS, UAVs often rely on IMUs and odometry-based localization. However, IMUs suffer from drift over time, leading to significant localization errors unless corrected by external references [4]. UAVs must rely on alternative localization methods such as vision- or LiDAR-based techniques such as Simultaneous Localization And Mapping (SLAM), usually complemented with measurements from onboard inertial measurement units (IMUs) [5].



Fig. 1. Aerial robot performing a flight in a real tunnel environment.

- **Feature-scarce and repetitive environments:** many tunnels have long, featureless sections or highly repetitive structures, and vision-based techniques that rely on detecting and matching environmental features over time can easily fail to distinguish between different areas [6]. This can cause loop closure failures in SLAM algorithms, leading to significant drift in localization [7]. There are some such data sets that allow developers to understand these challenging environments [8].
- **Harsh lighting conditions:** underground environments often suffer from extreme lighting variations, ranging from complete darkness to artificial lighting that creates harsh shadows and high contrast. This severely impacts visual odometry and other camera-based localization methods [9].
- **Dust and airborne particles:** tunnels, especially those under construction or in mining operations, contain airborne dust that can pose a risk to hardware and interfere with LiDAR and optical sensors, leading to noisy data and degraded mapping accuracy [10]. Moreover, the confined environment may affect aircraft stability and control.
- **Constrained spaces and irregular geometries:** unlike structured indoor environments, tunnels may have varying cross-sections, low ceilings, and tight turns. Such constraints pose difficulties for path planning and obstacle avoidance techniques [11].

Recent advancements in this field have focused on leveraging the unique characteristics of tunnel environments, such as

their geometric properties and RF signal propagation patterns, to develop more effective localization strategies [3] [12]. By combining multiple information sources and employing advanced algorithms, researchers are working towards creating systems that can navigate tunnels safely and efficiently, even at high speeds [13] [14].

Apart from these environmental constraints, UAVs face several key technical challenges when navigating tunnels:

- **LiDAR-based SLAM limitations:** while LiDAR sensors provide highly accurate depth information, they face challenges in tunnel environments due to surface reflections, uniform walls, and potential loss of distinctive features. Additionally, LiDAR mapping requires real-time processing, which can be computationally demanding on lightweight UAV platforms [15].
- **Computational constraints and real-time processing:** autonomous operation requires onboard processing capabilities for real-time localization. However, executing complex SLAM algorithms, integrating multi-sensor data, and making navigation decisions on embedded hardware can be challenging due to computational constraints [16].
- **Robust multi-sensor fusion requirements:** to compensate for individual sensor weaknesses, modern localization systems often rely on sensor fusion techniques that integrate IMUs, LiDAR, cameras, and even radar. However, fusing data from heterogeneous sensors introduces synchronization and calibration challenges, requiring advanced filtering methods such as Extended Kalman Filters (EKF) or graph-based optimization methods [17].

This paper explores state-of-the-art techniques for UAV localization in real tunnel environments, analyzing their strengths and limitations while proposing and evaluating workarounds to overcome key challenges and improve localization accuracy and reliability. Through a comparative performance assessment under real-world conditions (as can be seen in Fig. 1), we aim to identify the most effective approaches for robust and reliable localization in underground environments. By addressing these challenges, we aim to contribute to the advancement of autonomous UAV operations in such environments, opening up new possibilities for underground infrastructure inspection, disaster response, and scientific exploration.

II. EXPERIMENTAL SETUP AND ALGORITHM SELECTION

Under this section, we will focus on providing a description of the test environment and the hardware setup used to record all the data. Also, a brief description of all open-source algorithms tested under these conditions shall be provided.

A. Test environment

With the aim of validating the algorithms in a representative environment, the experiments have been carried out in one of the tunnels of the greenway of Coripe (Cadiz, Spain). The selected tunnel has an approximate length of 900 meters, a height of 5 meters and a width of 4.5 meters. The Fig. 2

shows the interior of the tunnel where these experiments have been carried out.



Fig. 2. View inside the Coripe tunnel. (Cadiz, Spain)

B. Hardware setup

The data has been gathered using the following sensors mounted on a custom UAV. This aerial robot has been specially designed and manufactured to work in these conditions of reduced visibility and dust. For this reason, among other protections made on the on-board electronics, the rotors used have a cover that prevents any material from entering the motor coil. In addition, there is an on-board artificial lighting system that allows to distinguish the aircraft in the dust or in the dark. In Fig. 3 is shown the CAD of the aerial robot.

In order to be able to capture information from the environment and, next steps, to perform autonomous operations in this kind of environments, the aircraft carries out the following sensors:

- **3D LiDAR Ouster OS0-128:** A point cloud at 10 Hz of 128 scans resolution and the internal IMU data of the tensor at 125 Hz will be obtained. Note that for safety reasons the sensor has a protection cage; therefore, small parts of the point cloud may appear occluded.
- **PixHawk Orange Cube Autopilot:** Providing raw, high-quality IMU data at a frequency of 100 Hz.
- **Teledyne FLIR Hadron 640R:** The FLIR Hadron 640R is a high-performance dual camera combining a 640×512 LWIR (Long-Wave Infrared, 8-14 μm) radiometric thermal sensor with a frame rate of 30 Hz and a 1080p RGB camera (1920×1080 resolution, 60 FPS), designed for drones, robotics, and security applications. This sensor has been integrated into the Gremsy G-Hadron gimbal to stabilize the thermal and visual sensors, reducing UAV vibrations and ensuring smooth, high-quality imagery.

In order to ensure that the algorithms run in a controlled hardware environment and that the results are comparable



Fig. 3. CAD Design of the custom aerial robot

and reproducible, all algorithms have been tested on a laptop **DELL Precision 7560** with the following specifications:

- **CPU:** 11th Gen Intel® Core™ i7-11850H @ 2.50GHz × 16
- **GPU:** NVIDIA Corporation RTX A2000 Mobile
- **RAM:** 16.0 GB
- **OS:** Ubuntu 20.04 LTS

It is important to note that although the algorithms were not executed on the embedded hardware (Intel® NUC 10 Performance), the specifications of the embedded hardware are similar to or even superior to those of the PC used, so there would be no issues running them on the embedded system online.

C. Selected algorithms for testing

In the following subsection, we provide a brief overview of state-of-the-art localization algorithms that have been tested with our dataset. We selected these algorithms because they are open-source, work with the same types of sensors as those used in our UAV, and have been proven to perform well under similar conditions. Additionally, these algorithms were chosen based on their adaptability to various operational conditions and their potential for delivering high accuracy in real-time localization task. Furthermore, we detail the parameter modifications made from their default values (when applicable) to achieve improved performance.

1) *LIO-SAM*: (LiDAR-Inertial Odometry via Smoothing and Mapping), [17], is a SLAM framework that fuses LiDAR and IMU data to estimate a system's position and orientation while simultaneously constructing a map of the environment. It builds upon LeGO-LOAM, [18], but enhances accuracy and robustness by using factor graph optimization via GTSAM (Georgia Tech Smoothing and Mapping library), [19]. The system begins by leveraging high-frequency IMU measurements for pre/integration, which estimates motion between LiDAR scans and provides an initial pose guess. This IMU preintegration also compensates for motion distortion in the LiDAR data. Meanwhile, LiDAR scans are processed to extract feature points, such as edges and planes, which are used to estimate odometry through scan-to-map registration, matching the current scan with a previously built global map.

2) *COIN-LIO*: (Complementary Intensity-Augmented LiDAR Inertial Odometry), [20], adopts the tightly coupled iEKF presented in FAST-LIO2 [21], for point-to-plane registration and extends it with photometric error minimization. Intensity images are processed from point clouds using a novel filter that improves brightness consistency and reduces sensor artifacts. The image features specifically selected provide information in uninformative directions of the pointcloud geometry. The feature management module examines the validity of tracked features and detects occlusions. Finally, the photometric residual is integrated into the Kalman filter.

The key innovation lies in the projection of LiDAR scans into a 2D image, along with the filtering and pre-processing steps that generate an intensity image rich in visual features. Additionally, the method establishes a precise correspondence between pixels and point cloud data to compute photogrammetric error, which is then used to improve the LIO estimation.

To address the issue of drift caused by features being detected at the edges of the drone (e.g., rotors, safety bars), we adjusted several parameters to mitigate the influence of erroneous feature points:

- **blind**: Set to 1.5 meters to exclude points within this range, preventing detections on the UAV's structure.
- **max_range**: Set to 40 meters to constrain the detection range within the tunnel.
- **suppression_radius**: Set to 7 to allow features to be closer to one another.
- **grad_min**: Set to 9 to increase the number of features detected.
- **ncc_threshold**: Set to 0.4 to filter out unreliable feature matches by removing tracked patches with a low Normalized Cross-Correlation (NCC) score.
- **erosion_margin**: Set to 19 to expand the disabled region around invalid points, preventing detections too close to the UAV's silhouette, as these points' intensities are somehow influenced by the intensity of valid points around them, as it can be seen in the Fig. 4.

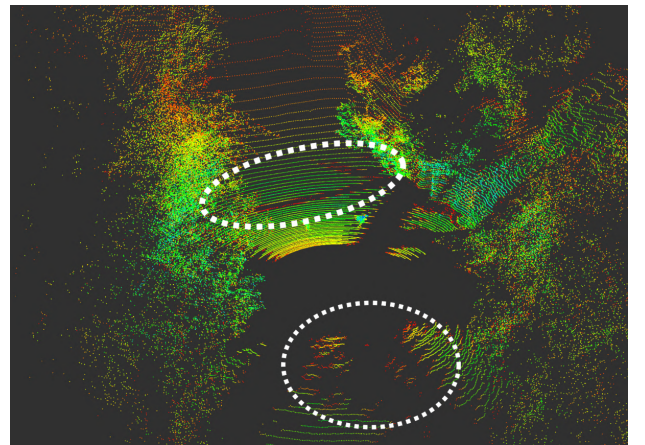


Fig. 4. Nearby objects affecting the intensity values of adjacent points, which seems to be a shortcoming of the sensor itself.

3) *R3LIVE*: (Robust, Real-time, RGB-colored, LiDAR-Inertial-Visual, tightly-coupled state Estimation and mapping), [22], is one of the state-of-the-art SLAM system that integrates LiDAR, an IMU, and an RGB camera for high-accuracy real-time localization and mapping. Unlike traditional SLAM approaches that rely solely on LiDAR or visual data, *R3LIVE* employs a tightly coupled multi-sensor fusion framework, enhancing robustness and precision across diverse environments. The algorithm consists of a LiDAR-Inertial Odometry (LIO) backend and a Visual-Inertial Odometry (VIO) frontend, both of which contribute to precise motion estimation. The LIO backend processes LiDAR features and refines poses through iterative nonlinear optimization, while IMU preintegration smooths trajectory estimation. The VIO frontend extracts visual features from the RGB camera, improving localization accuracy, particularly in environments with limited LiDAR features. Additionally, loop closure detection and global optimization techniques, such as pose graph optimization (PGO) and bundle adjustment, further correct accumulated drift and enhance long-term consistency.

4) *FAST-LIVO2*: (Fast, Direct LiDAR-Inertial-Visual Odometry), [23], is a framework employs a tightly-coupled sensor fusion approach, integrating LiDAR, inertial, and visual measurements through a sequentially updated Error-State Iterated Kalman Filter (ESIKF). *FAST-LIVO2* uses direct methods for both visual and LiDAR fusion, processing raw image patches and LiDAR points without the need for feature extraction. This approach allows for efficient handling of heterogeneous sensor data and addresses potential dimensional mismatches between different types of measurements. One of the key innovations of *FAST-LIVO2* is its ability to quickly and directly estimate the pose of the vehicle without complex optimization steps. The system leverages a single unified voxel map and employs plane priors for image alignment and dense reconstruction, contributing to its effectiveness in scenarios with feature scarcity, such as structured or textureless environments.

III. EXPERIMENTAL RESULTS

Several flights were conducted in the previously described location to capture environmental data. Given that all flights exhibited similar characteristics due to the tunnel's limited degrees of freedom for movement, the comparison of the algorithms will focus on a specific flight in which the aircraft was initially outside the tunnel, entered for approximately 80 meters, and then returned to the starting position to land. In these flights, the aerial robot was remotely controlled by an experienced pilot and the algorithms were executed offline. Accurate ground truth data could not be obtained for the flight campaigns due to the operational constraints of the test environment. The tunnel is a public infrastructure where the deployment of conventional localization systems—such as motion capture setups, Ultra-Wideband (UWB) anchors, or RTK-GPS—is either impractical or entirely unfeasible. Furthermore, GPS signals are unavailable inside the tunnel, and SLAM-based mapping solutions, while useful, cannot

provide absolute ground truth in such feature-deprived and repetitive environments. As a result, the evaluation of the tested localization algorithms is performed qualitatively.

Since all flight missions follow a nearly identical pattern—takeoff, tunnel entry (approximately 80 m), turnaround, and return to the takeoff point—the main indicator of localization performance is the estimated final pose at landing. Ideally, the pose should return to approximately (0, 0, 0), enabling an intuitive estimation of the drift accumulated over the trajectory.

It should also be noted that in the algorithms incorporating a visual odometry stage, an attention has been paid to mitigate illumination changes due to exterior-interior transitions and occlusions due to dust. To this end, the IR camera has been used instead of the RGB camera, since the tunnel interior is at a stable and constant temperature. This will allow the visual section to be unaffected by lighting changes and dust inside the tunnel. In Fig. 5, a comparison between the data captured by the RGB camera and the IR camera is shown. As can be seen, the IR camera would generate more consistent information regardless of environmental conditions (dust or lighting changes).



Fig. 5. Comparison between RGB camera (left) and IR camera (right) in challenging situations. Note that the aspect ratio of the images vary (4:3 for IR and 16:9 for RGB)

In Figure 6, a comparison of the position estimation of the four proposed algorithms is shown. It can be seen how LIO-SAM, in yellow color, is the first that starts to drift. This is caused by the fact that the initial section of the tunnel lacks a large number of features, and a pure LiDAR odometry cannot perform consistent geometric associations.

In the case of *R3LIVE*, shown in green, although it incorporates visual odometry to support position estimation, it diverges shortly after LIO-SAM. This behavior may be attributed to the algorithm's strong reliance on precise temporal synchronization between sensors, as well as its sensitivity to accurate extrinsic calibration. The camera on this platform is mounted on a gimbal to enable stabilization and pointing capabilities; however, the gimbal introduces slight variations in

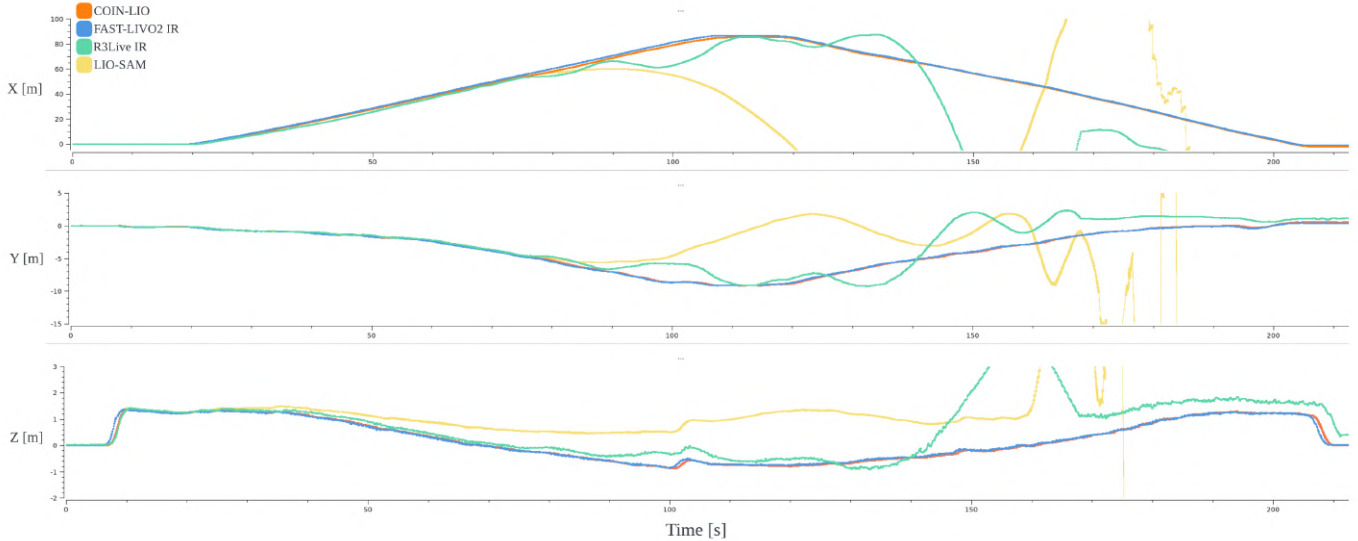


Fig. 6. Comparison between the position estimation of the different algorithms in the flight performed. (Legend can be found in the top-left side)

the extrinsic parameters between the LiDAR and the camera, which can accumulate over time and degrade performance. Furthermore, R3LIVE is designed to utilize RGB images for photometric error minimization within its visual-inertial odometry module. In this experiment, a thermal camera was employed in place of a conventional RGB camera due to the presence of dust and insufficient lighting conditions within the tunnel. Thermal cameras provide grayscale images based on temperature differentials, rather than visible spectrum color information. Consequently, the algorithm is unable to perform effective photometric error minimization, which may significantly diminish the impact of visual odometry and contribute to drift in geometrically repetitive environments such as the tunnel considered.

Finally, as can be seen, the results obtained by COIN-LIO (orange line) and FAST-LIVO2 (blue line) are very similar. This demonstrates that they are the most robust algorithms for these types of degraded environments. However, since COIN-LIO only uses the Lidar point cloud and generates an image from it, it is a less robust algorithm against dust.

In these types of underground environments, the presence of dust is very common, whether it is suspended in the air or generated by the aircraft's own flight. For this reason, it might be preferable to use algorithms such as FAST-LIVO2, where the visual part is performed with an IR camera. Thermal cameras can see through dust because they detect infrared radiation instead of visible light. Unlike visible light, which is easily scattered and blocked by dust particles, Long-Wave Infrared (LWIR) has longer wavelengths that can penetrate certain obstructions such as smoke, dust, or fog to some extent.

Another qualitative way to evaluate performance is by comparing the maps generated during the experiment. While there is no available ground-truth map for direct comparison, it is possible to qualitatively assess the maps produced by

different algorithms. Figure 7 shows a comparison between the maps generated by LIO-SAM (blue) and COIN-LIO (red). As observed, the map generated by COIN-LIO is not only denser and larger but also exhibits fewer misalignments, indicating superior mapping performance.

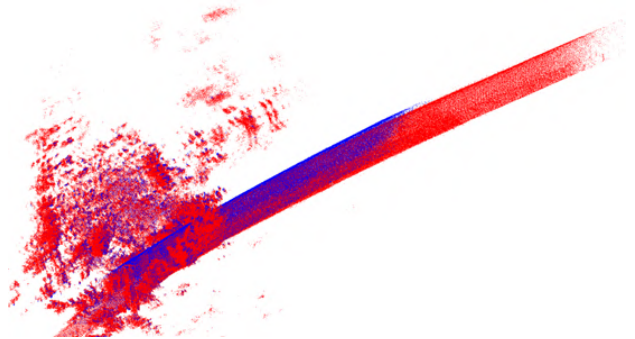


Fig. 7. 3D Point cloud map obtained using LIO-SAM (blue) and COIN-LIO (red)

IV. CONCLUSIONS

A. IMU Pre-Integration Additional Stage

Although some of the algorithms are capable of reporting a valid localization result, the pose estimation is performed at the frequency of the main sensor, the 3D Lidar, which is around 10Hz. To overcome this limitation, a modification to the previous algorithms is proposed. This modification is based on the integration of the algorithms into an IMU pre-integration graph-based optimization framework, similar to the approach used in LIO-SAM. The proposed scheme of creation of the additional pre-integration graph for any odometry algorithm operating at the sensor frequency is shown in Fig. 8.

The IMU pre-integration is based on [24]. An important

clarification is that to integrate the IMU measurements, the magnetometer is not used, only the angular velocities and linear accelerations. This increase in the frequency of the localization estimation is necessary since, due to the dynamics of the aircraft, to be able to control autonomously and safely, an odometry estimation of at least 100 Hz is recommended.

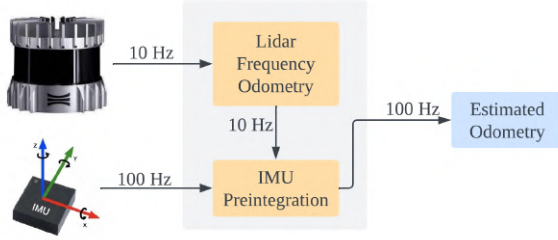


Fig. 8. Diagram of the IMU pre-integration additional stage.

B. Detection of the Onset of Estimation Degradation

LIO methods still face challenges in degraded environments such as tunnels or flat, featureless terrain. In tunnels, the most featureless zones and, by extension, the most complex to maintain a stable location estimate, are those that are geometrically-symmetric. Therefore, an approach to detect when a localization estimation might start to degrade and accumulate drift is through the study of the principal curvature components of the environment.

The principal curvature k_1^i, k_2^i (maximum and minimum, respectively) values were derived from LiDAR scans using the Point Cloud Library (PCL), an open-source library that provides various functions for processing point clouds, including methods for estimating surface roughness by analyzing local variations in point positions. Then, the mean curvature ratio was obtained using the equation 1.

$$R_{\text{mean}} = \frac{1}{N} \sum_{i=1}^N \frac{k_1^i}{k_2^i} \quad (1)$$

In Fig. 9 is shown how, after an initial high peak at the transition from outside to inside, the ratio stabilizes and remains constant once the sensor is inside the tunnel. This is because the curvature directions are more similar and constant. However, as the sensor moves deeper into the tunnel -where the walls are rougher- the ratio tends to increase and become noisier. Based on these experiments, a threshold can be established to predict when the LIO system is more likely to diverge, allowing for appropriate corrective action.

C. LiDAR Configuration: Dual Return Mode for Dust Mitigation

The Ouster LiDAR sensor used in this work supports a dual return mode, which was enabled during the experiments. This configuration allows the sensor to capture both the strongest and the last return for each emitted laser pulse. In environments such as tunnels, where the UAV rotor wash can

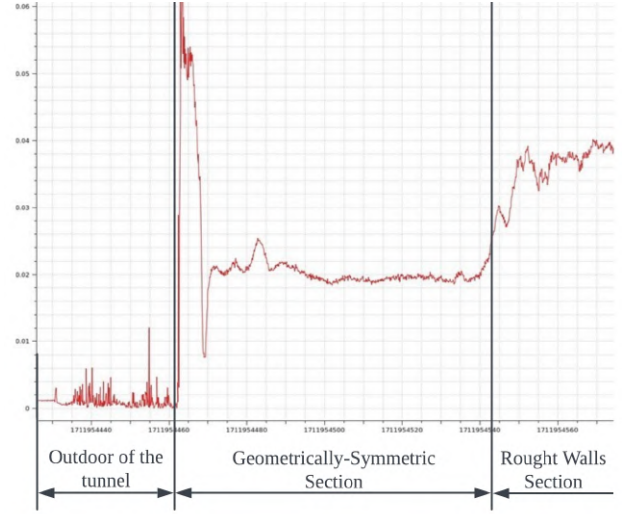


Fig. 9. Mean curvature ratio obtained in the tunnel experiment.

lift considerable amounts of dust, this feature significantly improves the quality of the point cloud.

By filtering out early returns caused by particles in suspension and retaining more stable surface reflections [10], the dual return mode helps reduce the influence of airborne dust on the localization system. This contributes to more consistent point cloud data, enabling more robust scan matching and improving the overall reliability of the LiDAR-based odometry, particularly in degraded visibility conditions.

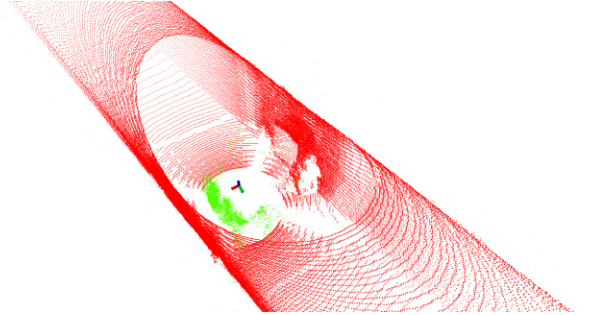


Fig. 10. Visualization in RViz showing the LiDAR point cloud: green points represent particles of dust suspended in the air, while red points correspond to the tunnel walls. The distinction between the two types of returns helps in filtering out the effects of dust and improving the accuracy of the localization system.

D. Future Steps

Throughout this work, the challenges presented by these types of environments have been discussed, as well as the importance and difficulty of achieving accurate positioning estimation at a high frequency. It has been concluded that through a solution based on 3D LiDAR, thermal imaging, and IMU, a reliable positioning estimation can be achieved. In future works, the integration of this GNSS-Denied localization solution with navigation and control algorithms is expected to begin, with the aim of demonstrating the feasibility of

carrying out fully autonomous missions in such degraded environments.

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