A drone-based reflectance transformation imaging system for capturing surface appearance in inaccessible areas of cultural heritage buildings

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Abstract[1]
Reflectance Transformation Imaging (RTI) has proven to be a powerful technique for enhancing the visual analysis of surface features in cultural heritage, archaeology, and material studies. However, conventional RTI systems—whether based on domes, movable light rigs, or manual acquisitions—are inherently limited to planar or moderately curved surfaces within easily accessible zones, typically at ground level. These spatial constraints restrict RTI deployment in many relevant cases, especially those involving architectural elements, ceilings, vaults, or large-scale immovable objects located at heights or in confined spaces. To address these limitations, this article evaluates an RTI system that uses a drone as a mobile light source carrier. This airborne setup aims to extend RTI capabilities to areas previously unreachable by decoupling light positioning from static ground arrangements. The article describes our implementation of H-RTI with a drone for real data acquisition and steps toward its automation. It highlights the scientific and technical importance and challenges of such a system for expanding RTI's operational scope in heritage and environmental documentation.

Keywords
Appearance, RTI, UAV, Cultural heritage

1. Introduction

The visual appearance of a surface results from a complex interplay of two domains: physical interactions between the surface and light, and the psychovisual perception mechanisms of the human visual system. Mastering surface appearance is a key challenge in various sectors, including luxury goods, cosmetics, packaging, aeronautics, automotive, cultural heritage, and the creative industries—where the demand for digitizing appearance is steadily growing. To meet this challenge, two main approaches are used:

1. Sensory analysis, which involves human inspection using visual-tactile feedback, remains the industry standard. However, this method is inherently subjective, making results difficult to replicate or quantify.
2. Instrumental methods, which rely on physical measurements of appearance-related attributes (e.g., surface roughness, reflectance, gloss), aim to provide objective, repeatable

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assessments. These methods pave the way for digital appearance capture, enabling more reliable control of production processes or preservation efforts in heritage contexts.

Among these instrumental techniques, reflectance-based imaging is particularly relevant. Reflectance is typically described through two components:

- an angular component, which depends on the geometry between the light source, the surface, and the observer or sensor;
- a spectral component, which describes how the surface reflects light across different wavelengths.

Both components can be measured by varying the position of the light source and filtering the reflected light accordingly.

One notable technique, Reflectance Transformation Imaging (RTI), focuses on capturing the angular component. RTI has been widely adopted in cultural heritage and is now emerging in industrial contexts. It mimics the intuitive behavior of human inspectors who, during sensory analysis, tilt or rotate objects under changing light angles to reveal surface details. RTI systematizes this process by digitally recording how surface appearance changes under different lighting directions.

Reflectance Transformation Imaging (RTI) is a computational photographic technique introduced by the article [1] to improve visualization of fine surface details by capturing variations in surface reflectance under different lighting directions. It was initially developed at HP Labs as a way to portray surface appearance more comprehensively than traditional static images. Instead of reconstructing 3D geometry, RTI focuses on appearance-based rendering, enabling scholars to examine how subtle surface features—such as scratches, tool marks, and inscriptions—react to oblique lighting. It has been widely adopted in cultural heritage applications because of its non-invasive nature and capacity to reveal features invisible under normal lighting, particularly in documenting inscriptions, coins, reliefs, and paintings [[2] [3]].

1.1. Principles of RTI and Data Utilization

RTI involves capturing a series of photographs from a fixed camera position, each under a different lighting direction. The resulting images are processed computationally to estimate the reflectance behavior at each pixel, typically using a Polynomial Texture Map (PTM), [1]; Hemisphere Harmonics model [4]; or more recently Discrete Modal Decomposition (DMD) [5], or Neural RTI [6].

The generated RTI file enables interactive relighting, allowing the viewer to dynamically change the virtual light direction to better reveal the surface geometry. Besides relighting, RTI data can also be used for analysis (segmentation, saliency maps, etc.) or for deriving local geometric attributes (Normal maps, slopes, curvatures, etc.) [7]. Figure 1 shows the RTI pipeline from acquisition to analysis.

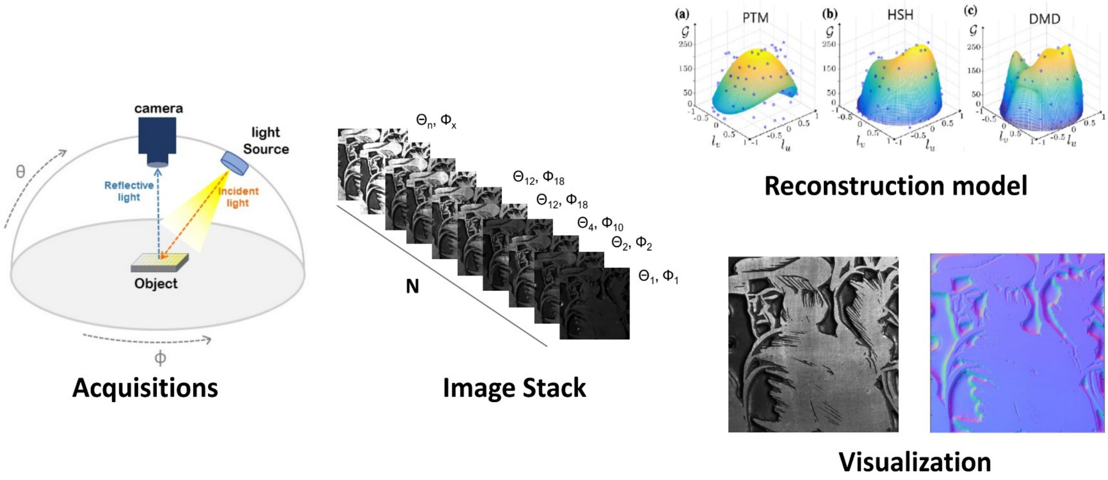

Figure 1: Principle of RTI data acquisition and exploitation

1.2. RTI Acquisition Modes and Their Limitations

Several hardware configurations have been developed to acquire RTI datasets:

- **Fixed LED domes**: precisely calibrated hemispherical structures with embedded LEDs [[2]; [3]]. While they offer reproducibility and speed, they are limited in size and generally require laboratory conditions.
- **Movable-light rigs**: allow the repositioning of a light source manually or automatically. These offer more flexibility but are often slower and more operator-dependent.
- **Highlight RTI**: a **free-form method** using a handheld light and a reflective sphere to estimate lighting direction for each frame. While suitable for in situ documentation, it suffers from lower accuracy and reproducibility [8].
- **Robotic arms or gantry systems**: allow for precise, automated control of the light but are bulky and less field-adaptable [9].
- **UAV based RTI**: To our knowledge, two articles have proposed an approach based on the use of drones [[10],[11]]. However, these articles lack technical details on the acquisition process and the explanation of the data.

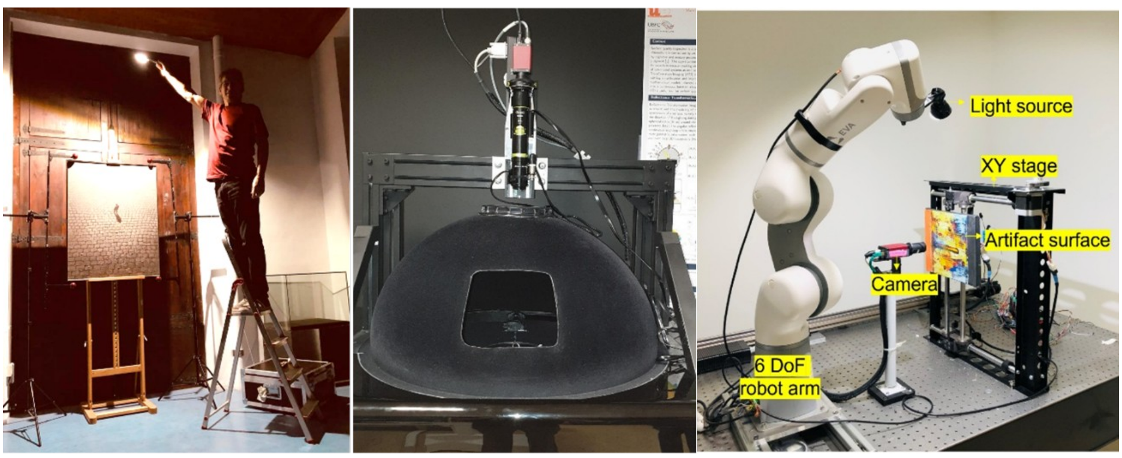

Figure 2: some examples of RTI implementation. Handhel (left), Dome-based (middle) and Robotic-arm based ((right)

All these methods require physical access to the object. This limits their use to surfaces that are flat, stable, and within human reach, excluding many important cultural heritage scenarios. In fact, many heritage surfaces of high scientific interest remain physically inaccessible: ceiling frescoes, high-reliefs, upper vaults, and fragile architectural elements. These locations often prevent the use of scaffolding or dome installation, making traditional RTI impossible. Figure 3 shows some objects from Cheminova Pilots that are inaccessible from a conventional RTI perspective.

Figure 3: Some artifacts and sites from Cheminova pilots requiring adaptation of RTI

To overcome this, we propose a **drone-based RTI system**, in which a UAV carries a calibrated light source and moves around a fixed camera to simulate RTI-like variable lighting. This concept is inspired by emerging studies on **mobile lighting systems** for 3D reconstruction and surface inspection; [12].

Developing such a system, however, requires more than flying a drone with a flashlight. It involves:

- Real-time **synchronization** between the UAV, the light source, and the camera.
- Accurate **tracking** of the drone's position and orientation (e.g. via motion capture or LiDAR).
- **Control over lighting geometry**, incidence angle, and photometric stability.
- Management of drone-induced **vibrations**, **motion blur**, and **light scattering**.
- Adequate pre-processing to compensate non uniform illumination as well as light positions distribution over the hemisphere
- Adequate methods for reconstruction and feature extraction

This article presents an **experimental setup** using a drone-mounted continuous LED light with synchronized acquisition, implementing H-RTI and steps towards automation.

2. Proposed approach

2.1. Real H-RTI Acquisitions

This section explains the practical setup of a drone-based RTI simulation for data acquisition of inaccessible zones with a fixed camera.

Environment: To validate the proof of concept (POC) we intend to implement, we conducted an RTI acquisition experiment inside a gymnasium with a sufficiently high ceiling (8 meters). This setting is similar to the interior of a heritage building, such as a cathedral, church, castle, or gallery. In the gymnasium, the lighting conditions are not fully controlled, much like in a church, and while there is some ambient light, it is relatively weak compared to the intensity of the active lighting directed towards the stage from an LED source.

Scene: To create a scene with ground truth that simulates real conditions, we positioned a painting on a support parallel to one of the gymnasium walls at a height of approximately 4 meters. A camera was set up on a tripod in front of the painting, 4.5 meters away and at a height of 3.8 meters. Prior to this, the painting was digitized in the laboratory using the H-RTI technique, which involved using a handheld light source. The POC we aim to validate in this experiment follows the H-RTI principle, which entails placing reflective spheres around the scene. These spheres serve to estimate the lighting directions, which are not known in advance.

Figure 4 illustrates the configuration of the camera stage and the arrangement of spheres around the painting for this proof of concept.

Figure 4: This proof of concept's setup (scene and camera).

Hardware: **Our implemented setup** utilizes readily available operational hardware with a few modifications and adaptations.

- **Drone**: A DJI Air 3s equipped with three batteries to ensure sufficient flight time.
- **Light Source**: A high-power LED extracted from a Milwaukee headlamp. This light source is mounted directly on the drone's gimbal, which has been lightened beforehand.

The drone, equipped with the light source, is shown in Figure 5.

Figure 5: The drone, equipped with the light source

- The camera: a Nikon D850 DSLR camera
- Setting up and triggering image capture: a Wi-Fi module called CamRanger allows us to remotely adjust camera parameters (exposure time, ISO, focus, etc.) and take images in each light direction.

Acquisition: Once the system is set up, the drone operator configures it to ensure the light source always points toward the scene's center. The operator also ensures the drone stays at the same distance from the scene at all stations. An image is captured and stored at each drone station, corresponding to a specific lighting direction using the camRanger wireless module. To cover the hemisphere around the scene, the drone is moved systematically along an arc to avoid missing any large areas. For this proof of concept (POC), approximately fifty lighting directions were tested over 50 minutes.

Figure 6 shows a moment during the acquisition process when we can see the scene, the drone camera, and the drone operator.

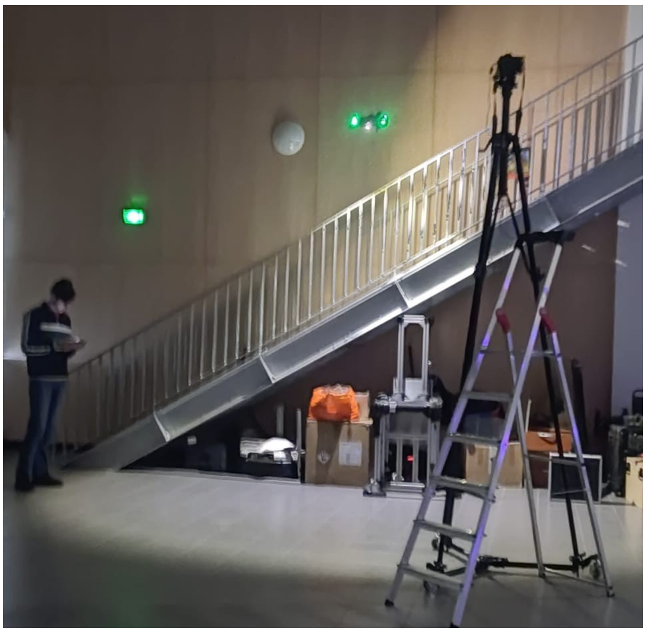

Figure 6: a moment during the acquisition.

2.2. Pre-processing and Reconstruction

2.2.1. Pre-processing

Some preprocessing is still necessary to effectively utilize the data collected with this method. The most important steps include:

- *Estimation of lighting directions*: This step is crucial because, in this free-form setup, the directions are not predefined and must be estimated using reflecting spheres. The spheres' perfect spherical shape and reflective surface allow us to detect the highlight spot and determine the light direction. Additionally, from the four directions identified on the four spheres, we can estimate lighting directions per pixel, enhancing our approach's robustness.

Figure 7 shows the bright spots detected on the four spheres, allowing us to estimate lighting directions.

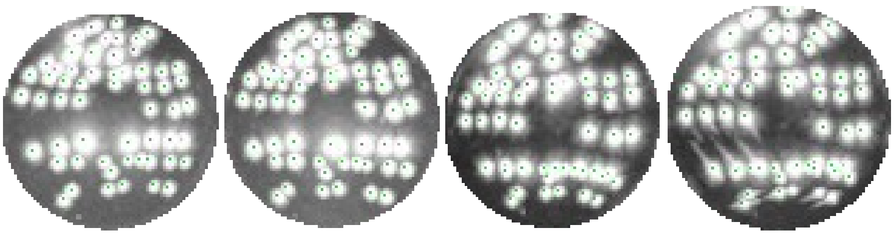

Figure 7: highlights spots on the spheres, allowing light direction estimation.

First, we observe that the extraction of lighting directions, corresponding to the drone's spatial positions, from the spheres with good accuracy has been successfully completed. This provides an initial validation of the concept.

- *Correction of uneven illumination and intensity*: changes based on the source's angle and distance from the scene's center.

Figure 8 shows the principle of these variations.

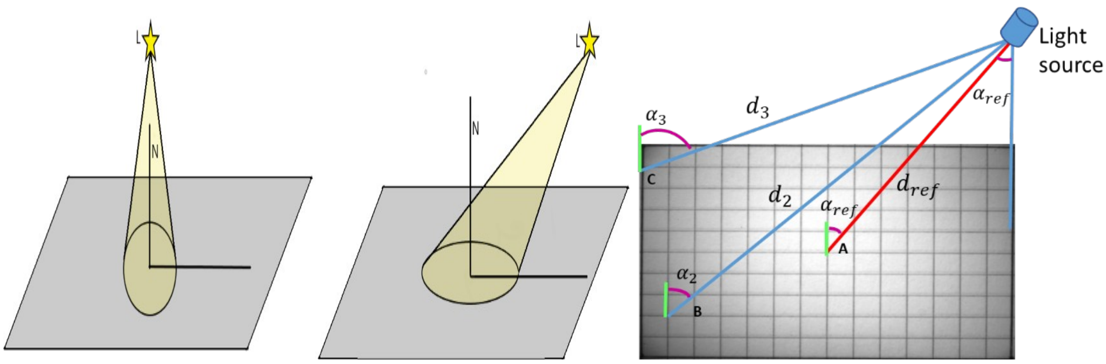

Figure 8: illustration of the unevenness of illumination due to angle and distance variations.

To overcome this imperfection, we use the method we have developed and proposed in the article. [13]

- *Calibration of the uneven distribution of lighting directions* in the hemispherical space around the scene. This calibration is essential when using reconstruction methods (PTM, HSH, and DMD) that assume a constant variance (uniform distribution). To accomplish this, we use the technique we developed, which weights the lighting directions based on the local density of directions [14]. We estimate the local density through a spatial mesh scan representing the lighting directions.

Thanks to this approach, images from areas with low density receive higher weight in the reconstruction. The principle of this method is illustrated in Figure 9.

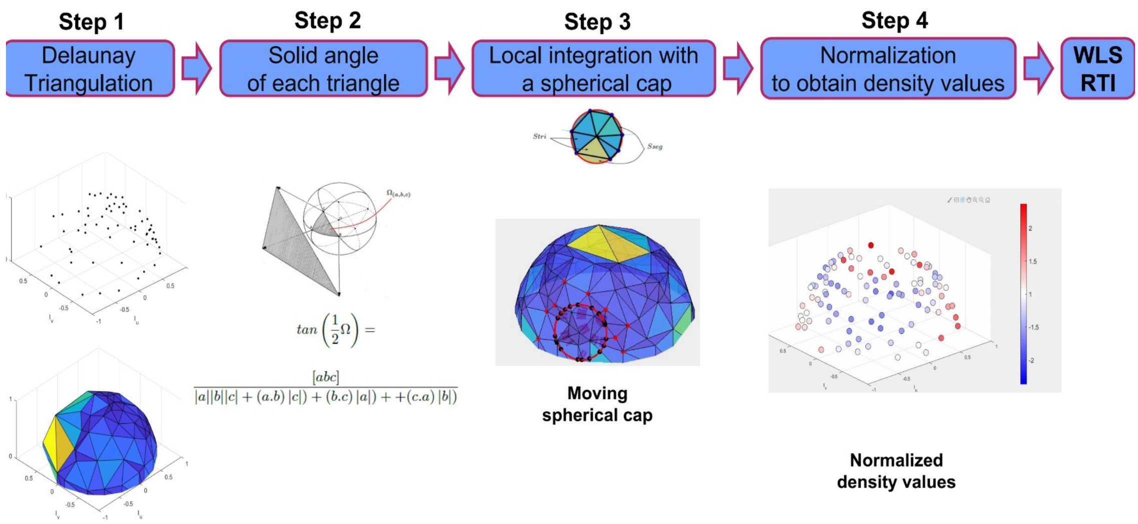

Figure 9: Pipeline of processing designed to estimate and calibrate the light distribution over the hemi-sphere.

2.2.2. Reconstruction

To validate the usability of the data collected during this indoor sequence with the drone-based system, we reconstructed the scene using the PTM and HSH methods and created relightings to simulate how the painting would appear under continuously changing illumination. As mentioned, this scene was previously captured by manually manipulating the lighting source. For both acquisitions (UAV and manual), we used the same number of lighting directions (50 lp), although they do not correspond exactly to the same directions. However, the spatial coverage is very similar.

Figure 10 displays the two relightings of the same scene obtained through the two methods. The visual comparison confirms that the data is valid, producing relightings that look similar to those from the manually acquired data.

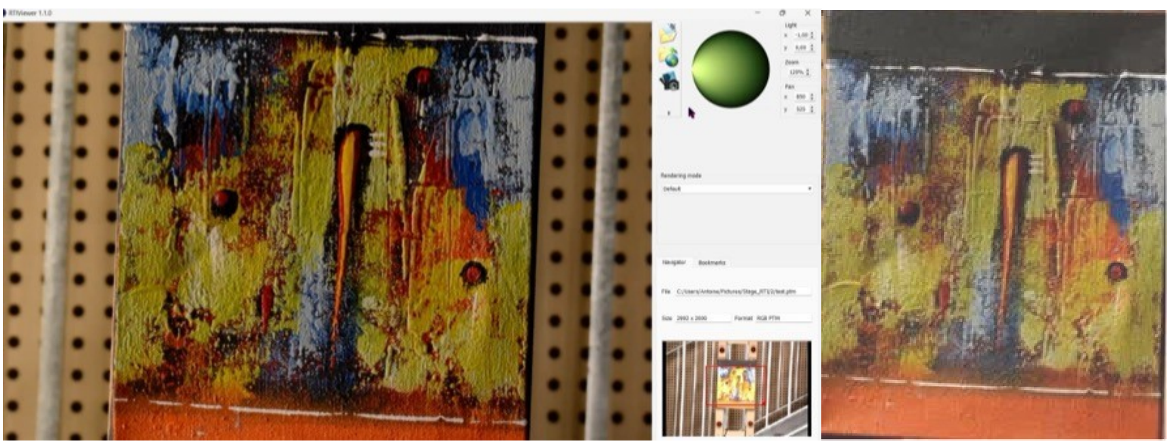

Figure 10: Relighting of the scene using data acquired by the drone (left) and data acquired handheld in the lab (right)

Additionally, using the RTI data collected with the drone, which also serve as photometric stereo data, we reconstructed the normal map. This map, shown in Figure 11, illustrates the orientation of points in the scene relative to the camera. The map appears to be highly accurate, especially for the four spheres. These spheres have perfect spherical geometry, and their distribution and distance from the camera are known, allowing us to validate the normal map.

Figure 11: normal map derived from acquired RTI data using the proposed setup.

2.3. Towards automation

In the first approach, we demonstrated the feasibility of real acquisition by implementing the H-RTI principle. This indicates the need to use reference spheres. However, placing the spheres under certain acquisition conditions may be impossible. For this reason, we tested a second approach to increase the automation of RTI acquisition using a drone.

For the H-RTI, reference spheres were used to determine the spatial positions of the light source. However, this information can be obtained if the drone is equipped with advanced positioning technologies such as RTK GPS, Ultra-Wideband (UWB), or visual-inertial SLAM to enhance spatial accuracy. The goal is to ensure the drone can independently map and capture the area with its camera. To achieve this, ROS was used. The ESP32 aboard the drone, equipped with its LiDAR and IMU, can then map the area and create a half-sphere around the object. Figure 12 shows the Drone used for H-RTI after equipping it with LiDAR and ESP32.

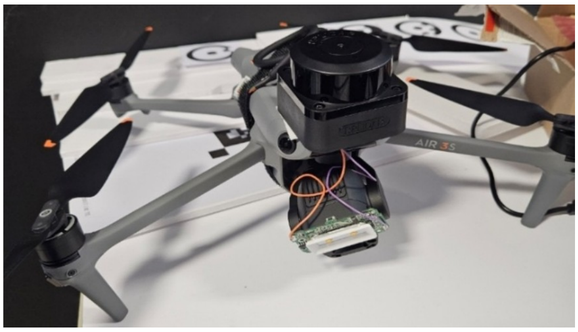

Figure 12: DJI Air3S, equipped with LiDAR and ESP32, allows it to map its environment from the camera stream.

We have completed initial mapping tests of the environment, which enable us to eliminate the spheres. The early results, shown in Figure 13, are very promising, as we have achieved relatively accurate mapping, especially of vertical walls and other obstacles.

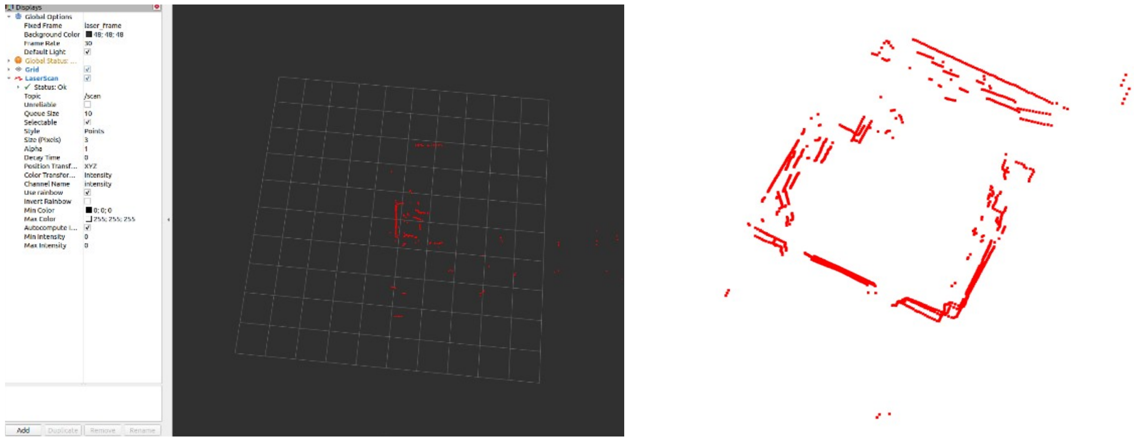

Figure 13: Environment mapping with modified DJI Air 3S. Mapping visualized from raw data with Python (left). Mapping visualized with Rviz in ROS.

After environment mapping, automated acquisition can be planned using pre-calculated positions. To ensure the system functions correctly, several key steps are necessary. First, the drone must automatically generate waypoints that position the light source optimally around the object. Next, it must adjust the light's orientation to properly aim at the surface. At each position, images are captured, and all relevant location and orientation data are recorded.

To ensure precise alignment between the light source and the object, the system must account for multiple coordinate systems—such as those of the world, the drone, and the sensor. This involves applying specific transformations to accurately relate their positions and angles.

3. Conclusion and future work

In this article, we have evaluated the feasibility of drone-based Reflectance Transformation Imaging (RTI) relying on a semi-manual configuration and steps oriented toward more automation. We have detailed the necessary implementation steps—from sensor integration and orientation control to acquisition protocols and post-processing routines—providing a replicable and scalable foundation for future deployments.

The manual H-RTI approach, based on reference spheres and a static camera setup, allowed us to validate the viability of airborne light-source positioning. The visual and geometric quality of the relightings and normal maps demonstrated strong consistency with conventional ground-based RTI, confirming the effectiveness of drone-based acquisition. Building on this, we described a more automated strategy, incorporating advanced UAV capabilities such as GNSS, IMU and LiDAR. This automated approache be further refined and evaluated in real-world conditions during upcoming acquisition campaigns at the pilot sites of Cheminova project in Valencia and Vienna. These field deployments will provide critical feedback on the system's robustness, repeatability, and integration with RTI processing pipelines, paving the way for broader adoption of drone-based RTI in the documentation of inaccessible or large-scale heritage structures.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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