Robots for the digitisation of hard-to-access cultural heritage sites

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Abstract

Europe has a wealth of cultural heritage sites and, according to UNESCO [1], Italy is the country that has the largest number in Europe. The conservation of such sites is a very challenging task, as it requires periodical surveys, where teams of experts need to carry heavy equipment on the field.

In this extended abstract we provide a brief overview the EU-FP7 ROVINA project [2]. ROVINA aims at making surveying of cultural heritage sites faster, cheaper and safer through the use of autonomous robots that will enable 3D reconstructions at a completely new scale and quality. The ROVINA robots can autonomously explore archeological sites. The data collected during the exploration is stored into the Cloud and is used to deliver advanced analysis services for structural engineers, historians and preservation experts. As the models are extremely accurate and visually appealing, ROVINA has created an online museum for the general public that is built on top of a WebGL virtual site viewer. The experimental evaluation of the ROVINA system will be performed in the S. Priscilla catacomb in Rome and the S. Gennaro catacomb in Naples selected by the International Council of Monuments and Sites as the most representative sites for this class of cultural heritage, both in terms of archeological impact and of robotic challenges.
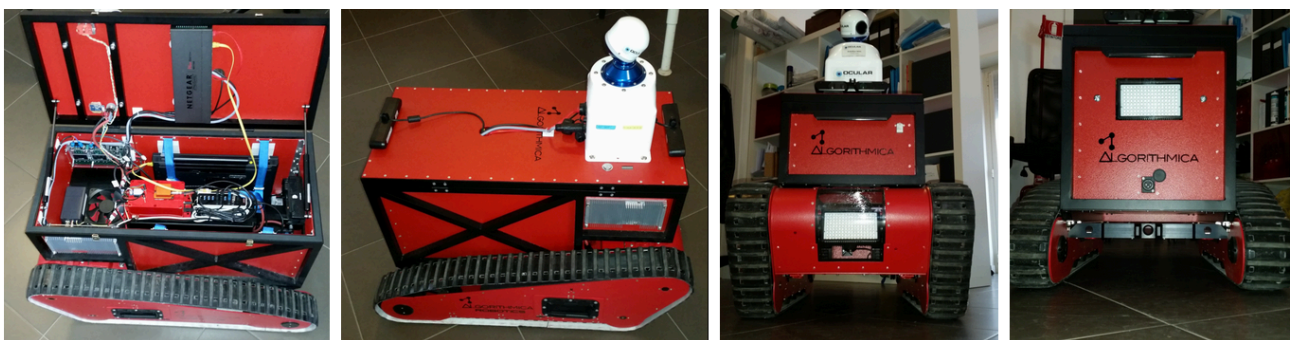
Figure 1: A preliminary prototype of the ROVINA robot.

At the core of the ROVINA project there are three robot prototypes (see Figure 1) that we will use to explore and collect data about the catacombs. This robot is used by cultural heritage experts, called surveyors, to explore and build 3D models of the archeological site at hand. Surveyors deploy the robot at the entrance of an archeological site and remotely operate it through a Mission Control Interface (MCI).

The MCI is multi-modal (see Figure 2), since it allows for different operations, including establishing the level of autonomy of the robot, assign mission targets, selecting regions of the environment and annotating them for further analysis, etc.

Figure 2: A mockup of the mission control interface in multi-modal mode.

The multi-modal configuration requires a large bandwidth that is provided by a dedicated point-to-point Wi-Fi connection. Since Wi-Fi has a limited range and performance in a catacomb, the robot is able to automatically create a local wireless network, by releasing Zigbee nodes along its path. These devices act as repeaters and allow for maintaining connectivity at the price of a lower bandwidth. The Zigbee nodes thus create a low-cost wireless mesh network that can last several years thanks to their low-power characteristics and that can act as a sensor network and continuously stream a wide set of data such as temperature, humidity and pressure.

In order for the operator to have a better understanding of the environment and to enable autonomous navigation, we have been developing beyond state of the art approaches for Simultaneous Localization and Mapping (SLAM). In particular, we are developing Graph SLAM variants that can run online during the mission [3]. The project's approach is characterised by an optimisation backend [4] and a number of heterogeneous frontends that take advantage of the sensors available on board (i.e., arrays of cameras, RGB-D cameras and 3D lidars). Catacombs are a very challenging environment and as such robustness of SLAM is crucial for avoiding the robot getting lost. To this end, we have devoted a considerable effort in making the approach more robust to outliers [5], [6], to assessing the degree of consistency of maps [7] and to automatically calibrating the sensors [8], [9]. Finally, we exploit a Structure From Motion (SFM) pipeline for dense reconstruction. SFM takes the SLAM output as an initial guess for the model in order to provide an output that is more accurate and dense, thanks to the data collected by 7 industrial cameras mounted on the robot. Semantic segmentation [10] is also used in order to add semantic information to the gathered data. Figure 3 shows some snapshots from one such reconstruction made in S. Priscilla.

Figure 3: Examples of dense 3D reconstructions.

Once the mission is over, the robot will have gathered an enormous amount of data from its sensors that include laser scans and pictures. Some of these datasets are available on our website [2]. These data are also uploaded to a cloud computing facility where they are used for offering a number of online services. The building block of these services will be an extremely accurate 3D model that will be built offline.

Based on the dense reconstruction and the semantic analysis performed on top of it, we can offer web-based services to a number of different users:

1) A viewer where virtual tourists can visit high quality 3D textured interactive reconstructions of the site.
2) An archive where humanists can classify, document and query for items and portions within the site.
3) Structural analysis tool where engineers can analyse the morphological aspects of the site performing measurements and analysing variations over time.

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