siar **s**ewer **i**nspection **a**utonomous **r**obot

D28.12 - Structural Inspection

SIAR Consortium

IDMind (IDM), PT

Universidad de Sevilla (USE), ES

Universidad Pablo de Olavide (UPO), ES

ECHORD

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1. Introduction

The SIAR platform has to offer a set of functionalities tailored to the application of sewer inspection. According to the Challenge Brief [ECHORD++, 2014] , these are:

- Determining the sewer serviceability
- Identify critical structural defects
- Sewer monitoring
- Water, air and sediment sampling

Serviceability inspection refers to the ability of the robot to determine whether the sewer is working properly or not. In particular, a sewer is considered to be in service if the sediments on the floor are below certain levels, if the water is flowing correctly or there is no water accumulated in the sewer.

The detection of Critical Structural Defects refers to damage inside the sewers, like cracks, fractures, breaks, breaks with loss and collapses.

Sewer monitoring refers to the measurement in real-time of the quality of air and water within the sewer.

Finally, the sampling functionality aims to gather physical samples from the air, water and sediments within the sewer for further analysis.

The SIAR platform provides the three first functionalities. Deliverable D28.10 described the approach to detect serviceability problems and for sewer monitoring. It also presented the operational concept for the inspection procedure.

This Deliverable extends the previous one by describing the methods for the detection of structural defects. The operational concept remains the same, and the current functionality is built on top of the elements described there.

The result is a module that is able to highlight potential defects automatically and in real-time, by analyzing online the data provided by the sensors onboard the robot. These alarms are geo-referenced by using the localization system of the robot, and can be further analyzed by the operators.

The document first describes the approach for automatic defect inspection in Section 2. Then, Section 3 presents the results obtained in the inspection tests carried out in Barcelona. The document finalizes with conclusions.

2. Automatic Inspection Module

Deliverable D28.10 described the perception module to estimate serviceability inspection problems. Here, we extend such module with the functionality for structural defects inspection. This constitutes the final complete system for automatic inspection in SIAR.

2.1 Overview

Regarding the “Serviceability Reduction Alarm”, the Challenge Brief [ECHORD++, 2014] mentions:

“On the basis of the scanning or the video made, the robot has to compare the obtained data with the available information of the sewers (mainly type and section) and identify where the sewer serviceability has been reduced. The operator should receive a “pop-up” alarm that indicates the location of the obstruction and helps to decide if the robot has to make an extra specific snapshot or video.”

The proposed system follows this strategy for both, serviceability and structural defects inspection. The robot is able to automatically recognize the section type which is traversing by using the 3D data provided by the robot sensors. It does this by comparing these data with the known section types in a database, which can be used to obtain a virtual 3D model of the sewer section. Information from the robot localization system [Alejo et al, 2017] can be also leveraged to estimate the section currently transversed.

Then, once the section type is determined, the system needs to focus on the gutter/bucket, the sill and the curbs to determine potential serviceability reductions, and also on the roof and walls for structural defects.

The system measures the deviation of the recorded 3D data from the ideal situation to raise alarms. A noise reduction and temporal consistency filters are finally applied to discard false alarms.

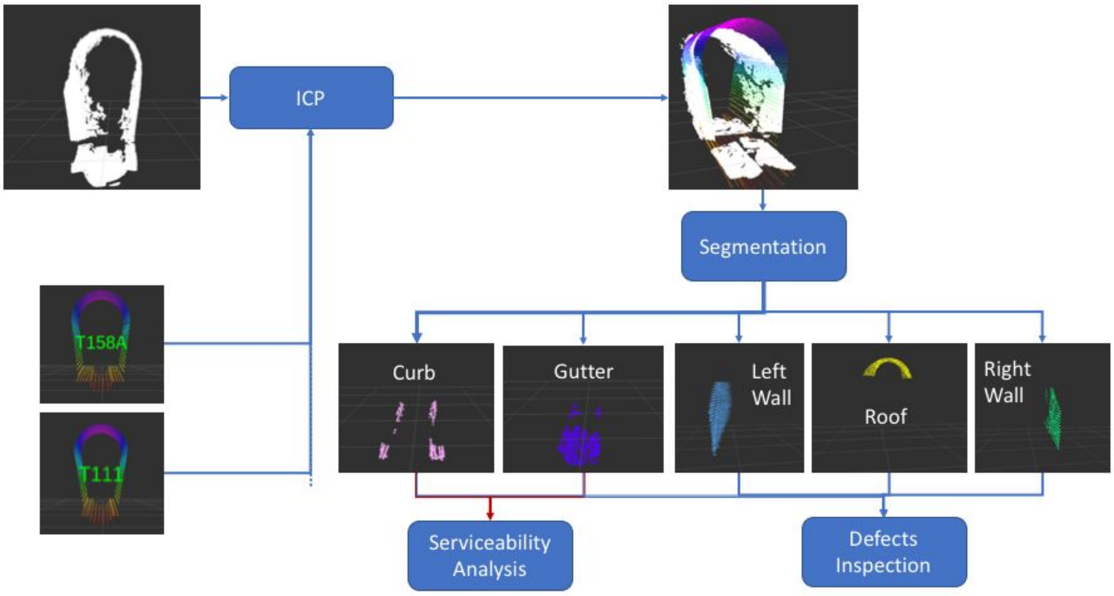

Figure 2.1: Main processing pipeline. ICP is used to estimate (and align) the current section type by comparing the 3D data (in white) with virtual models from the database. Then, the parts (curb, gutter, walls, roof) are segmented from the input point cloud. These parts are analyzed to estimate potential serviceability alarms (as described in D28.10) and defects.

Figure 2.1 summarizes the processing pipeline. The next sections detail these steps.

2.2 Automatic detection of sewer type

The first step in the processing pipeline is the detection of the sewer type. The objective is, given the 3D input from the sensors of the robot, to determine the most likely section type from the set of possible section types.

The robot stores a database of 3D virtual models of the different section types, according to the drawings of the different sections as provided (see Figs. 2.2 and 2.3). These virtual models also contain labels for the different parts of the sewer: gutter, curbs, walls and roof.

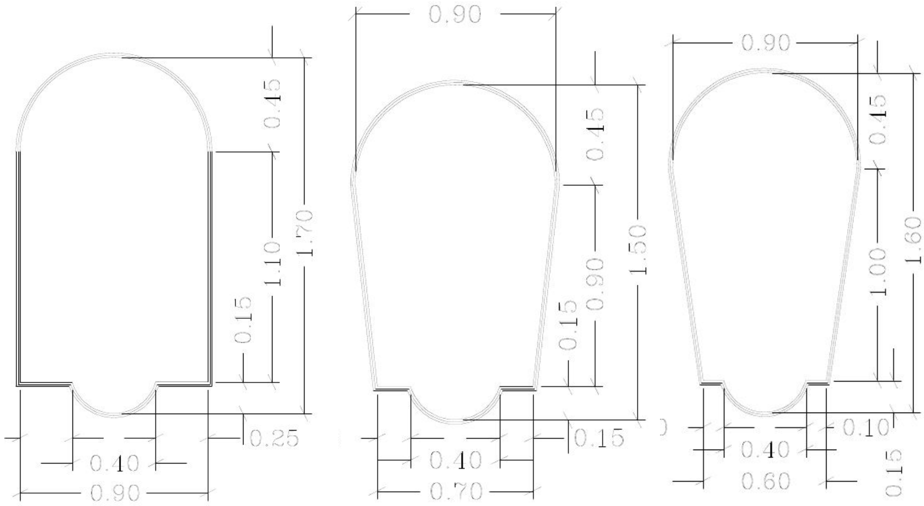

Figure 2.2: Different definitions of section types. Left: T135B. Center: T108. Right: T111

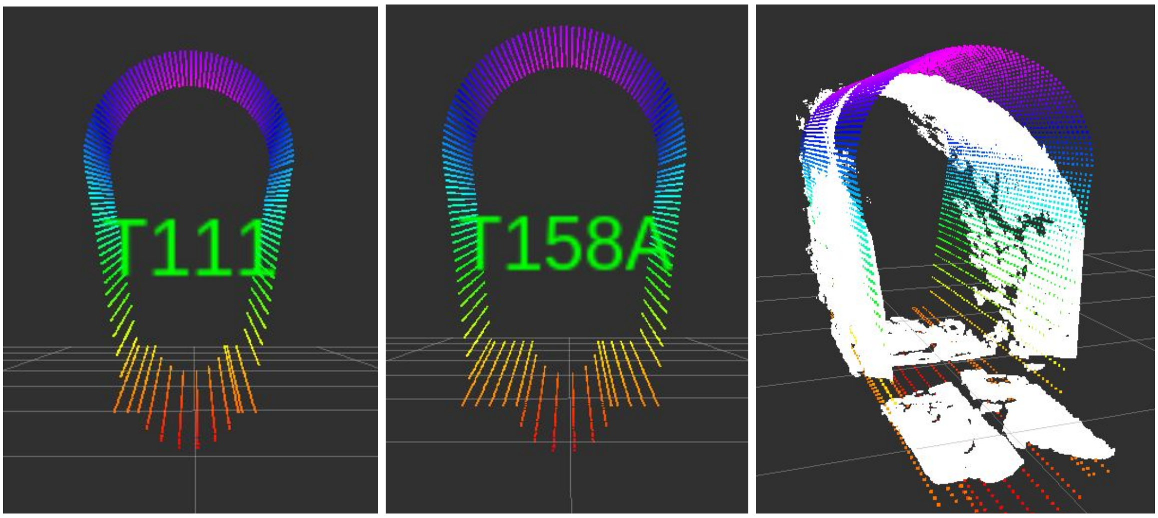

Figure 2.3: Left and center: Virtual ideal 3D models for section types T111 and T158A. Right: the current 3D data (white) is aligned using ICP to all the models in the database searching for the one that best fit the data.

The procedure to determine the section type is based on the Iterative Closest Point [Besl and McKay, 1992] algorithm. The current sensor data is matched, using ICP, to the different virtual models of the sections (see Fig. 2.3, right). To initialize ICP, the virtual model is created approximately aligned to the optical camera that provides the 3D data. The section types are ranked according to the residual of the alignment between the real data and the virtual model. The section with the lowest residual is selected as the current section type.

2.3 Segmentation of sewer elements

As an additional result of the alignment described in the previous section, the current point cloud is segmented into the different parts of the sewer; that is, each 3D point is classified as either gutter, curbs, walls or roof. Each point of the cloud is labeled according to the label of the closest point in the virtual 3D model of the sewer. Figure 2.4 shows the results of the segmentation.

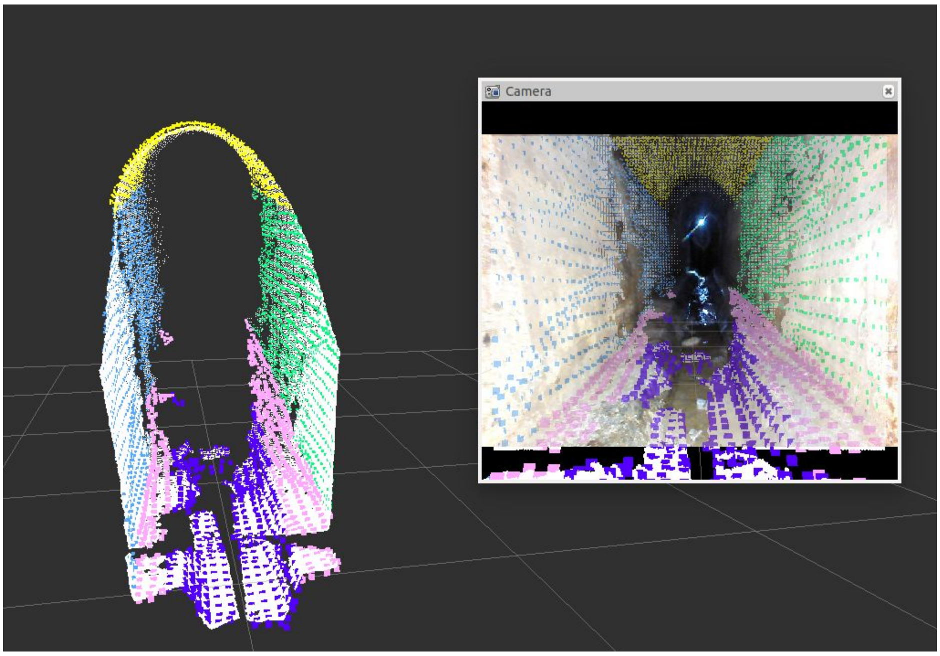

Figure 2.4: Point-cloud segmentation. After the alignment with the section, the points are segmented according to the different parts of the sewer. Left: points segmented as gutter (purple), curb (pink), left wall (blue), right wall (green) and roof (yellow). Insert: the points projected back on the frontal camera of the robot.

2.4 Automatic structural defects detection

Once the 3D data input has been aligned with respect to the section type and segmented into different parts (see Fig. 2.5), the structural defects inspection begins.

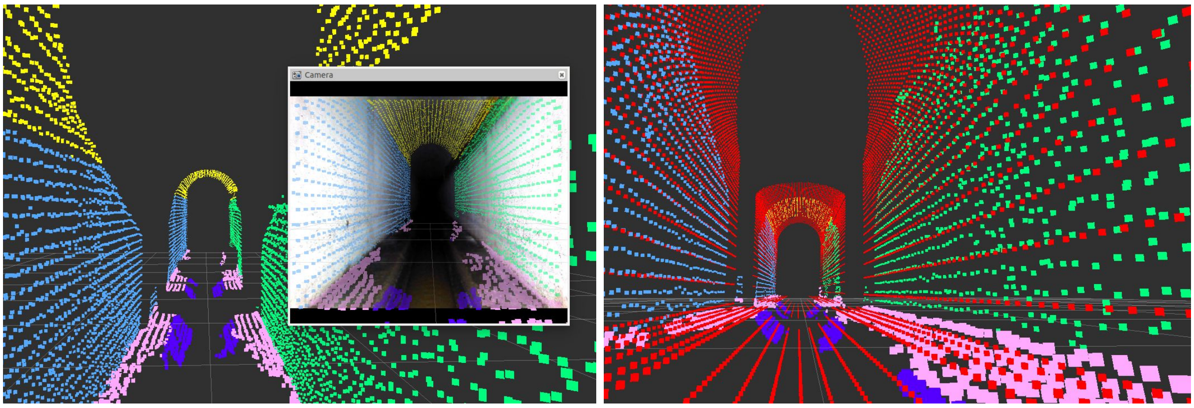

Figure 2.5: Left: the segmented point cloud. Right: the point cloud is aligned to the gallery virtual model (in red), according to the estimated most likely section.

Structural defects alarms can be raised by estimating the error between the ideal section model and the 3D data gathered by the sensor. This error is estimated by nearest neighbour search between each point in the cloud and the virtual model of the section. The points for which the error is above a threshold are candidates for potential defects. The threshold is user defined, and can be used to balance the size of the defects and the rate of false alarms.

Unfortunately, there has not been specific experiments to determine the resolution that the system can achieve when detecting small structural defects. To show the automatic detection of deviations between the sensorial data and the model, which can be used to raise potential failures, we have employed other features present in the environment and not in the model. Thus, Figure 2.6 illustrates how an element (an structure to hold cables) of some several centimeters can be detected as it deviates from the detected section type T130.

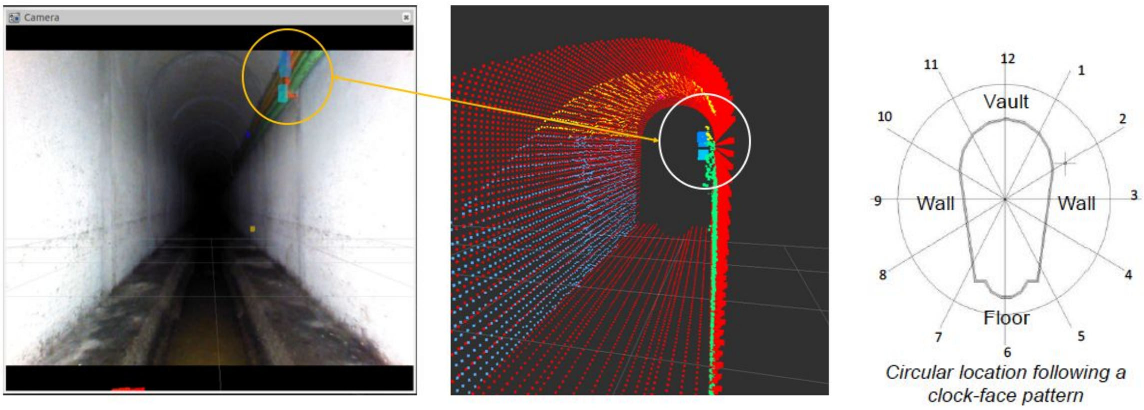

Figure 2.6: Left: the base station highlight a part of the image that deviate from the section model automatically estimated (T130 in this case). Centre: it can be seen how the points on the right wall and part of the roof (green and yellow) are misaligned with respect to the virtual model of the section (red). Right: as the 3D position of the points are known, it is possible to indicate the location of the defects following clock-face pattern.

Using data from different experiments carried out in the project, the approach has been able to detect some defects on sewers by using the system described in preliminary stages (see Fig. 2.7).

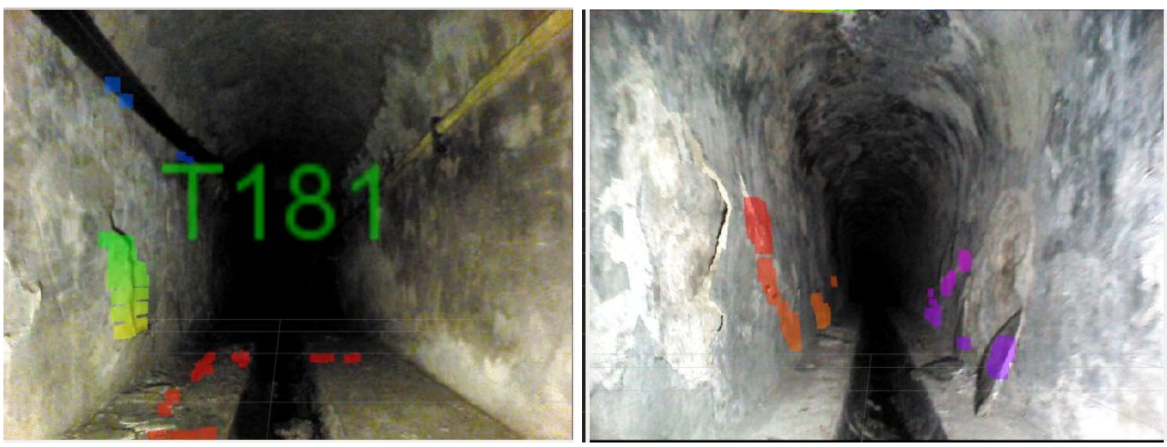

Figure 2.7: Defects detected using data from Phase II experiments.

2.5 Structural defects confirmation

SIAR carries now an arm with a camera onboard (Fig. 2.8), that can be used for close inspection and confirmation of the potential defects highlighted by the module.

Figure 2.8: The robot now carries a camera on an articulated arm, that can be directed to the automatically-generated alarms for confirmation and close-inspection purposes.

3. Experimental results on structural defect inspection

In the following section, we present the outcome of the structural defect inspection results obtained during the demonstration carried out in the Avinguda de Pearson on the 18th of October and 7th of November, 2018.

4.1 2018/18/10, 2018/11/07: Structural defect inspection in Av. Pearson

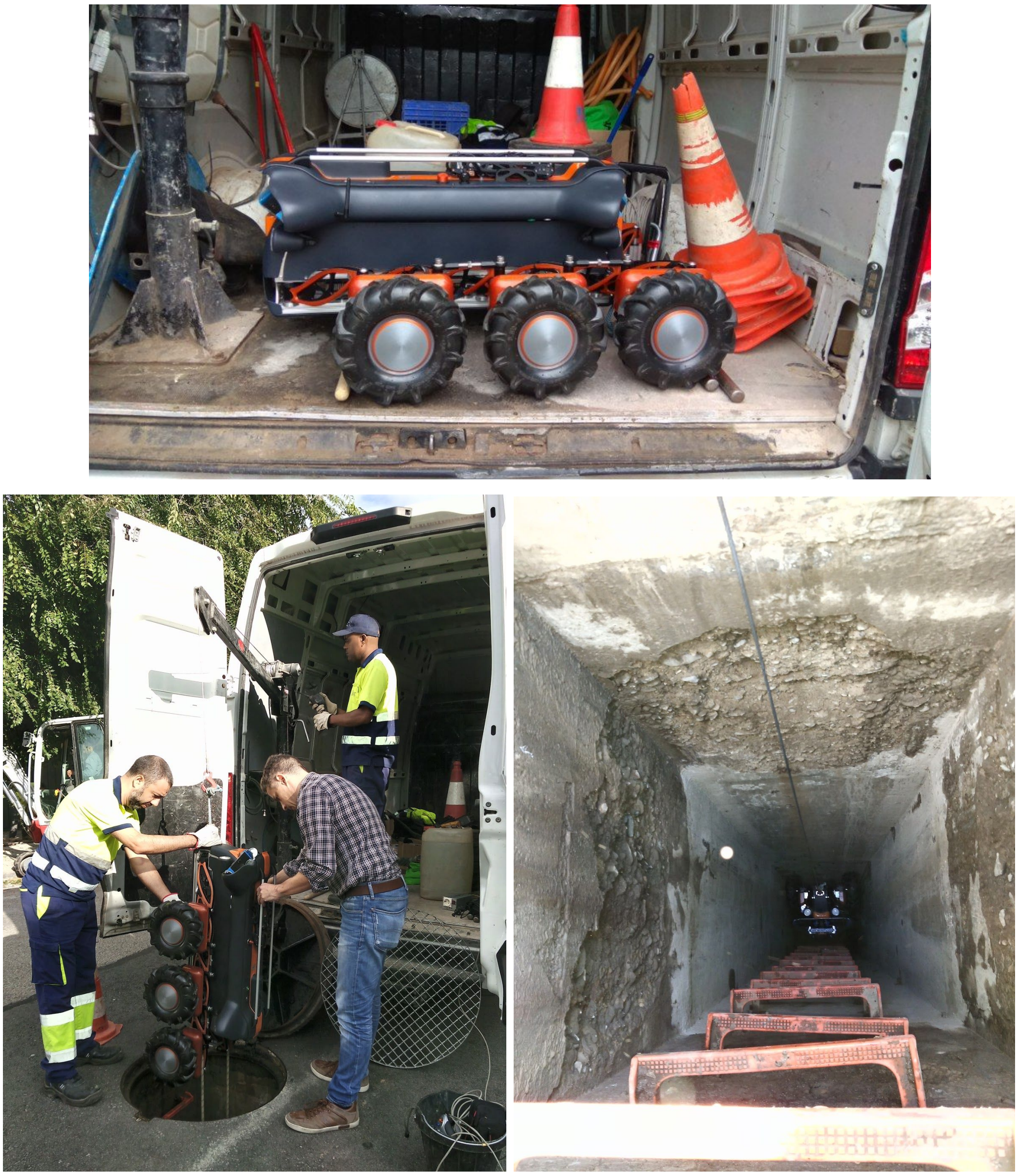

Figure 3.1: Top: the new SIAR platform on one of BCASA's vans. Bottom: the robot is deployed into sewer through a 10-meter manhole.

On the 7th of November, 2018, the structural defects inspection demonstration was performed in the Avinguda de Pearson. During the experiment, the new version of the SIAR robot was deployed and commanded from outside using the control station (see Figs. 3.1 and 3.2).

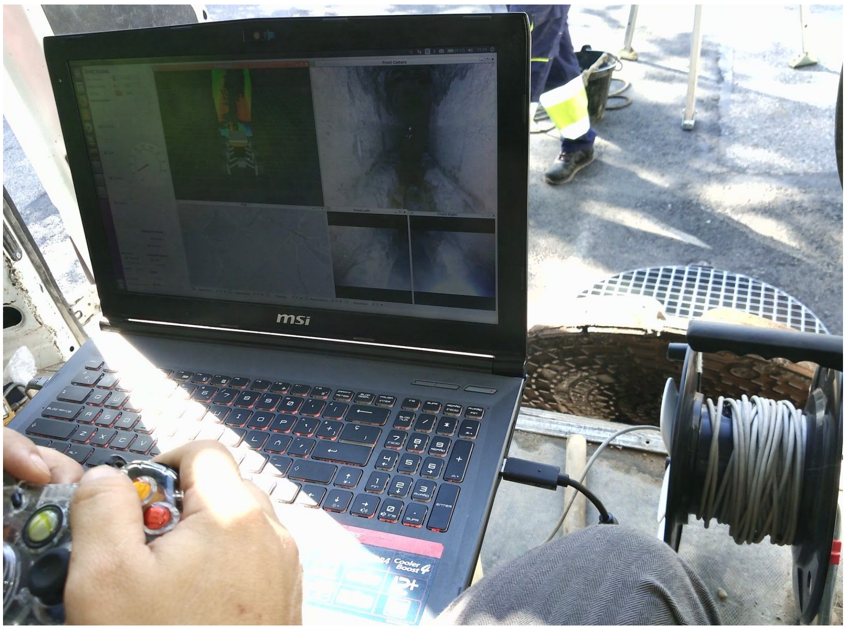

Figure 3.2: The robot is controlled from the Ground Station, which can run in a laptop, and shows visual and 3D information, including the view from the robot arm, as well as the automatically detected serviceability and structural defects alarms.

During the experiment, the whole inspection module was running, including the serviceability and structural defect inspection functionalities. The system automatically raises alarms so that the operator can confirm them by inspecting further the data provided by the robot. This can be done online (as during this inspection, for instance using the robot arm), but also offline by processing the data recorded by the robot.

In the sewer, a major collapse was localized at the end of the inspected sewer. Figures 3.3 and 3.4 show the data about the defect, and the extracted information.

Figure 3.3: Top: a view of the robot entering the place where a collapse has happened. Bottom: the view from the frontal camera of the robot (left), and the 3D point cloud of the scenario (right, also overlaid on the image). The 3D information can see the blocks on the far part of the tunnel.

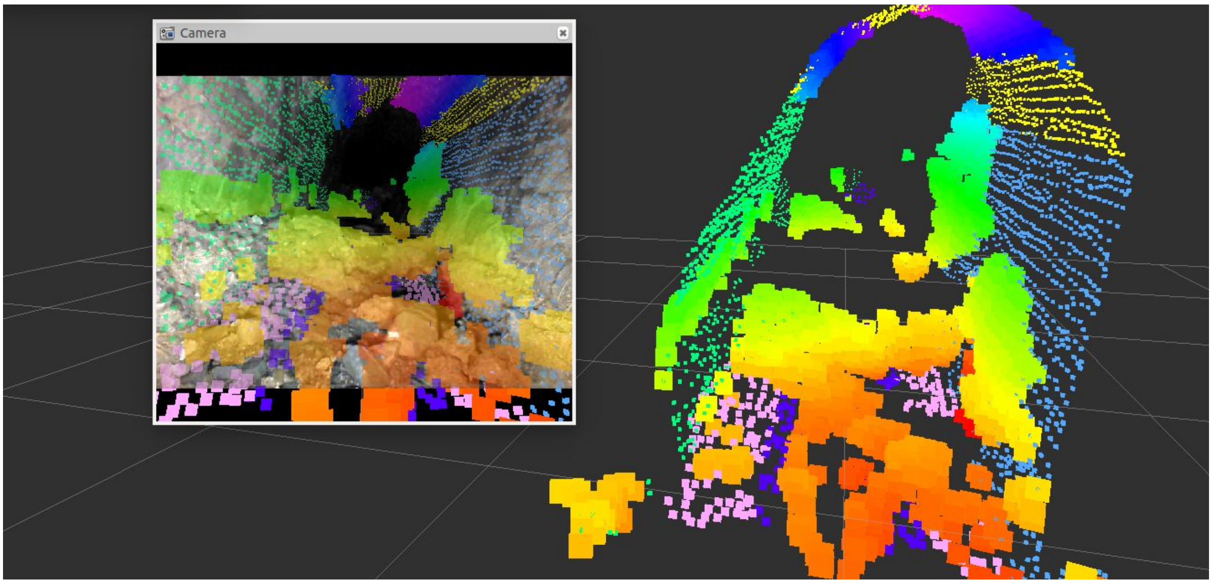

Figure 3.4: Automatic detection of potential defects. The method estimates a potential section type, even for such a damaged place, and highlight the different parts and potential defects on the floor and walls.

During the experiment on November 7, no serviceability alarms were raised.

A similar experiment was carried out on October 18, 2018. Besides the structural defect, a serviceability problem was also detected, due to sediments in the gutter and curb (problem that was not present during the experiments in Nov. 7). The problem is shown in Figs. 3.5 and 3.6:

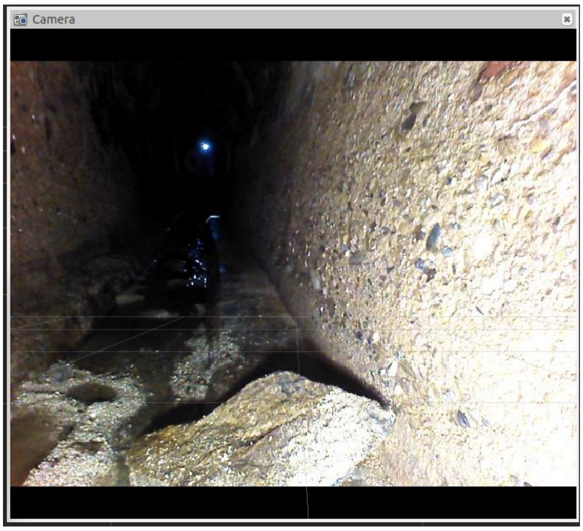

Figure 3.5: Automatic detection of a serviceability problem. The images gathered at the position where the alarm is raised show sediments and a big rock into the gutter.

Figure 3.6: Additional images of the serviceability problem from the 3 cameras looking forward of the robot.

As a summary, our algorithm detected the main zone where there are a very noticeable defects, and also serviceability issues.

6. Conclusions

This document presented the structural inspection tools developed by the SIAR team. These tools extend the inspection system for serviceability described in D28.10. The final system is able to permanently analyze the sewer searching for elements related to potential defects. This detection is performed online, and the resulting detections are shown to the operator immediately, which allows to allocate more resources to validate the defect or just gathering more information of interest.

The document also showed the results of the structural inspection tests performed in Barcelona in October/November 2018. These experiments considered for the first time the new version of the SIAR platform, and showed the whole system running from the control station, including the inspection module.

References

[Alejo et al, 2017] David Alejo, Fernando Caballero, and Luis Merino. RGBD-based Robot Localization in Sewer Networks. In Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, pp. 4070–4076, 2017.

[Besl and McKay, 1992] P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2, pp. 239-256, Feb. 1992. doi: 10.1109/34.121791

[ECHORD++, 2014] ECHORD++. “Utility infrastructures and condition monitoring for sewer network. Robots for the inspection and the clearance of the sewer network in cities”, Internal Report, 2014