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multi-Risk sciEnce for resilienT commUnities undeR a changiNgclimate

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2. ABSTRACT

This work presents a possible proposal for protocols and procedures dedicated to infrastructure inspection and damage detection using unmanned robotic systems integrated with Building Information Modeling (BIM) digital twins.

The proposed approach focuses on deploying autonomous robotic platforms, such as ground-based rovers, equipped with advanced sensors and high-resolution cameras for automated data acquisition in complex environments, including tunnels and other confined spaces.

The use of autonomous robotic systems is critical for improving the safety, efficiency, and consistency of data collection in infrastructure inspections. Unlike manual inspection methods, which can be time-consuming, labor-intensive, and subject to human error, autonomous robots can operate continuously in hazardous or hard-to-reach areas without exposing human operators to risk. Equipped with sophisticated navigation and obstacle avoidance systems, these robots can autonomously follow predefined paths or dynamically adapt their routes to ensure complete coverage of the inspection area. The result is a more reliable and repeatable data acquisition process, which is essential for generating high-quality datasets for subsequent analysis and integration into BIM-based digital twins.

During the inspection, the rovers continuously acquire high-density point clouds through LiDAR scanning. The post-processing phase involves several key steps: filtering and cleaning the raw point cloud data to remove noise and outliers, aligning and merging multiple scans using point cloud registration techniques to create a unified and highly accurate 3D model. Mesh reconstruction algorithms are then applied to convert the point cloud into a detailed surface representation.

For anomaly detection and structural health analysis, advanced algorithms based on machine learning and computer vision are utilized. Point cloud segmentation techniques, including region-growing and RANSAC (Random Sample Consensus), allow for the identification of specific structural features like joints, surfaces, and edges. Change detection algorithms compare the current model with historical data to detect deformations, cracks, and material loss. Deep learning approaches, particularly convolutional neural networks (CNNs), are also employed for automated crack detection and classification of surface defects, significantly improving the accuracy and reliability of the analysis.

Once the processed 3D model is integrated into the BIM-based digital twin, it becomes a powerful tool for real-time condition assessment and predictive maintenance. For instance, recurrent deviations in tunnel geometry can indicate potential subsidence or progressive damage, which can be detected through deformation analysis algorithms that calculate differences in point cloud density and curvature. This information is fed into the BIM environment, where rule-based systems and predictive models can trigger alerts and suggest maintenance actions.

A case study involving the inspection of tunnels illustrates the practical benefits of this approach. Autonomous rovers equipped with LiDAR and thermal imaging sensors collected comprehensive datasets, which were processed to generate 3D models and detect anomalies such as crack propagation and water infiltration. These insights were integrated into the BIM digital twin for long-term monitoring and lifecycle management, enabling a shift from reactive to proactive maintenance strategies.

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4.1 WP 4.2

4.1.1 Exploration of unknown environments

Exploring complex and unknown environments is a challenging robotic navigation task that has gained increasing attention in recent years. Unlike traditional robotic navigation, where a pre-existing map of the environment is available, and the objective is to reach a well-defined goal, exploration presents several additional difficulties.

In traditional navigation, the robot follows a predetermined global path while relying on a known map to plan and execute movements efficiently. However, in exploration, the environment is initially unknown, requiring the robot to construct a map dynamically as it moves through uncharted territory. This adds significant uncertainty and computational complexity, as the robot must balance mapping accuracy with real-time decision-making.

Furthermore, exploration lacks a clearly defined goal. Instead of navigating toward a fixed destination, the robot's primary objective is to maximize coverage of the environment, often without prior knowledge of its full extent.

This fundamental difference creates a divergence in objectives between the global planner and the local planner (or controller). While in traditional navigation both planners align toward reaching a specific target, in exploration, the global planner must focus on strategic coverage, and the local planner prioritizes real-time obstacle avoidance and adaptive path adjustments.

As a result, effective exploration strategies require custom algorithms and adaptive path planning techniques to handle the uncertainties inherent to unknown environments. Addressing these challenges is critical for applications such as search and rescue, underground geological assessment, mapping of unknown environments, and autonomous surveillance, where robots must operate autonomously in unpredictable settings without prior environmental knowledge.

This project aims to develop novel methodologies and technologies to address the challenge of autonomous exploration in hostile and unknown environments. The underground tunnel system of the Pietro Micca Civic Museum in Turin, represented in Figure 1., provides an ideal testing ground due to the varying width and height of its galleries. Beginning in the main gallery, characterized by wide and high passages, the goal is to extend navigation and mapping algorithms to narrow, challenging tunnels.

The main task of exploring can be divided into two subtasks. The first involves accurately localizing the rover within a fixed reference frame, typically corresponding to the mission's starting point. Since no prior map of the environment is available, the system must simultaneously build a map while determining the rover's position within it. This challenge, known in the robotics community as Simultaneous Localization and Mapping (SLAM), is fundamental for autonomous navigation in unknown environments.

The second subtask aims at autonomously navigating within the environment. As discussed before, the navigation system is composed of a global planner and a controller. The global planner is employed when the navigation requires planning over an area larger than the current sensors' observation. In an exploration scenario, the global planner must also implement an efficient policy to systematically explore unknown areas, ensuring optimal coverage of the environment. On the other hand, the controller is responsible for guiding the robot along obstacle-free trajectories by directly computing velocity commands. Unlike traditional navigation systems, which rely on predefined goals, exploration-based local planning must operate without a fixed destination, making navigation aimless.

Figure 1 The ClearPath Jackal UGV rover equipped with sensors and lights navigating the underground tunnel system of Pietro Micca Civic Museum in Turin

4.1.2 Localization and Mapping

Simultaneous Localization and Mapping (SLAM) is a fundamental problem in robotics that involves constructing a map of an unknown environment while simultaneously estimating the robot's position within it. Since no prior map is available, the robot must rely on its onboard sensors, such as LiDAR, cameras, or depth sensors, to incrementally build an environmental representation and update its location in real-time.

SLAM is particularly essential in tunnel exploration, where GPS signals are unavailable and traditional localization methods fail. In this context, accurate mapping and localization allow the rover to autonomously navigate through narrow, irregular passages while avoiding obstacles and efficiently covering unexplored areas.

For this project, we implemented SLAM Toolbox, the default ROS 2 SLAM suite, known for its real-time mapping and localization efficiency. SLAM Toolbox offers key features such as graph-based optimization, loop closure detection, and pose correction, making it well-suited for long-term autonomous exploration.

With this tool, we enable the rover to dynamically build a precise tunnel system map while maintaining accurate localization, ensuring reliable autonomous navigation even without an initial map.

4.1.3 Navigation

For this project, we developed a custom implementation of the classic Dynamic Window Approach (DWA) algorithm, a widely used motion control strategy in the robotics community. The DWA algorithm optimizes a cost function based on three weighted contributions:

- Distance from the goal, which encourages the robot to move toward a predefined destination.
- Distance from obstacles, which ensures collision avoidance by favouring safer trajectories.
- Velocity alignment, which encourages the robot to maintain an appropriate speed by minimizing deviations from the ideal velocity

Since exploration lacks a predefined goal, our implementation modifies the traditional DWA formulation by replacing the goal-attraction component. Instead of guiding the robot toward a fixed target, our controller pushes the agent away from its starting position as far as possible. This encourages outward movement until the robot encounters an impasse, such as a dead end or an area with no viable paths.

When the agent reaches an impasse, a global planner is employed to backtrack and redirect the exploration efforts toward unexplored areas. Additionally, by integrating a frontier-based exploration strategy, the system can identify new potential pathways and prioritize navigation toward them, ensuring more efficient coverage of the environment.

This implementation offers several advantages in an exploration setting. First, the robot autonomously expands its search area without requiring predefined waypoints. By pushing away from the starting point and handling impasses intelligently, the system avoids unnecessary revisits to already explored areas. Moreover, this approach is scalable. Namely, it can be adapted to various unknown environments, including caves, tunnels, and collapsed structures.

Furthermore, we implemented a return system that exploits the newly generated map to plan an optimal path back to the starting point. This capability is crucial, especially in extended underground explorations, where we expect to lose communication with the rover beyond a certain distance. In such scenarios, the rover must rely entirely on its onboard intelligence to navigate back to its origin without external commands.

The scientific literature on autonomous tunnel exploration remains relatively limited, with early works primarily focusing on frontier-based exploration [1-3]. A frontier is defined as the boundary between explored free space and unknown space. Since frontiers lie within the mapped portion of the environment, they are generally reachable and ensure continued exploration of adjacent unexplored regions.

In goal-less navigation problems, such as autonomous exploration, frontiers play a crucial role by serving as dynamic goals for global path planning. However, an effective local controller is still required to ensure smooth and efficient navigation while avoiding obstacles and handling environmental uncertainties. Many exploration frameworks in the literature consider the task complete when no more frontiers remain in the map [4-6].

Monte Carlo techniques such as Rao-Blackwellized particle filter[7,8] or based on Active loop-closure[9] have also been implemented to find new and fastest exploration routes.

However, a natural solution to the exploration problem resides in Deep Reinforcement Learning (DRL): the Exploration task is well-definable as a Markov Decision Problem (MDP), and contrary to human-designed exploration policy, DRL agents usually do not make strong a priori assumptions about environments and tasks, which may restrict the adaptability to complex dynamic and intricated scenarios.

DRL methods implemented in literature are usually model-free (since a model is not retrievable from a completely unknown environment) and divided into two macro-categories: 2-stage single agent and End-to-End single-agent policy.

Most 2-stage single agent methods exploit Deep Reinforcement Learning to improve frontier selection and navigation efficiency. Some works employ DRL to select the best next frontier to explore, after which a classical path planner generates a trajectory toward it [10-12]. Conversely, a less common approach involves using a non-learning method for frontier selection and then employing DRL to guide the agent along the path [13].

End-to-end learning-based methods, such as those leveraging Convolutional Neural Networks (CNNs), have also been explored. These approaches directly translate pixel data from the known map into action commands for the robot, bypassing traditional planning modules entirely [14-17]. While promising, these methods often require extensive training data and computational resources, making them less suitable for lightweight robotic platforms operating in real-time.

As demonstrated by Dang et al. [18], an alternative approach utilizes a Rapidly exploring Random Tree (RRT) to efficiently identify paths that maximize local exploration gain within a defined subspace. Their system employs a hierarchical architecture, where a local planner optimizes short-term exploration within a confined area, and a global planner incrementally constructs a sparse exploration graph, activating when the rover needs to reposition itself toward previously identified frontiers.

This method proves particularly effective for exploring large-scale, multi-branching, narrow, and structurally complex subterranean environments, as it maintains a lightweight yet highly scalable structure.

4.1.4 Deployment in Pietro Micca's Galleries

We have conducted a series of experimental tests in the underground tunnel system of the Pietro Micca Civic Museum in Turin. These tests aimed to validate the autonomous exploration capabilities of our system in a real-world, unstructured environment.

Our algorithms were deployed on a Clearpath Jackal rover, a compact, all-terrain robotic platform equipped with:

- LiDAR sensors for mapping and obstacle detection,
- Depth and color cameras for detection and mapping of 3D obstacles,
- High-intensity lights to improve visibility in the dark tunnel network.

The primary goal of our testing was to explore as much of the accessible tunnel system as possible in a fully autonomous manner, without human intervention. During the initial trials, the system encountered several challenges, including sudden narrowing of tunnels, which required dynamic path adjustments, rough and uneven terrain, which impacted the rover's stability and traction, and a general localization drift, leading to occasional mapping inaccuracies.

Through a trial-and-error approach, we systematically refined our system, fine-tuning controller parameters and SLAM configurations. As a result, subsequent tests demonstrated significant improvements, with the rover successfully navigating and autonomously mapping most of the tunnel network without human assistance.

4.1.5 Sensors Choice and Integration

To achieve real-time infrastructure monitoring and autonomous navigation within low power consumption constraints, careful sensor selection is critical. Sensors were chosen based on their ability to facilitate continuous data collection, detect anomalies early, and integrate effectively with an Unmanned Ground Vehicle (UGV) platform.

LiDAR was selected for its precision in environmental mapping and obstacle detection, while the IMU was included to monitor the UGV's orientation, velocity, and acceleration. RGBD cameras were chosen for visual inspection and contextual data collection while depth information can be used for mapping and environment reconstruction. 360°-degree camera was used to have a complete video acquisition of the surrounding environment.

To acquire camera streams, a set of lights was added to the UGV in order to create proper illumination of the surrounding environment. Even more complex sensors were tested, such as structured light scanners, but the results were not promising.

The Clearpath Jackal UGV was used as platform for integrating the selected sensors due to its rugged design and customization potential. Sensor integration involved securing hardware mounts for flexibility in sensor positioning and ensuring balanced weight distribution to maintain UGV stability.

Power management was optimized by utilizing the UGV's onboard supply along with supplementary low-power battery packs to provide redundancy. Communication interfaces such as USB and Ethernet were employed, depending on sensor specifications.

Robot Operating System 2 (ROS 2) was used to integrate and synchronize sensor data. Software configuration involved developing ROS 2 nodes for each sensor and implementing real-time data fusion to enhance situational awareness.

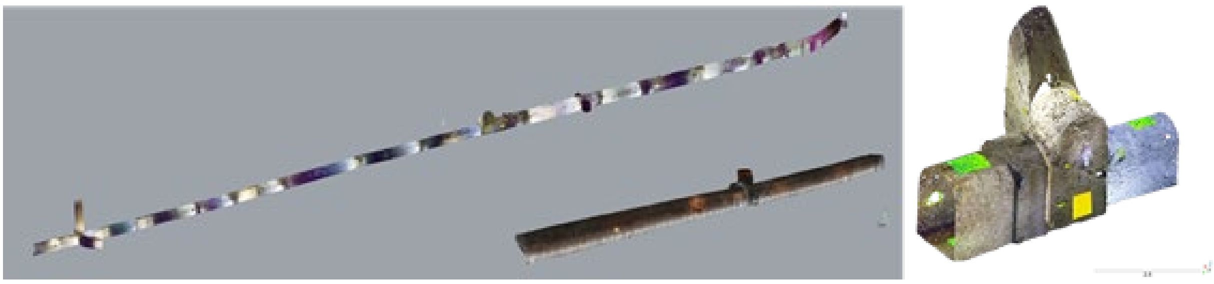

Figure 2 Reconstruction of the environment from recorded data

4.1.6 Construction of a Simulation Environment from Real Data

A virtual simulation environment replicating the Pietro Micca Museum's conditions was developed using real data to test and refine algorithms and systems. LiDAR data was processed to create a 3D point cloud of the museum's layout, supplemented by RGB and thermal camera imagery for visual and thermal context. Environmental data such as temperature and humidity were incorporated to enhance simulation accuracy.

Tools like Gazebo and Unity were employed to model the environment, including structural elements, textures, and lighting conditions. Sensor behavior was simulated using collected real-world data as input, and the Jackal UGV's dynamics were modeled for realistic navigation tests. The simulation's accuracy was validated by comparing sensor outputs from the virtual environment with real-world data, ensuring reliable testing of navigation and data collection algorithms before field deployment.

This environment is particularly useful for testing new algorithms and navigation strategies in a fast and efficient manner. This type of development is important to best transfer the technologies developed in simulation to the real environment. Especially in these difficult environments, for which organizing and conducting tests can result very complex.

4.1.7 3D data acquisition and modeling

Different techniques of three-dimensional surveying have been employed. Terrestrial Laser Scanner (TLS) using the Leica RTC360, a LiDAR-based VIS (Visual Inertial System) solution for real-time cloud data registration.

SLAM-based Mobile Mapping System (MMS) using KAARTA Stencil 2, composed of a Velodyne VLP-16, a MEMS (Micro Electronic Mechanical System) inertial platform, and a feature tracker camera connected to a processor Intel Core i7.

In Table 1 some specification. Even digital photogrammetry has been considered, using the spherical camera Insta360 One RS 1-inch edition co-engineered with Leica. The 360° module covers the entire 360x180° scene and consists of two fisheye sensors. The camera is equipped with a gyroscope to stabilize images in all conditions. Table 2 shows some camera specifications.

Table 1 – TLS and SLAM-MMS specifications.

Description	Leica RTC360	KAARTA Stencil 2
		
Acquisition speed	> 2.000.000 pts/sec	> 300.000 pts/sec
Field of view	360° (horizontal) 300° (vertical)	360° (horizontal)/ 30° (± 15° vertical)
Range	Min 0.5 m - Max 130 m	Min 1 m - Max 100 m
Lidar precision	1.0mm+10ppm	±3 cm

Table 2 – Insta360 One RS 1-inch camera specifications.

Description	Specifications
	
Image resolution	21 MPx
Focal length (equ.)	6.52mm
Focal Aperture	F2.2
Video Resolution	3840x1920@30/25/24fps 3040x1520@50fps
ISO Range Video	100-3200
Weight	0, 239 kg

The integration and post-processing of LiDAR data and images acquired with 360° cameras have been developed for the generation of complete 3D models. The process began with the processing of the point cloud and continued up to the reconstruction of the three-dimensional model.

Unlike traditional manually operated sensors, robotic systems autonomously collect high-frequency data, enhancing efficiency and accessibility in challenging environments like underground tunnels. While the classical approach may offer higher precision in controlled settings, it requires manual effort and is constrained by operator mobility. UGV-mounted sensors, however, adapt dynamically to environmental conditions, ensuring consistent coverage, especially in complex infrastructures.

Furthermore, starting from photogrammetric reconstructions obtained from spherical images acquired with low-cost sensors, the methods for converting from a TIN model to a NURBS surface have been optimized (Figure 2).

This transition represents a significant improvement for structural simulation, as NURBS surfaces provide a continuous and detailed representation of irregular and curved geometries, enabling more accurate FEM analysis compared to TIN models.

Even in the presence of partially noisy data collected with low-cost instruments, it was possible to generate a sufficiently detailed NURBS model, thus supporting future applications and the analysis of critical infrastructure in complex underground environments.

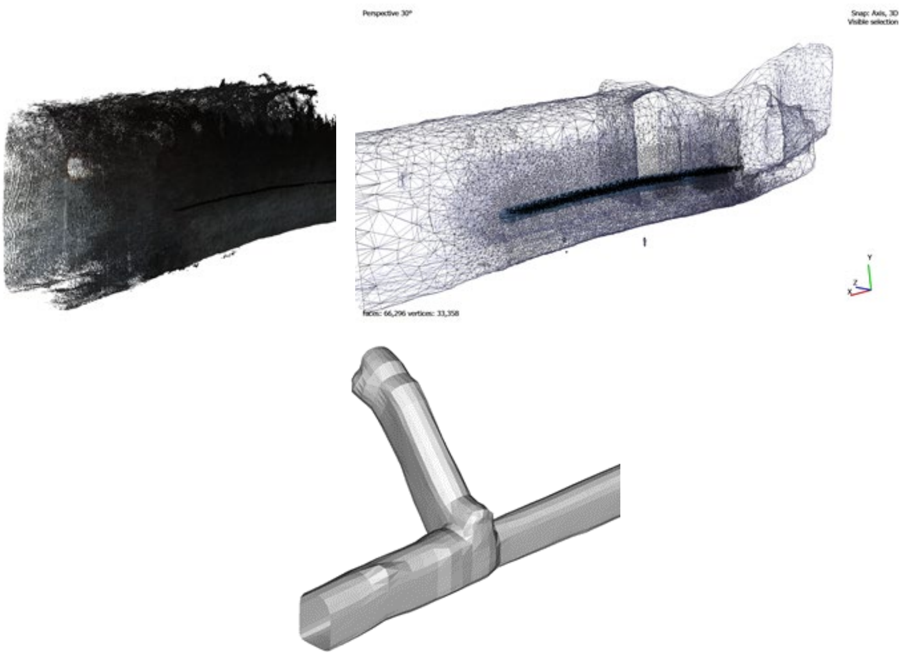

Figure 3: On the left, the point cloud obtained from photogrammetry elaboration by a low-cost sensor 360 camera. In the middle, (Triangulated Irregular Network) TIN model. On the right, the (Non-Uniform Rational B-Splines) NURBS model.

4.1.8 Automated Analysis for Damage Detection

Automated analysis of 3D models, based on point clouds and images, leverages advanced computer vision and machine learning techniques to identify elements of interest, such as cracks (Figure 4) and structural damage.

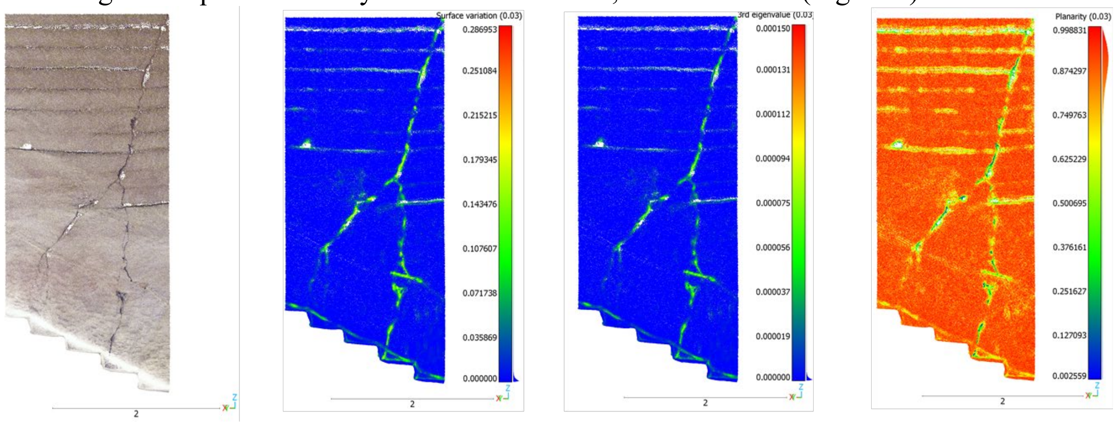

Figure 4: Geometric features based on point cloud for crack detection. On the left, RGB information, followed by surface variation, 3rd eigenvalue, and planarity.

For point clouds, deep learning algorithms like PointNet++ and KPConv enable semantic segmentation and surface classification, detecting areas with geometric anomalies. More traditional methods, such as RANSAC (Random Sample Consensus), can be used for surface fitting, highlighting deviations that may indicate damage.

For images, convolutional neural networks (CNNs) such as Mask R-CNN and U-Net are commonly employed for crack segmentation on surfaces, while approaches based on Vision Transformers (ViT) enhance detection capabilities on complex datasets. The integration of Structure from Motion (SfM) with multi-modal fusion of images and LiDAR data improves detection accuracy by combining geometric and radiometric information.

The combined use of AI-based approaches and traditional algorithms ensures robust analysis, which is essential for the inspection of complex infrastructures such underground environments.

4.1.9 Methodologies for advanced in-pipe sensing of water infrastructure degradation

The research tried to investigate the application of different methodologies and technologies to monitor water quality parameters in water distribution networks (WDN) and urban drainage systems (UDS). The goal is to ensure public health and address environmental concerns. Various sensors and technologies have been studied and developed for this purpose, allowing for a wide range of options in the market. Parameters such as temperature or pH can be directly measured, while others like salinity or dissolved matter concentration are measured indirectly through related measurements like redox potential, conductivity, or turbidity.

The advancement of computational algorithms improved measuring instruments, and the development of reliable and cost-effective microcontrollers have led to the innovation of new monitoring techniques. The Internet of Things (IoT) has played a crucial role in this advancement, enabling continuous real-time tracking and data retrieval. IoT refers to the application of devices connected via the internet to improve system quality.

It allows for the constant accessibility of sensors and data retrieval on demand. IoT has evolved and expanded its definition, encompassing technologies developed for connecting objects, instruments, and sensors to telecommunications networks. This concept of IoT aims to enhance the potential of various things and simplify interactions between people and computers. It has been demonstrated that IoT can contribute to achieving a digitized industry.

IoT technology development has revolutionized water quality monitoring by enabling continuous and remote access to sensors and data. This shift has led to the transition from traditional discontinuous monitoring, which involved sampling at specific points in the network, to real-time tracking at strategic locations using algorithms to detect contamination events.

Integrating IoT with simple and affordable hardware, such as Raspberry Pi and Arduino microcontrollers, has facilitated the development of IT solutions for direct interaction between people and computers. This has expanded the possibilities for enhancing everyday objects' functionality and complex sensors' functionality and potential.

Furthermore, the text highlights how the concept of IoT expands beyond its original definition, encompassing all technologies developed for connecting objects to the Internet. The aim is to simplify and improve various aspects of daily life and industries, including the development of digitized industry.

Ultimately, IoT in water quality monitoring has opened up new possibilities for efficient and reliable data collection, analysis, and decision-making, contributing to the ongoing efforts to ensure water safety and environmental protection.

4.1.10 The proposed methodological approach

Using the Bayesian approach, new information from the analysis is incorporated, allowing the operator to gain insight into the system once recent contamination events are detected, identified and monitored. Two main components are required to solve this problem: a calibrated model for hydraulic and water quality simulations in sewer systems and a Bayesian Artificial Intelligence (AI) solver for likelihood estimation and probability update. The EPA SWMM model was used to perform hydraulic and water quality simulations in this case. Decision-making support of the Bayesian Decision Network (BDN) type was implemented to position the water quality sensors.

A Bayesian network (BN) is a graphical structure that allows us to represent an uncertain domain. The BN is a robust and advantageous method for assessing risk and uncertainty, providing a complete framework for analysing all cause-effect relationships. The standard formulation of Bayesian posterior probability can be found in the literature.

The sensor location problem for identifying the illicit intrusion for the considered case study has already been investigated but uses genetic algorithms. Different single- and multi-objective optimisation procedures for optimally locating sensors in the sewer have been compared. Without pre-conditioning, all nodes had an equal probability of being the candidate nodes for sensor placement, and all nodes had an equal chance of being a brackish water intrusion source.

The likelihood function was slightly adapted in the analysis to comply with sewer networks instead of water distribution networks. The isolation likelihood F1 is expressed by the following equation:

$$F_1 = \frac{1}{S}\sum_{i=1}^{S} d_r \qquad (1)$$

Where S is the total number of analyzed contamination events, dr is one of the contamination was identified by the sensor network and is 0 otherwise. The indicator F1 provides information on the ability of the sensor network to locate the contamination source.

Therefore, contamination events are randomly simulated to evaluate each sensor's probability of identifying the source of contamination. The analytical approach was based on three phases:

- Based on available data, random simulations are used to explain available data with the position of the potential source of contamination; such degree provides the share of probabilities that contamination may be located in different parts of the network
- According to such probabilities, a possible sensor network is designed employing BN to maximize the ability of the network to detect the position of the contamination source (based on the maximization of the probability to detect the proper position of an unknown contamination source)
- An experimental search of the contamination source using the designed sensor network.

4.1.11 The sensor architecture: ERRAND sourcE tRacing wateR quAlity moNitoring Device

The system was developed to be a general-purpose platform to track sewer contamination.

The disk is designed to float on water surface, and it is available in two sizes with diameter equal to 8 cm and with diameter equal to 18 cm. The floating disk contain an acquisition board (currently based on Raspberry Pi4 but a cheaper Arduino configuration is possible), battery pack, inertial localization system (X-Y accelerometers and electronic gyroscope sensor).

Data are stored in a MicroSD card and a WiFi module can be implemented to transmit data in real time and to correct inertial localization data with a WiFi signal attenuation algorithm.

The basic configuration can be completed with different sensors depending on the application we would like to run. In this first version, designed to track sewer infiltration inflow, the sensors are:

- Temperature Sensor: PT1000 Class B, according to EN60751 2-wire technology, obtained at SensorShop24 Part number: KS-PT1000-1.0-330-2L
- pH electrode: Hanna Instruments HI73127, obtained through Hanna Instruments directly.
- EC probe: Hanna Instruments HI73311, obtained through Hanna Instruments directly.

Different additional sensors can be implemented if needed.

5. Conclusions

The integration of autonomous robotic systems with Building Information Modelling (BIM) digital twins represents a paradigm shift in the field of infrastructure inspection and maintenance. Traditional inspection methods, often reliant on manual data collection and visual assessments, present significant challenges in terms of efficiency, accuracy, and operator safety—especially in complex or hazardous environments such as tunnels, confined spaces, and large-scale infrastructure.

The deployment of autonomous rovers equipped with advanced sensors, including LiDAR and high-resolution imaging devices, addresses many of these limitations. These robots offer a highly reliable, repeatable, and automated approach to data acquisition, ensuring comprehensive and high-density datasets that form the foundation for accurate 3D modelling and in-depth structural analysis. The ability of these rovers to navigate autonomously, avoid obstacles, and adapt their scanning paths in real time ensures full coverage of the inspected areas without the need for constant human supervision.

The automated collection of point cloud data and its integration into BIM-based digital twins opens new possibilities for real-time condition monitoring, predictive maintenance, and lifecycle management of critical infrastructure. By leveraging advanced data processing techniques, including point cloud registration, surface reconstruction, and AI-based anomaly detection, this approach not only reduces inspection times but also significantly enhances the quality of the insights derived from the data. The comparison of newly collected 3D models with historical datasets allows for precise change detection and early identification of potential issues, such as cracks, deformations, and material degradation, enabling proactive interventions before problems escalate.

This methodology can be considered a new frontier for infrastructure diagnostics. Autonomous robotic systems combined with BIM digital twins lay the groundwork for a future where infrastructure is continuously monitored with minimal human intervention. This reduces operational risks, optimizes resource allocation, and ensures higher reliability and performance of assets over time. Furthermore, as robotic technology and machine learning algorithms continue to evolve, the potential for even more sophisticated, fully automated inspection and maintenance workflows becomes increasingly feasible.

A particularly promising area of future development is the coordination of multiple autonomous systems for large-scale infrastructure monitoring. This could involve integrating aerial drones for external inspections and ground-based rovers for internal assessments, all feeding data into a centralized BIM digital twin for holistic asset management. These multi-agent systems, operating in synergy, could provide unparalleled insight into the real-time condition of infrastructure, allowing for predictive analytics and fully automated maintenance decision-making processes.

The adoption of this technology will likely be accompanied by the development of new standards and regulations to ensure data consistency, interoperability, and safety. International organizations and industry bodies will play a crucial role in establishing guidelines for the collection, processing, and integration of point cloud data within BIM environments. These standards will be essential for fostering widespread adoption and ensuring the reliability and comparability of results across different projects and regions.

In conclusion, the use of autonomous robotic platforms and sensors for data collection, combined with advanced analysis techniques and digital twins, represents a transformative innovation in the field of infrastructure management. This approach not only enhances inspection accuracy and operational safety but also sets the foundation for the next generation of smart infrastructure solutions. The future lies in fully automated, data-driven workflows, where real-time monitoring and predictive analytics revolutionize how infrastructure is maintained and managed, ultimately improving safety, sustainability, and resilience.

6. References

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1. Yamauchi, B.; Schultz, A.; Adams, W. Mobile robot exploration and map-building with continuous localization. In Proceedings of the 1998 IEEE International Conference on Robotics and Automation (Cat. No. 98CH36146), Leuven, Belgium, 20 May 1998; Volume 4, pp. 3715–3720.
2. Yamauchi, B. A frontier-based approach for autonomous exploration. In Proceedings of the IEEE International Symposium on Computational Intelligence in Robotics and Automation CIRA’97.’Towards New Computational Principles for Robotics and Automation’, Monterey, CA, USA, 10–11 July 1997; pp. 146–151.
3. Yamauchi, B. Frontier-based exploration using multiple robots. In Proceedings of the Second International Conference on Autonomous Agents, St. Paul, MI, USA, 9–13 May 1998; pp. 47–53.
4. Carlone, L.; Du, J.; Ng, M.K.; Bona, B.; Indri, M. Active SLAM and exploration with particle filters using Kullback-Leibler divergence. J. Intell. Robot. Syst. 2014, 75, 291–311.
5. Dai, A.; Papatheodorou, S.; Funk, N.; Tzoumanikas, D.; Leutenegger, S. Fast Frontier-based Information-driven Autonomous Exploration with an MAV. arXiv 2020, arXiv:2002.04440.
6. Ravankar, A.A.; Ravankar, A.; Kobayashi, Y.; Emaru, T. Autonomous mapping and exploration with unmanned aerial vehicles using low-cost sensors. Multidiscip. Digit. Publ. Inst. Proc. 2018, 4, 44.
7. Stachniss, C.; Grisetti, G.; Burgard,W. Information gain-based exploration using rao-blackwellized particle filters. Robot. Sci. Syst. 2005, 2, 65–72.
8. Carlone, L.; Du, J.; Ng, M.K.; Bona, B.; Indri, M. Active SLAM and exploration with particle filters using Kullback-Leibler divergence. J. Intell. Robot. Syst. 2014, 75, 291–311.
9. Stachniss, C.; Hahnel, D.; Burgard, W. Exploration with active loop-closing for FastSLAM. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No. 04CH37566), Sendai, Japan, 28 September–2 October 2004; Volume 2, pp. 1505–1510.
10. F. Niroui, K. Zhang, Z. Kashino, and G. Nejat, “Deep reinforcement learning robot for search and rescue applications: Exploration in unknown cluttered environments,” IEEE Robot. Autom. Lett., vol. 4, no. 2, pp. 610–617, Apr. 2019.
11. D. Zhu, T. Li, D. Ho, C. Wang, and M. Q.-H. Meng, “Deep reinforcement learning supervised autonomous exploration in office environments,”in Proc. IEEE Int. Conf. Robot. Autom. (ICRA), May 2018, pp. 7548–7555.
12. H. Li, Z. Qichao, and D. Zhao, “Deep reinforcement learning-based automatic exploration for navigation in unknown environment,” IEEE Trans. Neural Netw. Learn. Syst., vol. 31, no. 6, pp. 2064–2076, Jun. 2019.
13. Y. Liu, H. Liu, and B.Wang, “Autonomous exploration for mobile robot using Q-learning,” in Proc. 2nd Int. Conf. Adv. Robot. Mechatronics (ICARM), Aug. 2017, pp. 614–619.
14. S. Josef and A. Degani, “Deep reinforcement learning for safe local planning of a ground vehicle in unknown rough terrain,” IEEE Robot. Autom. Lett., vol. 5, no. 4, pp. 6748–6755, Oct. 2020.
15. H. Van Hasselt, A. Guez, and D. Silver, “Deep reinforcement learning with double Q-learning,” in Proc. AAAI Conf. Artif. Intell., 2016, vol. 30, no. 1, pp. 2094–2100.
16. R. B. Issa, M. S. Rahman, M. Das, M. Barua, and M. G. R. Alam, “Reinforcement learning based autonomous vehicle for exploration and exploitation of undiscovered track,” in Proc. Int. Conf. Inf. Netw. (ICOIN), Jan. 2020, pp. 276–281.
17. E. Cetin, C. Barrado, G. Munoz, M. Macias, and E. Pastor, “Drone navigation and avoidance of obstacles through deep reinforcement learning,” in Proc. IEEE/AIAA 38th Digit. Avionics Syst. Conf. (DASC), Sep. 2019, pp. 1–7.
18. Dang, T., Tranzatto, M., Khattak, S., Mascarich, F., Alexis, K. and Hutter, M., 2020. Graph-based subterranean exploration path planning using aerial and legged robots. Journal of Field Robotics, 37(8), pp.1363-1388.

19. Navone A., Martini M., Angarano S., Chiaberge M., Online Learning of Wheel Odometry Correction for Mobile Robots with Attention-Based Neural Network, 2023 IEEE 19th International Conference on Automation Science and Engineering (CASE), 2023
20. Martini M., Eirale A., Cerrato S., Chiaberge M., Pic4rl-Gym: A Ros2 Modular Framework for Robots Autonomous Navigation with Deep Reinforcement Learning, 2023 3rd International Conference on Computer, Control and Robotics (ICCCR), IEEE, 2023
21. Albertin U., Pedone G., Brossa M., Squillero G., Chiaberge M., A Real-Time Novelty Recognition Framework Based on Machine Learning for Fault Detection, Algorithms, 2023
22. Spadaro A., Piras M., Chiaberge M., GeoAI for monitoring and risk analysis in critical infrastructures, 2GG - 2 Giorni di Geomatica, AUTeC, 2023
23. Spadaro A., Grasso N., Piras M., Giordan D., Parisi A., Analysis and comparison of SLAM and VIS geomatic techniques for the structural and geomechanical analysis of artificial cavities, 65° Convegno Nazionale SIFET (Società Italiana di Fotogrammetria e Topografia), 2023
24. Spadaro A., Grasso N., Piras M., Giordan D., Parisi A., Three-dimensional modelling of artificial caves for geomechanical analysis, ISPRS Technical Commission II Symposium, 2024
25. Spadaro A., Piras M., Chiaberge M., GeoAI for monitoring and risk analysis in critical infrastructures, 2GG - 2 Giorni di Geomatica, AUTeC, 2024
26. Spadaro A., Grasso N., Piras M., Giordan D., Parisi A. The role of advanced surveying technologies for geomechanical analysis of artificial caves: the case study of Gravina in Puglia (Puglia region, Southern Italy), Congresso congiunto SGI-SIMP, 2024
27. Spadaro A. Piras M., Chiaberge M., Ambrosio M., Dara G., RETURN project: AI and DL for unsupervised investigations in underground environments, ASITA 2024, Conferenza Nazionale di Geomatica e Informazione Geografica , 2024
28. Piazza, S., Sambito, M., & Freni, G. (2023). Analysis of Optimal Sensor Placement in Looped Water Distribution Networks Using Different Water Quality Models. Water, 15(3), 559.
29. S. Piazza, M. Sambito and G. Freni, "Experimental evidence of diffusion and dispersion impact on optimal positioning of water quality sensors in distribution networks," in AIP Conference Proceedings, 2021.
30. M. Sambito and G. Freni, "Strategies for improving optimal positioning of quality sensors in urban drainage systems for non-conservative contaminants," Water (Switzerland), vol. 13, no. 7, 2021.
31. M. Sambito, A. Severino, G. Freni and L. Neduzha, "A systematic review of the hydrological, environmental and durability performance of permeable pavement systems," Sustainability (Switzerland), vol. 13, no. 8, 2021.
32. Sambito, M. , Freni, G. (2023) Optimal deployment of moving sensors for water quality monitoring of sewer systems Proceedings of the IAHR World Congress , pp. 3192–3195
33. M. Weickgenannt, Z. Kapelan, M. Blokker and D. A. Savic, "Optimal Sensor Placement for the Efficient Contaminant Detec-tion in Water Distribution Systems," Water Distribution Systems Analysis, 2008.
34. M. Sambito, C. Di Cristo, G. Freni and A. Leopardi, "Optimal water quality sensor positioning in urban drainage systems for illicit intrusion identification," Journal of Hydroinformatics, vol. 22, no. 1, pp. 46-60, 1 January 2020.
35. K. Wang, X. Wen, D. Hou, D. Tu, N. Zhu e P. Huang, (2018) "Application of least-squares support vector machines for quanti-tative evaluation of known contaminant in water distribution system using water quality parameters" Sensors, n. 18.4, p. 938.
36. S. Piazza, M. Sambito, R. Feo, G. Freni and V. Puleo, "Optimal positioning of sensors in water distribution networks: com-parison of numerical and experimental results," Computing and Control for the Water Industry, 2017.
37. S. Piazza, E. J. M. Blokker, G. Freni, V. Puleo and M. Sambito, "Impact of diffusion and dispersion of contaminants in water distribution networks modelling and monitoring," Water Supply, vol. 20, no. 1, pp. 46-58, 2020.
38. L. Atzori, A. Iera and G. Morabito, "Understanding the Internet of Things: definition, potentials, and societal role of a fast-evolving paradigm.," Ad Hoc Networks, vol. 56, pp. 122-140, 2017.
39. F. Wortmann and K. Flüchter , "Internet of things," Business & Information Systems Eng., vol. 57, no. 3, pp. 221-224, 2015.
40. Korb K. B. & Nicholson A. E. (2010). Bayesian Artificial Intelligence. Second Edition. CRC Press.

41. Banik B. K., Di Cristo C., Leopardi A., and de Marinis G. (2017). Illicit intrusion characterisation in sewer systems. Urban Water J., 14(4), pp. 416-426.
42. Preis, A. & Ostfeld, A. (2008) Multiobjective contaminant sensor network design for water distribution systems. Journal of Water Resources Planning and Management, 134, 366–377