Universal Multi-layer Map Display and Improved Situational Awareness in Real-World Facilities

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Abstract— **This paper introduces a Universal Multi-layer Map Display designed to enhance situational awareness in real-world facilities like hospitals, factories, or disaster sites. The proposed system integrates multiple layers of spatial and semantic data into a unified, interactive interface, allowing users to navigate complex environments with improved clarity and decision-making capabilities. By combining metric maps, topological maps, and semantic information (e.g., room functions, hazard zones, and live sensor data), the multi-layer map enables operators and robot systems to visualize and interact with real-time data streams intuitively. The research explores the application of this system in dynamic, cluttered environments where real-time mapping and navigation are critical. Key innovations include the fusion of multi-modal sensor data, switching between map layers to suit different operational needs, and integrating context-aware alerts that provide up-to-date insights on environmental changes and potential hazards. The system improves situational awareness by offering a comprehensive view of the environment, enhancing decision-making and coordination in complex tasks such as emergency response, logistics, and facility management. The results emphasize the importance of multi-layered data representation and intuitive interfaces in environments where spatial awareness is critical to mission success.**

I. INTRODUCTION

In today's rapidly evolving world, real-world environments such as urban centers, industrial complexes, and critical infrastructures face increasing challenges in maintaining operational efficiency, safety, and resilience. These environments are complex and dynamic, encompassing diverse elements such as physical infrastructure, human activities, and cyber-physical systems. Ensuring robust situational awareness in such environments is essential for effective decision-making, risk management, and incident response. Situational awareness refers to the ability to perceive, comprehend, and predict events within a given environment. However, achieving high levels of situational awareness is inherently challenging due to the fragmented and siloed nature of existing monitoring and management systems. These systems often lack interoperability and do not provide a unified overview, leading to information gaps and delayed responses. To overcome these challenges, the concept of a Universal Multi-layer Map (UMM) has emerged as a transformative solution. The UMM integrates data from multiple sources and layers within an environment, creating a comprehensive and unified representation. This multi-layer approach encompasses various dimensions, including physical assets, environmental conditions, human activities, and cyber elements, offering a holistic view that enhances situational awareness.

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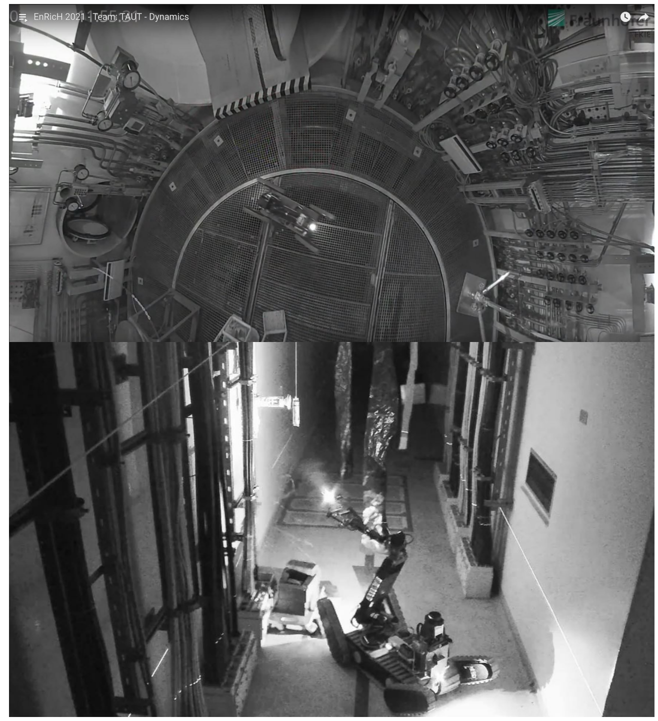

Fig. 1. Rescue robot during surveillance of the Zwentendorf nuclear power plant, inspection of pipelines, rescue of injured persons, measuring radiation in dark rooms, and manipulation of valves (Images Fraunhofer FKIE).

The Universal Multi-layer Map uses state-of-the-art technologies to collect, process, and analyze huge amounts of real-time data. By synthesizing information from disparate sources, the UMM provides a seamless and accurate depiction of the environment, enabling stakeholders to detect anomalies, assess risks, and respond to incidents more effectively. This integration improves operational efficiency and enhances the overall resilience and security of the environment. The paper describes the concept of a Universal Multi-layer Map, which was tested in a real-world nuclear facility. We explore the UMM's technical architecture, the data integration and analysis methodologies, and the benefits of this approach in enhancing situational awareness. Furthermore, we present a field experiment in which the UMM has been successfully deployed with a tracked rescue robot, demonstrating its impact on improving decision-making processes and operational outcomes. The Universal Multi-layer Map represents a significant advancement in situational awareness by providing a unified and comprehensive perspective. This paper aims to highlight UMM's importance in addressing the complexities of real-world environments and underscore its potential to revolutionize the management and security of these critical systems.

II. Related Work

Nowadays, digital map navigation systems for optimal vehicle route planning are standard equipment. They are expected to play an increasingly important role in transport systems shortly and will be even more interconnected to manage traffic in a time-optimized and highly safe manner. The information and the multitude of data are transmitted to the user in a freely configurable Graphical User Interface (GUI). [1] developed a lane-level map-supported route-planning algorithm with a seven-layer adaptive accuracy map architecture and fused the data in one lane-level map. [2] propose a representation of a multi-layer map with cluster matching technique and semantic memory map. Regions from different semantic maps are efficiently connected with their correspondences using central images, thus expanding the semantic information. Fankhauser et al. [3] developed a universal grid map library for mobile robot applications. K.Daun [4] proposed an online radiation mapping method and source localization using Gaussian Processes in one map representation. In [5], Henning et al. introduce a novel concept for situation-aware environment perception, which aims to optimize resource allocation in real-time by focusing on relevant data areas and selectively employing functional modules necessary for the current task.

Our generic mapping framework supports a multi-data layer and can process any sensor data and collect data in a more generalized approach for map visualization. Our methodology could also be applied to other sensor technologies and sensor types, and we visualize the data in a separate map layer to get an improved first overview of all the different data.

III. Methology

The primary purpose of multi-layer maps is to provide a comprehensive and integrated view of complex environments by aggregating data from multiple sources and layers. This holistic perspective is crucial for enhancing situational awareness, facilitating effective decision-making, improving management practices and includes the specific purposes:

- Data Integration: Combining diverse datasets from various domains, such as physical infrastructure, environmental conditions, human activities, and cyber elements, into a single cohesive framework.
- Enhanced Situational Awareness: It provides a detailed and multidimensional overview of the environment to better understand the current state, predict future developments, and identify potential problems or anomalies.
- Improved Decision-Making: Providing stakeholders with accurate, real-time information to support informed, timely decisions for routine operations or emergency responses.
- Risk Assessment and Management: Enabling the identification, analysis, and mitigation of risks by presenting a clear picture of vulnerabilities and threats across different layers of the environment.
- Operational Efficiency: Streamlining processes and improving coordination among various components of the environment, leading to more efficient resource utilization and operational effectiveness.

A model that fuses the data obtained from object classification and scene analysis into a "multi-layer map" and refers to the implementation of basic multi-layer operations and methods used in vector feature datasets see Fig. 2. Fires in enclosed spaces, such as underground garages, pose a particular danger and usually lead to longer response times. Multi-sensory visual perception based on machine learning methods can significantly improve and accelerate the development of situation awareness for autonomous systems.

A. Conceptual Design

The vision of intelligent firefighting is to harness advanced technologies to enhance the efficiency, effectiveness, and safety of firefighting operations. This involves integrating data from various sources to provide firefighters and emergency response teams with real-time, actionable insights. These tools are essential for making accurate predictions about the possible spread of fire, the escape of gases or chemical substances, or even the evacuation of injured persons. The realization of this vision would enable fire brigades to better coordinate with other urban services and organizations

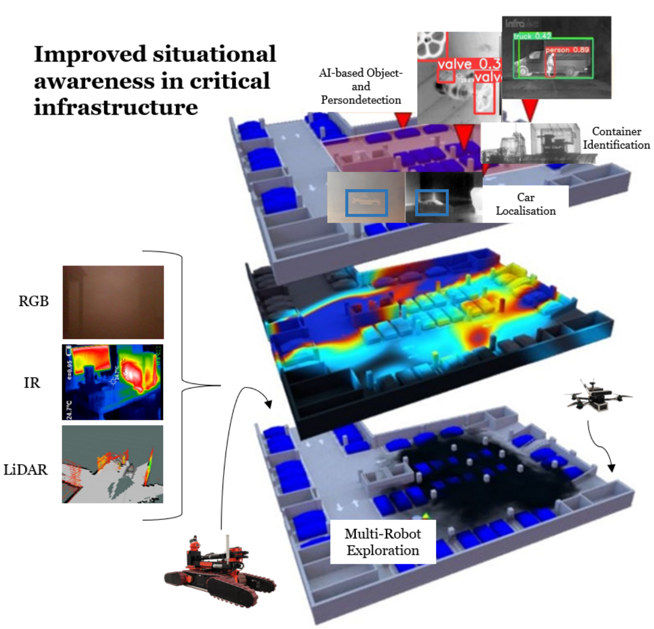

Fig. 2. Schematic Multi-layer Map: Building an improved situational awareness in the operational scenario.

and improve the conduct of complex rescue operations. The following aspects arise from this:

1) Object classification and recognition as part of scene analysis: Learning representations are also created to detect relevant scene elements. These can be specialized for the localization of fire sources, the classification of heat sources (fire, smoke, reflections), and the visual recognition of all relevant object classes (persons, vehicles, hydrants, emergency exits). The scene elements identified in this way are then placed in context with the existing infrastructure (e.g., garage model) via an environment representation.
2) Visual pose identification of objects and object parts: Learned local representations of object parts combined with geometric models allow robust approaches to perform pose determination with 6 degrees of freedom. This technological capability enables the automatic maneuvering of the robotic vehicle to functional scene elements, such as docking operations for fire extinguishers.
3) The vision of intelligent firefighting can be realized by harnessing the power of information from sensor and simulation technologies and communications to improve situational awareness, predictive modeling, and decision-making, as shown in Fig. 2.
4) Multi-layer mapping model: A model that fuses the data obtained from object classification and scene analysis into a "multi-layer map" and refers to the implementation of basic multi-layer operations and methods used in vector feature datasets, see Fig. 2.

The fused environment model generates a local representation of the environment in which the implemented mission-optimized robot platform can move safely. This should enable the automation of manipulation tasks during rescue and recovery operations and reduce the workload of the emergency services as much as possible. By overlaying all these layers in one view, operators can make informed decisions, improving the efficiency and safety of their operations, see Fig. 4.

B. Mapping and Sensor Fusion

Modeling the environment with complex structures is crucial to developing reliable, intelligent, autonomous search and rescue robots. The main goal of this paper is to integrate the developed UMM into a mobile rescue robot system and to improve Human-Robot Interaction (HRI). Our system can add OPIs (Object of Potential Interest) with semantic information to the metric map environment. The metric map environment is a spatial representation in which a robot maps its surroundings with precise geometric accuracy, typically using distance measurements in a coordinate system. This type of map allows the robot to understand the physical layout of its environment in terms of specific distances, dimensions, and locations of objects or obstacles. All sensor data are processed onboard and in real-time, which is crucial for realistic SAR deployments. The key idea is to classify the position of the objects extracted from the LiDAR sensor

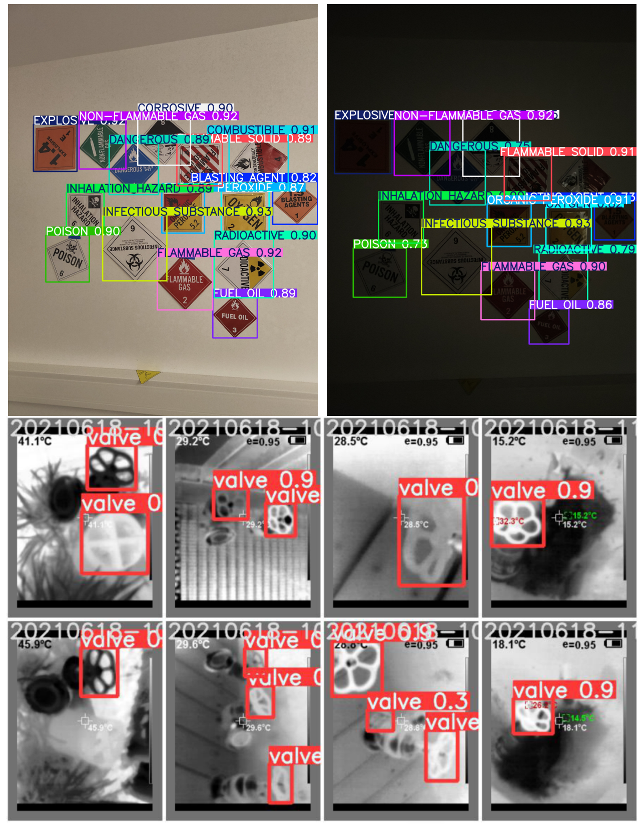

Fig. 3. Predicted object detection for hazmat labels in different lighting conditions with RGB camera **(top)** and predicted valve with a thermal camera **(bottom)** [6]

scan and camera images. Examples of typical observations with RGB and infrared cameras obtained in an indoor environment are shown in Fig. 3. [7] proposed a geometric world model with semantic information with extracted features from camera images and laser range data and subsequently classified via hidden Markov models. In our context, we focus on detecting OPIs, e.g., victims, hazmat label detection [6], fire extinguishers, or other general objects (doors, door handle) to increase the behavior planning for autonomous door opening [8]. [9] gives an overview of SLAM algorithms and the accuracy of the 3D maps produced with different algorithms (HDL Graph SLAM, LOAM, and A-LOAM) were compared in environments such as staircases, long corridors, and outdoor environments. A real-time LiDAR odometry and mapping (LOAM) method is proposed in [10] and describes the algorithm that divides and solves the recovery of motion and correction of motion distortion problems in the LiDAR cloud. The LiDAR frame is implemented by two algorithms running in parallel, where the LiDAR odometry part performs coarse processing to estimate higher frequency velocity. In contrast, the mapping algorithm performs fine processing to produce lower-frequency maps. The algorithm extracts edge and planar features and calculates the pose by minimizing point-to-plane and point-to-edge distance. However, distortion compensation and also laser odometry require iterative calculations that are still very computation-

$$R_s = R_z(\alpha)R_y(\beta)R_x(\gamma) = \underbrace{\begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{yaw} \cdot \underbrace{\begin{bmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{bmatrix}}_{pitch} \cdot \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma & \cos\gamma \end{bmatrix}}_{roll} \tag{1}$$

$$R_s = \begin{bmatrix} \cos\alpha\cos\beta & \cos\alpha\sin\beta\sin\gamma - \sin\alpha\cos\gamma & \cos\alpha\sin\beta\cos\gamma + \sin\alpha\sin\gamma \\ \sin\alpha\cos\beta & \sin\alpha\sin\beta\sin\gamma + \cos\alpha\cos\gamma & \sin\alpha\sin\beta\cos\gamma - \cos\alpha\sin\gamma \\ -\sin\beta & \cos\beta\sin\gamma & \cos\beta\cos\gamma \end{bmatrix} \tag{2}$$

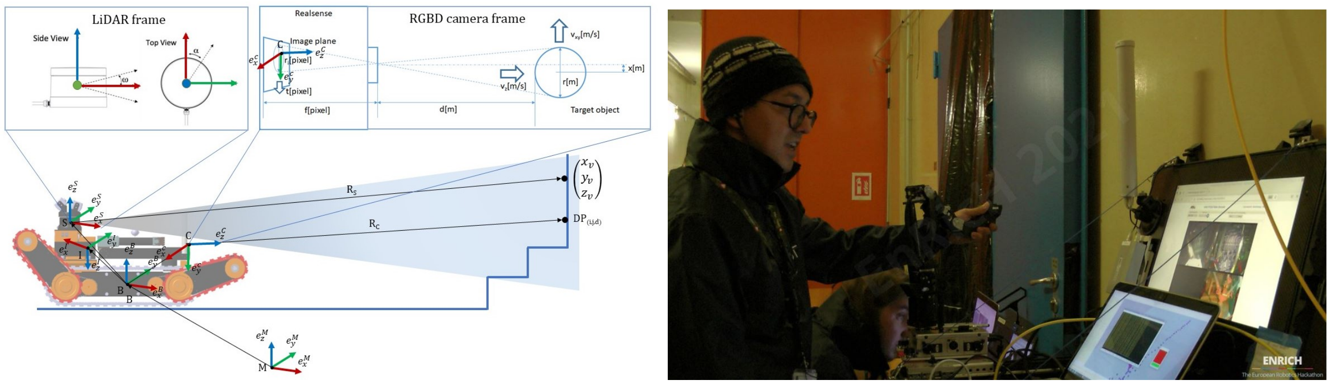

Fig. 4. Left figure: Robot coordinates frames of LiDAR and IMU - Schematic illustration of the coordinate frames used for mapping and object pose estimation. The state estimation of the robot forms the relationship between the map frame M and base frame B. The LiDAR sensor frame S and the IMU frame I are rigid transformations of base B, defined in the Unified Robot Description Format (URDF). Note that the camera frame C depends on the TCP and the joint states of the 6-DOF robot arm.
Right figure: In this experiment, we use a control system for a tracked rescue robot with an operator view involving a mechanical robot arm twin, PS5 controller, and sensor visualization using RViz on dual screens within a robust operator case (Image Fraunhofer FKIE).

ally intensive. The problem deals with the estimation of ego-motion estimation $k \in Z^+$ with point clouds P_k perceived by each 3D LiDAR sweep k and creates a map P_k for the environment.

Based on A-LOAM[1] we extended the framework with IMU data with the sensor and robot frame definitions, which follows the ROS coordinate frames for mobile platforms[2] with x - forward, y - left and z - upward. We provide a correct extrinsic transformation using a parameter file for the mapping algorithm. After that, you can calculate the rotation in roll, pitch, and yaw using trigonometry and calculate the rotation matrix in equations (1) and (2). The general definition of a rotating multi-beam LiDAR with the local frame X_v, Y_v, Z_v with its origin in the optical center and its X_v axis in the forward direction and Z_v pointing upwards. Fig. 4 illustrates the full robot coordinates with a Velodyne VLP-16 sensor. The multi-layer LiDAR scans points in spherical coordinates R, ω, α, which correspond to the Cartesian coordinates (x_v, y_v, z_v) for each measured point:

$$x_v = R_s \cos(\omega) cos(\alpha), \tag{3}$$
$$y_v = R_s \cos(\omega) sin(\alpha), \tag{4}$$
$$z_v = R_s \sin(\omega). \tag{5}$$

[1] https://github.com/HKUST-Aerial-Robotics/A-LOAM
[2] https://www.ros.org/reps/rep-0105.html

C. Approach for the Visualization of a Multi-layer Map

Modeling the environment with complex structures is crucial to reliable, intelligent, autonomous search and rescue robots. The main goal of this paper is to propose a mobile rescue robot for autonomous detection and mapping of objects and victims in USAR scenarios. Our system can add OPIs with semantic information to the metric map environment. All sensor data are processed onboard and in real-time, which is crucial for realistic SAR deployments. One of the most powerful and frequently used tools of a geographic information system is the overlay of cartographic information. Nowadays, navigation systems and online services such as Google Maps or Google Earth are stored on roads and with information such as hotels, petrol stations, parking spaces, or restaurants. This information argumentation can also be applied to mobile robot systems, allowing users to display other sensor modalities besides OPIs. The overlay function combines the spatial features and the dataset's attribute information. Robots typically move on flat terrain, and SLAM algorithms work in 2D. Occupancy Grid Mapping is a pivotal algorithm in probabilistic robotics, particularly for mobile robots. It addresses the challenge of creating accurate maps from data that are often noisy and uncertain [11]. Mobile ground (wheeled and tracked) and legged robots must navigate increasingly rough terrain; therefore, mapping algorithms must measure the surroundings in three dimensions. A popular approach is simplifying a 2.5D representation, also called elevation mapping, which stores and handles the height value as a grid map. Given the complexity and volume of sensor data in intelligent firefighting, effectively representing this data is critical to avoid overwhelming users, especially during high-stress situations. 2D and 3D mapping are already more or less seen as the standard representation for mobile robots. If path planning or the registration of found OPIs is also drawn into the map, one is gradually flooded with data. The tools often used in ROS [12] today, such as RQT or RViz, are already very well thought-out and provide every robot developer with a ready-made visualization of the sensor data. In RViz, however, you always need the cursor to show or hide the respective data. In our recent work, we have developed a universal multi-layer map that can be used with any robot type and visualizes different sensor modalities in different layers. Fig. 5 shows the base of the grid map layer and how each cell is occupied (see 2D Occupancy Grid Map) or can be occupied, as in the example of the traversability map as a 2.5 representation. The developed multi-layer maps are defined this way by default:

- **map layer:** represent the environment in 2D occupancy grid map and 3D point cloud
- **traversability layer:** represent the environment traversability map as 2.5D
- **object layer:** 2D occupancy grid map and OPI locations
- **hazard layer:** visualise e.g. CBRN measurements
- **additional layers:** e.g., visualization of other sensor data or Wifi signal strength

However, as shown in Fig. 6, this representation can be extended upwards and downwards with further layers.

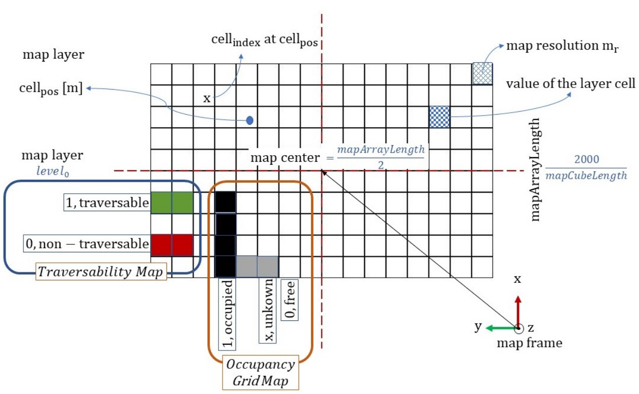

Fig. 5. Definition grid map layer: The geometry of each map (lengths, resolution, and position) is specified as the center of the map, which is relative to the grid map frame.

IV. EXPERIMENTAL RESULTS

We evaluated the proposed universal multi-map representation with terrain traversability mapping a real-world full-scale nuclear facility (online) and recorded sensor data, see Fig. 7. The UMM representation is implemented in C++ and runs with the robot operating system (ROS) [12] distributions Melodic and Noetic in Ubuntu Linux 18.04 and 20.04. The computing hardware used is either a laptop with an

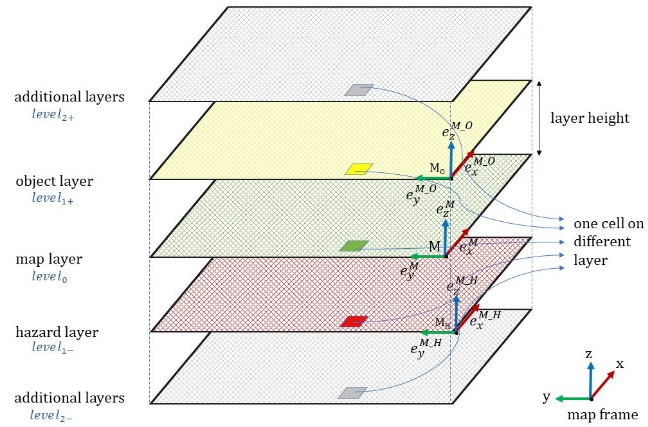

Fig. 6. Multi-layer grid map layer: Multiple layers represent and store data for different types of sensor information

i7 2.5GHz CPU and 16GB memory and an INTEL NUC (2D/3D mapping algorithm) or an NVIDIA Jetson Xavier AGV (object recognition and vision algorithms) for the robot onboard computing. The tracked rescue robot in Fig. 1 with a modular payload system [13] was developed for USAR applications and can be customized with different sensors and tools depending on the application and deployment scenario. The Zwentendorf NPP dataset was obtained during the 2021 EnRicH competition [14] by using two rescue robots (wheeled and tracked rescue robots) [15]. The mission time is 30 minutes, and as many tasks as possible must be solved. The tasks included mapping the building in 3D and creating a radiation map. The manipulation task involved identifying

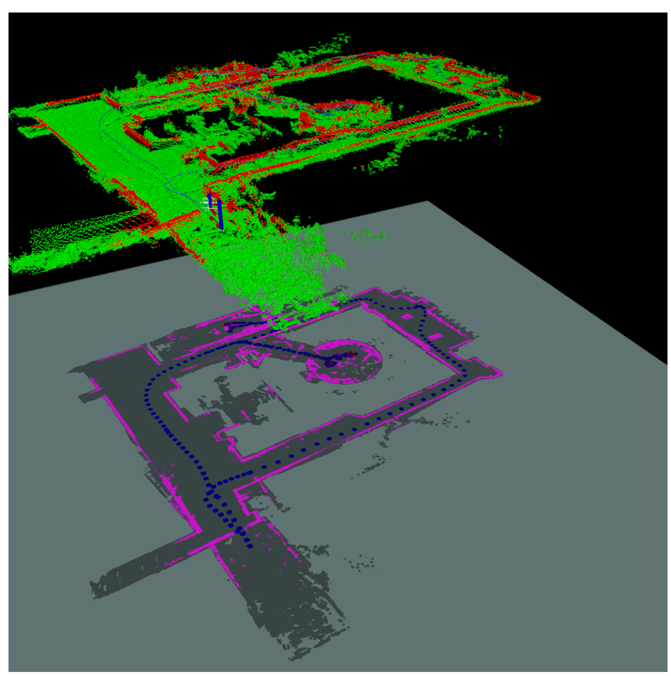

Fig. 7. Two-layer map: Multiple layers represent a traversability map (level 0) and cost-map with hazard information (dose rate on layer -1)

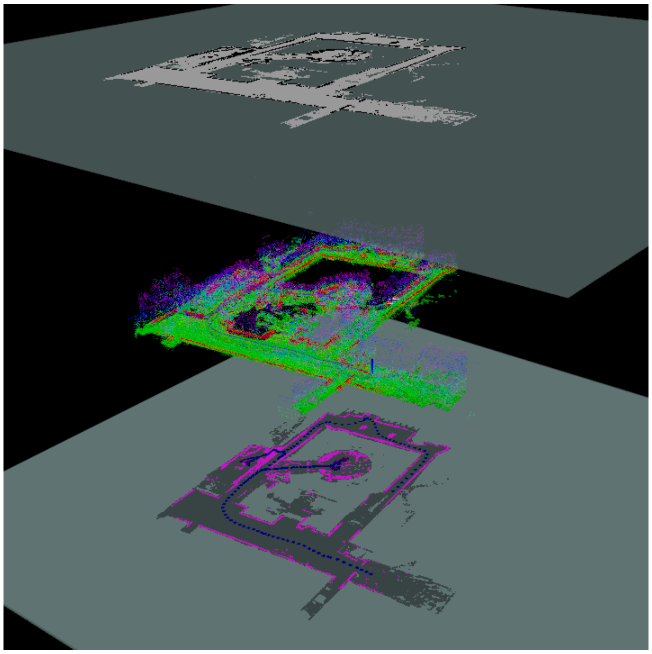

Fig. 8. Multi-layer map visualization in RViz from Zwentendorf NPP: The object layer (level 1+) shows an occupancy grid map, which is a projection of the 3D map of the map layer (level 0). The hazard layer (level 1-) shows the point-by-point distribution of radiation at the robot position and the location of the detected sources.

the radioactive sources and closing the corresponding valves. The last task was to rescue the injured person in the pump room. This person's position had to be marked on the map and brought to safety. The users, organizations, and visitors could follow the exploration during the demonstration. In Fig. 8, we present the results of our system using the NPP dataset sequence. The developed multi-layer mapping model merges the data obtained from object classification and scene analysis into a "multi-layer mapping" and refers to implementing basic multi-layer operations and methods used in vector feature datasets.

V. CONCLUSION

The developed Universal Multi-Layer Map Display is a sophisticated visualization tool designed to enhance situation awareness by integrating and displaying diverse types of data from multiple sources in an organized, multi-layered format. This system is particularly beneficial for complex and dynamic environments such as firefighting operations, facility management, and urban search and rescue missions. Using advanced technologies and machine learning, the UMM provides a comprehensive and unified view of complex environments, enabling better decision-making, risk management, and operational efficiency. This approach represents a significant advancement in managing and securing modern facilities, ensuring resilience and adaptability in an increasingly interconnected world, situational awareness, and managing complex environments. Multi-layer maps enhance decision-making, improve operational efficiency, and support effective risk management by offering a comprehensive, real-time, and integrated view of various layers. Their advantages make them indispensable tools for various applications, from urban planning and infrastructure management to emergency response and security operations.

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