Melanie Müßle*, Kate Clintworth*, Jürgen Steufmehl and Sascha Rülicke

Visualization of trouble spots for decontamination work and decision measurements with the help of BIM

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Abstract: The clearance of buildings is a central step in the decommissioning process of nuclear facilities. Typical nuclear power plants in Germany have 100,000 m^2 to 450,000 m^2 of concrete surfaces that need to be processed for clearance. For efficient planning of decommissioning tasks, precise and up to date information about the premises to be released is essential. Due to the early construction period of the nuclear power plants no digital 3D models from design phase exist. Therefore, accurate recording of the spatial data, in particular all building surfaces as well as the interfering objects contained therein is necessary for the planning and execution of the decision measurements. At the beginning of this project, spatial data acquisition was largely done manually. These methods were tedious and error prone. To counteract these problems, the research project ViSDeMe – Visualization of Trouble Spots for Decontamination Work and Decision Measurements with the Help of BIM – has been applied for. The aim of the research project was the digitalization and (at least partial) automation of relevant process steps of spatial data acquisition and the associated documentation for the building release of a nuclear facility. In this project both the 3D BIM model and the associated (semi-) automated processes such as the object detection were developed successfully. The digitalization process is being investigated and evaluated in cooperation with the project partner RWE Nuclear GmbH (RWE) using the example of the power plant in Mülheim-Kärlich, Germany. The results of the project are presented in this paper.

Keywords: clearance of buildings; spatial data acquisition; BIM; digitalization; automation

***Corresponding authors: Melanie Müßle and Kate Clintworth**, Karlsruhe Institute of Technology, Karlsruhe, Germany,
E-mail: melanie.muessle@kit.edu (M. Müßle), kate.clintworth@kit.edu (K. Clintworth)
Jürgen Steufmehl, RWE Nuclear GmbH, Mülheim-Kärlich, Germany
Sascha Rülicke, Externer Mitarbeiter RWE Nuclear GmbH, Mülheim-Kärlich, Germany

1 Introduction

Following the shutdown of a nuclear power plant, the operator is obliged to dismantle the facilities. In order to be able to remove plant components from nuclear power plants and release them in accordance with the Radiation Protection Ordinance, their activity must be below a limit value. Activity limits also apply to the building structure, compliance with which must be proven by measurements. For this purpose, all building areas to be released in the control area of a nuclear power plant are precisely recorded and documented with all relevant information. An accurate acquisition of the spatial data, in particular all building surfaces as well as the disturbing objects contained therein, such as anchor plates under the decontamination coating or pipe penetrations, is essential for the planning and execution of the decision measurements. Metal objects in particular have to be assessed separately from the surrounding concrete, among other things due to different release values (Bundesamt für Justiz 2018). Subsequently, radiological measurements are carried out and assigned to the recorded areas. The documentation of the spatial data acquisition and the measurements is carried out in a report, which must be submitted to the authority, to prove that all areas considered have been evaluated and that the limit values according to the Radiation Protection Ordinance have been complied with. Typical nuclear power plants in Germany have 100,000 m^2 to 450,000 m^2 of concrete surfaces (Gentes et al. 2015) that need to be processed for clearance.

The main construction phase for nuclear power plants in Germany was between the 1960s and 1980s. At that time, mainly non-digital planning methods were used. Since then, the buildings have undergone continuous changes. As a result, some of the buildings have insufficient information about the current state of their building structures. For this reason, the current condition of the building, including relevant structures, have to be assessed and re-measured.

At the beginning of this project, spatial data acquisition was largely done manually using a folding rule, pen and paper by appropriately trained measuring teams (see Figure 1). This method posed a problem in several different ways. Each object had to be measured individually, which is a tedious task and exposes the personnel to radiation for a longer period of time. At the same time, these personnel are lacking for other tasks, which is difficult in this industry due to the shortage of workers.

In addition, this process does not provide any digital building models or similar data which are needed in further process steps and therefore have to be processed accordingly. Manual data recording, continuous copying and transfer of data increases the susceptibility to errors.

Some relevant objects within the structures, especially anchor plates could not always be reliably recorded as they were overseen or were not even visible because they were hidden under a decontamination coating. This coating was applied on the building surfaces in nuclear facilities in order to protect them and enable easy decontamination of the surfaces (Dewi and Yuliyanto 2018). For the most part it is not transparent. Some of the coated anchor plates are well hidden within the walls and cannot be detected without the help of appropriate tools.

In summary due to the lack of digitalized documentation and processes within these structures, the efficiency of the workload is limited, costly and unclear.

Digitalization in the construction industry has optimized existing and enabled many novel processes. One of these processes, known as Building Information Modelling (BIM), describes a collaborative method in which information about an infrastructure project can be developed and managed throughout its entire life cycle (Borrmann et al. 2021). The basis of BIM often is a 3D visualization of the respective object, e.g. a parametric model or a point cloud. In addition, the model is supplemented by an associated database containing relevant metadata such as component types or materials (Borrmann et al. 2021). The BIM model contains relevant information needed about the design, maintenance or operation of the building. Building information modelling is a well-established working method and standard in the construction industry. Considering the dismantling and decommissioning of nuclear power plants, precise 3D BIM models can be used, among other things, for the planning, tracking and documentation of decontamination processes or clearance measurements. Another useful application is dismantling quantity estimation for nuclear power plants (Shin and Song 2024). According to the current state of the art, accurate as-built models of existing buildings are generated based on a digital as-built recording and largely manual modelling of the structures (Tang et al. 2010).

The aim of the research project ViSDeMe – Visualization of Trouble Spots for Decontamination Work and Decision Measurements with the Help of BIM – was the digitalization and (at least partial) automation of relevant process steps of spatial data acquisition and the associated documentation for the building release of a nuclear facility. The rooms and the disturbing objects have to be visualized in an integrated 3D model as accurate as necessary. This approach makes it possible to reduce resources and costs as well as the radiation exposure of the personnel. In addition, the susceptibility to errors in data collection and documentation can be reduced.

The process is being investigated and evaluated in cooperation with the project partner RWE Nuclear GmbH (RWE) using the example of the power plant in Mülheim-Kärlich, Germany. The results of the project are presented in this paper.

2 Methodology

The aim of the ViSDeMe research project is to digitalize relevant process steps of building clearance, in particular spatial data acquisition, measurement planning and documentation based on it. The prerequisite for this, is the digital recording and visualization of the building structures with

Figure 1: Manual measurement of the interior surfaces of the building and logging of the measurement data (PreussenElektra GmbH 2016).

the various disturbing objects in nuclear facilities with the help of Building Information Modelling (BIM). The rooms and the disturbing objects have to be recorded and visualized in an integrated 3D model as accurately as necessary. Another focus of the research project is the localization of non-visible or barely visible anchor plates, which are hidden under the decontamination coating and their exact localization in the digital model.

In the project a so-called Scan-to-BIM process is being developed, starting with the recording of the premises including all relevant trouble spots, the analysis of the captured data, and the visualization in a digital model. Based on this model, planning of decontamination works and decision measurements can be carried out digitally.

2.1 Case study

In order to evaluate the developed processes and methods proposed in this contribution, a case study is carried out. Selected parts in the controlled area of the nuclear power plant in Mülheim-Kärlich served as our test area. The selected rooms have largely been cleared out and many components such as pipes and beams have already been removed. Only the parts built into the building surfaces remained mostly. This condition is representative of the appearance of the rooms at the time of building clearance. In addition to the evaluation of our developed methods it is the goal of the case study to investigate the accordance of our processes with the requirements for accuracy and standardization in terms of areas, dimensions, room characteristics, data management and traceability, which were defined at the beginning of the project.

2.2 Digital recording and modelling of building structures

Basis of the digitalization process is the 3D inventory capture of the premises to be released. Within this project, the building structures were recorded with the help of a laser scanner. These devices combine LIDAR sensors and RGB imagery to perform their scanning measurements. As a result, a three-dimensional RGB point cloud was generated which has a high spatial resolution and can visualize smallest surface variations and structures. A detailed view of a section of this point cloud is shown in Figure 2.

Common difficulties and obstacles during the scanning process are interfering reflections or shadowed areas. Especially the second point is relevant in nuclear facilities due to heavy machines or scaffolds present there (see Figure 2). To handle this problem, a sufficient amount of measurements from different views has to be taken and combined.

Based on the point cloud, a common practice is to create a building model of the recorded structures in BIM software. To the current state of the art, BIM models are largely modelled manually with at most semi-automatic support for the modelling of single objects. There exist many approaches to automated modelling in research, but they are usually limited to buildings with simple, flat geometries, e.g. (Zbirovský and Nežerka 2025). According to (Kaufmann et al. 2022; Tang et al. 2010) the major challenges in automatic building modelling are to develop algorithms that are robust towards occlusions and that are capable to handle complex non-planar structures, both of them being highly relevant for modelling of nuclear facilities. These topics are still the subject of current research. However, the abstraction of the visual representation has multiple advantages. Point clouds in general represent a realistic and detailed depiction of a scene, but they require a large data storage and processing them is computationally expensive. Parametric modelling on the other hand represents a less complex and detailed environment but its processing is computationally more efficient (Kaufmann et al. 2022; Qu and Sun 2015). The level of detail of a BIM model is adapted to the task to be solved. The goal is to handle as little data as possible, but as much as necessary. From the parametric model, quantities like room size or the area of walls and other surfaces can be determined easily. If the objects are even linked to further information like costs or working hours, many more analyses will be possible (Borrmann et al. 2021).

2.3 Digital recording of disturbing objects

In the course of spatial data acquisition, all relevant trouble spots contained in the building surfaces to be released have to be recorded, since they have to be considered separately during the radiological measurements and their evaluation. In accordance with (Müßle 2023), these disturbing objects built into the concrete surfaces can geometrically be classified into three categories:

a) Openings in the concrete surface, such as (pipe) penetrations or windows
b) Components protruding from the concrete surfaces, such as the remains of cut-off steel I-beams or protruding anchor plates
c) Anchor plates lying flat in the concrete surfaces (either visually clearly visible or hidden under the decontamination coating and difficult or impossible to see)

Figure 2: Detailed view of the point cloud of the building structures to be released in Mülheim-Kärlich.

Examples of the built-in disturbing objects explained above are shown in Figure 3. The visually identifiable trouble spots in Figure 3 (A) can be recorded using optical methods such as the laser scanner described in section 2.2. For the anchor plates hidden under the decontamination coating (Figure 3 (B)), additional sensor technology must be used. For this purpose, suitable sensors were identified in the course of the project, checked and evaluated for their suitability and cost-effectiveness. The aim was to find a technique that allows a non-contact measurement that covers an area as large as possible at once. Based on our investigations, active thermography (Budzier and Gerlach 2019) emerged as the best technique. Active thermography is a proven method for non-destructive testing purposes. This technique combines active heating of the building surfaces in order to create artificial temperature differences between the different materials with subsequent thermal imaging. It could be shown that most anchor plates could be made visible reliably and reproducibly with this method.

2.4 Data evaluation and BIM integration of disturbing objects

The focus of the research project is on the digital recording and visualization of the disturbing objects built into the rooms to be released as a basis for further decommissioning planning. Due to the huge amount of relevant objects, on average, 12 properties per building surface, it is our aim not only to digitalize but also to automate (at least partially) relevant steps of this task. Therefore, we developed a so-called Scan-to-BIM process for the disturbing objects based on the collected data. The workflow is shown in Figure 4.

In the first step of this Scan-to-BIM process the recorded data from laser scanning and thermography is evaluated separately, resulting in a 3D point cloud and 2D thermal images. For better spatial localization of the thermal information, the thermograms are mapped into the point cloud. The next step of the Scan-to-BIM process is the automatic extraction of the relevant disturbing objects from the data.

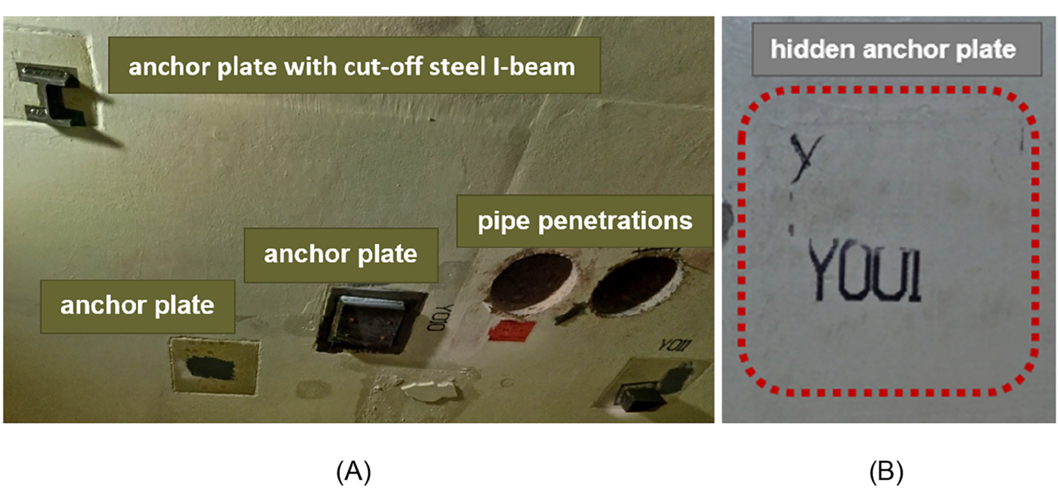


Figure 3: Examples of disturbing objects in the building surfaces to be released. (A) Containing visible objects and (B) containing an anchor plate hidden under the decontamination coating (Müßle 2024).

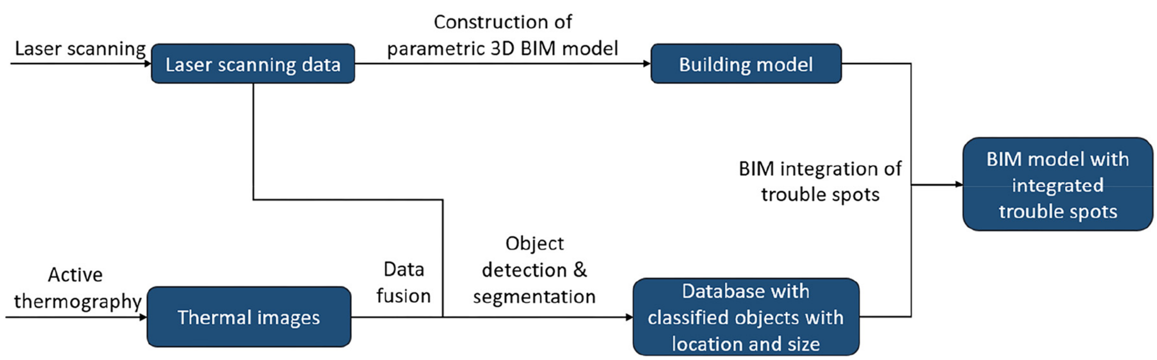


Figure 4: Developed scan-to-BIM process from data recording to evaluation to integrated BIM model.

To reduce the amount of computational power needed for detection tasks, the 3D data was projected to 2D data. The data was processed with classical Computer Vision and AI tools, to localize and classify the searched objects. Since many objects in the recorded area have more complex geometries and need to be defined precisely, image segmentation was chosen for this detection task. It describes the localization and pixel-wise classification of objects within images. This means, that each pixel of a 2D image is assigned to a class, either a relevant object-class or background. Dividing these classes into related segments for each individual object is referred to as instance segmentation. This way, each recognized object is classified in its own segment and can therefore be processed individually. A major advantage of this two-stage segmentation process is that the modelling can be adapted individually for each object class (Kaufmann et al. 2022).

The automated detection of objects is a complex task. AI-powered object recognition is mostly based on datasets, specialized for the respective application (Ertel 2025). Since there is no database for precisely this type of segmentation task available, corresponding data sets had to be created for this purpose. Therefore, the entire point cloud and the images derived from it were divided into training, validation, and test data sets. In the images used as training and validation data, the objects to be extracted were labelled. From those labels, the AI algorithm learns to recognize and distinguish the relevant objects. According to Section 2.3, we define four main object classes: openings, pipes, steel plates and beams, which together account for about 90 percent of the total properties.

After having extracted all relevant objects from the data, they have to be integrated into the building model, which is the last step of the Scan-to-BIM process. As a result of the above described object recognition process, the type and size as well as the position of the detected objects in the point cloud is obtained. To insert the detected objects into the BIM model, visual programming languages for BIM can be used. They enable to automate model generation through a graphical interface (Divin 2020). Automated Model generation is carried out in two main steps: First of all, a suitable BIM object class has to be assigned to each object and secondly, this object class has to be initialized and located with the appropriate specifications for each individual object. Based on the building model with all relevant disturbing objects, planning of decontamination works and decision measurements can be carried out digitally.

3 Results and discussion

3.1 Recording of building structures and disturbing objects

About 60 rooms of different sizes were recorded in our case study. In general, the visible objects were recorded with high accuracy and detail by the laser scanner. As the test area was under construction the recorded data shows some cluttering and also contains shaded areas due to scaffolding and covering of objects or insufficient lighting. Some rooms could only be partly scanned due to their limited accessibility.

Based on the point cloud, the building model of the rooms to be released is modelled in BIM software. In Figure 5 an excerpt from the resulting point cloud is shown in Figure 5 (A) and the corresponding 3D building model in Figure 5 (B).

The investigations to determine a method for the detection of hidden anchor plates showed that active thermography emerged as the best technique. In active thermography, heat is directed towards the building surfaces to artificially create a temperature difference between the steel plates and the surrounding concrete. After heating, the anchor plates stand out darker in the thermal image than their lighter concrete surroundings. Figure 6 (B) shows the result

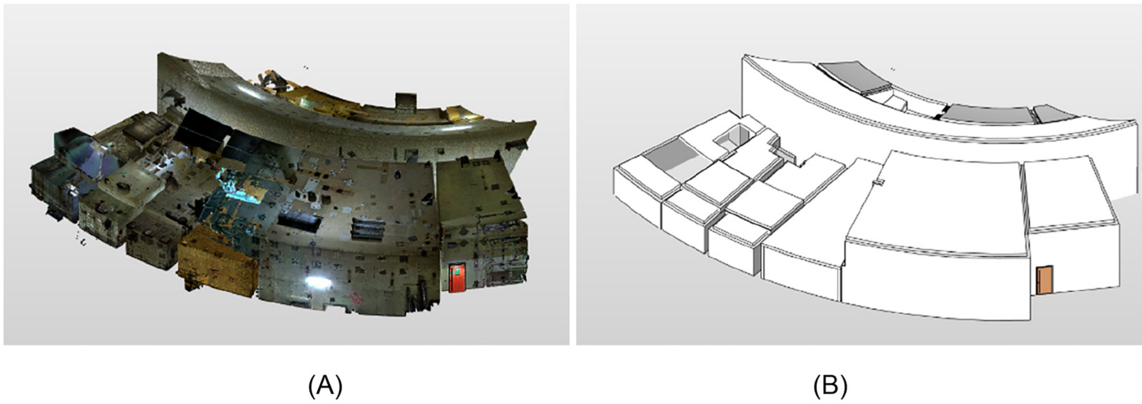


Figure 5: Excerpt from the point cloud (A) and the building model (B) of the nuclear facility in Mülheim-Kärlich.

of such a thermal imaging measurement of a wall with hidden anchor plates compared to the same wall in the point cloud (Figure 6 (A)).

Although active thermography was able to make the objects well visible, some factors have to be taken into account while recording: The active heating of the surfaces during this process is not always distributed equally, which results in partly low contrast imagery (see Figure 7). This makes it more difficult to automatically extract the anchor plates as they are less distinguishable from their surroundings. In addition, thermal images suffer from a relative low resolution compared to conventional RGB cameras. This has a direct influence on the recognition accuracy.

However, provided that a careful way of working is carried out, most anchor plates could be made visible reliably and reproducibly with this method.

3.2 Object detection in laser scanning data

In the first step, object detection based on YOLO11 (Jocher and Qiu 2024) was carried out on the laser scanning data to detect visible objects. The results of this object detection task contain type, size and localization of each object within the examined data. Figure 8 shows exemplary results of detected objects including their detection probabilities.

Relevant classes were selected from the model to show the detection performance of the chosen model. Figure 9 shows the normalized confusion matrix for object detection without integration of thermography data. This matrix evaluates the quality of the classification model for the visible objects. The relevant classes contain pipe openings, openings with different shapes and sizes, beams and steel plates/anchor plates. The “background” class is defined as everything that does not belong to the defined classes.

The correct predictions of the model are represented along the diagonal. Values along the row outside of the diagonal reflect the falsely recognized portions of the classes (false positives), along the column outside of the diagonal reflect the falsely undetected objects of the specific classes (false negatives). This matrix shows that the system detects (pipe) openings and steel beams very well. The low values outside the diagonal and background class indicate a low level of misidentification between the object classes. The

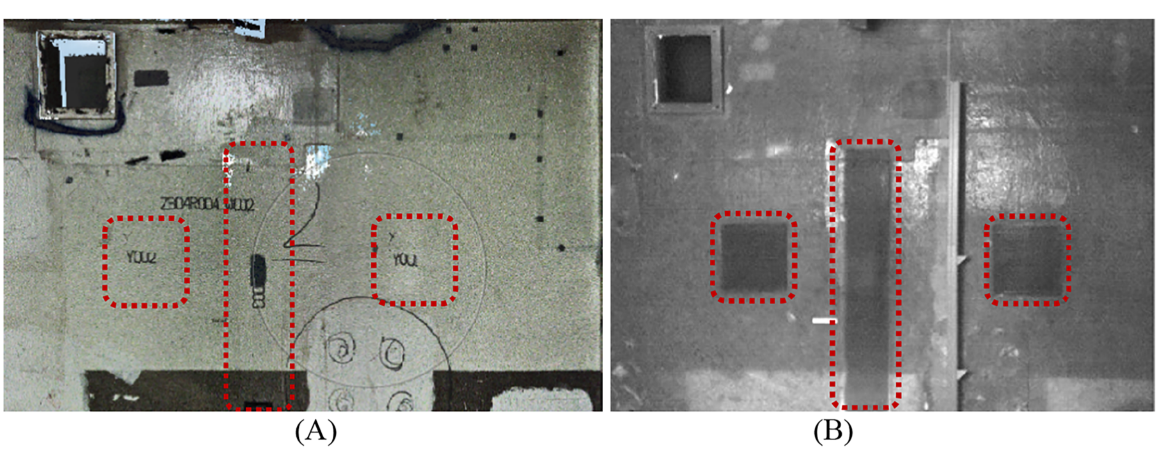
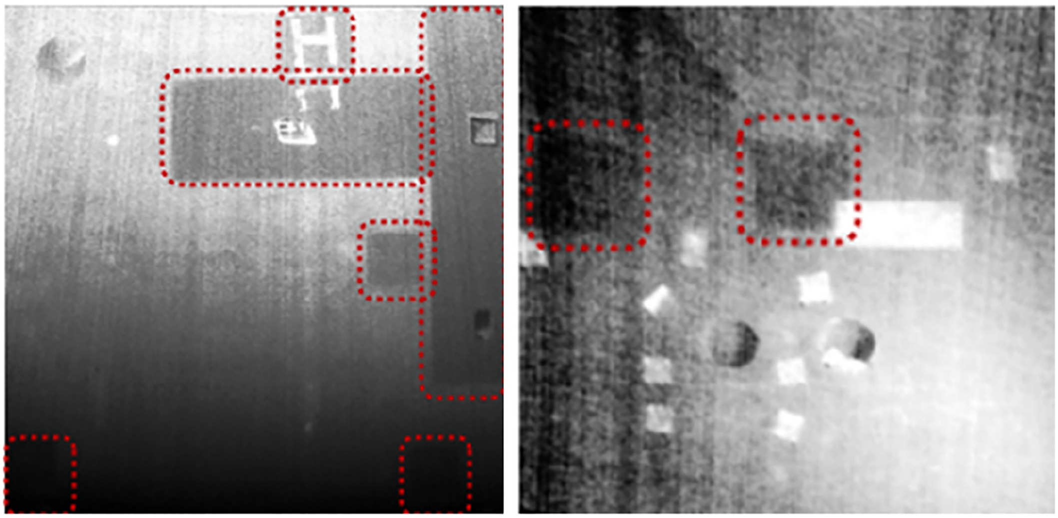


Figure 6: Wall with hidden anchor plates in point cloud (A) and thermal image (B) (Müßle 2024).



(A) (B)

Figure 7: Thermal images under varying brightness conditions.

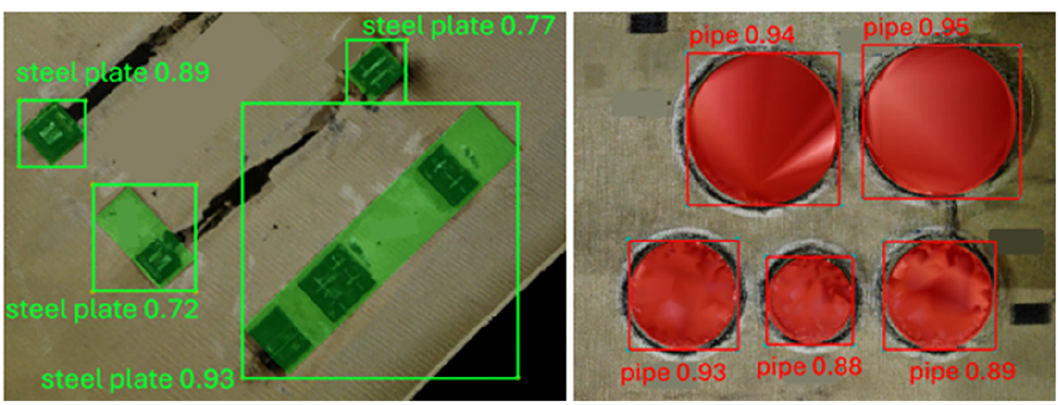


Figure 8: Detection results of object recognition in point cloud data.

Normalised confusion matrix of CNN without active thermography data

Predicted classes \ True classes	beams	openings	pipes	steel plates	background
beams	0.84	0.03	0	0.05	0.14
openings	0.02	0.87	0.01	0	0.13
pipes	0	0	0.91	0	0.17
steel plates	0	0.03	0	0.53	0.55
background	0.13	0.07	0.08	0.42	-

Figure 9: Confusion matrix of object recognition in point cloud data.

weaknesses of the model and the data become apparent in the anchor plate and background classes. About 53 % of the anchor plates are detected by the model. The other half of the anchor plates were falsely or not detected. This high rate of undetected objects coincides with the high rate of non-visible or barely visible anchor plates. About 46 % of the anchor plates in the used dataset are defined as non-visible.

The higher rates of false positives and negatives in the background class show that the model often detected non-existent objects or did not detect any objects at all. This is also due to the described cluttering within the recorded areas. For example, some of the openings could not be detected because they were covered up. It must be noted that some images containing anchor plate objects could not be used in any of the datasets used by the model as they were not detectable in the laser scanning data.

3.3 Object detection in thermal imagery

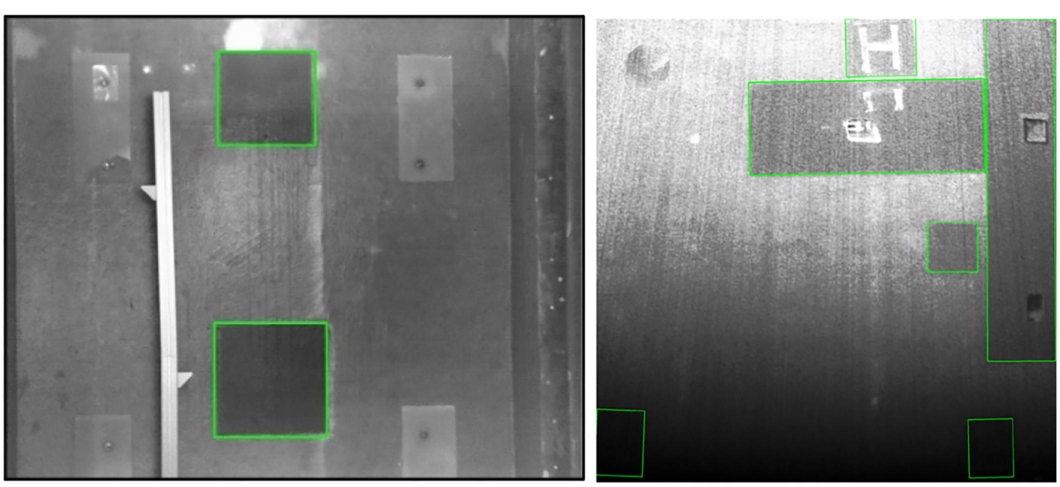
The SAM2-based segmentation process (Ravi et al. 2024) for the thermal imagery resulted in high detection and positioning accuracy. Examples of the detection results are shown in Figure 10. The percentage of correctly detected anchor plates rises from 53 % (as shown in Figure 9) to about 90 %. Both the amount of false detections and non-detections decreases significantly. The higher the contrast in the thermal images, the better the results of detection and segmentation of the anchor plates. The exemplary thermal image in Figure 10 (B) also shows excellent detection results outlined in green, even with fluctuating brightness conditions and low contrasts in the images. A more systematic approach during the warming up and recording stage will yield in even better results.

The matching format of both segmentation results allows their efficient fusion for combined further processing.

3.4 BIM integration of disturbing objects

In order to automatically integrate the detected objects into the building model, algorithms were developed using a visual programming language for BIM. In the first step, appropriate BIM object classes were selected, such as round or rectangular wall or ceiling openings. In the second step a representative of the corresponding object class is created for each individual object and located at the correct position into the building model. Figure 11 (B) and (C) show an example of the integrated BIM model for one single room. The corresponding point cloud of the room is shown in Figure 11 (A).

In addition to graphical visualization of the building structures and the disturbing objects contained therein, tabular outputs of the associated metadata were generated to support the further planning tasks based on our results. This data includes for example room numbers, type and size of the objects and further information that is useful for planning of decontamination tasks. The data has been prepared in such a way that it meets the usual standards of RWE in terms of spatial data acquisition and measurement planning.



(A) (B)

Figure 10: Detection results of object recognition in thermal images.

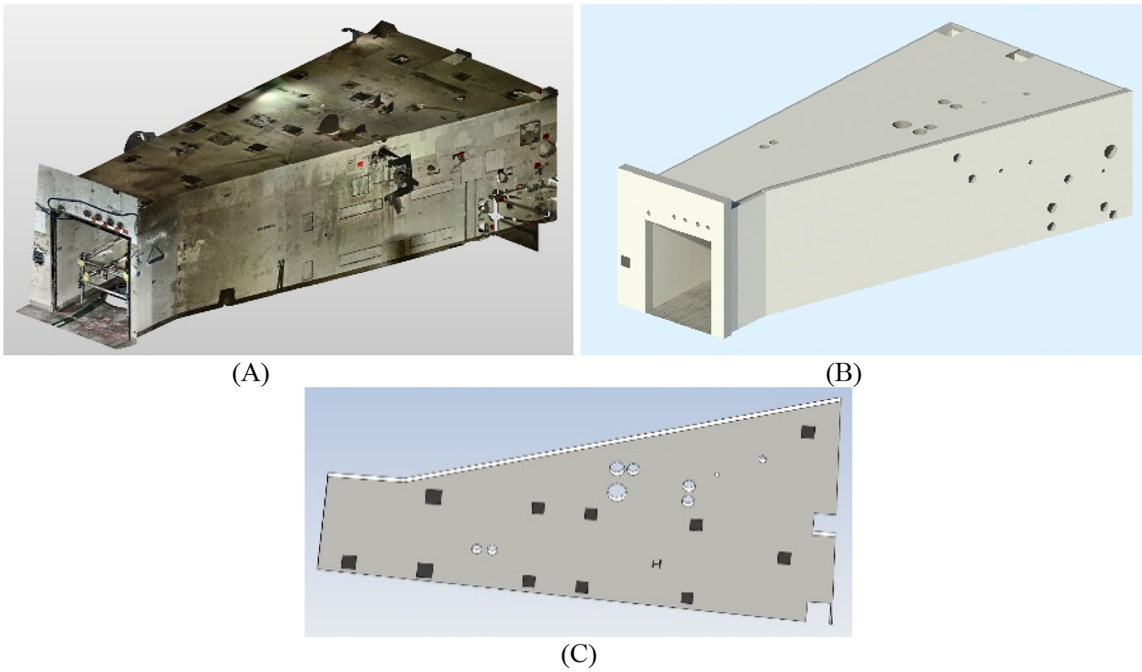


Figure 11: Point cloud (A) and model (B) of a room, interior view of the ceiling with disturbing objects (C) (Müßle 2023).

3.5 Validation

In order to validate our developed process against the conventional manual process of spatial data acquisition, we selected two rooms from our case study and compared the results of the two approaches in detail. The quantitative results of this comparison are shown in Figure 12. It can be seen that almost all of the openings and steel plates are detected by our algorithms. Only in room number 1 two anchor plates haven't been automatically detected in the recorded data. This can be explained by poor brightness conditions in the corresponding thermal images due to uneven heating of the wall. The two anchor plates are located at the far left edge of a wall. They are visible in the thermal image for a human viewer but they stand out only slightly against the background, since the centre of the heat was located in the middle of the wall. A comparable situation can be seen in Figure 7 (B). Low contrast is a major obstacle for automatic object recognition.

In room number 2, on the other hand, two anchor plates that by means of the conventional manual data recording had been overlooked were discovered by our developed methods. Concerning the openings, the detection rate is close to 100 %. Only two openings in room number 2 couldn't be detected because they were hidden under cover plates during the time of our scans. For a qualitative assessment of the two approaches we also compared the sizes of the acquired objects. Those results show that especially the steel plates are well detected by our algorithms with an average relative area deviation of only 0.05 % compared to the

Room number	Object class	Number of objects – manual recording	Number of objects – automated detection
1	Steel plates Round openings Rectangular openings	12 6 5	10 6 5
2	Steel plates Round openings Rectangular openings	10 4 5	12 3 4

Figure 12: Quantitative comparison between manual and automated object acquisition.

manually recorded plates. For the openings, we reach an average relative area deviation of 0.52 %. This relatively large value can be explained, among other things, by shaded areas in our point cloud, so that the openings appear larger in some cases than they are. All in all, the developed methods show very good results, especially for the steel plates. Active thermography was successfully used to localize and record hidden anchor plates, even such that were previously unknown.

3.6 Concept for digital work planning

As part of a practical phase, the developed processes and technologies were evaluated in an operational environment and corresponding concepts for digital work planning were developed. Basis for the concept to be developed is the BIM model including all disturbing objects relevant to the clearance measurements. Furthermore, the results of our object recognition were prepared in tabular form, containing relevant metadata about the building surfaces to be released and their built in disturbing objects. Leveraging this combined digital information, a comprehensive approach for the digital planning of decontamination tasks and clearance measurements was designed. The planning concept was refined collaboratively within the project team and involved iterative adaptation based on findings from internal workshops with RWE, the operational partner. The results indicate that the integration of both the data and its graphical visualization enables more targeted and efficient processing of areas relevant for clearance. The visualization capability, in particular, offers significant added value compared to exclusively tabular data acquisition. Unlike manual recording, which may neglect the positional relationship of objects within building surfaces, the digital approach ensures spatial context is maintained, providing a more accurate and actionable foundation for subsequent work planning and execution.

4 Conclusion and future work

The aim of the research project ViSDeMe was to digitally record and visualize rooms to be released in nuclear facilities including its relevant trouble spots by means of BIM. Based on the created BIM model, a concept for digital planning of clearance measurements was to be developed.

Numerous objectives were successfully achieved during this project. Tests and experimental evaluations using various devices and methodologies have shown that active thermography is fundamentally suitable for the contactless detection of visually invisible anchor plates under the decontamination coating. During our investigations, appropriate cameras and heating devices were identified and validated through practical testing.

Further successes can be attributed to the research and development of algorithms for combining thermal imagery with laser scanning data, as well as AI-supported extraction of trouble spots and automated integration of objects into the building model.

The methods developed for the digitalization and partial automation of spatial data acquisition offer various technical prospects for success. Notably, active thermography has proven to enable a more accurate and reliable detection of coated anchor plates during the spatial data collection process. Furthermore, algorithms for the automated extraction and visualization of trouble spots are intended to make the planning of clearance measurements and decontamination work in nuclear facilities faster, more efficient, and safer for those involved in decommissioning. Overall, the digitalized process contributes to a significant increase in the efficiency of the entire data collection and decision-making during decontamination operations.

The field of spatial data acquisition can be supplemented and optimized by further processing steps. One way to improve the developed methods is to conduct scientific research into automated building modelling. The manual or, at most, semi-automated modelling of the building structures carried out in the ViSDeMe project is very time-consuming, which is why it would be of great interest to scientifically investigate and develop appropriate algorithms for automation. The detection and recognition of trouble spots also offers opportunities for further scientific research, particularly in extending applicability to objects relevant in other nuclear facilities. Moreover, enhancing the recognition accuracy and optimizing algorithms, for instance by reducing the required volume of training data, should be further investigated to maximize efficiency and scalability.

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Informed consent: Not applicable.
Author contributions: M. M.: Carrying out and evaluating the experiments to record the hidden anchor plates, data recording by means of laser scanning and active thermography, data evaluation, combination of laser scanning and thermal data, preparation of data for object recognition, creation of building model, BIM integration of trouble spots, generation of tabular outputs, validation of results with reference data from manual data acquisition. K. C.: AI-supported object recognition, training and optimization of the neural network, evaluation of object recognition results,

J. S.: definition of requirements for the developed processes, evaluating the experiments to record the hidden anchor plates, provision of reference data from manual data acquisition for validation, S. R.: evaluating the experiments to record the hidden anchor plates, concept for digital work planning. All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

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