OBJECT DETECTION IN A FRAMEWORK FOR AUTOMATED NUCLEAR WASTE CLASSIFICATION

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ABSTRACT

In this paper, we present a new framework for automatically triaging nuclear waste classification inside a nuclear cell for decommissioning. The process of decommissioning includes a large amount of human involvement for decision making, physical inspections and even lifting and relocating radioactive waste items. The current process accounts for risks like close human contact with radioactive material for extended periods of time, and errors based on operator knowledge rather than automated detection systems. The aims of this new framework are to reduce cost and speed up the sort and segregation process by providing a list of expected waste items, their location within the cell, and expected waste classification autonomously. We aim to reduce the reliance on the subjectivity of human decisions by capturing, formalizing and codifying their knowledge and experience and reducing the potential for errors arising from reliance on individuals. This paper focuses on the design and description of the framework and demonstration of the first step of the framework through a case study drawn from a mockup of a nuclear cell. We perform planar segmentation and cylinder detection on a point cloud dataset using RANSAC based methods to, firstly, distinguish indoor walls from objects for processing, and to detect objects and their estimated parameters.

Key Words: Cylinder fitting, Planar segmentation, Point cloud, RANSAC, Nuclear waste classification.

1 INTRODUCTION

Detecting and localizing radioactive sources is a necessity for safe and secure decommissioning of nuclear facilities. An important aspect for the management of the sort-and-segregation process is establishing the waste objects, spatial distributions and quantities of the waste radionuclides, their type, corresponding activity and ultimately classification for disposal. The data received from surveys directly informs decommissioning plans, on-site incident management strategies, and approach needed for a new cell, as well as protecting workforce and the public. Manual classification of nuclear waste from a nuclear cell is time consuming, expensive and requires significant expertise to make the classification judgement call which may introduce human reliability issues associated with subjectivity. Also, in-cell decommissioning is still in its relative infancy and few techniques are well-developed. As with any repetitive and routine tasks, there is the opportunity to improve the task of classifying nuclear waste using autonomous systems and if operators had the capability to draw on early indicators of waste classification by performing a triage of waste in a nuclear cell, it would make the sort-and-segregation process straightforward and faster, and it is expected to significantly improve operator safety and reduce the risk of human errors when identifying and classifying wastes. The main difficulty when dealing with radiation is that we cannot see it and nuclear structures often and inadvertently pose difficulties when accessing certain zones. Remote sensing platforms mounted with visual and radiation sensors presents an ideal solution to these difficulties, eliminating the need for human operators and ultimately making the process of data collection more systematic, accurate and repeatable. Developments have been made in the past 10 years in the fields of robotics, visual odometry, radiation detectors and radiation localization to create a system that remotely maps radiation onto a contextual map. This concept is not new and has been used for medical imaging, however few attempts have been made to map radiation in the environment in 3D.

In this paper we present an autonomous visual processing system as part of a framework designed to triage waste in a nuclear cell and automate sort and segregation of nuclear waste as part of the pretreatment process. We present a proof-of-concept system that simulates the infrastructure in a nuclear cell using a case study drawn from a nuclear facility. This case study data is a 3D LiDAR scan of a mock-up nuclear cell, which is mainly made up of pipes entering/exiting a vessel, with radiometric overlay and spectroscopic information included. This demonstrates the designs potential feasibility while satisfying real-world environments (highly contaminated and heavily shielded). The tasks for the laboratory-based demonstration are:

- Visual object detection, recognition, and localisation of mock-up vessel typically found in a nuclear cell, and mockup pipes entering/exiting the vessel.
- 6D pose estimation and estimation of geometric properties (such as length, radius, etc), mapped to an inventory of possible items within cell.
- Radiation source localization combined with gathered visual evidence to classify waste.

The main success factor of the framework is whether the waste item or part of the waste item is ILW (Intermediate Level Waste) or LLW (Low Level Waste) and can be made without any (or little) human intervention. The main contributions of this paper focus on object detection and classification and the developed algorithms to detect the key primitives in the representative data set.

2 RELATED WORK

In this section we review state-of-the-art robots that fuse radiation and scene data and perform visual waste classification followed by a discussion of their applicability, then describe the waste treatment process at present and outlining the benefits of performing a triage of classification of waste.

2.1.1 State of the Art Mobile Robots in Nuclear Environments

Varieties of robots have been constructed for various uses within the nuclear sector, and there seems to be no standardized method to measuring and sampling using robots. The European Reference Network for Critical Infrastructure Protection (Erncip) established the Thematic Group on Radiological & Nuclear Threats to Critical Infrastructure which considers issues such as emergency preparedness, benefits and challenges of robotics and remote expert support, and communication to the public [16]. To summarize, the group believes robotics could prove useful in radiation applications, however the process in which we collect and manage data would need to be much more regularized. For example, Lawrence Berkeley National Laboratory coined the "Scene-Data-Fusion" concept which is a framework enabling the mapping of gamma-ray emissions and dose rates from a freely moving platform, tried a tested on a hand-pushed cart and aerial and ground robots. They used a Microsoft Kinect RBG-D camera and LiDAR combined with Simultaneous Localization and Mapping (SLAM) algorithms, GPS and inertial measurement units (IMU) to build a more robust 3D contextual model of the scene. Their framework resulted in faster and more accurate measurements of 3D environments with real-time observations and almost instantaneous feedback [1] [2]. RGB-D 3D modelling is less expensive than LiDAR and can provide details of the scene which lack indentations, making it a popular option [3]. [4] also used an RGB-D camera to estimate distances between a portable gamma-ray camera and source through triangulation and to decide if a source is behind or in front of objects. Photogrammetry is a form of visual odometry which overlaps multiple images of the environment to build a 3D model of the scene, and [3] exploited this method for their system which they used inside the Fukushima Daiichi Nuclear Power Station (FDNPS). A 3D radiation model was integrated with a 3D model of the environment using photogrammetry and then imported the data to a virtual reality system [5]. They developed a 3D reconstruction technique where Compton cones were projected onto a 3D space divided into voxels and took the sum of all the back projected Compton cones to achieve the 3D spatial distribution of radiation. In [6], they developed a system to autonomously map radiation in 3D in tunnel environments using aerial vehicles, and, in a similar fashion, [7] used their own custom-made UAV to capture data near Fukushima, and overlayed a 2D radiation map onto an elevation model produced by a range finder. However, this method experiences difficulties with ambiguity of source location. In [8], they discuss their Continuous Autonomous Radiation-Monitoring Assistance (CARMA) robot- a robot designed to perform radiological inspections of floor areas of nuclear environments which can detect alpha, beta and gamma radiation. A similar robot, the RICA (Robot d'Inspection pour Cellules Aveugles) robot, was developed by the French Alternative Energies and Atomic Energy Commission and Cyberia in France and has been deployed into decommissioning nuclear sites for gamma inspections [9].

2.1.2 Visual Waste Classification

Currently object nuclear waste classification is in its infancy. It is performed manually and without the inclusion of radiometric data, however some novel solutions have been proposed in recent years to automate this process for visualizing nuclear waste objects. In [10], a vision system that automatically classified waste objects using their 2D shape representation from a single monocular camera using a 'random forests' learning classifier was proposed and showed promising results. [11] performed RGBD-based detection and categorization of waste objects for nuclear decommissioning using a weakly-supervised deep learning approach on videos with effectiveness. In [12] they demonstrated the use of a reconfigurable rational agent-based robotic system using a time-of-flight camera, and high-level rational agent-based decision making and control framework. They identified cylindrical objects within the scene and estimated their parameters using Random Sample Consensus (RANSAC). Alternatively, some studies have shown success in 3D scanning data including creating a VR model [13], building a 3D CAD model [14] [15] and using laser rangefinders and conventional cameras [16].

2.1.3 Discussion

The above indicates there has been considerable progress in the field of robotics and visual odometry and mapping providing better navigation and localization. Similarly, a breakthrough is seen in the field of radiation detection, localization and characterization in 2D and more recently 3D. The integration of visual and radiation systems has brought us one step closer to the real-time visualization of radiation which will enable safer and more cost-effective decontamination tasks in nuclear facilities. Despite the amount of work on obtaining 3D radiation images as discussed, little exists in deriving benefit from them e.g., the decision support for monitoring nuclear facilities, object detection and determining object characteristics from visual maps, and automated classification of radioactive waste in terms of high/intermediate/low level waste. There is scope for further developments in these areas, with object detection being addressed in this paper.

2.2 Nuclear Waste Classification

Nuclear power plant decommissioning involves dismantling the infrastructure within a nuclear cell and sorting it into different categories of waste. These UK defined categories [17] are:

- High Level Waste (HLW): waste with high radiotoxicity, high heat output ($<2kWm^{-3}$), high β/γ and significant α.
- Intermediate Level Waste (ILW): waste with intermediate radiotoxicity, low heat output ($>2kWm^{-3}$), intermediate β/γ, and significant/insignificant α for long/short lived radionuclides respectively, and more than 4 GBq/te alpha and 12 GBq/te β/γ.

- Low Level Waste (LLW): waste with low radiotoxicity, insignificant heat output, low β/γ, significant/insignificant α for long/short lived radionuclides respectively, and less than 4 GBq/te alpha and 12 GBq/te β/γ.

The key boundary is the LLW/ILW boundary of 4 GBq/te alpha and 12 GBq/te β/γ and is the boundary used for classification here.

Currently, the waste is classified manually and requires significant man-power and various steps. Protective equipment for each operator is needed for the sort and segregation process and there can only be a few hours of productivity due to the nature of the working conditions. Once dismantled, a mixture of waste objects is placed into a container for transit to the waste treatment cell, and it may not necessarily be known exactly what is in each container. There are tools and robots to lift it from the container while avoiding damage to surrounding areas, and then trained operators with many years' experience are required for a knowledge-based approach to classify waste using radioactivity and physical characteristics. Once this process has been carried out, decisions are made to sort and segregate the waste into their grade classes, which requires moving the waste to the correct containers for disposal, while making the best use of space in each container. Oldbury Site typically sorts 2-6 drums per day, where the latter end of scale is achieved when the radioactivity is homogenous throughout and the objects are similar, and the lower output when the waste was very mixed. Performing a triage before dismantling would speed up the sort and segregation process by create an inventory of expected waste items and expected classification. A triage would also define waste objects and their location within a cell and then transfer this data to robots to dismantle automatically, eliminating the need for human operators [12] [18].

3 METHOD

We have developed a framework to triage nuclear waste in a nuclear cell, and the high-level process is outlined in Fig.1. To begin with we must collect visual and radiological data. In this instance, for proof of concept, we use a case study of a mock-up vessel and radioactive source located within the scene. A point cloud is generated using a FARO Focus device with 2D radiometric source overlay, generated by RadScan 3D gamma imaging system [19]. On this point cloud we perform object detection, initially focusing on cylindrical objects since pipework is significant in nuclear cells and indeed any industrial site. The approach can be extended to other commonly occurring primitives such as spheres and cubes. This is in preparation of characterizing the point cloud data by locating the objects within the scene and estimating the dimensions, material, degradation and mass of the objects detected in order to feature match them to an inventory of possible items found in that nuclear cell. Many items in nuclear cells are one-offs, have limited or poor drawings available, or have been modified since installation and have complex interiors which often and inadvertently pose difficulties when accessing certain zones and identifying waste remotely. Hence, this may require expert input to feature match objects. Radiological mapping is similarly to facilitate characterization of the nuclear cell in terms of radiation fields, including type of radiation, activity, and location within the nuclear cell. The two maps are merged, providing a more complete scene of the nuclear cell. Lastly, we look to combine the evidence from the fused data set (object parameters and location within the point cloud, and radiation source location and activity) to reveal the classification of the waste in Bq/kg thus enabling better decision making and monitoring for in-cell decommissioning. In this paper we address 3D mapping from Fig. 1, specifically object detection and characterization.

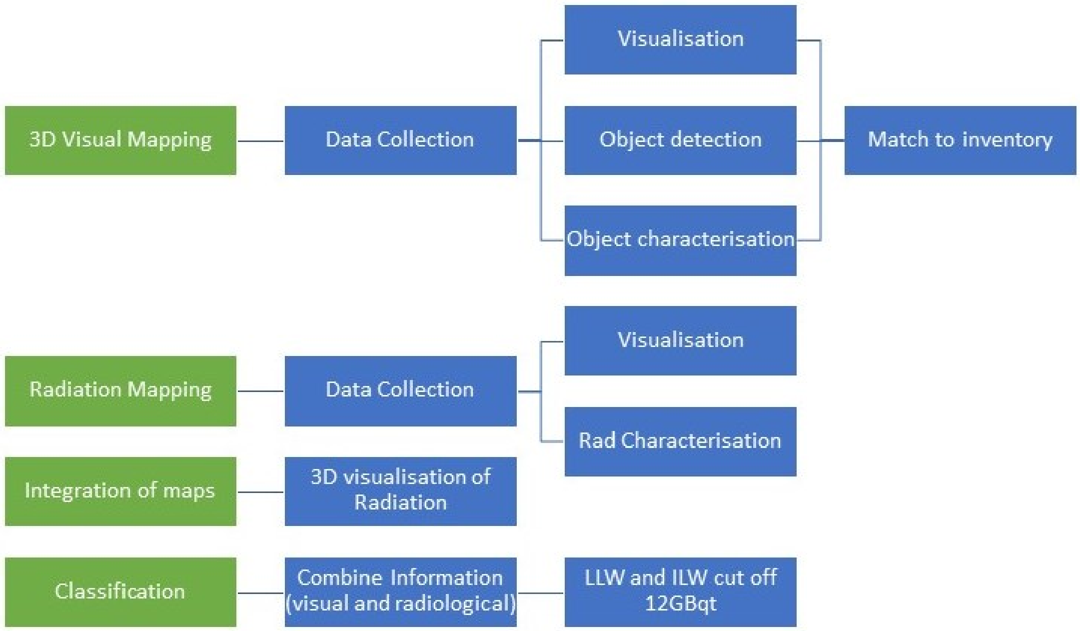

Figure 1 Proposed system for triage of classification of waste.

4 OBJECT DETECTION RESULTS AND DISCUSSION

4.1 Cylinder Detection

The first step of the new framework to triage waste inside a nuclear cell involves determining the waste's physical/visual characteristics and establish what it is. Object detection will focus initially on cylindrical objects, since pipework is significant in nuclear cells and indeed any industrial site, and predictions will be made on the geometric parameters. A Faro Focus Laser Scanner was used to create a point cloud of inside the mock-up cell, and initially we use the M-estimator SAmple Consensus (MSAC) algorithm, which is a generalization of the RANSAC estimator [20], to find the walls of the cell and extract them as shown in Fig.2 (left). This is to segment the objects within the cell from the walls containing them, as shown in Fig.2 (right). The algorithm chooses points at random and makes the assumption that these points lie on a plane. Then it decides if it really is a plane or not by inspecting the surrounding points, since there will be a lot of other points that lie close to that plane. It accepts the largest consensus set and those points are allocated to the first plane in the scene [21]. Then, after removing the points allocated to plane 1, the algorithm searches for the next largest consensus set, and, iteratively, finds all the planes in the point cloud. Certain thresholds are set and only points that lie within this threshold are used for planes. We apply the distance to model threshold where only points within this is a planar fit, and similarly we apply a threshold based on angular deviation between the normal and inlier points of the plane. Setting a region of interest also minimizes wrong planar fits. Then, we use the MSAC algorithm again to define and estimate a model for 3D cylinder segmentation, using additional orientation constraints specified by a 1-by-3 orientation vector, and distance to model threshold, to do so. Again, setting a region of interest also minimizes wrong cylinder fits. The detected vessel and its estimated parameters are given from the model cylinder as shown in Fig.3. Then, we extract the first cylinder from the remaining point cloud and repeat the process to find the next cylinder in the point cloud (the mockup pipe) as shown in Fig.4 (left).

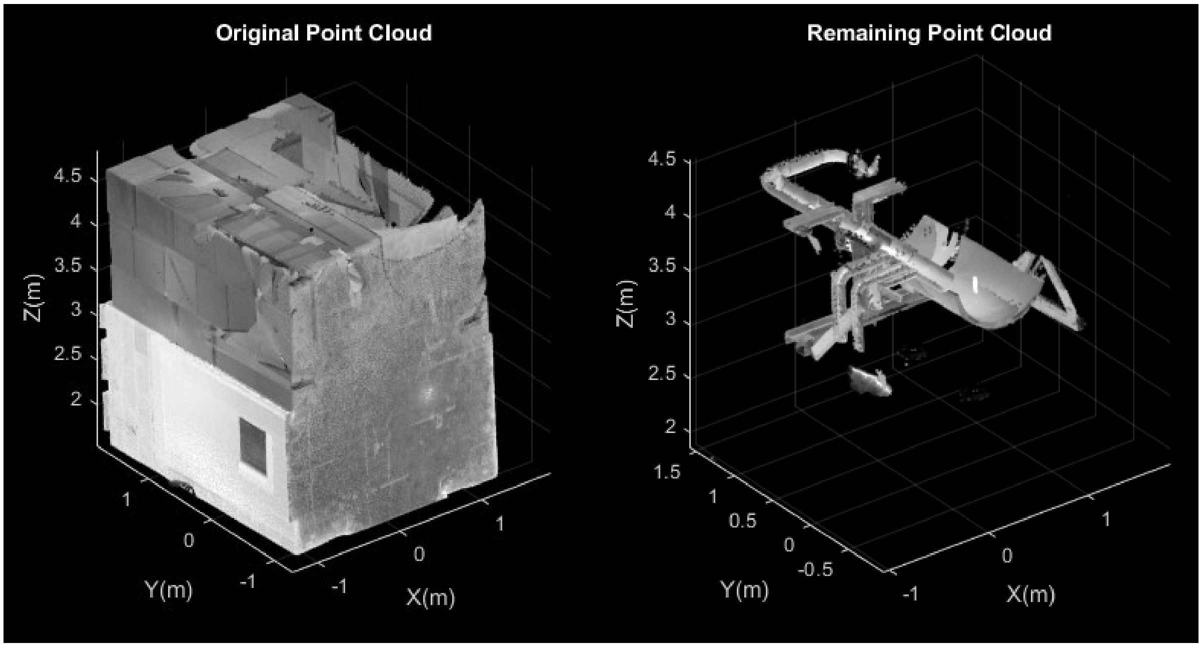

Figure 2: Original point cloud (left) and remaining point cloud (right) with walls of cell extracted revealing the mock-up vessel and pipes.

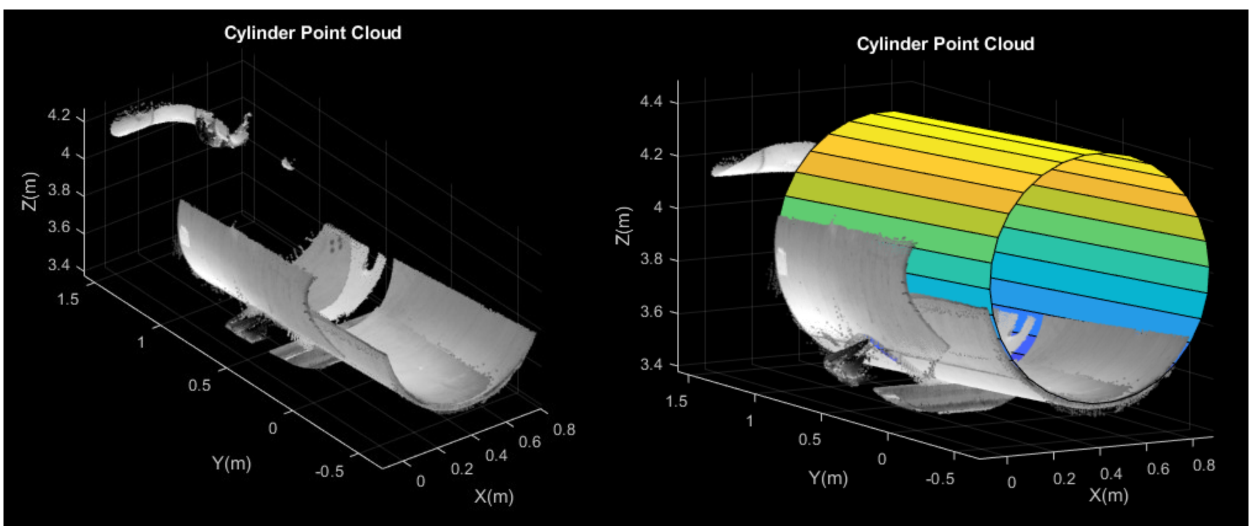

Figure 3: Detected cylinder from remaining point cloud (left) and model cylinder (right).

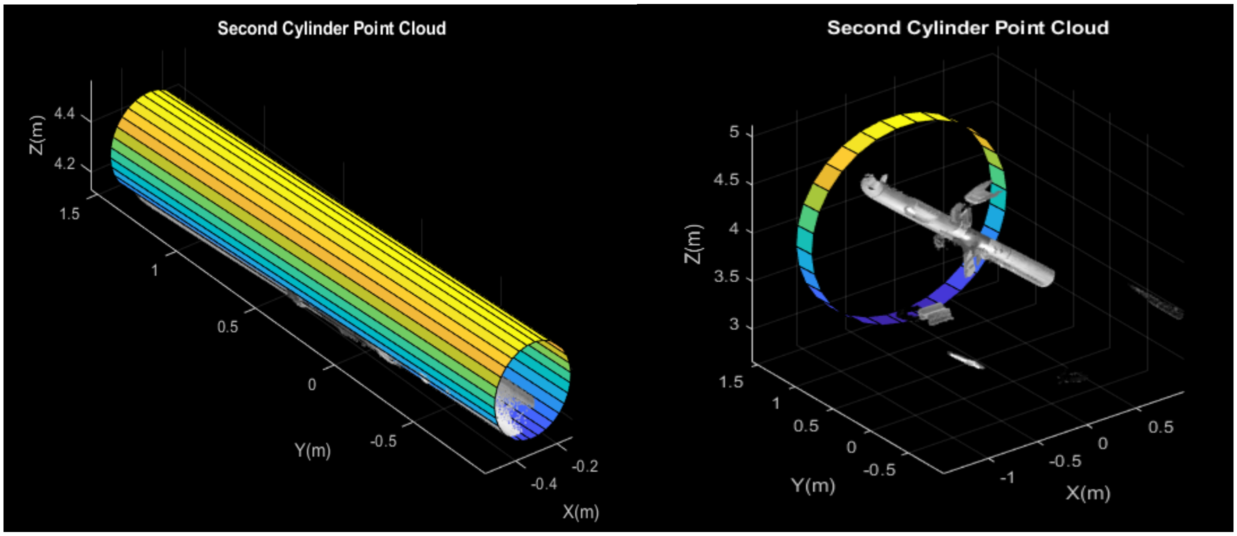

Figure 4: Second cylinder model extracted from point cloud, good fit (left), bad fit (right).

We choose MSAC for its simplicity and convenience, and it is considered more efficient than other methods of planar segmentation, like Hough transform [22]. This method has its merits works as a proof of concept for the framework, although it has disadvantages. Sometimes the MSAC algorithm can generate specious planes within indoor environments such as ours [23], and this is due to the nature of the RANSAC algorithm. We have occasionally come across this problem here and subsequently look to other methods to build a more robust system, such as the method outlined in [24]. The RANSAC based cylinder fitting method requires tuning of initial thresholds that need pre-selected by the user, which may also vary for different point cloud inputs. We have found that the algorithm tends to fit a good model for the first cylinder in the point cloud, but sometimes does not produce a valid solution thereafter for other cylinders present. We can visually see that it is not a good fit, as shown in Fig.4 (right), however we need a metric to determine a “good fit” and a “bad fit”. **This could be done initially by referring to an inventory of materials and their parameters. An important feature of this framework is how the system makes most decisions, and for the next step the system must map expected parameters extracted from the cylinders in the point cloud to real parameters from common objects found in a nuclear cell. We would autonomously check cylinder fitting validity by constraining the cylinder search to radius size and only cylinders that satisfy this constraint would go to the next phase of validation, as cylinders detected may still be specious even if they satisfy the radius constraint. An adaption of that seen in [25] may be adopted to verify cylinder fitting by comparing the cylinder model to the points around the detected cylinder. An extra step towards a more robust system is to implement a stopping criterion so that the algorithm finds all cylinders/objects in the point cloud and does not force cylinder fittings and overfit the data. For this we could relate back to the two phases of validation and when we have a few “bad fits” and accuracy decreases, the algorithm stops. In the interest of a robust, autonomous system that estimates object parameters accurately, future research may include the adoption of other cylinder detection and fitting methods, and many methods have been investigated, including Hierarchical segmentation [26], Hough-based methods [27], Gaussian sphere [28].**

5 CONCLUSIONS

We have presented a new framework for an autonomous approach to triage a nuclear cell for decommissioning. Moreover, we have shown a proof-of-concept example of the first feature of this framework, which is detecting the main primitive in a mock-up nuclear cell. We have estimated the location and radii of cylinders in the point cloud with success, using point cloud data of a mockup cell and implementing RANSAC based methods to conduct planar segmentation to separate indoor walls from waste objects for processing, and to detect the vessel and pipes via cylinder fitting.

We continue to work towards a more robust and autonomous system for object detection, carrying out validation steps, and a stopping criterion to differentiate good cylinder fits and bad ones. This is in preparation of the next step which is to match estimated objects within point cloud to actual objects, and from this we can determine characteristics like type of material and mass etc. which otherwise we cannot determine from point cloud alone.

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