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HUMAN-ROBOT COLLABORATIVE WORKFLOW FOR REMOTE DECOMMISSIONING AND DEMOLITION

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Abstract: The demand for new deconstruction and demolition approaches is escalating as structures built in 20th century development booms approach their end of life. Rehabilitation and careful deconstruction approaches are increasingly economically and environmentally motivating. For example, in Ontario, Canada multi-decade efforts to decommission nuclear power plants are challenging teams of engineers, researchers, venders, and laborers. In these hazardous scenarios, classical heavy demolition approaches are not an option, and the asset owners find that the costly development of novel workflows and technologies to plan and undergo these deconstruction operations is the only option. These trends present construction researchers with an opportunity to develop technologies and processes to achieve deconstruction project goals with improved efficiency, certainty, and safety. This paper presents a modular framework for remote human-robot collaboration for waste management in decommissioning and demolition. The proposed framework includes robotic platform reality data capture, scan processing (e.g., segmentation, surface estimation, and recognition), gamified waste packing in virtual reality (VR), and packing plan execution. A comprehensive review of state-of-the-art technologies of each module is explored from the standpoint of applicability to deconstruction and demolition. Then, an autonomous robotic platform for reality data capture is presented. A reconfigurable semi-automated VR platform for waste packing optimization is presented as an example of this process workflow in the context of remote deconstruction and demolition. Finally, the ideas of robotic packing plan execution are discussed as future work.

Keywords: 3D scanning, optimization, 3D irregular packing problem, virtual reality, robotics, SLAM, gamification, human-robot interaction, robotic bin packing, waste management, nuclear power plant

1 INTRODUCTION

Recent technological advancements such as enhanced three-dimensional scanning sensors, low-cost sensors, and an open-source software community have increased the feasibility of using robotic platforms in real-world applications. Historically, this research area has flourished around structural inspection and, more recently, construction. However, deconstruction and demolition (D&D) are an important part of the infrastructure lifecycle due to the unique challenges they present, including difficult-to-reach areas, unknown materials, BIM/as-built discrepancies, and hazardous materials. This paper details a remote human-robot collaborative modular framework for D&D activities, with a focus on waste packing optimization in nuclear facility decommissioning. The proposed framework includes a robot platform for rapid inspection, a three-dimensional model for data storage and demonstration, and a mixed reality platform for waste segmentation and packing optimization. To demonstrate this workflow in the context of remote decommissioning and demolition, an autonomous robot platform for rapid data collection and a reconfigurable virtual reality platform for waste segmentation and packing optimization are applied to two case studies.

2 LITERATURE REVIEW D&D of nuclear facilities

Globally, there are currently 443 nuclear reactors in operation as of May 13, 2021. 67.5% of the current operational nuclear reactors are older than 30 years, and around 25% are older than 40. According to IEA, around one-quarter of the current nuclear capacity in advanced economies is set to be shut down by 2025, and around 200 commercial reactors are to be shut down by 2040 [1,2]. The D&D of nuclear power plants often involves activities associated with the removal of fuel, safe storage, decontaminating structures and components, demolition of the building, and management of resulting waste [3]. There are two main decommissioning strategies: Immediate Dismantling (or Early Site Release/'Decon' in the USA) and Safe Enclosure ('Safstor') or deferred dismantling. In immediate dismantling, final dismantling or decontamination activities can begin within a few months after the facility is shut down. In the Safe Enclosure ('Safstor'), the nuclear plant is kept in storage with surveillance for an extended period after all fuel is removed from the reactor. The plant can be dismantled once radioactivity has decayed to lower levels and the safety risk to workers is substantially reduced [4].

Protecting and minimizing the impact on workers and optimizing disposal waste management are two of the core objectives of the D&D process [5]. The D&D of NPP presents workplace hazards since it exposes workers to hazardous environments and materials. Integrating remote robotic technology into the D&D workflow frees workers from physical contact with radiation environments and materials. It has been proven to be beneficial for protecting and minimizing the impact on workers. Using robotic technology to perform internal inspection, segmentation, and demolition of radioactive components, radioactive waste packing, and extensive cleanup activities can significantly reduce worker exposure and maximize worker safety. The D&D process also significantly grows radioactive waste inventory. The ability to efficiently and safely treat and dispose of radioactive materials has become an essential prerequisite for the nuclear facility D&D process [6]. Proactively managing the disposal of radioactive waste (L&ILW) could potentially save millions of dollars in D&D costs.

2.1 Robotic data capture

Research has demonstrated that robotic mapping systems, including those based on SLAM (Han 2015, Charron 2019, Phillips 2019, Palomer 2019) and structure from motion (SFM) (Lattanzi 2015, Khaloo 2018, Zhao 2021), are effective in civil engineering infrastructure applications. Robotics, computer vision, and data analysis techniques are usually adapted from their respective core research communities. Robotic platforms have been employed for tasks such as 3D scanning, mapping, automated defect detection, and disaster relief for example. Overall, civil robotics applications have advanced immensely over the past 10 years, however, they often lag a bit behind dedicated robotics work. This is likely due to the startup costs a civil lab faces in order to dedicate personnel and funding to developing the robotic platform.

Recently, private companies have brought sophisticated reality data capture packages to the market for relatively affordable prices. These offerings combine sensors such as light detection and ranging (Lidar), cameras, and inertial measurement units (IMU) with self-localization and mapping (SLAM) software to produce colorized point clouds of the scanned areas. These packages are often designed to mount on robots or handheld. These solutions greatly increase access to robotic data capture for scientists who seek to perform robotic scanning at a reasonable cost with a dramatically reduced learning curve. As a result, the opportunity for applications of robotic data is at an all-time high.

2.2 Object recognition and segmentation

There has been a proliferation in laser scanners since they have become more accurate and cheaper, which has found various applications such as autonomous driving, aerial scanning, inventory management, augmented reality, and robotics. For most of these applications in the industry, point clouds are one of the best ways to represent a three-dimensional object in virtual spaces, allowing measurement accuracy, bird's eye view of the site, and accessibility to the site from a computer. However, a point cloud has limited visual

data if it is not analyzed to detect objects or segmented by types of objects on-site, and its manual segmentation can be tedious. Point cloud analysis to find objects faces multiple challenges: sparse input, unordered geometry, variable point density due to nonuniform point sampling, noise due to minor vibrations, occlusion, and surface reflection [7]. The increase of scan data in point clouds format has generated greater interest in machine learning research to tackle the problems and generate detection and segmentation with higher accuracy and speed, empowering essential knowledge of the current infrastructure when decommissioning. There are multiple methods that neural networks use to do object recognition and segmentation, such as direct point cloud analysis, voxel, pixel grouping or volumetric pixel-based structures, hybrid point voxel structures, and point group feature analysis.

Direct point cloud analysis takes the points as input and outputs an object label or a segmented point cloud [8, 9, 10, 11]. The benefit of direct point cloud analysis is its higher accuracy of high-density point areas and linear features while using the points directly, which lowers the overhead preprocessing of points and leads to 58.8% mean Intersection over Union (mIoU) in Semantic KITTI benchmarks. [12,13] However, the larger the point cloud, the more process-intensive it is to process all the points in the point cloud. The volumetric pixel approach is gaining interest to circumvent overwhelming processing times [13,14]. The pixel grouping or volumetric pixels voxel-based point cloud analysis takes a point cloud and generates a regular eulerian grid coordinate system converted into raster volumetric pixels. The voxelization of a scene allows for a coarse view and faster processing of extensive point cloud data removing detail in favor of a more significant analysis of geometric features.[15,16] Recently, to maintain both speed and detail of the point cloud, research into voxel-point hybrid has proven optimal for object detection and segmentation[17, 18]. With this approach, we can get state-of-the-art segmentation results at 70.8% mIoU [19]. However, since most datasets have been generated for autonomous vehicles[13] or house and office spaces [20, 21], there is a need for industrial point cloud datasets to boost the analysis of NPP structures for asset management and decommissioning.

Understanding the current limits of the state-of-the-art and data availability, we opt to manually generate the segmentation of the proposed objects to be packed and contained while keeping an eager eye to automatic industrial NPP point cloud segmentation and object detection in the near future.

2.3 Decomposing and packing optimization

Decomposing and packing optimization of structure in decommissioning and demolition is an application of packing optimization problems. Packing optimization problems consist of arranging objects into one or a set of containers to optimize one or multiple objectives, such as maximizing the packing efficiency or minimizing the container's volume. The primary constraints of packing optimization problems are that the objects must not overlap and are entirely contained inside the containers [7]. The specific packing problem discussed in the paper involving packing optimization of the 3D irregular-shaped object can be referred to as 3D irregular cutting and packing (C&P) problems. There is a growing interest in 3D irregular C&P problems because of their broad applications and potential impacts in a multitude of industries. Three-dimensional irregular C&P problems can generally be applied both to traditional applications such as improving transport efficiency of building parts or pre-fabricated construction assemblies and emerging applications in civil engineering such as 3D printing in construction and facility waste management [8].

Researchers have proposed different solution approaches that can be classified into three categories: heuristics, metaheuristics, mathematical programming. Heuristics are rules of thumb used to guide, discover and reveal possible plausible but not necessarily, the correct solutions to solve a problem [9]. For instance, the most popular heuristic algorithm for 3D irregular packing problems is the Bottom-left-front algorithm, which packs pre-ordered objects one by one at the most bottom left front corner of the container's available space [10,11]. However, heuristics are generally relatively fast but can only explore limited packing configurations. Metaheuristics are combinatorial optimization techniques that provide guidelines to develop a process capable of escaping from local optima and finding a good solution [12]. Genetic algorithm

(GA), simulated annealing (SA), Tabu-search are some of the metaheuristics applied to the 3D irregular packing [13–15]. Metaheuristics explore more potential configurations resulting in significantly more computational time. Researchers have also tried to formulate the 3D irregular packing problem using

mathematical programming. The most successful approach is based on the phi-function, which provides a tool to mathematically describe non-overlapping and containment constraints [16,17]. Heuristics are then applied to reduce the problem into a sequence of subproblems with smaller dimensions and fewer constraints that can be solved using a nonlinear programming solver [16]. The drawback of the phi-function-based mathematical programming method is computationally costly and currently futile for arbitrary shapes. The 3D irregular cutting and packing problems are Np-hard [18]. In other words, the expected time to find an optimal solution is likely to increase exponentially as a function of the number of inputs [19]. None of the existing 3D irregular packing problem algorithms can find a globally optimal solution in polynomial time [11]. Overall, finding a suitable solution through autonomous approaches is currently computationally expensive and time-consuming.

When dealing with D&D of NPP, large reactor components or nuclear facilities are considered. The segmentation and packing optimization need to decompose large components or structures into packable parts. This problem is referred to as the decompose-and-pack problem or decomposing and packing problem, which is a variation of the irregular 3D packing problem. The decompose-and-pack problem not only requires optimizing the packing of parts but also seeks to decompose components or structures into packable parts, which can then be efficiently packed [20]. The coupling of decomposition and packing makes the solution search even harder. Vanek et al. [13] propose an algorithm that converts the 3D model into a shell, which is then divided into segments. The packing part follows the ensuing process. A placement heuristic that minimizes the waste parts between segments is used to build packing configurations. Tabu-search is then used to optimize the packing sequence. Yao et al. [21] propose an iterative process between decomposition and packing to find the decomposition with high qualities that produces minimum packing volume.

3 WORKFLOW OVERVIEW

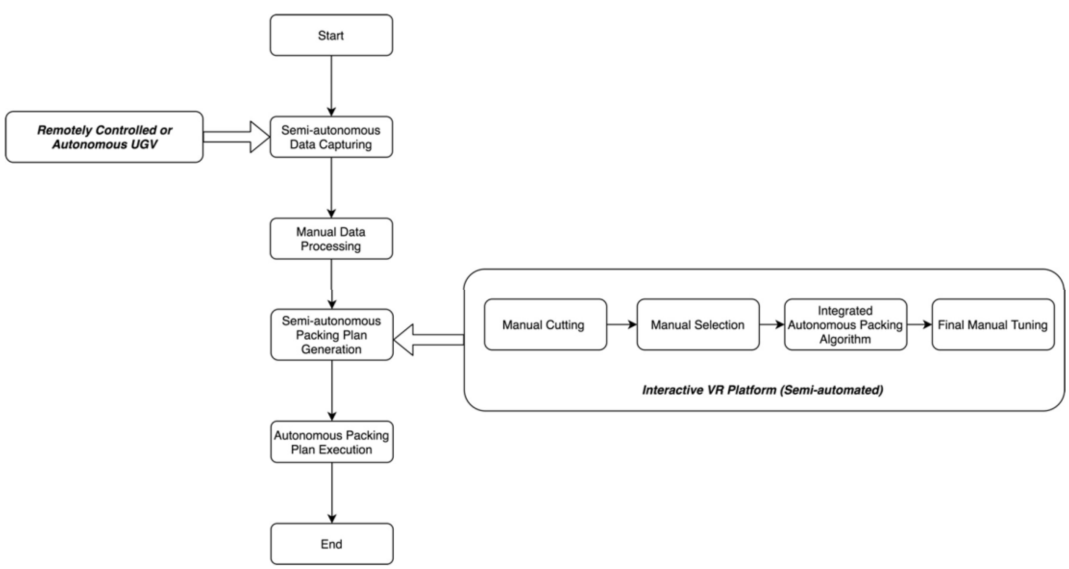

Figure 1: The overall human-robot collaborative workflow

The overall proposed workflow, an aggregation of robot inspection, human planning, heuristic algorithm, virtual reality, and robot execution, is outlined in Fig. 1 and discussed in the following sections. This workflow performs human-robot iterative waste packing optimization in remote decommissioning and demolition to minimize the final waste volume and ensure the effectiveness and safety of the process.

Data capturing (Robot inspection). The first step involves capturing the initial data for the waste after the demolition process using a remotely controlled or autonomous unmanned ground vehicle (UGV). The UGV, equipped with synchronized and calibrated sensors (e.g., GPS, IMU, Cameras, Lidar), can continuously track and generate a 3D map of the surroundings with simultaneous localization and mapping (SLAM) software. Implementing UGV in data capturing can increase the efficiency of the process and vastly decrease the risk of human exposure to hazardous environments.

Data processing. Once the 3D map is acquired, the second stage is to segment the target waste objects from the noisy environment and convert the corresponding raw point cloud data into mesh files. The purpose of having mesh files of the waste objects is to facilitate effective manipulation in the following packing configuration planning process. In this regard, a point cloud requires preprocessing to remove outliers and noise. Then, objects can be segmented and converted into a mesh format manually using the screened Poisson surface reconstruction algorithm in MeshLab [22].

Decomposing and packing planning. The decomposing and packing planning includes information about the structure's decomposition, the initial position, translation, and rotation of each decomposed component (here, a part is defined as a decomposed component of the structure). The optimal decomposing and packing planning process occurs in three stages on an interactive virtual reality (VR) platform. The first step requires the user to virtually assess the structure and, if necessary, decompose it to increase packing efficiency later. The decomposition strategy has an effect on how well the components can be packed. The user then initiates the second step, which is the execution of the autonomous packing algorithm. The autonomous algorithm is developed using metaheuristics to provide initial packing configurations that can be quickly fine-tuned to potentially achieve high packing efficiency. The final step enables humans to adjust the packing configuration as needed to achieve optimal decomposing and packing plans. The user receives immediate feedback on the current packing configuration via the virtual reality user interface in the virtual reality environment. This step leverages human instincts, strategic thinking, and the VR platform's ability to trial and error various packing configurations until the user is satisfied with the result. The packing configurations created in virtual reality planning scenarios can be executed later by humans or robots.

Packing plan execution. With the information depicted in the pre-planned packing configuration, a robot arm can replicate each part's trajectories and execute the packing plan in the physical environment with minimal human supervision.

4 DATA CAPTURING USING UGV

A UGV equipped for robotic data capture in deconstruction environments is presented.

Figure 2: UGV data collection platform

The mobility of the proposed solution is provided by a Clearpath Robotics Husky, an off-the-shelf platform that offers ruggedized differential-based steering and sensor payload support. With its large wheels and high torque, the Husky excels in mobility in unpredictable circumstances for a wheeled robot. However alternative methods such as dog-like robots are suited to construction and deconstruction environments as well.

The sensing kit for the proposed platform includes inertial multi-sensors (IMU), global positioning system (GPS) receivers, and a combination of cameras and light detection and ranging (LIDAR) for vision and ranging measurements. Each sensor type has strengths and weaknesses. For example, GPS measurements do not suffer localization drift, but offer low accuracy and fail when GPS coverage is occluded such as indoors.

Figure 3: Core sensing kit

A 360 degree horizontal field of view is proposed for coverage and to minimize data collection time. A 360 degree Lidar sensor positioned horizontally is sufficient to achieve this field of view for 3D range data. For image data, a combination of wide field of view (WFOV) camera lenses and a modular mounting plate are utilized to achieve a 360 degree field of view. In experimentation, WFOV lenses with greater than 180 degree coverage positioned in opposing directions are sufficient. However, WFOV lenses introduce greater image distortion, so a standard field of view camera is included for SLAM performance. The modular mounting plate allows a camera arrangement to be optimized to each data capture task. Finally, the handheld data capture sensor kit includes an IMU positioned closely to the Lidar frame of reference. Time synchronization refers to the centralization of time measurements required for analysis and data fusion of the sensor outputs. An Arduino-enabled Teensy 3.6 microcontroller is utilized to introduce a one-to-many relationship between the reference clock and the sensors. This prevents the tangled web of sensor connections resulting from sensor-to-sensor synchronization approaches. The microcontroller is capable of interfacing with any synchronization scheme that a sensor manufacturer implements. Calibration describes the process of determining intrinsic properties of each sensor, and the extrinsic transformations between sensors. Intrinsic calibrations are essential for relating sensor measurements to real world geometry and removing distortions introduced by sensor hardware.

Simultaneous Localization and Mapping (SLAM) refers to the algorithms and software a system uses to estimate the geometry of its surroundings and its position. In the proposed approach, the state-of-the-art open-source SLAM framework LVI-SAM is utilized. While the map produced during the SLAM process is often utilized as the final inspection map in literature, we propose decoupling the map building process from SLAM. Our framework allows any number or type of volumetric data to be combined into a single map, with noise removal and scan cropping techniques available at various stages along the map building pipeline. In the proposed approach, the globally consistent trajectory output from SLAM is used alongside visual and lidar odometry to interpolate high-rate locally consistent pose estimates at the time of any sensor reading. This sensor fusion approach improves inspection map quality, outperforming raw SLAM maps in surface density (point density), roughness, and planarity metrics in field testing.

Table 1: SLAM vs inspection map performance metrics

	SLAM Map	Inspection Map
Surface Density (points per 0.25m radius circle)	337.124	**31986.9**
Roughness (unitless)	3.637e-2	**2.576e-2**
Planarity (unitless)	4.686e-1	**6.546e-1**

5 VR DECOMPOSING AND PACKING PLATFORM Decompose mode

There are two modes available on the VR decomposing and packing platform: decompose mode and pack mode. After importing the structure into the VR packing environment, the user can switch to decompose mode and manually cut it into smaller pieces that will fit inside the containers and possibly be packed more efficiently. The decomposing feature is based on the Unity3D asset Mesh Slicer [23]. Mesh Slicer slices meshes with the aid of a cutting plane. As illustrated in figure 2a, a semi-transparent square indicates the cutting plane in the virtual reality environment. Given that a plane in Unity is an infinitely flat surface that divides three-dimensional space in half, it is possible to affect parts of objects that do not visually intersect with the cutting square (see figure 2b), which becomes problematic when slicing non-convex shapes, particularly large structures. The problem was resolved by rebinding ineffective cuts with Fixed Joint feature [24]. Additionally, large structures can be shrunk to meet user requirements in order to make them more manipulable in the VR environment.

a) b)

Figure 4: Screenshots of the decompose mode. (a) The semi-transparent square indicating the cutting direction. (b) Unwanted cuts being generated using Mesh Slicer

5.1 Pack mode

Once the structure has been decomposed, the user can switch to pack mode and initiate the autonomous algorithm to generate an initial packing configuration, which can then be fine-tuned (manually) if necessary, for example, to increase efficiency and adhere to constraints that have been exceeded. The integrated autonomous packing algorithm is based on Genetic algorithm (GA) proposed by [25] approach to search solutions with good packing sequences and rotations for each object and is implemented in C# using the GeneticSharp library [26], which includes built-in classes for standard GA functions. The autonomous algorithm is described in detail in [8].

Bottom-left-front (BLF) algorithm is implemented as the placement heuristic to convert each solution to the packing configuration by placing parts one by one at the bottom left front available space in the container. Each part starts from the right-up-back corner of the container and moves sequentially along negative z/y/x direction incrementally towards the bottom-left-front corner until it comes in touch with the container boundaries or previously packed parts, as illustrated in Figure 3. BLF will iterate through the three directions until no further improvement can be made.

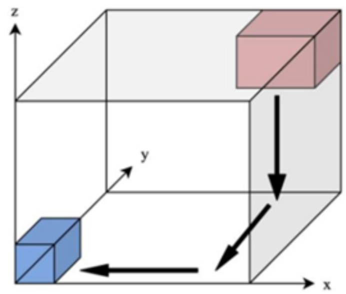

Figure 5: BLF placement heuristic

After being proposed by the autonomous packing algorithm, an initial packing configuration can be fine-tuned manually. Fine-tuning activities available to the user include adjusting the parts' orientations and locations in the packing configuration, remove parts, or add new parts to the packing configuration.

5.2 Packing configuration evaluation

There is a user interface canvas in the VR decomposing and packing planning platform. The following metrics are used to evaluate the packing configurations:

Packing efficiency. Packing efficiency is calculated as the ratio of the container volume occupied by the parts and the total container volume, which in other words, is the space utilization of the container. Packing outcome efficiency is directly related to the decommissioning cost, especially in nuclear applications where the cost of waste containers can be quite high and not re-usable.

Weight and radiation limits. Weight and radiation limits are constraints imposed on packing configurations to meet the transportation requirements and the waste acceptance requirements of storage facilities and repositories in nuclear waste packing and storage applications [27,28]. Violation of the two limits results in rework that wastes efforts and time, resulting in reduced efficiency and increased risk due to exposure for the workers.

Time. For applications such as packing nuclear waste, reducing the overall human exposure time to harmful radiation is the most crucial risk mitigation measure.

The VR user interface shows criteria values as real-time feedback to inform the user of the properties of the current packing configuration so that the user can make packing decisions accordingly. Warning messages are displayed to the user if weight or radiation limitations are exceeded, informing the user of unacceptable packing configurations.

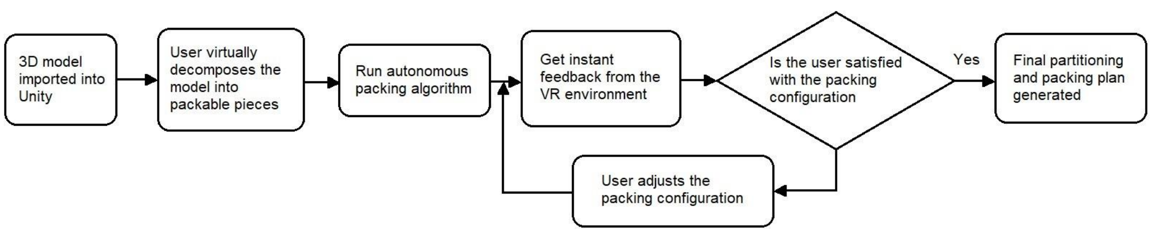

Figure 6: Workflow of the decomposing and packing optimization in the VR platform

5.3 Multiple containers

For large structures, multiple containers are needed to accommodate all the decomposed parts. When not all parts can fit into a single predefined container, the user can define the number and the dimensions of the containers to instantiate requested containers before the packing starts. The autonomous packing algorithm first attempts to fit all parts into the first container in situations involving multiple containers. Parts that cannot fit in the first container will be packed in the next container. So on and so forth. The autonomous algorithm stops once all parts are all packed inside the containers.

6 CONCLUSION

In this work, a modular framework for remote human-robot collaboration for waste management in decommissioning and demolition is discussed. The proposed framework includes robotic platform reality data capture, scan processing (e.g., segmentation, surface estimation, and recognition), gamified waste packing in virtual reality (VR), and packing plan execution. A modular robotic scanning platform is presented to demonstrate the data capture component. A reconfigurable semi-automated VR platform for waste packing optimization is presented as an example of this process workflow in the context of remote deconstruction and demolition.

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