An Application Study on Reconfigurable Robotic Workcells and Policy Adaptation for Electronic Waste Recycling

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Abstract—**The recycling of electronic waste (e-waste) presents significant challenges due to the diverse range of device models and conditions that need to be treated. This paper presents an application study that evaluates a reconfigurable modular robotic workcell platform and adaptation at different levels to address these challenges. The performance and effectiveness of the approach are assessed through two common use cases from the e-waste recycling industry: heat cost allocator disassembly and smoke detector disassembly, with the goal of battery removal. The initial setup time (the definition of dismantling procedures for a new device type), reconfiguration times (changing the workcell layout to switch between processes for different known device types) and cycle times (for dismantling one device) were assessed in terms of their key performance indicators (KPIs). The evaluation demonstrated the flexibility and adaptability of the workcell, which enables streamlined process development and efficient disassembly of electronic devices in different scenarios.**

I. Introduction

The automation of e-waste recycling is a significant challenge due to the wide variety of device models and their varying conditions. E-waste recycling is currently dominated by the "crush and separate" method, in which devices are crushed into smaller parts that are then physiochemically separated into reusable raw materials. However, this process often requires pre-treatment to remove hazardous components such as batteries or to disassemble parts that cannot be processed in the crusher. Due to the high variability of the parts to be removed, automation using traditional robotic systems, which typically operate within pre-programmed scenarios, is limited [1]. As a result, these operations continue to be a manual undertaking, adding to the overall cost of the recycling process. Current automation of recycling is limited to specific device models, starting with those that arrive at recyclers in the largest quantities. By incorporating the concept of robotic self-reconfiguration[2], the field of e-waste recycling can move towards automation and increased flexibility.

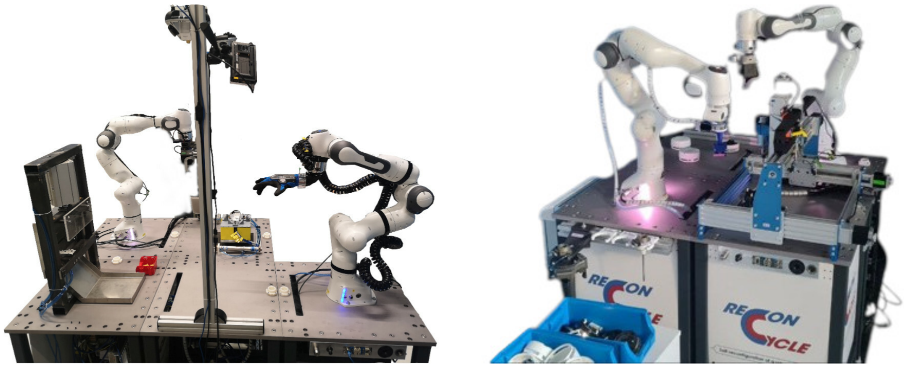
E-waste recycling often involves large batches of the same type of device, which limits variability at least to some extent, but at the same time we are faced with many different models within a given device type and the fact that they are in very different conditions. The high variability of electronic devices and the variability of device conditions after disposal require a flexible robotic system that can adapt to different conditions.

Although e-waste recycling still relies on manual labor, there has been a long-standing interest in automating recycling processes. A study from the early 1990s presented a conceptual design for a disassembly automation system that used multiple robots to reuse the resources in used products [3]. In more recent studies, Zhou et al. [4] focused on the recycling of battery packs and proposed a framework for safe and efficient disassembly using multiple cobots. Another study [5] focused on digitization in e-waste recycling and presented an automated system for device identification as the first step in the recycling process. Foo et. al. [1] conducted an evaluation of the current state of practice and the art in robotic disassembly, highlighting the complexities of implementing robotic disassembly systems in practice. They suggest that cognitive robotic methods and semi-automation should be explored to sufficiently address the variability of devices to be recycled and thereby increase the feasibility for robotic disassembly in the e-waste recycling domain. Laili et al. [6] investigated disassembly sequence planning for remanufacturing to develop an optimization model for robotic disassembly sequence planning. Another important aspect is that devices are often specifically not designed to be disassembled easily, necessitating for destructive disassembly steps [7].

In our work, we present a complete pipeline for electronic device disassembly and battery removal, which is a mandatory step before further recycling procedures. Our approach incorporates perception (device identification and integration of vision systems for precise localization and object detection) and uses its results to develop a comprehensive framework for handling different device models.

This paper focuses on the application of reconfigurable robotic workcells and the adaptation of the applied operations in the field of e-waste recycling. Specifically, we focus on the disassembly of two different types of e-waste: heat cost allocators and smoke detectors with the goal of battery removal. In our previous work, we presented a design of modular robotic workcell platform enabled by Plug & Produce connectors [8] and a modular software architecture to facilitate the implementation of such robotic workcells [9]. The proposed approach incorporates toolchains for an efficient setup, workcell calibration [10], and programming.

The modularity and reconfigurability of the developed workcell enables altering the layout of the workcell quickly and efficiently. This helps to handle different device types in the same workcell. To achieve the necessary level of flexibility to accommodate for the variability of the devices within the same family, we additionally rely on two types of adaptation in the recycling cell. We use vision-based action prediction for situations where multiple actions are possible to continue the



(a) Layout for heat cost allocator disassembly (b) Layout for smoke detector disassembly

Fig. 1. Two different layouts of a reconfigurable robotic workcell for automated recycling of electronic waste. The targeted recycling procedure involves the disassembly of two different families of electronic devices to remove printed circuit boards (PCBs) and batteries.

disassembly process. To account for different objects within the same device family, we used adaptation of disassembly skills.

The paper is organized as follows. In Section II we present the key aspects of the reconfigurable workcell and the accompanying tools with respect to the design of the dismantling workflow. We continue by the analysis of different heat cost allocators and smoke detectors. The disassembly workflows utilizing reconfiguration and adaptation of the workcell are presented in Section III. An experimental evaluation is provided in Section IV. Finally, in Section V we discuss the potential for further exploitation of the reconfigurable workcells in the field of e-waste recycling.

II. THE ROLE OF RECONFIGURATION AND ADAPTATATION IN AUTOMATED RECYCLING

A. *Modular hardware, soft robotics fixtures and grippers, and software paradigms facilitating user friendly programming*

The primary objective is to develop a workcell that can be easily adapted to the changes that occur in the products being recycled, while maintaining the ability to disassemble previous product versions by reconfiguration of the workcell. The modular nature of the workcell allows easy integration of different peripheral devices to support specific disassembly operations. In addition, adaptive hardware is employed, enabling the recycling of products of the same type without an extensive reconfiguration of the overall layout. For example, the workcell layout shown in Fig. 1 (a) is designed for the disassembly of heat cost allocators of different sizes and conditions, whereas the layout shown in Fig. 1 (a) is suitable for various smoke detectors.

To facilitate the programming process, we have introduced a hierarchical programming paradigm that enables end-users to intuitively translate their high-level knowledge of the disassembly process into a sequence of operations [9]. This is complemented by developing a skill library, which contains typical disassembly operations that can be readily executed.[1] The library triggers dedicated Robot Operating System (ROS) interfaces, which in turn provide references to the underlying low-level robot controllers or peripheral device interfaces. For task-level programming, a high-level behavior engine, FlexBE, has been employed. FlexBE supports creating, executing and monitoring complex robot behaviors as state machines [11]. Different FlexBE states encapsulate different actions of robots or periphery devices, which are designed for reuse across various operations. Multiple states are combined to describe parts or the entire disassembly sequence, offering flexibility and modularity in the programming approach.

To facilitate intuitive acquisition of robotic motions and the teaching of new skills, we rely on programming by demonstration [12], in particular on kinesthetic teaching [13] with incremental trajectory refinements [14]. However, it is important to note that not all tasks can be programmed by kinesthetic teaching alone. In situations where the positions of objects cannot be predetermined, vision-based detection of devices and parts placed on arbitrary modules, as well as the estimation of their location with respect to the specific module's coordinate frame is crucial for successful execution of various pickup operations within the disassembly process.

Finally, we employ compliant and soft robotic elements. Soft grippers allow for partial accommodation to different shapes of objects due to their ability to conform to the shape of the object being grasped, which is crucial for parts exhibiting different kinds of damage.

B. *Vision-based action prediction*

In our system, we rely on instance segmentation based on YOLOv8 [15] for identifying and determining positions of specific parts (see Fig. 2). To train the model we use a 80/10/10 train/validation/test data split with 40.000 automatically labeled images containing different device types and their parts, augmented from an initial dataset of 1250 manually labeled images. The initial dataset included images of two different device families (heat cost allocators and smoke detectors), each containing multiple device models (16 and 15, respectively). The images were taken on different hardware modules, and also contain the robot arms with different end-effectors attached. The images were taken under different lighting conditions. The augmented dataset was generated in the following manner: firstly, the device parts were cut out

[1]https://github.com/ReconCycle/reconcycle_flexbe

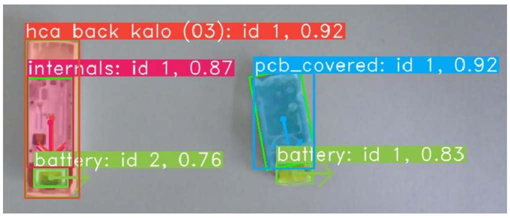


Fig. 2. Identification and localization of different devices based on instance segmentation.

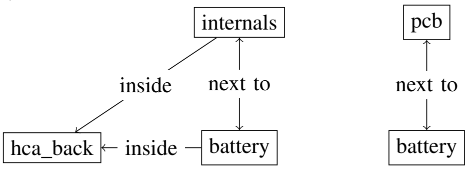


Fig. 3. Graph representation of detected parts relations.

and pasted onto different background images, thus increasing the variance with respect to the positioning of the devices and generating cluttered scenes. We additionally varied the lightning conditions in the augmented images synthetically. The trained model achieved mean average precision from 50% to 95% (mAP50-95) of 0.97 for the bounding boxes and 0.89 for segmentation masks over all classes.

In order to predict, which action we should take next, we need a higher level interpretation of the state of disassembly. To do this we create a graph of the identified device parts from the segmentation results, where nodes represent detections and edges one of the two possible relations: inside/next to (see Fig. 3). We then use these relations in combination with disassembly procedures (described in Sec. III) to determine, whether:

- grasping and moving of an object to a different module is possible,
- levering can be performed or there is a plastic clip that needs to be removed first,
- cutting can be performed,
- milling can be performed.

Based on the changes in the graph representation, we also check, if the actions were successful.

III. Battery Removal from Different Heat Cost Allocators and Smoke Detectors

Heat cost allocators (HCAs) and smoke detectors are mandatory in most residential and public buildings in most jurisdictions. As they need to be replaced in regular time intervals and typically can not be repurposed, they are one of the most common devices to finish their life at e-waste recycling plants. In both cases, the battery needs to be removed before proceeding with the recycling process, which usually involves physio-chemical separation of the raw materials. The battery in such devices poses a safety hazard if it is not removed beforehand. This is because the battery can catch fire if it is damaged. To remove the battery, the appropriate disassembly steps must be taken. These steps are not always straightforward, as the design of devices rarely takes into account the importance of ease of disassembly for recycling.

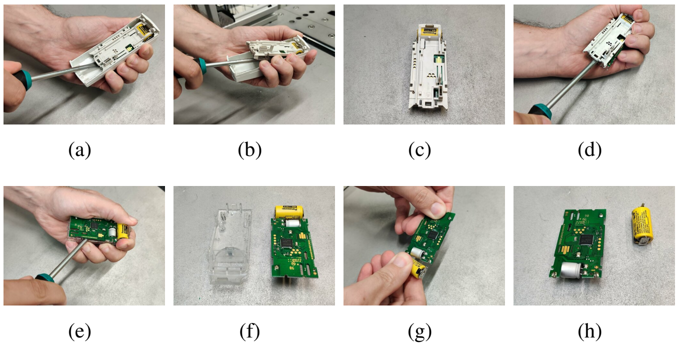


Fig. 4. Manual disassembly of a typical heat cost allocator. (a) To begin, a screwdriver is inserted into the gap at the rear of the HCA. (b) By leveraging the screwdriver, the internals of the HCA are carefully pried out. (c) The internals consist of a battery connected to the PCB, along with a white plastic top cover and a bottom transparent cover holding the display. (d) The white plastic top cover is then gently removed by levering it, (e) followed by the detachment of the PCB from the bottom transparent plastic cover. (f) At this stage, the PCB is completely free. (g) With the PCB and battery held in both hands, the battery is removed by ripping or cutting thin metal connections to the PCB. (h) Finally, the battery is detached from the PCB.

In many cases, the battery is specifically not designed to be removed by the end user.

A. Adaptive disassembly process for heat cost allocators

We first analyzed the disassembly as carried out by a human operator (see Fig. 4). This analysis served as the basis for specifying the automated workflow and the modules of the workcell to carry out the required operations. The steps are shown in Fig. 5. We equipped the archetypical modules (an archetypical module is the basic building block from which different workcells can be constructed [8]) with a pneumatic-driven vise and cutter and provided two robot modules. The other two modules are passive and are used for tool exchange and as an entry point for devices that need to be disassembled.

The first robot starts by picking up the HCA using the qb SoftHand Research gripper (based on the Pisa/IIT SoftHand [17]) and places it into the pneumatic vise, which clamps the housing firmly so that the second robot can remove the pin securing PCB in place (if present) and perform the levering operation to break the PCB out of the housing. The presence of a pin that must be removed before the PCB can be levered out is detected by a gap detection algorithm [18]. The levering operation uses a sinusoidal pattern and is encoded with periodic DMPs [19], [16]. The amplitude and frequency of the pattern are adjusted to adapt the force needed to lever the PCB from different HCA types, as demonstrated in Fig. 6 (b)-(c). The method also uses a force feedback based control algorithm to determine the contact points between the lever and the device (see Fig. 6 (a)).

When the PCB is released, the qb Variable Stiffness gripper (VSG, based on the VSA-CubeBot platform [20]) mounted on the second robot clamps and transfers it to the cutter module. At the same time, vise jaws are opened, allowing the first robot to pick up the empty housing using the qb SoftHand and transfer it to the designated container. When the battery is cut from the PCB, the second robot picks up the battery and places it into the container designated for the removed batteries. The high-level specification of the disassembly process was

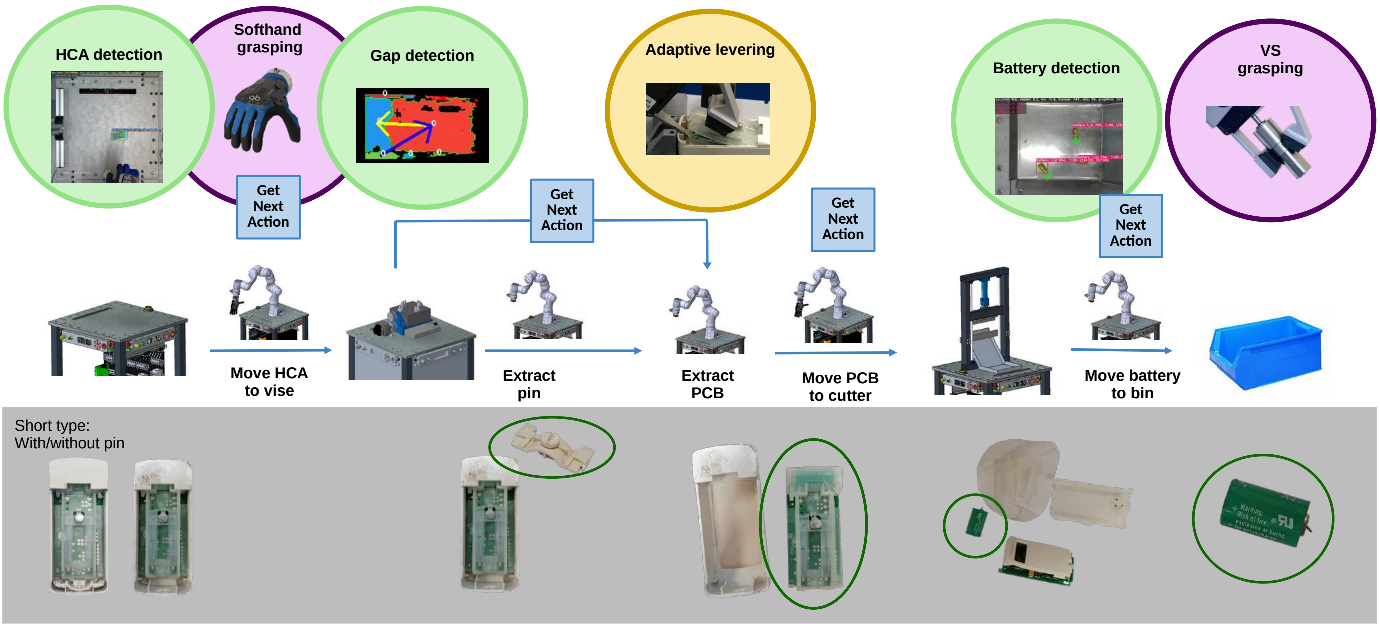
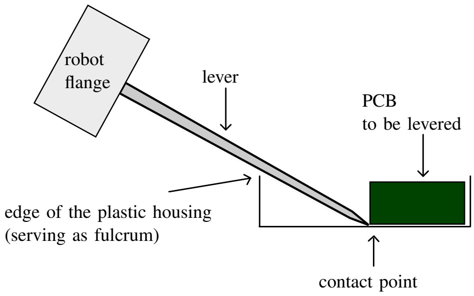


Fig. 5. Adaptive disassembly pipeline for heat cost allocators (HCAs) is shown in the middle row. The top row shows different adaptive features. Green bubbles show the application of vision for the part identification and determination of parameters for next step. Purple bubbles show the application of soft robotic elements to accommodate for the varying shape of the objects to be manipulated. The yellow bubble shows adaptive levering. The bottom row shows which part of the device is manipulated.



(a) Scheme of the levering process.

(b) Levering for shorter HCA type.

(c) Levering for longer HCA type.

Fig. 6. Adaptive levering can be executed for different device types.

programmed as a FlexBE behavior, while the robot configurations and trajectories needed to execute the required robot operations were obtained from robot vision (pickup locations for the smoke detector and battery, location for pin removal) or demonstrated by kinesthetic teaching.

The first part of the video in the supplementary materials shows how instance segmentation is used to perform semantic scene analysis, which was used to determine relations between the parts present in the scene in order to determine which of the possible follow-up actions should be performed. The second part of the video shows how the parameters of a predefined levering action are adapted to learn a levering behavior for a specific heat cost allocator.

B. Adaptive disassembly process for smoke detectors

We performed an analysis of different smoke detectors to determine their common features and to motivate the choice of tooling and disassembly procedures. Four different smoke detectors are shown in Fig. 8.

The smoke detectors were all round or cylindrical in shape, with a diameter between 90 and 120 mm and a height ranging from 25 to 60 mm. This suggests that a three-finger industrial pneumatic robot gripper (shown in Fig. 10) can be used to grasp them robustly. Such grippers are designed for grasping cylindrical objects. In addition, the three fingers move equal distances, which ensures that every grasped smoke detector is centered within the gripper. To maximize the amount of different smoke detectors that can be grasped, it is desirable that the gripper has a large stroke.

Different parts of smoke detectors (which mainly consist of a plastic cover and internal components) are held in place either by screws or by plastic tabs that lock the two parts together. In the case of screw connections, 2-4 Phillips, Torx, or Hex head screws are used. The unscrewing process is challenging to automate, considering the fact that unlike automatic screwing solutions where the screws are new, the screw heads may already be damaged when unscrewing. Disassembly of smoke detectors held in place by plastic tabs is also challenging to perform by a robot without a special tool. Tabs tend to require both high forces to remove them and precise robot gripper positioning. In some cases, multiple tabs must be pressed simultaneously, which is difficult to achieve with

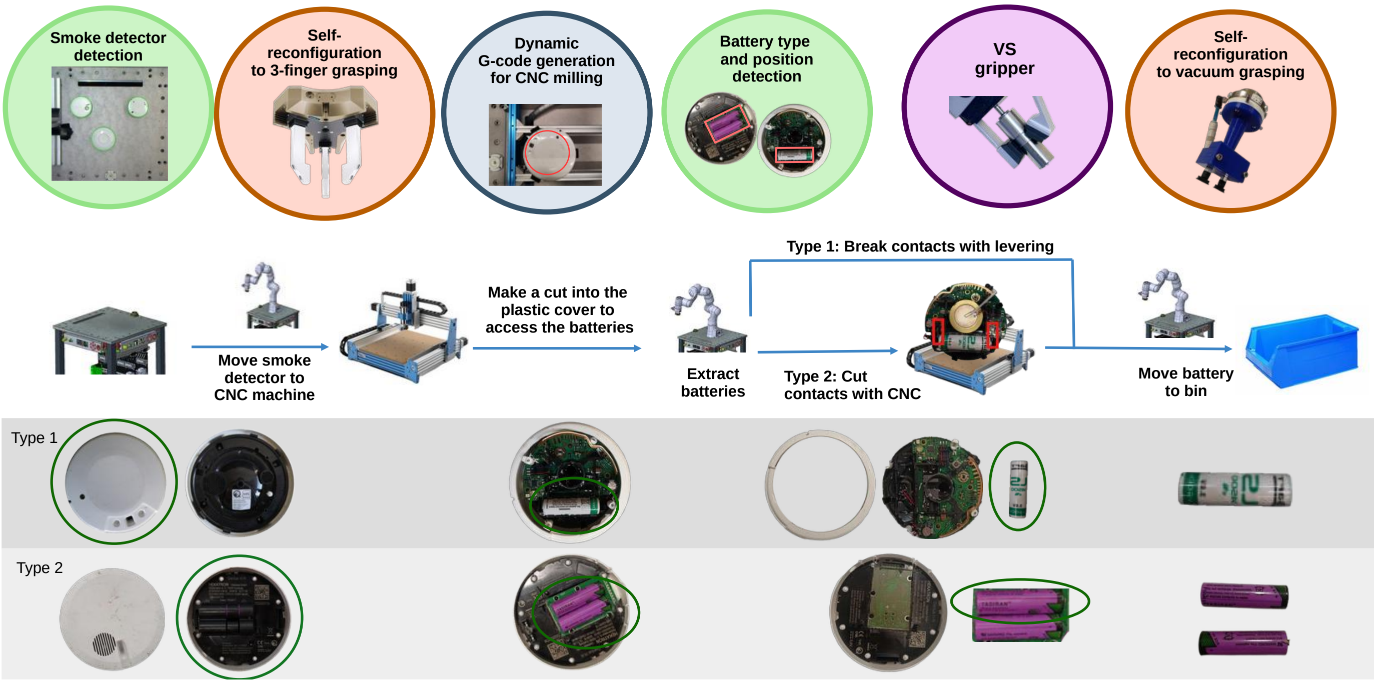


Fig. 7. Adaptive disassembly pipeline for smoke detectors. In the top row, the reconfiguration and adaptation features are highlighted. As in Fig. 5, the green bubbles show vision-based adaptation, the orange bubbles show hardware self-reconfiguration and the purple bubble shows soft-robotics elements. The blue bubble shows dynamic G-code generation based on the geometry of the smoke detector. The two bottom rows show which parts are being manipulated at different stages of the workflow for two example devices.

generic solutions and would require device-specific solutions. For this reason, in this paper we consider cutting an opening to access the batteries using a CNC mill.

A variety of battery types can be found in the analyzed smoke detectors. The batteries can be either button-type (CR 2032), AA-type (LS 14500 or CR 17450), while in other cases, cell packs of lithium batteries (such as 3CR2) are used. Some examples of batteries are shown in Fig. 9 (a). The removal steps for these batteries vary considerably. Button-type batteries are replaceable and not soldered in place, therefore they can be removed with, for example, a vacuum suction gripper. The AA-type batteries are usually soldered in place, as seen in Fig. 9 (b). This means a considerable force is required to remove them, so the contacts must usually be removed in some other fashion. Cell packs of lithium batteries are also complicated to remove. In most cases, the batteries are connected to the device via wires, as shown in Fig. 8 (third row). Cutting them requires care, as cutting both wires simultaneously can lead to a short-circuit and fire. In addition, the cell packs are usually epoxied within the plastic cover of the smoke detector, preventing their separation.

The analysis of the smoke detectors revealed that they nevertheless share some common features. This suggests that a standardized approach to disassembly can be developed so that the batteries found in these devices can be removed.

Since different smoke detectors have to be opened in a variety of ways, we decided to employ a CNC milling machine, which can be used to cut a desired shape into a device. This removes the need for less robust operations, such as unscrewing or precise levering at multiple locations. We use an off-the-shelf CNC milling machine Genmitsu PROVerXL 4030 (shown in Fig. 11). It operates based on input G-code, which specifies the sequence of milling operations. The initial G-code program is generated by an application engineer using an off-the-shelf CAD/CAM software package.The engineer decides which parts to cut based on the smoke detector's geometry and battery position within the smoke detector's internals. The G-code is designed for a single fixed pose of the smoke detector. If the position or orientation of the smoke detector changes, the path described by the G-code is dynamically translated and rotated based on the information provided by the vision system.

During the disassembly pipeline, machine vision is utilized at several steps, i.e., to detect the smoke detector location for pickup, to detect its orientation for computer numerical control (CNC) milling and to detect the battery location for extraction. At the start of the disassembly cycle, we employ machine vision to detect the location of a smoke detectors placed on the Material Input Module and transport them to the CNC Module. Vision is then further used to detect battery location and predict the optimal extraction method and to determine whether each disassembly step has been successful.

The three-finger gripper in the robot's end-effector is used to reliably grasp and center the smoke detector within the gripper. The robot transports the smoke detector into the milling machine, where it is securely clamped with a three-finger gripper similar to the one used on the robot. Once the smoke detector is placed in the CNC machine, its precise orientation must be determined. To do this, the second robot moves over the CNC machine and uses an eye-in-hand depth camera (Realsense D435) and the aforementioned YOLOv8. This orientation is then utilized to rotate the coordinates in the G-code. Subsequently, the CNC machine performs the milling to cut out the plastic part above the battery. A small tab is left in place to ensure that the plastic part does not fly off the machine or break the mill.

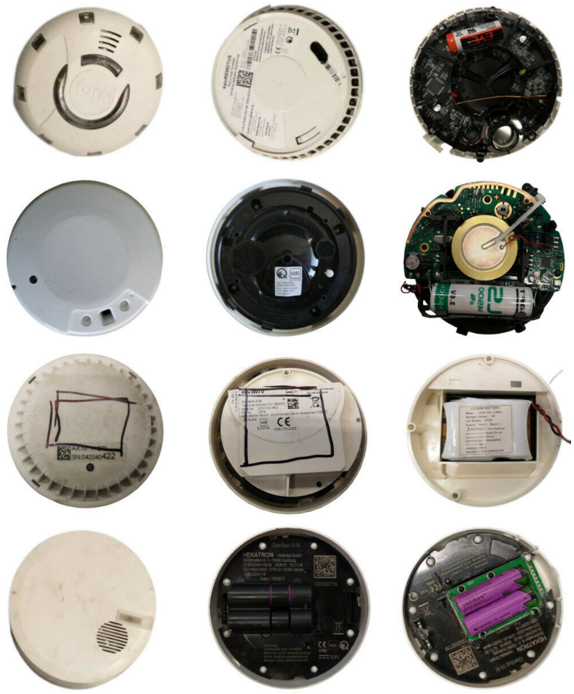
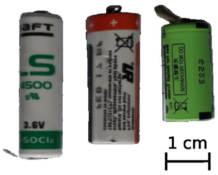


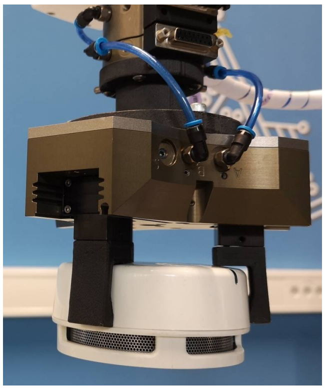
Fig. 8. Front, back and internal views of different smoke detectors.



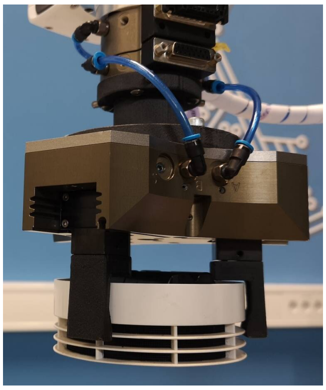
(a) Example batteries.

(b) Soldered connections.

Fig. 9. The example batteries found in smoke detectors. Most of them are soldered to the PCB, preventing easy disassembly.

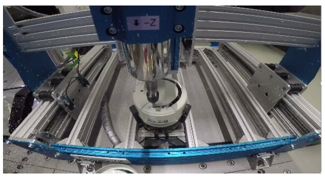


(a) Type 1.

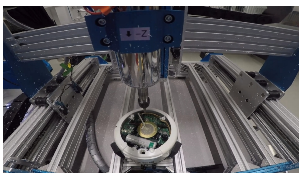


(b) Type 2.

Fig. 10. A three-finger gripper holding two different smoke detectors.



(a) Cutting.



(b) Smoke detector top removed.

Fig. 11. Removal of plastic cover from a smoke detector with a CNC milling machine.

Depending on the smoke detector type, the battery is either directly soldered onto the PCB or it is connected with wires. In both cases, the vision system can detect the battery. In case of direct solder connection, the battery is removed by milling away the contacts with the CNC machine. Alternatively, this could be achieved by performing a levering action with the second robot, which is equipped with the VSG. Finally, the battery is transferred to the dedicated bin using a vacuum suction gripper to lift the battery, which pose is detected by the eye-in-hand camera.

The third part of the video submitted as part of supplementary materials demonstrates the entire disassembly procedure for both smoth detectors.

IV. Evaluation

To benchmark the proposed dismantling processes, we defined several key performance indicators (KPIs). The desired KPIs are based on the economical feasibility study conducted within a partner recycling plant.

The time of hardware reconfiguration and software policy adaptation when switching the dismantling process from a known device of one family, to an unknown device of another family, provided that the device falls within the reconfiguration range of the existing hardware elements, should be less than 1 day. To manually reconfigure the cell layout for dismantling the HCAs into the layout suitable for dismantling smoke detectors, approximately 4 working hours were needed. Despite the modularity of the software infrastructure, some manual changes in the software initialization scripts and digital twin have to be made to reflect the updated cell layout. This time could be further reduced by including unique identifiers on each of the PNP connectors in the modules to be able determine the cell layout geometry automatically. It should be noted, however, that the main time burden lies in the development of hardware elements, e.g. the design of custom adapters for connecting new tools to tool exchange system, and the integration of the accompanying software.

The time needed for hardware reconfiguration and software policy adaptation when switching the dismantling process from a known device to an unknown device within the same family of devices, provided that the same sequence of operations can be applied (albeit with changed parameters) should be less than 15 minutes. In our use cases, this kind of policy adaptation was necessary for the adaptation of levering operation in the PCB removal step in HCA disassembly pipeline (see Fig. 5). The adaptation took less than 1 minute.

Time of hardware reconfiguration and software changes when switching the dismantling process from a known device of one family, to a known device of another family should be less than 5 minutes. In our system, this is handled within the disassembly pipeline, as the next step of the dismantling procedure along with parameters is obtained online based on scene analysis (see "Get next action" blocks in Figs. 5). If tool exchange is necessary, this increases the time by 10-15 seconds, depending on the initial and final positions where the robot is expected to be before and after the tool exchange.

To achieve desired throughput of at least 80 pieces per hour in the recycling line, the cycle time should be below 50 seconds. Although the current cycle times for dismantling

HCA types and smoke detectors range around 65-75 seconds (time varies depending on the number of repetitions of the movement pattern required to perform levering operation or prying out the battery by rocking motion), these can be reduced by optimizing the process flow. Apart from increasing the movement speed or reducing waiting times, the tasks could be parallelized (e.g. the first robot can already transfer the casing into designating bin, while the second is transferring the PCB to the cutter). Process optimization was however not the primary goal of this study.

As for the qualitative requirements, the reliability is crucial. To avoid potential fire, batteries have to be robustly detected and removed from the devices. This sets demanding KPIs for the vision system, which should be able to detect the presence of batteries with nearly no false negatives. The procedures for the manipulation of different device parts and the extraction of batteries from different electronic devices should be equally robust and reliable. In our experiments, we dismantled 80 exemplars of HCAs and 30 exemplars of smoke alarms, achieving more than 95% rate of successfully removed batteries. In the case of unsuccessful cutting, parts were put in a designated bin for manual inspection.

V. Conclusion and future work

In this paper we explored the application of self-reconfigurable hardware and software and policy adaptation for the disassembly of electronic devices. This is important to deal with the unique challenges of e-waste recycling that arise from the variability and unknown condition of the disposed devices. The introduction of reconfigurable robotic workcells in the e-waste recycling sector holds great potential for streamlining the recycling process and improving profitability, efficiency, and environmental impact.

Our approach is built upon a modular hardware and software platform that enables rapid integration, flexible reconfiguration, and efficient development [9], [8]. We have implemented the disassembly procedures for heat cost allocators and smoke detectors. The main contribution of the paper lies in the demonstration of the successful application of the proposed software and hardware architecture in the domain of e-waste recycling, thereby proving the importance of hardware reconfiguration and policy adaptation to handle the variability of the disposed electronic devices.

In addition to the proposed architecture, we believe that there are several other factors that can contribute to the advancement of e-waste recycling. In order to facilitate different recycling processes, it is crucial for the design of electronic devices to consider their end-of-life phase and the need for the removal of batteries. Better design choices, prioritizing easy removal of potentially hazardous components such as batteries, would contribute to the more effective e-waste recycling and resource recovery.

Our current work focuses on the further improvements of the proposed architecture, including design of general purpose fixtures to account for different device geometries, implementing additional operations such as unscrewing.

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