Towards Recycling E-Waste Using Vision and Robotic Manipulation

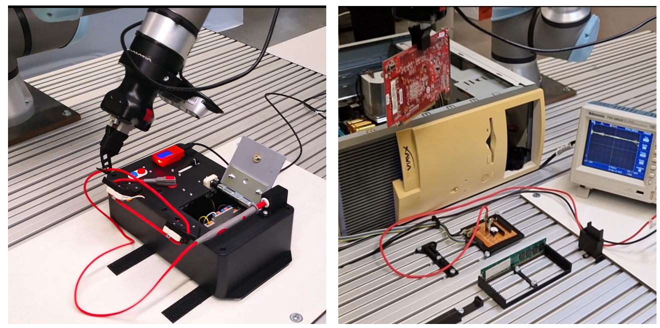
Philipp Kranz[1], **Usama Ali**[1,2], **Adrian Mueller**[1,2], **Maximilian Hornauer**[1], **Martin Loeser**[1], **Fouad Sukkar**[2], **Volker Willert**[1], **Tobias Kaupp**[1,2]
Technical University of Applied Sciences Wuerzburg-Schweinfurt[1]
Australian Cobotics Centre (ACC), University of Technology (UTS) Sydney[2]
philipp.kranz@thws.de

Abstract

The increasing amount of e-waste has become a major problem for society as the percentage of recycling or reuse is still insufficient. The need to find an economically viable solution to this problem is immense. One promising approach is the automatic disassembly of e-waste using robots. In this paper, lessons learned from three years of participation in the Robothon Grand Challenge, an international competition to find reusable robotic capabilities for e-waste disassembly, are presented. As winners of the competition in 2023 and 2021, we present our system architecture and describe the methodologies used to address the major challenges. We also demonstrate the transferability of our approach to a real-world e-waste problem. The evaluation focuses on the 2023 competition tasks. Experimental results are presented for task board localisation accuracy, execution time, and robustness. For execution time, a comparison of the automated solution with human performance is presented. A supplementary video can be found at `https://youtu.be/ypk0Al8kdNQ`.

1 Introduction

E-waste is a major problem for our environment and society. On average, each person on earth produces 7.3 kg of e-waste every year, of which 82.6% is not recycled and ends up in landfills [Forti *et al.*, 2020]. The concept of a circular economy aims to find a response to this waste of resources. It aims at not only reducing environmental degradation but also recovering rare materials from waste products [Van Buren *et al.*, 2016]. Dismantling end-of-life (EoL) products is an essential step in achieving a circular economy. At that point, the decision is made whether a product or its components can be reused, repaired, re-manufactured or recycled.



(a) Winding up a cable after probing a circuit. (b) Replacing faulty PC components.

Figure 1: E-waste manipulation during the Robothon Grand Challenge 2023.

Robotic manipulation is useful for the accurate and consistent execution of repetitive tasks, e.g. in assembly lines. However, in the context of robotic disassembly where many uncertainties about the state of the product exist, a standard pre-programmed manipulator has serious shortcomings compared to the ability of humans to intuitively disassemble products. This poses a significant obstacle to the widespread adoption of robotic disassembly in industry. Our goal is to close that gap and bring robotic systems close to the efficiency and flexibility of manual disassembly by improving hardware, optimising processes and perceptual capabilities. The Robothon Grand Challenge, an international competition focusing on minimising the e-waste problem, works toward this goal by identifying reusable robotic capabilities comparable to those of a human [MIRMI, 2023]. Examples of e-waste manipulation tasks conducted during the 2023 competition are shown in Fig. 1.

The Robothon Grand Challenge competition takes place remotely. A task board as shown in Fig. 2 is sent out to the accepted teams. The task board is instrumented with sensors and a microcontroller allowing the recording of task completion and execution times. The results of each trial run are automatically posted to a web dashboard allowing remote access and automatic data collection. This setup enables a fair performance comparison between the remote teams [So et al., 2022].

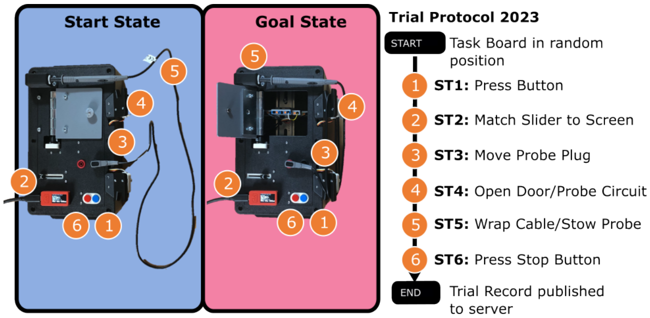


Figure 2: Competition task board from 2023, showing the start and goal state of the task board and the trial protocol which includes six manipulation tasks.

The participating teams have 30 days to solve a set of tasks using a robotic manipulator. The robotic platform must perform the tasks autonomously, i.e. without any human intervention, and manipulate the task board from a given start state to a desired target state as many times as possible within a 10 minutes time frame. After each attempt, the task board must be re-positioned on the work bench to prevent pre-programmed trajectories. In a live video-conference before a jury of robotics experts, each team has two attempts to solve the task board with their robotic platform. The jury evaluated teams against the following criteria: completeness of tasks, execution times, robustness and flexibility of their solutions.

In addition to solving the task board, each team is required to disassemble a device of their choice using their robotic system. The purpose of this so-called Bring Your Own Device (BYOD) task is to demonstrate the transferability of the developed system to a real-world e-waste problem.

To date, the competition has taken place three times as summarised in Table 1. The five best-performing teams are invited to an award ceremony that takes place at the renowned Automatica trade fair in Munich. Sponsors from industry award prize money to the finalists. Our teams have consisted of Bachelor and Masters students supported by senior academic and technical staff.

This paper makes the following contributions:

1. Detailed description of the system architecture and methods used to solve the 2023 task board and the BYOD task.
2. Analysis of individual teams' competition runs using data collected from the 2023 competition and a user study where participants were asked to carry out the same disassembly tasks for comparison.
3. Development of a custom, open-source ROS driver for the URe manipulator series capable of utilising the UR-provided force mode and gripper features.

Year	2021	2022	2023
No. of applications	16	25	31
No. of accepted teams	9	20	20
No. of developers	44	80	80
Total prize money (€)	12k	18k	20k
Our team's ranking	1.	5.	1.

Table 1: Key figures of the Robothon competitions to date.

The remainder of the paper is organised as follows. Sec. 2 discusses related work in the field of robotic disassembly. Sec. 3 describes the Robothon Grand Challenge 2023 tasks. Sec. 4 proposes a system architecture while Sec. 5 describes our methodology for solving each of the competition tasks. Sec. 6 presents experimental results for both the task board and the transferability task. Finally, Sec. 7 concludes and discusses future work.

2 Related Work

This section discusses related work in the field of robotic disassembly, with a focus on object detection and robotic manipulation.

[Weigl, 1994] describe the major challenges for disassembly tasks for electronic products. They include the generally uncertain conditions of the parts, their accessibility and graspability, jamming and wedging, and a need for temporary fixtures. Although these challenges have been identified thirty years ago, they presently remain unsolved [Foo et al., 2022].

According to [Foo et al., 2022] a successful robotic disassembly is affected by *external* and *system* factors. *External factors* are uncertainties arising from the EoL product such as variation in product families, product structure and condition. External factors also relate to the disassembly economy such as required output quality, market value of materials and components, the extent of disassembly and the uncertainty of the outcome of the operations. *System factors* are defined as methodologies to meet the external factors such as perception, tooling, level of automation, cost, robustness, modularity and user-friendliness. In this paper, we adopt some of the proposed system factors in our experimental evaluation.

To address the above-mentioned external factors of EoL products, various system architectures have been proposed in the literature, e.g. [Vongbunyong and Chen, 2015; Poschmann, 2021]. The proposed architectures typically consist of three modules: 1) an intelligent agent responsible for reasoning and planning, 2) a vision system and other sensors for object detection and state recognition, and 3) a mechanical system conducting the disassembly.

As stated in [Vongbunyong and Chen, 2015], the tasks performed by each module can be categorised into three levels of control as shown in Fig. 3. The intelligent agent mostly conducts high-level tasks such as planning and behaviour control. The vision and sensors system is concerned with data acquisition, processing and interpretation. The mechanical system is responsible for controlling the manipulator and path/trajectory planning. The scope of the Robothon competition and our study is on low- and mid-level control as shown in Fig. 3.

Control	Module		
	Intelligent agent	Vision system and sensors	Mechanical system
High-level	–Sequence planning –Process planning –Task planning –Knowledge base –Behaviour control	n/a	n/a
Mid-level	–Information flow	–Object localisation –Object recognition –Signal interpretation	–Operation procedure –Path planning –Trajectory control
Low-level	n/a	–Image pre-processing –Camera control –Image grabber –Data acquisition –Signal processing	–Motion control –Force-torque control

Levels addressed in this paper

Figure 3: Control levels and modules of a robotic disassembly system according to [Vongbunyong and Chen, 2015]. The scope of the Robothon competition is on low- and mid-level control.

3 Robothon Challenge Tasks

The competition's challenge for 2023 was focused on diagnosing the health of the electrical components by taking measurements. In order to carry this out, it was required to localise objects in the workspace, manipulate a cabled probe to take measurements and to clean up the workspace. These skills needed to be demonstrated on the task board as well as for a real-world use case chosen by the participating teams (BYOD task).

The start and end state of the task board as well as the individual tasks are shown in Fig. 2. A human starts the trial by pressing the button on the microcontroller board (0). The robotic system must subsequently localise the task board and press the blue button (1). A slider has to be set to two specific setpoints which are shown on a small LCD display (2). A measuring probe must be moved from one slot to another (3). A hinged door must be opened and a terminal block must be measured with the probe (4). The probe needs to be inserted back to the initial position and the cable has to be wound up (5). The robot presses the red button to end the trial (6).

To demonstrate the transferability of our general approach to a real product, we chose to diagnose and manipulate a PC mainboard with respect to two of its components: a GPU board and a RAM module (see Fig. 4). Due to their prevalence, high value, and continuing decrease in average life span, Personal Computers are a relevant e-waste problem commonly addressed by disassembly systems [Hohm *et al.*, 2000; Laszlo *et al.*, 2019].

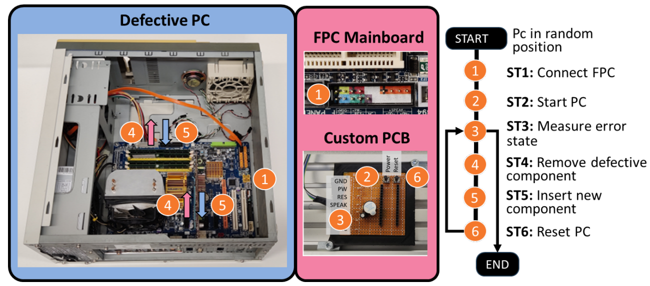


Figure 4: Our selected BYOD task: diagnosing GPU boards and RAM modules by inserting them into a PC mainboard and measuring the error code via an oscilloscope. The measurement is made using a custom PCB the robot connects to the mainboard via a standard plug.

4 System Architecture

This section describes the hardware and software architecture we developed in order to address the tasks from the previous section. The hardware setup is shown in Fig. 6. We use a Universal Robot UR5e manipulator and a Robotiq Hand-E gripper. Custom-made tools for specific manipulation tasks are 3D-printed. Two cameras are utilised: 1) a statically mounted IDS U3-3800CP camera responsible for localising objects in the workspace, and 2) a wrist-mounted Intel Realsense D435i camera used for manipulation tasks that require vision feedback. A Tektronix oscilloscope TDS 2002B is used for the BYOD task. The software architecture is set up using ROS Noetic, running on a PC with an Intel i7 8850 CPU, 16 GB of RAM and an Ubuntu 20.04 installation. For GPU processing a Nvidia RTX A2000 is used.

The overall system architecture is shown Fig. 5. It consists of a Sense, Plan, and Act module following the standard approach for robotic disassembly systems as discussed in Sec. 2.

Adopting the control levels from Fig. 3, the *Sense* module consists of the hardware mentioned above, low-level software drivers to read the sensor data, and three mid-level software modules (Board/Triangle/Component Detection) which are described in later sections. The IDS driver was custom-developed based on the manufacturer's API. The Realsense driver is a standard ROS package. The signals

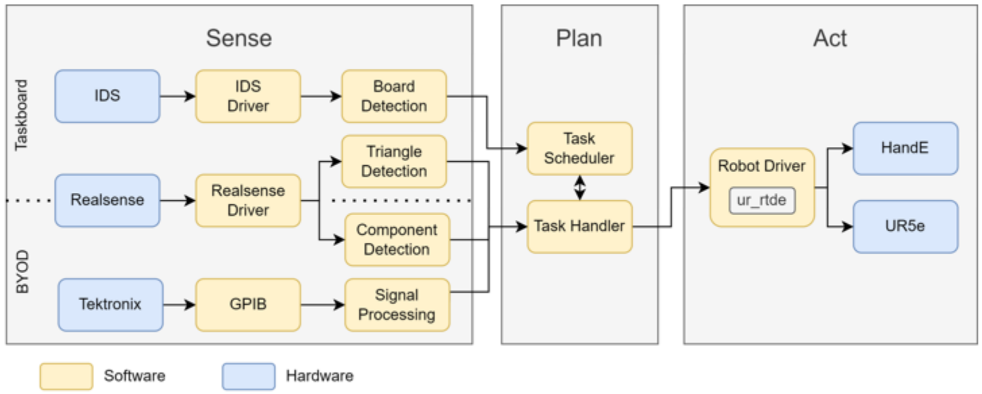


Figure 5: System architecture with the three modules Sense, Plan and Act. Arrows indicate the information flow. The software architecture is set up using ROS.

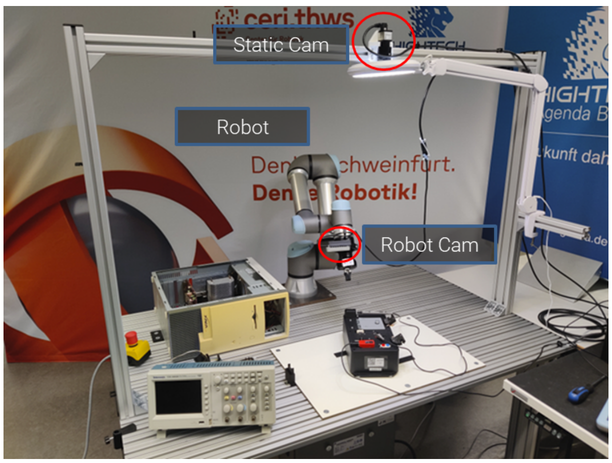


Figure 6: Hardware setup consisting of an UR5e, a statically mounted IDS camera, and a wrist-mounted Intel Realsense. An oscilloscope is used to take measurements on the PC for the BYOD task.

from the Tektronix oscilloscope are read via a GPIB interface and subsequently processed to detect and count the signal edges.

The *Plan* module evaluates the information from the Sense module and determines what action needs to be taken. It is split into two parts: Task Scheduler and Task Handler. The scheduler generates a sequence of tasks and observes their execution. In case of an error, it can reschedule the task or initiate a fallback action. It calls the functions defined in the Task Handler which execute the requested tasks.

The *Act* module consists of the manipulator and gripper hardware and a robot driver. The custom-developed driver is a ROS wrapper of the ur_rtde library[1] which provides a C++ and Python API for Real-Time Data Exchange (RTDE) of the UR Robot. Our driver enables the utilisation of the UR force mode, freedrive mode and provides advanced gripper control. Those features are not available with the standard ROS driver[2]. The authors have successfully used their driver in other projects and are planning to publish it under an open-source license after more testing and bug fixing has been completed.

5 Methodology

In this section, solutions to the main technical challenges of the Robothon competition are presented. This consists of our approach to 1) object detection, namely task board localisation and the detection of small objects on an LCD screen, and 2) manipulation, namely tooling and fault-tolerant design.

5.1 Task Board Localisation

One of the main challenges of the competition is the unknown location of the task board. This requirement is evaluated by random placements of the task board during the competition using Velcro strips. Therefore, a prerequisite to all subsequent manipulation tasks is to determine the absolute pose of the task board in the robot's workspace. Here, we decided for a fast vision-based localisation approach instead of a more time-consuming tactile sensing solution.

Vision-based localisation of objects with known geometry is based on finding point correspondences between known 3D coordinates of distinct features on the object and its correspondent camera measurements.

The general problem statement is simplified by the following two pre-conditions: the geometry of the task board is known, and the pose of the robot arm can be

[1] https://gitlab.com/sdurobotics/ur_rtde

[2] https://github.com/UniversalRobots/Universal_Robots_ROS_Driver

measured very precisely. This allows the use of any 2D or 3D camera at arbitrary known positions in the workspace. Decisions to be made are 1) where to place a camera, 2) what camera to use (2D or 3D), and 3) which features to select.

The position and orientation of the task board is limited to a planar workspace. Therefore, we use a static camera in bird's eye view to localise the task board as can be seen in Fig. 6. In this configuration the top of the task board is always front-to-parallel to the camera which means circular shapes on the task board remain circular on the image projected from any location of the task board, and the scale and the appearance of the visual features only vary slightly. Furthermore, a light source can be used for consistent illumination of the scene within the defined workspace.

Depth measurements from 3D cameras are prone to errors, their accuracy varies with distance and view point, and their calibration is non-trivial and sensible to temperature changes. Therefore, we use an RGB camera and extract 2D features from the image. As the corresponding 3D coordinates of the features on the task board are known, the Perspective-n-Point (PnP) problem can be solved via minimising the reprojection error [Lu, 2018] in order to estimate the pose of the task board.

The accuracy of the PnP pose estimation depends on the number of robustly extracted feature coordinates and its spatial configuration in space. There are a limited number of distinct and easy-to-detect visual features on the task board. As shown in [Acuna and Willert, 2018], the lower the number of features the more their spatial configuration affects the accuracy. A very stable configuration for 5 features are the corner points of a square plus the midpoint. In general, the larger the number of features the more accurate the estimate.

Given this background, the features we selected on the task board are shown in Fig. 7. All features are robustly detected via threshold-based colour segmentation, noise reduction via morphological filtering, and 2D coordinate extraction via the Hough circle transform [Jähne, 2005]. To disambiguate the orientation of the task board, the rectangular-shaped microcontroller is used.

5.2 Triangle Detection

Another challenge in 2023 is the detection of coloured triangles on a small LCD screen under varying lighting conditions and with overlapping triangles (see Fig. 8). The colour coding is as follows: the yellow triangle indicates the centre of the screen. The green triangle shows the goal point for the slider which is tracked via the red triangle. The task for the robot is to move the slider such that the red triangle firstly aligns with the yellow triangle and secondly with the green triangle. To address this, we implemented a closed-loop system con-

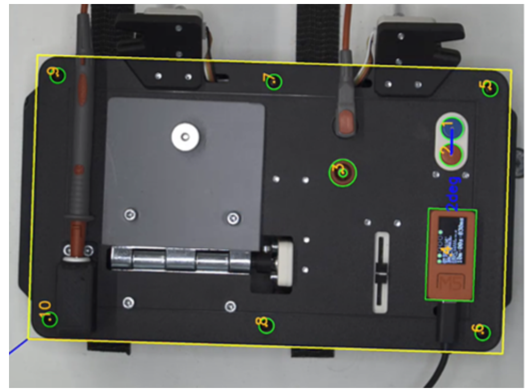


Figure 7: Distinct features selected for PnP pose estimation: Six screws, the blue/red buttons, the probe connector and the orange microcontroller. The yellow rectangle visualises the estimated task board pose.

Figure 8: Challenges of the triangle detection task: overlapping triangles and varying lighting conditions.

sisting of simultaneous triangle detection via the wrist-mounted camera and moving the slider with the UR5e. The system calculates a commanded velocity which is inversely proportional to the distance to the target position. This prevents the robot from overshooting while ensuring faster motion for larger distances.

With the wrist-camera and gripper setup described in Sec. 4, the resulting images are out-of-focus due to proximity to the task board making it difficult to segment the individual triangles based on shape. Therefore, our approach relies on colour detection. Images are captured in RGB colour space; however, RGB is sensitive to luminance and other ambient conditions and therefore unsuitable for our use case. We have also found that the hue oriented HSV colour space (see Fig. 9 left) is not well suited to robustly distinguish green from yellow. Instead, we use the L*a*b* colour space (see Fig. 9 right). Its colour channels are defined to achieve a perceptually uniform colour representation, i.e. the differences in the colour space are proportional to subjective differences in human perception. The L*a*b* colour space is known for its high classification accuracy [García-Mateos *et al.*, 2015].

5.3 End-Effector Tooling

Many of the Robothon manipulation tasks cannot be solved with a standard gripper and require specialised

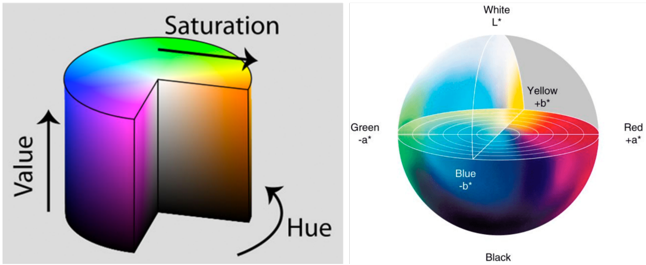


Figure 9: Comparison of the HSV (left) and L*a*b (right) colour spaces [Rosebrock, 2023]. Due to a better separation between yellow and green, we use L*a*b for the detection of the coloured triangles.

tooling. We have considered two types of custom-made designs for the Robothon: 1) fingertips that attach directly to the gripper, 2) graspable tools (see Fig. 10).

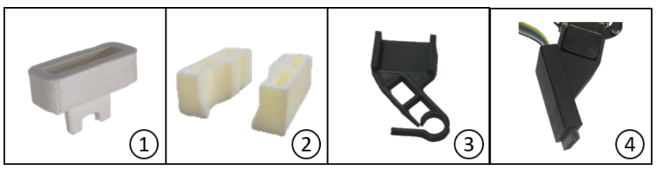


Figure 10: Two types of designs for specialised tooling: (1) and (2) show fingertips which are attached directly to the gripper used in the 2022 competition. (3) and (4) show graspable tools used in 2023: a hook for winding up the probe cable and a front panel connector (FPC) for the BYOD task.

The advantage of graspable tools is the ability to swap between suitable tools during execution based on the current task. On the other hand, a universal fingertip is more efficient in terms of the execution times since no tool changes are required. Due to the diversity of the tasks, the former approach was found to be more suitable.

The most challenging manipulation task in 2023 is the winding up of the cable. Handling deformable objects remains one of the more challenging and generally unsolved tasks in robotic manipulation [Zhu *et al.*, 2022]. We developed a graspable tool in form of a hook as shown in Fig. 10 (3). Another graspable tool was developed for our BYOD task providing a physical interface for the front panel connection on the PC (see Fig. 10 (4)).

5.4 Fault-Tolerant Design

The ability to react to failed tasks is important for disassembly due to uncertainty in the state of objects being manipulated and noisy perception. Thus, a fault-tolerant system capable of detecting failed tasks and recovering with fallback actions is necessary. Some example scenarios specific to the task board and our method for solving them are described here. These scenarios are representative of common faults and the general principle can be applied to wider disassembly tasks.

In the triangle detection task, the detection process occassionally fails to accurately identify the positions of the triangles due to varying lighting conditions and overlapping shapes (see Fig, 8). The fallback option is to move the slider over the entire range in an open-loop fashion. This guarantees task completion but significantly increases execution time.

Another fallback has been implemented for a failed button press. A job status on the LCD display indicates whether a button has been successfully pressed. Using the wrist-mounted camera, we check the status and repeat the task if a failure has occurred. This is useful for the task of pressing the red button after manipulating the probe cable which tends to be unreliable due to the flexible structure of the cable hook tool (see Fig. 10 (3)).

Another fault-tolerant design method is used to counter the insufficient accuracy of the task board localisation for fine manipulation tasks such as peg-in-hole operations. In the 2023 competition, inserting the probe plug is an example. To address this, a spiral search has been implemented. The TCP moves in a spiral motion around the target position with the plug touching its receptacle. A successful insertion into the receptacle is detected via feedback from the UR force-torque sensor, read via our custom-made ROS driver.

6 Results

This section presents experimental results for both the task board and the BYOD tasks from the 2023 Robothon competition.

6.1 Task Board

For the evaluation of the task board results, we adopt the taxonomy by [Foo *et al.*, 2022] introduced in Sec. 2. The authors identified a number of *system factors* that are crucial for an automated disassembly process. For our evaluation, we select *perception abilities* and *robustness*. We also add *execution time* which is crucial in industrial processes and is also a focus of the Robothon competition. Table 2 summarises the system factors used in this paper and shows the evaluation metric. The following section reports results in the same order as listed in the table.

System Factor	Evaluation Metric
Perception	Position/orientation error (mm/°)
Robustness	Task success rate (%)
Execution time	Time (s)

Table 2: System factors used in our evaluation.

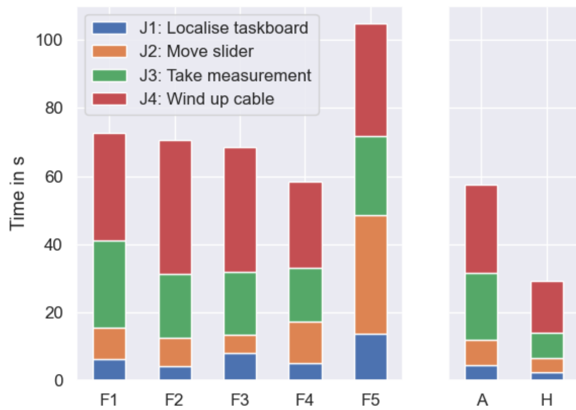


Figure 11: Results for total execution time per Job. F1 through F5: results for the top five teams, extracted from the 10min video submission (F1 is ours), A: improved version of our solution, H: human performance.

Perception capabilities are evaluated by the achieved accuracy of our task board localisation system described in Sec. 5.1. Ground truth is obtained by using the UR5e as a tactile sensor, i.e. touching the top and the sides of the task board to compute its pose via forward kinematics.

For our experiment, we placed the task board on the table in eight different positions and orientations. The detection was run three times for each pose providing a total of 24 data points. We calculated the position error to be $1.4 \pm 0.66mm$ and the orientation error to be $0.39 \pm 0.21°$. As a comparison, [So *et al.*, 2022] reported a positional error of $9.8 \pm 3.5mm$ and an orientation error of $0.72 \pm 0.32°$ for their benchmark implementation for the Robothon 2022.

Robustness is evaluated during the competition by successfully finishing five consecutive trial runs of all tasks with different orientations within a $10min$ time frame. Out of the 20 accepted teams, six including us achieved this goal (30%).

Execution time is evaluated on a per-task basis for the 2023 competition. Sec. 3 contains a detailed description of the trial run. For the purpose of our evaluation, we define the following four Jobs:

- J1: Localise task board
- J2: Move slider
- J3: Take measurement
- J4: Wind up cable

For each Job, we extracted the execution times from the 10 minutes video submission by the five finalists including ours. The videos include five trial runs: for each trial, the task board was placed in a different orientation. The videos show that teams F2 to F4 changed the orientation within approximately 45° whereas we covered a range of 270°. Secondly, we ran 20 trials on an improved version of our own system demonstrated to the jury during the video interview. Two main improvements were implemented: a) porting code from Python to C++, and b) adding blending to the robot motion. Finally, since one of main goals of the Robothon competition is to match human capabilities via an automated solution [MIRMI, 2023], we generated data of human performance.

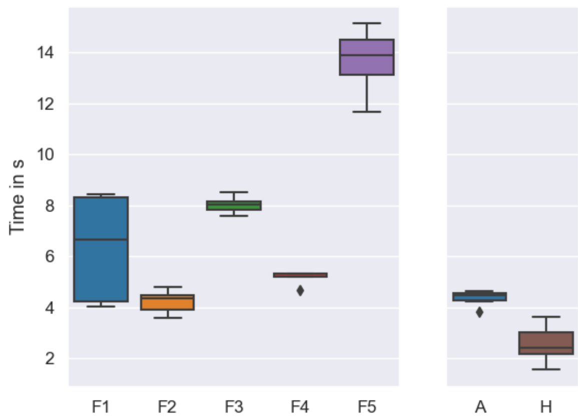
For our pilot user study, we asked 21 human subjects to perform the tasks manually. Participants are between 20 and 47 years old, 17 are male and 4 female, all have an engineering background. Each participant received a short introduction of the tasks. Subsequently, the task board was placed at a random orientation on the workspace out of the participants' view. The participants then conducted the tasks manually while the experimenter recorded the time per Job using a stopwatch. Each participant repeated the trial three times and we computed the average time per participant.

An overview of the total average execution times is shown in Fig. 11. The top 4 teams (F1-F4) achieved results between 58.5 and 72.7 seconds. With our improved version (A), we achieved an execution time of 57.5. Notably, the average human performance of 29.1 seconds is better than all automated solutions.

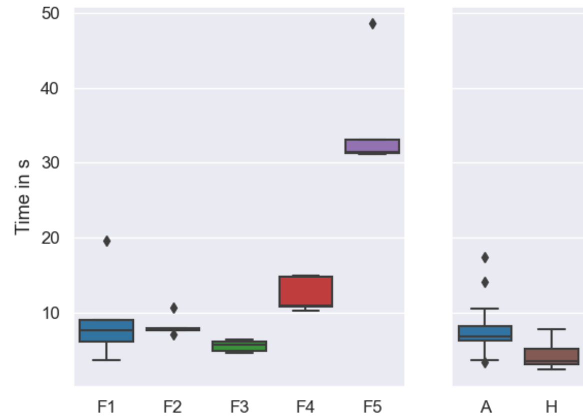
A breakdown of the execution times per Job is provided in Fig. 12. J1 represents the Job of localising the task board which is considered finished when the blue button is pressed. Task board localisation is a crucial prerequisite for the following manipulation tasks. Teams used different types of hardware to address the task: while teams F1, F2 and F5 used consumer-grade RGB-D cameras, teams F3 and F4 used commercially available solutions often used in bin picking applications. The approach yielded very consistent results as indicated by the small variances for F3 and F4. Nevertheless, their median results are not significantly better when compared to F1 and F2. From analysing the videos, it appears that the board recognition of the commercial systems (F3 and F4) was very fast but time was lost during the slow robot motion to press the blue button.

Another observation is that our improved solution (A) is significantly better than our initial solution (F1). The reduction in median and variance can both be explained by our port from Python to C++: processing time became faster and a multi-threading capability removed CPU clogging.

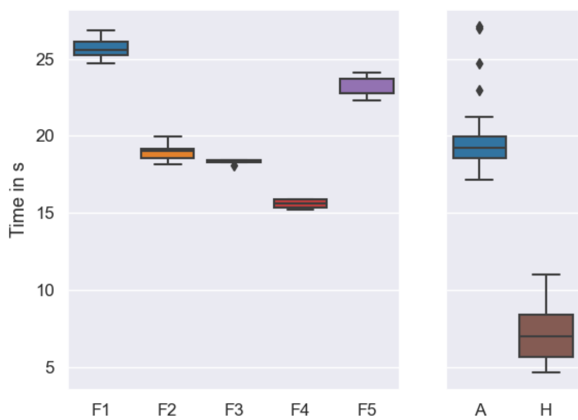
J2 represents the Job for moving the slider. Results for teams F1-F4 are close to each other when comparing the medians. The execution time variance can be



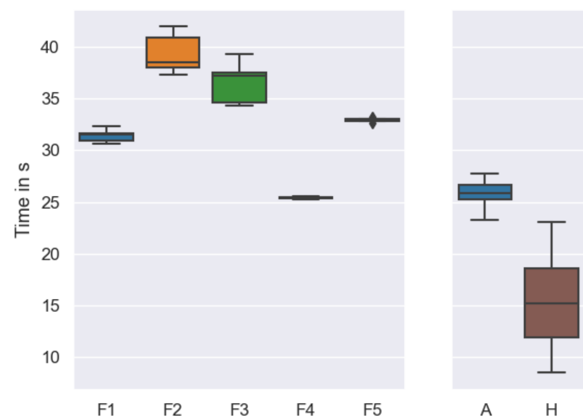
(a) J1: Localise task board



(b) J2: Move slider



(c) J3: Take measurement



(d) J4: Wind up cable

Figure 12: Comparison of execution times per Job. F1 through F5: results for the top five teams, extracted from the 10min video submission (F1 is ours), A: improved version of our solution, H: human performance. F1 through F5 have 5 data points each, A has 20 data points and H has 21 data points.

explained by the nature of task: the position of the triangles on the LCD screen are randomly generated leading to different execution times between trials. Outliers for our improved solution (A) occured when the triangle recognition failed and the fallback method described in Sec. 5.4 had to be used.

J3 represents the Job of taking a measurement which includes moving the probe plug, opening the door and probing the circuit (see Fig. 2). We chose opening the door using the probe to save time; however, this does not show in the plot since time was lost by taking the measurement slowly compared to the other teams. Similar to J2, the outliers of our improved solution (A) are explained by spiral search fallback method described in Sec. 5.4.

J4 represents the Job of winding up the cable which was the most challenging manipulation task of the competition. Team F4 achieved the best result in both median and variance. With our improved solution (A), we achieved a similar median as F4. Notably, we used 20 trials for A and covered a range of 360° for the task board orientations, demonstrating the robustness of our approach to all possible orientations.

For all four Jobs, the median of the human performance was better than the best automated solution. Humans did particularly well for J3 and J4 which require fine-grained and tactile manipulation skills. On the other hand, the automated solutions show a smaller variance compared to the manual labour, in particular for J4, indicating higher consistency and repeatability.

6.2 Transferability Task

This section describes results of the BYOD transferability task described in Sec. 3. As shown in Fig. 4, our PC diagnosis system works as follows. After localising the PC, the custom-made front panel connector (FPC) is plugged in by the robot before turning on the PC. Then, the error codes are read by detecting the edges of the voltage signal using the oscilloscope. The RAM error signal is shown in Fig. 13 top.

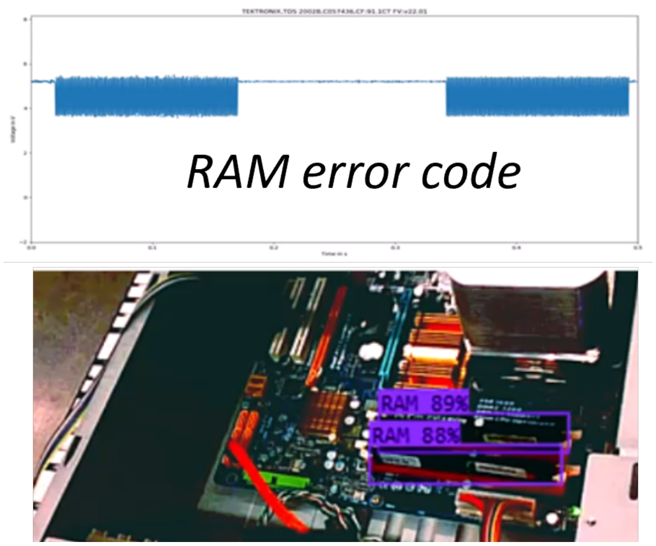


Figure 13: BYOD task: 1) RAM error signal measured with an oscilloscope, 2) Detection of the RAM cards with a YOLO neural network.

A detected error state can have two different causes: 1) missing component, or 2) defective component. In order to distinguish between the two causes, a visual detection of the GPU/RAM boards on the PC is required. We chose to train a YOLO v8 neural network[3] which provides bounding boxes for the detected boards as shown in Fig. 13 bottom. The network was trained using 3600 images: 1200 original images were labelled by hand and the roboflow tool[4] tripled the data set by varying their saturation and brightness. On a test data set of 18 images, roboflow reported a mean average precision (mAP) of 97.1%.

In the context of sustainability, our proposed system can be used in two ways as detailed in Figure 14:

1. PC diagnosis: If defective components are found, replace them and recycle the defective components.
2. Component (GPU/RAM) diagnosis: If components are faulty, recycle them. If they are functional, reuse them.

[3] https://github.com/ultralytics/ultralytics
[4] https://roboflow.com/model/yolov8

Therefore, three of the multiple R's of the circular economy are addressed, namely Repair, Recycle and Reuse [Kirchherr *et al.*, 2017].

	Component	Error Code	Detection	Action	Upcycle Type
Test Pc	RAM	✓	✓	Replace RAM	Repair, Recycle
	RAM	✓	×	Insert RAM	Repair
	GPU	✓	✓	Replace GPU	Repair, Recycle
	GPU	✓	×	Insert GPU	Repair
Test Components	RAM	✓	*	Recycle RAM	Recycle
	RAM	×	*	Reuse RAM	Reuse
	GPU	✓	*	Recycle GPU	Recycle
	GPU	×	*	Reuse GPU	Reuse

Figure 14: Two usage patterns of our BYOD task: 1) PC diagnosis, and 2) component (GPU/RAM) diagnosis. The system addresses three R's of the circular economy (Repair, Recycle and Reuse).

7 Conclusion and Future Work

In this paper, we have presented the developments and experiences made during three successful participations in the Robothon Grand Challenge competition. The Robothon aims at developing robot skills comparable to a human in the handling of e-waste. Our paper presents a robust and effective approach to address the challenges of the competition by describing our system architecture and developed methodologies.

Our experimental evaluation focuses on the 2023 competition tasks. We show high accuracy for the 2D pose detection of the task board using vision compared to tactile sensing. We compare our task execution times with those from other teams in the competition. We also show results from a pilot user study comparing execution times between the automated solution and manual labour. The results show that on average humans are faster for all tasks; however, our robotic solution carried out the tasks with lower execution time variance.

We also demonstrate the transferability of our proposed system to a real and highly relevant e-waste problem, namely the diagnosis of PCs and their components such as GPU and RAM modules. This is a valuable demonstration of our system being useful in the context of a circular economy.

In future work, we will combine the strengths of robots such as repeatability and accuracy with the fine manipulation skills and flexibility of humans. We believe that human-robot collaboration is well suited to address more complex disassembly tasks [Liu *et al.*, 2019].

Another avenue of future research in the context of disassembly is to replace pre-programmed motions by learning manipulation skills from human demonstrations [Nematollahi *et al.*, 2022]. The task board and the system presented in this paper will be used as a benchmark to evaluate those approaches.

Acknowledgements

The authors gratefully acknowledge the funding support provided by the Hans-Wilhelm Renkhoff Foundation and the ARC Industrial Transformation Training Centre for Collaborative Robotics in Advanced Manufacturing under grant IC200100001.

References

[Acuna and Willert, 2018] Raul Acuna and Volker Willert. Insights into the robustness of control point configurations for homography and planar pose estimation. *arXiv preprint arXiv:1803.03025*, 2018.

[Foo *et al.*, 2022] Gwendolyn Foo, Sami Kara, and Maurice Pagnucco. Challenges of robotic disassembly in practice. *Procedia CIRP*, 105:513–518, 2022.

[Forti *et al.*, 2020] Vanessa Forti, Cornelis Peter Baldé, Ruediger Kuehr, and Garam Bel. The global e-waste monitor 2020. *United Nations University (UNU), International Telecommunication Union (ITU) & International Solid Waste Association (ISWA), Bonn/Geneva/Rotterdam*, 120, 2020.

[García-Mateos *et al.*, 2015] G. García-Mateos, J.L. Hernández-Hernández, D. Escarabajal-Henarejos, S. Jaén-Terrones, and J.M. Molina-Martínez. Study and comparison of color models for automatic image analysis in irrigation management applications. *Agricultural Water Management*, 151:158–166, 2015.

[Hohm *et al.*, 2000] K.-H. Hohm, H. Hofstede, and H. Tolle. Robot assisted disassembly of electronic devices. volume 2, pages 1273 – 1278, 2000.

[Jähne, 2005] Bernd Jähne. *Digital image processing.* Springer Science & Business Media, 2005.

[Kirchherr *et al.*, 2017] Julian Kirchherr, Denise Reike, and Marko Hekkert. Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, conservation and recycling*, 127:221–232, 2017.

[Laszlo *et al.*, 2019] Rapolti Laszlo, Rodica Holonec, Romul Copîndean, and Florin Dragan. Sorting system for e-waste recycling using contour vision sensors. In *2019 8th International Conference on Modern Power Systems (MPS)*, pages 1–4, 2019.

[Liu *et al.*, 2019] Quan Liu, Zhihao Liu, Wenjun Xu, Quan Tang, Zude Zhou, and Duc Truong Pham. Human-robot collaboration in disassembly for sustainable manufacturing. *International Journal of Production Research*, 57(12):4027–4044, 2019.

[Lu, 2018] Xiao Xin Lu. A review of solutions for perspective-n-point problem in camera pose estimation. In *Journal of Physics: Conference Series*, volume 1087, page 052009. IOP Publishing, 2018.

[MIRMI, 2023] MIRMI. Robothon - the grand challenge series of munich-i: An international competition in robot manipulation. https://www.robothon-grand-challenge.com/, 2023.

[Nematollahi *et al.*, 2022] Iman Nematollahi, Erick Rosete-Beas, Adrian Röfer, Tim Welschehold, Abhinav Valada, and Wolfram Burgard. Robot skill adaptation via soft actor-critic gaussian mixture models. In *2022 International Conference on Robotics and Automation (ICRA)*, pages 8651–8657. IEEE, 2022.

[Poschmann, 2021] Hendrik Poschmann. *Konzeption und Entwicklung eines Robot Cognition Processors für adaptive Demontageanwendungen.* PhD thesis, 07 2021.

[Rosebrock, 2023] Rosebrock. Opencv color spaces (cv2.cvtcolor). https://pyimagesearch.com/2021/04/28/opencv-color-spaces-cv2-cvtcolor/, 2023.

[So *et al.*, 2022] Peter So, Jonas Wittmann, Patrick Ruhkamp, Andriy Sarabakha, and Sami Haddadin. Towards remote robotic competitions: An internet-connected task board and dashboard. *arXiv preprint arXiv:2201.09565*, 2022.

[Van Buren *et al.*, 2016] Nicole Van Buren, Marjolein Demmers, Rob Van der Heijden, and Frank Witlox. Towards a circular economy: The role of dutch logistics industries and governments. *Sustainability*, 8(7):647, 2016.

[Vongbunyong and Chen, 2015] Supachai Vongbunyong and Wei Hua Chen. *Disassembly Automation - Automated Systems with Cognitive Abilities (Series: Sustainable Production, Life Cycle Engineering and Management)*. 2015.

[Weigl, 1994] A. Weigl. Requirements for robot assisted disassembly of not appropriately designed electronic products: lessons from first studies. pages 337 – 342, 06 1994.

[Zhu *et al.*, 2022] Jihong Zhu, Andrea Cherubini, Claire Dune, David Navarro-Alarcon, Farshid Alambeigi, Dmitry Berenson, Fanny Ficuciello, Kensuke Harada, Jens Kober, Xiang Li, et al. Challenges and outlook in robotic manipulation of deformable objects. *IEEE Robotics & Automation Magazine*, 29(3):67–77, 2022.