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Disassembly Sequence Planning Considering Human-Robot Collaboration

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Abstract— **Disassembly currently is a labor-intensive process with limited automation. The main reason lies in the fact that disassembly usually has to address model variations from different brands, physical uncertainties resulting from component defects or damage during usage, and incomplete product information. To overcome these challenges and to automate the disassembly process through human-robot collaboration, this paper develops a disassembly sequence planner which distributes the disassembly task between human and robot in a human-robot collaborative setting. This sequence planner targets to address potential issues including distinctive products, variant orientations, and safety constraints of human operators. The proposed disassembly sequence planner identifies the locations and orientations of the to-be-disassembled items, determines the starting point, and generates the optimal disassembly sequence while complying with the disassembly rules and considering the safe constraints for human operators. This algorithm is validated by numerical and experimental tests: the robot can successfully locate and disassemble the pieces following the obtained optimal sequence, and complete the task via collaboration with the human operator without violating the constraints.**

1. INTRODUCTION

In the last decade, environmentally conscious manufacturing (ECM) [1] and product recycling have become a necessity for many companies in order to follow government regulations [2]. Subsequently, manufacturers have drawn more attention to return end of life (EOL) products [3] by customers and conduct the electronic product recycling and/or recovery process at minimum cost. The disassembling and reassembly of these products efficiently and cost-effectively becomes a critical step for this process.

Assembly/disassembly sequences are composed of subsequent actions. An action is usually determined from an engineering perspective, such as the establishment of a product from sub-assemblies into one item, or the separation of an assembly into sub-assemblies [4]. A typical electronic product can have a large number of feasible assembly/disassembly sequences and this number rises exponentially with the number of components. Considering the difficulty of representing every sequence separately, the development of a systematic and efficient way to represent all possible sequences and to obtain the optimal one is needed. As such, several algorithms, such as incidence matrix [5] [6], directed graphs [7], AND/OR graphs [8] establishment conditions, mixed-integer nonlinear programming [9], graph visualization [10], and precedence relationships [11] [12], have been proposed. Many kinds of research also investigate the task planning that can be described by an assembly drawing from a computer-aided design model [13]. For example, to find the optimal disassembly sequence, some of these studies are conducted based on the modified traveling salesman problem [14] which studies the problem of a salesperson traveling from a city to others and then returning to the original city. Most of the existing works attempt to automatically find the optimal sequence based on designated information, such as a fixed initial task, several common/parallel tasks, and the rules for the assembly/disassembly tasks [2].

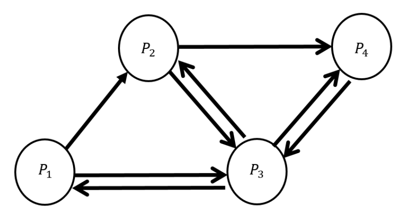

Fig. 1. Directed Graph Example

The assembly process usually is unique [15]: the assembly line is designed by a work-cell layout with consecutive workstations and exclusive fixtures [16] to maintain the orientation of the disassembling object. Such a process is usually done by robots which are programmed for repetitive tasks [17]. The disassembly process, on the other hand, becomes more challenging due to several reasons: (1) a variety of electronic wastes may be put to the same disassembly line to reduce the cost of building distinctive disassembly lines, and (2) disassembly is usually performed incompletely for collecting valuable components only [4]. In addition, (3) the to-be-recycled products may contain components with hazardous substances and need to be handled carefully; (4) distinctive disassembly products may be placed on the disassembly line with varied orientations and because of that, (5) the robot may perform unnecessary trips in order to reach the designated first task with the longest distance from the robot's location, in spite of the existence of the other optional

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first task having a shorter traveling time. As a result, the disassembly process is mainly performed by human [18] instead of an automated disassembly line.

In addition, if multiple starting points are available for a product in a disassembly line, the conventional hierarchical graph model [19] usually has more than one representation for the precedence relation of tasks. For instance, assuming that there are four tasks, P_1, P_2, P_3, P_4, and two disassembly rules are applied to them:

- Rule 1: Remove P_1 $\rightarrow$ Remove P_2
- Rule 2: Remove P_2 $\rightarrow$ Remove P_4

where Rule 1 indicates that task P_1 must be executed before task P_2; similarly, Rule 2 means that task P_2 must proceed prior to task P_4. The associated directed graph is shown in Figure 1, where the arcs are the tasks to be completed and the arrows denote the precedence relations among the four tasks. Depending on the decision of the starting arc, the tasks can be defined as parallel tasks or common tasks [2]. When the task planner selects P_1 as the initial task, the graph model will be represented in Figure 2, where P_2 and P_3 are parallel tasks. Otherwise, the sequence shown in Figure 3 will be generated if P_3 is obtained as the starting point, where P_1 to P_4 are all common tasks. It can be seen that because of the different choice of initial task, the decision tree of the graph model may be changed completely.

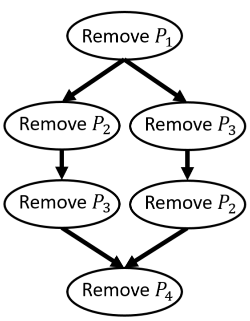

Fig. 2. Sequence Starting from P_1

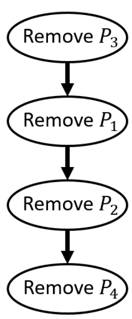

Fig. 3. Sequence Starting from P_3

Because of the assumed disorientation feature for the products fed into the disassembly line, the property of multiple starting points provides the opportunity to improve time efficiency for the disassembly tasks. The time consumption for each task can be considered as a part of the disassembly cost [2]. For example, the actions of screw rotation and tool changing performed by human or robot may take different lengths of time. Besides the time consumption, other factors, such as difficulty and geometric complexity of the parts, also need to be considered. Needless to say, the traveling time of reaching and leaving each disassembly task as well as the complexity to conduct a particular task may not be constant if the products' orientations are different. Moreover, due to possible hazard materials or an unsafe work environment [11], some of the disassembly tasks may not be executed by the human operator. Hence, it is possible to develop a decision-maker to assign robot or human workers for the disassembly tasks and to consider the safety constraints caused by unsafe conditions.

In brief, this paper seeks to automate the disassembly sequence planning which distributes the disassembly task between human and robot in a human-robot collaborative setting. The proposed disassembly sequence planner firstly identifies the locations and orientations of the to-be-disassembled items to determine the starting point, and then generates the optimal disassembly sequence while complying with the disassembly rules and considering safe conditions for human operators.

The remainder of this paper is organized as follows: Section 2 describes the considerations of the disassembly process, such as the formulation of disassembly rules, the calculation of the cost of operations by robot and human, and the concern of safety constraints of human operation. Section 3 gives the proposed problem formulation, followed by the simulations and experimental results of the disassembly task planning in Section 4. Section 5 concludes the paper.

2. DISASSEMBLY PROCESS CONSIDERATIONS

This paper considers the disassembly of a wooden toy box, as shown in Fig. 4, using human-robot collaboration.

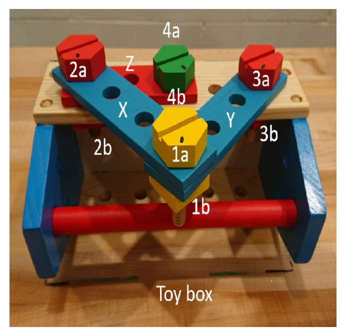

Fig. 4. To-be-disassembled Wooden Toy Box

It is necessary to acquire knowledge of the to-be-disassembled object, including the conditions and locations of its components before generating the disassembly sequences for distinctive products. If the locations and the unsafe conditions cannot be identified accordingly, the robot can not locate the component to-be-disassembled or the human operator may accidentally proceed with the unsafe task, resulting in a failed disassembly sequence or even safety issues in the disassembly line. Although disassembly sequence planning for distinctive products in the same disassembly line is possible, in this paper, we narrow down the scope to one wooden toy box with known components and focus on the optimal sequence planning and validation. Identification of the locations of these components is sufficient for planning the task sequence for the wooden toy box.

As shown in Fig. 4, the toy box that is used in this study consists of four screw sets, Screw 1 $(1a, 1b)$, Screw 2 $(2a, 2b)$, Screw 3 $(3a, 3b)$, and Screw 4 $(4a, 4b)$, and the rectangular parts, X, Y, and Z. Noting that a and b denote the hex-head screw and hex nut, respectively. Because the two parts of a screw set must be removed together, the components of the 4 screw sets will be simplified as Screw 1, Screw 2, Screw 3, and Screw 4 in this paper.

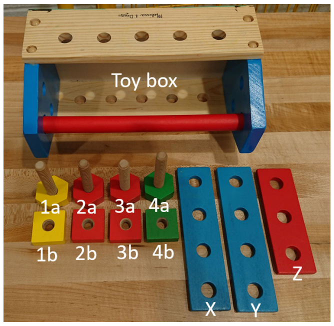

Fig. 5. Components of Toy Box

A. Disassembly rules

We construct a graph model, as shown in Fig. 1. This graph model gives useful information on all possible disassembly sequences. The action of removing a component is represented by the operation R. Initially, the rules for disassembling the toy box are (1) $R_1 \wedge R_2 \rightarrow R_X$, (2) $R_1 \wedge R_3 \rightarrow R_Y$, (3) $R_2 \wedge R_4 \rightarrow R_Z$. In this paper, to simplify this procedure, we assume that the rectangular parts X, Y, and Z can be immediately removed after conducting $R_1 \wedge R_2$, $R_1 \wedge R_3$, and $R_2 \wedge R_4$ respectively. In addition, Screw 2 and Screw 4 cannot be disassembled first because of the following issues: (i) the hex-nuts of Screw 2 have to support the weights of the component X after Screw 1 is removed; (ii) Screw 2 and the component Z must be removed prior to disassembling Screw 4. Therefore, the disassembly rules can be simplified as

- Rule 1: $R_1 \rightarrow R_2$
- Rule 2: $R_2 \rightarrow R_4$

Rule 1 means Screw 1 must be removed before dismantling Screw 2. Similarly, Rule 2 means Screw 2 must be removed prior to the removal of Screw 4. It is worth noting, the rules do not mean that Screw 2 must be removed immediately after Screw 1, or Screw 4 must be removed immediately after Screw 2.

B. Cost of operations by robot and human

In order to find the optimal sequence of disassembling a product, the cost for each disassembly action, which may be defined as the traveling time and the geometric complexity of the product, has to be determined. It is easy to know the time spent on each disassembly task by robot and human operator, but the geometric complexity needs to be determined carefully by running some preliminary tests.

C. Consideration of safety constraints of human operation

Additional constraints for disassembling a product may require the removal of hazardous materials. In this case, the human operator will not be suitable to remove the component, even though the cost by human operation may be lower than the robot. Thus, the safe condition should be included in determining the optimal task sequence.

3. Disassembly Sequence Planing: Formulation and Optimization

This section presents the optimization formulation of the disassembly sequence planning. The targets of this planner include the determination of the starting point and the optimal sequence such that the time and complexity of the disassembly are minimized. The planner considers the disassembly rules and the safety constraints of human operation. As such, two main terms are defined in the cost function: the cost of the disassembly task sequences and the distances between the robot's position and the screws. Therefore the sequence planning can be formulated into the following optimization problem:

$$\min_{\alpha_{ij}, x_{ij}, s_q} \left[\sum_{j=1}^{n} \sum_{i=1}^{n} c_{ij} x_{ij} + \gamma \sum_{q=1}^{n} s_q d_q \right] \tag{1}$$

subject to

$$\sum_{i=1}^{n} \left[\sum_{j=1}^{n} x_{ij} - \sum_{k=1}^{n} x_{ki} \right] = 0 \tag{2a}$$

$$x_{ij} \in \{0, 1\} \tag{2b}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij} = n - 1 \tag{2c}$$

$$c_{ij} = \alpha_{ij} r_{ij} + (1 - \alpha_{ij}) h_{ij} \tag{2d}$$

$$\alpha_{ij} \in \{0, 1\}, \quad c_{ij} \in \mathbb{R}^{+} \tag{2e}$$

$$\alpha_{ih} = 1 \tag{2f}$$

$$\gamma \in \mathbb{R}^{+} \tag{2g}$$

$$s_q \in \{0, 1\}, \quad \sum_{q=1}^{n} s_q = 1 \tag{2h}$$

$$d_q \in \mathbb{R}^{+} \tag{2i}$$

$$i, j, q = 1, 2, ..., n \tag{2j}$$

All the variables in (1) and (2) are briefly listed in Table I and illustrated in Fig. 6, and will be explained in detail in the following paragraphs.

The optimal sequence planning targets to solve the above optimization and obtain the values of the decision variables x_{ij}, α_{ij}, and s_q. As briefly listed in Table I, x_{ij} presents the decision on whether disassembling Screw j immediately after disassembling Screw i. The whole set of x_{ij}'s for i, j=$1, 2, .., n$ determines the optimal disassembly sequence. The constraints on x_{ij} in (2a) and (2b) ensure all disassembly tasks are performed at most for one time. Particularly, the terms inside the square bracket of (2a) indicate two constraints: (1) the workflow into a node is equal to the workflow out of the node if the node is neither a starting point nor a final point, and (2) the workflow out of the starting node is equal to the workflow into the ending node. The constraint (2c) guarantees that a successfully obtained task sequence with n nodes need to have $n-1$ decision variables which equal to 1.

Decision Variables' Definitions	
Variable	Definition
x_{ij}	'0' means task from i to j is not conducted. '1' means task from i to j is conducted.
α_{ij}	'0' means task from i to j is conducted by human. '1' means task from i to j is conducted by robot.
s_q	'0' means Screw q is not the starting point. '1' Screw q is the starting point.
Other Variables' Definitions	
Variable	Definition
i, j, and q	Node index
γ	Weighting factor in the cost function
d_q	Distance between robot's initial position and Screw q
n	Total number of components to be disassembled
h	Unsafe screw index

TABLE I
VARIABLES IN OPTIMIZATION

The c_{ij} denotes the combined cost of traveling from i to j and removing the component j. Considering the human-robot setting, c_{ij} is represented by the disassembly cost using the robot, r_{ij}, and the disassembly cost using the human operator, h_{ij}. The decision variable α_{ij} is used to determine whether it will be done by human or by robot, as described in (2d) and (2e). In addition, if an unsafe condition occurs at Screw h, the corresponding decision variable α_{ih} will be set to 1 to force the robot to proceed with the unsafe task, as expressed in (2f). For instance, Screw 2 in Fig. 6 is marked as an unsafe part for human operator. The decision variables of α_{12} and α_{32} are therefore set to 1, forcing the robot, instead of the human operator, to disassemble Screw 2.

The α_{ij} indicates the decision variable that determines whether the task is done by the robot or the human operator. For example, if a hazardous component is identified at node p_2 in Figure 6, the task planner will make α_{12} and α_{32} equal to one, so that the robot will be forced to execute the sequence of x_{12} or x_{32}, where x_{ij} is defined as a directed path between p_i and p_j. In this case,

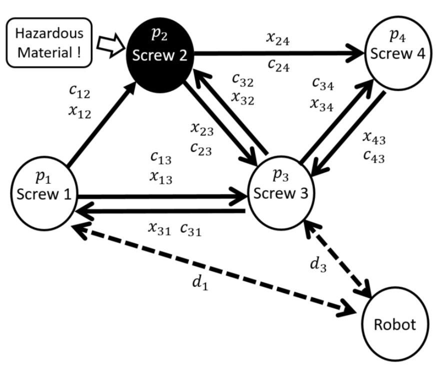

Fig. 6. Disassembly Sequence Illustration

$$c_{12} = 1 \cdot r_{12} + 0 \cdot h_{12} = r_{12}$$

and

$$c_{32} = 1 \cdot r_{32} + 0 \cdot h_{32} = r_{32}$$

Lastly, the γ denotes the weighting factor to balance the two main terms in (1); s_q is a decision variable which determines the starting point. For example, $s_1 = 1$ means the starting point is Screw 1. The d_q is the distance between the robot's initial position and the q^{th} screw, as defined in (2h) and (2i).

4. VALIDATION

This section presents the validation of the proposed disassembly sequence planner considering human and robot collaboration. Firstly, we randomly place the toy box on the table and identify the to-be-disassembled components by the camera using binary square fiducial markers [20]. Secondly, the information is sent to the computer for sequence planning. The planner optimizes the disassembly sequence over all feasible ones. After the optimal sequence is obtained, it is sent to both the robot and the human to conduct the task collaboratively. To simplify the experimental setting, all the screws are assumed to be in the reachable range of the human and robot. In this validation, we vary two variables of the toy box: the orientation and the component that contains hazardous materials. Also, to further simplify the scenario, we assume the costs for the disassembly tasks by robot and human, i.e., r_{ij} and h_{ij} are given in advance in the validation.

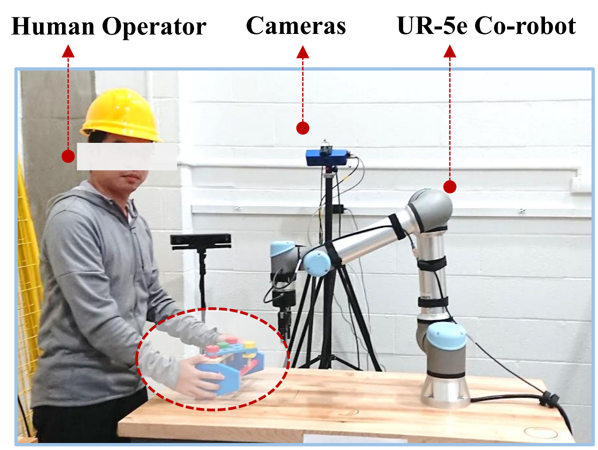

Fig. 7. Experimental Test Setup

The experimental test that is used in this paper is as shown in Fig. 7. The experimental setup consists of a Universal Robot (UR) that collaborates with the human operator and the cameras that are used to identify the locations of the screws and the toy box.

Case 1: Screw 1 is closest to the robot and Screw 3 is unsafe for the human operator.

In this scenario, the toy box is placed on the table such that Screw 1 is the closest screw to the robot. We assume Screw 3 is unsafe for human operators, as shown in Fig. 8 (Step a). The locations of the four screws are identified by the camera, as shown in Fig. 8 (Step b), and sent to the computer for planning. The planner generates all possible disassembly

Fig. 8. Step 1. Identification of Locations of Screws and the Robot

sequences, as shown in Fig. 9 (Step c), in which the white hexagram and the white dots indicate the robot's position and the screws that can be safely operated by a human operator, and the red dot indicates that the screw is not safe for human operation. After incorporating this information, the planner obtains the optimal sequence, as shown in Fig. 9 (Step d), in which the cyan-colored arrows denote the directed paths between the screws to be removed.

Fig. 9. Step 2. Optimal Disassembly Sequence Planning.

It is worth noting that because Screw 3 in this simulation has an assumed unsafe condition, the task planner will assign the robot to handle the disassembly sequence safely, meaning that the decision variable α_{13}, α_{23}, and α_{43} will be set to 1 to force the robot to execute the task. As such, the obtained optimal sequence is $x_{12} = x_{24} = x_{43} = 1$ with the associated decision variables that distribute tasks between human and robot, i.e., $\alpha_{12} = 0$, $\alpha_{24} = 1$, $\alpha_{43} = 1$, as well as the decision variables that determine the starting point, i.e., $s_1 = 1$ and $s_{2,3,4} = 0$. The Steps a to d have been done numerically by the computer.

The obtained optimal sequence is given to both human and robot to complete the disassembly task. Figure 10 demonstrates the four steps, i.e., Step 1 to Step 4, of the experiment process. Based on the obtained operation decision variables, α_{ij}, s_q, and x_{ij}, the robot and human will perform the collaborative task without conflicting. As shown in Figure 10 (1), the robot moves to the starting point, Screw 1, and conducts the disassembly, following which the human operator moves to Screw 2 to conduct the task, as shown in Fig. 10 (2). Then, the robot disassemble the remaining two screws, as shown in Fig. 10 (3) and (4).

The whole process in Figures 8 to 10 can be summarized as follows, in which Steps (a) to (d) are done in the computer and Steps (1) to (4) are done by the actual robot and human operator.

- a. The toy box is put on the table.
- b. Positions of the screws are identified.
- c. Possible feasible sequences are generated.
- d. The optimal sequence is obtained as follows: $R_1 \rightarrow R_2 \rightarrow R_4 \rightarrow R_3$.

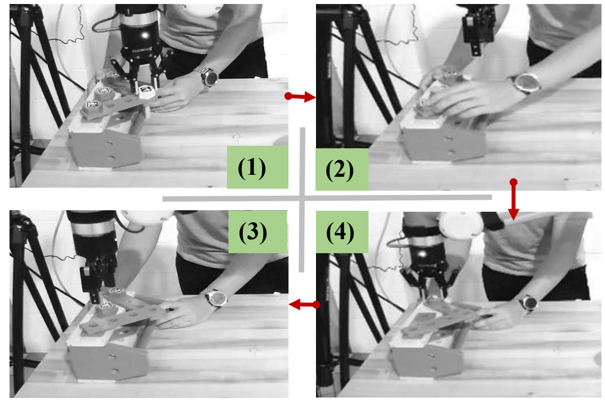

Fig. 10. Step 3. Human-robot collaboration to Complete Disassembly Task

- 1. The robot approaches Screw 1 to disassemble.
- 2. The human operator disassembles Screw 2.
- 3. The robot disassembles Screw 4.
- 4. The robot continues disassembling Screw 3.

Case 2: Screw 3 is closest to the robot and Screw 1 is unsafe for the human operator.

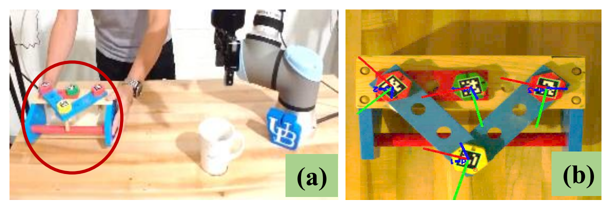

Fig. 11. Step 1. Identification of Locations of Screws and Robot

In this scenario, as shown in Fig. 11(a) the toy box is put onto the table such that the Screw 3 is the one that is closest to the robot. We assume Screw 1 is unsafe for the human operator. The locations of the four screws are identified by the camera, as shown in Fig. 11(b). Based on the locations and a different unsafe screw, Screw 1, a new set of feasible sequences are generated, as shown in Fig. 12(c), and a new optimal sequence is obtained $R_3 \rightarrow R_1 \rightarrow R_2 \rightarrow R_4$, with the following decision variables: $x_{31} = x_{12} = x_{24} = 1$, $\alpha_{31} = \alpha_{24} = 1$, and $s_3 = 1$. After these decision variables and the optimal sequence is obtained, they will be sent to both the human and the robot to conduct the collaborative task, as shown in Fig, 13, Step 1 to Step 4.

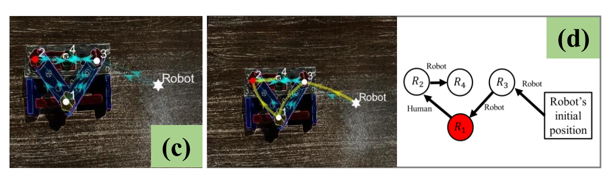

Fig. 12. Step 2. Optimal Disassembly Sequence Planning

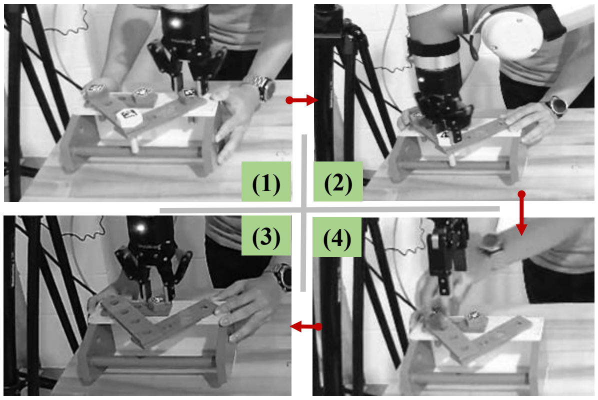

Fig. 13. Step 3. Human-robot collaboration to Complete Disassembly Task

5. Conclusions

This paper presents the formulation of the optimal disassembly sequence planning problem in the human-robot collaborative setting. Currently, disassembly is a labor-intensive process because of various unique properties such as random orientations and incomplete information for all the components. This paper targets to automate this process using human-robot collaboration. As a preliminary work, this paper presents several important considerations while formulating the planning problem. These considerations, different from the assembly sequence planning, include the different disassembly cost by robot and human, the various starting points, the safety consideration for human operators, and the feasible operations for robot. These considerations are raised for the scenarios when distinctive electronic wastes are fed into the disassembly line with different positions, orientations, and consists of hazardous materials in different components. By taking these considerations into account, the disassembly sequence is formulated into an optimization problem.

This paper also conducts the validation using a combined numerical and experimental method. The wooden toy box is used to emulate a real electronic product in the validation. It is randomly placed on the table, and the locations of these screws are identified using the camera. One particular screw is considered to consist of hazardous materials and is unsafe for human operation. This information is sent to the computer to generate all the feasible tasks and obtain the optimal task sequence considering both human and robot. After the optimal sequence is generated, it is sent to the human and the robot to complete the disassembly task. The experimental test shows that the robot and human complete the task without violating the rules and the safety constraints.

6. Acknowledgment

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