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Learning and revision in cognitive robotics disassembly automation

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ABSTRACT

Disassembly is a key step for an efficient treatment of end-of-life (EOL) products. A principle of cognitive robotics is implemented to address the problem regarding uncertainties and variations in the automatic disassembly process. In this article, advanced behaviour control based on two cognitive abilities, namely learning and revision, are proposed. The knowledge related to the disassembly process of a particular model of product is learned by the cognitive robotic agent (CRA) and will be implemented when the same model has been seen again. This knowledge is able to be used as a disassembly sequence plan (DSP) and disassembly process plan (DPP). The agent autonomously learns by reasoning throughout the process. In case of an unresolved condition, human assistance is given and the corresponding knowledge will be learned by demonstration. The process can be performed more efficiently by applying a revision strategy that optimises the operation plans. As a result, the performance of the process regarding time and level of autonomy are improved. The validation was done on various models of a case-study product, Liquid Crystal Display (LCD) screen.

1. Introduction

Due to the growth of the world population, the demand and the level of consumption of products have increased dramatically. The life cycle of these products – especially electronics and electrical products – has become shorter and resulted in an increasing number of EOL disposals. As a result, the treatment of the EOL products has become more important in order to reduce the environmental impacts and increase the value recovered. Disassembly is one of the key steps for the efficient EOL treatment but mostly ignored since the process is generally economically infeasible due to the labour cost especially in developed countries. Robotic systems are one of the potential options to address this economical issue by replacing the human labour with low-cost full automation. However, the flexibility and robustness of the system are the obstacles due to the variations and uncertainties of the products returned [1]. In this research, an automated system which is flexible to deal with various models of product in a product family without specific information supplied a priori is developed. The research consists of two phases. The first phase of the research involves the basic behaviour part which is earlier presented in [2] and the second phase related to the advanced behaviour part is presented in this article.

1.1. Uncertainties in automated disassembly

Vongbunyong et al. [2] summarised the variations and uncertainties that must be addressed at product and process levels. The variations in the properties of a type of EOL products are: main product structure, appearance-quantity-location of the components, and other physical uncertainties. Consequently, these variations lead to uncertainties in disassembly process plan (DPP), i.e. disassembly sequence plans (DSP), disassembly operation plan, and process parameters. Unlike the traditional disassembly conducted by human operators, these uncertainties are more problematic for the automated disassembly system due to the limited capability to react with the product. The limited perception of the product and process leads to a lack of information to make decisions in order to conduct the operation properly.

A number of attempts have been made to address these uncertainties in automated disassembly systems. To address the uncertainties at the planning and the operation level, sensor systems are integrated to the disassembly planner which is an intelligent agent generating DPP to control the operation sequences of the system [3–9]. Much research focused on the uncertainties at the planning level; for example ElSayed

List of Abbreviations: CRM, Cognitive robotics module; *DOM*, Disassembly operation module; *VSM*, Vision system module; *CRA*, Cognitive robotics agent; *KB*, Knowledge base; *DSP*, Disassembly sequence plan; *DPP*, Disassembly process plan; *EOL*, End-of-Life; *LCD*, Liquid crystal display; *PCB*, Printed circuit board

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et al. [9] used Genetic Algorithms (GA) for generating an optimal operation sequence according to the current components and supplied bill-of-material. Torres et al. [5] developed a task planner generating paths for two cooperative multi-sensorial robots. Bailey et al. [10] developed a tool path generator with error recovery.

In general, automated disassembly systems operate based on the two primary sources of inputs, including (1) *prior knowledge* and (2) *knowledge detected during the process*, which are expected to be accurate. The first type of input is the information regarding product specifications, e.g. product structure, geometry and quantity of components, etc. They need to be specified before the process but generally impractical in an industrial practice due to a massive number of unknown models of the returned products. Another kind of the input is perceived during the disassembly process, typically by using a vision system. However, the detection result is unreliable in case that the features are not visually detectable, e.g. quasi or virtual, occluded, hidden, and unknown components [11]. The uncertainty at the operation level occurs in this case. A number of techniques, e.g. innovative disassembly tools for disestablishing specific connectors [12–15] and (semi-) destructive approaches [16,17], are developed to resolve these problems. These techniques may be effective for the uncertainties in specific problems and the operations are supposed to be achievable even the perceived information is less accurate. However, in an actual disassembly process, the achievement of disassembly cannot be guaranteed because the process will fail if there is even one connexion remained. One of the challenging problems is to develop a system that can automatically realise this failure, especially at the operation level, and try to resolve it. The trial-and-error strategy presented in [2] makes the system more robust to these uncertainties. However, the operation can fail if the required actions are too different from the actions generated by the predefined rules.

1.2. Learning in disassembly domain

In manufacturing processes, machine learning (ML) is used to improve the performance of the process and effectively handle uncertainties. However, a little research associated with learning has been conducted in the disassembly domain. The existing research was conducted in two approaches: (1) to optimise the parameters, DSP, and disassembly process planning (DPP) by learning with a significant number of generated data points and (2) to reuse the knowledge previously learned from past experience.

For the first approach, Tang et al. [18] used a Disassembly Petri-net (DPN) with Bayesian Network (BN) to solve the DPP problem. The learning of BN parameters through the performed operations allows the planner to handle uncertainties, i.e. current system resources, human factor, and level of defect. The principle of DPN is extended to improve flexibility and efficiency of disassembly plans, [19–22]. In addition, Yeh [23] investigated the effect of learning on the DSP by using simplified swarm optimisation. The parameters of the plan are revised by considering disassembly method penalty, recycling technique, and material types, for a pair of components. As a result the efficiency of the DSP, i.e. disassembly time, was improved after repeating a significant number of the generated data samples.

For the second approach, Zeid et al. [24] proposed a framework using a case-based reasoning (CBR) approach on DPP. The successful and efficient disassembly plans are generated by applying rules according to the constraints, states, and goal. The disassembly plans are initially generated according to rule-based reasoning and then learned as cases. The cases learned from past experience will be used for CBR which is able to adapt to the new products in the future. The principle of CBR was extended to be more flexible to multiple product platforms [25].

The existing research typically focuses on learning at the strategic planning level, including DSP and EOL treatment. Less attention has been paid to the operation level, for instance the disassembly operation is defined as one of the factors of the strategic plan [23]. As discussed in Section 1.1, the operation for removing main components is essential since the unresolvable uncertainties can lead to failure of the disassembly process. The optimal disassembly plan will be useless if the process cannot be carried out due to the failure at the operation level. However, no research has explored learning strategies at the operation level in detail. In addition, none of these learning strategies have been implemented on an automated disassembly system yet. In this article, the learning and revision strategy of the plan and the operation using cognitive robotics is proposed.

1.3. Human involvement in disassembly and cognitive robotics

Human-machine cooperation occurs in various forms during the disassembly process. Kim et al. [26,27] proposed a hybrid disassembly system where human operators manually disassemble in case the automatic operation has failed. The uncertainties due to unreliable inputs stated in Section 1.1 can be resolved. Although this approach may be economically feasible due to the efficiency and time consumption, the limitation of human direct exposure occurs in case the product contains hazardous components, e.g. toxic or high-voltage.

The principle of cognitive robotics allows classical artificial intelligence (AI) to be more effective in performing tasks in complex environments as well as interactions with human [28]. According to the cognitive robotics architecture close-perception action loop [29], the behaviour of the system is controlled by cognitive functions. As a result, the system is able to reason about the external dynamic world, react, adapt to it, and learn. The human also interacts with the system in a collaborative way, for instance, as implemented in the cognitive factory [30]. This research proposed using the learning capability of cognitive robotics to address the aforementioned problem. The system is expected to learn from user demonstration remotely [31] and becomes autonomous afterwards.

1.4. Research overview

In this research, cognitive robotics is used to emulate the behaviours of human operator which is capable of handling the uncertainties at the planning and operation levels. In *Phase-I*, the basic behaviour is driven by two cognitive functions, (1) reasoning and (2) execution monitoring, which are able to address a certain level of uncertainties [2]. The basic behaviour control focuses on autonomous disassembly by using trial-and-error strategy to address the variations and uncertainties. A major contribution is the system that is able to deal with various models of products without specific information supplied.

In this article, the system has been extended to *Phase-II* by implementing the advanced behaviour control driven by two functions: (1) learning and (2) revision. A significant improvement is the strategy to improve the process performance regarding the time and degree of autonomy. With human assistance, the system can address the uncertainties that are unresolvable by the basic behaviours. The revision focused on process improvement and optimisation at the operation level where the uncertainties in vision system and disassembly operation units are directly involved. Eventually, the system is capable of handling various models of product and automatically generates the DSP and DPP after a certain number of revisions.

This article is organised as follows. An overview of our disassembly automation focused on the basic behaviours is explained in Section 2. In regard to the learning and revision, a knowledge model in regard to the disassembly domain is explained in Section 3. Methodology for learning and revision are described in Sections 4–5. Finally, the experimental results and conclusion are given in Section 6.