Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 98 (2021) 282–287

www.elsevier.com/locate/procedia

28th CIRP Conference on Life Cycle Engineering

Fostering End-of-Life Utilization by Information-driven Robotic Disassembly

Hendrik Poschmann[a*], Holger Brüggemann[a], Daniel Goldmann[b]

[a]*Institute of Production Technology, Ostfalia University of Applied Sciences, Salzdahlumer Straße 46/48, 38302 Wolfenbuettel, Germany*
[b]*Institute of Mineral and Waste Processing, Waste Disposal and Geomechanics, Clausthal University of Technology, Walther-Nernst-Str. 9, 38678 Clausthal-Zellerfeld, Germany*

* Corresponding author. Tel.: +49-5331-939-45880; fax: +49-5331-939-45882. *E-mail address:* he.poschmann@ostfalia.de

Abstract

Economic and ecological feasibility are the key factors for companies to engage in circular economy processes. Disassembly plays a major role in this environment, as it is one of the most complex and labor-intensive steps in end-of-life processing. For this reason, an automation of the disassembly in order to facilitate performing the necessary tasks is highly favorable. In this contribution, an agent-based robotic disassembly system, evolved from the innovation cluster "Recycling 4.0", is presented. The proposed system features a novel information-driven control architecture, combining a superordinate, cloud-based knowledge base and comprehensive sensory perception. In pursuance to find an optimized utilization strategy for each part to be disassembled, various features, such as individual life-cycle data, material composition and optical rating are taken into account for an artificial intelligence based multi-criteria assessment in order to determine an appropriate end-of-life option for each of the part's components. It is shown that the developed system is able to operate in a collaborative scenario of an electric vehicle traction-battery disassembly, deciding upon the level of disassembly for the end-of-life option chosen based on the available information, which is acquired through a system-wide interoperability standard. Being able to actively contribute to the overall knowledge base of the framework by processing validated product- and process-knowledge back to the knowledge base, the robotic system fosters a feasible progression towards closed-loop supply-chains in a circular economy and enables new market participants to engage in recycling operations.

Keywords: disassembly; robotics; recycling; circular economy; decision-making.

1. Introduction

Global challenges, such as climate change and the limitation of rare natural resources, threaten established industries and economies. According to the United Nations Sustainable Development Goals (SDGs), responsible production and consumption are key elements in the strategy to manage the necessary change [1]. In order to successfully introduce circular economy patterns as a solution, the sustainable feasibility of end-of-life (EoL) processing needs to be ensured. Disassembly is a key topic, both in recycling and remanufacturing processes. Being shaped by manual work processes and a high number of product variants and conditions, increasing its efficiency by intelligent automation concepts is desirable. In this work, a robotic disassembly framework is presented, capable of dealing with complex decisions regarding EoL-options depending on individual product information acquired by vision and sensory perception as well as a superordinate data management concept.

Conceptualized as a cognitive, agent based system including the results of former research, such as *Vongbunyong et al.* [2] and *Jungbluth et al.* [3], the approach presented offers a new aspect of including the entire vertical and horizontal range of stakeholders in the EoL value-chain by connecting the system bi-directionally to a comprehensive information marketplace, employing a standardized information model for individually assigning product and process specific (lifecycle-)knowledge.

10.1016/j.procir.2021.01.104

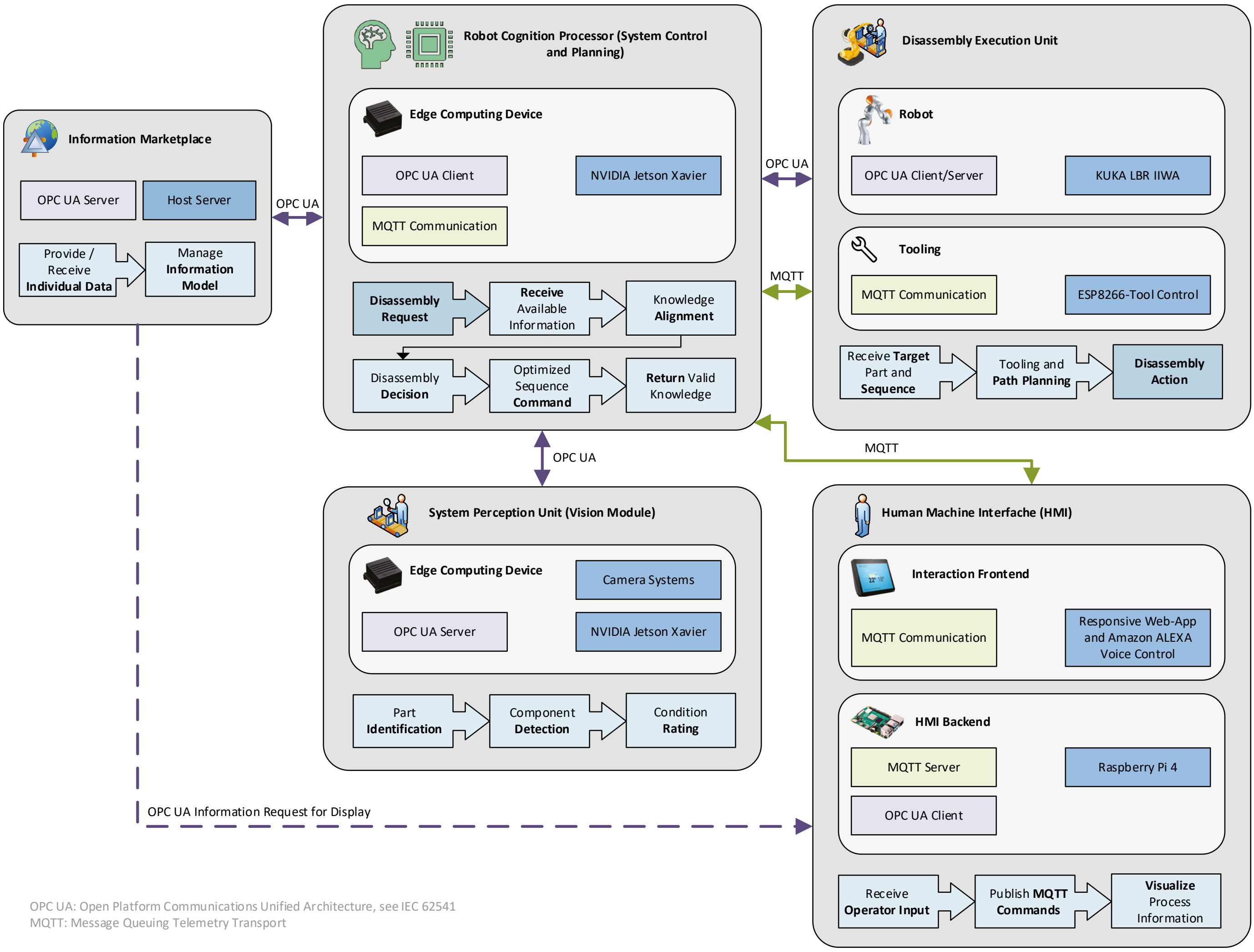

Fig. 1. System Framework for Information-driven Robotic Disassembly

The herein proposed use of human-robot-collaboration (HRC) for disassembly tasks has already been validated by various projects, such as [4] and [5]. Decision processes in disassembly aiming for sustainable decisions by integrating multiple criteria [6], taking quality and cost variations into account [7, 8] or proposing simplified direct cost-benefit models [9] are complemented by a novel machine learning model for individual in-process decisions, determining the most suitable EoL option based on a vast number of relevant features and a constant learning input from disassembly carried out within the framework (see 2.2). In contrast to the previous approaches mentioned above, this contribution proposes the use of a neural network instead of decision-trees or fuzzy-logic. Moreover, a holistic review of robotics in disassembly can be found in [10].

The structure of the paper is as follows: Section 2 describes the system framework in detail, presenting the main features and modules in specific subsections. A case study of electric vehicle battery disassembly from the research project “Recycling 4.0” is shown in section 3. Finally, a conclusion on the topic is given in section 4, summarizing the results of this research and giving impulses for future projects.

2. System Framework

The main goal of the system proposed is to enable automated disassembly processes to be economically, ecologically and socially viable, therefore sustainable, while fostering a higher utilization rate for EoL products in order to progress towards the concept of a circular economy. To satisfy this requirement, the following system framework is proposed.

2.1. Architecture

The architecture of the robotic disassembly system as displayed in Fig. 1 is built following the principle of an intelligent agent in order to allow adaptive behavior and target-oriented implementation. Cognitive robotics thereby include the ability to reason and plan complex tasks in unknown environments [11].

Starting in a process-oriented approach, the reception of a disassembly request triggers the robot cognition processor (RCP) to request the related information model from the disassembly data cloud via an external information marketplace [12]. The system perception unit (SPU) gathers visual information, such as part identification, component detection and a condition rating, making use of its unique position in the EoL process as the first physical evaluation opportunity of each individual part. The result of the SPU's evaluation and the dataset from the external marketplace are combined to an aligned, object-specific knowledge model in the RCP. Based on this model, the decision regarding the most suitable EoL option is made for each component level of the product to be disassembled. A quantitative order and precedence relation thereby determine the optimized disassembly sequence. These steps can be applied to all levels of subassemblies. The disassembly operation itself is selective, which implies the object is not to be fully disassembled necessarily. In the next step, the disassembly execution unit (DEU) receives the target part and sequence command and carries out the disassembly collaboratively. Valid process knowledge is transferred back to the external data cloud. The entire process is controlled and monitored by an intuitive HMI capable of providing a web-based application and voice control for the operator to allow efficient handling and transparent documentation.

2.1.1. Robot Cognition Processor (RCP)

Being the main control module of the robotic disassembly system, the RCP is responsible for system-level information management, iterative decision-making and coordinating information requests and contributions, both to and from the different modules and the external database, as displayed in Fig. 2. Receiving a disassembly request, the RCP acquires the visual information from the SPU and aligns them with the digital model from the superordinate knowledge base in the OPC address space. This single attributed dataframe per object represents the available lifecycle data as well as a current (optical) status and integrity rating of the part. Based on this dataset, the core process of the RCP is to make a decision upon the EoL-utilization option compliant to economic, ecological and social objectives. In order to make these decisions, the following assumptions have to be made:

i) An initial decision about the overall feasibility of the highest assembly-group of the core part (e.g. the car itself) has been made.
ii) The required information could be supplied by the disassembly database and purchased without affecting the overall business case negatively.
iii) As the machine learning strategy applied relies on a certain amount of training data as an initial input before operation phase, this data must be provided in the form of historic data or generic samples.

Taking these assumptions into account, a machine learning sub-process of stepwise classification of eligibility for either

a) disassembly for reuse or remanufacturing (retaining the components functional integrity for resale)
b) disassembly for improved material recycling or
c) disposal (highest feasible level of disassembly reached)

is taking place. If the system is not able to make a decision, a manual teaching and decision input is possible by the operator. The product model hierarchy of the OPC UA server provides precedence information, thus allowing the RCP to consider precedence relation. Based on these relations and the decision outcome, a product individual disassembly sequence and level is determined and gets forwarded to the DEU.

A decision upon the EoL-option is made for each component level and each subassembly level stepwise and individually. The decision process thereby considers all dimensions of sustainability by taking economic, environmental and social factors into account. The individual dataset contains information, such as the core price, material prices and composition, component resale prices, market demand and historic process costs for economic aspects, production date, condition (optical and diagnosed, e.g. state of health), hazmat and, if available, LCA factors for environmental aspects as well

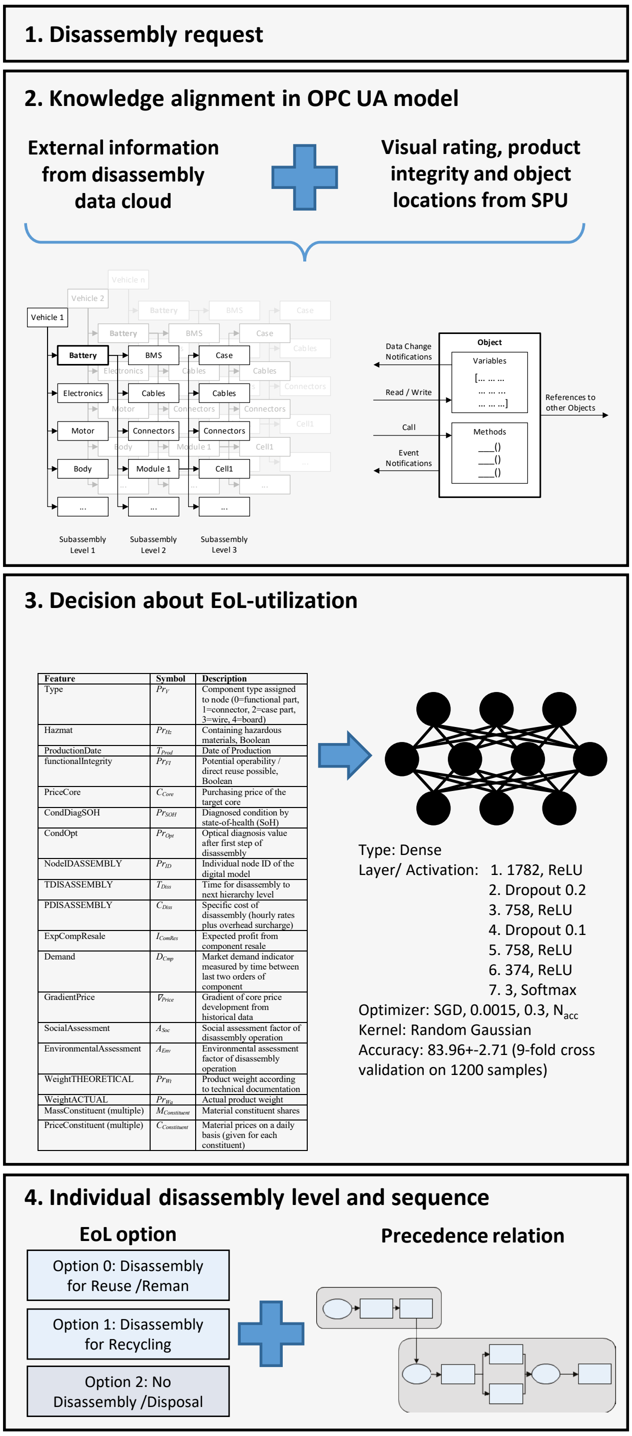

Fig. 2. RCP working principle

as a social assessment factor, based on raw materials critical to the supply-chain and a predicted economic value added for future treatments, such as remanufacturing. However, in contrast to fully deterministic approaches, such as [13], the proposed decision system will not necessarily fulfill feasibility criteria in all relevant categories. Due to the working principle of the machine learning approach, certain features may be weighted stronger than others and without hard constraints this may lead to an infeasible category (e.g. economic) in favor of another (e.g. environmental).

2.1.2. System Perception Unit (SPU)

All external perception of the robotic disassembly system is carried out by the SPU. It consists of two different camera systems, connected to an edge-computing device, representing a modular and efficient approach to an integrated robot-vision solution.

The main module is a stereovision system consisting of Sony IMX577 sensors with a maximum resolution of 4056x3040 pixels, connected via 4 lanes of CSI-2 interface (10 Gbit/s in total) each. The high resolution is required, as the camera system is supposed to perform over a wide field of view, capturing the entire disassembly object and still be able to reliably detect and differentiate small objects (less than 32^2 pixels), such as different types of screws. The task of this system is the identification and localization as well a quality rating for the components and connectors (see Fig. 3, A). To implement these functions, the TensorFlow object detection API is used, in which Faster RCNN with an Inception ResNet V2 structure is employed [14]. The detection model is trained in a supervised training process on a set of 500 labelled images per specific object, also using data augmentation to extend the amount of different images. The rating functionality should be able to determine the visual condition of the part. In a first step of realization of this feature, a rust detection is implemented, using a set of 3500 available pictures for training. The negative status rating is given if the bounding box of the rust detector overlaps with a detected object by 40% or more. In an evaluation of the SPU's detection and localization functionality, an accuracy of 73.71% for TX30_M6x12 screws as the smallest objects in the scene is ascertained, while the localization precision is 0.86 mm on mean average with a standard deviation of 2.48 mm. However, the high deviation and precision scattering is depending heavily on the position, increasing progressively towards the edges of the image.

The second module of the SPU is mainly used for safety applications in HRC operations. An Intel Realsense D435i

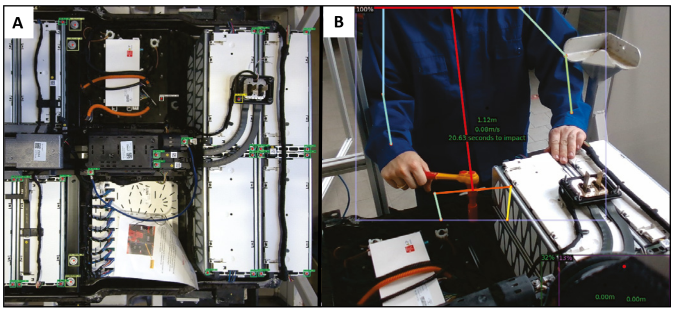

Fig. 3. A) Detection of small objects (screws) B) Human key point workspace surveillance

depth camera with an inertial measurement unit incorporated is used for this task, equipped with a 1280x720 pixel active infrared stereo-vision sensor as well as an RGB sensor, being connected with a USB 3.1 Gen. 1 connection (5 Gbit/s). This module is mounted on the tool of the robot and used for workspace surveillance. To realize a safe and efficient collision avoidance, the Detectron2 object detection algorithm [15] is used for human key point detection (see Fig. 3, B). If a key point comes close to the path of the robot, the application is paused until the workspace is clear of any human obstacle.

2.1.3. Disassembly Execution Unit (DEU) and Human Machine Interface (HMI)

The DEU and the HMI are the two system units in direct contact with the disassembly operators. As the disassembly process itself is collaborative and not fully automated in this approach, they both contribute equally to a successful execution of the disassembly task.

The DEU consists of a robot arm (KUKA LBR iiwa 14) and a tool module. The robot receives the target part operation coordinates (e.g. for unscrewing) and sequence from the RCP via the OPC UA protocol. In addition, the tool control is implemented modularly on an ESP8266 microcontroller using the MQTT-protocol for direct start/stop commands by the robot program via a wireless network connection. The advantage of this principle is that it can be applied to various different tools in distinct disassembly settings. The case study presented in section 3 uses an unscrewing tool similar to [13], various other concepts, such as a multi-purpose disassembly tool [16] may be used with the same method as well. After a successful operation, process parameters, such as the required amount of time and therefore the validated information about the operation cost, are transferred back to the external disassembly database, being stored in the allocated OPC UA model.

The HMI is made up of a web-based application and an Amazon Alexa voice control module as an interaction frontend while an MQTT server and OPC UA client for information retrieval provide the backend. The operator can interact directly with the system by touch-control via the web interface or give the same commands via voice-control for hands-free operation. The interface is designed according to DIN EN ISO 9241 for ergonomic usability and follows a process-oriented approach in which the operator is guided by the system but still has the opportunity to change individual decisions made and also comment or document product-related flaws not detected by the system or process-related errors. The HMI host device is connected to a local network to ensure security requirements.

2.2. Communication

The system's communication is divided into two different machine-to-machine protocols for the front-end and back-end system. The platform independent interoperability standard OPC UA (Open Platform Communications Unified Architecture, see IEC 62541) [17] is selected for product specific information transfer by creating OPC UA models for each component representing the entire product structure and relation as well as assigning relevant lifecycle information, such as production date and material composition, in a semantic description. This information can be edited in the process and transferred bi-directionally. The control frontend is realized by the use of MQTT (Message Queuing Telemetry Transport), a lightweight open publisher-subscriber protocol enabling effective control with a focus on reliability and minimum network bandwidth usage. This distribution of task specific protocols represents the process requirements and the strengths of each communication standard while maintaining optimal performance on limited system resources [18].

3. Case Study

To validate the concept in a real disassembly scenario, a case study of electric vehicle battery disassembly is conceptualized. As a disassembly object, the battery module of a 2013 Volkswagen e-Up is chosen. The entire system is realized in a demonstrator disassembly cell for the step of module disassembly in an HRC scenario (see Fig. 4). For the initial training of the RCP decision module, 1200 samples of generic batteries (composition according to [19]) with complete datasets are used. The aim of the concept validation is to show a full functionality in terms of horizontal and vertical communication by enabling the system to decide about EoL utilization strategies for the individual modules of the battery and also process the generated information back to the external storage database.

Fig. 4. Case study scenario on electric vehicle battery disassembly

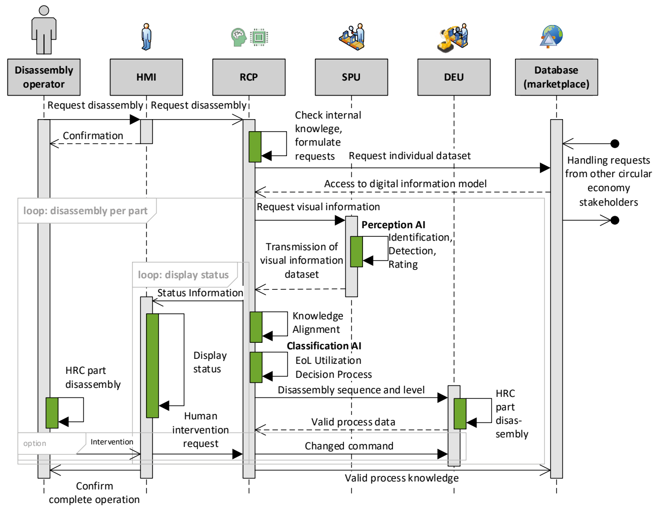

Fig. 5. UML sequence diagram of case study implementation

The analysis of the demonstrator system shows the outcome depicted as a UML sequence diagram in Fig. 5. All communication systems, both the OPC UA as well as the MQTT protocol, are able to establish the relevant connections. The disassembly request for the target module is entered into the HMI and the command is eventually transmitted to the RCP. In a full scale facility, this step could also be automated. Hence, the RCP requests the OPC UA model to be provided with the dataset concerned form the data cloud. Simultaneously, a request for the visual information is sent to the SPU. Thus, the perception module captures an image of the electric vehicle battery and transmits the relevant positions of the screws for the first module to be disassembled as well as the visual condition factor to the RCP. Consequently, the decision process takes place at the first hierarchy level of the battery, derived from the digital product model. The EoL-utilization option is decided upon and in cases of an option including disassembly, the concrete command is composed as a sequence representation including the available information for the chosen components as well as precedence feasibility data. However, this step is only performed for the first level of parts in our case scenario and will be refined for subsections of the battery in future research. The DEU, namely the robot, receives the task coordinates from the RCP and moves to the desired position, using the internal planning algorithm while taking the boundaries of the disassembly cell and the workspace surveillance data from the SPU's wrist camera into account. As a next step, the four corner screws of the target module are removed by the robot, while the command for the tool module is sent from the robot controller after a successful sensitive approach maneuver. As a final step of the disassembly case, the operator receives a notification on the HMI that the robot operation was successful and the module can be taken out manually. The operator may also work on other parts of the battery simultaneously during the robot operation, as the workspace surveillance provides the required safety functions to prevent collisions. Optical rating influence could not be validated in reality yet, as the number of disassembly objects is too small to proof relevance. However, the generic validation dataset for the RCP contained optical ratings as well and correlation to the EoL decision is traceable there.

All process monitoring data, such as the overall disassembly time, are assigned to the digital model as valid process information and transferred back to the disassembly database. The human intervention option can be triggered via the HMI in case of a problem regarding the process or previously unnoticed product damage. The information entered has to be selected from pre-classified categories in order to allow an integration into the calculation of the actual component status.

4. Conclusion

Disassembly is a major challenge in lifecycle operations. In this paper, a cognitive robotic system is presented which is capable of integrating individual product lifecycle data to decide upon the actual degree of disassembly in regard to the most suitable EoL utilization option. The system is composed in a modular, agent-based structure which is adaptable and scalable for multiple applications throughout production and retro-production systems while employing efficient edge computing technology and Industry 4.0 interoperability standards, such as OPC UA and MQTT.

A case study on the disassembly of electric vehicle traction batteries shows that the system proposal is fully functional in terms of information transfer and task fulfillment of the specific modules for cognition, perception, execution and operation in a realistic HRC case scenario. As a next step, a quantitative evaluation and comparison to manual work will be carried out. On top of that, a benchmark of different models on a common reference object would be a sensible addition.

However, from the first experiments, there are still potentials for improvement in terms of cycle-time and an evaluation of the principle in a continuous disassembly facility. Furthermore, the decision process as a key factor for the establishment of suitable utilization strategies can be linked to a superordinate system taking the entire circular economy processes into account as described in a framework idea in [20].

In conclusion, the application of modern robotic approaches in the realm of circular economy can foster EoL-utilization by creating feasible processing scenarios due to a holistic information management concept in order to make recycling and product-oriented lifecycle management more attractive to all possible participants in circular economy models.

Acknowledgements

This paper evolved from the research project Recycling 4.0 (Digitalization as the Key to the Advanced Circular Economy using the Example of Innovative Vehicle Systems) which is funded by the European Regional Development Fund (EFRE | ZW 6-85017703) and managed by the Project Management Agency NBank, Germany.

The authors would like to thank Volkswagen AG as a project partner of Recycling 4.0 for the facilitation of the battery for research purposes.

References

[1] General Assembly of the United Nations, 2015. Resolution adopted by the General Assembly on 25 September 2015: A/RES/70/1.
[2] Vongbunyong, S., Chen, W.H., 2015. Disassembly Automation. Springer International Publishing, Cham.
[3] Jungbluth, J., Gerke, W., Plapper, P., 2018. Robotix-Academy Conference for Industrial Robotics (RACIR) 2018: Recent Progress Toward Intelligent Robot Assistants for Non-Destructive Disassembly, 1st edn. Shaker, Herzogenrath.
[4] Chen, W.H., Wegener, K., Dietrich, F., 2014. A robot assistant for unscrewing in hybrid human-robot disassembly, p. 536.
[5] Bdiwi, M., Rashid, A., Pfeifer, M., Putz, M., 2017. Disassembly of Unknown Models of Electrical Vehicle Motors Using Innovative Human Robot Cooperation, in Proceedings of the Companion of the 2017 AaCMIEEE International Conference on Human-Robot Interaction, ACM, New York, NY, p. 85.
[6] Li, J., Barwood, M., Rahimifard, S., 2019. A multi-criteria assessment of robotic disassembly to support recycling and recovery 140, p. 158.
[7] Tian, G., Zhou, M., Li, P., 2018. Disassembly Sequence Planning Considering Fuzzy Component Quality and Varying Operational Cost 15, p. 748.
[8] Feng, Y., Gao, Y., Tian, G., Li, Z. et al., 2019. Flexible Process Planning and End-of-Life Decision-Making for Product Recovery Optimization Based on Hybrid Disassembly 16, p. 311.
[9] Alfaro-Algaba, M., Ramirez, F.J., 2020. Techno-economic and environmental disassembly planning of lithium-ion electric vehicle battery packs for remanufacturing 154, p. 104461.
[10] Poschmann, H., Brüggemann, H., Goldmann, D., 2020. Disassembly 4.0: A Review on Using Robotics in Disassembly Tasks as a Way of Automation 92.
[11] Levesque, H., Lakemeyer, G., 2008. Chapter 23 Cognitive Robotics, in Handbook of knowledge representation, Elsevier, Amsterdam, Boston, p. 869.
[12] Kintscher, L., Lawrenz, S., Poschmann, H., Sharma, P., 2020. Recycling 4.0 - Digitalization as a key for the advanced circular economy 15.
[13] Duflou, J.R., Seliger, G., Kara, S., Umeda, Y. et al., 2008. Efficiency and feasibility of product disassembly: A case-based study 57, p. 583.
[14] Szegedy, C., Ioffe, S., Vanhoucke, Vincent, Alemi, Alexander A., 2017. Inception-v4, inception-ResNet and the impact of residual connections on learning, in Proceedings of the Thirty-First AAAI Conference on Artifical Intelligence, AAAI Press, San Francisco, California, USA, p. 4278.
[15] Wu, Y., Kirilov, A., Massa, F., Lo, W.-Y., Girshick, R. Detectron 2. https://github.com/facebookresearch/detectron2. Accessed 23 July 2020.
[16] Borràs, J., Heudorfer, R., Rader, S., Kaiser, P. et al., 2018. The KIT Swiss Knife Gripper for Disassembly Tasks: A Multi-Functional Gripper for Bimanual Manipulation with a Single Arm, in Towards a Robotic Society: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems October, 1-5, 2018, Madrid, Spain, Madrid Municipal Conference Centre, IEEE, [Piscataway, NJ], p. 4589.
[17] OPC Foundation. OPC Unified Architecture. Part 1 Overview and Concepts: Release 1.04. https://opcfoundation.org/developer-tools/specifications-unified-architecture/part-1-overview-and-concepts/. Accessed 23 July 2020.
[18] Profanter, S., Tekat, A., Dorofeev, K., Rickert, M. et al., 2019. OPC UA versus ROS, DDS, and MQTT: Performance Evaluation of Industry 4.0 Protocols, in Proceedings, 2019 IEEE International Conference on Industrial Technology (ICIT): Melbourne Convention and Exhibition Centre, Melbourne, Australia, 13-15 February, 2019, IEEE, Piscataway, NJ, p. 955.
[19] Diekmann, J., Hanisch, C., Froböse, L., Schälicke, G. et al., 2017. Ecological Recycling of Lithium-Ion Batteries from Electric Vehicles with Focus on Mechanical Processes 164, A6184-A6191.
[20] Bloemeke, S., Mennenga, M., Herrmann, C., Nippraschk, M. et al. Recycling 4.0 An Integrated Approach Towards an Advanced Circular Economy 2020.