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A literature review on non-destructive disassembly

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Review

Human–robot collaboration in industrial environments: A literature review on non-destructive disassembly☆

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ABSTRACT

Nowadays, numerous companies and industries introduce recycling processes in their production, aiming to increase the sustainable use of the planet's natural resources. Nevertheless, these processes remain inefficient due to the high degree of complexity and variation in the products. In order to remedy this, industry stakeholders adopt the circular economy business model and introduce take-back programmes and remanufacturing processes for their End of Life products in their own supply chains. Take-back programmes enable the re-sourcing of sub-assemblies and components of previously manufactured products while remanufacturing processes encourage non-destructive disassembly. Due to the uncertain conditions of the re-sourced products, fully automated cells cannot cope with the demanding disassembly processes. Therefore, there is a need to establish hybrid disassembly robot cells where humans and robots work closely together in a process known as human–robot collaborative disassembly (HRCD). This paper examines the landscape of HRCD and reviews the progress in the field during the period 2009–2020. The analysis investigates principles and elements of human–robot collaboration in industrial environments such as safety standards and collaborative operation modes, HRI communication interfaces, and the design characteristics of a disassembly process. Additionally, the various technical challenges of HRCD are explored, and a review of existing systems supporting HRCD is presented. This review aims to support the robotics community in the future development of HRCD systems, discuss identified literature gaps, and suggest future research directions in this area.

1. Introduction

The rapid progression in technology over the last decades has changed the world's consumptive behaviour significantly. However, with the current business model, this trend is not environmentally and economically sustainable [1]. A significant number of manufacturers have initiated a paradigm shift by applying various recycling processes in the production lines. For example, they attempt to reduce the number of raw materials that have to be extracted from Earth, by sending the excess amount directly back to their vendors; an action that has already shown environmental and economical benefits [2].

However, this remains insufficient; therefore, policy providers have discussed and promoted the so-called circular economy business models (CEBMs) in UN- and EU-summits [1,3,4] and significant industrial stakeholders, such as Bosch [5], Grundfos [6] and Apple Inc. [7] have already started to adopt this model. Fig. 1 illustrates the central concept behind circular economy, which is to reuse/remanufacture parts and components of products, that have reached their End-Of-Life (EOL) stage and as a result extend the life of sub-assemblies and single components.

Fig. 1 illustrates the central concept behind circular economy, where the aim is to extend the life of sub-assemblies and single components of products, by reuse-/remanufacturing parts and components of products, which have reached their End-Of-Life (EOL) stage.

Traditional manufacturing practices that require, e.g. shredding and reproduction of raw materials, can be less environmentally friendly compared to the remanufacturing/requalification reproduction process for the following reasons: (i) contains non-environmentally friendly chemicals, (ii) is energy consuming, (iii) the new component still has to be produced, (iv) the requalification of used parts is economically more viable than their recycling [8]. In addition, a report from Ellen MacArthur Foundation [9] outlines the fact that the CEBM brings the following benefits for manufacturing companies:

(i) Substantial net material savings

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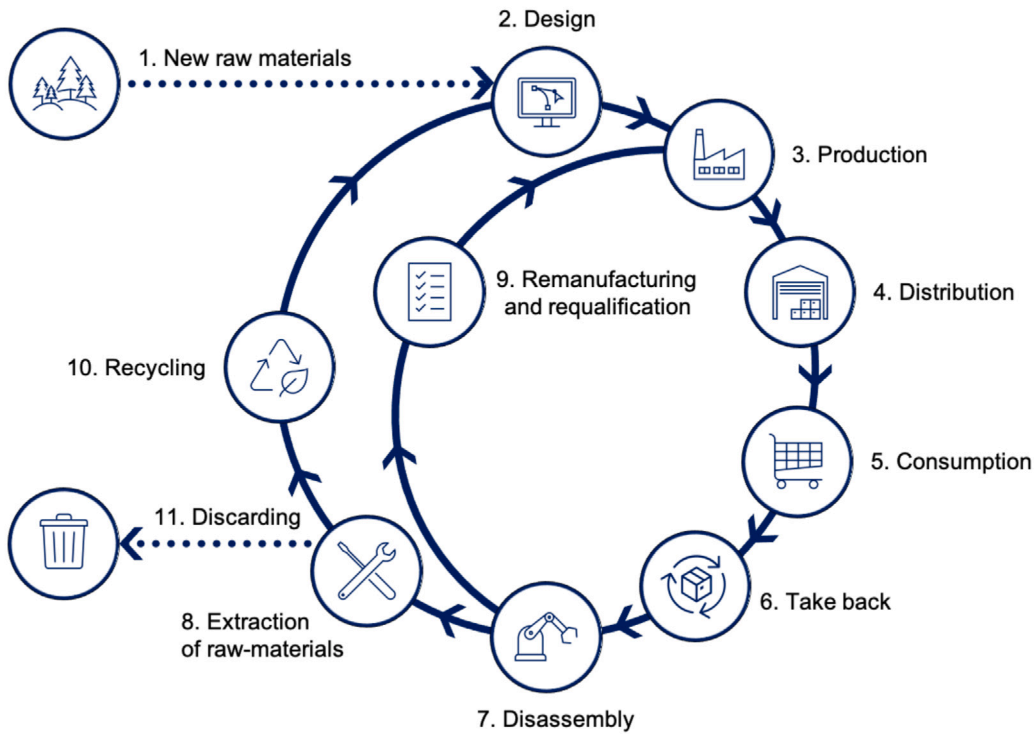

Fig. 1. Abstract visualization of the resource life cycle according to the circular economy business model. 01: New raw materials enter the production; 02: Design & manufacturing of sub-components; 03: Production of final product; 04: Distribution of the product to customers; 05: Consumption of the product; 06: Take back of the EOL product (EOLP); 07: Disassembly of the EOLP; 08: Extraction of raw materials; 09: Remanufacturing and requalification of extracted sub-components; 10: Recycling of raw materials; 11: Discarding non-recyclable raw materials.

(ii) Reduced exposure to price volatility
(iii) Increased economic development
(iv) Increased innovation and job creation potential
(v) Increased resilience in living systems and the economy

These findings are further backed by Li et al. [10], where in a case study for the analysis of a disassembly process where robots are used for the recovery of strategically important materials from electric vehicles, concluded that an average 95% of the materials and their associated recovery values could be extracted. It also states that it is crucial to take the design for disassembly (DfD) of products into account as a pre-treatment process for future EOL vehicles as it has a direct and positive influence on the efficiency of disassembly processes. Consequently, this leads to a reduction in material lost during the recycling process. According to Graedel et al. [11], this can be traced back to the increased complexity of multi-material products. Therefore, companies that adopt this business model still face major challenges in the following three fields:

Logistics/ Take-back programme: Take-back programmes serve the purpose of souring EOL products from customers and end-consumers to extract reusable sub-assemblies and components. Establishing and maintaining a take-back programme profitable remains a major challenge for most companies.

Disassembly Process: The disassembly process itself focuses on the extraction of sub-assemblies and individual components of EOLPs in such a way that they can be re-used/-manufactured. Non-destructive disassembly of final products remains a process highly dependable on the original design and assembly of the product.

Requalification Process: The requalification process is another essential area for the realization of the circular economy. Here, the disassembled sub-assembly or components are tested to evaluate if they are suited to be introduced back into the manufacturing process and integrated into a new product. The design of such evaluation process to identify all potential defects and predict the future life span of said sub-assembly/component remains a major challenge.

Table 1
Technological challenges for de-/remanufacturing system. [12].

Challenges
• High variability in the conditions of post-use parts
• Poor information about return products
• Increasing product complexity
• Short life-cycle of products and high product variety
• Increasing quality requirements on recovered materials and component
• Pressure on costs and efficiency

The main challenges between these three areas lay in the technological challenges, as stated in [12]: “The role of advanced de- and remanufacturing technologies and systems is fundamental to achieve the required quality and efficiency of the regeneration process”. Additionally, some major challenges that were pointed out are presented in Table 1. As recently pointed out in [13], the economic viability of the take-back programme is affected by its high proportion of manual labour. There was concluded that the cycle time for the disassembly of a product takes three minutes, compared to a cycle time of 20 s for a conventional recycling setup (i.e., shredding).

In order to make CEBM viable for any manufacturer, it is necessary to automate the disassembly process. One of the main technological enablers that facilitate the automation of the vast majority of manufacturing processes and consequently disassembly is industrial manipulators [14].

However, as stated previously and also concluded in an analysis of the structural design of LCD TVs for automatic disassembly by Elo et al. [15], the major challenge for a disassembly system is the variability and uncertainties concerning the state of the product, e.g., in-homogeneous materials, the mixture of materials, component location and the variation of the structural rigidity of the components.

This variability and uncertainty can make it impossible for a fully automated system to complete the process in an economically viable time or even complete it at all.

Therefore, it is necessary to keep the human-in-the-loop and create a hybrid automated disassembly cell in which humans and robots support each other to complete a given disassembly task. Such implementation introduces a new set of challenges to the disassembly process with regards to the collaboration between humans and robots, i.e., task sharing/allocation/programming and safety in human–robot interaction/collaboration.

This paper aims to clarify these challenges and provide the reader with an overview of the progress during the past decade in the field of human–robot collaborative disassembly (HRCD). The contributions of the paper are:

(i) An analysis of the way that human–robot collaboration (HRC) is currently interpreted and implemented within the field of robotic disassembly in industrial settings.
(ii) An insight on the main components of a robotic disassembly process.
(iii) A framework for identification and classification of research papers focused on human–robot collaborative disassembly systems

The paper continues with a description of the methodology to identify and select relevant papers in Section 2. In Sections 3 and 4, the necessary background knowledge for the analysis of the current state of the art in the field of HRCD is provided. Section 3 presents the definition of HRC, an overview of standards and methods ensuring robot safety, and a summary of communication methods that enable HRC in industrial settings. Section 4 explores the various areas composing disassembly processes i.e., Task Definition, Task Planning and Task Implementation. Section 5, highlights the literature which explicitly covers the topic of HRCD. Lastly, Sections 6 and 7, evaluate the most relevant papers and conclude with a summary of the gained knowledge, several discussion and reflection points and a list of identified research gaps in the research area.

2. Search methodology

In order to solve the challenges associated with the disassembly of EOLPs (see Table 1), multiple robotic technologies and concepts have been developed since the 1990s. Although numerous surveys and reviews on HRC in industrial settings have been proposed, to the best of the authors' knowledge, only one extensive literature review exists on the topic of robotic solutions for disassembly tasks and was conducted by Poschmann et al. [16].

That particular work highlights that the current research trend within this field moves towards completely autonomous robotic disassembly cells and the improvement of HRC process implementations. The importance of HRC in disassembly is also solidified by acknowledging its investment value for companies in terms of complexity and adaptability compared to fully automated solutions. However, [16] mainly focuses on robotic disassembly in a contextual sense. It does not provide an analysis of the research outside of the field of disassembly that might be beneficial for this field.

On the contrary, the objective of this review is to provide an overview and an analysis of autonomous robotic disassembly systems as well as robotic solutions used for industrial disassembly tasks while incorporating various forms of HRC. For this aim, a broad literature survey was executed, and the contents of more than 400 papers in related areas were researched and reviewed. A summary of the chosen search criteria can be found in Table 2. Furthermore, a visualization of the selection process of related literature is illustrated in Fig. 2. Initially, an extensive search on web-based databases (i.e., Google Scholar, Scopus, WebofScience) for the related works in the area of HRC within disassembly for the period from 2009 to 2020 was conducted. Several search terms related to the application context were used, such as: "Human-Robot Collaboration" AND "Disassembly", "robot assisted disassembly", and "Human-Robot Collaborative Disassembly". The selection of these terms was based on the argumentation that they must include a relation to the process (i.e. disassembly), a robotic mechanism as well as indicate a supportive/role by either one or multiple of the autonomous quantities (i.e. human operators and robots) involved in the process.

At the same time, search terms relevant to the general area of industrial disassembly but were not suitable for the scope of this review had to be excluded. For example, since HRC encapsulates any form of HRI in industrial processes, the authors decided to exclude HRI as a search term in this review. Moreover, papers with a contextual background of economic evaluation/feasibility studies of a disassembly line and profitability scores are excluded. Most companies focus on the economic feasibility and profitability of the disassembly line itself rather than the choice of a robot or a specific enabler of the technology. Therefore, most of these studies focused on cycle time and regained/preserved value of the components rather than on the technology enabling the disassembly of a product.

Besides, literature discussing the process optimization of disassembly line designs is excluded from the paper selection. The authors believe that such studies do not add significant value to analysing how and what technology/approach is currently used to realize a human–robot collaborative disassembly system. Lastly, literature presenting the design of tools is excluded because the general practice of designing a tool that can be safety-certified for an HRC application is identical regardless of the task.

The period for this search was selected to cover from January 2009 until September 2020. The beginning of this period was chosen because the first collaborative enabled industrial manipulator was made available for purchase in 2008 [17]. Furthermore, new standards were put in place in 2009, allowing the incorporation to of HRC on shop-floors.

Taking all these parameters into consideration, the initial search resulted in 425 possible relevant publications, while after eliminating the duplicates, they resulted in 383 publications. A later screening of the papers based on title and abstract information and the search/review criteria of Table 2, resulted in **9** publications that are relevant in the field of *human–robot collaboration in disassembly*.

3. Principles of Human–Robot Collaboration

The topic of HRC has been discussed before the first collaborative enabled industrial manipulator (i.e., KUKA LWR 4) was made available in 2008 [17]. However, there is an ongoing debate about the definition and interpretation of the non-normative terms HRC and human–robot interaction within academia and industry. This debate was summarized by Vicentini, where an overview was presented over the different interpretations across the community and also highlighted the risks and consequences of enforcing the labels in the real-world by using the term "collaboration" for branding purposes [18].

Some of the different viewpoints in this debate were explored in [19,20], where definitions and various levels/subcategories of HRI and HRC were presented. According to Hentout et al. [19], HRI can be categorized into the following categories: (i) human–robot coexistence, (ii) human–robot cooperation, (iii) human–robot collaboration, where human–robot collaboration can be split into *physical collaborations* and *contact-less collaborations*.

At the same time, other viewpoints regarding which category embodies the most immersive/direct interaction between humans and robots exist within the research community. On the one hand, Haddadin et al. [21] supported the categorization based on physical proximity between a human and a robot. This interpretation classifies cooperative robot interactions as being in closer proximity than collaborative robot interactions. As a result, human–robot cooperation (HRCoop) occurs when a robot and a human are at the closest possible distance and human–robot coexistence (HRCox) when they are farthest

Table 2
Overview of the various review criteria applied during the search process for relevant literature.

Search Criteria	Description
Search terms	"Human-Robot Collaboration" AND "Disassembly", "robot assisted disassembly", "Human-Robot Collaborative Disassembly"
Time period	January 2009–September 2020
Publication type	peer-reviewed academic conference paper, journal articles and books
Exclusion criteria	**Description**
Language	non-English
Contextual	economical evaluation/feasibility studies, profitability scores, process optimization disassembly line design, tool design

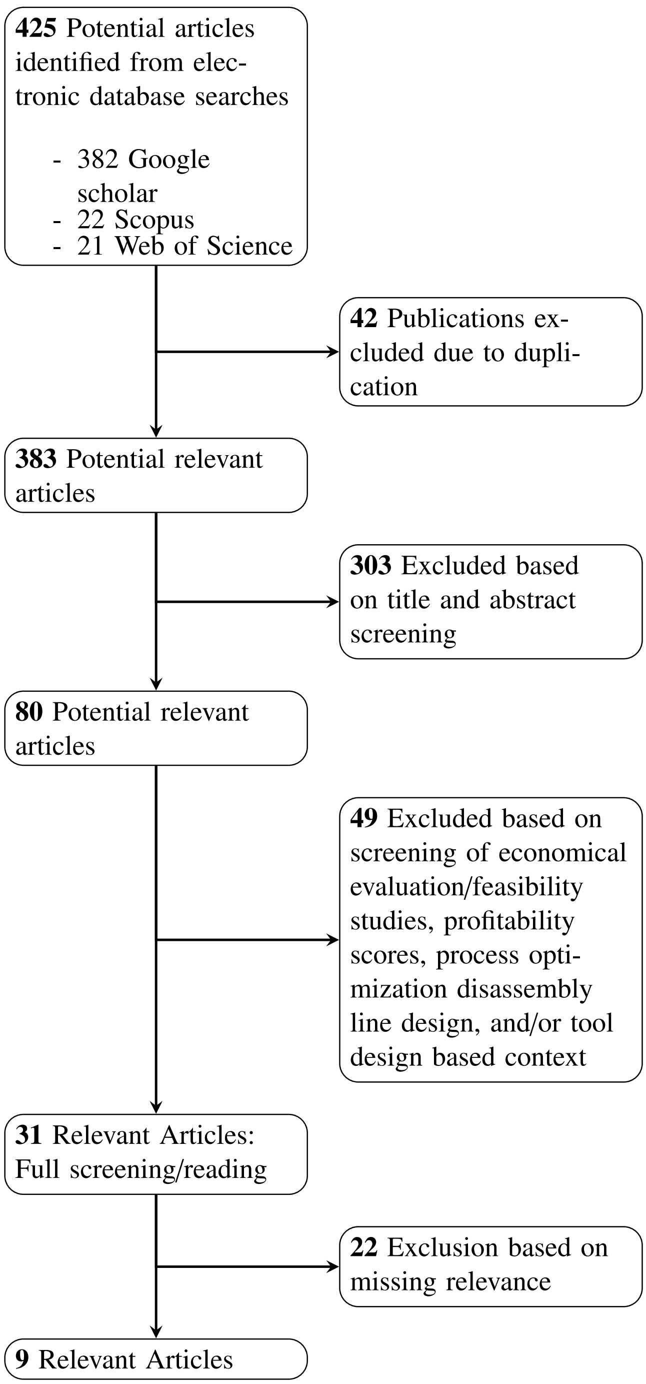

Fig. 2. Visualization of the literature selection process for identified literature related to human–robot collaborative disassembly.

apart. On the other hand, Kolbeinsson et al. [22] mentioned that HRC is based on how humans and robots share their workspace and tasks. Therefore, they interpret HRC as more immersive as human–robot cooperation (see Fig. 3).

In the meantime, most industry stakeholders have a different interpretation of HRC where they assume that any robot that can operate without a fence is collaborative. Different elements of HRC in industrial environments are examined by Villani et al. [23] who have reviewed the topic and identified the main challenges as: (i) safety issues, (ii) HRI communication interfaces, (iii) HRI process design methods.

In our paper we tackle the element of safety by covering the *safety standards* and *collaborative operation modes*; the HRI communication interfaces by covering *programming approaches*, *input modes*, and *reality enhancement*, and lastly we cover the design characteristics of a disassembly process by discussing *task definition*, *task sequence planning* and *automated disassembly applications*.

3.1. Robot Safety

The current trends in the industry according to [24] go towards robotic setups, which are fenceless and intrinsically safe by considering the static force and speed of the robot as well as the human's reflex actions. An extensive survey that summarizes the field of HRC and HRI was conducted by Vicentini in [25]. The research found that physical interactions between robots and humans can, in general, be categorized into *desired* and *undesired contacts*. In this context, undesired contact is being classified as collisions. Haddadin et al. have made an extensive investigation into the different forms/kinds of collisions and their corresponding critical contact force values in [26,27]. There Haddadin et al. differentiated between the following forms of impacts: (i) unconstrained impacts, (ii) clamping in the robot structure, (iii) constrained impacts (iii) partially constrained impacts, (iv) resulting in secondary impacts. This investigation was expanded in [28] to cover different severity levels for various types of injuries depending on the collision types. Based on these investigations, Haddadin et al. progressed with analysing extensively model-based algorithms designed for real-time collision detection, isolation, and identification of pHRIs [29] and Golz et al. classified contact types to intended and unintended ones to highlight the importance of detecting and interpreting contacts for safe pHRI [30].

3.1.1. ISO standards

In an attempt to classify HRC in a general and robot safety context, several ISO standards were put in place and are regularly updated. The introduction of these standards aims to categorize the different forms of collaboration and interaction based on their kind (e.g. verbal, non-verbal), severity, and control modes.

ISO 8373

The ISO 8373 standard [31] specifies the vocabulary used within the area of HRC, in the context of robots, the interaction between humans and robot (HRI), and other relevant terms related to robots and control system/strategies.

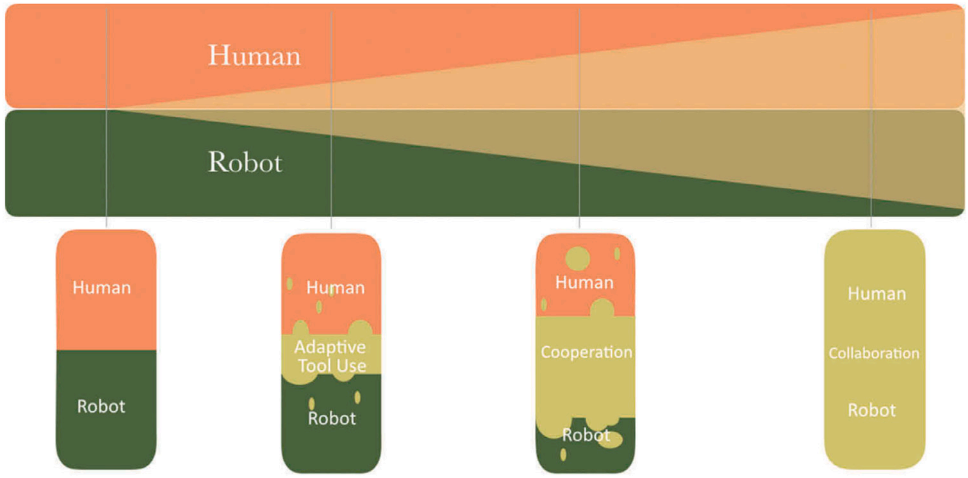

Fig. 3. A visualization of the various levels of interaction, according to Kolbeinsson et al. [22]. The outer left of the graph represents the absence of interaction between human and robot. The most right part of the graph represents a level of interaction between human and robot which classifies as collaborative.

ISO 10218

The ISO 10218-1/2 standard, in general, describes the concepts of collaborative enabled robots, workspaces and operations. ISO 10218 is comprised the following two parts: (i) ISO 10218-1 [32] concerns the specification of the requirement and limitations of the robot's behaviour when interacting with an operator in collaborative operation. (ii) *ISO 10218-2* [33] defines the requirements for the robot systems concerning the safety when applied in an HRC setting.

ISO 15066

ISO 15066 [34] attempts to further specify HRC by supplementing the requirements and guidelines established in ISO 10218. More precisely, this standard defines the appropriate procedure for the limitation of speed values, which keeps force and pressure values within the defined pain sensitivity threshold for humans in collision scenarios with robots. It defines twelve specific areas for testing on the human body as well as the maximum permissible pressure and force values, specific formulas to obtain the maximal permissible energy transfer for each body of the defined areas on the human body, and lastly the speed limit values for transient contact between a human body and a part of a robot system. Derived from these specifications, the following four-level (see Fig. 4) of control modes are defined:

Safety-rated Monitored Speed (SMS) enables humans and manipulators to have a shared workspace, but they cannot work in this workspace at the same time. As soon as the human operator enters the shared workspace, the robot stops immediately until the operator leaves the shard workspace again.

Hand-Guidance (HG), methods are designed for the manual guidance of robot systems. Control methods falling into this category have no defined upper limit in terms of speed with regards to the robot or forces acting on the human body but the generation of the motion input. It requires but not limited to that the risks of: (i) unintentional commands given by the human and (ii) mismatched commanded and executed motion

Speed and Separation Monitoring (SSM) control schemes enable human operators to share the same workspace with the manipulator while being in motion. However, the robot motion is like SMS proximate on the distance between the operator and the robot. The difference is that the SSM can adapt the velocity of the manipulator based on the proximity-based zones between human and manipulator. This ensures that the protective distance at which the robot has to stop can be made smaller compared to SMS.

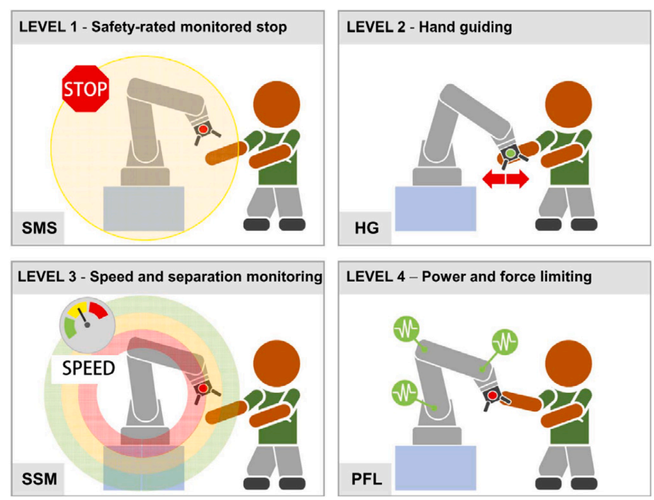

Fig. 4. Visualization of the four different control levels. [23].

Power and force limitation (PFL) reduces the effects of unintended contact between human and robot. This can be achieved by implementing control schemes which control the motion of the robot in such a way that the forces and momentum upon impact with the operator are within the set limits to avoid injury.

3.2. Enablers of Human–Robot Collaboration

Previously in this work, the debate regarding the definition of the HRC was discussed, followed by an overview of the various safety standards related to robots. However, regardless of the chosen definition of HRC and which of the safety standards must be followed to enable a safe implementation, they all require the same thing; the so-called *Enablers*, which are control strategies and human–robot communication techniques equally necessary so the human worker can interact safely as well as intuitively with the robot.

3.2.1. Control

One of the main concerns in the implementation of industrial HRC is the classification of physical contact, an area in which De Santis et al. examined thoroughly and analysed the different aspects and requirements for safe pHRI [35]. One conclusion of that work is that control methods cannot compensate for a poor mechanical design on their own; however, they remain an essential aspect when it comes to performance, reduction of the sensitivity to uncertainties, and improvement of reliability.

Control schemes, in general, can be divided into the following two types:

(i) Pre-collision
(ii) Post-collision

3.2.2. Pre-collision strategies

Pre-collision control strategies focus on preventing harmful contact between the robot and its environment with so-called collision avoidance. These strategies use sensory input (e.g., camera, laser sensors) to adjust the velocity or the motion of the manipulator based on the distance to autonomous quantities and their behaviour in the manipulator's work environment.

Along with these ideas, Safeea et al. used various sensors (i.e., cameras, lasers, IMUs) to capture the human operator's position and motion to adapt the manipulator's pre-defined/planned path based on a framework incorporating artificial potential fields [36]. In parallel, Chen et al. explored a collision-free motion path planner for a 6-DoF serial manipulator [37]. The presented method tracks dynamic obstacles in the manipulator's workspace by utilizing depth images captured by multiple KinectV2 cameras. Based on the estimated position and velocity of the obstacle, an artificial potential field is adapted, such that the manipulator's nullspace can avoid the obstacle while preserving the original end-effector's trajectory.

For the generation of a collision-free path in an HRC setting, Landi et al. proposed an optimization-based method that utilizes safety barriers positioned around the robot links [38]. It also minimizes the differential between the nominal input and commanded acceleration such that the manipulator can adapt its motion accordingly to obstacles detected by depth visual sensors. Another method for addressing the challenge of avoiding joint limits and Cartesian obstacles was presented by Scheurer et al. in [39]. This approach used a closed-loop-inverse-kinematic control approach on velocity level and was evaluated on a 12-DoF mobile manipulator.

Liu et al. presented a dynamic modified SSM method to enable HRC while maintaining a certain productivity level [40]. The setup consists of a vision-based detection system based on which the risk assessment and response strategy for industrial HRC can be dynamically adapted. Another effective online collision avoidance was proposed by Mohammad et al. where they utilize an augmented environment containing a three-dimensional virtual model of the manipulator and real images of human operators captured by depth cameras [41]. The manipulator adapts its behaviour based on four strategies, either alerting the operator, halting the manipulator in its motion, moving it into a safe position, or modifying its trajectory.

Even though the examples for pre-collision control schemes mentioned above enable the robot to avoid collisions, they cannot guarantee that it will not come to harmful contact between human and robot. As pointed out by Haddadin et al. this happened because the relative motions between robot and human can be hard to predict as the use of exteroceptive sensors monitoring the workspace and adapting the robot's movement may not be sufficient for the prevention of collisions [42]. This observation is also highlighted by De Santis et al. who mention that to ensure a safe robot motion, pure motion control is inadequate, as it might generate undesirable contact forces in case of collisions [35]. Thus, it is necessary to implement a post-collision control strategy capable of limiting the contact forces between humans and robots to a desirable level.

3.2.3. Post-collision strategies

Contrary to pre-collision control strategies, post-collision control strategies do not prevent possible contact between humans and robots but instead limit the contact force and the energy exchange between the two entities to a safe limited [43]. Such post-collision control strategies are also known as ''interaction control strategies'', where the two most prominent sub-categories are direct and indirect control strategies. The former includes so-called hybrid control strategies, whereas the latter includes Admittance and Impedance control schemes.

Direct-force control approaches control the manipulator's force along the constrain as well as the motion along with the directions of the unconstrained path by measuring the force.[44]. As aforementioned, a prominent subcategory of Direct-force control approaches is the so-called hybrid force/motion control.

Yip and Camarillo [45] propose a hybrid position/force control approach capable of manipulating the manipulator's end-effector position and force in the presence of unknown body constraints. This method enables manipulators with complex joint mechanics to navigate when subject to unknown environmental constraint. Leite et al. [46] presents a hybrid control scheme that combines adaptive visual servoing and direct force control enabling non-redundant robotic manipulators to perform interaction tasks on smooth surfaces. The presented method enables the manipulator to exert a predefined contact force with its end-effector with a smooth surface for visually tracking the desired path. Another adaptive position and force control approach for a robotic manipulator in interaction with a flexible environment is presented by Gierlak and Szuster in [47]. It utilizes a manipulator–environment system model that takes various parameters such as motion resistance and environment elasticity into account, intending to define the position and force control task.

Compared to direct-force control, indirect force control schemes achieve force control via motion control, instead of closing the force feedback loop resulting in nonlinear and coupled impedance or admittance [44].

Admittance control schemes manipulate the virtual model dynamics of a system by creating an adequate response to the measured forces caused by interactions with a human operator. Keemink et al. provided a comprehensive overview and analysis of admittance control applied in pHRIs in terms of framework, the influence of feed-forward control, force signal filtering, post-sensor inertia compensation, internal robot flexibility, the effect of virtual damping on the systems stability, passivity and other performance-critical criteria [48].

An approach for this kind of control strategy was put forward by Dimeas et al. where a variable admittance control approach for human–robot cooperation tasks is presented [49]. It combines a Fuzzy Inference System designed to adjust the damping of the manipulator's admittance based on force introduced by the human operator and its measured velocity. A Fuzzy Model Reference Learning Controller adjusted the Fuzzy Inference Systems response based on the minimum jerk trajectory model.

Additionally, Ranatunga et al. proposed an adaptive admittance controller capable of adapting to human intent and variations of the manipulator's dynamics [50]. The control strategies consist of an outer and inner control loop with the outer-loop using an adaptive inverse control technique and the inner-loop linearizing the robot dynamics via a neuro-adaptive controller. This control strategy enables an efficient online adaptation of the manipulator's admittance model for different operators and a smooth human–robot interaction due to the reduction of jerks.

For improving the performance of HRC tasks, Bea et al. combined a variable admittance control strategy with virtual stiffness guidance [51]. The approach prevents unnecessary adjustments of the damping parameters based on the classification of the operator's intentions and additionally aiding the operator via virtual spring supporting the task, which the operator can adjust.

Impedance Control schemes measure the displacement/motion caused by the interaction and create a reactive force to compensate for this displacement. In an experimental study on human–robot co-manipulation for kinematically redundant manipulators conducted by Ficuciello et al. it was investigated that the manipulator's performance during pHRIs, can be enhanced by the combination of Cartesian impedance modulation and redundancy resolution [52]. A Cartesian impedance control strategy enables the manipulator to handle the forces introduced by the human–robot operator due to its compliant nature. The study established that variable impedance strategies with a suitable modulation strategy outperform non-variable impedance control strategies when it comes to the perceived comfort by human operators during manual interaction like guidance.

Additionally, Ficuciello et al. presented another Impedance control paradigm, focused on the control of redundant robot manipulators in the task space [53]. Its null-space impedance control approach allows for the safe reaction of the manipulator during intentional and unintentional/accidental physical interaction with its environment. Laffrance et al. proposed an energy-based control strategy for enabling manipulators to work closely with humans by bounding their behaviour in the first instance of an impact between the two entities [54]. This is achieved by limiting the energy stored into the system to a set maximum value of the position-based controller, which adapts the position trajectory reference in correlation with the set maximum energy value. Raiola et al. investigated the impedance control scheme, which enables safe human–robot interaction through energy and power limitation. In addition to the limited energy and power of the manipulator, the system's passivity is also ensured due to the implemented energy tanks [55]. Vanderborght et al. provided an extensive insight on the topic of Variable Impedance Actuators (VIA) by giving a structured overview [56]. This work classifies the VIA based on how the variable stiffness and damping were implemented. Ott et al. presented a hybrid reactive control strategy capable of continuously switching and interpolating between Impedance and Admittance Control [57]. Thereby merging robustness properties of Impedance Control and the accuracy in free motion associated with Admittance Control.

Regardless if a control strategy is designed to avoid collisions or minimize contact forces, they both face the challenge of possible restrictions in their workspace due to the location/placement of the manipulator in an environment with limited space (e.g., existing production lines and residential houses). However, manipulators controlled by an interaction control strategy are more exposed to this problem. This is due to the compliance introduced to the system by the control scheme; thereby, enabling the robotics system to adapt to unplanned interactions with its environment by deviating from its original planned trajectory.

3.2.4. Workspace restrictions

Therefore, workspace restrictions are necessary when implementing such control strategies, and to enforce these restrictions/constraints, various methods have been developed to restrict the manipulator's workspaces. To begin with, Kimmel et al. presented a method that enforces Cartesian constraint with an invariance control scheme approach in combination with a discrete-time Euler solver to reduce oscillations when encountering the constraints [58]. Similarly, Rauscher et al. imposed Cartesian workspace-restrictions for a redundant robot successfully by combining an impedance control strategy with control-barrier-functions and quadratic programming [59].

The work conducted by Dimeas et al. presented a method hindering the operator from forcing the manipulator into a configuration, which reduces its performance capabilities [60]. The methods consist of virtual constraints and a Cartesian admittance control scheme, which adapts based on the kinematic manipulability index.

Han et al. focused on an operational-space-control (OSC) framework capable of handling the encounter of joint limits and singularities [61]. The energy-aware control scheme from Raiola et al. [55], previously discussed in this work, was extended by Hjorth et al. [62] by implementing the concept of artificial potential fields, first introduced in [63], for the enforcement of workspace restriction for collaborative enabled robots while being in a compliant state (see Fig. 5).

Fig. 5. Visualization of the enforcement of virtual workspace constraints while the manipulator is in a compliant state [62].

A method proposed by Flacco et al. saturates the manipulator's Nullspace by combining the Stack-of-Tasks approach with quadratic programming [64]. This approach can be adapted to restrict the manipulator's workspace as it is designed to keep the manipulator within a set of hard constraints for its positions, velocities and accelerations within its configuration space. Muñoz Osorio et al. extended this method and transformed the algorithm to a torque-based approach [65],by combining the Operation Space Control formulation with the stack-of-task technique. The creation of high priority tasks in the task stack enables the restriction of the manipulator's motion within the Cartesian and configuration space, respectively.

3.2.5. Human–Robot Communication

There are several ways for an operator to interact with a robot on the production floor. As mentioned before, sharing the same workspace is a fundamental element in HRC. Humans tend to communicate their intentions during the collaboration over a shared task via a variety of verbal and non–verbal cues either in real or virtual work environments [66].

In this work, these ways of communication are grouped in two broad categories, i.e., *verbal* where voice control and speech recognition are the key elements and *non–verbal* where methods including gesture recognition, human pose and skeleton tracking, gaze detection, and intention recognition are considered. A short overview of how these enablers of human–robot communication in industrial HRC are applied in augmented, virtual and mixed realities is also presented. The main focus remains within industrial applications; however, approaches used in social robotics and present great potential to be introduced in manufacturing are also briefly discussed.

Verbal communication. Voice control and speech recognition are primarily used in manufacturing applications as interfaces for robot control [67]. Maksymova et al. presented a wide range of different models for the voice control of an industrial robot such as logical, semantic networks, frame model and Petri Nets in the context of an assembly task [68]. Bingol and Aydogmus investigated the performance of a natural speech recognition system based on deep neural networks for the classification of different commands during the interactive control of a KUKA KR Agilus robot arm in multiple industrial tasks [69].

Fig. 6. Example of a pointing gesture identification validation setup from [75].

González-Docasal et al. progressed a step further to integrate a semantic interpreter who, with the support of a knowledge manager, extracted semantic information from transcribed spoken content and enabled an industrial robot to understand the intention of the operator and execute a collaborative task accordingly [70].

However, most of the applications solely based on speech recognition may face performance issues due to background noise that usually exists in industrial environments [71]. Thus, speech recognition is often combined with other modalities such as gesture recognition [72], eye gaze detection [73] and haptic control [74] to enhance HRC and improve the accuracy of human action recognition. More specifically, Maurtua et al. examined a semantic approach for multimodal interaction between human workers and industrial robots to enhance the dependability and naturalness of the collaboration between them in real industrial settings [75]. The approach is based on the recognition of verbal commands and gestures which communicate requests for processing and execution of a disassembly task (involving screwing and unscrewing operations) and deburring of wax pieces (see Fig. 6).

Additionally, Markis et al. presented a multimodal framework for interaction with dual-arm robots. It is based on a hierarchical model that handles various inputs from gestures, voice commands, and intuitive graphical user interfaces to decompose the working tasks into different abstraction levels [76]. Neto et al. incorporated wearable sensors and inertial measurement units (IMUs) to capture the human upper body gestures, which afterwards act as inputs to an artificial neural network (ANN) for gesture classification. This multimodal approach in combination with a parameterized task manager based on speech and visual feedback enables the human operator to complete collaborative robot tasks such as handover and delivery of parts [77].

Hongyi et al. introduced a deep learning framework for multimodal control of an industrial robot where voice, hand motion and body posture recognition are combined based on Convolutional Neural Networks (CNNs) and a multilayer perceptron model (MLP) to dynamically affect the programming of the robot [78,79]. Gustavsson et al. presented a pilot study where speech recognition and haptic control are combined to control a UR3 robot. Naturally, inexperienced users discovered the challenges of operating a voice-controlled interface in a noisy environment. However, the robot's haptic control altered the overall impression of the participants who evaluated the concept as intuitive to use [80]. Mohammed and Wang explored the behaviour of the human brain using electroencephalography (EEG) to develop a brainwave-driven robotic application to assist the HRC during the assembly of a car engine manifold [81]. The major advantages of such a framework are its easy integration with voice, gestures and haptic commands and the ability to free up the mental and physical capacity of the operators to allow them to control the robot while performing a shared task.

Non-verbal communication. Human–robot interaction systems based on visual cues can often compliment the ones based on verbal communication and even replace them in cases where the communication is unreliable [82,83]. *Visual* systems based on recognizing gestures have been a cornerstone of a repertoire of HRI techniques used in many manufacturing scenarios. Berman and Stern explored the wide range of the sensors used in gesture recognition systems. They divided their taxonomy into three significant components, i.e., sensor stimuli, the context of use, and sensor platform [84]. There are a plethora of methods in the literature that use a mixture of these components for gesture-based control of robots in HRC scenarios.

Fig. 7. Two of the manipulation gestures used in [101].

To begin with, a crucial point in the vast majority of gesture recognition methods is the detection of the pose or skeleton outline of the operator [72]. There are numerous sensors used to produce robust detection and tracking of the pose of the operator mostly based on RGB-D cameras such as the Kinect v2 [85,86] and Intel Realsense [87,88] while other sensors such as Leap motion can be used for specialized tracking of the hand and fingers for robot control [89,90]. Similarly, accurate pose detections can be achieved by using IMU sensors [91], thermal cameras [92] and various wearable sensors [93], however, their restrictive mobility, low resolution and time-consuming setup render them less popular.

During the past decade, machine learning methods have been widely used in recognizing human actions and classifying them to respective commands for robot control in industrial HRC. Traditional machine learning methods such as Gaussian Mixture Models (GMM) [94], Hidden Markov Models (HMM) [95] and Support Vector Machines (SVM) [96] have been used for the detection of humans with high accuracy ranging from 80 to 90%. To achieve more accurate results, researchers have used Deep Learning techniques where 3D-CNNs perform close to 96% accuracy [97–99] and a combination of a novel 3D descriptor for detection of joints and MLP for classification can achieve close to 98% accuracy [100].

In parallel, there is intriguing research that examines the effect of gesture-based communication when the robots themselves produce the gestures. Sheikholeslami et al. explored the efficiency of gestures performed by various robot hand configurations in cooperative industrial tasks [101]. They concluded that the robot could communicate its intentions robustly and led to a higher acceptance rate from the operators. Gleeson et al. produced a lexicon of communicative terms and robot gestures to characterize the steps of commonly used industrial tasks such as part acquisition and fastening of screws [102]. The lexicon used in a representative HRC industrial task, i.e. vehicle door assembly, where it proved adequate for an intuitive and efficient human–robot communication (see Fig. 7).

Other than gesture and pose recognition methods, several methods have also been proposed in the literature to track the gaze and attention of the operators to improve the communication with robots in industrial HRC. Eye gaze tracking has been studied extensively as a human–computer interaction interface where multiple intrusive and non-intrusive techniques have been identified [103]. Palinko et al. used gaze tracking as means of human–robot communication and proved that eye tracking is superior to head tracking techniques in HRC with an iCub robot as the robot was able to exploit richer information from tracking the eye gaze of the operators than tracking the position of their head [104]. Similarly, in industrial settings, eye gaze tracking techniques have been used to improve robustness during robot manipulation tasks [105], to assess the comfort levels of the operators during an HRC task [106], and as an aspect of a shared attention interaction model that affected the timing of human–robot handover tasks [107] positively.

In addition to gaze tracking, researchers have used tactile and haptic feedback to ensure robust communication with industrial robots. Casalino et al. introduced tactile feedback directly at the fingers of the operators to track their operational awareness. A Bayesian recursive classifier was utilized to estimate the human intention, while a wearable vibrotactile ring provided feedback about the different stages of HRC [108]. Salvietti et al. explored a bilateral haptic interface where a soft gripper was used in combination with a wearable, remote ring interface to improve the effectiveness of the collaboration [109]. Bergner et al. used an innovative interface based on distributed cells acting as a large scale skin around robot manipulators which computes the joint torque in the contact points to enable more intuitive human–robot communication based solely on touch [110]. Similarly, Tang et al. developed a novel signalling system based on robot light skin that improved the reaction time of the users significantly and reduced the mental workload of the operators resulting in fewer errors during the execution of simple industrial tasks [111].

Human–Robot Communication in virtual, augmented and mixed realities. Furthermore, due to the technological advancements in computer-generated simulations and the increase of available computational power, human–robot communication in virtual, augmented, and mixed reality workspaces has become more feasible. The main differences in this virtuality continuum originate from the level of immersion into the virtual environment the methods support. In virtual reality, there is a total immersion in a virtual environment. In contrast, in augmented reality applications, the real world is enhanced with some virtual details, and in a mixed reality environment, the real and virtual world intertwines, enabling manipulation with physical and virtual objects.

In general, Augmented and Virtual reality (AR/VR) techniques have been used extensively in manufacturing settings [112,113] for worker training [114] and support [115], digital twin implementations [116], and optimization of industrial processes such as polishing [117], assembly [118–120], laser welding [121,122] and prefabrication of raw materials [123].

More specifically, AR techniques have been utilized in connection with HRC to understand robot intentions in shared workspaces, where Andersen et al. projected related task information on physical objects, e.g., car doors, inside the collaborative environment, to assist human co-workers [124]. Similarly, Liu and Lihui developed an AR-based instruction system that empowers the human worker to access assembly instructions of industrial components from the AR device [125] while Papanastasiou et al. used AR glasses in combination with feedback from smart watches to monitor industrial assembly processes and ensure a seamless human–robot collaboration [126].

Koppenborg et al. recreated robot's motions in VR to study the impact of the robot's speed and predictability of its trajectory in HRC cases. As expected, as the robot moved faster, it was more challenging to predict its desired position, resulting in feelings of uncertainty, more mental workload from the operators and a decreased sense of safety [127]. Moving a step further, Matsas et al. implemented proactive and adaptive techniques in highly interactive and immersive VR environments based on multiple cognitive aids to enhance the feeling of safety from the operators [128].

In cases where manipulating real objects in restricted environments is required, mixed reality (MR) interfaces offer sufficient solutions. Chen et al. developed an MR interface based on a stereo vision in combination with virtual fixtures to create a novel stereo vision-guided teleoperation control method for manipulating mobile manipulators and teaching them new tasks [129] (see Fig. 8). At the same time, MR interfaces offer flexible solutions for programming robot manipulators. Ostanin et al. showcased that programming of a UR10e and a KUKA iiwa for geometrical path planning and trajectory generation is possible with an interface based on Hololens glasses [130]. Munoz et al. used MR methods in the area of quality control to automatically detect defects on a car body with a high success rate [131].

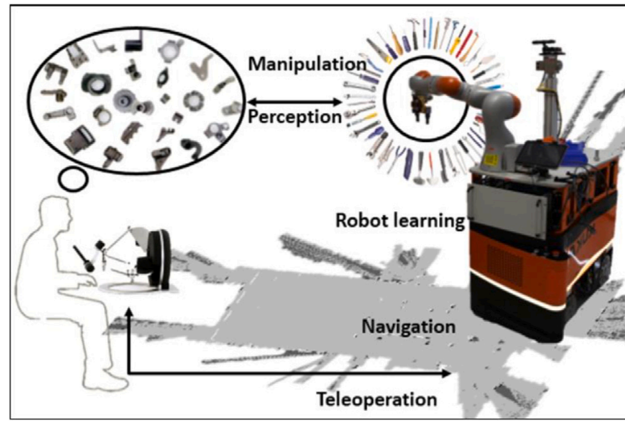

Fig. 8. Visualization of the conceptual representation of the work presented in [129].

4. Characteristics of a disassembly process

The disassembly process of an industrial component is not as trivial as just its reversed assembly process. This is partly due to the fact that the links joining sub-components of a product together are designed to make the assembly process more straightforward (e.g. Snap fittings, glueing, riveting). However, connecting sub-components in this way makes it hard and, most times impossible, to disassemble a product in a non-destructive way.

As mentioned earlier, de/remanufacturing systems face several technological challenges (see Table 1), most of which are related to the states of a product, as they can differ significantly between the observed, the actual and the original state. The added uncertainty makes the disassembly process a non-trivial operation, especially when considering that components or sub-assemblies are not allowed to be damaged to qualify for requalification. This section will cover the following three subtopics of a (disassembly) process: Task Definition, Task Planning, Automated Disassembly applications. As aforementioned, the focus of this paper is on the topic of disassembly; however, some parts of the process is either directly or closely related to assembly operation. Therefore, some of the presented publications in this section have their origin within assembly applications.

4.1. Task Definition

In general, a task is comprised of a set of skills as stated by [137]. For example, a typical pick and place operation consists of multiple sub-tasks such as a pick, move and place task, which all have different characteristics and parameters. The human analogy of these three elementary tasks is so-called skills. In other words, skills are a way of defining/quantifying various low-level operation/tasks to enable the operator to formulate tasks based on human terms. However, this definition is quite broad, as skills can be related to several areas, such as Socio-Cognitive Skills [138], Communication Skills [139] and more task-specific skills. The latter will be the focus in the remainder of this work, more specifically on the various frameworks for the definition of executable robotic skills such as screwing and pick and place operations.

CoSTAR [140,141] is a cross-platform architecture for describing industrial robot task plans. As most skill-based programming approaches for industrial manipulators, it provides the capability of performing various tasks and enables non-expert users to programme the manipulators. Rather than relying on an extensive task library, CoSTAR relies on the end-user to specify a task based on a limited set of geometric states (i.e. InFrontOf, LeftOf). In addition to a Behaviour Tree-based graphical user interface, the user

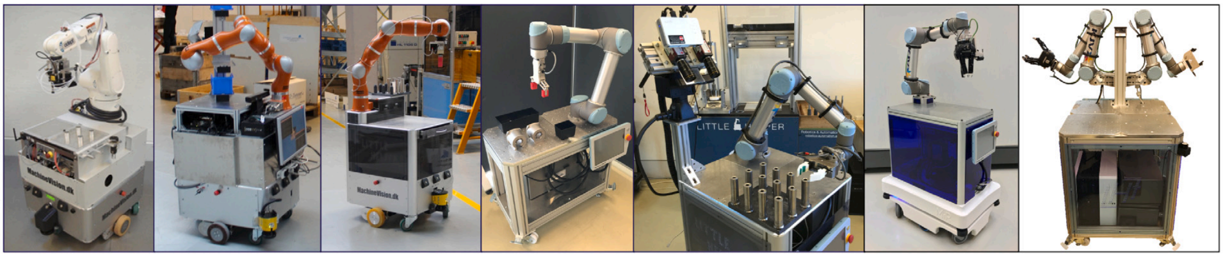

Fig. 9. Various Little helper setup utilizing SBS in the projects like TAPAS [132], CARLOS [133],ACAT [134], CARMEN [135], and [136].

can programme the robot through kinaesthetic teaching methods and predefined analogies to achieve high-level task specifications. *Skill-Based-System (SBS)* is a framework, which was first presented by Schou et al. [142] in 2013. It provides a human–robot interface for the utilization of skills in industrial settings. The central point of SBS is the user interface designed accordingly to facilitate the intuitive configuration of complex tasks from non-expert users. SBS contains an extended library of skills and execution engines for managing the execution of parameterized skills and ensuring the sequential description of a task for proper execution. Since its development it has been used in multiple national and international research projects such as TAPAS [132], ACAT [134], CARMEN [135], CARLOS [133] (see Fig. 9) as well as in use-cases in advanced production lines [143] and shipyards [144].

Motion Primitives is a task definition which was utilized by Stenmark et al. in [145] as a user interface that assists the kinaesthetic teaching mode of a collaborative enabled industrial robot. This allows the capturing of semantic information while working with the robot. The programming can be done via the following two modalities: graphical point-and-click and natural language. Another utilization of motion primitives is presented by Canal et al. [146], which combined a high-level task-planner and the low-level motion primitives for enabling an adaptive HRI. The low-level actions are taught to the system beforehand via demonstration and can be adapted to variations in the current situation by tracking relevant entities.

Additional Skill-based methods are presented by:

(i) Saukkoriipi et al. [147] presented a tool for programming robot skills offline. The utilized skills are conceptually similar to SBS, specified by configuration parameters, and offer integrated tool support. The Skills are executable sequences specified as UML action diagrams enabling them to be executed as robot programmes on various robotic platforms and PLC platforms. However, compared to SBS, the specification of the parameters is done offline, and it heavily relies on the use of CAD models in a simulation environment to define a task successfully.

(ii) Wallhoff et al. [137] introduced a system that combines high-level skills to reach a predefined goal in a hybrid assembly station. This system consists of a human operator, industrial manipulator, and a multi-sensory perception system overseeing the shared workspace between humans and robots. The skills in this work consist of various basic blocks with actions, e.g., opening/closing the gripper, moving to position, and picking up operation. The controller then breaks these skills down into "atomic operations" such that the manipulator is capable of executing the associated motions.

(iii) Huckaby et al. [148] proposed a method utilizing model-based system engineering in combination with Systems Modelling Language (SysML), which is a modelling language for the creation of simplified and reusable software modules for the programming of the robotic system.

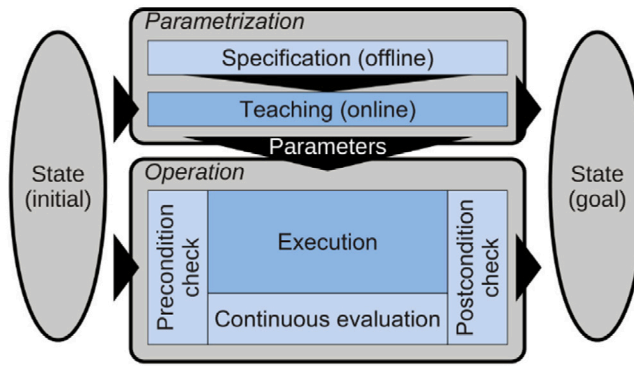

Fig. 10. A representation of the skill model including both operation and manual parameterization [149].

The skill primitives utilized in this work are basic atomic action/operations each robot can be associated with a specific motion.

Skill acquisition methods focus on the specification of the above-mentioned skill definition. Most of these methods rely on Graphical User Interfaces (GUI) or a simple programming interface for this step, requiring a certain level of expert knowledge. Therefore, different methods have been proposed to acquire and teach these skills in a more intuitive way.

(i) Schou et al. extended the SBS to incorporate Programming by demonstration (PbD) in [149]. This extension enables novice operators to use a more hands-on and practical way of programming industrial tasks on the fly. A visualization of the adaption to the original skill Framework can be seen in Fig. 10.

(ii) The work of Vongbunyong et al. in [150] presented a platform for capturing disassembly skills/operations done by a skilled operator such that an intelligent agent can acquire these skills. The system utilizes an RGB-D camera as a capturing device and marker equipped tools. The markers on the tool serve the purpose of identifying and tracking the tool's position, orientation, and operation sequence of the disassembly process.

(iii) Another method for teaching skills was proposed by Abu-Dakka et al. in [151]. There a framework was developed to enable the teaching of variable impedance skills, such that the manipulator is capable of performing force-based tasks by adapting its variable stiffness. The framework computes the stiffness estimate based on human demonstrations and a probabilistic model of the skill enabling the manipulator to execute force-based tasks.

4.2. Task sequence planning

Task sequence planning is used to identify a sequence of sub-tasks to successfully solve an overall task (i.e., assembly, disassembly). In the case of assembly, the objective is to have a complete product constructed of multiple sub-assemblies/components. In order to get to that stage, the final product has to be assembled in a specific order. This is where the planning of the sequence of different steps come into place, which in most cases can be straight forward as products are designed for assembly. For the disassembly of products, this process is not as straight forward since most products are not designed for disassembly. Additionally, the state of the used products can vary based on, e.g., their work environment, workload and maintenance cycle. The planning of task sequences can, in general, can be divided into the following two steps:

(i) Disassembly/assembly task modelling (Sequence generation)
(ii) Task Sequence Optimization

During the disassembly/assembly task modelling phase, a sequence is generated based on the product's layout and state. This sequence can then be optimized based on various criteria and constraints, e.g., time, number tool-changes, and cost. The review by Zhou et al. [152] analysed the different characteristics of the main disassembly sequence planning methods in disassembly mode, disassembly modelling and planning process and highlights future trends and current gaps in the existing research.

It proposes that the generation of models for planning of disassembly sequences, is based on *Petri net-based*, *Model type-based*, *Graph-based* and *Matrix-based* methods with the last two being the most prominent ones in literature. Examples of research works using *Graph-based* and *Matrix-based* methods for disassembly sequence planning are listed in Table 3. The general conclusion drawn in this survey was that most of the research has focused on: (i) complete and sequential disassembly planning, (ii) offline planning approaches, and (iii) purely economic factors rather than investigating environmental factors. Additionally, they suggest that future research should focus on dynamic systems capable of handling uncertainties, exploring the dynamic economic and environmental factors affecting the disassembly of EOL products as well as the possibility of combining *Disassembly Sequence Planning* with integrated obstacle avoidance and path planning for robots.

This observation also aligns with a recent publication by Xu et al. which proposed a Disassembly sequence planner for human–robot collaboration based on a discrete Bees algorithm [159]. The approach firstly generates a feasible disassembly sequence based on a disassembly model. Secondly, the resulting disassembly tasks are classified based on their difficulty, followed by developing a disassembly sequence for HRC. Lastly, the generated sequence is evaluated and optimized to minimize the disassembly time, cost and difficulty.

A similar approach Liu et al. investigated using a so-called *enhanced discrete bee algorithm* algorithm to minimize the disassembly time in order to minimize the disassembly time [160]. However, the authors have found that the calculation of specific parameters can be time-consuming, especially for products with a high number of components.

In addition to finding the most time-efficient disassembly sequence on purely the order operation, Li et al. proposed a method that takes the strain during the human workforce associated with continuous manual labour. This method aims is to minimize the total disassembly time for HRCD [161].

Besides the planning algorithms for disassembly tasks, there have been various approaches within assembly planning, which show promising results and possible application within disassembly. One of these applications is a two-armed robotic autonomous assembly system for aluminium profiles designed by Rodriguez et al. [162], which could apply to disassembly as well. The system based on deducting semantic assembly constraints before matching critical features on the semantic level with the help of graph matching. Later, it is followed by applying pattern recognition and classification based on transferring the knowledge of constraints for the different sub-assemblies into the overall assembly of the part through the utilization of machine learning.

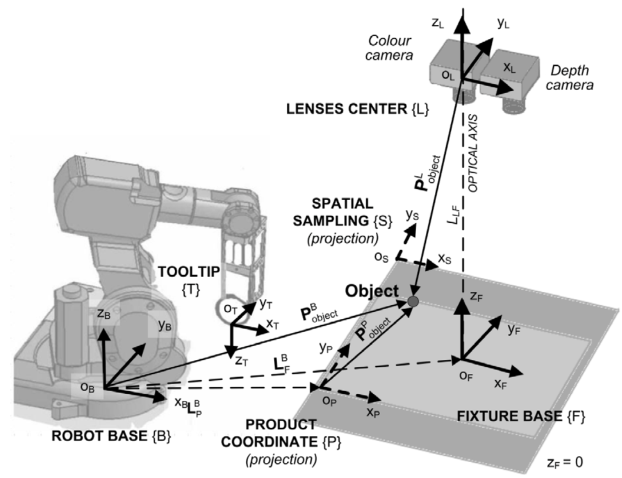

Fig. 11. An abstract representation of the robotic cell utilized by Vongbunyong et al. [167].

Moreover, Rodriguez et al. presented a method to iteratively refine feasibility checks for sequence planning in robotic assembly, which was experimentally validated for the assembly of aluminium profiles and could be further investigated for its use in disassembly [163].

4.3. Existing automated disassembly cells

During the last decade, numerous (semi-) automated robotic disassembly systems have been presented in the research community. Vongbunyong et al. investigated extensively the utilization of a cognitive robotics-based system for the (semi-)destructive disassembly, which is capable of reasoning, execution monitoring, learning and revision. It was also shown that the vision-based disassembly system (see Fig. 11) was capable of adjusting to any product model without prior information [155,164–167].

A system for the disassembly process of electric motors where they utilize an image processing algorithm for the autonomous detection and classification of screws was investigated by Bdiwi et al. [168]. The applied algorithm detects the screws based on their characteristics concerning their greyscale, depth and Hue, Saturation and Value (HSV) colour space values and does not need a database of templates for matching.

Schneider et al. explored using an algorithm to compute complex nonlinear disassembly paths for two objects that collide in their initial state and the disassembly path. This is done by incorporating the information about the flexible and rigid parts together with connected components of intersection volumes to a motion planner [169]. Whereas, Chen et al. [170] proposed an ontology and case-based reasoning (CBR) method which enables the computer to understand complex structures of various mechanical products and fully automates the disassembly decision-making process of products.

An extensive study on robotic disassembly for the recycling and reuse of cellphones was conducted by Figueiredo in [171]. The study shows an in-depth analysis of the different components within three phones from other manufacturers and what forces and tools are needed to extract the various parts. The developed system consists of a robotic manipulator, vision system, decision-making system and focuses on the prying operation. The developed decision-making system utilizes captured images of the vision system to detect the current state of the

Table 3
Examples for Graph and Matrix-based Disassembly sequence planning methods based on [152].

Authors	Summary
Graph-based	
Behdad et al. [153]	Presented an Immersive Computing Technology method to optimize disassembly sequences of a product by considering the cost involved in the process and estimation of possible damage during the process in a virtual disassembly simulation with Dynamic programming.
Alshibli et al. [154]	Presented a Tabu search algorithm for Disassembly Sequencing to minimize the travelled distance by the industrial manipulator, a number of disassembly method changes and eliminating unnecessary operations.
Vongbunyong et al. [155]	Proposed a cognitive robotic agent capable of learning by reasoning throughout the disassembly process.
Matrix-based	
Jin et al. [156]	Developed an approach for generating a disassembly solution space for LCD televisions. This approach generates an interference matrices based on a CAD model, which is used to represent the spatial relationship between components in a Cartesian workspace.
Wang et al. [157]	Designed a method to break apart assemblies containing interlocking components into sub-assemblies. This was achieved by generating feasible disassembly sequences by definitions and derivations of a contact and relation matrix.
Xia et al. [158]	Presented a simplified teaching-learning-based optimization algorithm for the planning of disassembly sequences of Waste Electrical and Electronic Equipment (WEEE).

cellphone and thereby enables the system to handle multiple types of uncertainties associated with the cellphone's state.

The challenges associated with the autonomous generation and execution of disassembly actions is tackled by Chen et al. [172], where the robotic system used in this work is equipped with three different tools (i.e., screwdriver, hole-saw and angle-grinder) and utilizes a method based on a geometrical estimation to asses and selects a corresponding disassembly action. The proposed method is tested and validated on various models of LCDs.

The extraction of cylindrical components from their fixtures can often result in the jamming or wedging of the component; thereby, applying unnecessary forces and strain on the extracted component, which can reduce the chance of passing the re-qualification process. In order to minimize and mitigate the occurrence of such scenarios, Zang et al. [173] used a theoretical derived method utilizing active compliance and key parameters such as the location of the compliance centre, initial compliance, degree of compliance. Also, Zang et al. concluded on the effect of the presented method based on experimental validation. Another proof-of-concept presented by Bulh et al. [136] integrated two UR5 robotic manipulators in a dual-arm disassembly cell to showcase the potential of disassembly of mockup mobile phones in a smart production facility.

Liu et al. investigated a framework for the use of a service platform for robotic disassembly planning in remanufacturing [174]. This investigation aimed to find the optimal solutions for both robotic disassembly sequence and line configuration. Finally, they verified their analysis of the service platform with a case study on an idler shaft.

5. HRC in the field of disassembly

HRC in Disassembly (HRCD) is a timely topic that has become the focus of industry stakeholders and researchers during the last decade. Due to its complexity, it requires several advancements both in HRC technologies and standardization policies in terms of take-back requirements, product interfaces and possible serviceability to become profitable and environmentally viable. As mentioned earlier, the collaboration between humans and robots for the disassembly of EOLPs has many advantages compared to fully automatic systems. In this section, the results of the literature survey on human–robot collaborative solutions for disassembly are presented.

Liu et al. introduced a systematic development framework towards human–robot collaborative disassembly based on perception, cognition, decision, execution and evolution [175]. The implementation for enabling HRCD is presented, where technologies such as cyber–physical production systems (CPPS) and artificial intelligence (AI) are combined. The framework's feasibility regarding perception, decision making, and control was explored and verified with a case study. The case study consists of a non-collaborative ABB manipulator while a discrete bees algorithm was used to optimize disassembly sequence planner by assessing the condition of various objects with quality indicators based on the stage of the disassembly process. Finally, a motion-driven control method utilized in combination with a safety assurance strategy.

The same research team worked on a deep learning system enabling a fluent and natural interaction between a human operator and an industrial manipulator for an industrial human–robot cooperative disassembly scenario [176]. The system utilized a CNN–LSTM network to predict the motion of the human operator purely on the inputs of a vision system without the need for wearable devices or tags. The approach was validated in a case study for the disassembly of personal computers, which tested the system capable of identifying and predicting the motions of the human operators based on the tools, parts or scenarios.

Huang et al. investigated the integration of HRC in disassembly processes for a case study of press-fitted components [177]. In the study, the press-fitted component originates from an automotive water pump. The setup consists of a manual operated press and three jigs for the fixation and handling of the components during the disassembly process and KUKA LBR iiwa 14 R800 equipped with a Robotiq 2-FINGER 140 gripper.

The separate steps of the disassembly process are as follows: Firstly, the operator actuates the press to separate the first sub-assembly of the pump, with the robot waiting with its gripper underneath the press to support the extraction process. In the other process, the robot places the extracted sub-assembly in the press and waits again underneath the press for the sub-components to be pressed out by the manual operated press (Fig. 12). The overall process time of this procedure is approximately five minutes and can be adapted to pumps that require the same basic operations for their disassembly.

The majority of industrial products contain a large number of screws that hold them together. Therefore, an essential aspect of a disassembly system is its ability to unscrew. In that context, Chen et al. proposed a hybrid disassembly station equipped with a compliant robot with a bit-changing mechanism for unscrewing battery screws from electric vehicles [178]. The control strategy uses a skill-based formulation based on a finite state machine approach meaning that the different states of the manipulator are described by a sequence of primitive motions, which a human operator can teach. This state machine allows the authors to programme the engagement and removal of a threaded fastener and an autonomous bit exchange. The authors also highlight that implementing an Impedance control scheme enables the manipulator to handle direct physical interaction between a robot and human, thereby allowing seamless integration of such a

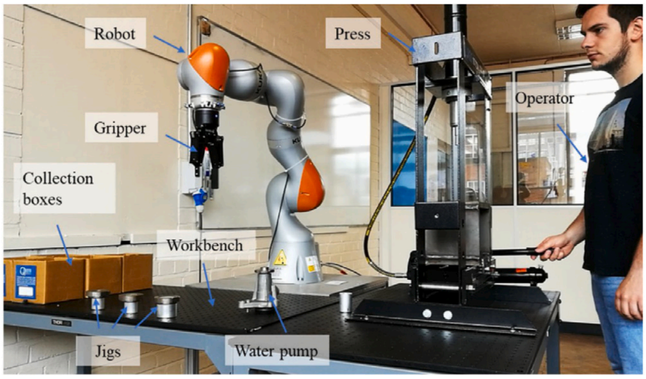

Fig. 12. The setup of the robotic cell for the extraction of press fit components used in [177].

robotic assistant for disassembly tasks, which would lead to an increase in the through-put in labour-intensive tasks. In order to address the challenge of unfastening hexagonal headed screws, Li et al. introduced an automated method [179]. It was accomplished by implementing an electric nutrunner spindle equipped with a geared offset adapter at the TCP of a collaborative enabled robot. The tool and location strategy of the screws were demonstrated in a disassembly case study of a turbocharger. The location strategy is implemented in the form of a novel spiral search technique based on force/torque feedback, which can detect if the tool is engaged with the screw.

The research works of Jungbluth et al. [180,181] aim to add the concept of HRC to a cognitive robotics based framework for the disassembly of EOLP as proposed in [165]. Initially, Jungbluth et al. aimed to enable a robotic system to act autonomously to execute disassembly task and improve the ergonomics of disassembly workstations with the utilization of knowledge and skills [180]. This was achieved by providing information on the product model to an intelligent agent to generate the disassembly sequence. This sequence is then utilized to create a series of disassembly actions for the robot assistant. At a later stage, this research focused on implementing a multi-agent control architecture [181]. This control architecture is based on product and process-based knowledge models and enables the workers to choose labour division between themselves and the robot for each disassembly task. According to the authors, this approach allows the system to assist the human co-worker in complex disassembly processes.

Axenopulos et al. described a framework for a hybrid human–robotic recycling plant for electrical and electronic equipment [182]. This framework aims to optimize the process of extracting valuable resource and reducing the risks involved for humans in this process by introducing HRC to this process. The authors of this work mention that a key aim of the framework is to enhance the disassembly process by introducing HRC cells comprising a single human operator that collaborates with several robots. In pursuance of achieving this goal, the proposed framework foundation consists out of the following pillars: (i) Factory-level modelling and orchestration (ii) Cell-level perception methods (iii) Robotic actions planning and control (iv) Principles of moral actions and ethics engine (v) HRC schemes.

Lastly, Ding et al. investigated the possibility of transferring the valuable knowledge of disassembling EOLPs from the human operators to an HRCD system [183]. This investigation utilized the combination of a video capturing system, a Natural Language Processing (NLP) algorithm and a graph-based knowledge representation. The collected knowledge was then used to improve the robot's capability to support the human during the HRCD task.

In order to summarize the key elements of the aforementioned works in HRCD, we present an overview in Table 4 while we discuss the important findings in Section 6.

6. Discussion

The article reviewed the literature and state-of-the-art methods in HRCD for the period 2009–2020 based on current technological advancements in relevant areas. Firstly, it was identified that the currently applied research related to industrial fully automated disassembly systems is focused on consumer electronics (i.e., TVs and smartphones). A potential explanation for this trend could be derived from the fact that the amount of WEEE produced every year is proportionally disadvantageous with the current available capacity for recycling and remanufacturing of such waste. Additionally, many of these systems tend to utilize destructive operations in their attempts to extract sub-assemblies and components for remanufacturing uses, resulting in inefficient processes.

Moreover, it can be derived that due to the increase in the complexity and variability of mechatronic and mechanical EOLPs, the existing automated disassembly systems cannot cope with the complexity of the disassembly task. Therefore, more solutions incorporating human workers in the process showed up during the past decade. As a result, ensuring safety remains one of the most challenging concepts of HRC in industrial environments, and specifically in disassembly tasks. Multiple methods incorporating safety have been identified and analysed. However, it is evident that regardless of the vast amount of standards and communication methods applied in HRC, the amount of task-sharing between a robot and a human defines the final implementation. Similarly to Vicentini's conclusions in [18], only a few research works of the identified literature promote physical interaction and focus mostly on cooperative and coexistent tasks rather than collaborative.

Regarding the current implementations of HRCD systems, there is a lack of post-collision control schemes in the context of pHRI. The absence of such post-collision control schemes concerns as, during HRC tasks in the disassembly domain, a human worker may interfere physically with the manipulator and engage in a collaboration phase accidentally. In order to keep the interaction safe, the manipulator must be able to adapt its behaviour safely based on the exchange of contact forces. Taking this into account, it is also essential to highlight that an HRCD system, like any other HRC system, enables symbiotic collaboration with humans only when an appropriate tool is used for the task at hand. Regardless of the robot and its task, the tool remains a potential risk of severe hazards. These safety aspects can be improved by introducing energy-aware control schemes and using tools with human-aware design.

In an ideal scenario, human–robot collaboration should feel the same as a human–human collaboration; however, there are several areas where the current state-of-the-art in the field can be improved. Human workers still surpass their robotic partners with their cognitive, adaptation and problem-solving abilities. When it comes to the field of disassembly, the main oversight of the explored HRC systems is the absence of skill acquisition interfaces (see Table 4). Such interfaces would enable a more intuitive definition and teaching of tasks to the robots and allow humans to transfer their domain knowledge and cognitive abilities to them.

At the same time, researchers have presented complete frameworks that can support HRCD without practical implementations at this current stage [182]. It will be interesting to witness the evaluation of the integration of a complete cell where a robot and a human worker would collaborate in a disassembly task based on that framework. Additionally, available research has been presented showcasing the application of robotic task-oriented knowledge graph in HRCD [183]. However, the lack of presentation of the key implementation details of the robot cell makes it difficult to conclude on the type of collaboration and related aspects explored in Table 4.

In addition, various kinds of HRI that are usually used in other domains, e.g., social and service robotics, are rarely implemented in HRCD systems. A potential explanation for this gap could be that several audiovisual and learning techniques can still face demanding

Table 4
Overview over the utilization/form of implementation of the different key-elements for (future) human–robot collaborative disassembly applications. SMS: Safety-rated Monitored Speed, HG: Hand-Guidance, SSM: Speed and Separation Monitoring, PFL: Power and force limitation. ✓, — indicate if the listed attributes are included in the work and **?** indicates the absence of information from which a conclusion can be draw from.

Publications		Liu et al. [175]	Liu et al. [176]	Huang et al. [177]	Chen et al. [178]	Li et al.[179]	Jungbluth et al. [180]	Jungbluth et al. [181]	Axenopulos et al. [182]	Ding et al. [183]
Task		—	Computer	extraction of press fit components	unscrewing	unscrewing	Disassembly of mechatronic drive	Disassembly of mechatronic drive	Disassembly of WEEE	Disassembly of Roller chain
Robot		ABB IRB1200	ABB IRB1200	KUKA LBR iiwa 14 R820	KUKA LWR IV	KUKA LBR iiwa 14 R820	KUKA LBR iiwa 14 R820	KUKA LBR iiwa 14 R820	—	KUKA LBR iiwa 14 R820
Human–robot coexistence		—	—	—	—	—	—	—	—	?
Human–robot cooperation		—	✓	✓	—	—	✓	✓	—	?
Human–robot collaboration		✓	—	—	✓	—	—	—	✓	—
ISO 15066		SSM	SSM	SSM	—	—	—	HG	HG, SSM, PFL	?
pre-collision control scheme		✓	✓	✓	—	—	—	—	✓	—
post-collision control scheme		—	—	✓	✓	✓	—	—	✓	—
verbal HRI		✓	—	—	—	—	—	✓	✓	✓
visual HRI		✓	✓	—	—	—	—	in progress	✓	—
physical HRI		—	—	—	—	—	—	—	✓	—
Task Definition	Skills	—	—	—	✓	—	✓	✓	—	—
	Skill acquisition	—	—	—	—	—	—	—	—	—
Task sequence planning		✓	—	—	—	—	✓	✓	✓	?

challenges with the environmental conditions in industrial environments. The addressing of these challenges would result in a more efficient and safe work environment and enable people who are limited in their physical and mental capabilities to be included in HRCD systems.

7. Concluding remarks

Given the importance of production's environmental and economic sustainability, the CEBM has started to be adopted across various companies and industries. This adoption poses a number of challenges regarding the resourcing, the disassembly, and the remanufacturing/qualification of ELOPs. This paper started by investigating the principles of human–robot collaboration in industrial environments and the characteristics of a disassembly process. Later, it presents an investigation into the existing literature on HRCD covering hybrid disassembly robot cells to disassemble EOLPs.

In the last part of this survey paper, the gaps in the existing literature on HRCD systems are discussed, based on which it was suggested that future research could move towards the investigation and implementation of (i) Control strategies which not just focus on the avoidance of contact between the manipulator and the worker but enables safe pHRI (ii) Skill teaching approaches which intuitively enable workers to expand the skill set of the robotic system (iii) Interaction through a combination of verbal and non-verbal communication methods enables a more immersive interaction between robots and humans.

CRediT authorship contribution statement

Sebastian Hjorth: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Dimitrios Chrysostomou:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.rcim.2021.102208.

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