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Enhancing Disassembly Practices for Electric Vehicle Battery Packs: A Narrative Comprehensive Review

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Abstract: In the context of current societal challenges, such as climate neutrality, industry digitization, and circular economy, this paper addresses the importance of improving recycling practices for electric vehicle (EV) battery packs, with a specific focus on lithium–ion batteries (LIBs). To achieve this, the paper conducts a systematic review (using Google Scholar, Scopus, and Web of Science as search engines), considering the last 10 years, to examine existing recycling methods, robotic/collaborative disassembly cells, and associated control techniques. The aim is to provide a comprehensive and detailed review that can serve as a valuable resource for future research in the industrial domain. By analyzing the current state of the field, this review identifies emerging needs and challenges that need to be addressed for the successful implementation of automatic robotic disassembly cells for end-of-life (EOL) electronic products, such as EV LIBs. The findings presented in this paper enhance our understanding of recycling practices and lay the groundwork for more precise research directions in this important area.

Keywords: recycling; electric vehicles (EVs); lithium–ion batteries (LIBs); circular economy; end-of-life (EOL) products; robotic disassembly cells

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1. Introduction

In the present era, there is a growing and significant focus on addressing complex societal challenges, such as climate neutrality, global production sustainability, and the integration of circular economy business models. The transportation sector, responsible for a third of the global energy demand and one-sixth of greenhouse gas emissions (GGEs), has been compelled by society to develop innovative technologies for sustainable mobility, aiming to reduce the environmental impact of petroleum-based infrastructure [1].

Electric vehicles (EVs) are seen as the best options w.r.t. internal combustion engine (ICE) vehicles. By means of EVs, it would be possible to obtain a more environmentally friendly mobility. Their widespread adoption is expected to significantly reduce greenhouse gas emissions related to road transportation, providing a solution to the global climate change issue [2]. The finite nature of fossil fuel resources and advancements in different fields, such as battery design and production, fuel cells, electric motors, and power electronics, are making electric vehicles attractive [3]. Electric vehicles exist in various forms [1], and the electric vehicle market must experience rapid growth to meet global greenhouse gas emissions targets, increase the quality of the air in city areas, and satisfy consumer preferences. This drive is primarily fueled by incentives dispensed by the governments and customers' demand for fuel efficiency and cleaner transportation [4].

The advancements in lithium–ion (Li–ion) battery technologies have significantly contributed to the practicality and attractiveness of electrically-driven vehicles [5]. Li–ion batteries are widely recognized as the most efficient and economically viable type of rechargeable battery for use in the electronics and automotive industries. They are valued for their compact size, high voltage, high energy density, long cycle life, and low self-discharge [6]. Lithium–ion battery cells contain valuable materials, such as lithium, copper, and cobalt, in metallic form or in the form of inorganic metallic compounds [7]. These materials are also extensively used in modern electronic devices such as mobile phones, personal computers, LCD screens, and video cameras, further exacerbating their criticality. The shortened product life cycle driven by market trends and consumer behavior has led to a growing number of end-of-life (EOL) disposals, including lithium–ion batteries (LIBs). Proper treatment of EOL products, including LIBs, is crucial for reducing environmental impacts and maximizing the recovery of valuable materials [8].

The increasing volume of EOL electronic and electric products is a global concern, as it generates a substantial amount of waste materials each year, compounded by the continuous growth of the world population [9]. Meeting the high market demand requires lithium battery manufacturers to produce large quantities of batteries, which poses challenges for the management of EOL lithium batteries to mitigate environmental pollution [10]. However, this waste management challenge presents an opportunity as a valuable secondary source of raw materials through the recycling process of EOL lithium–ion batteries from electric vehicles and electronic devices [11,12]. The development of recycling, remanufacturing, and reusing technologies and processes, along with sustainable design-manufacturing methods, can provide manufacturers access to key components and strategic elements in the EV production cycle, reducing the overall production-to-recycling environmental footprint of these products [13,14]. The European Commission has implemented directives to regulate 'The Waste of Electrical and Electronic Equipment (WEEE)' [15], Directive 2012/19/EU (recast 2018/849/EC). This directive enforces the collection of WEEE separately for sorting and recycling. It also establishes a comprehensive framework for extended producer responsibility, encouraging improved design of electrical and electronic equipment to facilitate recycling and prevent waste generation. The primary objective is to promote reuse, recycling, and other forms of recovery [15].

Currently, the global municipal solid waste generation level stands at approximately 1.3 billion tons per year. It is projected to rise to about 2.2 billion tons per year by 2025 and further escalate to 3.4 billion tons per year by 2050. This surge in waste production identifies electronic waste (e-waste) as the fastest-growing sector in waste generation. According to the US Environmental Protection Agency, only 15–20% of e-waste undergoes recycling, while the rest is disposed of in landfills and incinerators. In 2016, the collective worth of materials found in all e-waste was estimated to be around USD 55 billion [16]. Numerous challenges are present in the treatment of e-waste. This is especially due to the combination and concatenation of hazardous and valuable materials. However, being able to treat e-waste has a high potential, particularly considering the material scarcity and the potentially reduced environmental impact caused by mining and refining operations [17]. Indeed, the whole product life has to be managed: from the design stage (design for disassembly), passing through the consumer's delivery, until the end-of-life stage [18–20]. In Europe, the recycling of electric vehicles and hybrid electric vehicles (EVs-HEVs) is primarily governed by the End-of-life Vehicles Directive (Directive 2000/53/EC of the European Parliament and of the Council on end-of-life vehicles, amended by Directive 2018/849). The main purpose of this directive is to minimize waste generation from end-of-life vehicles and to promote the reuse, recycling, and recovery of these vehicles and their components. It establishes specific targets for the collection rates of reusable, recoverable, and recyclable materials. Additionally, the directive places product responsibility on manufacturers and mandates the removal of batteries before the shredding and post-shredding sorting processes [15].

The current (established in 2015) minimum targets for reuse, recycling, and recovery are particularly relevant in this context, with rates set at 85% (reuse + recycling) and 95% (reuse + recovery), respectively. Special attention is also given to de-polluting fluids and specific components, such as batteries [3]. The Battery Directive (Directive 2018/849 of the European Parliament and of the Council) plays a crucial role in regulating the market for batteries and accumulators. It prohibits the use of hazardous substances in batteries and establishes rules for their collection, treatment, recycling, and disposal [15]. For industrial and traction batteries like LIB and NiMH batteries, battery recycling processes must meet a minimum recycling efficiency of 50% by average weight. Additionally, member states have been obligated to achieve a minimum collection rate for spent batteries and accumulators of 25% by 2012 and 45% by 2016 [3,7]. This political application aims to eliminate the toxic waste generated by products at their end of life, thereby reducing the environmental damage caused [18].

The ongoing shift towards a more environmentally friendly society necessitates a comprehensive consideration of various life cycle aspects of products, optimizing their value and benefits from engineering, assembly, servicing, and maintenance, to the end-of-life (EoL) phases. The emerging business model objectives are centered around reducing the environmental impact and adhering to restrictions throughout the product's life cycle. This transformation aims to replace the traditional cradle-to-grave petrol-based economy framework with a circular economy, all within the context of free enterprise rules [21]. An important takeaway from this approach is the recognition that sustainability solutions must be underpinned by sustainable business models [4].

On the basis of the above-provided context, this paper provides a state-of-the-art review of existing recycling methods, automatic/robotic/collaborative disassembly cells, and associated control techniques. Indeed, the main aim of this paper is to highlight and analyze the state-of-the-art techniques in EV battery pack disassembly, providing a comprehensive overview of the topic, together with future directions.

The structure of the paper is as follows: Section 3 provides an analysis of the massive and challenging theme of battery recycling, including disassembly planning and some insight into future development. In Section 4, a state-of-the-art summary of automatic disassembly is given, also considering human–robot collaborative systems. Section 5 reports control methods for automatic and collaborative disassembly processes. Section 7 states the conclusions.

2. Approach for a Systematic Literature Review

In this paper, we conduct a systematic literature review (SLR) to investigate current research on automatic disassembly and its application to electric vehicle (EV) battery packs, with a particular focus on lithium–ion batteries (LIBs). While robotics research has mainly concentrated on assembly tasks in industrial production, disassembly has not received significant attention so far. Thus, this SLR aims to review the state-of-the-art at the intersection of robotic technologies and the circular economy (CE) research fields. The research questions are designed to validate pre-assessed problems, identify research momentum, and reveal gaps and directions for future research proposals.

The research process spanned approximately 3–4 months, primarily utilizing Google Scholar, Scopus, and Web of Science as the search engines. The initial keywords "robotic disassembly", "EV battery pack disassembly", "LIB disassembly", "battery pack disassembly", and "battery recycling" were employed, followed by broadening the scope with "automatic disassembly", "disassembly planning", "robotic disassembly control", "human-robot collaboration for disassembly", "collaborative disassembly", and "human-robot collaboration". This approach resulted in a collection of nearly 200 articles. Further analysis involved exploring the most relevant citations in those articles, expanding the pool to 320 articles. Finally, for this paper, we considered only the most pertinent and recent works within the last 10 years, resulting in the analysis of 195 articles.

The paper provides an overview of the landscape of robotic disassembly for EV's LIB and reviews the progress in the field from 2012 to (May) 2023. Groundbreaking articles are reported, and the origins of the current development are characterized by including some older articles briefly.

The analysis process follows similar steps to [22], exploring principles and elements of fully automated disassembly cells, human–robot collaboration characteristics in industrial environments (e.g., safety standards, collaborative operation modes, and human–robot interaction), and various technical challenges of human–robot collaborative disassembly (HRCD). Existing control systems are reviewed both for fully automated cells and HRCD scenarios. The paper aims to provide insights into the progress and challenges of robotic disassembly, contributing to future research in this field.

3. Disassembly and Recycling of Lithium–Ion Batteries

Recycling involves a focused process centered on the recovery of materials. This encompasses collecting and reprocessing materials, both from manufacturing process residues and the materials used in the actual products [23]. In this paper, the following main elements are considered in the typical traction system: the main battery system, housing the battery pack connected to a battery management system (BMS), power electronics, and a heating/cooling system. Furthermore, the battery system consists of multiple components contained within an insulated housing fastened with a complex array of screws and adhesives [6]. It is worth noting that significant value is present in manufactured lithium–ion batteries (LIBs), and therefore, it is proposed that their use should follow a hierarchy of applications to optimize material utilization and minimize life cycle impacts [4].

In a broad sense, end-of-life (EoL) strategies for electric vehicles (EVs) can be categorized into three main groups: reuse, remanufacturing, and recycling. These strategies have gained significance as EVs are considered the automotive industry's response to international directives that demand greener and more sustainable vehicles. By focusing on the reuse, remanufacturing, and recycling of EVs, potential solutions are sought to address various environmental challenges, such as resource scarcity, sustainable economic growth, and efficient waste management [1]. Recycling, in particular, presents an opportunity to reduce their environmental impact. Economically, EV battery costs play a pivotal role from a commercial point of view, considering the whole battery life (i.e., including the EoL phase). Exhausted batteries still hold significant value. In fact, valuable materials can be still extracted (e.g., from cells and power electronics) to be reused [1].

The recycling process aims to reduce scrap volume, effectively separate battery components, recover valuable metals, and minimize the environmental impact of spent lithium–ion batteries (LIBs). To achieve these objectives, two primary classes of recycling processes have been utilized: physical processes and chemical processes. Physical processes encompass mechanical processes, thermal treatment, mechano-chemical processes, and dissolution processes, while chemical processes involve acid leaching or base leaching, bioleaching, solvent extraction, chemical precipitation, and electrochemical processes [13,24]. These techniques will be further discussed in Section 3.3. Pilot-scale or semi-industrial processes predominantly focus on recovering cobalt, nickel, copper, and lithium due to their substantial economic value.

Considering that the expansion of electromobility is poised to bring significant changes to vehicle recycling practices in the near future [1], this paper aims to provide a comprehensive overview of techniques addressing the complex challenge of end-of-life (EOL) LIB management. Firstly, it will examine the components requiring treatment, particularly EV traction batteries, offering a brief overview of the current market landscape. Subsequently, the paper will focus on the intricate aspects of 3R (reuse, remanufacturing, recycling), which inevitably involve disassembly processes. Section 3.4 will highlight the critical role of disassembly in the EOL treatment and recovery.

3.1. Current Market Situation

Recycling processes play a fundamental role in the circular economy (CE) [25]. They offer a viable solution for reintroducing LIB compounds back into the economic cycle. By utilizing recovered components, valuable savings can be achieved in terms of raw materials, manufacturing costs, and energy consumption, leading to a reduced environmental impact [25–27]. In recent developments, new LIB recycling systems have been proposed to target a broader spectrum of material compounds. Additionally, to achieve the expected

CO_2 reduction from LIB-powered transportation, it is ideal for the energy used in their production to be derived from renewable sources [25]. The successful implementation of a CE also relies on favorable environmental, political, and financial conditions, with the potential to contribute significantly to environmental preservation and yield economic profits for firms [28].

The adoption of electric vehicles (EVs) has witnessed significant global growth in recent years, largely due to government support aimed at reducing CO_2 emissions and promoting clean technologies. Projections indicate that worldwide EV sales will rise from the current 1.1 million to 11 million in 2025 and 30 million in 2030 [3]. China leads the global electric car market, followed by Europe and the USA [3]. It is anticipated that China will account for 50% of the global EV market by 2025 [28]. Consequently, as the adoption of EVs increases, addressing the recovery process of EVBs within the framework of reverse logistics management of waste electrical and electronic equipment (WEEE) becomes a crucial challenge [29].

The rapid growth of electric car production is expected to generate a substantial amount of EVs that will require recycling by 2030 [1]. As the use of Li–ion batteries in the automotive industry continues to expand globally, the electric vehicle market is projected to reach USD 25 billion by 2025 [30]. Given the increasing development of electric vehicles, the volume of EV lithium–ion batteries (EVBs) available for repurposing or recycling is expected to grow substantially within the next 5–10 years. Estimates suggest that by 2030, 120 GWh/year of EVBs will be available for recycling [31]. With this growth in mind, legislation is likely to demand higher collection and recycling rates for EVBs, as evidenced by the newly proposed regulation by the European Parliament and the Council concerning batteries and waste in December 2020 [32]. The recycling of ELVs and WEEE is of paramount importance, and legislative ELV recycling systems have been established in various countries such as the EU, Japan, Korea, and China [33]. However, recycling practices in many cases emphasize economic benefits over environmental and social considerations [16]. Given the increasing adoption of (H)EVs (hybrid EVs) and FCEVs (fuel cell electric vehicles), efficient recycling technologies for these complex end-of-life (EOL) products are essential for economic and environmental reasons. These vehicles contain a broad spectrum of materials, including precious metals and rare earth elements, which need to be recovered for sustainability and resource conservation [3]. Huge benefits might be achieved from End-of-life LIB recycling. In particular, economic benefits can be achieved. In addition, avoiding new mineral extraction will lower the ecological impact. Based on that, increased resilience against vulnerable links and supply risks in the LIB supply chain can be achieved [4]. The importance of considering end-of-life issues during product design has become evident, and gaining insights into future recycling and disassembly technologies is crucial [34]. Companies need to be aware of future technologies when designing products for recycling and disassembly to ensure sustainable practices are implemented [34].

3.2. Currently Utilized LIB Batteries for EV

As reported by Heelan [35], in 1972, Whittingham at Exxon introduced the first lithium metal battery, showing practical issues. Simultaneously, Lazzari et al. [36] adopted insertion materials that could accept Li–ions as the cathode and anode. The first Li–ion battery technology was indeed available at the end of the 1980s. Goodenough proposed a more advanced cathode chemistry using the formula Li_xMO_2 (M = Co, Ni, or Mn), which became widely used in modern Li–ion batteries [37]. In 1991, a new battery ($LiCoO_2$ cathode; carbon as the anode) was taken to the market by Sony Corporation. For safety and capacity reasons, cation substitutes for Co, such as Ni, Al, Ga, Mg, or Ti, were applied [35]. LIBs have gained popularity in recent years and are being extensively used in electric vehicles (EVs) due to their high energy density to weight ratio, lack of memory effect, and long life cycle.

The global market for LIBs had reached USD 25 billion by 2017 [38]. Furthermore, the LIB recycling market is projected to grow from USD 12.2 billion in 2025 to USD 18.1 billion by 2030, at a compound annual growth rate of 8.2% from 2025 to 2030 [39].

Currently, there are four main EVB technologies in use: lead–acid, nickel–metal hybrid, lithium–ion (Li–ion), and sodium-nickel chloride [28,40]. Li–ion secondary cells can be categorized into three main shapes: cylindrical, pouch, and prismatic [41], having specific pros/cons at both manufacturing and application levels. Cylindrical cells, being tightly coiled, present distinct challenges in electrode separation for recycling processes. Prismatic and pouch cells, instead, are characterized by flat electrodes [4].

The cell serves as the fundamental and modular component in all lithium–ion batteries (LIBs), consisting of various elements: a cathode composed of a transition metal compound, an anode made of graphite, current collectors of Al and Cu, Li salt acting as the electrolyte, a polymeric separator, and a metallic cell casing [42,43]. The cathode, typically a lithiated transition metal oxide/phosphate, establishes the achievable voltage of the LIB when the anode material remains unchanged. In most commercialized LIBs, $LiCoO_2$ is a commonly used cathodic material due to its favorable attributes, including high energy density and ease of manufacturing. As for the anode material, graphite is typically used, though some stationary applications may employ $Li_4Ti_5O_{12}$.

The electrodes are composed of particulate active material, carbon conductive additive, polymeric binder, and current collector. Carbon conductive additives play a crucial role in facilitating electron transport to the site of lithium intercalation within the electrode. When the mass fraction of the additives, such as carbon spheres, carbon black, carbon fibers, and carbon tubes, surpasses the percolation threshold, a connected, percolating network is established throughout the electrode [44]. The electrolyte consists of a Li-salt dissolved in an organic solvent, facilitating the efficient conduction of Li ions between electrodes [35]. LiPF6 is frequently utilized in commercial products because of its lack of toxicity and thermal durability.

PVDF (polyvinylidene difluoride) serves as a binding material for the cell. It needs a high mechanical strength and chemical/environmental endurance. The electric current is carried through Al and Cu foils linked to the cathode and anode [35]. Aluminum, an abundantly available and lightweight metal, functions as the current collector for the cathode. Nevertheless, copper is commonly used instead of aluminum. In fact, together with lithium aluminum forms an alloy at low potentials, making it unsuitable for anode current collectors usage. The polymeric separator serves a crucial role in Li–ion batteries, as it is placed between the electrodes to prevent direct contact and avoid short circuits. It needs to have sufficient porosity to enable Li–ion migration. The separator has two main functions: (1) preventing physical contact between the electrodes to avoid internal short-circuiting, and (2) providing an ionic conduction path for the liquid electrolyte. Porous polyolefin membranes are widely used as separators in Li–ion batteries with liquid electrolytes due to their comprehensive advantages in terms of performance, safety, and cost-effectiveness [43,45].

The structure of the cell includes enclosing the components in an Al, Fe, or plastic casing. The specific capacity, measured in mAh/g, indicates the amount of electricity delivered by a cell [43]. The rate capability, cycle life, Coulombic efficiency, operating temperature range, and safety of Li–ion batteries are largely determined by the electrolyte composition and cathode material. The wide variety of mixed LIB chemistries found in recycling streams are already presenting challenges in recycling processes [13,25,28,35].

Materials are responsible for one-third of the manufacturing costs for a portable Li–ion battery cell. In fact, high-value metals are present in the Li–ion battery cells [7]. The lithium–ion technology is preferred in comparison with other battery technologies (Ni-MH or Ni-Cd). Thanks to their higher energy density, a more compact design can be obtained, together with reduced production costs. As battery cells contain valuable active materials (e.g., Al, Co, Li, or Cu) Through affordable recycling methods, it becomes feasible to economically recover valuable metals from spent batteries, significantly reducing the life cycle costs of lithium–ion batteries [46].

Lithium–ion batteries (LIBs) possess several pros w.r.t. other chemistries. Lithium (Li) has the lowest reduction potential of any element, resulting in the highest possible cell potential for Li-based batteries. In addition, LIBs exhibit lower self-discharge, no memory effect, longer lifecycle, and compact size. Moreover, Li is the third-lightest element and possesses one of the most compact ionic radii among all singly charged ions. These characteristics contribute to the high gravimetric and volumetric capacity and power density of Li-based batteries. The high energy efficiency of Li–ion batteries opens up various electric grid applications (e.g., energy harvested from renewable sources) [6,38,47].

Today, lithium–ion batteries (LIBs) have established themselves as crucial electrochemical energy storage devices, powering a wide range of electronic mobile devices and electric vehicles. In addition, as the push for electric vehicles is driven by government and societal awareness of climate change, lithium–ion batteries (LIBs) have emerged as a promising option for reducing CO_2 emissions [25]. Over the last few decades, various Li–ion cathode materials have been developed, encompassing different chemistries (e.g., $LiCoO_2$, NCA, $LiMnO_4$). Currently, lithium nickel–manganese–cobalt oxide (NMC) stands as the most desired technology for electric vehicle batteries (EVBs) because of its reduced self-heating rate and impressive energy density [28,48].

As efforts to recycle LIBs broaden their focus to encompass a wider range of metals, it becomes imperative to enhance recycling technology to attain greater efficiencies and selectivity in recovering the desired metals. Considering the various sizes, configurations, and cathode compositions of LIBs, there exists the possibility of a greatly mixed and uncertain waste stream if preliminary sorting based on cathode type is neglected. To address the anticipated surge in end-of-life LIBs entering the waste stream, it is imperative to develop viable, automated, and cost-efficient recycling processes, as highlighted by Wang [38].

One key operation in LIB recycling is efficiently organizing batteries with varying chemistries to streamline the separation processes. A straightforward and effective approach involves comprehensive labeling, utilizing various forms such as physical labels, QR codes, and RFID tags. The Battery Recycling Committee of the Society of Automotive Engineers (SAE) has introduced a labeling system designed for placement on EV battery packs, facilitating the separate processing of different battery types [49]. Moreover, a recent report from the World Economic Forum and the Global Battery Alliance recommends the establishment of battery diagnostic systems or battery passports, especially for EV batteries. Implementing such systems directly within batteries or as separate tools could provide critical information, including battery chemistry, origin, health status, and custody history, which can be captured by battery recyclers at recycling facilities [39]. The pre-recycling process is strategically designed to achieve material segregation, with a particular focus on the metallic portion, while establishing clear targets for subsequent recycling procedures. Implementing sorting by cathode chemistry before pre-treatment can significantly reduce uncertainties in input materials, leading to enhanced purity of output streams. Consequently, the adoption of battery labeling systems can play a crucial role in facilitating successful pre-recycling processes [38]. For the effective reduction of CO_2 emissions from LIB-powered transportation, it is essential that the energy used in their production comes from renewable sources. However, current industrial-scale LIB recycling processes face inefficiencies, leading to inevitable material losses. Additionally, state-of-the-art (SoA) technologies are found to be lagging approximately four years behind the physical and chemical complexities of LIB compounds [35]. Given the material focus of LIB recycling processes, market value and criticality play significant roles. Consequently, Co and metallic fractions are currently the primary targets. Pyrometallurgical processes typically recover metallic components as metallic alloys, while mechanical dismantling handles the recovery of large casing materials. However, in most cases, materials such as Li compounds, electrolytes, plastics, and organic substances are lost during the recycling process, except in China and South Korea, where Li is recovered as $LiCo_3$ [50].

The current disparity between recycling capacities and production requirements has resulted in escalating exploitation of mineral deposits to meet the raw material needs of the LIB market. Unfortunately, natural mineral deposits are now reaching critical levels of valuable metals, leading to economic losses and environmental risks. This gap also intensifies the demand for virgin raw materials, which contradicts efforts to combat climate change through electrically powered products, particularly electric vehicles (EVs) [7,25,35,51]. The intricacy of the material composition, along with the handling of potentially dangerous chemicals, adds complexity to the initial disassembly process needed for recycling. Consequently, disassembling a lithium–ion battery system can present hazards to workers, especially in manual disassembly. Battery packs used in automotive applications necessitate that operators receive training on high-voltage procedures and use insulated tools to mitigate the risks of electrocution or short-circuits. Such incidents can result in rapid discharge, overheating, and potential thermal runaway. Thermal runaway can produce harmful byproducts, such as HF gas, which, when combined with other generated gases, may become confined and contribute to cell explosions [46]. Additionally, the cells within lithium–ion batteries present chemical risks owing to the presence of a combustible electrolyte, toxic and carcinogenic electrolyte additives, and potentially hazardous or carcinogenic electrode materials.

Disassembling battery cells shows the risk of high-voltage injuries and triggering thermal or chemical reactions if the cell sustains damage during the process. This may result in the release of hydrofluoric acid when it comes into contact with water or the potential for an organic solvent electrolyte to ignite due to a short circuit [46]. Stockpiling waste batteries is an undesirable option in terms of safety and environmental responsibility. If the reuse of a LIB module is not feasible, it should be either repaired or subjected to recycling. Recycling end-of-life LIBs can yield significant economic benefits by obviating the need for new mineral extraction [4].

3.3. Traditional Methods for Recycling, Remanufacturing, and Reuse

The recycling industry lags behind the development and commercialization of Li–ion batteries, resulting in approximately 95% of Li–ion batteries being land-filled instead of recycled at end-of-life [35]. Implementing a flexible closed-loop recycling system can significantly increase Li–ion battery recycling rates, diverting millions of pounds of batteries from entering the waste stream annually. The dominant use of Li–ion batteries in consumer electronics, electric vehicles, and renewable energy storage has sparked great interest and investments in the battery sector. Recycling these batteries can provide a solution to address supply chain issues, reduce dependence on foreign sources, stabilize material prices, and lower the cost of batteries and electric vehicles [39].

The recycling process for Li–ion batteries involves several stages, including discharging, disassembling, sorting, mechanical shredding, and metallurgical processes (pyrometallurgy and hydrometallurgy) to recover valuable metals like nickel, cobalt, and copper [24]. Proper assessment of the state of health and charge of used batteries is essential for battery repurposing in other applications, such as stationary energy storage, to ensure safety and efficiency in recycling processes [4]. The waste management hierarchy emphasizes prevention, reuse, and recycling as crucial steps for sustainable battery recycling [4]. Recycling processes can be classified as pyrometallurgical, hydrometallurgical, or a combination of both. Direct recycling is an emerging strategy that aims to reclaim and regenerate active cathode materials without affecting their morphology for reuse in new battery production [23,25]. Numerous recycling technologies and methods have been developed by various companies and research groups, and ongoing research focuses on improving recycling efficiency and reducing environmental impacts [10,24]. Remanufacturing is considered an economically and environmentally sound option in the recovery process of end-of-life products, allowing for the renewal of products to at least their original performance specification [9,52]. Before disassembly, an analysis of the condition of battery modules is essential to determine whether they are suitable for reuse, secondary use, or chemical recycling for precious material recovery [10]. Li–ion batteries have the potential to contribute to building an energy-sustainable economy by improving the quality of energy harvested from renewable sources and promoting their widespread use in electric grid applications [47].

3.4. Disassembly Procedure Design

Disassembly, defined as the systematic separation of a product into its constituent parts and components, is a critical step for efficient end-of-life (EOL) treatment. However, economic infeasibility, especially in developed countries due to labor costs, often hinders disassembly [8]. Disassembly planning involves generating a de-manufacturing plan to remove components from an assembled product, and automation remains challenging for EV batteries due to lot size variations, design complexities, and material instability, making manual disassembly more prevalent [28,53,54]. Disassembly not only aids in material recycling but also enables "noble recycling" to preserve the functional value of components and valuable materials and energy [55]. Various aspects, such as the complexity of operations, profit maximization with minimized environmental impact, and safety during the manipulation of chemical materials, need consideration in disassembly planning [24,56].

To promote sustainability, Li–ion batteries in EVs are often disassembled during the recycling process for secondary use or recovery of valuable materials and components. However, the current disassembly process is time-consuming and expensive, partly due to the non-standardized design of battery packs across car models, leading to inefficient disassembly and suboptimal recyclability [6,57]. Disassembly offers benefits such as the removal of toxic components, recovery of valuable materials, and the disassembly of operative components for reuse [20,58]. However, disassembly of battery packs from automotive applications poses hazards due to high voltage and chemical risks, making manual disassembly labor-intensive and unsafe for technicians [4,59]. The European Community's RoHS law mandates the removal of toxic materials from electrical and electronic equipment before recycling [56]. Design for disassembly (DfD) principles are essential for economically and environmentally viable recycling, and several guidelines have been proposed to enhance disassembly ability [60–62]. Determining the optimal disassembly level and sequence is crucial for efficiency and cost reduction. Intelligent optimization algorithms and meta-heuristic methods are employed to find near-optimal solutions [9,53]. Computer-aided disassembly planning plays a crucial role in optimizing solutions, improving product design, and facilitating disassembly plant control [56]. However, challenges such as uncertainties in end-of-life products, limited data availability, and computational complexities still impede the full implementation of computer-aided systems [56]. Manual disassembly of spent lithium–ion batteries (LIBs) involves multiple steps, but the automation of repetitive or hazardous tasks using robots has the potential to significantly enhance the disassembly process [14,59].

3.5. Future Development for Intelligent Disassembly

Today, millions of pounds of Li–ion batteries are being land-filled instead of recycled each year, depleting valuable natural resources like cobalt, nickel, and lithium. Large-scale recycling of Li–ion batteries is crucial to creating a more sustainable and circular society that recovers materials instead of discarding them. However, the prevalence of Li–ion battery recycling is limited due to several reasons: (1) Current commercialized recycling technologies often yield products that are less valuable than the original batteries, making the business model less robust; (2) the constantly evolving cathode chemistries of Li–ion batteries pose challenges for recycling companies to adapt their processes; (3) government mandates for recycling end-of-life Li–ion batteries are lacking in many countries [35].

Disassembly is a critical step in the recycling process and is expected to see significant expansion. However, the current manual disassembly process for recycling is not scalable to handle the increasing volume of electronic waste. Automation, such as using robots, could greatly improve the efficiency and safety of the disassembly process [11,63]. The economic efficiency of battery recycling could be enhanced through automation, leading to improved separation of battery components. However, many current batteries are not designed for easy disassembly, making automation challenging. Encouraging manufacturers to standardize cell and pack construction would facilitate simple and automated disassembly processes [39].

Establishing disassembly families, which are groups of similar or different products requiring similar disassembly operations, could enhance flexibility and reduce costs in the disassembly process [63]. Implementing battery labeling systems could be a significant step in improving pre-recycling processes and developing feasible, automated, low-cost recycling techniques to handle the increasing volume of end-of-life Li–ion batteries [38]. To address the challenges in recycling Li–ion batteries and other electronic waste, automation, robot-assisted disassembly, and the development of efficient recycling technologies and processes are necessary. It is essential for governments and industries to collaborate in formulating policies, regulations, and industry standards to promote greener recycling practices and reduce pollution caused by waste batteries [12,24].

4. Automatic Disassembly Systems

4.1. Considerations on Automation for Disassembly Operations

The main characteristics of a human operator's behavior that contribute to the flexibility and robustness of the disassembly process include real-time perception of the product's structure, the ability to assess outcomes and adapt if necessary, broad operation schemes, and learning from past experiences [64]. Disassembly is a critical process in the industry for recovering reusable components and separating materials from products. Due to the vast array of products that need to be disassembled, automated processes with high agility are necessary [65]. As of now, there are no automated commercial disassembly processes in the UK and Europe, including the automotive industry. Nonetheless, the automation of end-of-life electric vehicle disassembly has the potential to improve remanufacturing initiatives and optimize the retrieval of valuable materials present in EV electronic components [12]. The traditional manual recovery method relies heavily on human labor, making it essential to develop intelligent, automatic, or semi-automatic frameworks for efficient and rapid disassembly and recovery of retired batteries [10]. The pursuit of automating the disassembly process is driven by its current inefficiency and economic infeasibility for many potential disassembly products. Although attempts have been made to automate disassembly for complex products like cars, industrial-scale automation for lithium–ion batteries has not been achieved yet [22].

To increase the cost-effectiveness of disassembly, automating a subset of disassembly steps is crucial. However, the lack of inbound identification systems or standardized labeling presents challenges, particularly when the cell chemistry of lithium–ion batteries is unknown [46,63]. Vehicle design often prioritizes crash safety, the center of gravity, and space optimization, which can compromise serviceability and recyclability. Consequently, manual disassembly of vehicles can be time-consuming [4]. Disassembly in traditional ELV dismantling processes is a valuable stage, allowing car dismantlers to resell disassembled components as spare parts on the secondary market [1]. Automation offers a possible solution for cost-effective disassembly, and as electronic waste continues to increase globally, automating disassembly for electronic devices becomes essential. Currently, only pilot projects for fully automated single-purpose solutions, limited to specific types of products, have been realized [63]. Using a flexible and automated manufacturing cell for disassembly work is advantageous if it offers customizability and adaptability for different products. This ensures a consistent cadence in the process and justifies its automation. The system must be robust, versatile, and capable of precise recognition tasks [66]. To meet flexibility requirements in disassembly processes, efficient information management and modular technologies are essential. Suitable sensors for product and state identification, as well as process control of dismantling operations, are needed to support intelligent disassembly [67]. Industrial automation is facing challenges related to flexibility requirements arising from prototyping processes applied to serial productions, geometrically variable workpieces or products, and functionally variable products based on modules [68].

Robotic battery disassembly has the potential to reduce the risk of harm to human workers and make recycling economically viable. Automation improves mechanical separation, enhances material purity, and increases efficiency in downstream separation and recycling processes. Robots in automation perform pre-programmed actions with high precision in structured environments, outperforming human workers in repetitive tasks [4]. Robotic and autonomous disassembly have gained attention, but their industrial application for end-of-life products remains limited, except for manufacturers' initiatives to refurbish their own products. Highly extensible and easily reconfigurable robot tooling that does not rely heavily on vision systems opens up possibilities for adaptable robot assistants in manual disassembly facilities, even without access to manufacturers' product information [9,11]. Currently, automotive lithium–ion battery dismantling is mainly done manually, and robotics are employed for simple tasks or human assistance. Manual processes are time-consuming and require highly skilled personnel. Partial disassembly, achieving maximum profit while reducing environmental impact, might be the optimal approach due to its profitability [32,69]. Automated systems offer advantages, such as robustness, lower cost, reduced injuries and exposure to toxic chemicals, enhanced workplace attractiveness, scalability, and efficient separation of components into high-value streams for recycling. Fully automated disassembly of electric vehicle batteries is likely in the future, but challenges remain due to variations and uncertainties in used products [32,69]. In the pursuit of an economically viable and efficient disassembly process, automation has been identified as a key solution. The Critical Materials Institute (CMI) developed an automated system that can be easily reconfigured to handle various battery stacks, emphasizing the value added by such automation [69]. Automated disassembly offers several advantages, including the elimination of toxic substances, the concentration of valuable materials for ecological and economic benefits, and the profitable reuse of components such as energy sources and memory chips. However, due to the variations and uncertainties in returned products, the disassembly system must be flexible and robust to accommodate these challenges [8,70,71].

Considering the resource life cycles, the disassembly process plays a crucial role in closing the loop of the circular economy (CE). However, at present, the disassembly industry lacks automation, and most disassembly operations for EV Li–ion batteries are manual due to the complex and non-standardized designs, making automation challenging [6]. The inclusion of labeling standards for electric-vehicle batteries could greatly aid the recycling process. Machine-readable features on battery components could provide valuable information, but their utility depends on accessibility and data format. Efforts towards standardization and open data formats could enhance the effectiveness of such labeling [4,67]. Disassembly processes are critical and complex in the recycling chain, involving a large number of employees and intricacies due to product complexity and design. Disassembly is more complex than general assembly tasks, making it a challenging yet crucial step in EOL treatments [22]. For efficient disassembly, it is essential to separate battery cells from other components while maintaining the quality of recovered raw materials. However, manual disassembly is costly and may pose safety risks, while full automation is currently impractical due to product variations and small volumes. Standardization in EV battery design remains a challenge, as different manufacturers and models use varied designs [5]. An automatic disassembly process is most justified when it is carried out in a flexible manufacturing cell capable of continuous disassembly operations. This is in contrast to assembly processes, where products of the same type are introduced sequentially based on demand, while disassembly involves a wide variety of models and product types, creating uncertainty regarding their order and structural configuration [19]. Several factors limit a higher degree of automation in disassembly: non-uniformity of returned product models, questionable economic benefits, custom-developed implementations, and potential damage or corrosion of returned products [65]. Automating the disassembly process has been a challenge due to uncertainties associated with end-of-life (EOL) products. These uncertainties arise from the physical conditions of EOL products, product variety, and complexity in process planning and operations. These factors have made automation difficult for both human operators and machines [4].

The disassembly of lithium–ion battery systems from automotive applications is complex and time-consuming due to varying battery designs, flexible components, and safety hazards associated with high voltage and chemicals. Flexibility in the design of battery modules, fastening in inaccessible areas, and handling of cables and joints pose additional challenges to disassembly and future automation concepts [6,14]. Creating control algorithms and software that enable cheap hardware to behave flexibly and intelligently is crucial for handling the complexity of disassembly problems. Advanced robotic perception through sensors, including computer vision and tactile capabilities, will play a vital role in enabling robots to interact with materials during the disassembly process [4].

Automated disassembly systems face challenges, particularly related to economic reasons, rather than technical issues. Factors, like too many product types, small numbers of products of the same type, non-design for disassembly (DfD) products, return logistics problems, variations in returned products, and damaged or corroded parts hinder the broad realization of mechanized disassembly. Nevertheless, implementing mechanized disassembly could reduce disassembling costs, optimize recycling processes, and improve working conditions in disassembly factories [63]. Disassembly of battery packs can be time-consuming, especially when design conflicts arise between vehicle safety and service-friendly installation positions. Lack of information about the products' usage condition contributes to uncertainties in identifying the most favorable disassembly strategy. Complementary monitoring and quality verification techniques are essential for determining the usage condition of products and components [23,56]. Uncertainties and variations in returned EOL products pose challenges for disassembly processes, making automation more difficult due to the lack of flexibility in sensing and decision-making compared to human operators [72]. The progress of automation in electronic waste recycling's disassembly processes is hindered by the lack of automated procedures for screw detection and removal. A generic solution for automated disassembly, particularly for detecting screws, is urgently needed due to the diverse range of electronic device variants [73]. Successful disassembly relies not only on automation but also on efficient collection systems and competitive market prices for recycled materials [34]. Technological constraints, especially in handling uncertainties related to end-of-life product variation and condition, limit the application of robotic disassembly and disassembly automation in the industry [58]. The research in this field has primarily centered around four key disassembly challenges: evaluating the disassembly process, developing disassembly cells, devising disassembly motions and sequences, and employing intelligent sensors and flexible actuators for product disassembly. However, sensor-based robot motions for disassembly have received relatively less attention, as most endeavors have been focused on using vision sensors to localize and identify components [57]. To address uncertainties during planning and operations, disassembly systems rely on two primary sources of inputs: prior knowledge and knowledge detected during the process. Sensor systems are integrated into the disassembly planner to generate a Disassembly Process Plan (DPP) and control the operation sequences based on information gathered during disassembly [8]. In large-scale battery disassembly, classifying batteries properly is a challenging problem due to variations in size and structure, leading to potential battery damage and safety issues. Improving the flexibility of the disassembly process is crucial to enhancing safety and preventing injuries and property damage during battery disassembly [10]. Despite advancements in robotics, disassembly tooling, and system design, several inhibitors, including sequencing, disassembly range, product variants, flexibility of disassembly facilities, tooling, part conditions, logistics, and limited information flow, hinder the successful implementation of robotic automation in disassembly [22]. To achieve robust and flexible automatic disassembly, several requirements need to be met, such as the ability to remove fasteners and separate connections between components, sensor-guided robots for disassembly, evaluation of necessary tools and grippers, implementation of artificial intelligence in cell control, suitable vision systems, and integration of vision systems in semi-automated cells [58,63]. Real-time constraints and the need for precise recognition tasks in disassembly processes demand planning and scheduling approaches that integrate online planning phases. Automated disassembly requires robust positioning, grasping, and operating tasks while considering kinematic constraints, product position, and orientation [65]. The process of automated disassembly relies on three-dimensional object recognition and location using computer vision techniques. However, in cases where features are not visually detectable, detection results can be unreliable. Addressing failure in the disassembly process and resolving it is a challenging problem that requires intelligent systems [8].

At present, the automation solutions in use are primarily tailored to specific requirements and may not fully adapt to the dynamic nature of the disassembly environment. This is due to the diverse range of products that need to be disassembled, along with their varying shapes and configurations [65]. The disassembly ability of industrial batteries can be improved either through modifying their design and increasing standardization or developing new technologies to make the process smarter and more efficient, as explored in the research of Choux et al. [32]. The process typically involves testing and discharging the battery, removing screws and adhesives, disconnecting external components, cutting wires and connectors, and disassembling stack holders to obtain battery modules and cells [6]. Choice points in the disassembly process can be categorized into three types, including product structure and type of components, disassembly operation plans, and process parameters, each with various technical feasibility considerations [64]. Automating the disassembly and recycling of batteries is crucial for reducing e-waste and obtaining profits from extracted materials or components. Manual disassembly processes for EV batteries are costly and inefficient, requiring skilled technicians and posing safety risks. Automation can improve the overall disassembly time and revenue gain, justifying the implementation of automation infrastructures [6]. Digitalization technologies and Industry 4.0 developments, especially with cooperative and collaborative robots, can advance disassembly automation, making it state-of-the-art in the industrial context in the next decade [22]. The principles of circular economy (CE), particularly 3R (reuse, recycle, and recover), and closed-loop supply chains play a vital role in recycling and managing electronic waste effectively. Employing IoT and Industry 4.0 technologies can enhance product quality, reduce costs, and create intelligent value chains, leading to improved sustainability and profitability in recycling processes [22]. Advanced disassembly techniques can lead to "inverse" factories that work in symbiosis with traditional factories to close the production cycle completely. As the global robotics market grows, intelligent automation and robotics, along with AI technologies, contribute to more flexible use cases and can positively impact future jobs and employment, with human and machine workers complementing each other [22,65].

4.2. Fully Automated Disassembly

In the field of autonomous robot disassembly of various end-of-life (EOL) products, such as electronics and spent lithium–ion batteries (LIBs), several relevant articles discuss the progress and development:

- Zhang et al. proposed a teleoperated mobile six-degree-of-freedom robot equipped with a vision system to remove the exhausted battery to be charged with a wireless station [74].
- Harper et al. highlighted the promising tools of computer vision, artificial intelligence, and robotics for addressing the challenges of automated disassembly processes for electric-vehicle batteries [4].

- Zhou et al. emphasized the use of advanced devices and AI techniques for achieving automatic disassembly of retired battery packs through various robot operations, including image acquisition, target object detection, identification, positioning, and task planning [10].
- Kay et al. explored battery disassembly using industrial robots, envisioning and testing a robotic method for automating the disassembly process of battery packs [59].
- Choux et al. developed an autonomous task planner using a computer vision system for dismantling EV lithium–ion battery packs to a module level, showcasing the system's autonomous decision-making capability [32].
- Li et al. presented a semi-destructive robotic disassembly process using a flexible robot cell with specially designed tools to disassemble and extract strategically important materials (SIMs) from EV components [12].
- Researchers at the Oak Ridge National Laboratory developed an automated disassembly system for spent electric vehicle battery packs, which can be easily reconfigured for different battery stacks to reduce human exposure to toxic chemicals [69].
- Ramirez et al. proposed an optimization model for efficient decision-making in partial disassembly processes, applied to robotic disassembly, and demonstrated its suitability in resolving the disassembly process and achieving optimal economic profit and recovery options [9].
- Li et al. designed an automatic mechanical separation methodology for EOL pouch LIBs, specifically for dismantling and separating cathode sheets, anode sheets, separators, and polymer-laminated aluminum film housing from lithium–ion pouch cells [41].
- Figueiredo et al. developed a robotic system prototype for the disassembly of cell phones, successfully disconnecting flat flexible cable connectors using compliant tools with a moving pivot motion [75].
- Vongbuyong et al. developed a cognitive HR collaborative robotics-based system for semi-destructive disassembly, incorporating a cognitive robotic agent, mechanical units, and a vision system to perform the disassembly process effectively [64].
- Chen et al. designed a multi-head tool for robotic disassembly of LCD screens, utilizing a screwdriver, hole saw, and angle grinder to take advantage of both destructive and non-destructive techniques [58].
- Borras et al. introduced a robotic gripper for electromechanical device disassembly with innovative features, including interchangeable built-in tools, repositioning grasped objects, and dual-arm manipulation capability [76].
- Kasperzyk et al. presented a robotic prefabrication system (RPS) that employs "re-fabrication" for automatic disassembly and reconstruction of prefabricated structures according to new designs [77].
- Rastegarpanah et al. proposed automated unfastening of hexagonal nuts for dismantling electric vehicle battery packs using surface exploration with a compliant robot, achieving a high success rate in exploration and unfastening [78].
- Li et al. addressed cutting depth determination in robotic disassembly of LCD screens using an automated method with an electric nut-runner spindle and a spiral search technique based on force/torque feedback [79].
- Jungbluth et al. presented an informed software agent for robot-assisted disassembly, using product models to build a coarse disassembly plan and a detailed plan for robot program execution [80].
- Vongbuyong et al. proposed a skill-transferring platform, where human-assisted disassembly processes are represented and transferred to robots for automated disassembly [81].
- Lan et al. addressed the interlocking problem in disassembly, proposing solutions based on identifying subassemblies and generating hierarchical disassembly sequence plans [82]. Schneider et al. explored an algorithm to compute complex nonlinear disas-

sembly paths for colliding objects, considering flexible and rigid parts and intersection volumes in a motion planner [83].

- Filipescu et al. presented a method to reverse an assembly line for complete disassembly, using a generalized synchronized hybrid Petri net (SHPN) model-based control of an assembly/disassembly mechatronics line served by a wheeled mobile robot equipped with a robotic manipulator [84].
- Chen et al. proposed an ontology and case-based reasoning (CBR) method for automated disassembly decision-making of various mechanical products [85].
- Chen et al. tackled challenges in autonomous disassembly action generation and execution using a robotic system equipped with three tools and a method based on geometrical estimation for disassembly action selection [86].
- Buhl et al. integrated dual UR5 robotic manipulators in a smart disassembly cell for mockup mobile phones, showcasing the potential of dual-arm disassembly [87].
- Knoth et al. presented a flexible, modular system for intelligent disassembly with a practical application on printed circuit boards (PCBs), removing reusable and hazardous components [63].
- Gerbers et al. discussed the potential of automated disassembly systems and human–robot collaborations, highlighting the attractiveness of partially automated disassembly for electronics goods and the future potential for fully automated disassembly [54].

These articles showcase the progress and potential of autonomous and collaborative robot disassembly across various industries and products. The integration of computer vision, artificial intelligence, and robotic technologies has been instrumental in automating disassembly processes for effective recycling and recovery. Notably, the distinction between collaborative and autonomous robotics lies in considering external and internal sensors to avoid physical harm to humans during cooperative tasks. Incorporating cooperative control techniques in automatic disassembly systems offers advantages like reduced disassembly time and cost savings. These improvements hold significant promise for industrial applications involving cooperative work in the disassembly process [18].

4.3. Human–Robot Collaborative Disassembly

Human–robot collaboration has become a topic of great interest in recent years, as it offers the potential to create hybrid workspaces where robots and human operators can work together seamlessly without the need for safety barriers. These workstations enable flexible and reconfigurable production systems, with humans focusing on complex tasks that require intricate sensing and motions, while robots handle monotonous, repetitive, and unergonomic tasks. This setup is particularly advantageous for industries with small-scale productions and a wide variety of products [54].

In the specific context of lithium–ion battery (LIB) pack disassembly, research has demonstrated that human–robot collaboration is the most effective approach. Robots can efficiently cut the battery pack, while technicians can quickly sort battery components and handle connectors or fasteners that might be challenging for robots. This collaborative approach improves both safety, as the risk of shorting battery cells during cutting is eliminated, and time efficiency [59]. Partially automated disassembly systems offer several benefits, including managing larger lot sizes with a smaller team, reducing human exposure to potentially harmful situations, and providing the necessary flexibility to adapt to new product designs and unexpected events [11]. In manufacturing environments, robot assistants have shown promise in various tasks, such as fetching and carrying, assembly, handling, machining, and measuring [68].

To achieve effective collaboration between humans and robots, it is important to understand the nature of interactions between these components. Interactions can occur at both a symbolic level, involving the exchange of digital messages on a network, and at a physical level, which includes visual, tactile, and acoustic interactions [88]. Cooperation, coordination, and communication play vital roles in compensating for uncertainties and ensuring successful human–robot interactions [89].

Cesta et al. [90] introduced a dynamic task sequencing system to foster robust human–robot collaboration. They utilized AI techniques to address temporal variance and dynamically adapt task plans based on the behavior of the human–robot pair. When implementing human–robot collaboration for lithium–ion battery (LIB) disassembly, several important considerations come into play. Safety, robot acceptance, and control architecture are crucial aspects that need to be carefully addressed. Adhering to ISO standards, such as ISO 8373 [91], ISO 10218-1/2 [92], and ISO 15066 [93], is essential to ensure safe human–robot interaction in collaborative workspaces [54]. In the implementation of human–robot collaboration for battery disassembly, a hybrid workstation was utilized, where a lightweight KUKA lightweight robot (LWR) was responsible for unscrewing tasks using a modified cordless electric screwdriver mounted on the robot flange. This setup allowed the robot and the human operator to share a common workspace, enabling efficient collaboration. The human operator demonstrated or detected the locations of fasteners, guiding the robot in performing the unscrewing task [5].

Gerbers et al. [54] developed an automated disassembly workstation with human support to address challenges related to computer vision reliability. The presence of a human operator allowed verification of computer vision results, checking for false positives, and directly teaching new positions to the robot. This facilitated intuitive programming and reduced software requirements. Through the hybrid workstation and the implementation of developed machine interfaces, tools, and algorithms, the study demonstrated the feasibility of achieving efficient partial-automated disassembly of battery systems. The approach successfully achieved a balance between productivity, ergonomics, and safety in the disassembly process [54]. The implementation of successful human–robot collaboration for disassembly tasks holds promise for economic rationalization and variant flexibility, making it a viable approach for large-scale recycling of battery systems in high-wage countries [54].

Chen et al. [11] proposed a concept and conducted initial investigations on a hybrid disassembly workstation featuring a compliant robot for the unscrewing task. Such a system must have access to information from a database, vision system, or be teachable by a human user to perform the required skills. Obtaining product structure information before manual disassembly can be time-consuming and challenging. Although using a vision system for component and fastener recognition is beneficial, it becomes complex when minimal product assumptions can be made. Hence, the option of allowing users to directly teach new positions to the robot was explored.

The researchers introduced an innovative bit-changing mechanism that utilized commonly available socket wrench bits and a straightforward mechanical design without external actuation. This design made the system adaptable to variations within and between products, resulting in reduced setup time and costs associated with tool replacement. In the hybrid workstation, both the human worker and the robot had access to their respective tools, with enough workspace to allow them to perform their tasks independently without hindering each other.

The robot's primary role in the workstation was to handle computationally straightforward tasks, such as unscrewing, while the human worker focused on more complex tasks and managed the dismantled parts, placing them into appropriate recycling containers. The robot was designed to move smoothly and without appearing threatening, featuring intuitive operation and capabilities that can be taught by the human operator. Additionally, the robot's behavior was engineered to respond appropriately to unexpected interactions with humans, such as collisions, as discussed in subsection [11].

The KUKA lightweight robot 4+, equipped with torque sensors in each joint and offering 7 degrees of freedom, proved to be a suitable choice for the human–robot collaboration setup. Its low inertia feature was particularly advantageous, as it helped minimize potential damage in case of a collision during close physical interaction with the robot [11]. Such a setup holds great potential for integrating easily configurable robot assistants seamlessly in labor-intensive areas like disassembly, resulting in increased throughput [11].

In a study conducted by Vongbunyoong et al. [8], they developed an automated system capable of handling various product models within a product family without relying on specific a priori information. To address uncertainties at the planning and operational level, the researchers integrated sensor systems into the disassembly planner, creating an intelligent agent that generated disassembly process plans (DPPs) to control the system's operation sequences. Automated disassembly systems typically rely on two sources of inputs: (1) prior knowledge, which requires specifying information like product structure, geometry, and component quantity beforehand, but is impractical for unknown product models in industrial practice; and (2) knowledge detected during the disassembly process, often acquired through a vision system. However, the detection results may be unreliable when certain features are not visually detectable, such as quasi or virtual, occluded, hidden, and unknown components [94].

The experiments validated the concept of cognitive robotics in the disassembly process. The performance of the cognitive robotic agent (CRA) was assessed based on three key performance indices (KPIs): (1) completeness of the disassembly, (2) time consumption, and (3) the need for human assistance [8]. In an actual disassembly process, achieving disassembly is not guaranteed because even if one connection remains, the process can fail. Addressing this challenge requires developing a system that can automatically identify such failures, especially at the operation level, and attempt to resolve them. Human–machine cooperation takes various forms during the disassembly process [8].

Kim et al. [95,96] suggested a hybrid disassembly system wherein human operators intervene to manually disassemble the product when automated procedures encounter issues. While this approach may offer economic advantages in terms of efficiency and time savings, a drawback is the potential direct exposure of human workers to hazardous components, including toxic or high-voltage materials, in cases where the product contains such elements [95,96].

Hjorth et al. [97] discuss the various ways operators interact with robots on the production floor. During collaboration, communication between humans and robots involves both verbal and non-verbal cues in real and virtual work environments [98]. The categorization of these communication methods includes verbal communication, which encompasses voice control and speech recognition, and non-verbal communication, which involves gesture recognition, human pose and skeleton tracking, gaze detection, and intention recognition. An overview of the application of these communication enablers in industrial human–robot collaboration (HRC) within augmented, virtual, and mixed realities is also presented based on the discussions in [97].

Verbal communication (such as voice control), is commonly adopted in industrial settings to implement a natural human–robot interaction interface [99]. Maksymova et al. [100] explored different methodologies to voice-control a manipulator, with a strong focus on assembly tasks and Petri nets. Bingol and Aydogmus [101], instead, addressed natural speech recognition approaches making use of deep neural networks, with the aim to classify user's input while interacting with a KUKA KR Agilus robot. Speech recognition has also been combined with other human–robot interaction approaches, such as gesture recognition [102], eye gaze detection [103], and haptic control [104].

Researchers have also explored multimodal approaches for human–robot interaction. Ref. [105] focused on a semantic approach for multimodal interaction between human workers and industrial robots in real industrial settings, integrating pointing gesture identification. Ref. [106] considered a dual-arm robotic system, introducing a multimodal framework for human–robot collaboration. In this context, a hierarchical model managing gestures and voice commands was conceived. Ref. [107,108] proposed a deep learning framework for multimodal control of a manipulator. In this work, voice, hand motion, and body posture recognition were considered. Convolutional Neural Networks (CNNs) and a multilayer perception model (MLP) were used to design the proposed framework, making it possible to dynamically affect the robot's programming by exploiting the adopted inputs.

In a pilot study, Gustavsson et al. [109] combined speech recognition and haptic control to enhance the responsiveness of a UR3 robot to human commands.

In a unique exploration, Mohammed and Wang [110] utilized electroencephalography to understand human brain behavior and developed a brainwave-driven robotic application for assisting in human–robot collaboration (HRC) during the assembly of a car engine manifold. On the other hand, non-verbal communication also plays a crucial role in human–robot interaction [97]. Visual cues in HRI can complement or even replace verbal communication when communication is unreliable [111,112].

Recognizing gestures through visual systems has been extensively used in various manufacturing scenarios. To achieve robust detection and tracking of the operator's pose, numerous sensors are employed, including RGBD cameras like Kinect V2 [113,114] and Intel RealSense [115,116]. Additionally, specialized sensors like Leap motion have been used for tracking hand and finger movements to control robots [117,118]. These visual systems enable effective non-verbal communication between humans and robots in collaborative work environments.

Several methods have been explored for accurate pose detection in human–robot interaction (HRI). Different sensors have been tested to address this problem, such as cameras (even thermal), EMGs, IMUs, etc. However, several related issues have been identified in their usage (e.g., time-consuming, not reliable measurements, etc.), limiting their adoption [119–121].

Traditional machine learning techniques (like Gaussian mixture models—GMMs) have achieved high accuracy in human detection, ranging from 80% to 90%. However, for more precise results, Deep Learning techniques have been employed. Specifically, 3D-CNNs have achieved close to 96% accuracy, and a novel 3D descriptor for joint detection has reached close to 98% accuracy [122–128].

Gaze tracking has been explored as a means of human–robot communication, with eye tracking proving superior to head tracking techniques in HRI. Robots can benefit from richer information obtained through tracking the eye gaze of operators [129–132]. Tactile feedback has been investigated to track operational awareness, with wearable vibrotactile rings providing feedback about different stages of HRI [133]. Bilateral haptic interfaces, combining soft grippers with wearable remote ring interfaces, have been utilized to enhance collaboration effectiveness [134,135].

A novel signaling system using robot light skin was developed by Tang et al. [136] to improve users' reaction time and reduce the mental workload of operators during simple industrial tasks, leading to fewer errors.

In their research, Hjorth et al. [97] explored the realm of human–robot communication with multiple solutions, including virtual reality (VR), augmented reality (AR), and mixed reality (MR). The possibilities for human–robot interaction in these settings have significantly improved thanks to increased computational power and advanced simulation environments.

Augmented reality techniques have been applied to foster human–robot collaboration and comprehend robot intentions in shared workspaces. For instance, Andersen et al. [137] projected task-related information onto physical objects in collaborative environments, providing valuable assistance to human co-workers.

Liu et al. [138] pioneered an augmented reality (AR) instruction system enabling human workers to access assembly instructions for industrial components through AR devices. Simultaneously, Papanastasiou and collaborators [139] harnessed AR glasses in combination with feedback from smartwatches to oversee industrial assembly processes and promote seamless human–robot collaboration.

In their work, Matsas et al. [140] introduced proactive and adaptive techniques within highly interactive and immersive VR environments. These techniques integrated various cognitive aids to enhance operator safety.

Chen et al. [141] developed a mixed reality (MR) interface that utilized stereo vision and virtual fixtures. This innovative MR interface was designed to facilitate stereo vision-guided teleoperation control, enabling the manipulation of mobile manipulators and the teaching of new tasks.

Liu et al. [142] presented a comprehensive framework for human–robot collaborative disassembly (HRCD), structured around perception, cognition, decision-making, execution, and evolution stages. Their approach seamlessly integrated technologies like cyber-physical production systems (CPPSs) and artificial intelligence (AI) to enable HRCD. To assess the viability of their framework, they carried out a case study featuring a non-collaborative ABB manipulator. Within this study, they fine-tuned the disassembly sequence planner by leveraging a discrete bees algorithm and devised a motion-driven control methodology complemented by a safety assurance strategy.

Incorporating the concept of human–robot collaboration (HRC), Jungbluth et al. [80] introduced a cognitive robotics-based framework tailored for the disassembly of end-of-life products (EOLPs). The primary objective of their work was to empower robotic systems to independently execute disassembly tasks while enhancing the ergonomic aspects of disassembly workstations. To realize this vision, they employed an intelligent agent equipped with knowledge of the product model. This agent was responsible for generating the disassembly sequence, which in turn guided the actions of the robot assistant.

In their study, Axenopulos et al. [143] outlined a framework for a hybrid recycling plant dedicated to electrical and electronic equipment. The core objective of this framework was to optimize the disassembly process by implementing human–robot collaboration (HRC) cells. Within these cells, a sole human operator collaborates with multiple robots to streamline the recycling operations.

Ding et al. [144] conducted a study to explore the transfer of valuable knowledge related to disassembling end-of-life products (EOLPs) from human operators to a human–robot collaborative disassembly (HRCD) system. Their approach involved a combination of technologies, including a video-capturing system, a natural language processing (NLP) algorithm, and a graph-based knowledge representation. This innovative approach enabled the efficient collection of knowledge and notably enhanced the robot's ability to assist humans during HRCD tasks.

HRC in disassembly (HRCD) has gained significant attention from industry stakeholders and researchers in the past decade. To make HRCD profitable and environmentally viable, advancements in HRC technologies and standardization policies related to take-back requirements, product interfaces, and serviceability are required. Collaborative disassembly between humans and robots offers several advantages compared to fully automatic systems, and safety measures have been developed and analyzed. However, current HRCD implementations lack post-collision control schemes, which are crucial for safe human–robot interaction (HRI) during disassembly tasks. The adaptation of robot behavior based on contact forces exchange is necessary to ensure safety when physical interaction occurs between the human worker and the manipulator. The choice of appropriate tools for HRCD tasks is essential to mitigate potential risks. Energy-aware control schemes and human-aware tool designs can improve safety aspects in HRC systems. Robot assistants play a key role in intelligent manufacturing, augmenting worker performance and accessing their intelligence in the workplace. As companies and industries adopt the circular economy business model (CEBM) for sustainability, challenges arise in resourcing, disassembly, and remanufacturing of end-of-life products (EOLPs). Future research can focus on developing control strategies that enable safe HRI, intuitive skill teaching approaches to expand the robot's skill set and a combination of verbal and non-verbal communication methods for more immersive interactions between robots and humans. Ensuring the safety-conformable design of robot assistants, especially in physically interacting scenarios, is of paramount importance. Although cooperative task execution with robot assistants is not yet fully cost-effective and widely accepted, the immediate success and further development of these robot assistants should focus on real manufacturing scenarios that capitalize on their advantages. The evolution of industrial robots into robot assistants holds promise for the flexible and agile production requirements of the future, and technologies for safe and effective man-machine interaction are actively under development [89].

5. Control Techniques for Robotic Disassembly

In this section, we aim to explore various robotic control techniques presented in the literature, focusing on enabling task specification and ensuring process safety in two distinct scenarios: fully automated processes (Section 5.2) and human–robot collaborative implementations (Section 5.3). As highlighted in the previous works mentioned in Section 4.2, the vision systems of a flexible automated disassembly cell play a crucial role in successfully completing the disassembly process. Therefore, we have dedicated a specific section (Section 5.1) to discuss different image processing and analysis methods that facilitate the location and identification of various types of linking components, such as screws. This task is particularly challenging due to the variability in screw shapes and appearances across different electronic devices.

5.1. Vision Systems

In this subsection, we will discuss theoretical aspects related to different visual recognition and identification methods proposed in recent years, along with their main characteristics and capabilities. Subsequently, we will explain some of the most relevant practical implementations of the above-mentioned techniques.

The visual detection of targets can be categorized into two groups as explained by Vazquez et al. [66]. The first category involves using gray values and recognition based on known patterns, while the second category utilizes contour characteristics to determine a two-dimensional geometry model from local structures represented as edges. Merdan et al. [65] highlighted the significance of vision systems in identifying and locating workpiece components, using ontology-based cognitive knowledge with a set of basic visual features for positioning the robot relative to the workpiece and designing nonlinear feedback and tracking control. Buker et al. [145] analyzed the field of 3-dimensional object recognition and identified two main streams: structural or primitive-based approaches and view- or appearance-based approaches. They employed an active stereo camera system with a combination of gray value and contour-based object recognition and a position measurement approach with implicit detection of occlusions for unscrewing tire bolts. Torres et al. [19] outlined the recognition process's two basic objectives: determining the product and its components and detecting the components to be disassembled based on the features stored in the corresponding database. They used a pair of motorized cameras at the end of a y-z Cartesian robot for image acquisition. Gil et al. [20] emphasized the need for robots to recognize objects in a disassembly cell, similar to human object recognition, to interact effectively in an unstructured environment. Yildiz [73] proposed a visual screw detection scheme based on the combination of deep learning methods and classical computer vision methods, empowering the detection of screws based on their characteristics. Wegener [5] trained a Haar Cascade on a set of manually-cropped images to detect screws on battery modules. Bdiwi et al. [146] used an image processing algorithm based on screw characteristics, including grayscale, depth, and HSV values, for the autonomous detection and classification of screws during motor disassembly. Vongbunyong et al. [72,147] suggested disassembly automation with cognitive ability using a vision system with RGB-D space for sensing and execution monitoring. El Sayed et al. [148] designed a sensory module for acquiring and recognizing part descriptions and coordinates through the usage of range and 2-D sensors combined with pattern-matching vision algorithms.

In summary, the literature highlights a variety of visual recognition and identification techniques applied to robotic disassembly systems, ranging from traditional computer vision methods to deep learning-based approaches, all contributing to the automation and efficiency of the disassembly process.

5.2. Control Techniques for Fully Automated Disassembly

In this subsection, we will address the most relevant articles and works published in the literature in a span of 10 years regarding the control techniques that allow a fully automated disassembly of EOL electronic products.

Vongbunyong et al. [64,72] introduced a "Cognitive robotics" framework. The main goal was to improve the flexibility and robustness of automated disassembly applications, emulating human-level expertise at the perception and decision-making levels. The cognitive robotics principles adopted in this research emulated human behaviors based in several ways: (1) unnecessary prior knowledge—only gathered online data were employed; (2) automatic operations outcome assessment with failure recognition; (3) online adaptation skills; (4) exploitation of past experiences and data to face failures.

The cognitive robotic architecture was based on a closed perception-action loop and implemented as a multi-agent system (MAS), where the cognitive robotic agent (CRA) controlled the system's behavior based on the perception of the environment and existing knowledge. The behavior was influenced by four cognitive functions: reasoning, execution monitoring, learning, and program revision, as described in [64,72]. The cognitive robotic agent possessed a range of fundamental skills and behaviors at its disposal, which it could orchestrate to execute a designated task. This capability enabled the system to adapt effectively and flexibly to unpredictable conditions within the dynamic environment, ultimately leading to the accomplishment of desired objectives.

In the practical application of cognitive robotics within autonomous systems, three primary disciplines come into play: knowledge representation, reasoning, and high-level robot control. The cognitive robotic agent assumes the responsibility of devising a sequence of operations aimed at achieving a predefined goal state within the environment. Nevertheless, given the inherent limitations of incomplete knowledge and the inherent non-deterministic nature of the external world, it becomes imperative to incorporate sensing actions. These actions are essential for assessing the current state of the environment and addressing uncertainties as they arise.

In this study, the creation of the cognitive robotic agent was realized through the utilization of IndiGolog, a high-level cognitive robotics programming language. IndiGolog is an extended version of Golog, endowed with the capability to manage exogenous actions and sensing. This choice was driven by the distinct advantage of Golog, which seamlessly merges domain-specific heuristics with search-based planning. This amalgamation empowers the programming of intricate behaviors for the cognitive robotic agent and bestows comprehensive high-level control over the entire system.

In tasks, the necessity for adjustable process parameters arose with a dual objective. Primarily, these parameters functioned to offset position errors attributed to imprecise localization. Secondly, they facilitated the identification of crucial positions that might otherwise remain undetectable. Throughout the disassembly process, the application of rule-based reasoning played a pivotal role in refining the search space for potential operations.

The cognitive robotics (CR) module comprised two essential components: the cognitive robot agent (CRA) and the knowledge base (KB). The overall system encompassed three autonomous operating modules: the cognitive robotics (CR) module, the vision system (VS) module, and the disassembly operation (DO) module, as elaborated in [64,72]. Within this framework, the CRA assumed control over the system's planning and operational aspects. Cognitive functions were categorized into two tiers: basic-level behaviors and advanced-level behaviors. Basic behaviors, such as reasoning and execution monitoring, were autonomously executed by the agent throughout the disassembly process. In contrast, advanced behaviors were triggered in specific scenarios, involving learning and interacting with human users.

After the execution of a sequence of primitive actions, the system performed execution monitoring to determine the success of the outcome. If successful, the system proceeded to the next disassembly state; otherwise, the agent backtracked and tried executing the current plan with new process parameters. This process continued until the main component could be removed. If all available operation plans were exhausted and the removal process could not be achieved, human assistance would be sought as a final solution.

The reasoning process in the cognitive robotic agent involves three types of knowledge: (1) predefined knowledge stored in the knowledge base (KB); (2) knowledge of the current conditions within the agent; and (3) knowledge about the external world. To achieve the disassembly task, the agent needs to reason about various issues, including: (1) identifying the types and specifications of components; (2) devising a suitable disassembly operation plan; (3) determining the appropriate process parameters; (4) assessing the success of each operation; (5) understanding the current situation of the agent; and (6) defining the initial and goal states of the disassembly process.

With the broad knowledge specified, the cognitive robotic agent can autonomously complete the disassembly process using four cognitive functions while incorporating information perceived from the external world. In cases where the agent encounters failure or uncertainty, the user can demonstrate the required solution, and the system learns from this interaction, adapting and modifying the cognitive robotics disassembly program accordingly. This ability to learn from human interaction and adapt the disassembly process enhances the system's flexibility and robustness.

In the research carried out by Vongbunyong and colleagues [64,72], an evaluation was conducted to assess the cognitive robotic agent's competence in overseeing the disassembly of LCD screens from models it had not previously encountered. The agent, equipped with external knowledge obtained through the sensing module adeptly and autonomously supervised each stage of the disassembly process. One remarkable outcome of the study was the system's remarkable adaptability. It exhibited the capability to handle a diverse array of product models without necessitating specific information pertaining to the products and their respective operations.

In contrast, Elsayed and colleagues presented an innovative approach in their study [148]. Their focus was on developing an online genetic algorithm model for selective robotic disassembly with the goal of achieving optimal or near-optimal disassembly sequencing.

The foundation of their model rested on the premise of a known hierarchical disassembly path. To bring their vision to life, they established an intelligent automated disassembly cell, equipped with essential components, including an industrial robotic manipulator, a camera for vision, range sensing capabilities, and advanced algorithms for component segmentation. The system hinged on two core modules:

- Sensory-driven visual and range acquisition and recovery system: This module was responsible for acquiring sensory data, incorporating both visual and range information. It played a crucial role in capturing essential data about the disassembly process;
- Online genetic algorithm (GA) model: The heart of their approach lies in the online genetic algorithm model. This component was tasked with intelligently analyzing the acquired data, optimizing disassembly sequences, and making real-time decisions to improve the overall disassembly process.

This combination of advanced technology and algorithmic intelligence showcased a unique approach to selective robotic disassembly, with a focus on achieving efficiency and optimization in real-world disassembly scenarios.

The sensory-driven module played a pivotal role in this study by employing advanced recognition techniques to identify individual components within the assembly, meticulously capturing their precise spatial coordinates. These coordinates were subsequently fed into the Genetic Algorithm (GA) module, a computational powerhouse with the capability to generate disassembly sequences optimized for efficiency.

Within the GA module, complex algorithms harnessed the part coordinates to devise disassembly sequences that aimed to achieve near-optimal or optimal performance. These sequences, coupled with the corresponding part coordinates, were seamlessly communicated to the robot arm manipulator—a sophisticated mechanical apparatus that executed the sequences with precision.

As the robot arm manipulator systematically removed each recognized component, an active and adaptive sensory module came into play. This module remained vigilant throughout the disassembly process, continuously scanning the evolving environment for newly accessible components. When new components were detected, the system exhibited its flexibility by promptly generating a fresh disassembly sequence tailored specifically to these newfound parts.

However, in scenarios where the sensory module did not detect any new components, the ongoing sequence continued seamlessly. This dynamic adaptability, marked by the generation of new sequences for emerging parts and the retention of the existing sequence for remaining components, exemplified the system's ability to optimize disassembly in real-time, showcasing its prowess in complex disassembly scenarios.

In both works, the integration of cognitive functions and sensory information played a crucial role in enabling efficient and autonomous disassembly processes, even when dealing with previously unseen product models.

Choux et al. [32] presented a task planner for the dismantling of lithium–ion battery (LIB) components, which included three main functions: (1) identifying components and their locations, (2) creating a feasible dismantling plan, and (3) Moving the robot to the detected dismantling positions. The task planner utilized a state-of-the-art 3D camera system with high accuracy, eliminating the need for CAD models of the battery pack and its components. This was advantageous, as EOL products may differ from their original CAD models due to maintenance, deformations, or corrosion. The main loop of the task planner involved taking 2D and 3D images, detecting and identifying components, determining their positions in the world reference frame, defining an order of operations, removing the components, and repeating these actions until the goal state was achieved. The robot was positioned in various predefined poses to observe different parts of the LIB pack, with an in-hand camera used for this purpose.

To enhance accuracy, multiple pictures (up to eight) were captured, especially when dealing with screws on the lateral sides of the battery. However, for determining the removal sequence, only one image was utilized, taken from a lower camera angle relative to a horizontal plane. Images with higher inclination were reserved solely for object detection. The implementation employed the You Only Look Once (YOLO) algorithm, specifically YOLOv3, to detect and locate components within the dismantling arena. YOLOv3 processed the 2D image of the EV lithium–ion battery (EVB) pack, identifying components, acquiring bounding box coordinates and class probabilities, and storing this information in a text file. The positions of detected objects in different images were combined using a weighted mean approach. Subsequently, the object detection data were utilized in a pose estimation process, aligning the 2D images and YOLO results with the 3D datasets to determine the coordinates of the components.

Choux and his team introduced a novel task planner that revolutionized the component removal order by meticulously analyzing detected screw positions and conducting sophisticated computer vision analysis for each specific component [32].

This intelligent system further enhanced the disassembly process by dynamically adding the remaining parts to the list, considering their probability of being positioned over other components. To bridge the gap between 2D and 3D information, the system ingeniously converted the object positions from 2D camera coordinates to precise 3D points, leveraging the depth information obtained from the cutting-edge 3D vision system [32].

Armed with the meticulously crafted removal order and accurate component positions, the dismantling process was set in motion, and the system skillfully executed the removal operation for each component, ensuring a seamless and efficient disassembly [32].

The task planner's efficacy was thoroughly validated through rigorous lab tests, revealing its remarkable adaptability in handling variations or new models of EVBs [32].

Leveraging a combination of reinforcement learning and machine reasoning algorithms, the system demonstrated its ability to learn and effectively disassemble new battery pack models even with limited information from human operators.

The paper underscored the potential for achieving autonomous and complete disassembly through the cognitive robotic concept, capitalizing on recent strides in 3D vision systems and fast object detection algorithms [32]. Impressively, the algorithm exhibited excellent performance, accurately detecting the main components.

The ROS main, when implemented in manual mode at 25% of the robot's maximum speed, yielded satisfactory results, and running it at full speed (100%) was projected to significantly reduce the total disassembly sequence time [32]. While the eye-in-hand configuration proved effective, it was not without drawbacks, primarily concerning potential collisions of the camera with the environment during continuous moves and removal operations. With measurement errors below 5 mm, the proposed method exemplified the seamless integration of computer vision, robotics, and battery disassembly [32].

The task planner's versatility in handling products with significant variations and uncertainties were evident, offering a promising pathway for future autonomous disassembly applications. Kay and Farhad [59] presented a novel approach to EV/HEV LIB disassembly, employing offline simulation and path planning. The offline path planning allowed precise control and tool paths, with robot programming accomplished through direct user inputs using the teach pendant or manual positioning.

The approach offered flexibility, making it suitable for technicians without prior knowledge, as the path planning was situationally dependent. CAD geometry models were utilized for offline simulation, enabling precise waypoint definition and alternative disassembly techniques [59]. The gripper was controlled using a linear quadratic regulator (LQR) system, and planar linkages were represented through a batch least squares estimator for gripper control.

The robot's kinematic model was developed using Denavit-Hartenberg representations, and both forward and inverse kinematics solvers were employed to determine the robot's position and pose [59].

MathWorks' Robotics System Toolbox and Simscape Multibody dynamics software packages in MATLAB/Simulink were utilized for motion analysis and offline path planning. The approach demonstrated robustness, though it proved slightly less successful in real-time compared to human technicians. As a result, human–robot collaboration was deemed the most effective option for LIB pack/module disassembly, with the robot efficiently cutting the battery pack while the technician handled component removal and sorting.

In Chen Foo's research [58], discrete–continuous control was employed for robotic disassembly, implementing each action or skill as a finite state machine. The control function defined the robot's behavior and executed monitoring [58].

The vision system consisted of basic and advanced modules for reliable perception, positioning of objects, and extracting detailed geometric information of parts. Designed to be easily programmable by non-experts in robotics or computer vision, these modules were user-friendly and effective for accurate disassembly tasks.

Both studies contribute significantly to the field of automated disassembly, utilizing cognitive robotics principles, genetic algorithms, 3D vision systems with machine learning, offline simulation, and path planning. These advancements hold promise for achieving effective and autonomous disassembly of EOL electronic products, supporting enhanced recycling and resource recovery to reduce the environmental impact of electronic waste and promote a circular economy [58,59].

An important issue to be considered is also related to force overshoot control, both when approaching the target components and when applying the disassembly forces. In this directions; refs. [149–153,153] are providing compliant overshoot-free controllers.

5.3. Control Techniques for Human–Robot Collaborative Disassembly

In the following subsections, different control techniques adopted in the field of collaborative disassembly and their aspects of safety will be analyzed. Pre-collision control and post-collision control will be discussed in Sections 5.3.1 and 5.3.2, respectively.

Hjorth et al. [97] provide insight into various skill teaching and acquisition techniques used in collaborative disassembly. A task typically consists of a set of skills, which are low-level operations or tasks that allow the operator to define tasks based on human terms [154]. Experimental works by Saukkoriipi et al. [155], Wallhoff et al. [154], and Huckaby et al. [156] demonstrate different skill-definition methods. For example, Saukkoriipi et al. presented a tool for programming robot skills offline, specified as Unified Modelling Language (UML) action diagrams, allowing execution on various robotic platforms [155]. Wallhoff et al. introduced a system that combined high-level skills in a hybrid assembly station to achieve a predefined goal [154]. Huckaby et al. proposed a method using model-based system engineering and systems modeling language to create simplified and reusable software modules for robotic system programming [156]. Recent works related to skill specification and acquisition methods include Schou et al. [157], Vongbunyong et al. [81], and Dakka et al. [158]. Schou et al. extended skill based systems (SBSs) to incorporate programming by demonstration (PbD), enabling novice operators to program industrial tasks practically on-the-fly [157]. Vongbunyong et al. presented a platform to capture disassembly skills performed by skilled operators, allowing intelligent agents to acquire these skills using an RGB-D camera and marker-equipped tools [81]. Dakka et al. developed a framework for teaching variable impedance skills, enabling the manipulator to perform force-based tasks by adapting its variable stiffness based on human demonstrations and a probabilistic model [158].

These techniques and approaches contribute to the advancement of collaborative disassembly, offering flexible and practical ways for operators and robots to work together effectively and safely.

5.3.1. Pre-Collision Strategies

In recent years, robotics researchers have increasingly focused on human–robot interaction to enable close collaboration between humans and robots. Achieving natural and intuitive interaction from the human perspective is crucial in such scenarios [159].

Pre-collision control strategies are vital for preventing harmful contact between robots and their environment, and they rely on collision avoidance techniques. These strategies utilize sensory inputs to adjust the manipulator's velocity or motion based on the distance to obstacles and their behavior in the work environment [97]. Human–robot collaboration has been explored in assembly lines, showcasing the benefits of hybrid assembly systems that combine the efficiency of robots with the flexibility of humans [160,161]. Ensuring the safety of human operators in environments where humans and robots coexist is a significant challenge. This involves both passively detecting possible collisions in real-time and actively avoiding collisions through robot control. Vision-based methods, using 3D surveillance through motion, color, and texture analysis, and inertial sensor-based methods, using special suits for motion capture, have been applied to human–robot collaboration [162,163]. Various approaches, including multi-camera systems, emergency-stop methods, and depth sensor-based systems, have been explored for collision detection and avoidance [164–167]. Direct sensor-based methods, like visual servoing, are considered better solutions for intuitive human–robot interaction compared to planning techniques relying on a priori models [168]. In human–robot collaborative systems, controllers rely on various sensing modalities such as cameras, force/torque sensors, skin (for tact), or proprioception (for positioning). Hybrid sensor control, such as hybrid force/position or hybrid force/vision control, merges data from different sensing modalities directly at the control level [159]. This approach has been extended to incorporate vision, force, and tact for physical interaction tasks [169]. Researchers have proposed various algorithms and methods for safe and collision-free motion in human–robot collaboration scenarios. Examples include utilizing cameras, lasers, and Inertia Measurement Units (IMU) to adapt the robot's planned path based on artificial potential fields [170], using multiple Kinect V2 cameras to track dynamic obstacles and plan collision-free motion paths [171], and allocating humans and robots adaptively in hybrid assembly systems [172]. Optimization-based methods have been proposed to generate collision-free paths using safety barriers positioned around robot links [173], and dynamic modified speed and separation monitoring (SSM) methods have been developed for industrial HRC [174]. Additionally, methods using augmented environments with virtual models of the manipulator and real images of human operators have been explored for collision detection and avoidance [175]. Compliance control, where the robot compensates for positioning errors and follows a low joint impedance, has been used in collaborative robot assistants for tasks like unscrewing during disassembly [11]. Finite state machines have been employed to represent different robot "skills," where each state triggers the activation of the following state based on user input, sensory input, or calculated quantities [11]. A remarkable contribution to pre-collision control strategies in the field is the concept introduced by Gerbers et al. [54]. Their innovative approach combined intuitive robot programming and advanced control technologies with appropriate safety measures to create a concept that eliminated the need for conventional robot programming. This concept facilitated the safe sharing of disassembly tasks between robots and human operators. The robot's programming was conducted through an interactive and intuitive user interface, empowering operators to identify the required disassembly phases. The robot's trajectories were computed from 3D camera data, allowing the robotic disassembly process to run concurrently with manual disassembly tasks. To ensure safety, a sophisticated 3D measuring technology monitored the human–robot distance, dynamically adjusting the robot's speed as needed. Additionally, the system explored the integration of handheld devices with intuitive user interfaces and gesture control to enable seamless and intuitive adjustment of the robot's position.

In conclusion, pre-collision control strategies and collision avoidance play crucial roles in enabling safe and efficient human–robot collaboration. Researchers have explored various methods, including vision-based approaches, sensor fusion techniques, compliance control, and intuitive robot programming interfaces, to enhance the safety and usability of human–robot collaborative systems. These advancements pave the way for the seamless integration of robots as assistants in labor-dominated areas like disassembly, where human flexibility and adaptability are essential, but repetitive tasks can be automated for increased productivity.

5.3.2. Post-Collision Strategies

In a collaborative environment, prioritizing safety is paramount for both human operators and robots. Efficient collision avoidance strategies are crucial, along with the ability to detect potential collisions and respond appropriately to minimize risks. Post-collision control strategies, also known as 'interaction control strategies,' aim to limit contact force and energy exchange between humans and robots within safe thresholds, thus mitigating the risk of injury [97].

Direct-force control approaches focus on precisely controlling the interaction force between the robot and its environment along the target-constrained task directions [97]. In addition, hybrid controllers have been developed to position/velocity-tracking the robot's motion along unconstrained directions. Yip and Camarillo proposed a hybrid position/force control approach capable of manipulating the robot's end-effector position and force even when dealing with unknown body constraints, making it suitable for manipulators with complex joint mechanics [176].

Leite et al. introduced a hybrid control framework that melds adaptive visual servoing with direct force control. This integrated approach empowers robotic manipulators to adeptly engage in interaction tasks executed on seamlessly contoured surfaces [177].

In a similar vein, Gierlak and Szuster devised an adaptive hybrid control system, seamlessly blending position and force control strategies. This system is specifically designed for manipulators engaged in interactions with flexible environments, taking into account the intricate dynamics of motion resistance and the elasticity inherent to the environment itself [178].

In contrast, indirect force control schemes offer an alternative approach to achieving force control by modulating the motion control, all while avoiding the closure of the force feedback loop. This method results in the emergence of nonlinear and interconnected impedance or admittance control paradigms. Specifically, admittance control strategies manipulate the virtual model dynamics of a system in direct response to the measured forces generated through interactions with a human operator [97].

In their analysis, Keemink et al. conducted an in-depth investigation into the domain of admittance control, with a particular focus on the assessment of its stability. This comprehensive examination encompassed various influential factors, including but not limited to feed-forward control mechanisms, the utilization of force signal filtering, compensation for inertia effects, consideration of robot flexibility, and the incorporation of virtual damping strategies [179].

Dimeas et al. introduced an innovative approach within the realm of human–robot cooperation tasks. Their method centered on a variable admittance control strategy, employing a fuzzy inference system (FIS) to dynamically adapt the manipulator's damping properties. This adaptation was contingent upon the force and velocity inputs introduced by the human operator, fostering a more responsive and cooperative interaction between the human and the robot [180].

Ranatunga and colleagues devised an adaptive admittance controller distinguished by its capacity to dynamically adapt to human intent and accommodate fluctuations in manipulator dynamics, thereby enhancing the efficacy of human–robot interactions [181].

Concurrently, Bae et al. innovatively integrated a variable admittance control approach with the concept of virtual stiffness guidance. This fusion strategy served to augment the anticipation and responsiveness to the operator's intentions, further refining the quality of human–robot interactions [182].

Variable impedance strategies have demonstrated superior performance in human–robot collaboration for kinematically redundant robots compared to fixed impedance strategies, particularly in terms of the comfort reported by human operators during collaborative tasks [183]. Energy-based control methods have also been proposed to enable safe human–robot interaction by adapting position trajectory references in correlation with set maximum values of the position-based controller [184,185]. Other variable impedance control frameworks can be found in [186–190], where preference-based optimization has also been exploited to customize the robot controller on the basis of the user's feedback [191]. Vanderborght et al. provided an extensive overview of variable impedance actuators (VIAs), classifying actuators based on the implementation of variable stiffness and damping [192]. Ott et al. proposed a hybrid reactive control strategy that merged the robustness properties of impedance control with the accuracy in free motion associated with admittance control, allowing for continuous switching and interpolation between impedance and admittance control [193]. This approach has been also extended in [194].

These diverse control strategies and approaches form a comprehensive foundation for ensuring safety and effective collaboration between humans and robots in various scenarios. By combining direct and indirect control methods and leveraging the potential of variable impedance strategies, researchers can develop more advanced and adaptable human–robot collaborative systems in the future.

6. Future Directions

It is the opinion of the authors that the following solutions (and their combination) would indeed improve the disassembly processes for EV battery packs:

- Artificial intelligence (AI): As shown in the recent developments related to machine vision and automation (including robotics), AI techniques (including machine learning algorithms) might be useful to enhance disassembly operations. In fact, by combining advanced machine vision, reasoning, and adaptive controllers, the automatic or collaborative disassembly system might gather the required skills to perform this complex task;

- Massive agent-simulation environments: With the development of advanced simulation and AI-based training environments (e.g., the GPU-based Isaac Gym environment [195]), the disassembly task learning and transfer to the real system would be easier. In such simulation and learning environments, it is possible to simulate thousands of different scenarios, gathering a huge amount of data to be used for the execution of the real task;
- New hardware capabilities: With the continuous improvement of hardware, robotic and automatic systems are improving their capabilities in terms of applied disassembly forces/torques, safety, control performance, etc. Indeed, this technological advancement is of fundamental importance to realize safe and powerful disassembly systems to perform such delicate disassembly operations.

7. Conclusions

The exponential growth of literature in fields such as sustainable recycling of end-of-life (EOL) products, disassembly planning, and robotic implementation clearly indicates the potential for the industrial development of human–robot flexible cognitive collaborative disassembly and recycling cells for products like electric vehicle (EV) lithium–ion batteries (LIBs). These advanced cells offer an effective means of reintroducing precious materials and components into the circular economy and align with global efforts to integrate sustainable practices. However, to make these cells a practical reality, their economic viability must be thoroughly assessed. While this paper presents numerous examples from the past decade, offering a comprehensive overview of how scientists and industries are responding to the challenges ahead, a comprehensive economic analysis is still necessary.

Throughout this paper, various directions that researchers are exploring to enhance the existing framework for dealing with complex EOL products like EV LIBs have been identified and analyzed. These directions encompass cognitive robotics principles, genetic algorithms for selective disassembly, integration of 3D vision systems with machine learning for component recognition and pose estimation, and offline simulation and path planning for robot disassembly. These emerging approaches indicate promising paths for achieving efficient and autonomous disassembly, which can significantly contribute to recycling and resource recovery. However, it is essential to acknowledge that this work is not exhaustive and should serve as a foundation for future research. By providing an accurate state-of-the-art review, it identifies the most relevant persisting challenges and the proposed solutions found in the existing literature. Future research can build upon these findings to address the remaining obstacles and further refine the implementation of human–robot collaborative disassembly and recycling cells, pushing the boundaries of sustainable recycling practices. The collaboration between academia, industry, and policy-makers will be vital in shaping the future of recycling and achieving a more sustainable and environmentally friendly world.

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