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A Robotic Teleoperation System with Integrated Augmented Reality and Digital Twin Technologies for Disassembling End-of-Life Batteries

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Abstract: Disassembly is a key step in remanufacturing, especially for end-of-life (EoL) products such as electric vehicle (EV) batteries, which are challenging to dismantle due to uncertainties in their condition and potential risks of fire, fumes, explosions, and electrical shock. To address these challenges, this paper presents a robotic teleoperation system that leverages augmented reality (AR) and digital twin (DT) technologies to enable a human operator to work away from the danger zone. By integrating AR and DTs, the system not only provides a real-time visual representation of the robot's status but also enables remote control via gesture recognition. A bidirectional communication framework established within the system synchronises the virtual robot with its physical counterpart in an AR environment, which enhances the operator's understanding of both the robot and task statuses. In the event of anomalies, the operator can interact with the virtual robot through intuitive gestures based on information displayed on the AR interface, thereby improving decision-making efficiency and operational safety. The application of this system is demonstrated through a case study involving the disassembly of a busbar from an EoL EV battery. Furthermore, the performance of the system in terms of task completion time and operator workload was evaluated and compared with that of AR-based control methods without informational cues and 'smartpad' controls. The findings indicate that the proposed system reduces operation time and enhances user experience, delivering its broad application potential in complex industrial settings.

Keywords: EV batteries; remanufacturing; disassembly; digital twin; augmented reality; robot teleoperation

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1. Introduction

Handling end-of-life (EoL) electric vehicle (EV) batteries has become an increasingly severe problem. With the widespread adoption of electric vehicles, a substantial number of batteries are reaching the end of their service life [1]. Due to the characteristics of waste electrical and electronic equipment, it is undesirable to dispose of these batteries in landfills. This is because landfill disposal not only fails to recover valuable materials but also poses a risk of severe environmental pollution due to the toxic and corrosive electrolytes and metals present in the batteries [2]. Remanufacturing is an environmentally friendly, resource-conserving, and cost-effective strategy to address this issue [3–5]. Remanufacturing can restore used products to at least their original quality and performance through repair and updates [6,7]. Disassembly, the first step in the remanufacturing process chain, is a critical step that can heavily influence subsequent operations in the chain. With advancements in robotics research, there is an increasing focus on employing robots for the autonomous disassembly of EV batteries. This approach not only enhances work efficiency and reduces labour costs but also ensures the safety of operators [8]. However, as the batteries reach the end of their life cycle, their physical conditions are unpredictable due to prolonged wear or damage [9]. This uncertainty renders predefined automation programmes inadequate for addressing all potential issues, thereby increasing the importance of real-time human intervention and remote control.

Augmented reality (AR) technology enhances interactions between humans and machines by overlaying virtual images and information onto the user's line of sight [10]. In the field of robotics, AR is not only utilised for programming [11] and displaying critical information during task execution [12] but also for improving safety [13]. In remote control applications, AR merges virtual images and data with the operational environment, enabling operators to observe the actual surroundings and overlaid virtual information from a safe distance, thereby enhancing the informational context for remote robot operations [14]. By utilising the virtual control interface displayed by AR, operators can gain detailed information on the robot's status and control its movements through intuitive interaction methods, thereby enhancing the accuracy and responsiveness of remote operations. However, despite the substantial potential demonstrated by AR in information display and real-time feedback, further optimising the presentation of information within the AR environment to reduce misunderstandings and enhance operators' decision-making and control capabilities remains a critical research direction in the development of remote control technologies.

Digital twin (DT) technology enables the creation of high-fidelity digital replicas of physical entities, allowing for real-time monitoring, predictive analysis, and diagnosis of the entity's condition [15]. In robotics, DTs play a crucial role in monitoring the operational status of robots, forecasting maintenance requirements, and optimising robot operations [16]. The integration of AR with DT technology facilitates a seamless fusion of the virtual and real worlds, providing operators with an intuitive means to observe and control robotic systems [17]. Current research has enabled operators to use the AR interface to view the robot's DT, thereby visually monitoring the robot's performance in a virtual environment while concurrently controlling the actual robot's movements, ensuring high synchronicity and predictiveness in operations [18]. Research on integrating AR and DT technologies for robot control has made some progress. However, there are still obstacles in effectively incorporating information feedback and visualisation, as well as fully leveraging this feedback for achieving precise remote control.

This paper presents a robotic teleoperation system that integrates AR and DT technologies for disassembling EoL EV batteries. The main contributions include, based on the establishment of bidirectional communication between the physical robot and its digital representation, the synchronisation of the virtual and physical robot's motions through the AR interface and the presentation of key operational information in multiple visual formats. Additionally, the system supports operator intervention when the system detects a problem, enhances decision-making through the real-time presentation of multidimensional robot information via the AR interface, and allows control of the physical robot through intuitive gesture interactions to ensure the successful completion of tasks in disassembling EoL EV batteries.

This paper is organised as follows: Section 2 provides a literature review on the topics pertinent to this research. Section 3 details the architectural framework of the proposed system. Section 4 elaborates on a practical case study and evaluates the performance of the system. The benefits and current limitations of the system, along with suggestions for enhancements, are examined in Section 5. Finally, Section 6 concludes the paper and proposes directions for future research.

2. Related Work

This paper presents a remotely controlled robotic disassembly system developed by integrating AR and DT technologies. The system enables operators to access enhanced status information of the physical robot within an AR interface, allowing for intuitive control over the robot as it performs disassembly tasks on EV batteries. This section summarises the recent advancements in AR-assisted robot applications and DTs in robotics.

2.1. AR-Assisted Robotic Application

AR enhances user interaction by overlaying computer-generated images or information onto the real-world view, thereby improving operational intuitiveness [19,20], particularly in complex robotic operations and executions. For instance, in the field of robot programming, AR technology simplifies the programming process for both expert and nonexpert users through intuitive graphical interfaces, facilitating rapid robot path planning and task programming. Ong et al. proposed an AR-assisted robot programming system that transforms the work cell of a serial industrial robot into an AR environment. The use of an AR user interface and a handheld pointer enables intuitive task programming while employing sensor data and algorithms for robot motion planning, collision detection, and plan validation, enhancing both programming efficiency and user performance [11]. In terms of safety, AR technology provides real-time critical operation information and safety alerts, aiding operators in avoiding potential hazards and thus reducing workplace accident rates. Li et al. proposed a solution for safe robot motion in human–robot collaboration using AR technology and deep reinforcement learning. It offered an intuitive interface for task commands and scene coordination, using AR devices to represent humans, robots, and scenes. This method employs end-to-end deep reinforcement learning to handle uncertainties in robot perception and decision-making, ensuring safe robot motion with policy simulation, motion previewing, and collision detection [21]. Furthermore, AR is utilised for real-time monitoring, covering essential data on machine operation status, thereby enhancing operation efficiency. Michalos et al. implemented a robotic system for advanced human–robot collaboration assembly, integrating AR technology to support human operators effectively. AR facilitated manual guidance techniques and utilised wearables such as AR glasses and smartwatches, enabling operators to receive real-time information and instructions from the system. This integration enhances operator performance and safety during collaborative tasks [22].

Robot teleoperation involves remotely controlling a robot located in inaccessible or hazardous environments, allowing operators to perform tasks from a distance where direct interaction would be impractical or dangerous [23]. Current cutting-edge methods for robot remote control include using electronic skin [24], neural interfaces, and brain–machine interfaces [25], as well as AR and virtual reality. Among these, AR technology provides operators with a more intuitive and immersive interface, which is why many studies are focusing on how to utilise it for effective robot teleoperation. With AR, operators are not limited by their physical location; instead, they can interact with a robot's environment virtually through augmented overlays. This ability to visualise the robot's operations in real time and manipulate virtual elements enhances operational safety and efficiency [26]. Pan et al. introduced an AR-based robot teleoperation system utilising RGB-D imaging and an attitude teaching device to enable efficient remote robot programming. The system allowed operators to select key positions and compute 3D coordinates using colour images, while a virtual robot model was superimposed on these images to facilitate the attitude teaching process [27]. González et al. developed a remote control system for industrial robots to assist human operators in performing complex surface treatment tasks such as sanding, deburring, and polishing. The system combines robotic strength and precision with augmented virtuality and haptic feedback to provide an immersive virtual experience, enhancing the operator's security and comfort. Experiments using a 6R robotic arm demonstrated the system's effectiveness in treating car body surfaces, with performance comparisons indicating superior results over manual methods by an expert, highlighting the system's suitability for enhancing industrial tasks with robotic assistance [28]. The authors of [29] introduced an AR-based teleoperation interface for robot manipulators, which used an AR headset to project graphics onto the real environment and a gamepad for issuing robot commands. Compared to traditional teach pendants, usability tests on a 6R industrial robot demonstrated that this method not only made the interface more intuitive and ergonomic but also accelerated teleoperation tasks. Brizzi et al. investigated the use of AR to enhance teleoperation in robotics by employing an AR setup with RGB-D cameras and a head-mounted display integrated with the Baxter robot. Through experiments involving participants performing a pick-and-place task, AR was found to improve task accuracy and efficiency and reduce skill discrepancies among operators. Additionally, AR enhances participants' sense of presence and embodiment, highlighting its potential to improve collaborative human–robot teleoperation [30].

2.2. DTs in Robotics

DT technology involves the creation of precise virtual replicas of physical entities, facilitating their simulation and analysis within a virtual environment [31,32]. This technology has shown substantial potential in industrial robotics, especially in applications involving real-time data monitoring [33], performance optimisation [34], and prediction [35]. Li et al. introduced a semantic-enhanced DT system that improved the real-time monitoring of robot–environment interactions using exteroceptive and proprioceptive modalities. The system utilised a 3D graphic model embedded with dynamic contact and sensor data to accurately reflect and analyse real-world interactions. Validated in a kitchen scene object sorting task, the system demonstrated effective real-time monitoring and semantic reasoning, showcasing its practical feasibility and effectiveness [36]. DT technology is also used to optimise the performance of robotic systems. Zhu et al. developed an optimisation method for dynamically reconfiguring intelligent manufacturing systems with human–robot collaboration using the DT concept to enhance production efficiency. It optimises task allocation between humans and robots by considering their distinct characteristics and employing the nondominated sorting genetic algorithm-II [37]. Using DT technology to predict the lifecycle time of machinery, Aivaliotis et al. introduced a methodology that calculates the remaining useful life of machinery by integrating physics-based simulation models with the DT concept. The system predicted the remaining useful life of an industrial robot by using data from machine controllers and external sensors to update and simulate digital models. This approach enabled the accurate non-invasive monitoring and prediction of machine status [38].

Given that DTs are model-based and require real-time interactive control, the integration of AR into DT systems has naturally progressed. AR and DT enhance the fusion of virtual and physical worlds, providing operators with an intuitive interface for interacting with digital replicas. Li et al. proposed a multirobot collaborative manufacturing system enhanced by AR and DT technologies. The DTs of industrial robots were linked to their physical counterparts and visualised via AR glasses, complemented by a reinforcement learning algorithm for advanced motion planning. The system featured three interactive AR-assisted DT modes—real time, planned, and monitoring control—proven through experiments including a peg-in-hole task and multirobot tasks, demonstrating its potential for complex manufacturing applications [18]. Soares et al. developed an industrial prototype of a human–machine interaction system using AR and DT technologies designed to allow operators without programming experience to easily control robots. The system used a tracking mechanism to capture hand movements and a translator to convert these movements into robot commands [39]. Gallala et al. developed a DT framework to enhance human–robot interactions, which could address the inefficiencies of traditional robot programming and interactions. By leveraging DTs, AR, the Internet of Things, collaborative robots, and artificial intelligence, operators can control robots by manipulating virtual objects. The experimental results demonstrate that this approach enables efficient human–robot interactions, even for operators without programming skills [40].

From the above literature, current research primarily focuses on establishing bidirectional communication between virtual and physical entities but does not fully exploit AR technology to display robot statuses and use these status updates to control physical robots. By establishing robust communication, optimising data processing and visualisation, and enhancing user interaction, these studies improve the real-time operation and safety of robotic handling, opening new possibilities for complex industrial tasks.

3. System Design and Implementation

3.1. Overall System Architecture

The system proposed in this paper integrates the advantages of AR and DT technologies. As illustrated in Figure 1, the system architecture encompasses the creation and registration of a digital replica of a physical robot within an AR environment. This setup not only facilitates real-time representation of the robot's state but also enables user interaction with the virtual robot through intuitive gesture controls, thereby allowing remote control of the physical robot.

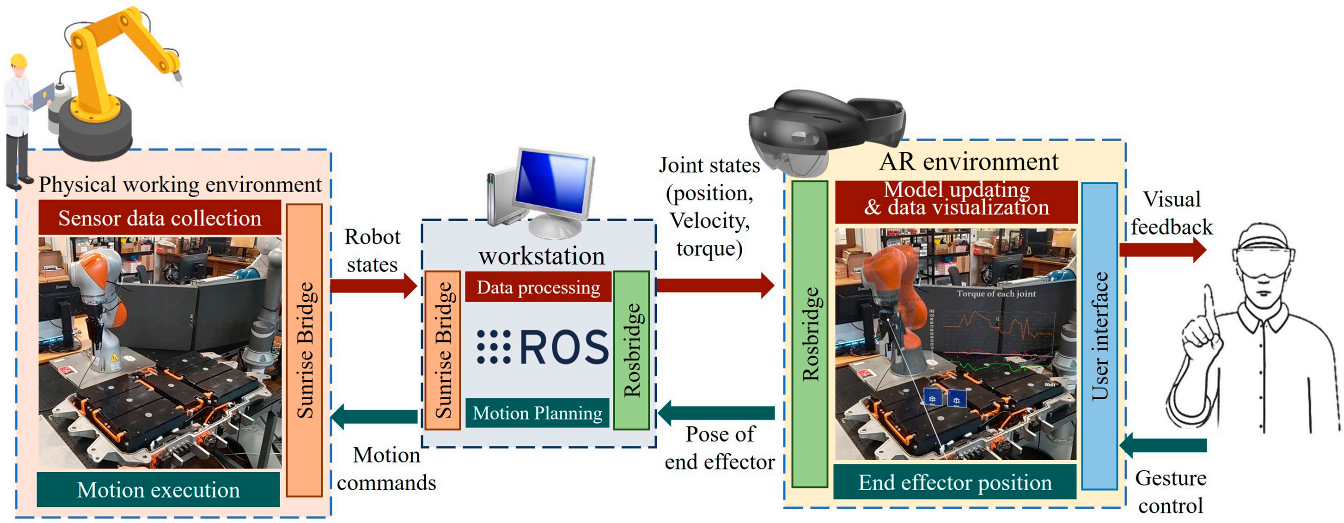


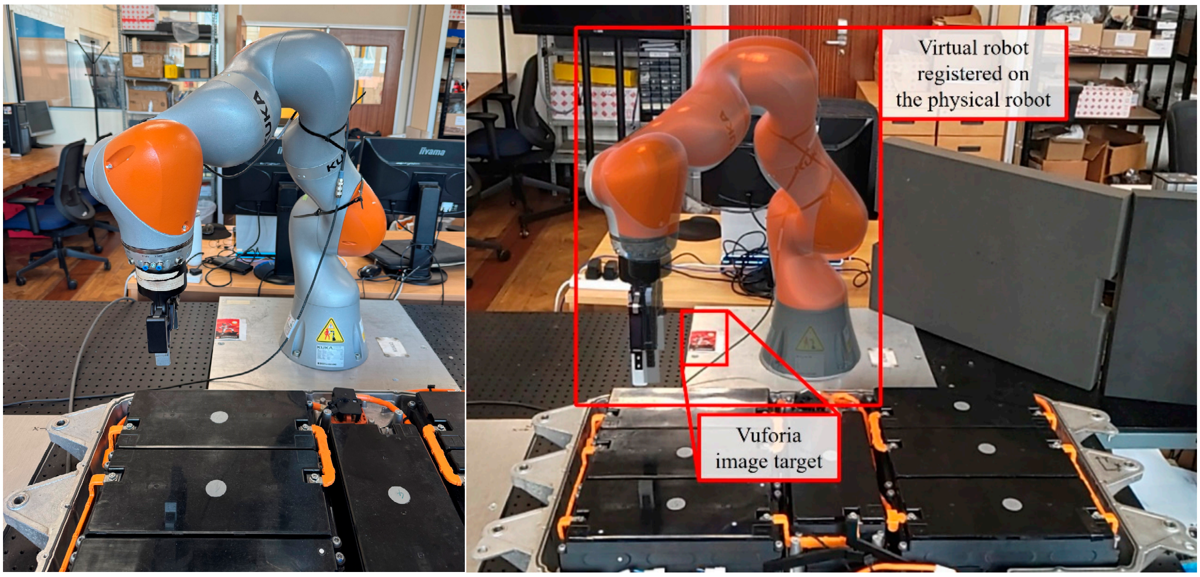
Figure 1. Framework of the proposed system.

Specifically, as the physical robot performs tasks, the system continuously collects state information in real time and transmits these data to the workstation for further data preprocessing, calibration, and classification. The processed data are then relayed back to the virtual robot within the AR environment, ensuring that the virtual representation accurately reflects the physical robot's movements. Furthermore, by presenting detailed information and line charts of joint torques alongside the virtual robot, the system further enhances user comprehension of the robot's current status and task execution. Operators can interact with the virtual robot using gesture control based on real-time state information provided through the AR interface. This interactive process is not only intuitive but also achieves precise remote control over the physical robot, improving operational convenience and efficiency. Consequently, the system enhances the accuracy and responsiveness of remote robot control while providing a more intuitive and interactive user experience.

3.2. AR Visualisation and Data Synchronisation

A key feature of the DT system is the bidirectional communication between a physical entity and its digital counterpart. This study utilises the ROS to establish the communication framework. Initially, the process of establishing information transmission from physical robots to virtual robots in an AR environment, which mainly includes two parts, was introduced. First, it ensures that the virtual robots in the AR environment can fully synchronise with the movements of the physical robots; second, it involves displaying the information of the physical robots on the AR interface after processing. The combination of these two methods allows operators to more comprehensively understand the status of the robots and the progress of task execution.

Initially, a virtual robot model is created using Unity3D, and the virtual robot is registered onto the physical robot using Vuforia's image target. Figure 2a shows the real robot, while Figure 2b demonstrates how the orange virtual robot created in Unity3D is accurately superimposed on the physical robot using image targets in Vuforia. Subsequently, by creating a series of ROS nodes, a communication bridge is established between the ROS environment, the KUKA Sunrise controller, and Unity. When the physical robot begins to execute a task, the system subscribes to topics related to sensor data. These raw data are transmitted to a workstation for further processing through nodes configured within the ROS environment. The raw data received by the workstation undergoes a series of preprocessing steps, including data extraction, denoising, and calibration, to ensure the accuracy and usability of the data.

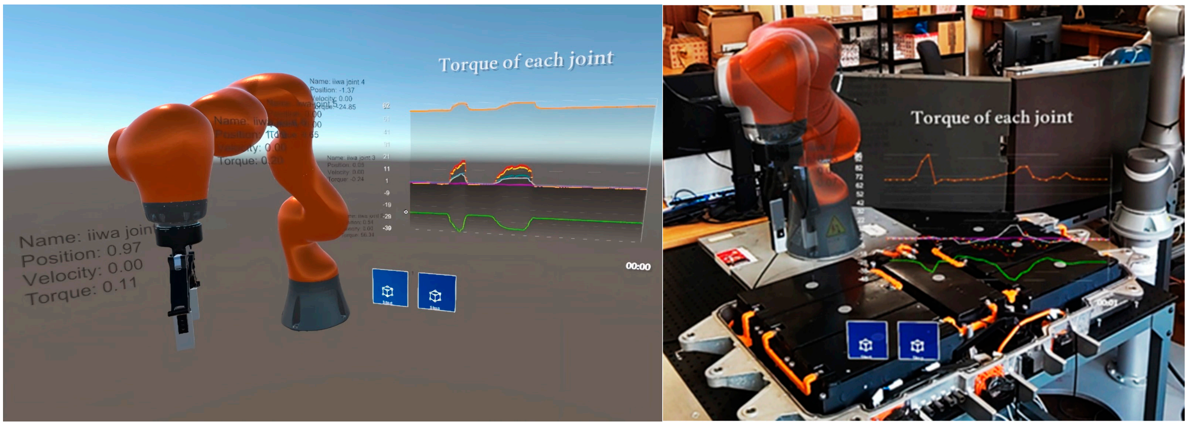


(a) (b)

Figure 2. The physical robot and virtual robot. (**a**) Physical robot in the physical environment; (**b**) virtual robot registered on the physical robot by using the Vuforia image target.

To synchronise the movements of the virtual robot with those of the physical robot in the AR environment, a dedicated topic is created in the ROS to publish processed joint position information, which is transmitted to Unity in real time via Rosbridge. The virtual robot model in Unity updates its joint states based on the received real-time joint position information, thereby accurately reflecting the dynamics of the physical robot, as shown in Figure 2b.

To enable operators to comprehensively understand the robot's status and monitor the progress of task execution in real time, this study employs two methods to display key information about the robot's joints in the AR interface. Initially, basic information about the robot's joints, including joint names, positions (angles), velocities, and torques, is collected through a series of nodes in the ROS system. These data, obtained from the robot's sensors and subjected to a series of preprocessing steps, are then published in real time through specific ROS topics and transmitted to the Unity environment using Rosbridge. In the Unity environment, the received data undergo further processing, including conversion into a format compatible with AR head-mounted display (HMD) devices, such as JSON. The processed information about the robot's joints is subsequently displayed in text form beside the corresponding joints of the virtual robot, allowing operators to accurately obtain real-time status information for each joint, as illustrated in Figure 3a.



(a) (b)

Figure 3. Key information in the AR interface. (**a**) Display in the Unity environment; (**b**) display in the AR HMD devices.

Additionally, to provide intuitive feedback on the robot's force conditions, special attention is given to the variations in joint torque, which are displayed as line graphs in the AR interface. This representation allows operators to intuitively observe the changes in joint torque over time, which is crucial for assessing the robot's ability to perform specific tasks, as shown in Figure 3b. For instance, during a disassembly task, a sudden increase in joint torque might indicate that the robot has encountered an unexpected obstruction, and the force applied may be too great, potentially causing damage to parts or even to the robot itself. By monitoring the joint torque in real time and displaying it as a line graph, operators can quickly identify and address potential issues, ensuring the smooth progression of the task.

Leveraging the information displayed in the AR interface, operators can gain an in-depth understanding of the current status of the robot and the progress of task execution, thereby facilitating more precise operational decisions. This design capitalises on the advantages of AR technology to achieve an intuitive visualisation of robot data, presenting complex information in a user-friendly manner.

3.3. AR-Based Interactive Control

To remotely control the physical robot, an AR interface based on HoloLens 2 is developed that enables intuitive control of industrial robots through natural user interactions. As detailed in Section 3.2, users first see the virtual robot overlaid onto the physical robot, which accurately reflects the current position and state of the physical robot. By utilising the gesture recognition capabilities provided by the Microsoft Mixed Reality Toolkit (MRTK), users can interact with a virtual robot in an intuitive manner. The primary interaction mechanism involves emitting a ray from the user's index finger to select the robot's end effector. Subsequent manipulations are performed using pinching gestures involving the thumb and index finger, as illustrated in Figure 4a. These gestures enable the user to execute commands such as selecting, grabbing, and dragging virtual objects. For instance, the user extends their index finger to direct a ray towards the desired virtual end effector and performs a pinch gesture with their thumb and index finger to grab it. The virtual end effector can then be dragged to a new location by moving the fingers accordingly, as shown in Figure 4b. This mode of interaction not only mimics natural human behaviours but also enhances user immersion and intuitive control, thereby improving the overall interaction experience within the mixed reality environment.

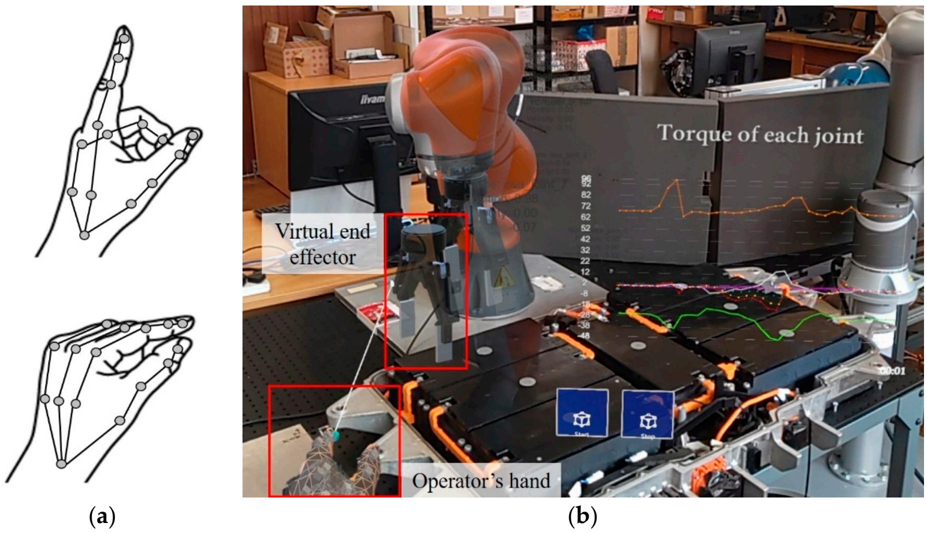


Figure 4. AR-based robot control method. (**a**) Gesture recognition; (**b**) AR robot control interface.

A coordinate system integration method has been implemented to ensure that operations in the virtual environment are precisely mapped to the actual actions of the industrial robot. This method facilitates seamless interaction between virtual and real entities by aligning the virtual space coordinate system within the AR environment with the robot's actual spatial coordinate system. Upon system startup, the initial coordinate system of the AR is set based on the position of the HoloLens 2 and is precisely calibrated using a marker-based approach. There are five coordinate systems, as shown in Figure 5, which are the AR coordinate system Ψ_{AR}, world coordinate system Ψ_{world}, marker coordinate system Ψ_{marker}, robot base coordinate system Ψ_{base}, and robot target coordinate system Ψ_{target}.

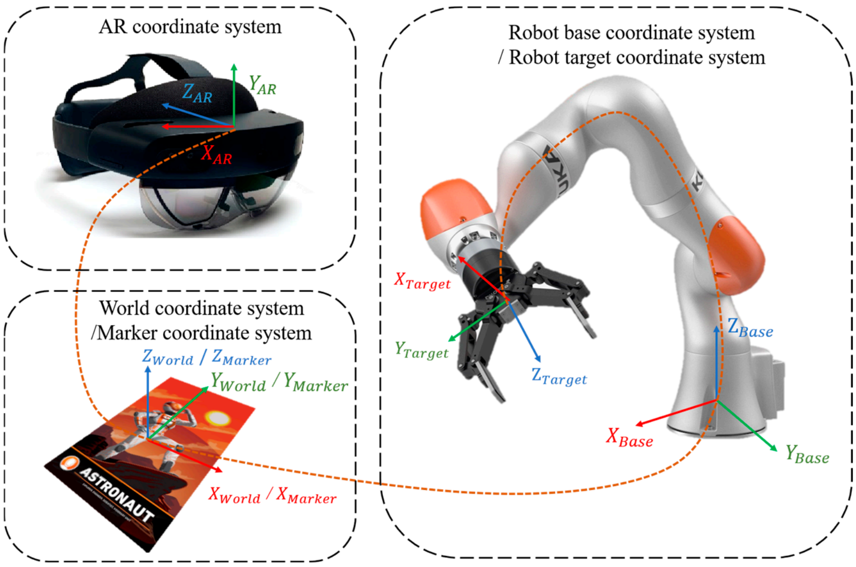


Figure 5. Coordinate system transformation.

The transformation matrix ${}^{AR}_{base}H$ represents the homogeneous transformation of the robot base coordinate system Ψ_{base} assigned from the world coordinate system Ψ_{world} to the AR coordinate system Ψ_{AR}. By calculating ${}^{AR}_{base}H$, the virtual robot in the AR coordinate system can be configured. As previously noted, this configuration results in the superposition of the virtual robot onto the physical robot, aligning the physical robot base system Ψ_{base} with the virtual robot base system $\Psi_{base'}$. The poses of the marker in the AR coordinate system, represented by ${}^{AR}_{marker}H$, are determined using the spatial localisation features of AR glasses. During the coordinate configuration process, the AR coordinate system is aligned with the marker coordinate system, as illustrated in Figure 5. A constant translation is manually defined to represent the relationship between the robot base coordinate system and the marker coordinate system. Consequently, the transformation matrices ${}^{world}_{base}H$ and ${}^{marker}_{world}H$ are obtained. The transformation matrix from the robot base to the AR coordinate system, denoted as ${}^{AR}_{base}H$, can be calculated using the following relationship:

$$ {}^{AR}_{base}H = {}^{AR}_{marker}H \cdot {}^{marker}_{world}H \cdot {}^{world}_{base}H \tag{1} $$

Additionally, the detailed transformation from the world coordinate system to the robot base coordinate system is given by the following equation:

$$ \begin{bmatrix} X_{Base} \\ Y_{Base} \\ Z_{Base} \\ 1 \end{bmatrix} = \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_{World} \\ Y_{World} \\ Z_{World} \\ 1 \end{bmatrix} \tag{2} $$

where R is a 3×3 rotation matrix and T is a 3×1 translation vector. The objective of this mathematical section is to present the coordinate of the virtual robot target within the physical robot base system. The transformation matrix ${}^{base}_{target}H$ is given by

$$ {}^{base}_{target}H = {}^{base}_{marker}H \cdot {}^{marker}_{world}H \cdot {}^{world}_{target}H \tag{3} $$

where ${}^{world}_{target}H$ is undetermined in Equation (3). ${}^{world}_{target}H$ represents the homogeneous transformation of the robot target pose coordinate system Ψ_{target} assigned from the AR coordinate system Ψ_{AR} to the world coordinate system Ψ_{world}. As discussed above, AR glasses can detect the poses of the target and the marker. Therefore, ${}^{world}_{target}H$ is given by

$$ {}^{world}_{target}H = {}^{world}_{AR}H \cdot {}^{AR}_{target}H \tag{4} $$

Ultimately, utilising ${}^{base}_{target}H$, the physical robot is capable of driving the end effector to the target pose Ψ_{target}, with joint configurations managed by the inverse kinematics (IK) solver within the ROS.

When the virtual robot's end effector is selected and moved to a designated position by a user in the AR interface, these positional data are transmitted in real time to the ROS environment via Rosbridge. Within the ROS, detailed motion planning is conducted by MoveIt, which receives these data. Kinematic and dynamic calculations for the robot are performed using the Kinematics and Dynamics Library (KDL), while path planning in complex environments is primarily handled by the Open Motion Planning Library (OMPL).

By integrating AR visualisation and data synchronisation, real-time insights into the robot's status are provided. Coupled with the designed AR-based interactive control method, direct interaction through simple gestures is offered, enabling precise real-time adjustments based on the feedback displayed in the AR interface. The system's coordinate transformation functionality ensures the accurate alignment of virtual inputs with actual robotic actions, enhancing the precision and responsiveness of operations and thereby optimising the efficiency and reliability of remote operations.

4. Case Study and System Evaluation

4.1. Experimental Setup

The proposed system was applied to remove the busbar from an EoL plug-in hybrid EV battery in a teleoperated robotic disassembly platform to demonstrate the feasibility of the system. As shown in Figure 6, the key equipment used in the experiment included the KUKA LBR IIWA 14 R820 robot (by KUKA Robotics, Augsburg, Germany), a Robotiq 2F-140 gripper (by Robotiq, Levis, QC, Canada), and Microsoft HoloLens 2 AR glasses (by

Microsoft, Washington, DC, USA). The development of the AR environment was carried out on an external PC workstation equipped with an Intel Core i7-11800H CPU (by Intel Corporation, Santa Clara, CA, USA), 3.2 GHz, 32 GB RAM, and an Nvidia RTX 3070 8GB GPU (by Nvidia Corporation, Santa Clara, CA, USA) running Microsoft Windows 10. Furthermore, the system utilised Visual Studio 2019 as the integrated development environment (IDE), along with tools such as Unity LTS version 2020.3.42f1 and the Mixed Reality Toolkit. The ROS, which serves as the core communication framework, was deployed on an external PC running the Ubuntu 20.04 OS, which is responsible for data exchange and command transmission between the AR interface and the physical robot. Additionally, a wireless router with wired ethernet ports was used to connect and communicate between equipment.

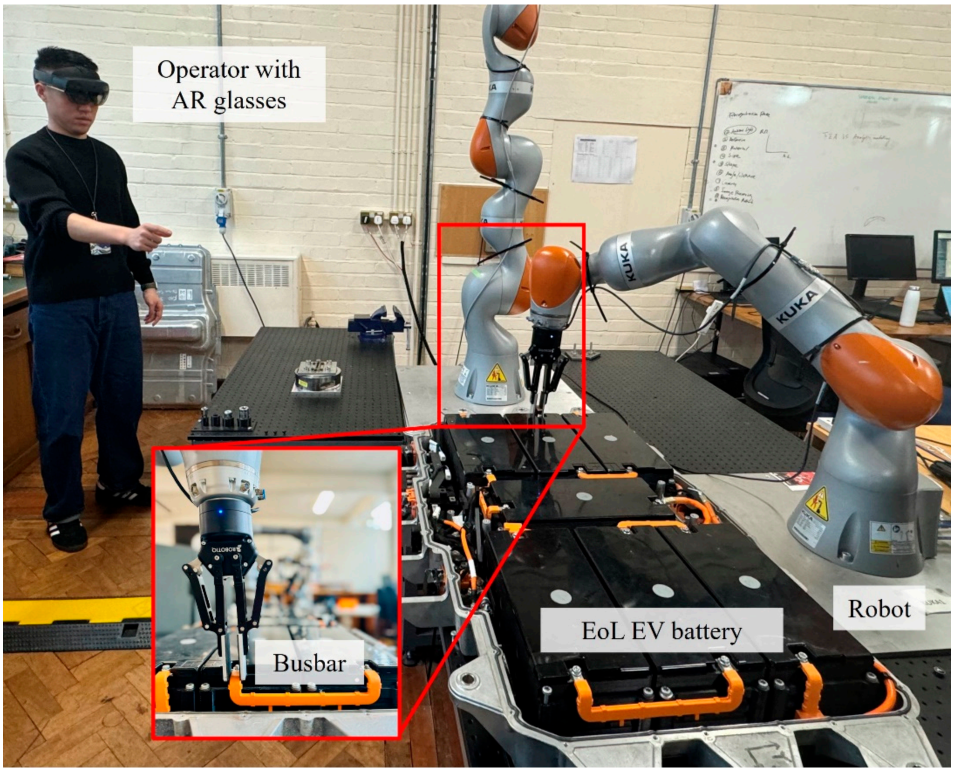


Figure 6. Teleoperated human–robot collaborative disassembly platform.

4.2. Demonstration

Initially, the robot was initialised by loading a predefined programme designed for busbar disassembly, as shown in Figure 7a. During operation, sensors continuously collected data on the robot's performance. These data were then transmitted to a processing unit for analysis. Simultaneously, the DT system was updated in real time within the AR interface, which visually represented the processed data, as depicted in Figure 7b. This included real-time updates of the virtual robot's pose in the AR environment to ensure synchronisation with the physical robot's movements. Additionally, information about each joint and torque dataset was displayed in text and line graph formats, enabling operators to intuitively understand the current status.

During the busbar disassembly process, challenges arose as the busbar was mounted on two studs through two holes. Typically, the robot clamps one end of the busbar for removal. However, difficulties were encountered when the force applied by the robot was uneven or misdirected, leading to situations where the busbar might not slide smoothly off the studs. Specifically, the busbar could become stuck near the other end, hindering smooth disassembly, as illustrated in Figure 8. Throughout the disassembly process, operators were able to monitor the robot's status via the AR interface, as shown in Figure 7c. If anomalies occurred, operators received alerts and could promptly intervene through the AR interface.

Based on the critical information displayed, such as torque graphs, operators finely adjusted the robot's end effector using gesture control to make necessary modifications, as shown in Figure 7d. Subsequently, the new motion plans were uploaded to the robot's control module for execution, as indicated in Figure 7e. The operators continuously assessed whether further adjustments were needed to ensure the successful completion of the disassembly task.

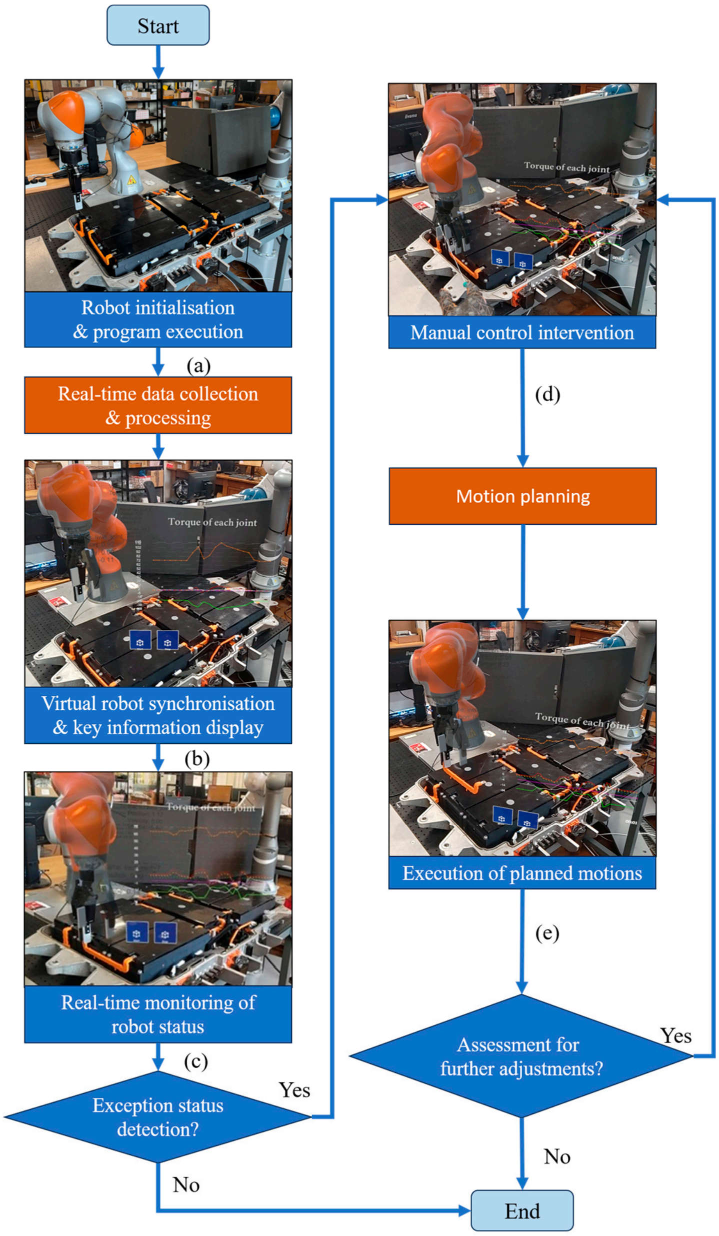
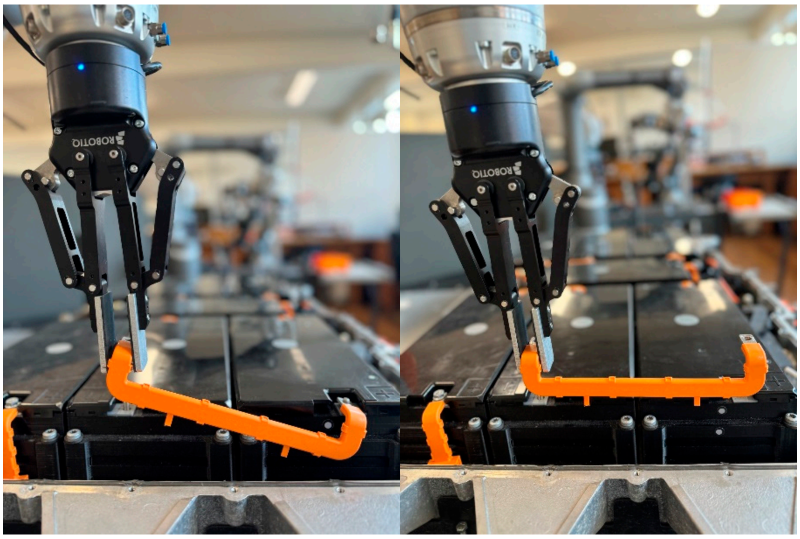


Figure 7. Workflow of busbar disassembly using the proposed system. (**a**) Robot initialisation and programme execution; (**b**) virtual robot synchronisation and key information display; (**c**) real-time monitoring of robot status; (**d**) manual control intervention; (**e**) execution of planned motions.

The application of the proposed system in busbar disassembly showcased its ability to enhance operational accuracy and safety in complex industrial tasks. The system's real-time data integration and interactive AR feedback allowed for proactive adjustments, ensuring smoother and more reliable disassembly processes. This case highlights the potential of the proposed system to be applied across various industrial scenarios.



(**a**) (**b**)

Figure 8. Busbar disassembly. (**a**) Busbar jammed on studs; (**b**) successful disassembly of the busbar.

4.3. Evaluation and Results

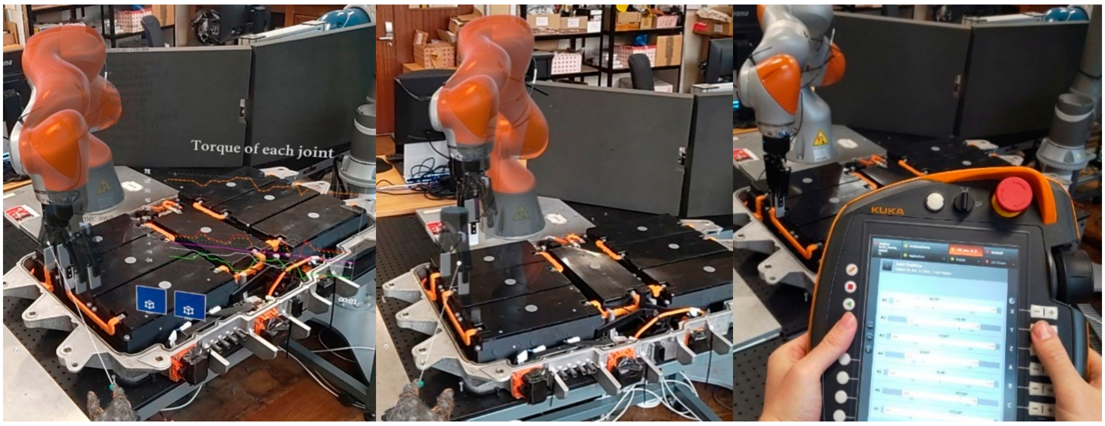
This study aims to evaluate the performance and effectiveness of the proposed system by comparing different robotic remote control methods. These methods include remote control of the robot using a smartpad (smartpad control); AR-based remote control, which is the most commonly used method in current research and does not display additional detailed information (AR-based control); and the system proposed in this paper, which employs AR technology and displays detailed information such as torque in real time (AR-enhanced control). The task of disassembling a busbar from an EV battery was selected as the experimental case, where the completion time, success rate, and workload were recorded. The workload was assessed using the NASA Raw Task Load Index (NASA RTLX) [41], a widely recognised tool for evaluating perceived workload across various tasks, covering mental, physical, and temporal demands; performance; effort; and frustration levels. Through this experiment, the proposed AR-enhanced control method was compared with the traditional remote control method and AR-based control method to quantify the benefits of AR technology and real-time feedback information and to explore how these technologies improve task efficiency and reduce operator workload.

4.3.1. Participants

Twenty participants, whose ages ranged from 21 to 42 years, including 13 males and seven females, were recruited for this study. All were either university students or staff. They possessed foundational knowledge in robotic control, which provided a baseline understanding necessary for the tasks involved in this experiment. However, none of the participants had experience with Microsoft HoloLens AR devices. This lack of prior experience with the specified AR technology ensured that all experimental conditions remained consistent across individuals, facilitating an unbiased evaluation of the distinct remote control methods under investigation.

4.3.2. Experimental Procedure

The experimental setup is depicted in Figure 9. As shown in Figure 9a, the operator remotely manipulated the robot by using the proposed system. In contrast, as illustrated in Figure 9b, another AR remote control approach involves participants controlling the virtual robot through gestures without access to robot information. A non-AR method of control, demonstrated in Figure 9c, relies on a smartpad-based control panel to operate the physical robot, which is a method widely employed in the industrial sector.



(**a**) (**b**) (**c**)

Figure 9. Three robot teleoperation methods. (**a**) Proposed system; (**b**) AR-based control; (**c**) smartpad control.

Before the experiment commenced, all participants received specialised training on the three remote control methods to ensure comprehensive familiarity with each operation. In the training for the AR-based teleoperation method, participants learned how to manipulate the robot through gesture controls within the AR interface and how to interpret key robot information displayed to effectively control the robot. Training on the smartpad control panel focused on instructing participants on how to operate the robot using the Cartesian coordinate mode and joint control mode. The training session also included a practical component, allowing participants under supervision to practise and familiarise themselves with each control system. Following the training, each participant was tasked with using the two AR methods and the smartpad control method to remove a busbar from an EV battery. The time taken to complete the disassembly task was recorded for each participant. Additionally, after completing the task with each method, participants were required to complete the NASA RTLX questionnaire to assess their subjective workload during the execution of the task.

4.3.3. Analysis of Experimental Results

In this study, a one-way analysis of variance (ANOVA) followed by Tukey's honest significant difference (HSD) test was conducted to assess the efficiency and workload of different remote control methods employed for the task of disassembling a busbar from an EV battery. The ANOVA results revealed a significant difference in task completion times between the control methods ($F(2, 57) = 241.11$, $p < 0.001$). Subsequent analysis with Tukey's HSD indicated that the proposed system significantly reduced task completion times compared to the other methods.

More precisely, the proposed system reduced the task completion time by an average of 12.35 s (95% CI: 8.33 to 16.37 s, $p < 0.001$) compared to the AR-based control method. It also outperformed the smartpad control method by an average of 36.05 s (95% CI: 32.03 to 40.07 s, $p < 0.001$). Furthermore, a significant time reduction of 23.70 s (95% CI: 19.68 to 27.72 s, $p < 0.001$) was also observed between the proposed system and the smartpad control method.

Within the scope of these methods, the proposed system exhibited an average task completion time of 29.7 s (SD = 4.38), the AR-based control method had an average of 42.05 s (SD = 3.99), and the smartpad control method lagged at an average of 65.75 s (SD = 6.96), as shown in Figure 10. These findings underscore the advantages of providing real-time operational information within an AR system for complex remote control tasks.

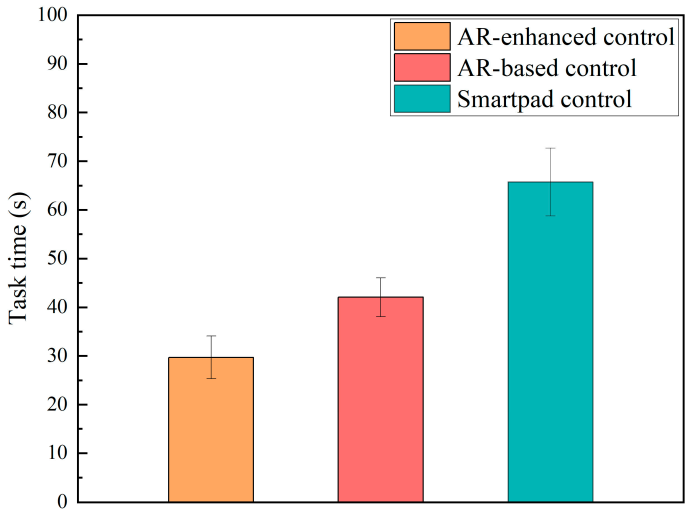


Figure 10. Disassembly times for different control methods.

Regarding the NASA RTLX results, ANOVA was employed to examine differences in perceived workload among the three control methods, revealing significant differences (F value of 91.81, p value < 0.001). Subsequent Tukey HSD tests further demonstrated that the AR-enhanced control method significantly reduced user workload compared to both AR-based control (mean difference in -10.95, p value < 0.001) and smartpad control (mean difference of 22.20, p value < 0.001). Additionally, significant differences were also observed between the AR-based control group and the smartpad control group (mean difference of 11.25, p value < 0.001).

Specifically, as shown in Figure 11, the AR-enhanced control method achieved a significantly lower average NASA-TLX score of 38.24 (SD = 4.72) than the AR-based control (average score of 49.19, SD = 5.31) and smartpad control (average score of 60.44, SD = 5.48) methods. These findings suggest that integrating AR technology with real-time feedback significantly reduces the perceived workload in remote control tasks for industrial robots, thereby enhancing operational efficiency and reducing task complexity.

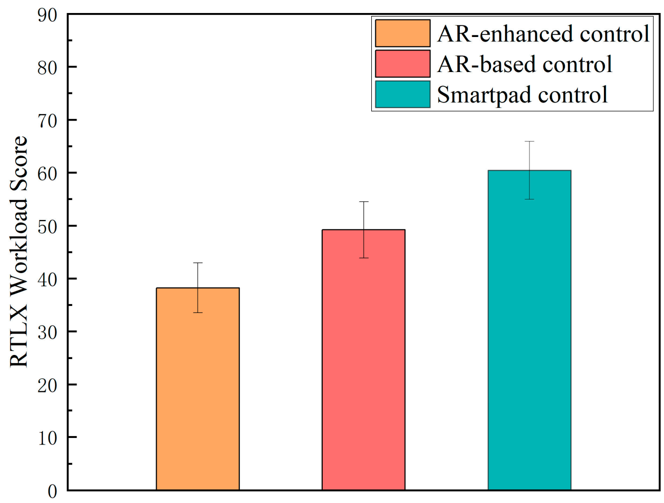


Figure 11. Average NASA RTLX scores for different control methods.

Subsequently, three key dimensions were focused upon, namely mental demand, effort, and frustration, based on the following considerations: first, mental demand is directly linked to the complexity of operations and cognitive burden, serving as a critical indicator of the psychological stress experienced by users employing different control methods.

Second, effort reflects the energy and exertion required to complete tasks, representing an essential measure of task difficulty. Finally, frustration evaluates the emotional response of users when they encounter operational difficulties, directly affecting their satisfaction and the sustainability of their performance. By assessing these dimensions, a more detailed understanding was obtained of how different remote control methods impact user experience. As illustrated in Figure 12, the results revealed that participants using the AR-enhanced control method scored significantly lower in mental demand, with an average of 53.9 (SD = 7.17) compared to those using AR-based control at 68.05 (SD = 7.79) and smartpad control at 74.1 (SD = 8.14). This indicates a superior reduction in psychological burden by the AR-enhanced control method. Similarly, this method also exhibited lower average scores in effort, at 52.85 (SD = 7.04) compared to 66.25 (SD = 7.75) for AR-based control and 72.6 (SD = 7.69) for smartpad control, further confirming its benefits in reducing user effort. Additionally, the AR-enhanced control method scored more favourably in frustration, with an average of 33.4 (SD = 6.0) versus 46.65 (SD = 9.09) for AR-based control and 66.1 (SD = 10.47) for smartpad control. Lower frustration scores suggest fewer difficulties or more effective problem handling by users employing AR-enhanced control.

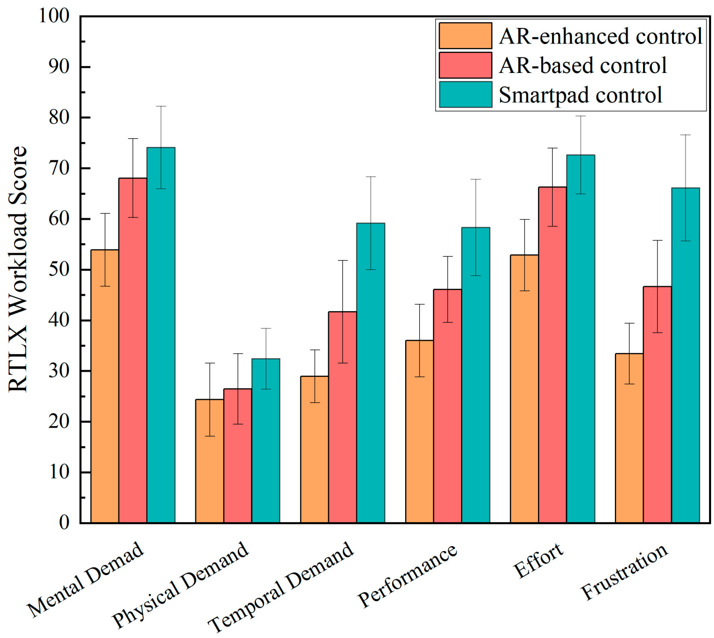


Figure 12. NASA RTLX indicator scores for different control methods.

The analysis of task completion times and NASA RTLX scores clearly demonstrates the better efficiency and user experience provided by the proposed AR-enhanced control system compared to the AR-based control system and smartpad control. The AR-enhanced control system reduces the time required to complete tasks, attributable to the rich information about the robot's states during task execution displayed in the AR interface. This allows operators to understand the current task status and make more precise judgments. Furthermore, intuitive gesture recognition facilitates the efficient remote disassembly of busbars. In terms of workload, the system also exhibits distinct advantages, particularly in key dimensions such as mental demand, effort, and frustration levels. The real-time information about the physical robot presented on the AR interface not only helps operators understand the status of both the robot and the task, enhancing their confidence and reducing mental demand, but also eases the control process. The integration of robot information provided on the AR interface with gesture recognition reduces the effort required and alleviates feelings of frustration. These results indicate that combining an intuitive AR interface with real-time feedback on the robot's status can effectively improve operational efficiency and user satisfaction, making it suitable for industrial environments that demand high precision in operations.

5. Discussion

In this study, a system integrating AR and DT technologies was developed, enhancing the efficiency and safety of remote control for industrial robots. A virtual robot is registered within the AR environment onto a physical robot, allowing operators to observe the robot's operations in real time. Critical joint information is displayed by the synchronised virtual robot, and the torque data on each joint are monitored through real-time line graphs, assisting in fault diagnosis and preventing mechanical overload. Moreover, in the event of anomalies, operators can intervene and remotely control the robot based on its real-time status using intuitive interaction methods. The design of the system is suitable not only for specific tasks such as disassembling busbars from EV batteries but also for other complex and hazardous industrial applications due to its intuitive remote operation and precise control.

Despite the advantages of this system, some challenges and limitations have been identified. First, the operational range is limited; studies have shown that hand rays are effective within a distance of 5 m, beyond which the accuracy of interactions decreases. To overcome this limitation, the integration of high-resolution cameras and advanced sensor technologies, along with the reconstruction of the work scene at the remote side, could enable operation without distance constraints. Second, positioning accuracy within the AR environment remains a challenge; precise registration and tracking are crucial for enhancing system reliability. Future work will focus on integrating machine learning algorithms and enhanced sensor feedback to optimise AR registration and tracking methods, thus improving positioning accuracy. Additionally, due to the limitations related to the robot's load capacity and range of motion, the system has restrictions on the size and weight of the objects it can handle, which may affect its applicability to larger equipment. Future research will explore how to expand the system's capability to accommodate the operational needs of larger equipment.

The work reported in this paper is an initial case study exploring AR/DT-assisted robotic disassembly techniques. We have used the removal of busbars from one make of EV batteries to illustrate the application of our proposed method. To assess the effectiveness of the method in different scenarios, future work will cover a wider range of disassembly tasks involving various battery makes and types. Expanding the scope of the study in this way will help us validate the applicability of our method and refine it for eventual practical implementation in EV battery remanufacturing.

6. Conclusions

This paper presents a system that integrates AR and DT technologies for the remote control of industrial robots for the disassembly of EoL EV batteries. The core of the system lies in creating a digital replica of a physical robot within an AR environment and synchronising it in real time with the state of the physical robot. The AR interface provides display- and gesture-based control capabilities for remote manipulation. The contribution of this system includes the real-time collection and processing of robot state data to ensure that the actions of the digital replica are consistent with those of the physical robot. Additionally, the AR interface allows operators to visualise the detailed status information of the robot; operators can intuitively control the virtual robot through gestures based on this information, thereby enabling more precise control of the physical robot.

The effectiveness of the proposed system was demonstrated through the disassembly of busbars from EV batteries. Further usability tests were conducted by comparing the proposed system against AR-based control methods without informational cues and smart-pad control methods in terms of task completion time and operator workload. The results demonstrated the advantage of the proposed system in terms of task completion time, with an average of 29.7 s, lower than the 42.05 s for the AR-based control method and 65.75 s for the smartpad control method. Regarding user experience, the NASA-TLX score for the proposed system averaged 38.24, which is lower than the AR-based control (average score of 49.19) and smartpad control (average score of 60.44) methods. These findings highlight the efficiency and enhanced user experience offered by the proposed system compared to other control methods.

Future work will focus on integrating machine learning algorithms and advanced sensor feedback to optimise registration and tracking in AR. This enhancement will help improve the positioning accuracy and extend the system's application scope. With these advancements, efficient and precise remote control operations can be achieved across a broader range of industrial applications.

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References

1. IEA. Global EV Data Explorer. Available online: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer (accessed on 7 November 2023).
2. Harper, G.; Sommerville, R.; Kendrick, E.; Driscoll, L.; Slater, P.; Stolkin, R.; Walton, A.; Christensen, P.; Heidrich, O.; Lambert, S.; et al. Recycling lithium-ion batteries from electric vehicles. *Nature* **2019**, *575*, 75–86. [CrossRef] [PubMed]
3. Ramírez, F.J.; Aledo, J.A.; Gamez, J.A.; Pham, D.T. Economic modelling of robotic disassembly in end-of-life product recovery for remanufacturing. *Comput. Ind. Eng.* **2020**, *142*, 106339. [CrossRef]
4. Caterino, M.; Fera, M.; Macchiaroli, R.; Pham, D.T. Cloud remanufacturing: Remanufacturing enhanced through cloud technologies. *J. Manuf. Syst.* **2022**, *64*, 133–148. [CrossRef]
5. Kerin, M.; Pham, D.T.; Huang, J.; Hadall, J. A generic asset model for implementing product digital twins in smart remanufacturing. *Int. J. Adv. Manuf. Technol.* **2023**, *124*, 3021–3038. [CrossRef]
6. Xu, W.; Tang, Q.; Liu, J.; Liu, Z.; Zhou, Z.; Pham, D.T. Disassembly sequence planning using discrete Bees algorithm for human-robot collaboration in remanufacturing. *Robot. Comput.-Integr. Manuf.* **2020**, *62*, 101860. [CrossRef]
7. Huang, J.; Pham, D.T.; Li, R.; Qu, M.; Wang, Y.; Kerin, M.; Su, S.; Ji, C.; Mahomed, O.; Khalil, R.; et al. An experimental human-robot collaborative disassembly cell. *Comput. Ind. Eng.* **2021**, *155*, 107189. [CrossRef]
8. Peng, Y.; Li, W.; Liang, Y.; Pham, D.T. Robotic disassembly of screws for end-of-life product remanufacturing enabled by deep reinforcement learning. *J. Clean. Prod.* **2024**, *439*, 140863. [CrossRef]
9. Zhang, X.; Fu, A.; Zhan, C.; Pham, D.T.; Zhao, Q.; Qiang, T.; Aljuaid, M.; Fu, C. Selective disassembly sequence planning under uncertainty using trapezoidal fuzzy numbers: A novel hybrid metaheuristic algorithm. *Eng. Appl. Artif. Intell.* **2024**, *128*, 107459. [CrossRef]
10. Reljić, V.; Milenković, I.; Dudić, S.; Šulc, J.; Bajči, B. Augmented reality applications in industry 4.0 environment. *Appl. Sci.* **2021**, *11*, 5592. [CrossRef]
11. Ong, S.K.; Yew, A.W.W.; Thanigaivel, N.K.; Nee, A.Y. Augmented reality-assisted robot programming system for industrial applications. *Robot. Comput.-Integr. Manuf.* **2020**, *61*, 101820. [CrossRef]
12. Michalos, G.; Karagiannis, P.; Makris, S.; Tokçalar, Ö.; Chryssolouris, G. Augmented reality (AR) applications for supporting human-robot interactive cooperation. *Procedia CIRP* **2016**, *41*, 370–375. [CrossRef]
13. Li, C.; Zheng, P.; Yin, Y.; Pang, Y.M.; Huo, S. An AR-assisted Deep Reinforcement Learning-based approach towards mutual-cognitive safe human-robot interaction. *Robot. Comput.-Integr. Manuf.* **2023**, *80*, 102471. [CrossRef]
14. Su, Y.P.; Chen, X.Q.; Zhou, T.; Pretty, C.; Chase, G. Mixed-reality-enhanced human–robot interaction with an imitation-based mapping approach for intuitive teleoperation of a robotic arm-hand system. *Appl. Sci.* **2022**, *12*, 4740. [CrossRef]
15. Tao, F.; Xiao, B.; Qi, Q.; Cheng, J.; Ji, P. Digital twin modeling. *J. Manuf. Syst.* **2022**, *64*, 372–389. [CrossRef]

16. Ma, X.; Qi, Q.; Cheng, J.; Tao, F. A consistency method for digital twin model of human-robot collaboration. *J. Manuf. Syst.* **2022**, *65*, 550–563. [CrossRef]
17. Cai, Y.; Wang, Y.; Burnett, M. Using augmented reality to build digital twin for reconfigurable additive manufacturing system. *J. Manuf. Syst.* **2020**, *56*, 598–604. [CrossRef]
18. Li, C.; Zheng, P.; Li, S.; Pang, Y.; Lee, C.K. AR-assisted digital twin-enabled robot collaborative manufacturing system with human-in-the-loop. Robot. *Comput.-Integr. Manuf.* **2022**, *76*, 102321. [CrossRef]
19. Craig, A.B. *Understanding Augmented Reality: Concepts and Applications*; Focal Press: Waltham, MA, USA, 2013.
20. Egger, J.; Masood, T. Augmented reality in support of intelligent manufacturing–a systematic literature review. *Comput. Ind. Eng.* **2020**, *140*, 106195. [CrossRef]
21. Li, C.; Zheng, P.; Zhou, P.; Yin, Y.; Lee, C.K.; Wang, L. Unleashing mixed-reality capability in Deep Reinforcement Learning-based robot motion generation towards safe human–robot collaboration. *J. Manuf. Syst.* **2024**, *74*, 411–421. [CrossRef]
22. Michalos, G.; Kousi, N.; Karagiannis, P.; Gkournelos, C.; Dimoulas, K.; Koukas, S.; Mparis, K.; Papavasileiou, A.; Makris, S. Seamless human robot collaborative assembly–An automotive case study. *Mechatronics* **2018**, *55*, 194–211. [CrossRef]
23. Kofman, J.; Wu, X.; Luu, T.J.; Verma, S. Teleoperation of a robot manipulator using a vision-based human-robot interface. *IEEE Trans. Ind. Electron.* **2005**, *52*, 1206–1219. [CrossRef]
24. Zhong, C.; Zhao, S.; Liu, Y.; Li, Z.; Kan, Z.; Feng, Y. A flexible wearable e-skin sensing system for robotic teleoperation. *Robotica* **2023**, *41*, 1025–1038. [CrossRef]
25. Li, H.; Bi, L.; Li, X.; Gan, H. Robust predictive control for EEG-based brain–robot teleoperation. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 9130–9140. [CrossRef]
26. Arévalo Arboleda, S.; Rücker, F.; Dierks, T.; Gerken, J. Assisting manipulation and grasping in robot teleoperation with augmented reality visual cues. In Proceedings of the ACM Human Factors in Computing Systems, Yokohama Japan, 8–13 May 2021; pp. 1–14. [CrossRef]
27. Pan, Y.; Chen, C.; Li, D.; Zhao, Z.; Hong, J. Augmented reality-based robot teleoperation system using RGB-D imaging and attitude teaching device. *Robot. Comput.-Integr. Manuf.* **2021**, *71*, 102167. [CrossRef]
28. González, C.; Solanes, J.E.; Munoz, A.; Gracia, L.; Girbés-Juan, V.; Tornero, J. Advanced teleoperation and control system for industrial robots based on augmented virtuality and haptic feedback. *J. Manuf. Syst.* **2021**, *59*, 283–298. [CrossRef]
29. Solanes, J.E.; Muñoz, A.; Gracia, L.; Martí, A.; Girbés-Juan, V.; Tornero, J. Teleoperation of industrial robot manipulators based on augmented reality. *Int. J. Adv. Manuf. Technol.* **2020**, *111*, 1077–1097. [CrossRef]
30. Brizzi, F.; Peppoloni, L.; Graziano, A.; Di Stefano, E.; Avizzano, C.A.; Ruffaldi, E. Effects of augmented reality on the performance of teleoperated industrial assembly tasks in a robotic embodiment. *IEEE Trans. Hum.-Mach. Syst.* **2017**, *48*, 197–206. [CrossRef]
31. Qi, Q.; Tao, F. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access* **2018**, *6*, 3585–3593. [CrossRef]
32. Zhou, G.; Zhang, C.; Li, Z.; Ding, K.; Wang, C. Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing. *Int. J. Prod. Res.* **2020**, *58*, 1034–1051. [CrossRef]
33. Wang, K.J.; Lee, Y.H.; Angelica, S. Digital twin design for real-time monitoring—A case study of die cutting machine. *Int. J. Prod. Res.* **2021**, *59*, 6471–6485. [CrossRef]
34. Min, Q.; Lu, Y.; Liu, Z.; Su, C.; Wang, B. Machine learning based digital twin framework for production optimization in petrochemical industry. *Int. J. Inf. Manag.* **2019**, *49*, 502–519. [CrossRef]
35. Mi, S.; Feng, Y.; Zheng, H.; Wang, Y.; Gao, Y.; Tan, J. Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework. *J. Manuf. Syst.* **2021**, *58*, 329–345. [CrossRef]
36. Li, X.; He, B.; Wang, Z.; Zhou, Y.; Li, G.; Jiang, R. Semantic-enhanced digital twin system for robot–environment interaction monitoring. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 7502113. [CrossRef]
37. Zhu, Q.; Huang, S.; Wang, G.; Moghaddam, S.K.; Lu, Y.; Yan, Y. Dynamic reconfiguration optimization of intelligent manufacturing system with human-robot collaboration based on digital twin. *J. Manuf. Syst.* **2022**, *65*, 330–338. [CrossRef]
38. Aivaliotis, P.; Georgoulias, K.; Chryssolouris, G. The use of Digital Twin for predictive maintenance in manufacturing. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 1067–1080. [CrossRef]
39. Soares, I.; Petry, M.; Moreira, A.P. Programming robots by demonstration using augmented reality. *Sensors* **2021**, *21*, 5976. [CrossRef]
40. Gallala, A.; Kumar, A.A.; Hichri, B.; Plapper, P. Digital Twin for human–robot interactions by means of Industry 4.0 Enabling Technologies. *Sensors* **2022**, *22*, 4950. [CrossRef]
41. Hart, S.G. NASA-task load index (NASA-TLX); 20 years later. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Los Angeles, CA, USA, 16–20 October 2006; Sage Publications: Los Angeles, CA, USA, 2006; Volume 50, pp. 904–908. [CrossRef]