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AR-assisted Digital Twin-enabled Robot Collaborative Manufacturing System with Human-in-the-loop

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***Abstract*—The teleoperation and coordination of multiple industrial robots play an important role in today's industrial internet-based collaborative manufacturing systems. The user-friendly teleoperation approach allows operators from different manufacturing domains to reduce redundant learning costs and intuitively control the robot in advance. Nevertheless, only a few preliminary works have been introduced very recently, let alone its effective implementation in the manufacturing scenarios. To address the gap, this research proposes a novel multi-robot collaborative manufacturing system with human-in-the-loop control by leveraging the cutting-edge augmented reality (AR) and digital twin (DT) techniques. In the proposed system, the DTs of industrial robots are firstly mapped to physical robots and visualize them in the AR glasses. Meanwhile, a multi-robot communication mechanism is designed and implemented, to synchronize the state of robots in the twin. Moreover, a reinforcement learning algorithm is integrated into the robot motion planning to replace the conventional kinematics-based robot movement with corresponding target positions. Finally, three interactive AR-assisted DT modes, including real-time motion control, planned motion control, and robot monitoring mode are generated, which can be readily switched by human operators. Two experimental studies are conducted on 1) a single robot with a commonly used peg-in-hole experiment, and 2) the motion planning of multi-robot collaborative tasks, respectively. From the experimental results, it can be found that the proposed system can well handle the multi-robot teleoperation tasks with high efficiency and owns great potentials to be adopted in other complicated manufacturing scenarios in the near future.**

***Index Terms*—Augmented Reality, Digital Twin, Collaborative Manufacturing System, Reinforcement Learning, Human-in-the-loop Control**

I. Introduction

In today's increasingly competitive market, the manufacturing paradigm is shifting toward large-scale individualization and personalization, which accordingly, result in an ever high level of flexible and automatic requirement of manufacturing systems. To achieve mass personalization in manufacturing, various manufacturing "things" and human operators are permeated through the production loop [1], alongside with industrial robots which have been well developed and playing a significant role in handling complex manufacturing tasks with high efficiency [2][3]. However, most existing robotic systems conduct the pre-programmed tasks in a routine manner without much intelligence, let alone to well-handle personalized tasks in a collaborative manner [4][5]. To solve this issue, two effective human-robot collaborative approaches can be promising. One is to train the robot by leveraging the cutting-edge artificial intelligence, which is known as robot learning [6], while the other is to put a human expert in-the-loop to teach or teleoperate the robot remotely.

Integrating human intelligence in the multi-robot collaborative manufacturing process plays a promising role in today's smart manufacturing to extend the existing capabilities of both humans and robots. In this context, different from the broadly-defined human-robot collaboration, multi-robot collaborative manufacturing with human-in-the-loop neither requires workers to present in the workspace, nor collaborate in the physical space only. Rather, it can perform manufacturing activities with other manufacturing equipment collaboratively in the digitalized cyber space by teleoperating the robot remotely. Such a paradigm is spatially, safely, and technologically flexible, and hence bridges the gap between fully automated manufacturing and fully manual manufacturing [7]. It has great potential for application in the current manufacturing process of large-scale personalized products.

Nevertheless, due to the complex scenarios in manufacturing, there still exist several challenges to realize human-in-the-loop collaborative manufacturing. One major challenge is that the existing industrial robot program still requires an experienced operator to edit or programming [8]. It is still a great obstacle for users who are experts in the manufacturing field but lacking experience in robot operation [9]. As one basis for the collaborative manufacturing system, teleoperation of industrial robots has been emphasized and investigated much recently [10] [11]. However, how to make the robot teleoperation user-friendly and further to collaborate with other operators or automated robots is rarely explored, which can largely reduce the extra workload required by human operators and increase efficiency.

Aiming to fill this research gap, the wearable AR-assisted system and DT technologies allow users to observe and teleoperate the real robots accurately in an intuitive manner. With the characteristic of intuitionistic and scalability of AR and DT technologies, this paper proposed an AR-assisted DT-enabled multi-robot collaborative manufacturing system with human-in-the-loop. The rest of this paper is organized as follows. Section II reviews related works of multi-robot collaborative manufacturing, AR-assisted robot teleoperation, and DT applications in the field of industrial robot control.

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Section III presents the key designs of the proposed system, such as communication mechanism, AR-assisted teleoperation, DT-enabled motion planning, and various designs of robot control mode. In section IV, single-robot and multi-robot demonstrative experiments are carried out stepwise to show their capabilities and effectiveness in today's manufacturing shopfloor. Section V discusses the problems that occurred during the implementation and other potential improvements, while the conclusion and future research directions are highlighted in Section VI at last.

II. Related Work

This section summarizes the recent advancements of multi-agent collaborative manufacturing, AR-assisted robot teleoperation, and DT applications in the robot area as follows.

A. Multi-agent based Collaborative Manufacturing

Over the past two decades, industrial robots have gradually taken on a more important role in the collaborative manufacturing domain with higher productivity and a more flexible range of applications [12]. For instances, in the manufacturing assembly process, Marvel et al. summarized multi-robot assembly applications and methods for common industrial robot platforms such as industrial robot arms, robot hands, and autonomous mobile platforms [13]. Common algorithms for simultaneous multi-robot motion and cooperative operations were recapped with future trends and insights presented for multi-robot assembly problems. Meanwhile, Jinyu et al. designed a series of end-effectors for assembly operations in the 3C industry in a multi-robot collaborative manufacturing system [14]. As for the robot-based additive manufacturing process, Hongyao et al. proposed a large, flexible, and scalable 3D printing system consisting of multiple robots working in concert and discusses the impact of multi-robot layouts on the maximum reachable area and geometric adaptation in the paper [15]. Also, Luis et al. proposed a new approach for process automation design, enhanced implementation and real-time monitoring of operations, in response to the need for multi-robot collaborative systems that require the integration of robots from different manufacturers [16]. The approach created a DT of the manufacturing process with an immersive virtual reality interface that can be used as a physical implementation prior to a virtual test-bed and can also be effectively used for operator training and feasibility studies of solutions.

On the other hand, with the ever increasing complexity of robot control strategies and personalization requests, experienced human operators have been inevitably engaged in the collaborative manufacturing system with higher flexibility [17]. The main research works in this field have focused on proposing technological solutions to improve safety, productivity, and reduce costs. To address the safety issues, Martina et al. [18] introduced a strategy which can correctly handle human safety by combining the relative positions and velocities of the human operator and the robot with defining a safety index. It also can satisfy the demand for increasingly strong cooperation between humans and robots. Meanwhile, Robla et. al [19] comprehensively reviewed the main safety systems proposed and applied in the industrial robot environment and reviewed the current regulations and the new concepts introduced therein. To address the problem of cost-effective task assignment in human multi-robot systems, a generic mixed-integer linear programming problem was formulated in [20]. It aims to minimize the overall execution time while optimizing the quality of the executed tasks and the workload of both humans and robots. Meanwhile, a real-time adaptive assembly scheduling method for human-multi-robot collaboration was proposed by modeling and incorporating the changing human operator capabilities, and a genetic algorithm was designed to find a feasible solution for the formulated adaptive assembly scheduling problem [21].

B. AR-assisted Robot Teleoperation

Robot teleoperation denotes that the user remotely operates the robot manually without contact, through a suitable interface (gamepad, keyboard, etc.). Benefiting from a close coupling of user input to robot actions, the robot teleoperation control paradigm is now broadly studied in the field of robot control. Meanwhile, owing to its good adaptability (time, spatial), robot teleoperation has been widely used in surgical robots [22], robotic manipulators [11] to aerial robots [23], and underwater robots [24].

Meanwhile, AR is a technology that allows the projection of computer-generated virtual objects into a physical environment [25]. It is an important component of the Industry 4.0 concept, allowing workers to access physical and virtual information in a hybrid scenario and to interact with virtual objects [26][27]. Such interaction way makes AR naturally suitable for robot teleoperation, and it could be ad used in many applications to bridge the gap between human and machine systems, for example, manufacturing activity guidance [28], human-robot collaboration assistance [29], etc.

In the last few years, an amount of work has combined both technologies, i.e., AR technology and robot teleoperation. Yong et al. presented an AR-based robot teleoperation system using RGB-D imaging and a posture demonstration device. The system sends the color and depth images of the remote robot environment to the local area, where the operator can perceive the environment and perform the robot teleoperation [10]. [30] proposed an augmented reality (AR)-assisted robot programming system that converts robot work scenes into AR scenes to enable fast and intuitive robot path planning and task programming. AR was also employed to help workers visualize information about the robot in real time by overlaying information related to maintenance tasks on the corresponding objects [31]. This system can help human workers to identify and visualize machine errors and can simplify the complexity of robot maintenance tasks. Moreover, Stephanine et al. facilitated task performance in remote robot manipulation and grasping by using AR to provide additional visual information about the environment and the robot, aiming to enhance the visual space of the robot operator with cues about the robot gripper's position in the workspace and in relation to the target, thus improving task performance [32].

C. Digital Twin in Robot Applications

In smart manufacturing, DT technology is deemed the core to represent the physical space in the virtual replica [33][34]. The DT allows modeling the parameters of the production system at different levels including assembly process, production station, and line level, and DT allows dynamically updating the twin in runtime, synthesizing data from multiple 2D–3D sensors to have up-to-date information about the actual production process [35][36]. Except for its widely adoption in manufacturing process, recent works began to establish the robot DT for device control purposes. For instance, Marius et al. created a DT of the robot arm in the Unity engine to learn manufacturing skills virtually, where the physical robot arm could replicate the learned skills in physical space afterwards [37]. Richard et al. design a DT solution to provide users' ability to predict the battery charge of the mobile robot and designing for user a visual interface of the mobile robot's movements using an AR device as a medium to display this digital data [38]. Meanwhile, the DT has been also widely adopted in cloud robotics, of which the digital model in the cloud may not reflect the real state of the physical robot manufacturing system. To solve it, Wenjun et al. proposed a DT-based framework for industrial cloud robotics and the framework combines data from physical industrial robots, digital industrial robots, robot control services, and DTs to enable digital robotics and bi-directional interaction between physical robots [39]. It can efficiently synchronize and merge digital and physical robots, and thus ultimately enable fine-grained sensing control of cloud robots system.

Currently, smart manufacturing systems usually avoid human intervention in the manufacturing process, and automated control methods have proven successful in many applications [40]. However, in some cases of high uncertainty or flexibility, human involvement is still beneficial and even necessary. For such "human-in-the-loop" control approaches, the issue of human information perception and the way to interact with the system must be addressed. Enes et al. used a combination of DTs and virtual reality (VR) interfaces to design an immersive human-in-the-loop robotic assembly system [41]. Meanwhile, a DT platform for robot teleoperation with a human-in-the-loop was presented in [42], where the DT effectively acted as an intermediate layer between the operator and a controlled machine (e.g., a robot arm), to interact with the operator and monitor the quality of the remote task through an intuitive low-latency interface. Moreover, Ridhi et al. [43]. used simulation and control software to design DTs for manufacturing environments and utilized ant colony optimization for programming industrial robots in DTs and transferring them to real robots after manual inspection, which can largely reduce human intervention in the solution of assembly tasks.

From the above literature, current studies mainly focus on collaborative manufacturing systems which treat the worker or robot as individual human-in-the-loop robot-robot collaboration considerations. Among the few studies considering human existence, they emphasized the efficient scheduling and allocation of different working tasks, instead of the controlling or guiding robots to perform manufacturing tasks. It is certainly deserved the deep exploration of human-in-the-loop collaborative manufacturing system.

III. System Design and Implementation

The overall framework of the proposed AR-assisted DT-enabled robot collaborative manufacturing system is presented in Figure 1. Firstly, a mechanism of multi-node communication is introduced, which serves as the fundamental to ensure the effective communication among multiple robots and multiple clients in the same system. Next, the fundamental design of the AR-based robot teleoperation system, including pose registration and motion planning are presented. Then, the model-free reinforcement learning is adopted to complete the robot motion planning control task. Finally, the three DT-enabled interaction approaches, including Cyber2Physical real-time teleoperation, Cyber2Physical planning teleoperation, and Physical2Cyber monitoring are developed to accomplish the closed-loop between the virtual and physical robot.

A. Multi-robot Multi-client Communication

The communication and state synchronization among the multiple robot control system, which are treated as the fundamentals of implementing DT [40]. In this research, the socket communication protocol is employed in a cloud-edge industrial internet infrastructure for multi-robot multi-client communications, as shown in Figure 2. This mechanism allows each robots to be controlled simultaneously by a client , as well as to allow part of the clients to observe the others without control permissions. In essence, the states of all robots are synchronized to a cloud server (i.e., a master node). Meanwhile, all clients send requests to a cloud server to acquire the latest states of robots in the system. The responsibility of Cloud master node and edge node is detailed as follows:

- *Cloud node:* The cloud node continuously receives the state updates from each robot in the manufacturing system. Meanwhile, the states of individual robots will be distributed to each slave node that is connected to the same network.
- *Edge node:* The edge nodes have two types. One type is the node connect to the robot operator, such type of nodes need to upload the state of the corresponding robot and receive the latest state of other robots sent by the master node. The other node type is for observer only, and such type of nodes only needs to synchronize the state of all robots in the system from the master node.

Nevertheless, the communication security issue during teleoperation needs to take extra attention to avoid accidents during the manufacturing process as well. To address that, the prototype system adopted following several measures at the user control stage and information transportation stage. In user input stage, we not only require the authentication before joining the industrial network, but also provides individual username and password authentication when establishing a socket connection to each robot. Besides these, the control command could not be interrupted by other operating commands except the protective stop command to keep operation safety and complement. While the information transportation

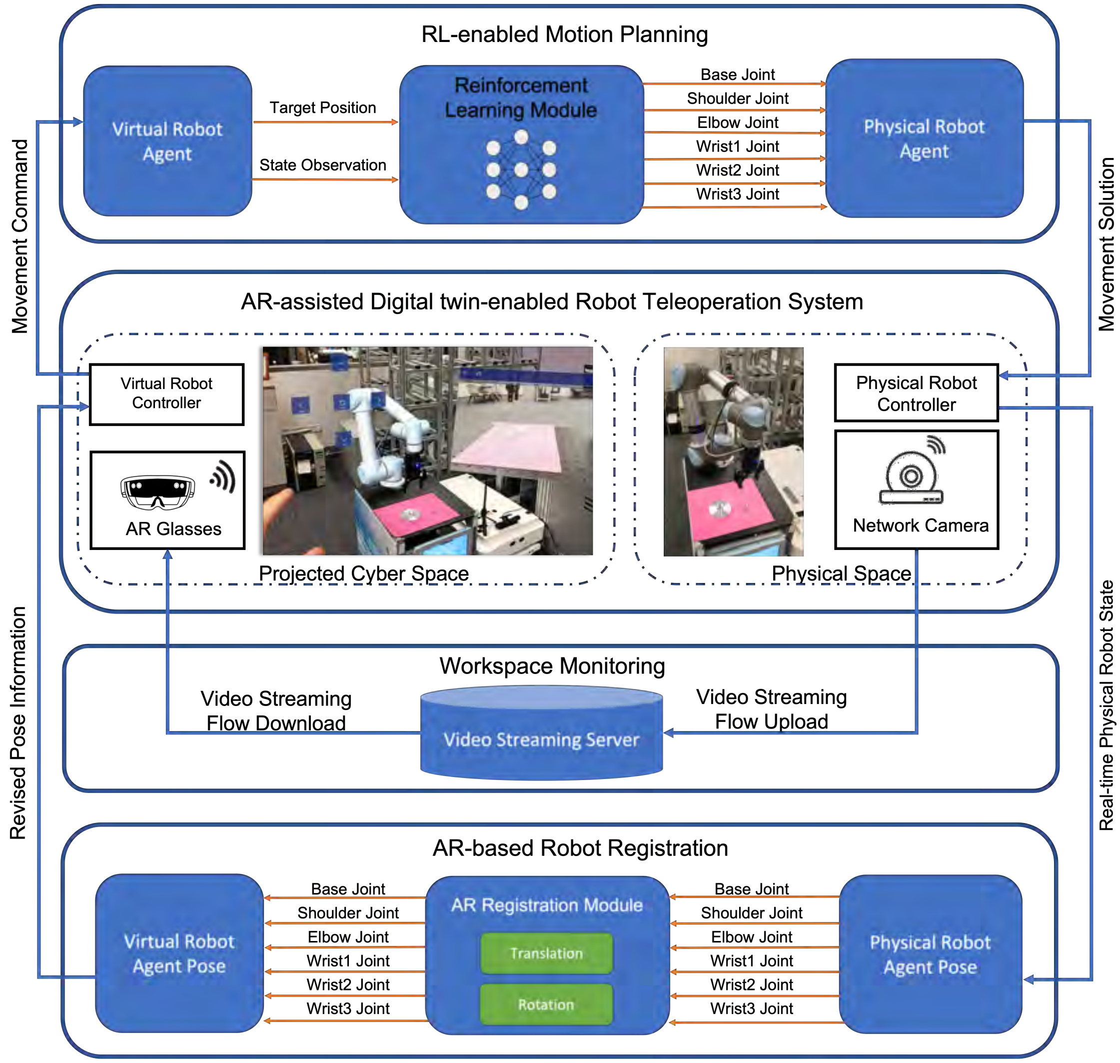

Figure 1. Overview of the proposed system framework.

stage, the control communication flow between each robot and client is encrypted by hash table. Furthermore, in manufacturing practice, the system adopts the commercial cloud servers and the Secure Sockets Layer and Secure Socket Tunneling Protocol series encryption approaches to ensure the system stability and security.

B. AR-assisted Robot Teleoperation System

To meet the idea of multi-robot collaborative manufacturing system with human-in-the-loop control, a DT of the physical robot is modeled with the Unity game engine. Meanwhile, the robot twin is ported to the AR glasses to increase the immersive experience. Furthermore, it could offer a teleoperation approach and an observation approach of the robot more friendly.

Specifically, in the AR glass, the DT of robot synchronized with the real robot is projected as a hologram at the remote workspace. With the mapped DT of the physical robot, the movement of the physical robot can be controlled remotely, while the state of the physical robot can be monitored and visualized by the robot DT. Furthermore, with integrating the proposed communication mechanism in section III-A and multiple AR teleoperation system, it allows users to work together even when they are distributed in different places, and it aligns with the collaborative manufacturing paradigm. In general, the advantages of a robot control method aided by AR technology are obvious compared to the direct control of the robot. Firstly, the system provides predictability for final posture and motion trajectories physical robot. As the physical robot imitates the motion of the DT, the trajectories can be visualized to avoid some potential safety issues. Besides, the system provides a user-friendly pattern, the manufacturing system can be manipulated not limited to spatial and human factors. While we achieve the AR-assisted Digital-twin enabled collaborative manufacturing, some key functionalities need to be detailed as follows.

1) AR-based Robot Registration: When implementing Cyber-Physical synchronize functions of the proposed robot control system, the physical robot and the twin not only require the pose bidirectional mapping between them and need the twin of physical robot own the motion planning capability which could transfer to the physical robot and

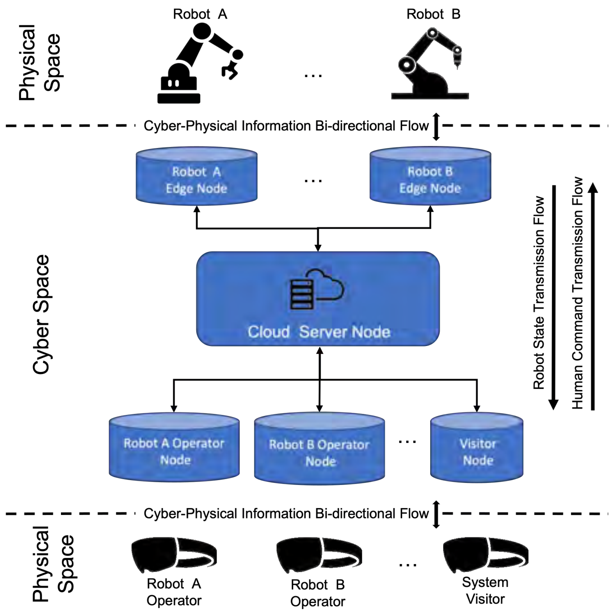

Figure 2. The Architecture of Multi-robot Multi-client Communication Mechanism.

drive the movement. The calculation process of transferring the pose of DT to the physical robot, which is known as registration. It mainly consists of two stages: displayed model alignment and joint alignment. In the model alignment stage, with the ready-designed virtual 3D robot model, the Vuforia Engine[1] is adopted to align the model target between physical and virtual robots to synchronize the displayed robot pose. Then, the joint value alignment is to calculate a joint-value transformation matrix based on pose-aligned models, which could convert the DT's joint values in the AR coordinate system to the physical robot's joint values in the real-world coordinate system. For every iteration of the physical robot pose update loop, the expected physical robot's end-effector position is set by humans in the AR glasses and the feasible joint value solution is calculated by RL-based motion planning algorithm (detailed in subsection III-B2). Afterward, the joint value of the physical robot is transformed into the virtual robot's joint solution. By this transformation, joint values of the virtual robot in the AR-glass scene mapping to the corresponding joint value of the physical robot, enabling the physical robot to synchronically operate with the DT. Lastly, with the tiny difference between virtual and real robot model and detection accuracy, the joint values of physical robots will be sent back to the virtual robots after finishing movement to revise the pose of the virtual robot. With the above procedures, the pose synchronization can form as a closed-loop process to remain system stable and avoid errors. The visualization is demonstrated in Fig. 7.

2) RL-enabled Motion Planning: RL is widely used in smart manufacturing processes and used to build intelligent systems that can perform tasks such as path searching [44], resource scheduling [45], and manipulation decisions making [46]. In addition, RL-driven robot control has also been widely used. Hence, to drive the physical robot movement, the model-free RL algorithm is employed to plan the movement of robot in the proposed system. Using model-free RL approach, it initializes the robot control policy by correlating the state of the task environment with its own motion parameters (i.e., the action space of robot). Then, the corresponding control policy is improved by RL algorithm through return reward and continuous trial-and-error interaction with the environment to meet the expected performance/goal (reach a specific position in our task)[47]. In addition, the control policy is approximated by collecting trajectory data and does not depend on the environment model and any human prior knowledge just through the interaction. In such way, the robot control policy function can be approximated instead of needing the kinematic model, which requires a lot of expertise to design. Additionally, the planning solution doesn't require to be calculated by inverse kinematic but requires a forward propagation in neural network in RL improve the time efficiency. In general, RL-based motion planning can reduce, remove tedious calculations of manual modeling, and improve the generalization. Afterward, by outputed motion control policy function, the solution of robot motion for the DT can also be applied to the physical robot via the stated synchronized registration function. The detailed pipeline for RL-algorithm is illustrated in following sections.

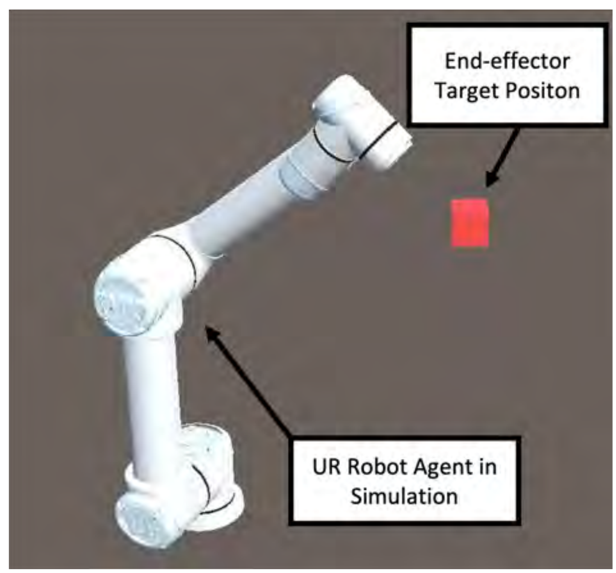

Figure 3. RL-enabled motion planning: the robots' end-effector attempt to chase and touch the cube target. The position of cube can be dragged and guided by human intention.

In the robot motion planning phase, the planning process is treated as a sequential decision-making problem and solved as an episodic task by model-free RL approach. In each episode, the interaction trajectory is formulated as a Markov Decision Process (MDP). The MDP is defined by a tuple consisting of the following sets $(S, A, P_{sa}, R, \gamma)$, where the elements refer to:

- State space (S) is the state/observation set of the whole planning process. The state representation s in this set consists of four components:

[1]https://www.vuforia.com/

- The existence of the robot agent.
- Setting the target position based on robot coordinate system.
- End-effector position based on robot coordinate system.
- The vector of the distance between above target position and end-effector position.

The robot coordinate system is based on the base joint center of the robot as the coordinate origin, the positive direction of the y-axis is the direction in which the wires extend, and the positive direction of the z-axis is the direction in which the upward of base joint . Direction of x-axis is determined by right-handed coordinate rules.

- Action Space(A) is the number of joints that the robot can rotate independently (i.e. Degree of Freedom) and a is the chosen action.
- Reward (R) is the sum of expected return reward.

$$R_t = \sum_{t'=t} \gamma^{t'-t} r\left(s_{t'}, a_{t'}\right) \tag{1}$$

The element $r(s, a)$ of the set is determined by the state s which the agent in and the corresponding action a executed by the agent. The reward function is shaped by following components:

- The absolute value of scalar distance between target position and end-effector position.
- The end-effector reaches target position (bonus term).
- The joint of end-effector gets out of the setting working area (penalty term).
- The sum of each joints' height (optional, applicable to task series of perpendicular grasping).

- P_{sa} represents the transition probability distribution of executing action a under state s, i.e.

$$P_{ss'}^{a} = P(S_{t+1} = s' \mid S_t = s, A_t = a) \tag{2}$$

- $\gamma \in [0, 1]$ is a discount factor. It defines the decay of future accumulated rewards.

With above settings, a task episode starts from an initial state s_0 and the robot agent samples an action $a \in A$ during each decision interval from the parametric stochastic policy $\pi(a_t|s_t)$ to adjust the robot pose. Afterwards, the successor state s_{t+1} of next decision interval is given according to P_{sa}, and robot agent gains a return reward value $r(s, a)$ from the environment (i.e simulator). Essentially, RL algorithm is to optimize the policy π based on performing exploratory actions and reinforcing the actions which lead to better performance than expectation of the agent. The expectation of the agent is modeled by a state-value function V. The H is the time horizon of the episodic task. The formulation of the state-value function is shown:

$$V^{\pi}(s_t) = E_{\pi}\left[\sum_{t=i}^{H} \gamma^t r_t | s_0 = s\right] \tag{3}$$

For robot control, since the industrial robot owns continuously action space, the RL algorithm with outputting the action space distribution is more suitable for solving such problem. Hence, the algorithm we picked is a model-free policy-based RL algorithm named Proximal Policy Optimization (PPO) [48]. It used to be the baseline algorithm of OpenAI and DeepMind and also a classical approach in actor-critic RL algorithm family. Comparing with other actor-critic RL algorithms, the PPO-based agent performs exploration in the environment and compares the actual gained reward for every state-action pair with the estimated reward to form the advantage function, as shown in Equation 4.

$$A(s_t, a_t) = R_t - V^{\pi}(s_t) \tag{4}$$

Meanwhile, PPO algorithm optimizes the sample efficiency using importance sampling and the ρ_t is the ratio of the probability between the updated and original policies generated by importance sampling. Despite that, an intuitive and effective surrogate clip function is proposed with the constraint of the loss function, where ϵ is the range of clip-term:

$$\begin{aligned} L^{\text{CLIP}}(\theta) == \mathbb{E}_{\tau}\Bigg[\sum_{t=0}^{T} &\min(\rho_t(\theta), \\ &\text{clip}(\rho_t(\theta), 1-\epsilon, 1+\epsilon))A_t \end{aligned} \tag{5}$$

With the help of clip-term, the policy update offset between the old and new strategies exceeds a predefined interval and the clip-term clip the agent objective so that the policy function update is limited to a certain interval to prevent the strategy update from converging too fast or converging too slow, which improves the training speed and implementability of the algorithm. At the same time, the exploration method of random strategy is retained, and the robot motion planning method will have better exploration and robustness when the sampling sample satisfies the maximum likelihood probability. With the policy function update, the updated policy assigns higher probability to state-action pairs, resulting in higher cumulative reward. With the description of PPO RL algorithm, the training scenario for the physical robot's DT motion planning task is shown in Fig. 3.

3) Workspace Monitoring: In addition to the control problem of the robot, how to observe the environmental information of the workspace where the robot is in and its state of performing the manufacturing task, also remain as a problem to be solved in the system construction. In our proposed system, the workspace is monitored by IP cameras, and the video generated from it is further projected to the AR glasses through the video streaming server. In this way, not only the status of the robot, but also the real-time status of the workspace can be presented in the AR glasses, with improving the remote monitoring efficiency, as shown in Figure 4.

C. Digital Twin-enabled Human-in-the-loop Interaction

To meet our potential application scenarios for bridging the state between virtual and physical industrial robots, three DT-enabled interaction modes are developed, namely, Cyber2Physical real-time control mode, Cyber2Physical planning control mode and Physical2Cyber mode. In the Cyber2Physical real-time mode, the state between the physical

Figure 4. Demonstration of workspace observation approach.

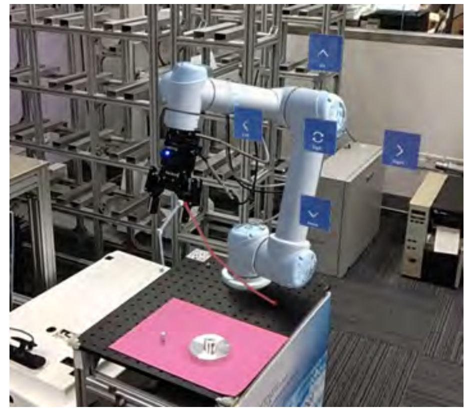

Figure 5. Visualization of past and planned trajectories. The white dot lines are past trajectories and red dots means undergoing path.

robot and the DT is replicated in real time (i.e., identical standard teleportation). The physical robot responds to the users' input instantly to take actions to match the DT of the physical robot in a standard teleoperation form. Meanwhile, the Cyber2Physical planning mode can perform the pre-planned execution mechanism in a synchronized manner. For both functions, the preliminary trajectory monitoring function is managed and shown in Figure 5. Finally, the motion of the physical robot can be monitored via AR glass. The detail of the three modes is detailed in the following parts.

1) Cyber2Physical Real-time Mode: The real-time control paradigm uses AR technology to present the user with a digital twin of the physical robot in the user's workspace, which has the same specifications as the physical robot in terms of its working range and working environment. In addition, the physical model and DOF of the digital twin robot are designed to be identical to the physical model. In this mode, the user′s teleoperation commands are sent to the digital twin robot and bridged to a physical robot rather than directly control the physical robot via robot system interface. While implementing the real-time control, the digital twin of the physical robot's pose is continuously updated by the user and sent as the real-time target pose of the physical robot in a fixed frequency. As the physical robot reaches a given pose, it is continuously updated according to the latest pose command. Essentially, the physical robot constantly imitates the real-time state of the digital twin robot controlled by users.

2) Cyber2Physical Planning Mode: The control paradigm could be thought as a design extension of the real-time control paradigm, and it could provide a support for predefined motion planning. In the real-time control mode, when the remote operator controls the DT of a physical robot, the corresponding physical robot will instantly mimic the DT's pose. However, during the planning process of this control mode, the DT of the physical robot move, follow the real-time command, and record the coordinate with the user manipulated in the augmented reality coordinate system. After completing the path design, the user sends a signal to the DT of the physical robot to drive the physical robot to start executing the planned trajectory. In practical usage, such design will help users to intuitively understand and foresee how a physical robot reacts to users' commands, and the users own a chance to detect, prevent and fix erroneous commands before the execution of physical robots.

3) Physical2Cyber Mode: This control mode is essentially a reverse design of the real-time control mode, and it is designed primarily to monitor the robot and to collect production data. In the Cyber2Physical mode, the pose of the physical robot (i.e., joint values) is transmitted back to the DT of the physical robot in real time as the operator controls the movement of the physical robot, so that the pose of the physical robot is aligned with its DT for real-time monitoring. In addition to the joint information, the current, voltage information is visualized as the joint is triggered, like shown in Fig. 8. Furthermore, the motion trajectories of different manufacturing tasks via human demonstration in real robot can be collected in this mode. In further robot applications, such dataset can drive robot learning algorithms (i.e., imitation learning [49], reinforcement learning [50]) to gain good performance in replicated manufacturing tasks.

IV. Experimental Results

A. Experimental Setup

The setup of the robot control module in real applications consists of a UR5 collaborative 6-Joints robot with a Robotiq-85 gripper; a wrist camera and a force torque sensor attached between the connection of the robot body and the gripper; in addition to the robotic system itself, the peripherals include an AR headset, Microsoft HoloLens AR glasses. The proposed AR module (see Section III-B), was developed in an external PC workstation (Intel Core i7-6700 CPU 3.40GHz, RAM 16 GB, and a Nvidia GTX 1060 6GB GPU) with the following software: Microsoft Windows 10 as the operating system; Visual Studio 2019 was used as an integrated development environment (IDE); and Unity LTS release 2020.1.10f1 by using tools such as MixedReality Toolkit Unity. The relay module for bridging the AR module and the robot control module was implemented on an external PC with the following software: Ubuntu 18.04 as the operating system; also, an Ethernet switch router was used to connect and communicate among the robot system, the relay module, and the AR module. Meanwhile, the IP camera was connected to the PC of relay module and transmitted to the AR headset via wireless connection.

B. Demonstration

Before deploying of the above-mentioned PPO algorithm, the PPO algorithm is trained in a scene of Unity with ML-Agents toolkit as shown in Fig. 3, and the position of the red cube is the target position of the robot required to reach. With gradient descent optimization, after 2 millions time steps' learning, the Fig. 6 shows that the reward curve of the model is converged and remain stable. Adopting that model powered by RL, the success rate of reaching tasks is around 98.7% by executing 5000 experiments. In the Fig. 6, the horizontal axis refers to time steps, and the vertical axis refers to the value of reward the whole training process costs around 8 hours. The experiments were executed on a PC with Intel Core i9-9980H 8-Core Processor 2.30GHz CPU with 32GB Memory.

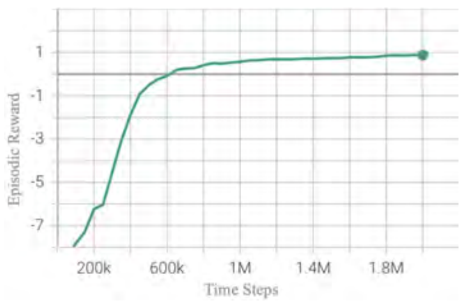

Figure 6. Mean episodic reward curve of training process with the DT of robot in simulated environment. The curve is smoothed to show the learning trends.

With the RL-enabled robot controller being settled, the first experiment is carried out to demonstrate single-robot teleoperation, which was designed to present the functionality and performance of the proposed method, as shown in Figure 7. Regardless of the various manufacturing scenarios, the human operator can teleoperate the UR5 robot to perform the peg-in-hole experiment by inserting a bear into the base. The operator observes the task environment information via video streaming (i.e., the position of the target workpiece and the position of the base) and then completes the operations accordingly.

Figure 7. Screenshots of the demonstrative Case I: a peg-in-hole experiment.

Moreover, in the second experiment, a multi-robot collaborative disassemebly work was conducted in order to evaluate the usability of the proposed collaborative control framework, as shown in Figure 8. In this setup, a KUKA iiwa robot was added to the experiment scene and the UR robot was equipped with the AGV base to improve the collaboration flexibility. The idea is to demonstrate how the dual-robot with human-in-the-loop to carry out the collaborative disassembly work efficiently. In this experiment, the target position of AGV is provided and the KUKA robot autonomously finish the predefined tasks, such as push the box, cut cable, and etc. Meanwhile, the UR robot is under teleoperated by human to perform assistant work for disassembly like drag, pickplace and so on. In general, such a collaborative manufacturing paradigm can be extended to welding, polishing and other tasks as well.

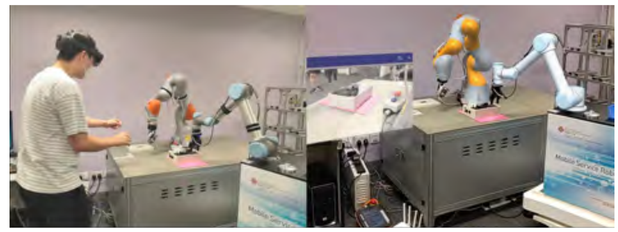

Figure 8. Demonstrative Case II: the AR-assisted DT-enabled multi-robot collaborative manufacturing system.

V. Discussion

In this paper, the authors propose an AR-assisted DT-enabled multi-robot collaborative manufacturing system that provides different modes of the human teleoperation of multiple industrial robots. It can be well adopted in many manufacturing shop-floor scenarios (e.g., personalized product assembly/disassembly, welding, etc.), where human beings cannot readily or safely carry out on-site operations, and professionals from various manufacturing fields can be located in different places but still collaborate in the manufacturing process. Meanwhile, the proposed system can be also implemented as a generic reference model for other scenarios, such as hazardous manufacturing scenarios [51] or fully automated plant troubleshooting. Another novelty lies in the RL-enabled robot motion planning approach to replace the conventional kinematics-based planning process, and such attempts provide a solution which could fuse more information to make decisions for driving robots [17]. Our proposed system, with AR and DT technology adopted, makes an initial attempt to integrate RL to real production scenarios.

Despite its advantages, several limitations still exist in this research work. For instance, as the algorithm is deployed in a real production environment, the accuracy limitation of DT model can be reflected in some specific manufacturing activities other than the robot reaching task. Moreover, networking latency and positioning accuracy remain a challenge in our lab-based demonstration. To address the prior one, novel communication mechanism (e.g., time sensitive network) and technology (e.g. 5G) can be further implemented. For the latter one, the elastic robot control mechanism should also be further explored.

VI. Conclusion

In this paper, a novel AR-assisted DT-enabled multi-robot collaborative manufacturing system with human-in-the-loop control was introduced and performed in a multi-robot collaborative teleoperation assembly work. The main contribution can be summarized as three-fold:

- A multi-robot multi-client-based communication mechanism is presented to keep each operation state synchronized among multiple clients.
- The DT of the physical robot is utilized to develop two different teleoperation modes, i.e., Cyber2Physical real-time mode, Cyber2Physical planning mode. The Physical2Cyber mode and the embedded display module are also used to provide the operator with an immediate view of the production environment.
- An RL algorithm is adopted for motion control and planning of the multi-robots with learning intelligence. The work also provides a bridging approach to make the learning algorithm trained on a virtual environment but a physical environment deployed.

Furthermore, two application cases are carried out on single and multiple robot collaborative teleoperations, which demonstrates the great potential of our proposed system to be generalized in many application scenarios. Except for these achievements, several potential future research directions are also highlighted, namely: 1) multimodal human-robot interaction approaches can be further implemented other than the button-based one, such as hand gestures, eye gaze, etc., 2) elastic robot control mechanism should be adopted to further improve the RL-based motion planning, and 3) the high-fidelity synchronization of multi-robot DTs can be further improved with cost-effectiveness.

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