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Human-Aware Reactive Task Planning of Sequential Robotic Manipulation Tasks

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Abstract—The recent emergence of Industry 5.0 underscores the need for increased autonomy in humanrobot interaction (HRI), presenting both motivation and challenges in achieving resilient and energy-efficient production systems. To address this, we introduce a strategy for seamless collaboration between humans and robots in manufacturing and maintenance tasks. Our method enables smooth switching between temporary HRI (humanaware mode) and long-horizon automated manufacturing (fully automatic mode), effectively solving the human-robot coexistence problem. We develop a task progress monitor that decomposes complex tasks into robot-centric action sequences, further divided into three-phase subtasks. A trigger signal orchestrates mode switches based on detected human actions and their contribution to the task. Additionally, we introduce a human agent coefficient matrix, computed using selected environmental features, to determine cut-points for reactive execution by each robot. To validate our approach, we conducted extensive experiments involving robotic manipulators performing representative manufacturing tasks in collaboration with humans. The results show promise for advancing HRI, offering pathways to enhancing sustainability within Industry 5.0. Our work lays the foundation for intelligent manufacturing processes in future societies, marking a pivotal step towards realizing the full potential of human-robot collaboration.

Index Terms—Sequential robotic manipulation, reactive task planning, autonomy level, human-robot interaction.

I. INTRODUCTION

I N the recently proposed Industry 5.0 paradigm, as highlighted by Li et al. [1], the emphasis is placed on achieving seamless collaboration between humans and robots to jointly perform manufacturing processes. This paradigm embodies the concept of full automation with short-term Human-Robot Interaction (HRI), applicable in scenarios where both robots

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Fig. 1: The typical changes on task progress after humanaware mode: (a) fully automatic mode, (b) no changes on task progress, (c) the human-aware mode advances the task progress, (d) a past subtask is activated, (e) the system needs to complete the interrupted subtask properly and then switches to the newly active subtask.

and human workers contribute their respective skills and strengths, such as collaboratively assembling components, or where robots must safely respond to humans operating in close proximity, such as during maintenance tasks. However, to realize this level of human-robot coexistence, several technical challenges must be addressed. Firstly, the system must effectively monitor the progress of manufacturing tasks amidst the unpredictable behavior of human agents (the typical changes on task progress after human-aware mode can be represented with the structure shown in Fig. 1). Secondly, it should operate in a human-aware mode, detecting and responding to human presence or passive contributions to the task. Lastly, the system should autonomously transition between automatic and human-aware modes to fulfill expected functions based on the sensed environmental state. Despite recent advancements in HRI and intelligent manufacturing, achieving these advanced capabilities remains an open research problem in the literature. This paper aims to address these challenges.

Numerous studies on HRI have explored various aspects such as perception [2], [3], communication [4], role assignment [5], [6], task allocation [7], [8], etc. A common factor in these studies is the continuous collaboration that combines the dexterity and intelligence of human workers with the stability and endurance of automated machines. However, a more comprehensive approach to practical manufacturing processes involves developing methods that allow a fully automated

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robotic system to temporarily interact with humans. In such an HRI paradigm, a human worker may enter the production area and/or collaboratively contribute to the task [9], [10]. After this interim coexistence scenario, a swift automatic operation resumption can enhance the robustness and environmental friendliness of the manufacturing system. Motivated by these frontier industrial requirements, our paper investigates efficient robot control strategies to smoothly switch between a fully automatic mode (AM) and human-aware mode (HM) while continuing the sharing operation [11]. To switch from AM to HM, we adopt a safety-rated monitored operation stop in accordance with the ISO/TS 15066 standard guidelines. In this scenario, the robot halts if a human enters the collaborative workspace and resumes its tasks when the human leaves it [9], [12], [13]. Therefore, our study focuses on strategies to switch from HM to AM.

HRI can be classified into three categories: human-robot coexistence, cooperation, and collaboration. These classifications are based on factors such as space, contact, task, and context awareness [14]. The process of transitioning between these HRI types is known as autonomy level (AL) adjustment [15]. In this framework, an increase in the robotic system's AL correlates with a decrease in the necessity for human-robot interaction. Various strategies have been devised to accommodate different ALs, such as evaluating the effectiveness of humanrobot teams to determine the appropriate AL [16], adapting policies for joint dyadic tasks [17], adjusting AL for remote vehicle control [18], managing multiple interactions among humans, robots, and their environment [19], and optimizing production cycles by allowing robots to undertake alternative tasks while human operators are engaged in the process [20]. Despite these advancements, existing decision-making and trajectory-planning methods often overlook the nuances of switching from human manipulation (HM) to automated manipulation (AM) and lack the ability required for varied sequential tasks. Regarding the switch between manual and automatic modes, there have been different methods to deal with it. For example, [21] used temporal logic specifications to synthesize the switching. [22] leveraged behavior trees to coordinate humans and robots to complete a task. [23] developed an online robot execution time estimation approach to increase the efficacy of the human-aware controller. By contrast, our switching strategy is able to deal with long sequential tasks, which makes it more suitable for a complex manufacturing scenarios.

To implement AL adjustment, [15] proposed a method based on reinforcement learning that allows for automatic AL decrease when the system needs to adapt to workspaces of varying sizes or changes in the human operator's rewards. However, this method is tailored to a specific task (placing an object in a container), limiting its applicability to more complex tasks, such as those of a sequential nature. Role assignment is another strategy related to AL adjustment. For example, some approaches design two separate motion planning modules for leader-follower robots [6], while others utilize a weighting function to enable a continuous transition between these behaviors [5]. Nevertheless, most existing methods are designed for specific tasks and cannot be directly applied to the HM/AM transitioning scenario addressed in this paper, where a sequential manipulation task must be jointly performed by a human-robot team [24].

Resuming the operation of long-horizon tasks in AM is more complex than merely restarting a machine after a human intervention. This complexity arises from the sequential nature of such tasks, where the context and subtasks determine the overall progress. Unlike simple machine restarts, resuming a long-horizon task with HM requires analyzing the phases constituting the process. Achieving this necessitates developing an intelligent method to monitor task progress and identify the appropriate cut-point for effectively switching from HM to AM. Many works have utilized task scheduling or allocation to replan these types of sequential tasks. For instance, [25] proposed an algorithm to allocate tasks to robots, taking energy consumption into account. Similarly, [26] drew parallels between selecting chess piece moves and decision-making in human-robot collaboration assembly, while [27] introduced a task priority matrix to establish the correct priority order. Additionally, [28] designed a task-priority-based controller for a rescue robot applications. However, these methods are not sufficiently general to provide cut-points for AL adjustment in sequential manipulation tasks conducted by single/multiple robotic systems.

As a feasible solution to the aforementioned issues, this paper introduces a novel reactive task-planning method, making the following original contributions:

- We develop a general structure that decomposes and schedules sequential robotic manipulation tasks taking into account the impact of both human agents and other robots involved in the task.
- We develop an automatic/human-aware trigger algorithm capable of detecting human motion and assessing its contribution to task progress.
- We conduct a comprehensive experimental study to validate the proposed method using representative sequential manipulation tasks.

The rest of this paper is organized as follows: Sec. II formulates the problem; Sec. III and IV describe the proposed methodology; Sec. V presents the experimental results; Sec. VI gives final conclusions.

II. PROBLEM FORMULATION

Notation and Nomenclature. Bold capital, bold small, and italic small letters denote matrices, column vectors, and scalars, respectively. \land , \lor , and \neg represent the AND, OR, and NOT Boolean operators, respectively.

- *n*: number of human-robot agents in the system.
- N_k : number of subtasks for the *k*-th robot.
- *i*, *j*, *k*: indices of the subtasks, phases, and agents.
- S_k^i : *i*-th subtask for the *k*-th robot.
- \mathcal{A}_k , \mathbf{x}_k : *k*-th agent, and its pose.
- \mathbf{y}_k^i : home pose of the *k*-th robot when S_k^i ends.
- \mathcal{O}_k^i , \mathbf{o}_k^i , \mathbf{o}_k^{i*} : object manipulated by the *k*-th robot during \mathcal{S}_k^i , its pose, and its target pose.
- a_k^i : active coefficient of S_k^i for the k-th robot.



Fig. 2: Robot-centric task progress monitor and three-phase structure of subtasks.

- \mathbf{r}_k^i , $\bar{\mathbf{r}}_k^i$: phases' feature vectors for the *k*-th agent during S_k^i . The former uses the information related to the *k*-th agent and the latter uses the information related to the other agents.
- \mathbf{p}_k^i , $\hat{\mathbf{p}}_k^i$: phase priority of the *k*-th agent during the *i*-th subtask under AM and HM, respectively.
- m_k, m̂_k: task progress monitor of the k-th agent under AM and HM, respectively.
- h: automatic/human-aware mode trigger signal.
- d_k^{ij} : geometric features to describe the phases.
- **f**: environmental feature vector of the reactive tasks.
- Ω_H : human agent coefficient matrix.

Definition 1 (Substask S_k^i): In this work, a manipulation subtask S_k^i represents a *pick-and-place*-like behavior that contains a single physical engagement of the robot agent A_k with the object \mathcal{O}_k^i . The subtask S_k^i is composed of the following 3 basic manipulation phases: (1) *approach:* The agent A_k moves towards the object \mathcal{O}_k^i ; (2) *manipulate:* The agent physically interacts with the object (e.g., by grasping, pushing, holding, transporting, etc.); (3) *leave:* The agent A_k disengages with the object \mathcal{O}_k^i and returns to its home position.

For our developments, we consider a class of sequential manipulation tasks that can be represented as the concatenation of multiple subtasks. This task is conducted by single/multiple robotic systems in AM, and a human may enter the scene to (possibly) contribute/modify the task's progress. To command this robotic system to reactively (i.e., with awareness of the human's actions) perform the manipulation task, there are three problems that must be solved.

- Model. The total sequential manipulation task should be decomposed into multiple robot-centric action sequences, each of which is constructed with several subtasks.
- Context. The system should be able to compute the changes introduced to the task by the human.
- Control. The robotic agents should reactively adapt to the new context and complete the manipulation task.

In the following sections, we present our proposed methodology to address these problems, whose overall control architecture is conceptually depicted in Fig. 1.

III. TASK PROGRESS MONITOR OF SEQUENTIAL MANIPULATION TASKS

A. Three-Phase Structure of the Substask

The sequential manipulation tasks considered in this study consist of a series of basic actions, each serving distinct purposes. Some actions directly influence the configuration of objects, while others facilitate transitions between these physical interactions. The proposed **three-phase structure** is constructed with *approach*, *manipulate*, and *leave* to model this sequential procedure. These three phases are denoted for the *k*-th robot during the *i*-th subtask as S_k^{i1} , S_k^{i2} , and S_k^{i3} , respectively. The corresponding features are $d_k^{i1} = ||\mathbf{x}_k - \mathbf{o}_k^i||$, $d_k^{i2} = ||\mathbf{o}_k^i - \mathbf{o}_k^{i*}||$, $d_k^{i3} = ||\mathbf{x}_k - \mathbf{y}_k^i||$. Define the feature domain D_k for the action sequence of the *k*-th robot and D for the whole system as follows:

$$D_k = \left\{ d_k^{ij} | i = 0, 1, \dots, N_k, j = 1, 2, 3 \right\}, \quad D = \bigcup_{k=1}^{n-1} D_k.$$
(1)

We quantify these phases with the Boolean vector $\mathbf{r}_k^i = [r_k^{i1}, r_k^{i2}, r_k^{i3}]^\top \in \mathbb{R}^3$, which is computed based on geometric feedback as follows:

$$\mathbf{r}_k^i = \begin{bmatrix} \mathbf{1}(d_k^{i1}), & \mathbf{1}(d_k^{i2}), & \mathbf{1}(d_k^{i3}) \end{bmatrix}^\top$$
(2)

where $\mathbf{1}(x)$ is the Heaviside step function defined as:

$$\mathbf{1}(x) = \begin{cases} 1, & \text{if } x > 0, \\ 0, & \text{otherwise.} \end{cases}$$
(3)

The Boolean coordinates of \mathbf{r}_k^i activate under the following condition: (1) When the robot pose \mathbf{x}_k is different from the object's pose \mathbf{o}_k^i (this provides a signal that disables once the robot reaches with the object, and that is used for the *approach* phase); (2) When the object pose \mathbf{o}_k^i is different from the target object pose \mathbf{o}_k^{i*} (this provides a signal that disables once the object reaches the desired configuration, and that is used for the *manipulate* phase); (3) When the robot pose \mathbf{x}_k is different from the target from the home pose \mathbf{y}_k^i (this provides a signal that disables once the object reaches its respective home position, and that is used for the *leave* phase).

To properly synchronize the phases among different robots collaborating on the task, we introduce the vector $\vec{\mathbf{r}}_k^i = [\vec{r}_k^{i1}, \vec{r}_k^{i2}, \vec{r}_k^{i3}]^{\mathsf{T}}$, and which is computed with a functional Boolean operation g:

$$\bar{r}_k^{ij} = g(\Phi_k^i) : \mathbb{R}^{3(n-2)} \mapsto \mathbb{R}^3, \mathbb{R}^{L_{kij}} \mapsto \mathbb{R}^1$$
(4)

$$\Phi_k^i = \left[\mathbf{1}(\phi_1), \dots, \mathbf{1}(\phi_l), \dots, \mathbf{1}(\phi_{L_{kij}})\right]^\top, \phi_l \in D/D_k.$$
(5)

where L_{kij} is the number of the features relative to S_k^{ij} The vector $\mathbf{\bar{r}}_{k}^{i}$ is related to the geometric features of *approach*, *manipulate*, and *leave* of the other n-1 collaborating agents including human. Its purpose is to signal the k-th robot \mathcal{A}_k to complete its current phase based on task assignment or collaboration conditions. Specially, $\mathbf{r}_k^0 = \mathbf{0}_3$ as well as $\mathbf{\bar{r}}_{k}^{0}$ indicates the condition to start the first subtask in the collaboration. For example, consider the subtask of A_1 that requires to simultaneously move an object along A_2 . When the robot A_1 has already grasped the object, its approach phase should not end although the respective feature $r_1^{i1} = 0$; To complete this phase, the robot A_1 needs to wait for A_2 to grasp the other end, i.e., $\bar{r}_1^{i1} = \mathbf{1}(\|\mathbf{x}_2 - \mathbf{o}_2^q\|) \rightarrow 0$, therefore, the manipulate phase can begin, and both robots jointly move the object. Sec. V provides multiple examples of the construction of the two Boolean vectors \mathbf{r}_k^i and $\overline{\mathbf{r}}_k^i$.

B. Task Progress Monitor

Based on the proposed three-phase model, locate the task progress in the schedule at the phase with the highest priority. For that, we introduce the **phase priority vector** for each subtask S_k^i , for $i = 0, 1, ..., N_k$ and k = 1, ..., n-1 as follows:

$$\mathbf{p}_k^i = a_k^i \cdot \mathbf{\Omega}_k^i (\mathbf{r}_k^i + \bar{\mathbf{r}}_k^i) = [p_k^{i1}, p_k^{i2}, p_k^{i3}]^\top \in \mathbb{R}^3, \tag{6}$$

where

$$\Omega_{k}^{i} = \begin{bmatrix} \neg r_{k}^{(i-1)3} \land \neg \bar{r}_{k}^{(i-1)3} & 0 & 0\\ 0 & \neg r_{k}^{i1} \land \neg \bar{r}_{k}^{i1} & 0\\ 0 & 0 & \neg r_{k}^{i2} \land \neg \bar{r}_{k}^{i2} \end{bmatrix}.$$
 (7)

Specifically, we set $\mathbf{r}_k^0 = \mathbf{0}_3$. The diagonal matrix Ω_k^i guarantees that the previous phase is always completed before a new phase is activated. The Boolean coordinates of \mathbf{p}_k^i signify the active phase with the highest priority, denoted by assigning a value of 1. It is designed such that only one coordinate can have a value of 1 at any given time. This priority vector needs to be computed for all robots and subtasks. Upon evaluating the values of these coordinates, robot \mathcal{A}_k then proceeds to execute the phase with the highest priority.

To schedule all subtasks in the correct order, we introduce the **active coefficient**, which is computed with the following unified rules:

$$a_k^i = \begin{cases} \neg r_k^{(i-1)2} \wedge r_k^{i2}, & \mathbf{o}_k^{i*} \text{ is the latest target of } \mathcal{O}_k^i, \\ 0, & \mathcal{O}_k^i \text{ has a new target.} \end{cases}$$
(8)

The proposed active coefficient a_k^i guarantees that a subtask can only be activated if its goal has not been reached and its previous subtask has been completed. The subtask would be silenced from the whole sequence if the goal of the object related to it has been updated in the future.

Then, our task progress monitor in the equation below integrates all phase priorities into a long column vector. The only coordinate with a value of 1 is the specific phase that must be conducted in the action sequence of the robot.

$$\mathbf{m}_{k} = \left[\mathbf{p}_{k}^{1\top}, \cdots, \mathbf{p}_{k}^{i\top}, \cdots, \mathbf{p}_{k}^{N_{k}\top}\right]^{\top} \in \mathbb{R}^{3N_{k}}$$
(9)

This method allows the system to reschedule or extend the task by moving or adding phase priority vectors in the monitor.

IV. HUMAN-AWARE REACTIVE TASK PLANNING

A. Mode Switching from HM to AM

To switch mode at a proper timing, it is imperative to define the mode trigger, denoted as h. It can be designed to suit the specific needs of the system. In this paper, we focus on two key factors: safety and effectiveness, which are encapsulated in the design of the mode trigger as $h = h_s + h_e$.

For safety considerations, the speed of A_n is taken into account, resulting in $h_s = \mathbf{1}(\|\dot{\mathbf{x}}_n\|)$. This formulation ensures that mode switching to HM is activated (h = 1) only when a human agent is detected in motion. In terms of effectiveness, we evaluate the contribution of A_n to the manipulation goal. This is determined by examining the time derivative of features related to the "manipulate" phase. Specifically, we define that A_n contributes to the subtask when $d_k^{i2} < 0$ or any $\phi_l < 0$,

 TABLE I: Truth Table of Three Human Agent Coefficient

 Matrices for Reactive Tasks

(a) Ω_H^1	(b) Ω_H^2	(c) Ω_H^3
$f_1, f_2 \mid j_k^*$	f_1, f_2, f_3 .	$f_1, f_2, f_3, f_4 \mid j_k^*$
1, 1 1 1, 0 2 0, - 3	1, 1, - 1, 0, 1 1, 0, 0 0, -, -	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$

 $(l = 1, ..., L_{ki2})$. In essence, if A_n 's actions lead to a decrease in d_k^{i2} or any ϕ_l , the mode trigger is activated to switch to HM. Otherwise, HM remains inactive (h = 0), indicating that AM continues. To sum up, the mode trigger is

$$h = h_s + h_e = \mathbf{1}(\|\dot{\mathbf{x}}_n\|) + \bigvee_{l=1}^{L_{ki2}} \mathbf{1}(-\dot{\phi}_l) + \mathbf{1}(-d_k^{i2}).$$
(10)

Note that, if a phase depends on the NOT operation of a feature $(\neg \mathbf{1}(\phi_l))$ which means the opposite change of the feature (the distance gets larger) is required, the logic is $\dot{\phi}_l > 0 \rightarrow -\dot{\phi}_l < 0 \rightarrow \mathbf{1}(-\dot{\phi}_l) = 0 \rightarrow \neg \mathbf{1}(-\dot{\phi}_l) = 1$.

Next, the process of the mode switching from HM to AM is stated. The influence caused by A_n can be modeled by introducing a human coefficient agent matrix Ω_H to extend Eq. (6) and (9) to the following forms:

$$\hat{\mathbf{p}}_k^i = a_k^i \Omega_H \Omega_k^i (\mathbf{r}_k^i + \bar{\mathbf{r}}_k^i) = [\hat{p}_k^{i1}, \hat{p}_k^{i2}, \hat{p}_k^{i3}]^\top \in \mathbb{R}^3, \quad (11)$$

$$\hat{\mathbf{m}}_{k} = \left[\hat{\mathbf{p}}_{k}^{1\top}, \cdots, \hat{\mathbf{p}}_{k}^{i\top}, \cdots, \hat{\mathbf{p}}_{k}^{N_{k}\top}\right]^{\top} \in \mathbb{R}^{3N_{k}}$$
(12)

Given the phase priority computed by (11), during the mode switching, A_k should conduct the phase $S_k^{ij_k^*}$ to end the interrupted *i*-th subtask, then conduct $S_k^{i_k^*}$ that is newly activated after S_k^i has been completed, where

$$j_k^* = \operatorname*{argmax}_{j=1,2,3} \hat{p}_k^{ij}, \text{ and } i_k^* = \operatorname*{argmax}_i a_k^i.$$
 (13)

All robotic agents execute their cut-points in chronological order in the task progress monitor.

B. Reactive Task Design

Given that the environment has been altered by the human agent during HM, the robotic system must update its understanding of the environment and task progress to identify appropriate cut-points for switching back to AM. Consequently, it is crucial to select suitable environmental features that accurately describe the environment and aid in designing the necessary functions. Denote the distance between the human agent and \mathcal{O}_k^i as $d_n^{ki} = \|\mathbf{x}_n - \mathbf{o}_k^i\|$. In our study, we select four key features, that is, $f_1 = \mathbf{1}(d_k^{i2}), f_2 = \mathbf{1}(d_k^{i1}), f_3 = \mathbf{1}(d_n^{ki}), and$ $f_4 = \mathbf{1}(i - i_k^*)$. The truth values of these features indicate the following: S_k^i has not been completed, the k-th robot does not engage with \mathcal{O}_k^l , the human agent does not engage with \mathcal{O}_k^l , and a previous subtask is active again. In many cases, these features are essential for updating the system's understanding of the environment and determining the appropriate transition points between AM and HM.

Given specific combinations of these selected environmental features, various human agent coefficient matrices (introduced in Eq. (11) to describe the human influence) can be designed to achieve different desired reactive tasks. The complexity of the reactive tasks dictates the number of environmental features to be utilized. Each combination maps to a single phase, serving as a cut-point in the interrupted subtask. Boolean operations can then be applied to derive a specific solution for Ω_H . In our research, we present three examples, with their corresponding truth tables displayed in Table I.

1) The feature vector is $\mathbf{f} = [\mathbf{f}_1, \mathbf{f}_2]^\top$: When the interrupted S_k^i is incomplete $(f_1 = 1)$, \mathcal{A}_k should approach \mathcal{O}_k^i if \mathcal{A}_k is not engaged with \mathcal{O}_k^i $(f_2 = 1)$, and manipulate \mathcal{O}_k^i if \mathcal{A}_k is engaged with \mathcal{O}_k^i $(f_2 = 0)$. When the interrupted S_k^i is complete $(f_1 = 0)$, \mathcal{A}_k should leave. The solution is given by:

$$\Omega_{H}^{1} = \begin{bmatrix} f_{1}f_{2} & 0 & 0\\ 0 & f_{1}(1-f_{2}) & 0\\ 0 & 0 & 1-f_{1} \end{bmatrix}.$$
 (14)

2) The feature vector is $\mathbf{f} = [\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3]^\top$: Besides the above functions, the privilege of \mathcal{A}_n is taken into account. If both \mathcal{A}_n and \mathcal{A}_k are touching \mathcal{O}_k^i simultaneously $(f_2 = 0, f_3 = 0)$, \mathcal{A}_k should *leave*. If only \mathcal{A}_n is touching \mathcal{O}_k^i $(f_3 = 0)$, \mathcal{A}_k should *approach*. The solution is given by:

$$\Omega_{H}^{2} = \begin{bmatrix} f_{1}f_{2}f_{3} & 0 & 0\\ 0 & f_{1}(1-f_{2})f_{3} & 0\\ 0 & 0 & 1-f_{1}+f_{1}(1-f_{3}) \end{bmatrix}.$$
 (15)

3) The feature vector is $\mathbf{f} = [\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3, \mathbf{f}_4]^\top$: In sequential manipulation tasks, the success of a subtask often depends on previous subtasks. If a previous subtask is reactivated $(f_4 = 1)$, \mathcal{A}_k should redo the subtask after withdrawing the current one. Otherwise $(f_4 = 0)$, \mathcal{A}_k follows the scheduled subtasks. Further, when $f_4 = 1$, if \mathcal{A}_k is engaged with \mathcal{O}_k^i $(f_2 = 0)$, \mathcal{A}_k should approach the pose where \mathcal{A}_k gets engaged with \mathcal{O}_k^i to safely release \mathcal{O}_k^i before execute the active subtask, and if \mathcal{A}_k is available $(f_2 = 1)$, it should *leave*. The solution is given by:

$$\Omega_{H}^{3} = \begin{bmatrix} \omega_{1} & 0 & 0\\ 0 & \omega_{2} & 0\\ 0 & 0 & \omega_{3} \end{bmatrix}, \text{ where}$$

$$\omega_{1} = f_{1}f_{2}f_{3}(1-f_{4}) + (1-f_{2})f_{4}, \qquad (16)$$

$$\omega_{2} = f_{1}(1-f_{2})f_{3}(1-f_{4}), \qquad (3)$$

$$\omega_{3} = (1-f_{1})(1-f_{4}) + f_{1}(1-f_{3})(1-f_{4}) + f_{2}f_{4}.$$

V. CASES OF STUDY

It is assumed that the manipulation can be automatically conducted by robot, which is reasonable in a smart factory adopting HRI techniques for intelligent and resilient systems. To validate our proposed method, we conducted studies on three manipulation tasks: single-arm stacking, dual-arm assembly, and dual-arm packing. We used MediaPipe [29] to detect human gestures in the environment. For more details, refer to the video¹ and the attached document.



Fig. 3: The task progress monitor and the corresponding environmental features under AM of single-arm stacking task.



Fig. 4: The task progress monitor and the corresponding environmental features under AM of dual-arm assembly task. The top row is A_1 and the bottom row is A_2 .

A. Automatic Mode of the Tasks

The task progress monitor and the corresponding environmental features of three sequential manipulations are illustrated in Fig. 3, 4, and 5. In these figures, d(a,b) represents the Euclidean distance between a and b. Three distances correspond to r_k^{i1} , r_k^{i2} , and r_k^{i3} . In the Gantt-like chart, (ST)i-jin the row for \mathcal{A}_k represents \mathcal{S}_k^{ij} , which is the *j*-th phase of the *i*-th subtask for \mathcal{A}_k .

1) Single-arm stacking: In this case, there are two agents (n = 2): the robot A_1 and the human agent A_2 . Since the task is executed by a single arm, the collaboration is modeled as $\bar{\mathbf{r}}_1^i = \mathbf{0}_3$. This task involves placing blue blocks in a straight line at the bottom and positioning yellow blocks at the top between adjacent blue blocks, comprising a series of pick-and-place subtasks. The AM for single-arm stacking facilitates the addition of new objects in the environment by continuously detecting if any object is not at its target pose.

2) Dual-arm assembly: In this case, there are three agents (n = 3): the left robotic arm A_1 , and right robotic arm A_2 , and the human agent A_3 . This task aims to arrange yellow blocks in a specific order, ensuring the purple patterns form a heart. Following this, a green bar is threaded through the middle



Fig. 5: The task progress monitor and the corresponding environmental features under AM of dual-arm packing task. The top row is A_1 and the bottom row is A_2 .

of the yellow blocks, which are then pushed tightly together. Finally, two robotic arms move the green bar holding the yellow blocks to a frame. This task comprises heterogeneous subtasks, including pick-and-place and pushing actions.

The manipulation patterns of A_1 are pick-and-place, pickand-place, hold, push, pick-and-place; The manipulation patterns of A_2 are pick-and-place, push, pick-and-place. Define the function for contact detection at \mathbf{o}_k^i as follows:

$$c(\mathbf{o}_k^i) = \bigvee_{q=1, q \neq k}^n \mathbf{1}(\|\mathbf{x}_q - \mathbf{o}_k^i\|).$$
(17)

 $c(\mathbf{o}_k^i) = 1$ means there is at least one agent contacts \mathbf{o}_k^i . The collaboration is modeled as follows:

$$\begin{split} \bar{\mathbf{r}}_{1}^{0} &= \mathbf{0}_{3}, \quad \bar{\mathbf{r}}_{1}^{1} &= \mathbf{0}_{3}, \\ \bar{\mathbf{r}}_{1}^{2} &= \begin{bmatrix} 0 & 0 & \mathbf{1}(\|\mathbf{o}_{2}^{1} - \mathbf{o}_{2}^{1*}\|) \wedge \mathbf{1}(\|\mathbf{x}_{2} - \mathbf{y}_{2}^{1}\|) \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{1}^{3} &= \begin{bmatrix} 0 & c(\mathbf{o}_{2}^{3}) & 0 \end{bmatrix}^{\top}, \quad \bar{\mathbf{r}}_{1}^{4} &= \mathbf{0}_{3}, \quad \bar{\mathbf{r}}_{1}^{5} &= \begin{bmatrix} c(\mathbf{o}_{2}^{3}) & 0 & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{0} &= \begin{bmatrix} 0 & 0 & \mathbf{1}(\|\mathbf{o}_{1}^{2} - \mathbf{o}_{1}^{2*}\|) \wedge \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{y}_{1}^{2}\|) \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{1} &= \begin{bmatrix} 0 & 0 & \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{o}_{1}^{3}\|) \wedge \mathbf{1}(\|\mathbf{o}_{1}^{3} - \mathbf{o}_{1}^{3*}\|) \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{2} &= \mathbf{0}_{3}, \quad \bar{\mathbf{r}}_{2}^{3} &= \begin{bmatrix} c(\mathbf{o}_{1}^{5}) & 0 & 0 \end{bmatrix}^{\top}. \end{split}$$

3) Dual-arm packing: In this case, there are three agents (n = 3): the left robotic arm \mathcal{A}_1 , and right robotic arm \mathcal{A}_2 , and the human agent \mathcal{A}_3 . This task involves placing a long linear soft object into a compact box through sequential subtasks. Due to the object's elasticity, it tends to pop up from the box after being placed. Additionally, when the robot finishes placing the object and opens the gripper to release it, the gripper is pressed by the elastic object and the walls of the box, causing the object to be pulled out. To address this challenge, the robots collaborate by alternately performing pick-and-place and fixing actions to successfully complete the task.

The manipulation patterns of A_1 are pick-and-place, pickand-place, fix, fix; The manipulation patterns of A_2 are fix, fix,



Fig. 6: Stacking Case (f). (1) Robot movement: moving \mathcal{O}_1^4 to the target. (2)-(4) Human movement: take over \mathcal{O}_1^4 and put it at the target. (5) Robot reaction: leave \mathcal{O}_1^4 and reset.

pick-and-place, fix. The collaboration is modeled as follows (refer to the supplementary document for more details):

$$\begin{split} \bar{\mathbf{r}}_{1}^{0} &= \mathbf{0}_{3}, \quad \bar{\mathbf{r}}_{1}^{1} = \begin{bmatrix} 0 & c(\mathbf{o}_{2}^{1}) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{1}^{2} &= \begin{bmatrix} 0 & \neg \mathbf{1}(\|\mathbf{x}_{2} - \mathbf{o}_{2}^{1}\|) \wedge c(\mathbf{o}_{2}^{2}) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{1}^{3} &= \begin{bmatrix} 0 & \neg \mathbf{1}(\|\mathbf{x}_{2} - \mathbf{o}_{2}^{2}\|) \wedge c(\mathbf{o}_{2}^{3}) \wedge \mathbf{1}(\|\mathbf{o}_{2}^{3} - \mathbf{o}_{2}^{3*}\|) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{1}^{4} &= \begin{bmatrix} 0 & \neg \mathbf{1}(\|\mathbf{x}_{2} - \mathbf{o}_{2}^{3}\|) \wedge c(\mathbf{o}_{2}^{3}) \wedge \mathbf{1}(\|\mathbf{o}_{2}^{4} - \mathbf{o}_{2}^{4*}\|) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{0} &= \begin{bmatrix} 0 & 0 & \mathbf{1}(\|\mathbf{o}_{1}^{1} - \mathbf{o}_{1}^{1*}\|) \wedge c(\mathbf{o}_{1}^{1}) \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{1} &= \begin{bmatrix} 0 & \neg \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{o}_{1}^{1}\|) \wedge c(\mathbf{o}_{1}^{2}) \wedge \mathbf{1}(\|\mathbf{o}_{1}^{2} - \mathbf{o}_{1}^{2*}\|) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{2} &= \begin{bmatrix} 0 & \neg \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{o}_{1}^{2}\|) \wedge c(\mathbf{o}_{1}^{3}) \wedge \mathbf{1}(\|\mathbf{o}_{1}^{3} - \mathbf{o}_{1}^{3*}\|) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{3} &= \begin{bmatrix} 0 & \neg \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{o}_{1}^{3}\|) \wedge c(\mathbf{o}_{1}^{4}) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{4} &= \begin{bmatrix} 0 & \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{v}_{1}^{4}\|) & 0 \end{bmatrix}^{\top}, \\ \bar{\mathbf{r}}_{2}^{4} &= \begin{bmatrix} 0 & \mathbf{1}(\|\mathbf{x}_{1} - \mathbf{v}_{1}^{4}\|) & 0 \end{bmatrix}^{\top}, \\ \end{array}$$

where two typical collaborative behaviors are (1) $\bar{\mathbf{r}}_1^2$: \mathcal{A}_1 ends the *manipulate* phase of \mathcal{S}_1^2 and then starts the *leave* phase of \mathcal{S}_1^2 if \mathcal{A}_2 safely leaves \mathcal{O}_2^1 and there is an agent touching \mathcal{O}_2^2 ; (2) $\bar{\mathbf{r}}_1^3$: \mathcal{A}_1 ends the *manipulate* phase of \mathcal{S}_1^3 and starts the *leave* phase of \mathcal{S}_1^3 if \mathcal{A}_2 safely leaves \mathcal{O}_2^2 , there is an agent touching \mathcal{O}_2^3 , and \mathcal{O}_2^3 reaches its target position.



Fig. 7: The task progress monitor and features of single-arm stacking under HM. object-i is manipulated in S_1^i .

B. Experimental Results of Reactive Tasks

We conducted a series of interactions with the robotic system, designed for different purposes, to validate the effectiveness of our proposed method. The robots' reactions were guided by the human agent coefficient matrices, which were designed based on the feature vector $\mathbf{f} = [f_1, f_2, f_3, f_4]^{\top}$. The task progress monitors and three features for each of the three cases are shown in Fig. 7, 8, and 9. In these figures, $\lambda_1 = \|\mathbf{o}_k^i - \mathbf{o}_k^{i*}\|, \lambda_2 = \|\mathbf{x}_k^i - \mathbf{o}_k^i\|, \text{ and } \lambda_3 = \|\mathbf{x}_n^i - \mathbf{o}_k^i\|$. The black dashed lines represent the 0-1 boundaries. The detailed interactions are as follows.

1) Single-arm stacking: S-(a): A_2 approaches to pick O_1^1 while A_1 is also approaching O_1^1 . Then A_2 places O_1^1 at its target location. The reaction is that A_1 leaves O_1^1 and proceeds to execute S_1^2 . **S-(b)**: A_2 adds O_1^4 when A_1 is holding O_1^2 . The reaction is that A_1 resumes to *manipulate* \mathcal{O}_1^2 . **S**-(c): A_2 moves \mathcal{O}_1^2 away from its target place when \mathcal{A}_1 is moving \mathcal{O}_1^3 . The reaction is that A_1 approaches the initial grasped pose to release O_1^3 and then redoes S_1^2 . **S-(d)**: A_2 adds O_1^5 when \mathcal{A}_1 is placing \mathcal{O}_1^2 at its target. The reaction is that \mathcal{A}_1 leaves \mathcal{O}_1^2 . **S-(e)-1**: \mathcal{A}_2 hands over \mathcal{O}_1^3 to \mathcal{A}_1 . The reaction is that \mathcal{A}_1 approaches to grasp \mathcal{O}_1^3 . S-(e)-2: \mathcal{A}_2 leaves after \mathcal{A}_1 grasps \mathcal{O}_1^3 . The reaction is that \mathcal{A}_1 resume *manipulating* \mathcal{O}_1^3 . **S**-(**f**)-1: \mathcal{A}_2 takes over \mathcal{O}_1^4 from \mathcal{A}_1 . The reaction is that \mathcal{A}_1 leaves O_1^4 by opening its grippers. S-(f)-2: A_2 immediately places O_1^4 at its target. The reaction is that A_1 resume *leaving*. Two interactions of S-(f) are demonstrated in the Fig. 6. S-(g): A_2 holds O_1^5 to fix it while A_1 places O_1^5 at its target. The reaction is that A_1 resume *leaving*.



Fig. 8: The task progress monitors and features of dual-arm assembly under HM. object-k-i is manipulated in S_{k}^{i} .



Fig. 9: The task progress monitors and features of dual-arm packing under HM. object-k-i is manipulated in S_k^i .

2) Dual-arm assembly: A-(a): A_3 approaches to touch O_1^3 with the intention of taking over from A_1 . The reaction is that \mathcal{A}_1 leaves \mathcal{O}_1^3 by opening the grippers and \mathcal{A}_2 remains stationary. A-(b): \mathcal{A}_3 replaces \mathcal{A}_1 to push \mathcal{O}_1^4 to its target position while A_1 is holding O_1^3 . The reaction is that A_1 skips S_1^4 and proceeds directly to S_1^5 , and A_2 remains stationary. A-(c): A_3 first exits the environment and then moves away O_2^2 from its target. The reaction is that A_1 approaches to grasp O_1^3 and \mathcal{A}_2 leaves \mathcal{O}_2^3 to redo pushing \mathcal{O}_2^2 . Since the cut-point of A_1 occurs earlier than A_2 , A_2 waits in S_2^{32} for A_1 to finish S_1^{31} (grasping \mathcal{O}_1^3). After \mathcal{A}_1 completes \mathcal{S}_1^{31} , $\tilde{\mathcal{A}}_2$ proceeds to \mathcal{S}_2^{31} to place O_2^3 back in its initial position. Since the initial pose of O_2^3 is the same as the grasped pose, A_2 skips the redundant motions and directly performs S_2^{33} , then redoes S_2^2 to push O_2^2 to the target. This case demonstrates our task progress monitor can intelligently provide an appropriate solution (phase) for

execution from a long-term perspective based on the local solution provided by the human agent coefficient matrix.

3) Dual-arm packing: **P-(a)-1**: A_3 passes O_1^2 to A_1 . The reaction is that A_1 approaches to grasp O_1^2 and A_2 remains stationary. **P-(a)-2**: After A_1 grasps O_1^2 , A_3 exits the environment. The reaction is that A_1 resumes placing (manipulating) \mathcal{O}_1^2 at the target and \mathcal{A}_2 continues fixing \mathcal{O}_2^1 . **P-(b)**: \mathcal{A}_3 touches the O_1^2 while A_1 is moving it to the target. The reaction is that A_1 leaves by opening the grippers and A_2 remains stationary. **P-(c)-1**: A_3 replaces A_2 to fix O_2^1 . The reaction is that A_1 leaves to perform S_1^2 and A_2 waits for A_1 before *leaving* to reset. For A_2 , there are four stages (highlighted in shadows in Fig. 9(c)) for analysis: (1) black box: the human is moving, $h_s = 1$; (2) red box: $\dot{d}_1^{13} > 0 \rightarrow \mathbf{1}(\dot{d}_1^{13}) \rightarrow h_e = 1$; (3) green box: $\dot{d}_1^{21} < 0 \rightarrow \mathbf{1}(-\dot{d}_1^{21}) \rightarrow h_e = 1$; (4) yellow box: $\dot{d}_1^{22} < 0 \rightarrow \mathbf{1}(-\dot{d}_1^{22}) \rightarrow h_e = 1$. The HM ends when \mathcal{A}_1 places O_1^2 at its target, resulting in h = 0. This case shows the flexibility of our mode trigger in guiding multiple robots, balancing safety and task effectiveness. P-(c)-2: A_3 exits the environment while A_1 is holding O_1^2 at its target and A_2 is fixing O_2^2 . The reaction is that A_1 leaves O_1^2 to proceed to the next subtask and A_2 continues fixing (manipulating) O_2^2 before leaving.

C. Summary of Human Intentions

These HRI cases illustrate the essential functions required to appropriately respond to human agent intentions in realworld applications: (1) In cases S-(e)-1 and P-(a)-1, the human agent hands over objects to facilitate the robot's grasping at a better pose or with an enhanced view. (2) The human agent manipulates objects in advance to save time or enhance collaboration in cases S-(a), A-(b), and P-(c)-1- A_1 . (3) The human agent takes over grasped objects in cases S-(f)-1, A-(a), and P-(b). (4) In cases S-(e)-2, P-(a)-2, P-(c)-1-A₂, and P-(c)-2, the human agent passes by or exits the environment. (5) The human agent signals the system to redo a subtask to correct results or improve performance in cases S-(c) and A-(c). (6) The human agent aids by holding and fixing objects in cases S-(f)-2 and S-(g). (7) The human agent introduces new objects into the environment in cases S-(b) and S-(d). These cases demonstrate the diverse and critical roles a human agent plays in enhancing robotic performance and ensuring seamless collaboration in various manipulation tasks.

D. Comparison of Human Agent Coefficient Matrix

The environmental features and the results of three human agent coefficient matrices (Eq. (14), (15), (16)) are summarized in Table (II), (III), and (IV). Occasionally, these three matrices yield identical results. However, in complex reactive tasks, such as reactivating a past subtask (S-(c), A-(c)- A_2) and when the human agent intends to take over (S-(f)-1, A-(a)- A_1 , P-(b)- A_1), additional environmental features should be incorporated. This ensures that robots respond with greater intelligence and security, thereby improving the overall task success rate. In some cases, the system must determine the priority between the human agent (who always has the highest priority in the studied cases) and robots when both

 TABLE II: Comparison of Three Human Agent Coefficient

 Matrices – Single-Arm Stacking

Case	Feature	$\operatorname{diag}(\Omega^1_H)/j^*_k$	$\operatorname{diag}(\Omega_H^2)/j_k^*$	$\operatorname{diag}(\Omega_H^3)/j_k^*$
S-(a)	0110	[0 0 1]/3	[0 0 1]/3	[0 0 1]/3
S-(b)	1010	[0 1 0]/2	[0 1 0]/2	[0 1 0]/2
S-(c)	1011	[0 1 0]/2	[0 1 0]/2	[1 0 0]/1
S-(d)	0010	[0 0 1]/3	[0 0 1]/3	[0 0 1]/3
S-(e)-1	1100	[1 0 0]/1	[1 0 0]/1	[1 0 0]/1
S-(e)-2	1010	[0 1 0]/2	[0 1 0]/2	[0 1 0]/2
S-(f)-1	1000	[0 1 0]/2	[0 0 1]/3	[0 0 1]/3
S-(f)-2	0100	[0 0 1]/3	[0 0 1]/3	[0 0 1]/3
S-(g)	0000	[0 0 1]/3	[0 0 1]/3	[0 0 1]/3

 TABLE III: Comparison of Three Human Agent Coefficient

 Matrices – Dual-Arm Assembly

Case	Feature	diag $(\Omega_H^1)/j_k^*$	$\operatorname{diag}(\Omega_H^2)/j_k^*$	$ \operatorname{diag}(\Omega_H^3)/j_k^*$
$\begin{array}{c} A-(a)-{\cal A}_1 \\ A-(b)-{\cal A}_1 \\ A-(c)-{\cal A}_1 \\ A-(c)-{\cal A}_2 \end{array}$	$ \begin{array}{c} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \end{array} $	[0 1 0]/2 [0 0 1]/3 [1 0 0]/1 [0 1 0]/2	[0 0 1]/3 [0 0 1]/3 [1 0 0]/1 [0 1 0]/2	[0 0 1]/3 [0 0 1]/3 [1 0 0]/1 [0 0 1]/1

TABLE IV: Comparison of Three Human Agent Coefficient Matrices – Dual-Arm Packing

Case	Feature	$\mathrm{diag}(\Omega^1_H)\big/j^*_k$	$\mathrm{diag}(\Omega_H^2)/j_k^*$	$\operatorname{diag}(\Omega_H^3)/j_k^*$
$P-(a)-1-\mathcal{A}_1$	1100	[1 0 0]/1	[1 0 0]/1	[1 0 0]/1
$P-(a)-2-\mathcal{A}_1$ $P-(b)-\mathcal{A}_1$	1010	$[0 \ 1 \ 0]/2$ $[0 \ 1 \ 0]/2$	$[0\ 1\ 0]/2$ $[0\ 0\ 1]/3$	$[0 \ 1 \ 0]/2$ $[0 \ 0 \ 1]/3$
P-(c)-1-A ₁	0110	[0 0 1]/3	[0 0 1]/3	[0 0 1]/3
$P-(c)-1-A_2$	0100	$[0 \ 0 \ 1]/3$	$[0 \ 0 \ 1]/3$	$[0 \ 0 \ 1]/3$
$P-(c)-2-A_1$ $P-(c)-2-A_2$	1010	$[0 \ 1 \ 0]/3$ $[0 \ 1 \ 0]/2$	$[0\ 0\ 1]/3$ $[0\ 1\ 0]/2$	$[0\ 0\ 1]/3$ $[0\ 1\ 0]/2$

are interacting with an object, particularly considering human strength (e.g., robots should not release the object if it is too heavy). To address this, the weight and volume of objects to be manipulated should be factored into the priority determination.

E. Independence from Specific Actions

Due to the unpredictable nature of human agent movements, understanding human intentions or translating them into robotic actions is challenging. This unpredictability can cause disruptions in task progress tracking under HM. A significant advantage of the proposed mode switching strategy is its independence from specific tasks and actions. To highlight this advantage, in this section, all robots operate under HM, meaning AM is active whenever a robot is moving. Consequently, reactive tasks are executed in AM. The features used to construct the task progress monitor, mode trigger, and reactive tasks are based on temporal and spatial relationships (e.g., distances between agents and objects, distances between objects and their targets, completion status of a subtask) rather than specific actions (e.g., pick-and-place, push, fix). Based on the above discussion, our solution ensures that unrecorded actions do not lead to unexpected consequences, as validated by the experiments shown in Fig. 10.

The independence from specific tasks limits our strategy in terms of applications, as its effectiveness heavily relies on the system's capabilities under AM and the principles defined



Fig. 10: (1) The planned actions in AM (shown in Fig. 5): the left robot A_1 grasps and places the object \mathcal{O}_1^1 in the box, the right robot A_2 fixes the object \mathcal{O}_2^1 , A_1 leaves \mathcal{O}_1^1 without damage; Human intervention in HM: the human agent stays in the environment and keeps fixing after grasping and placing the object \mathcal{O}_2^1 in the box. (2) A_1 grasps \mathcal{O}_1^2 and places it in the box. (3) A_2 fixes \mathcal{O}_2^2 to help A_1 leave \mathcal{O}_1^2 without damage.

by users. For instance, if a human agent introduces a new object into the environment, the mode switching strategy will fail if the system cannot recognize the new object under AM. In such cases, the mode switching strategy becomes irrelevant. Therefore, it is essential for the human agent to either upgrade the AM capabilities or avoid expecting the robot to handle new objects to prevent this type of failure.

F. Ablation Experiments

In the existing works, when it comes to the execution of AM/HM mode switching (especially from HM to AM), the interaction is as simple as pick-and-place so that the robotic systems do not need intelligent reactions. In the more complicated tasks, the robotic system and the human operator can inflexibly wait for each other to finish the current action. Meanwhile, most research efforts typically focus on rescheduling entire tasks in response to critical failures. However, this approach is often unsuitable when only local adjustments are needed. Moreover, the solutions of switching paths or halting the robot to avoid collisions with human agents often neglect the implicit collaborative intentions of human agents. Furthermore, most works limits the interaction between the human operator with single arm. Therefore, the comprehensive and necessary HM/AM switching execution and the interaction between human operator with single/multiple robots remains an open problem. Our work addresses this gap by exploring more flexible and efficient execution strategies. We achieve this by identifying optimal timing cut-points through a proposed task progress monitoring monitor.

To sum up, there are three critical functionalities of our algorithm: (1) accurate task progress tracking considering the collaboration among robots and the randomness of the human agent's movements, (2) reactive task planner for flexible disengagement of the intervened subtask and a suitable timing cutpoint on the task progress monitor to realize specific customerdesigned effects, and (3) intelligent mode trigger balancing safety and efficiency to facilitate seamless switching between AM and HM considering human movements and intentions. This section firstly makes a comparison with other works about these three critical functionalities (as listed in Table V) and then presents a series of ablation experiments aimed at validating the efficacy and significance of our algorithm to facilitate seamless switching between AM and HM.

TABLE V: Comparison with Other Works

	Agent number		Intervened subtask		Mode trigger	
	Single	Multiple	Current	Past	Safe	Efficient
[30]	1	X	1	X	1	X
[31]	1	×	1	X	1	X
[32]	1	1	1	X	1	X
[33]	1	1	1	1	1	X
Ours	1	1	1	1	1	1



Fig. 11: The human agent A_3 disengages from replacing the left robot A_1 and initiates interaction with the right robot A_2 by reactivating its previous subtask. (2) With our method, A_1 regrasps the green bar in preparation for A_2 's redoing of the object pushing task. (3) Without accounting for the collaboration of robots, the system resumes operation at an inopportune moment, resulting in task failure.

The results of these experiments, illustrated in Fig. 11-14, serve to demonstrate the robustness and versatility of our proposed approach.

1) Accurate task progress tracking considering the collaboration among robots: As shown in Fig. 11, the human agent A_3 initially replaces the left robot A_1 to grasp the green bar, subsequently releasing it to displace an object, thereby triggering the reactivation of a prior subtask for the right robot A_2 . In the absence of our method: the green bar lacks a fixed endpoint following A_2 's gripper release, attributed to A_1 's inability to recover from intervention; during the reactivated subtask execution by A_2 (pushing the right yellow block towards the center), an unexpected bias occurs in the position of the green bar, indicated by deviations from vertical midlines; ultimately, A_2 fails to grasp the green bar. Leveraging our method for accurate task progress tracking considering the influence among the robots, A_1 adeptly regrasps the green bar by strategically timing its actions based on the task progress monitor, though at this stage, A_3 doesn't interact with it. This allows A_2 to relinquish control of the green bar and resume pushing the yellow block, ensuring smooth task continuity.

2) Reactive task planner for flexible disengagement of the intervened subtask: As shown in Fig. 12, the robot A_1 is tasked with placing \mathcal{O}_1^3 onto both \mathcal{O}_1^1 and \mathcal{O}_1^2 , while human agent A_2 moves \mathcal{O}_1^2 (already positioned at its target) aside. Leveraging our method to design reactive tasks based on as many relevant environmental features as possible, A_1 can return the grasped object to its initial position, a crucial step for successfully completing the interrupted task. In the absence of our method, the results obtained from the human agent coefficient matrices,



Fig. 12: (1) The robot A_1 is going to place \mathcal{O}_1^3 onto \mathcal{O}_1^1 and \mathcal{O}_1^2 , while the human agent A_2 moves \mathcal{O}_1^2 away. (2) Without our method, A_1 continues the intervened subtask leading to the task failure. (3) With our method, A_1 can properly disengage the intervened subtask to redo the reactivated subtask.



Fig. 13: (1) The human agent A_3 replaces the left robot A_1 to put the object in the box. (2) Without our method, a collision between A_1 and A_3 occurs. (3) With our method, A_3 can safely replace A_1 to work in the environment and the right robot A_2 can resume operation.

defined by two or three environmental features in **S**-(**c**), reveal that insufficient environmental features guide A_1 to resume manipulation within the interrupted subtask. This invariably leads to task failure, with O_1^3 toppling from the surface of O_1^1 .

3) Intelligent mode trigger balancing safety and efficiency:

Human motion detection is fundamental for ensuring safety in HRI tasks. As illustrated in Fig. 13, our mode trigger can activate HM and pause the robots to prevent collisions when a human agent is detected moving. However, it is inefficient for the robots to remain stationary as long as a human agent is detected, as a static human agent can contribute to manipulation or collaboration. As shown in Fig. 14, the left robot A_1 grasps the object and places it in the box while the human agent A_3 replaces the right robot A_2 to fix the object. In the absence of our method, the robots pause for safety whenever A_3 is detected, leading to a halt in the manipulation process. Additionally, it is impractical for all robots to switch modes simultaneously. Leveraging our method to assess a static human agent's contribution to manipulation or collaboration, each robot can switch modes at different times, resulting in an intelligent mode-switching process. In Fig. 14 (a-b), our mode trigger guides A_1 to resume its subtasks AM since the static A_3 does not contribute to its task, while A_2 remains in HM because A_3 is assisting A_2 by replacing it to fix the object. In Fig. 14 (c), our mode trigger guides A_2 switches from HM to AM because A_3 does not contribute to A_2 's current subtask.



Fig. 14: (1) The left robot A_1 grasps the object and places it in the box while the human agent A_3 replaces the right robot A_2 to fix the object. (2) Without our method, the robots pause for safety whenever A_3 is detected leading to a stuck manipulation. (3) With our method, the HM can be activated when a static human agent contributes to the task.

VI. CONCLUSIONS

In this study, we have introduced an innovative approach for seamlessly switching robotic systems from short-term humanaware mode (HM) back to long-horizon automatic mode (AM) while effectively executing customer-designed reactive tasks.

Initially, we proposed a comprehensive task progress monitor tailored for sequential manipulation that enables continuous tracking of task progress even amidst random human interventions. To achieve this, we devised a methodology to decompose complex tasks into robot-centric action sequences, subsequently segmenting them into homogeneous or heterogeneous subtasks based on manipulation-related core features. To model these subtasks, we introduced a three-phase framework comprising approach, manipulate, and leave phases, accounting for the influence of all robotic agents involved. We then designed a mode trigger algorithm to balance safety and efficiency, serving as a signal for AM/HM switching. Our mode trigger can activate HM not only in common occasions when a human is detected moving but also in collaborations when a static human contributes to the task. Additionally, we introduced a human agent coefficient matrix to facilitate the execution of reactive tasks during mode transitions, specifying the cut-point for AM activation and the subsequent subtask reactivation. Through extensive experimentation, we validated the efficacy and versatility of our proposed method across various sequential manipulation tasks executed by single/multiple robotic systems, accommodating diverse human intentions.

Our method excels in swiftly identifying suitable cut-points within the AM timeline with minimal computational overhead, enabling the robotic system to operate intelligently. However, it is worth noting a limitation of our approach: the feasibility of task completion post-reaction heavily relies on AM functionality. Future research avenues include exploring automated task segmentation based on multimodal data integration and leveraging large language models for enhanced task understanding.

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