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Task Planning and Execution for Human Robot Team Performing a Shared Task in a Shared Workspace

by

Tuly Hazbar

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science
in Electrical and Microelectronic Engineering

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Dedication

I dedicate this work to my family for their endless love and support.

Acknowledgments

I would like to thank my advisor Dr. Ferat Sahin for his guidance and support throughout my studies and research at RIT. I would like to thank my peers at the Multi-Agent Biorobotics Laboratory and CM Collaborative Robotics Laboratory for making my time at RIT a memorable learning experience. I would like to thank Shitij Kumar for his input and the great discussions about human-robot collaboration.

Abstract

Task Planning and Execution for Human Robot Team Performing a Shared Task in a Shared Workspace

Tuly Hazbar

Supervising Professor: Dr. Ferat Sahin

A cyber-physical system is developed to enable a human-robot team perform a shared task in a shared workspace. The system setup is suitable for the implementation of a tabletop manipulation task, a common human-robot collaboration scenario. The system integrates elements that exist in the physical (real) and virtual world. In this work, we report the insights we gathered throughout our exploration in understanding and implementing task planning and execution for human-robot team.

List of Contributions

- Designing and implementing a system capable of autonomously tracking and performing table-top object manipulation tasks with a human.
- Outline the main elements of an HRC testbed that enables a human and a robot to perform a shared task in a shared workspace.
- Leveraging the concept of Digital Twin in human robot collaboration scenario.

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Chapter 1

Introduction

Robotics applications are becoming more prevalent in many industries such as manufacturing, military, and healthcare, to name few. This has led to making the idea of robots sharing the human workspace more common. To support this idea, a new type of robots, Collaborative Robots, have emerged.

1.1 Collaborative Robots

Collaborative robots are specifically designed for direct interaction with humans. These robots incorporate features that make them safe to work alongside humans. For example, Sawyer, the collaborative robot by Rethink Robotics, has Series Elastic Actuators that directly measure torque at every joint to detect and respond to contact [2]. Even in the case of contact, these robots are designed with no sharp and all-round shapes, which allow them to disperse the pressure of an impact. They are easy to program. The force and speed settings can be easily adjusted and programmed to suit the application. For example, these robots can be programmed to operate with slower speeds when they are near a human or go a little faster in the absence of the human operator in the workspace. Hand guiding or path teach is another feature of collaborative robots. It allows the human worker to rapidly and intuitively interact and program the robot to do a certain task.

1.2 Degrees of Collaboration and Types of Work-cells

Collaborative robots introduced changes in the way we think about how robots can interact with humans and share a workspace. Figure 1.1 describe four levels of human-robot interaction in a workspace. Tradition industrial robots are not meant to interact with humans; therefore, fences are used to separate traditional industrial robots from workers. With coexistence, the human and the robot work next to each other. However, their workspace does not overlap, and the concept does not provide for contact with the robot. In this type of interaction, robots are equipped with sensors that can detect collisions so they can slow down or alter their path to avoid collisions, then restart on their own, limiting the need for human interaction. Synchronized interaction is when robots share the workspace with humans in turns, allowing only either the human or the robot to occupy the workspace at a time. Cooperation is when the human and the robot share a common workspace, but do not work hand in hand during each work step. Instead, there is a defined intervention zone in which the robot decreases its speed as soon as the human enters. With collaboration, the human and the robot work in a shared workspace. Contact between the two is permitted, and the velocity is adapted so that safety is ensured at all times. Collaborative robots can work with humans in the same parts. However, improved environmental awareness provides better safety and makes it easier to deploy alongside human workers [3].

In this research, the type of interaction of interest is collaboration. The human and the robot will share a workspace, and they have a set of overlapping workpieces to manipulate.

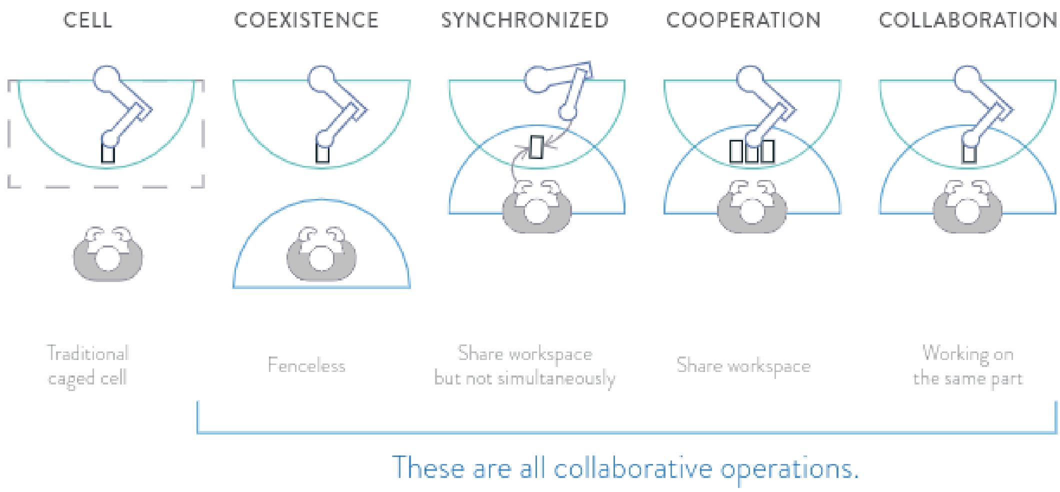

Figure 1.1: Degrees of Collaborative Operation [1]

1.3 Why Human-Robot Collaboration

In industry, some tasks are hard to be fully automated, and for industries that undergo frequent changes in their production line, reconfigurability and adaptability are of great importance. By teaming a robot with a human, the collaboration benefits the decision-making ability that comes from the human ability to adapt, and integrate prior knowledge across domains whereas the robot ability to execute some actions with high speed and precision can complement human skills. The particular differences between humans and robots make them especially well-suited to explore complex tasks together as a team.

1.4 Gaps in Human-Robot Collaboration

However, counting on the human's decision-making skills by having the human plan for his/her own actions and the robot's actions does not make the robot a collaborator but a recipient of human commands. This type of interaction becomes a turn-taking based, which has many disadvantages towards the overall performance of the team; one apparent drawback is the decrease in productivity of the team.

Although collaborative robots have become safe and reliable enough to operate close to humans, human-robot teaming still lacks many aspects that make the collaboration successful, especially when compared to a human-human team executing a shared task. Typically, when a group of two humans works together, they display a high level of action coordination, and on the fly work distribution and scheduling. One aim of the HRC research is to reach this level of coordination referred to as fluency in human-robot teams [4]. In such a team the two partners are capable of planning their own actions, and coordinate their execution with one another. Similar to other research in HRC, we believe that the transition from robots as recipients of human instructions to robots as capable collaborators hinges around their ability to select their own action and coordinate its execution with a human partner[5].

1.5 Problem Description and Motivation

While robots are becoming more widespread across industries; I envision a future where human-robot collaboration will be essential. The success of this type of collaboration hinges on the ability of robots to integrate with humans as teammates. The goal of my research is to enable a robot to be a teammate where it fluently collaborates with a human partner in performing a shared task in a shared workspace.

I am particularly interested in an HRC scenario where the team consists of a single human and a single robot. The team members will follow the equal partner teamwork model, where each team member makes decisions on which action to take next and coordinate the action execution with the other team member. This teamwork model follows a decentralized decision-making approach adopted by systems and human teams to reduce delays associated with escalating the decision-making to a centralized unit, improve the quality of decisions due to the rich local context of the problem and taking into account the facts that might change during the waiting period for a decision to be made by a centralize unit.

The HRC scenario this research studies, is where the robot is expected to achieve multiple object manipulations by taking into account, at every stage, the actions of the human partner and the changes he/she introduces in the workspace. The robot must be able to move and act in a safe, efficient, and fluent way.

In our experiment, the human and the robot are given a task where they have to put a set of workpieces in a given specific arrangement. The human and robot manipulate an overlapping set on workpieces without restrictions or agreement on who can manipulate which workpiece before the experiment starts. However, there is a constraint that the human and robot cannot simultaneously choose to manipulate the same workpiece. Given a set of actions to be performed (to pick, to manipulate, to place) and the set workpieces on which the actions are performed on, the robot should select workpiece and perform the action autonomously but being aware of the human actions and the changes in the workspace.

Chapter 2

Background Literature

This chapter provides background information and literature review of related research in task planning and execution for a human-robot team. It summarizes some of the existing practices for human-robot collaboration setups in research and industry. A brief discussion of similar and related research of HRC platforms is also presented.

2.1 Human-Robot Collaborative Tasks

The rich literature on human-robot collaboration is mostly concerned with performing physical tasks. A collaborative task can be as simple as setting up objects on a table [5], to complex tasks, like assembling furniture [6]. The task is often specified by a shared plan or learned from a human expert [7]. What makes a task simple is the fact it does not have a fixed order of action selection; however, a complex task can have dependencies of actions. Also, some tasks require more than one agent to be performed, like carrying a table [8].

2.1.1 Fixed vs. Any-order Actions

In a task, subtasks can have different dependencies between them. They can have relations that enforce a fixed order of actions. These dependencies can mean that one action must be completed before another action, influencing the order of action selection [9]. Fixed order actions tasks include the construction of furniture [6], building structures, and cooking tasks [10]. An example of any-order action tasks can be cleaning up a table [11].

2.1.2 Independent vs. Joint Action

Independent action is one that can be performed by a single agent, for example, picking and placing an object [5]. In contrast, joint action is where two agents are needed to perform the action. For example, a joint action rakes place when one agent needs to hold a part while the other performs the construction [12].

In this work, I focus on common HRC task that falls under table-top manipulation. This task requires the selection and manipulating of a set of workpieces to satisfy a given final workpieces arrangement. Our task consists of selecting workpieces in any-order, and the actions can be performed by any teammate independently.

The HRC scenario this research studies, is where the robot is expected to achieve multiple object manipulations by taking into account, at every stage, the actions of the human partner and the changes he/she introduces in the workspace. The robot must be able to move and act in a safe, efficient, and fluent way.

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2.2 Requirements For Improving Human-Robot Collaboration

In most HRC scenarios, it is insufficient to plan a single sequence of actions and blindly execute it at run-time. Having a human in the loop results in dynamic and partially unknown environments where the robot needs to adapt to it. Therefore, the robot has to exhibit adaptive task planning. The team members typically act in real-time; therefore, they must make decisions on the fly. Researcher in the field focused on improving different aspects of HRC. They have set different constrains when performing task planning and action selection to improve a specific aspect of the collaboration. For example, favoring actions that avoid plans where the human spends a lot of his/her time being idle [13], plans focus on reducing the cognitive and the physical load on the human [10] and avoiding plans which can be misinterpreted by the human [14].

Research in HRC is inspired by humans ability to collaborate on tasks. This suggested having multiple layers integrated with each other to mimic human cognitive abilities. One clear fact is that the robot needs some individual and collaborative cognitive skills similar to what we human have to collaborate with a human successfully. Some of these cognitive skills that have been implemented on robots are geometric reasoning and situation assessment based on perspective-taking [15] and affordance analysis [16]; acquisition and representation of knowledge models regarding the other teammate [17], the environment and the task; and explicit and implicit communication between agents [18]. However, integrating one or more of these modules as a single system architecture has been a challenge [19].

Perceiving humans is a topic that has been the focus of robotics for many years, especially for safety purposes. But when put in HRC context, perceiving a human as a dynamic obstacle that needs to be avoided for his/her safety is not enough. A key element that makes humans great collaborators is their ability to recognized and anticipate the intentions and actions of their teammates. Much of work in the field of HRC has been dealing with estimating human poses [20], and determining their gaze [21] as a mean to detect the human activity and intention. This can be leveraged to coordinate the robot actions selection and execution with the human actions seamlessly. Full human action and activity recognition is a task that requires knowledge and reasoning both on high-level facts like goals, intentions, and plans, as well as bottom-up data from human and object motions[22]. Similar to other work in the literature [23], we recognize human actions through the human arm motion within the workspace to enable task planning and execution.

2.3 Task Planning and Action Selection

One major research thread in human robot collaboration is task Planning. Task planning is a key ability for intelligent systems, increasing their autonomy through the construction of sequences of actions to achieve a final goal. Action selection is a way of characterizing the most basic problem of intelligent systems: what to do next. However, when working in a team, planning for the sequence of actions without taking into consideration the actions of the other team members is not enough, especially when collaborating in achieving a common task. In the context of human robot collaboration,task planning faces many challenges. One challenge is the ability to handle state and goal updates from the changing world while execution. This ability is referred to re-planning. Another challenge is the use of belief models of the human teammate to enhance the plan.

Below we describe various approaches to action selection used in artificial intelligence systems in general. Action selection mechanisms can be divided into two main categories: classical planning, dynamic planning and some approaches are hybrid of both.

- **Classical Planning:** With this approach, an agent chooses what to do next by computing an optimal plan (a sequence of actions), and then execute that plan. This approach separates planning and executing as they do not take-place simultaneously. This approach requires describing the robot environment, all potential actions the agent can preform and all of the agent goals in some form of predicate logic. This approach is slow in real-time planning and it is still unlikely to produce optimal plans because reducing descriptions of the environment to logic is a process prone to errors[24].

- **Dynamic planning:** Dynamic planning methods is characterized as a system that performs action selection with simple look-up at the current environment every instant for the best action to perform right then. Sometimes it is combined with classical planning, leading to a so-called hybrid approach. Dynamic planning techniques are extremely popular in real-time interactive applications like computer games because they cope well with environments that are dynamic and unpredictable in nature. There are several approaches to implement dynamic planning. One technique relies on *Condition Action Rules*, where the conditions are typically boolean, and the action either performed or not based on the defined conditions. The rules are organized in flat or in hierarchical structures, for example, decision trees. The *Finite State Machine (FSM)* is another type of modeling an intelligent system behavior. A typical FSM consists of a set of states and transitions between these states. The transitions are condition–action rules. One state of the FSM is active in every instant, and its transitions are evaluated. If a transition holds, it activates another state. FSMs require enumerating all possible states for the agent, which might be not easy to do for some applications. An FSM state can also be broken down into substates, and a hierarchical FSM (HFSM) can be exploited. Both action-condition rules and FSMs can be combined with either stochastic preconditions. In this case, the conditions, states, and actions are no longer boolean or deterministic; rather, they become probabilistic. Consequently, resulting behavior can be smoother. However, evaluation of such conditions can introduce delays compared to the evaluation of their discrete counterparts [24].

Chapter 3

Proposed Method

This chapter explains our approach to enable the robot to collaborate with a human in preforming a joint task within a shared workspace. We created a system that integrates four different modules namely: Robot Perception, Robot Knowledge and Robot Intelligence including Action Selection and Execution. The way these modules are integrated is depicted in Figure 3.1. It is worth pointing out that articulating multiple independent software modules in one coherent robotic architecture is not only a technical challenge, but also a design and architectural challenge.

3.1 Robot Perception

The robot teammate should be aware of the human partner and the task workpeices. Through sensing, the robot will have perception of these two components. These are important prerequisites to establish a human robot collaboration system.

3.1.1 Perception of the human arm trajectory

Human arm position tracking is crucial for our HRC scenario. This information will be utilized by other parts of the system to calculate and define the following: (a) human-workpieces euclidean distances to infer the human goal (b) human current arm position for safety purposes.

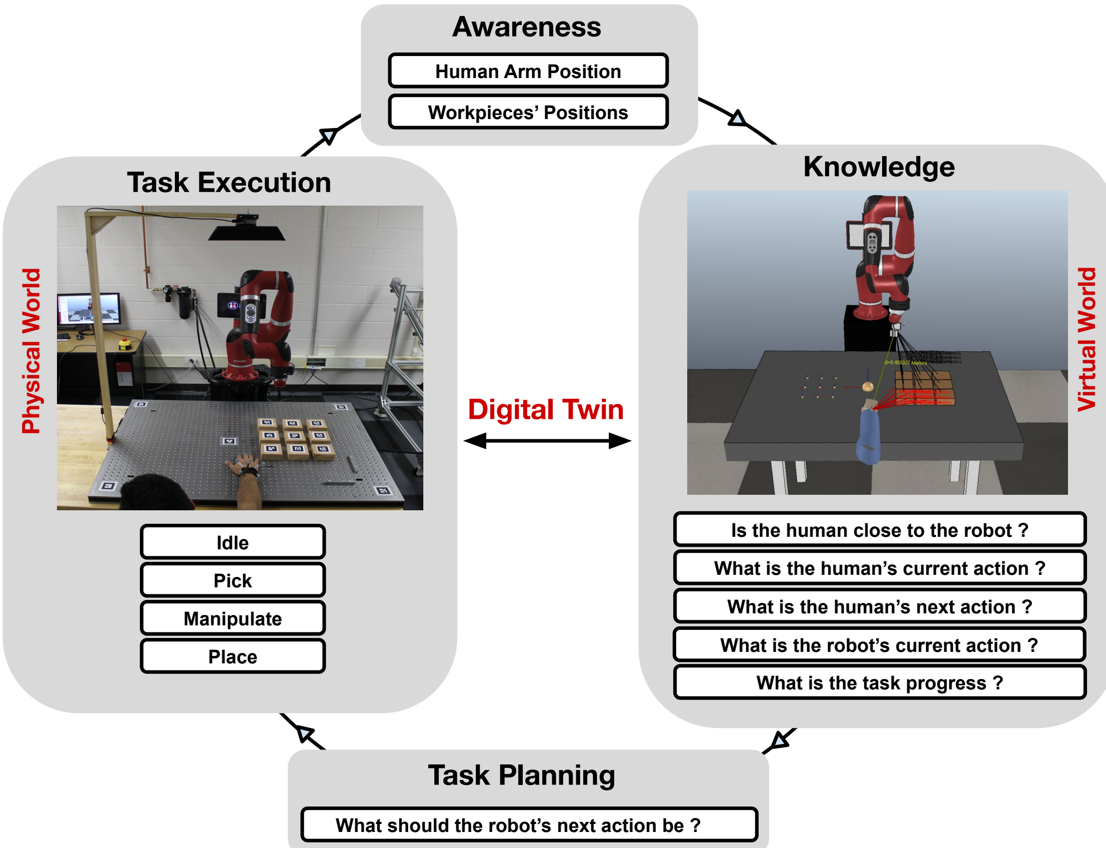

Figure 3.1: Overview of the HRC cyber-physical testbed. It is composed of 4 main modules. These modules are integrated through the digital twin concept.

3.1.2 Perception of the workpieces

For tabletop manipulation task, it is essential to know the position of the workpieces in the workspace at all times. The robot uses this information for motion planning and defining task progress to select its action.

3.2 Robot Knowledge

In general, the fundamental elements that characterize an HRC scenario include the following: the agents, the work environment, and the workpieces. Using the information gathered through perception is not enough to help the robot make decisions on the actions it needs to preform to achieve the task final goal. This is due to the fact that the perception module gathered information about the HRC elements in isolation. For example, the output of the perception module can be the human arm and workpeices positions without any information which workpiece the human is manipulating. This type of knowledge is vital for robot autonomy, enabling collaboration, and enhancing the collaboration quality.

The robot needs to have an understanding of the changes in the environment. The type of data it gathers through perception is not enough to support it is process of decision making. The human is far superior to its robot counterpart in terms of forming connections and contextualising the data it gathers through the human senses. It is important to compensate for the unbalance of capabilities as a first step towards studying and improving any aspect in any HRC scenario. For this purpose, we need to have a setup that supports studying and implementing the strategies we envision for improving task planning and execution for human-robot team.

In this research the knowledge the robot creates can be divided into two levels: low and high level knowledge as shown in figure 3.2. The low level knowledge come through two different sources: the task information and the perception module. The task information is a static type of information that is loaded once at run-time. It include scenario-specific knowledge like the number of workpeices to be manipulated and their final placement locations in the workspace. The second part of the knowledge is acquired from perception module at run-time. This type of knowledge is crated and shared during task planning and execution. These data sets are dynamic and depend on the perception data. At this level simple distance and area calculations are preformed to find a relations between the HRC elements mentioned earlier. This takes place in the digital twin of our setup.

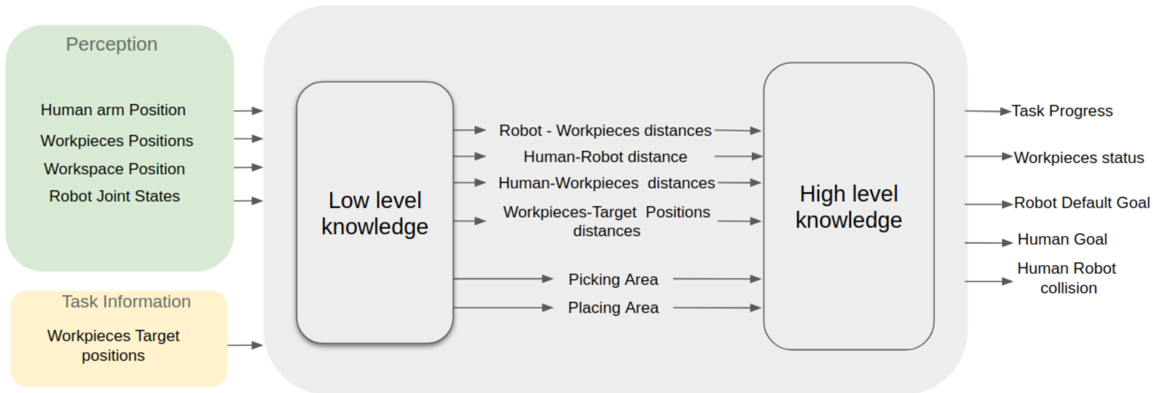

Figure 3.2: Two levels of knowledge: high and low. The input to the knowledge module is the data acquired through perception at run-time and the task related information acquired once when starting the collaboration. The output of the knowledge module is high level information utilized by the robot to make better decisions.

We choose to leverage the concept of **Digital Twin** in forming a comprehensive knowledge about all the components that make up the HRC scenario through the use of the physics engines, and the calculation modules available in the virtual platform. This facilitates relating both the human and the robot activity with each other in real time. Also, depicting the agents' interaction with the workpieces and the overall task progress.

We believe this explicit integration of all components in a virtual platform is useful for the following reasons:

- A virtual representation of the workspace can be utilized to set spatial limits in the virtual world that are necessary for the robot during the interaction. Also, define the description of the end goal of the shared task in the virtual world that is necessary for the robot to complete the task — for example, markers on the target locations of where the workpieces need to be placed. This is used by the robot for path planning. We can eliminate the need for adding markers in the physical world, which is specifically harder to control in an industrial setting compared to a lab environment.

- Real-time HRC diagnostic through visualizing and monitoring the state of the human, the robot, the workspace, and the workpieces. This can serve as a way to aggregate and organize the data acquired in a way that can support researchers in the process of analyzing the robot behavior during and post the interaction.

- Although the virtual world does not account for the uncertainties of the real world, virtual testing is proven to be a powerful approach for testing HRC algorithms being developed. Having a realistic data of the human arm trajectory and actions when performing the task can be used to compare different robot behaviors against it virtually. This gives valuable insight into the robot behavior being developed through in-depth analysis while maintaining human safety.

For the reasons mentioned above, we believe the digital twin is a vital factor in supporting the design, build, control, monitor, and evaluation of an HRC scenario. We consider it one of the main elements in our HRC testbed.

The high level knowledge takes the results of the calculation performed by the low level knowledge and transform it to a higher level understanding of the current situation regarding the human and the task. The following is a description of the output of the higher level knowledge module:

- **Human Location:** This information is the spatial relation between the human arm and the workspace areas. The workspace has two main areas: 1) the picking area: where the un-arranged workpieces are located. 2) the placing area: where the final arrangement of the workpeices take-place. The robot will be able to know if the human arm is within the picking area or the placing area.

- **Human Goal:** We refer to the workpiece the human is intending to manipulate as a human goal. Recognizing the human goal is vital in the robot goal selection process. In our HRC scenario, it is based on the Euclidean distance between the human arm position against the workpieces in the workspace. A probabilistic approach can be used to assign probabilities on the workpieces the human is intending to manipulate; the robot can utilize this information in its goal selection process.

- **Robot Default Goal:** This is the workpiece closest to the robot end effector. The euclidean distance between the robot's end effector and the workpieces that need to be manipulated is calculated and the work piece with the minimum distance value is set to be the robot default goal.

- **Workpieces Status:** This information relates the current work piece location in workspace and whether is needs to be manipulated or not. The work piece during the task can have one of these four different status: being manipulate by the human , or by the robot, in its final placement location or needs to be manipulated.

- **Task Progress:** This information tells how many workpeices need to be manipulated to achieve the final task goal.

The set of knowledge mentioned above is computed by a dedicated process that continuously runs in the background. This is importance for our HRC scenario since the robot behavior is event-based. another approach could be computing a specific set of knowledge when needed but this might introduce some delay.

3.3 Robot Intelligence

The robot needs to select and execute -on the fly- an action from a set of possible actions taking into consideration the human activity. The action can be either external (i.e., to operate on the environment), or internal (e.g.,evaluate a new set of rules). The robot ability to plan for its own actions takes place on two levels of planning: High and low level planning. In high level planning the robot reason about which workpiece it should manipulate which is an internal action. In low level planning the robot selects the actions needed to successfully and safely place the workpiece in its finial location and this is when the robot actions causes changes in the environment. The following sections explain these two levels of planning.

3.3.1 High Level Planning: Robot Goal Selection

With the use of the acquired knowledge, the robot can decide which workpiece it should manipulate. The selection process will be in favor of minimizing the disruption of human activity when sharing the workspace and workpieces to be manipulated. In other words, goal-selection algorithm is a conflict resolution mechanism to avoid the scenario where both teammates try to manipulate the same workpiece. Therefore, the robot should have the ability to reason about which workpiece the human is going to choose to manipulate, refer to as the human goal. Then the robot should eliminate the human goal from the set of workpieces it can manipulate, and choose the closest workpiece relative to its current end effector position. Procedure 3.3.1 presents the algorithm used to computes the robot goal.

Procedure 3.1 Robot Goal Selection

```
Input: HumanGoal, TaskProgress, WorkpieceStatus
Output: RobotGoal
if TaskCompleted = True then
    Terminate Execution
else
    for workpeices do
        Get robot-workpiece distance
        Check this workpiece status
        if WorkpieceStatus = InPickingArea then
            Add to robot possible goals
    Get HumanGoal
    Eliminate HumanGoal from robot possible goals
    Find the workpiece with minimum robot-workpiece distance from the robot possible goals
    return RobotGoal
```

3.3.2 Low Level Planning: Robot Task Planning and Execution

After goal selection, the robot starts executing a sequence of actions needed to place the workpiece in the location defined by the task's end goal. During execution, the robot should still be aware of the human partner actions and arm position within the workspace to adapt to changes that require the robot to change its action on the fly. The distinction between task planning and execution at this level is blurred since planning, and execution occur intermixed at various levels, but we will attempt on separating them in our explanation for clarification purposes. At this level, there are certain expectations on the robot behavior that has to be met regarding its action selection and execution. The robot should be reactive to events taking place in its environment. The robot should be able to prioritize some actions over some others. A lower priority task should be preempted if a higher priority task needs to be preformed. For example, an action towards preventing collision with a human should be at higher priority compared to performing an action towards the completion of the task.

However the preempted task should resume as soon as the higher priority task gives the control back to it. The robot behavior should support concurrency, where multiple tasks can run in parallel. While Finite State Machine make a good approach in in programming reactive systems, It is difficult to represent complex systems with classical FSM models. This is due to the flatness of the state model and its lack of support for concurrency. We use a formalism that combines Concurrency with Hierarchical State Machines introduced in [25].

The simplest state machine contains no sub-state machines and no transitions. Its activity function computes output values based on input values and local variables. More complex state machines contain sub-state machines and may be execute sequentially or concurrently. In a concurrent state machine, there are no transitions - all the sub-state machines are active concurrently whenever the parent state machine is active. The parent state outcome is determined by the outcome policies of its sub-states defined at construction. In a sequential state machine, exactly one sub-state machine is active at any instant. Transitions transfer control from one sub-state machine to another. A state machine's activity function is responsible for computing output values based on the values returned from sub-state machines. The activity function for a sequential state machine is often quite simple; output values are computed based on the output values of the single active sub-state machine. On the other hand, the activity function for a concurrent state machine must compute a set of output values based on the output values of multiple active sub-state machines.

In our HRC scenario the robot needs to preform basic pick and place actions. Actions are parametrized with a workpiece to be picked and a location at which the workpiece needs to be placed. The workpiece choice is based on the output of the high-level planner explained in subsection 3.3.1 and the location of workpiece placement is acquired form the priori knowledge described in section 3.2. For picking, the robot needs to follow this sequence of actions: *Get the location of the workpiece*, *Move to the picking area*, *Approach the workpiece*, *Close gripper* and *Retract*. Similar routine applies to placing the workpiece: *Get the workpiece placement location*, *Move to the placing area*, *Approach the workpiece placement location*, *Open gripper* and *Retract*.

At this level of planning, the robot also reasons about the safety of the human partner when executing the actions. In our system, the robot chooses to be idle when the human-robot minimum distance is below a certain threshold and then resume its action until the distance is above that threshold. This behavior is modeled through concurrency state. In such state, two sub-states are activated, one for monitoring the human-robot distance and other for preforming the action. the concurrent state terminates when the monitoring state indicated the threshold being violated that cause the robot to transition to the idle state.

Chapter 4

Implementation

To study joint task planning and execution dynamics that take place when varying the type of task and the robot goal selection process, I develop an end-to-end system for joint task planing and execution that allows a robot to perform object manipulation actions as well as monitor the execution of the same actions by a human. This section, presents the details of the system.

4.1 Platform

Our system is built on the Sawyer, Rethink Robotics research robot. Sawyer has one seven degrees-of-freedom and 1260 mm reach giving it a large workable space for tabletop manipulation tasks. Sawyer is inherently safe, designed to work alongside people, and certified that it meets ISO requirements by TÜV Rheinland (ISO 10218-1:2011 and PLd Cat. 3). Due to the sensitive torque sensors embedded into every joint, Sawyer's built-in force sensing capabilities allow it to work precisely, while operating safely around humans. By controlling both force and position, Sawyer controls the amount of force it applies to different directions, the same way people do when performing tasks. Most of the system was designed independently of the platform while the action execution part was designed for and with Sawyer robot. The following sections explain each module and how they are integrated with each other with each other.

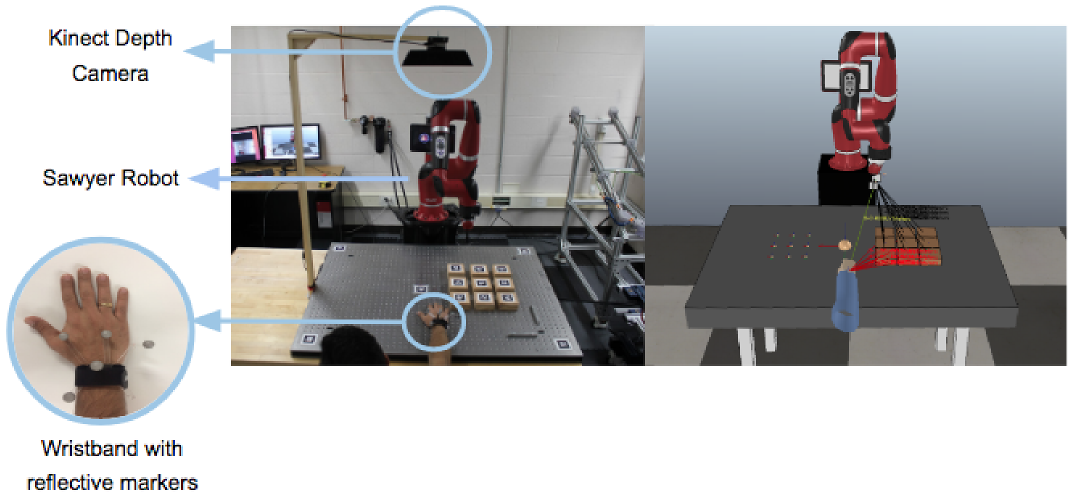

Figure 4.1: Experiment setup includes the sensors we use for perception, the robot and the workpeices. We also create a digital replica of the physical-world of the experiment setup

4.2 Perception

In our system, the human arm position is tracked using the OptiTrack 3D tracking system. OptiTrack tracks the human arm using cameras with low-latency and high precision. This system requires the human partner to have an on body markers; therefore the human wears a wrist band shown in Figure 4.1 on the hand he/she prefers to use while performing the task. We are particularly interested in tracking the current pose of the human arm relative to the world frame.

To determine the workpieces poses in the workspace, each workpiece is labeled with unique 2D fiducial marker attached on top on it. We have used ALVAR package for detecting and estimating the pose of the markers therefore the workpieces. A Kinect, RGB-D sensor, is mounted in a way that it captures the top view of the workspace as shown in Figure 4.1. Kinect was mounted that way to minimize the chances of workpieces occlusion.

The tf(transform) ROS package is used to keep track of the coordinate frames and create tree structure of the transform data within an entire system that consists of: the robot, the human arm and the workpeices. This is necessary for easily finding transformations between different sets of coordinate frames[26].

Rviz, ROS 3D visualizer, is used for displaying sensors data, the coordinate frames and the robot states as shown in Figure 4.2

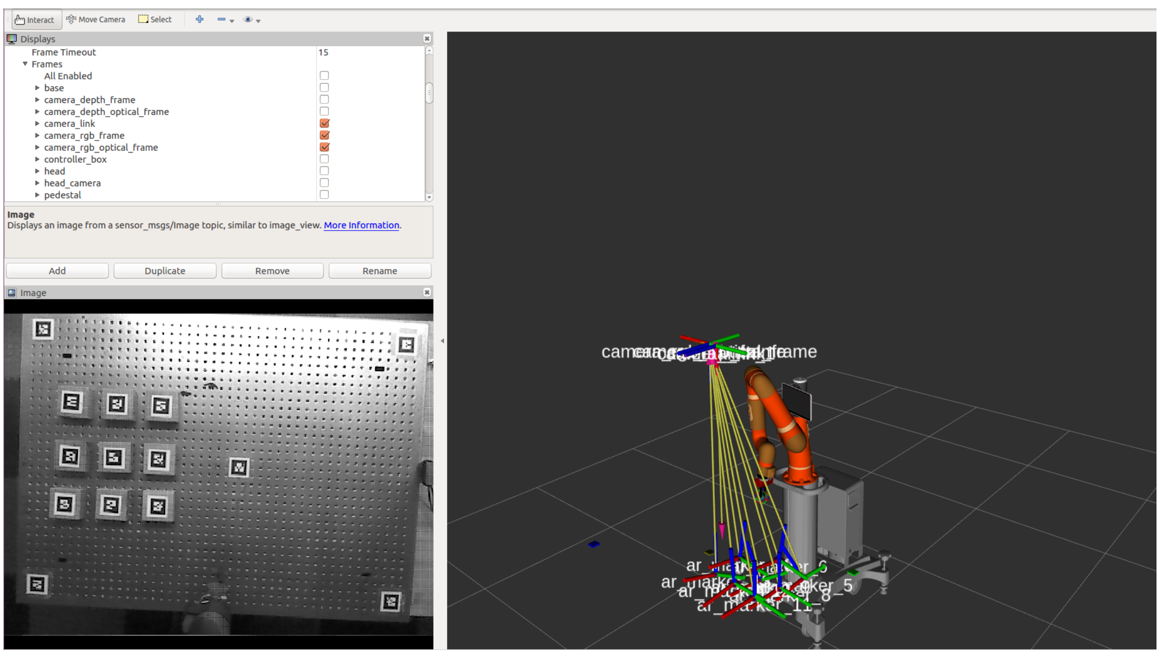

Figure 4.2: A visualization of the output of the perception module. The fiducial markers are being detected by the Kinect.

4.3 Knowledge

As explained in section 3.2 we are leveraging the concept of digital twin where we are allowing the exchange of information between the physical entity (real world) and virtual entity (simulation) to be as seamless as possible to have a better way of implementing our system. We choose the Virtual Robot Experimentation Platform (V-REP) [27] as our platform for our virtual entity. V-REP presents an easy and intuitive environment to create virtual system where robots, objects, sensors and humans can be added. Every element in the physical world that affects the HRC scenario has a counterpart in the VREP simulation scene as seen in Figure 4.1. The input to the virtual world is the data acquired from the perception component: robot joint states, human arm position, and workpieces positions to control the simulated robot, simulated human arm, and simulated workpieces respectively. As a result they will mirror their real world counterpart state in real-time.

This is achieved by remote API interface that allows communication between V-REP and an external application via socket communication. It is composed by remote API server services and remote API clients. Each object in the simulation scene is associated with a ROS node that acts as a remote API client that that facilitate streaming the perception data to a specific object in V-REP scene. The scene objects we have are rarely used on their own, they rather operate in conjunction with other scene objects (e.g. a human arm reaching to a workpiece to pick). V-REP offers several calculation modules that can directly operate on one or several scene objects. These calculations are the output of the virtual world. they represent integrated knowledge that relates the scene objects with each other (see Figure 4.3).

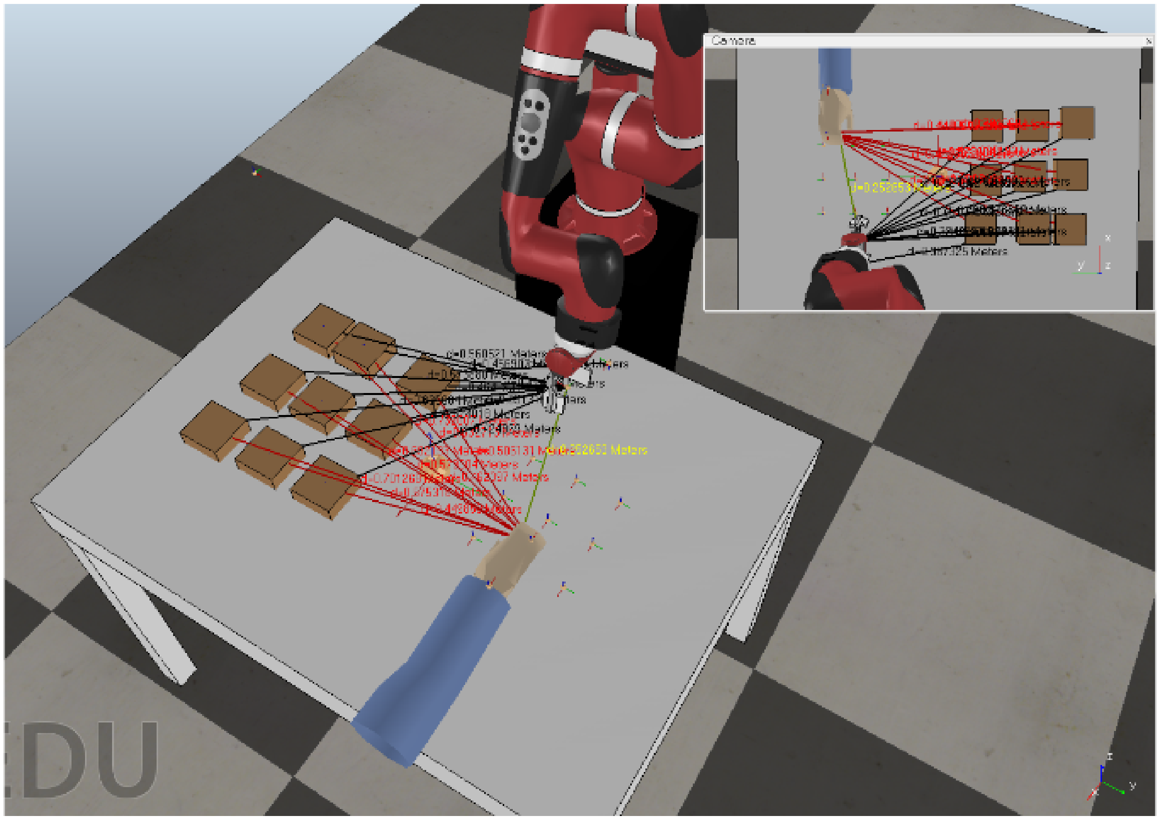

Figure 4.3: The distance calculations acquired from the digital twin. The minimum distance between the robot end effector and the workpieces is shown in black. The minimum stances between the workpieces and the human arm shown in red. The human robot distance is shown in green.

4.4 Planning

Planning takes place in two different levels as explained in section 3.3: Higher-level planning and low-level planning. The high level planner responsible for selecting the robot goal is implemented as ROS service. As explained in procedure 3.3.1, the robot selects its goal after evaluating the information from the acquired from the knowledge module. This ROS service will receive a call request from the low level planner when the robot is ready to manipulate a workpiece. The request is made by the *BLOCK-CHOICE* state. The low level planner is models as Concurrent Hierarchical State Machine (CHSM) see Figure

4.6. The state machine ran as a single ROS node. Our system utilized a python library called SMACH to build and execute hierarchical concurrent state machines[28]. SMACH has several modules which allow integration with ROS constructs like messages, topics, actionlib actions and services. In this contexts, a state corresponds to a state of execution. In other words it corresponds to the system performing some task. This is different from the formal state machine definition, where each state describes a given configuration of the system. In the graph chart in Figure 4.6, states are represented in circular shape, and each arc represents a state transition. States are defined as single execute function which blocks until function returns an outcome from the set of potential outcomes defined for that state. A Rectangular shape represents a container state, which is a collection of one or more states. Containers define different execution policies based on their child states and outcomes.

In our CHSM we defined different types of states that integrates with ROS constructs:

- **ServiceState:** represents execution of a ROS service as a SMACH state.
- **SimpleActionState:** A state to interface with ROS actionlib to call an action.
- **MonitorState:** A state that subscribes to a ROS topic and blocks while a condition holds.

The CHSM includes two different types of containers: concurrence container and simple state machine container. Unlike a state machine, which executes one state at a time in series, the Concurrence executes more than one state simultaneously. The outcomes of a Concurrence can be determined by one of several outcome policies defined at construction.

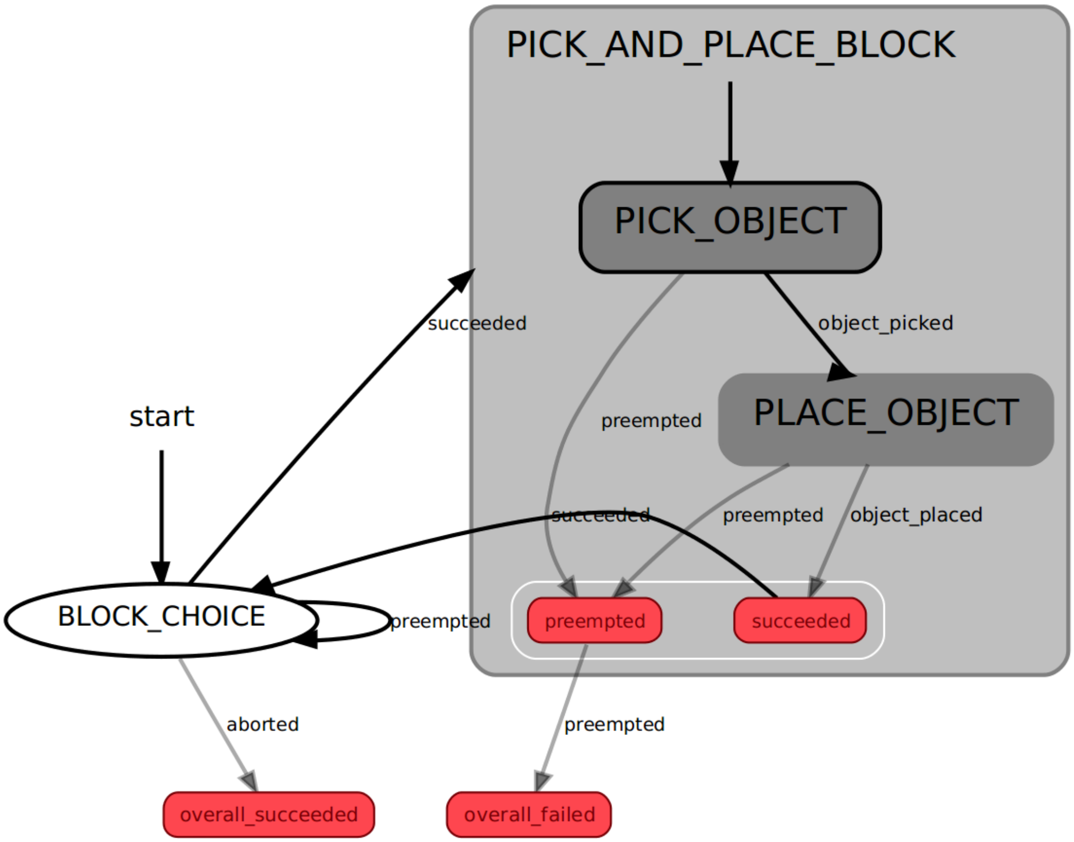

Figure 4.4: top level state machine

As seen in 4.4, the CHSM starts with executing the *BLOCK-CHOICE* state. This state is a ServiceState that acts as a service client to high-level planner implemented as ROS service. The service replies with a workpiece ID that needs to be picked and this is when the execution of the *PICK-AND-PLACE-BLOCK* action sequence starts. This super state has two states that run in sequence *PICK-OBJECT* and *PLACE-OBJECT*. If the sequence executes with no error *PICK-AND-PLACE-BLOCK* returns succeeded outcome and transition to *BLOCK-CHOICE* state to request another workpiece to manipulate.

Going into lower levels of the state machine, we will explain here the *PICK-OBJECT* container state. Figure 4.5 shows the states and containers nested in this state container. *PICK-OBJECT* state starts with with the *GET-PICK-UP-POSITION*. This state execute a function that requests the pose of the workpiece that needs to be picked. Note that we already know the workpiece ID of the workpiece the robot needs to manipulate before transitioning into this state. Then the state machine transition to the next container state *MOVE-TO-RESERVE-AREA*. This is a concurrent state container, it will activate the *MONITOR-HUMAN-ROBOT-DISTANCE* and *PICK-BLOCK* sub-states simultaneously.

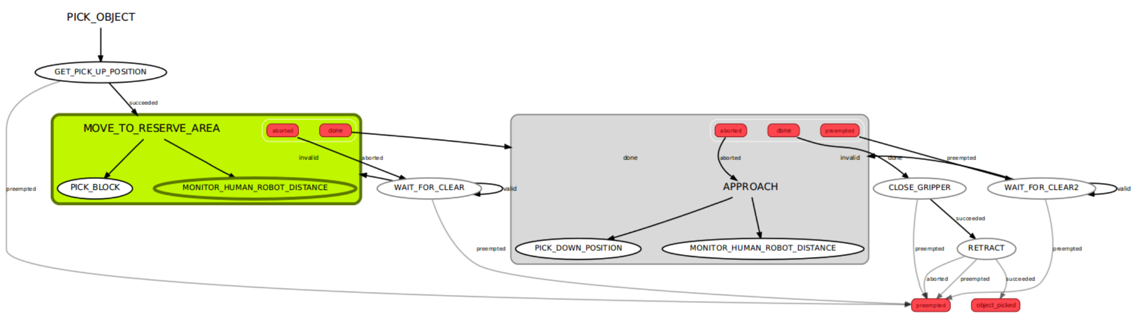

Figure 4.5: Pick an Object container state: it consists of sub-states needed to preform the action of picking a workpiece. it starts with getting the location of the workpiece to be picked, then performing the action of moving to the workpiece location, the approaching the workpiece, picking it up, and recreating to be ready for the next sequence of actions

The *PICK-BLOCK* sub-state is a SimpleActionState. This state will call the ROS action interface (actionlib) specifically the Joint Trajectory Action Server, a node that provides a ROS action interface for tracking trajectory execution. This action takes in goals of the type FollowJointTrajectoryAction that describes the trajectory for the robot to follow. We have created a ROS service that utilizes MoveIt, a ROS motion planner package, to supply these these trajectories. This service will generate a desired trajectory in response to our motion plan request. The trajectory goals will be passed to the to the joint trajectory action through the SimpleActionState *PICK-BLOCK* all the way to the sawyer trajectory controller, and reports success when it finished executing.

The robot should reason about the human safety when it is planning and executing its actions. Therefore, the distance between the human hand and the robot end effector is monitored whenever the robot start executing an action. This is done by *MONITOR-HUMAN-ROBOT-DISTANCE* state. It is of MonitorState type, where it checks if a ROS message has been received to the /human-robot-distance ROS topic. If the state machine is in state *PICK-BLOCK* and a ROS message is sent to /human-robot-distance indicating the human-robot-distance is below the safe threshold, *PICK-BLOCK* will be preempted, and the state machine transitions to *WAIT-FOR-CLEAR*. *WAIT-FOR-CLEAR* state is a MonitorState, it will check if human-robot-distance ROS topic indicates the human robot distance is above the threshold so it can transition back to *MOVE-TO-RESERVE-AREA* and resume *PICK-BLOCK* action. If *PICK-BLOCK* is completed, *MONITOR-HUMAN-ROBOT-DISTANCE* is preempted and the concurrent state container *MOVE-TO-RESERVE-AREA* returns succeed and the state machine transitions to the next concurrent state container *APPROACH*. In this is state the same idea used in *MOVE-TO-RESERVE-AREA* states container of implementing preemption, using a concurrence container and monitor state is used. In *APPROACH* state the robot moves down to reach the workpieces while still monitoring the human robot distance. When the state return succeed , the state machine transition to *RETRACT*, which another SimpleActionState and under go the same process discussed earlier in *PICK-BLOCK*. With the successfully completing *RETRACT* the superstate *PICK-OBJECT* returns *object-picked* outcome.

At this point the *PICK-AND-PLACE-BLOCK* transition to *PLACE-OBJECT* container to place the workpiece in it final location according to the final task state goal. The way we implemented the *PLACE-OBJECT* contair state follows the same principle explined in *PICK-OBJECT* state container (see Figure 4.6).

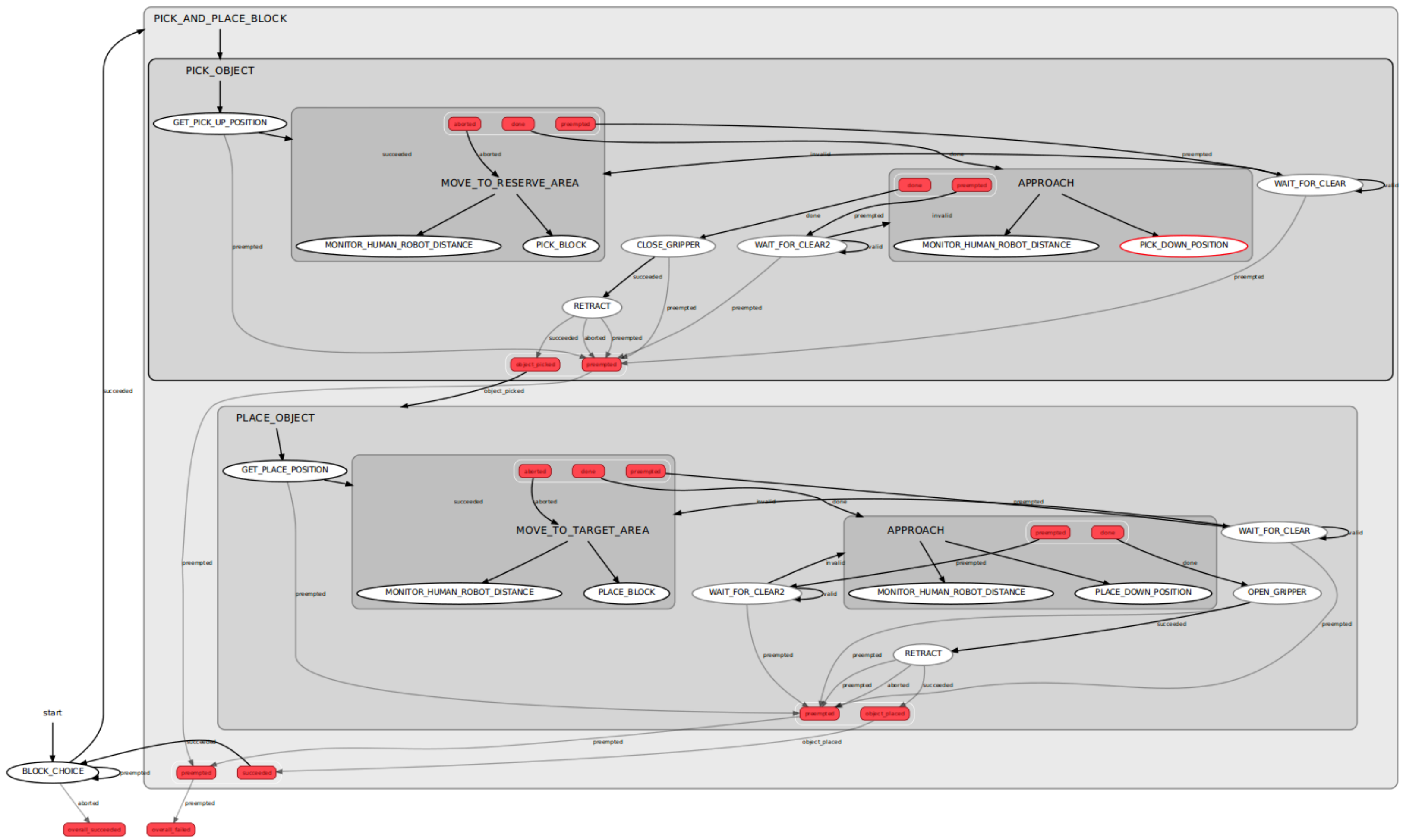

Figure 4.6: A visualization of the CHSM that shows all the states needed to successfully perform a pick and place of a workpiece.

Chapter 5

Human-Robot Teaming: User Study

To validate the developed system, a case study with one participant was performed. This chapter describes the task, the experiment setup and procedure followed to conduct and evaluate the system.

5.1 Task Description

Through the user studies, I would like to observer the joint task planning and execution dynamics that take place when varying the type of task (low cognitive load vs high cognitive load) and the robot goal selection process. Two different task has been created a low and high cognitive load task. A low cognitive task is a task that is simple enough to be be preformed by the human without challenging the human perception ability. In the study the team is asked to transfer a set of workpieces from the picking to the placing area while maintaining their initial spatial order(see Figure 5.1). Based on the pilot studies this type of task is simple for the human to perform. The high cognitive load task is a task that challenges the human perception ability. The participant has to pick a workpiece and figure out where it should be placed after comparing it to the one-page pictorial description of the final goal state of the task (see Figure 5.2). I hypothesize that this will create different types of human participant behavior when executing the task that is important for the robot to account for while planning and executing its own actions.

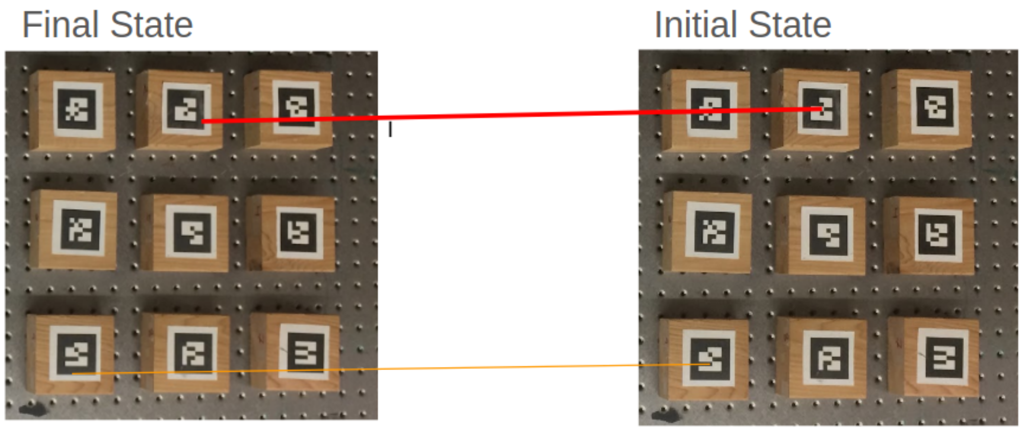

Figure 5.1: low cognitive load task given to the participant indicating the initial and final state of the task. The two lines drawn in the figure is shown here for clarification purposes however this is not given to the participant.

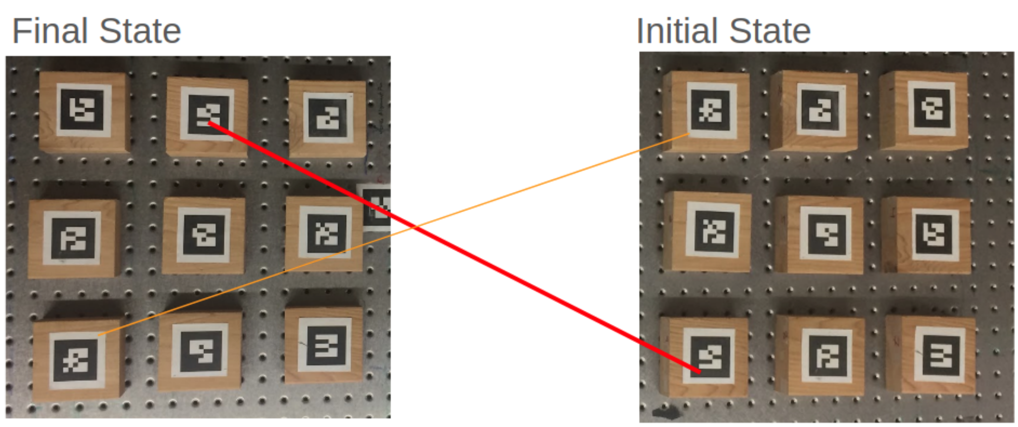

Figure 5.2: A pictorial description of the high cognitive load task given to the participant indicating the initial and final state of the task. The two lines drawn in the figure is shown here for clarification purposes however this is not given to the participant.

The second type of variation is the change of robot sequence of actions against these two tasks. The first robot behavior is considered more efficient in terms of the over all motion in the workspace when preforming the task. When the robot stats executing the sequence of actions for picking a workpiece it can simple start the execution from any point in the workspace. we hypothesis that this is more efficient for the robot over all motion in the workspace but it might be a burden on the human partner since the human does not know when the robot is going to do after its done placing the workpiece. Therefore, we create a more legible action sequence to eliminate this ambiguity in picking an workpiece phase. The robot will go to a specific position before it starts picking a workpiece. I hypothesize this will be favorable by the human partner since he/she will be able to understand that the robot is about to enter the picking area.

Therefore, a user study consists of the following sub-studies:

- **User study A :** Low cognitive load task with legible over all motion sequence
- **User study B :** Low cognitive load task with efficient over all motion sequence
- **User study C :** High cognitive load task with legible over all motion sequence
- **User study D :** High cognitive load task with efficient over all motion sequence

5.2 Experiment Setup

There are nine workpieces that the human and the robot need to manipulate based on a given final task goal. In this HRC scenario we do not put any restrictions on the participant on which workpieces he/she can manipulate, or create exclusive workspace zones for any of team members. This will help in creating a similar human-human team kind of interaction that we hypothesize is more fluent. The table surface is the “workspace” the human and the robot share. The human and the robot shared task is to manipulate a set of blocks “workpieces” to place them on the other side of the workspace in specific spatial arrangement given to them at the start of the experiment. The Workspace is divided into two work areas, the Picking Area and the Placing Area. The Picking Area is reserved to hold the workpieces in their initial states. The Placing Area is where the workpieces need to be placed based on the given final workpieces states that indicates the completion of the task. The robot has prior knowledge about what the final state of the workpieces should be. Figure 5.3 shows a sequence of the experiment setup while the human and robot performing the task.

5.3 Evaluating Fluency of Human-Robot Collaboration

We choose to evaluate the collaboration through both objective and subjective metrics. The following explains the objective metrics of interest:

- **Robot Idle Time** Percentage of time out of the total task time, during which the robot has been not active. The robot can be idle due to predefined rules to prevent the human-robot collision.
- **Human Idle Time** Percentage of time out of the total task time, during which the human has been not active.
- **Number of Collisions** between human and robot :(*Note: Collision is defined as the event where the minimum distance between human and robot is below a predefined threshold.*)
- **Functional Delay:** Percentage of time out of the total task time, between the end of one agent's action and the beginning of the other agent's action.
- **Concurrent activity:** Percentage of time out of the total task time, during which both agents have been active at the same time.

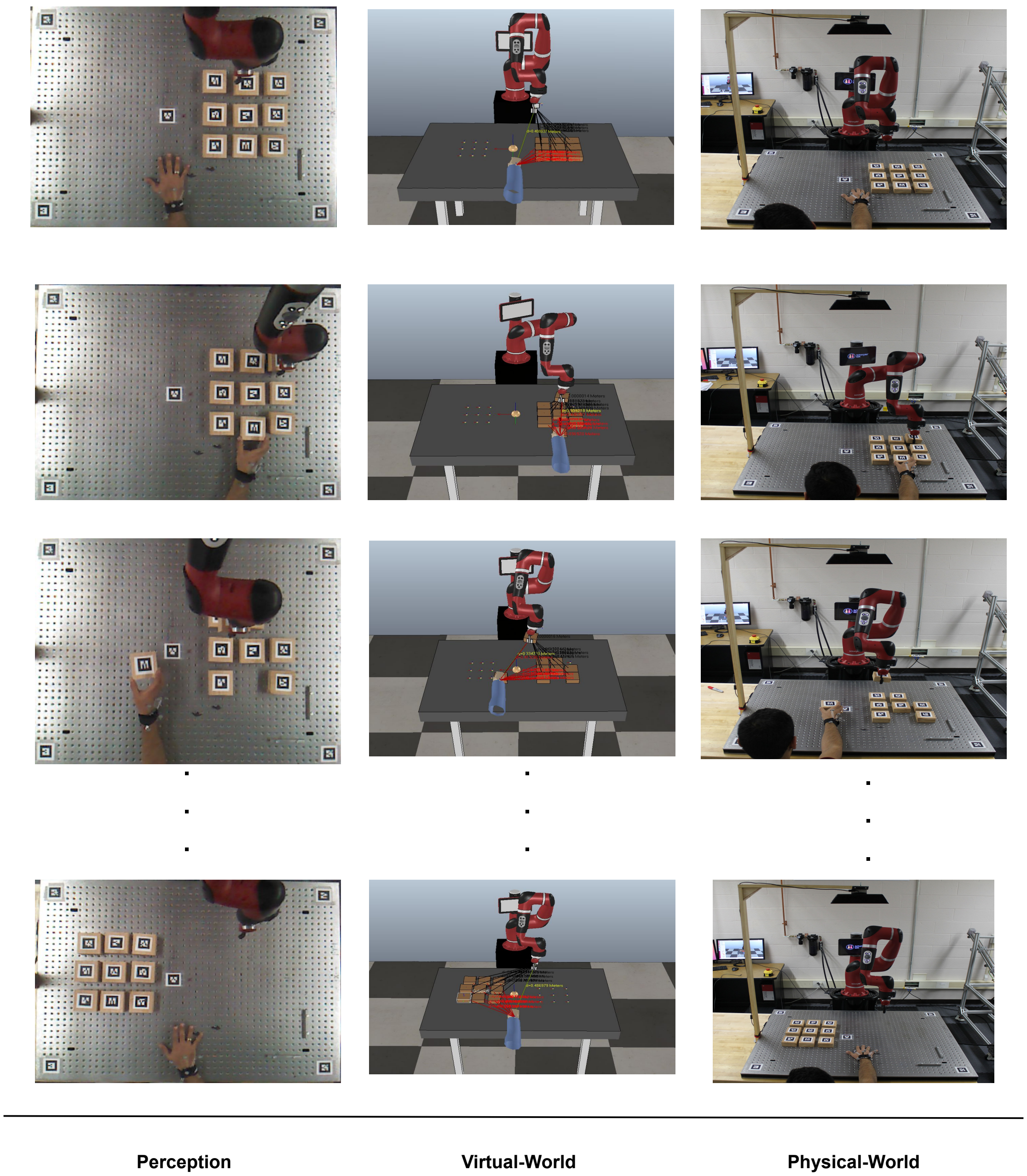

Figure 5.3: The figure above shows the sequence of actions associated with the experiment of performing the collaborative task. The first column of the frames represents the Perception view from the camera of the shared workspace. The second column shows the virtual world representation i.e. digital twin of human, robot, and objects, as shown in the physical world (last column). The last row shows the completion of the human-robot task.

- **Concurrent activity in the same workspace area:** Percentage of time out of the total task time, during which both agents have been active at the same time within the same workspace area.

- **Number of actions performed by each agent**: In our HRC scenario, we count the number of workpieces manipulated by each agent.

- **Time to complete task**: i.e. the time taken to place the 9 workpieces in their target locations.

These metrics are based on the guidelines set by [4] to evaluate the fluency of the human-robot collaboration and the insights of[13] to improve human-robot team performance.

To measure the participant perceived sense of robot collaboration, the participant is asked to answer a seven-point Likert scale survey. The survey can be found in the appendix section.

5.4 Procedure

We first explain the purpose of the study to the participant and ask her/him to sign a consent form. Any questions the participant might have will be answered by the researcher. The participant will be taken to the participant's seat which is across from the robot. The participant will be introduced to the robot and the workspace. The participant will be briefed on the procedure of the experiment. An additional one-page pictorial description of the task will be given to the participant that involve:(a) the set of objects and targets locations involved in the task; (b) the final state of the workspace that shows the final arrangement of the objects on the other side of the table when the task is complete. This description will be placed on the side of the table where it is visible to the participant during the experiment. The robot will be activated to perform a demonstration of its movement in the workspace so the participant can be familiar with it before performing the experiment. The participant will be asked to wear a wristband that has reflective markers utilized by the OptiTrack motion tracking systems. The collaborative task will be initialized and the participant will be informed to start. A total of 4 experiments will be performed where we run two different robot behaviors against two different type of task we developed and explained earlier. During the Experiment, we will measure experiment parameters that are not related specifically to the human subject such as: Human-Robot absolute minimum distance, Robot Idle Time, Human Idle Time, Human-Robot simultaneous movement time and Task Completion Time. At the end of each experiment, the participant will be asked to fill a survey to measure the subjective human satisfaction with each algorithm through a seven-point Likert scale survey to evaluate the participant perceived sense of robot collaboration.

5.5 Results

To validate some of the initial hypotheses explained earlier,some pilot studies were conducted where the human and the robot preform the tasks on their own. The result of the main four study cases are presented in this section.

5.5.1 Human and Robot Only Experiments

A participant was asked to perform the two types of tasks to confirm the assumption on the high cognitive load task requires the human participant more time to accomplish compared to the low cognitive task. As shown in Table 5.1, it takes the participant 1 minute and 30 seconds more to perform the high cognitive task compared to the low cognitive task which confirms that this task is more challenging on the participant.

Table 5.1 The time it takes the human to complete the two tasks designed for this research

Task Type	Time to complete task
Low cognitive load task	37 seconds
High cognitive load task	2 minutes and 7 seconds

When the robot performs the task, as shown in Table 5.2 the time it takes the robot to complete the task with legible motion takes longer time compared to the case of efficient motion. Therefore, to improve the time it takes the robot to perform a task, efficient motion will be more suitable for that. However, its overall effect on the fluency of the collaboration needs to be investigated with user studies.

Table 5.2 The time it takes the robot to complete the two types tasks against the two different robot behaviors

Task Type/Robot Motion	Legible Motion	Efficient Motion
Low cognitive load task	2 minutes and 8 seconds	2 minutes and 7 seconds
High cognitive load task	2 minutes ans 25 seconds	2 minutes and 10 seconds

5.5.2 Human-Robot Collaboration Experiments

The objective measures of the four studies conducted with one participant are shown in Table 5.3. In general, there is no significant difference in the number of workpieces manipulated by the human across the different studies. However, the participant manipulates fewer workpieces in the studies where the robot and the human have to preform the high cognitive task. This is due to the time needed by the participant to find where the workpiece needs to be placed. In general, the robot takes more time to successfully manipulate a workpiece compared to the human teammate and hence, the difference in the number of workpieces manipulated by the robot and human.

The number of collisions was low in this study. However, it affects the robot idle time measure. After the collision takes place and the robot chooses to be idle, it takes some time to resume its action.

The time taken to complete the task when the human and robot collaborate with each other is significantly less when compared to the human or the robot performing the task alone except for one case where the human is performing the low cognitive load task. In general, it takes longer to perform the high cognitive load task. Also, when the robot is following the more efficient motion sequence, the time taken to complete the task improves. However, this not true when more collisions take place.

The concurrent activity across all the studies was high, except for user study C. This drop was due to the increase in the human idle time. However, it can be seen that even the concurrent activity was the highest during user study D (95 %), the concurrent activity was not within the same workspace area.

The Idle human time was the greatest in user study C. In this particular case; it was due to the human taking longer to start preforming the task. The robot idle time is dependent on the number of collisions that task place during the interaction.

Table 5.3 The objective measures of fluency and efficiency collected during the four studies.

Metrics	User Study A	User Study B	User Study C	User Study D
Number of workpieces manipulated by the human	6	6	5	5
Number of workpieces manipulated by the robot	3	3	4	4
Number of collisions	0	1	1	0
Time of completion	52. 17 seconds	52.22 seconds	1 minute 6 seconds	1 minute
Concurrent activity	84.35% (44.01/52.17)	83.16 % (43.43/52.22)	74%(49 66.25)	95%(57/60)
Concurrent activity in the same area	17.49% (7.7/44.01)	31.15% (13.53/43.43)	20% (9.82/49)	7% (4/57)
Human idle time	8.16 sec	7.85 sec	13.56 sec	3 sec
Robot idle time	0 sec	1.01 sec	1.13 sec	0 sec

Chapter 6

Conclusions

A cyber-physical testbed was created to enable a human-robot team to perform a shared task in a collaborative workspace. A digital twin of the HRC scenario was created and used during a human-robot collaborative tabletop manipulation task in a shared workspace. This setup was successfully used to test robot task planning and execution based on the states represented and reported using the digital twin, thus validating the importance of using a virtual world representation of all actors: human, robots, and objects during a human-robot collaborative task and its significance in task execution and planning.

From the initial user studies, a difference in the dynamics of the collaboration when varying robot behavior against different types of tasks were observed. From our initial results, the number of manipulated workpieces seems to exceed the number of workpieces manipulated by the robot. This is due to the fact the human can perform a pick and place of a workpiece faster than the robot. However, we notice a small drop in the number as the task type change. In general, the time it takes to complete the task is related to the number of collisions that happen during the collaborations. More collisions lead to an increase in task time completion. The concurrent activity, in general, was high during most of the studies. However, we see a variation in the concurrent activity happening the same workspace area.

The user study we performed is just a validation of the system developed, but to gather more insights about the dynamics of the collaboration, more user studies has to be performed.

Chapter 7

Future Work

More insights will be gathered through our explorations of understanding and implementing task planning and execution alongside performing human-subject experiments and evaluating them based on the proposed metrics. The IRB approval is completed. Also, including some aspect of the anticipation of human actions will be tested to improve the collaboration fluency. In my future work, I would also like to incorporate MUTUAL ADAPTATION model in high-level task planning. This could allow the robot to take information-seeking actions to infer online on how the human goal is affected by the robot's selection. As a result, human and robot mutually adapt to each other; the robot builds online a model of how the human adapts to the robot and adapts its actions in return.

Appendix A

Appendix

A.1 Study Questionnaire - Subjective Metrics

- **Robot's contribution**
- The robot contributed equally to the team performance.
- I was the most important team member on the team.
- The robot was the most important team member on the team.
- I had to carry the weight to make the human-robot team better.

  Trust in Robot

- I trusted the robot to do the right thing at the right time.

  Robot Teammate Traits

- The robot was intelligent.
- The robot was trustworthy.
- The robot was committed to the task.

  Working Alliance for Human-Robot Team

- The robot perceives accurately what my goals are.

- The robot does not understand what I am trying to accomplish.

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