UHTP: A User-aware Hierarchical Task Planning Framework for Human-Robot Collaboration

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***Abstract*—In this paper, we present a online planning framework for human-robot collaboration that can adapt to varying human preferences in real-time. The proposed framework, called the User-aware Hierarchical Task Planning (UHTP) framework, uses a modified Hierarchical Task Network (HTN) to perform role and cost assignment, maintain the current state of the task and reason about alternative execution paths. UHTP enables the robot to actively infer the human partner's intent and choose actions that complement the human's behavior as well as minimize the overall cost of the task execution path. We validate the performance of our proposed framework with a user study of a collaborative drill assembly.**

***Index Terms*—Human-Robot Collaboration, Robot Manipulation, Task Planning, Hierarchical Task Networks**

I. Introduction

Collaborative robots that can work in human environments are becoming more common in various industries, such as manufacturing, logistics and healthcare [1]. Although collaborative robots are built to operate safely around humans, these robots are not equipped to perform shared manipulation tasks with human users. A major challenge in enabling human-robot collaborative manipulation is dealing with uncertainty in human preferences and performing online robot decision-making to adapt to this uncertainty. Prior work in planning for human-robot collaboration has found success in leveraging hierarchical task models, such as behavior trees [2], AND/OR graphs [3], [4] and Hierarchical Task Networks (HTNs) [5]. These methods use the task model directly to search for the least cost execution path [2], [3], or convert them into a probabilistic model to plan agent actions [4], [5]. However, all these methods assign actions to and communicate with the human partner during task execution which is inefficient. Allocating actions to the human also limits the human's freedom to execute actions of their own preference.

In this work, we present a novel planning framework for human-robot collaborative manipulation, the User-aware Hierarchical Task Planning (UHTP) framework, that plans robot actions solely based on a HTN representation of the task and sensor-based human activity feedback. The contributions of this work are: i) a modified HTN that encodes actions, agent roles and agent-specific costs in a single representation, ii) an online task planning algorithm to update the modified HTN using human activity feedback and search the HTN for the least cost execution path, and iii) a validation of UHTP's performance via a user study of a collaborative drill assembly task.

II. User-aware Hierarchical Task Planning Framework

We introduce the UHTP framework for human-robot collaboration and describe the modified HTN representation used. Standard HTNs were designed to encode multiple ways to perform a task, however they do not provide any collaborative capabilities by themselves. UHTP extends the HTN representation to aid in collaborative task planning by assigning action nodes to individual agents and propagating agent-specific costs throughout the model. Specifically, action nodes in the HTN are assigned to individual agents based on which agent is capable of performing the action. Shared action nodes that can be executed by both human and robot are converted into decision nodes with two children – each child being an action node assigned to a single agent. Each action node is also assigned an agent-specific cost, which is the average time taken by the agent to perform the action. Abstract or high-level nodes are given both a tuple of agent-specific costs and a total scalar cost. These costs are calculated by aggregating the costs of their children using Characteristic Accumulation Functions (CAFs) defined for each node type, as in Chen et al. [6]. In this way, UHTP uses a single task representation to encode actions, action allocations to agents and agent-specific node costs.

Adaptive Task Execution: We now explain how the modified HTN is used in task planning to adapt to changing human preferences. At every step, UHTP queries the latest HTN for a list of available robot plans $\mathbf{\Pi}_r$. For each individual plan $\Pi_r^k \in \mathbf{\Pi}_r$, UHTP create a copy of the HTN and prunes decision branches inconsistent with Π_r^k. We define the execution cost of path Π_r^k as the total cost value of the root node in the pruned HTN, which is calculated by updating the node costs. Additionally, UHTP estimates the cost of the robot remaining idle by creating an HTN in which all decision branches containing robot actions are pruned. Finally, the robot chooses the plan with the least execution cost and performs the first robot action in that plan. The HTN is concurrently updated by actively pruning completed actions from the tree. Thus, continuously updating the HTN and querying for the latest execution paths enables UHTP to infer the human's intent and accordingly plan robot actions. We continue this cycle of updating the HTN and planning actions until the collaborative task is complete.

III. User Study Design and Results

To evaluate the performance of our proposed planning framework, we conducted a within-subjects user study in which participants play the role of an assembly worker and team up with a real robot arm to assemble power drills. In each round, users were asked to construct drills of two different colors (Blue, Yellow) with the help of our 7-Degrees of Freedom JACO robot arm. Since the user chooses which color drill to build first, the robot agent must infer the user's choice of ordering and bring the required parts in order to complete the assembly in minimum time.

Validation Scenarios: Each user was presented with two validation scenarios – S_{UHTP} in which the robot is controlled by the UHTP framework and S_{FIX} in which the robot executes a predefined sequence of actions. The ordering of scenarios was counter-balanced to reduce participant bias in our results. For scenario S_{UHTP}, we tracked the user's body pose via an Azure Kinect camera and classified the pose data into discrete action labels using a pretrained feed-forward neural network (NN). This real-time human activity feedback was used to prune nodes from the HTN.

Measured Variables: During each scenario, we measured the total time taken by the human-robot team to assemble four power drills. After each scenario, we asked the user to fill a questionnaire with four Likert scale questions about the robot's behavior and a NASA-TLX survey to measure their mental workload [7]. At the end of the study, users were asked to rank both scenarios based on the robot's ability to track drill color, the scenario with the least user idle time and the user's personal preference.

Results: We recruited 35 participants from the local community for our user study, of which five participants were excluded from the data analysis due to hardware malfunctioning and participants deviating from the study protocol. We evaluate the responses of the remaining 30 participants to compare the performance of the UHTP-controlled robot with the predefined-sequence robot. We perform statistical analysis using a non-parametric test – the Wilcoxon Signed-Rank test – to measure the significance of differences in measured variables. The significance value is set at $\alpha = 0.05$.

Figure 1 compares the total task execution times measured during both scenarios. We find that the mean execution time for scenario S_{UHTP} (M=392.6, SD=53.60) is lower than that of scenario S_{FIX} (M=435.6, SD=62.59). Statistical analysis reveals that the difference in execution times between scenarios is significant ($p < 0.001$, n=30 scenarios). Figure 2 shows the participant responses for some of the questions in the post-scenario survey. Participant responses indicate that 1. more users did not receive the drill parts they needed at the right time during S_{FIX} (Q1 and Q2), and 2. more users had to pause or modify their assembly during S_{FIX} because the robot provided them with the wrong drill part (Q3 and Q4).

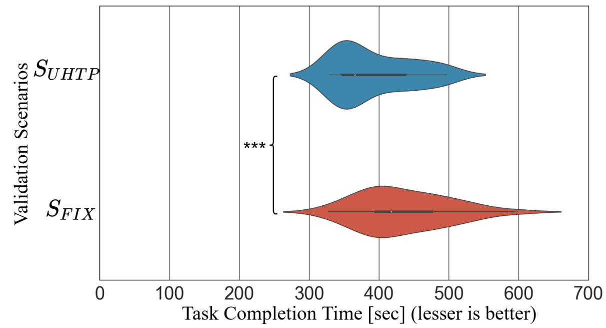

Fig. 1: Comparison of task execution times between S_U and S_F scenarios

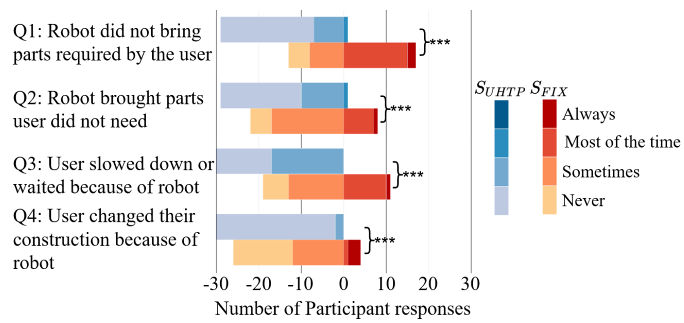

Fig. 2: Participant responses about their experience during each validation scenario

Additionally, the difference in participant responses between scenarios is statistically significant for questions Q1-Q4 with a p-value of less than 0.001 (n=30 scenarios). Furthermore, we observe from the mental workload scores that the average score of participants was higher in S_{FIX} (M=11.9, SD=2.54) than in S_{UHTP} (M=11.1, SD=1.90). Again, statistical analysis reveals a significant difference in the workload scores between scenarios ($p = 0.005$, n=30 scenarios).

IV. Conclusion

We introduced UHTP- a User-aware Hierarchical Task Planning framework for human-robot collaboration. UHTP uses a modified HTN as a task model to encode actions, costs and agent allocations in a single representation. The proposed framework performs task planning by actively updating the HTN with human activity feedback and using node costs to identify the least cost execution path compatible with the latest HTN. We validated our proposed framework by conducting a user study of a collaborative drill assembly to compare the performance of a UHTP-controlled robot to that of a predefined-sequence robot. The results from our study show that – 1. the UHTP-controlled robot results in lower task execution times than the predefined-sequence robot, 2. participants rank the UHTP-controlled robot higher than the predefined-sequence robot in inferring the user's intent and fulfilling the user's requirement, and 3. participants experience less mental workload when interacting with a UHTP-controlled robot than with a predefined-sequence robot.

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