Transferring Human Preferences from Canonical to Complex Assembly Tasks for Effective Robot Assistance

Nidhya Shivakumar – 23nidhyas@gmail.com
The Harker School, Class of 2023
USC Viterbi Department of Computer Science, ICAROS Lab, SHINE 2021

Motivation

- In complex manual assembly tasks, various workers performing the same task could execute it slightly differently
- A robot would need to assist workers based on their individual preference

Problem

- Problem: to learn the dominant preferences of each worker in a complex assembly task
- We cannot ask a user to perform complex assembly tasks to learn their preferences, as it can be very time consuming.
- Instead, learn preferences from demonstrations in a **canonical task** that the user is able to perform quickly

Key Insight

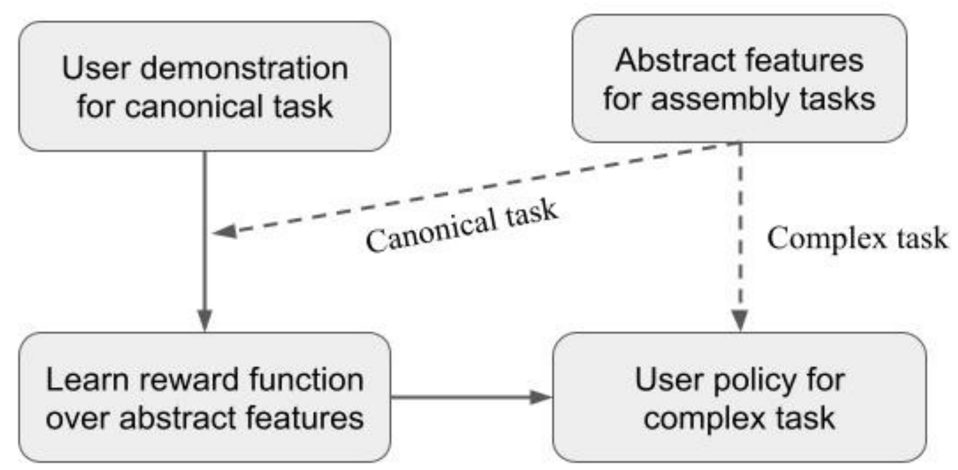
- Human preferences depend on abstract features e.g. mental, physical effort
- Rewards learned over these abstract features can be transferred to other assembly tasks

Features that Govern Human Preference

Based on literature review:
User preferences in assembly and manufacturing tasks are affected by several factors like fatigue [1], ergonomics [2], and trust [3]. In a pedal car assembly user study, users required more support as they became more fatigued. Users can also have preferences over task ergonomics based on physical characteristics (e.g. sitting/standing) and physical features (e.g. short/tall). Moreover, trust can also affect user preference over the responsibilities of a robot in collaborative assemblies.

However, previous work does not explore how these features inform human decision making in assembly tasks.
Based on a preliminary study, we shortlisted the following features that inform human preference: **physical effort, mental effort**

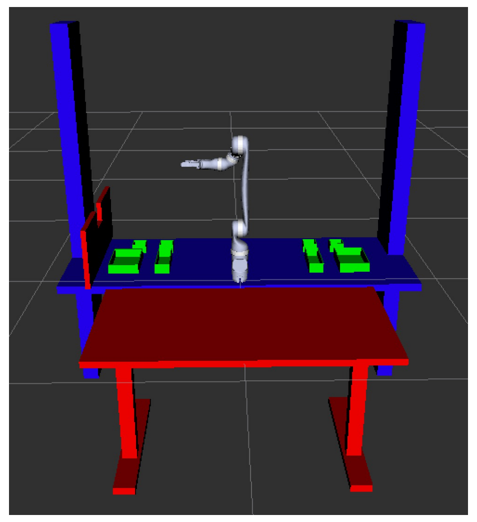
Methodology



Robot Motion Planning

- In order to deliver a part according to the user's preference, the robot needs to plan a motion from the current location to the target location, indicated by the position of the object to pick up.
- To accomplish this task, we used the RRT Algorithm (Rapidly Exploring Random Trees), which is a method for motion planning.
- Pseudocode for RRT:
  - Randomly generate points in the space
    - Random points must not interfere with obstacles
  - Connect it to the closest point in the existing path
  - Once in a while, use the target as random node in order to guide the path in the right direction
  - Check if new node is close to goal, and if it is, return path to goal
- For collision detection: Create Unified Robot Description Formats (URDF) to represent all of the containers, the storage, and the workbench in the world.

Figure 1, Right: Picture of virtual setup



- Next, target axes (TSR) were made on each object, so that the hand could grab the robot in the correct location. Inverse kinematics was used in order to find the hand configuration and joint angles (for the robot) so that it would be able to grab each object.

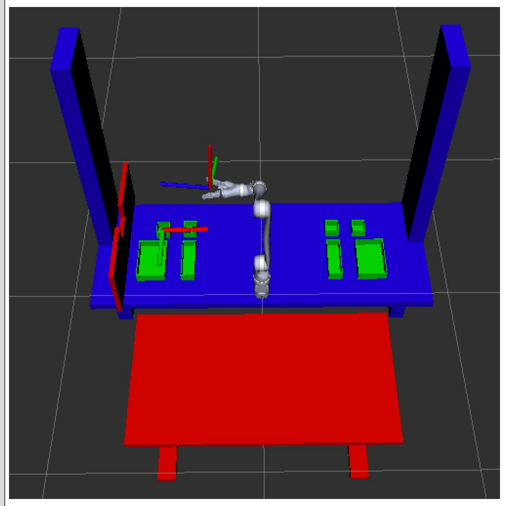


Figure 2, Left: TSRs for the robot and container it will pick up.

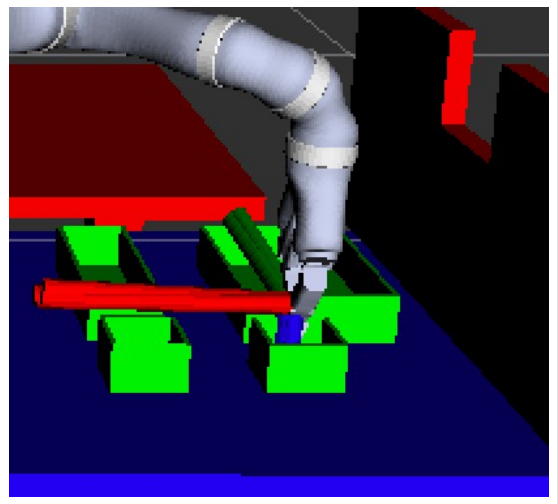


Figure 3, Right: TSR of the hand (robot) aligns with the TSR of the container, and the robot grabs it.

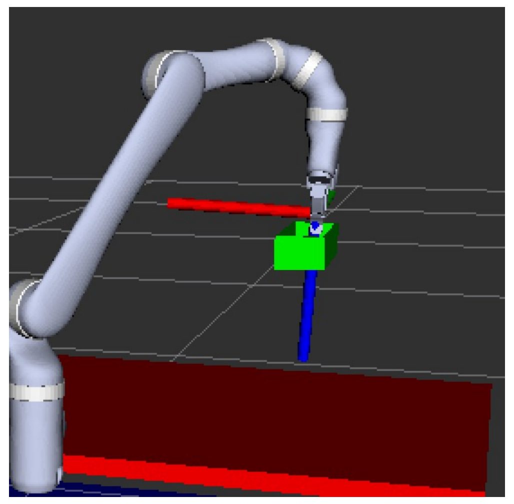


Figure 4, Left: The robot picks up the container and lifts it up.

- After grasping the object, it needs to be lifted and placed on the workbench. For this, we used the Jacobian transformation in order to keep the container parallel to the ground (so that the contents would not fall out).
- This was coded in python, and we used ROS (Robot Operating System) to run the robot software and RVIZ to visualize the simulation.

Outcome

- Robot was able to plan a path from its location to the container in the storage area, and move it to the workbench
- Learned about what factors govern human preference, and how that affects their behavior while performing an assembly task
- Learned how the robot plans its path to move between two locations.

Impacts

This research will lead to greater productivity in humans as they will not need to perform the assistive tasks such as fetching parts, and also, some of these tasks can potentially be a risk to humans.

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