Industrial Robot Imitation Learning for Manufacturing Assembly Tasks

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Mission objective: Decrease automation costs of high-mix customized tasks

- **The aerospace manufacturing pipeline consists of many high–mix customized tasks**
  - E.g., sanding and painting aircraft, welding unique components, and **assembly/disassembly of parts**

- Skilled manufacturers can adapt to new tasks but there are **large coordination costs when automating tasks**
  - E.g., communicating with robot technician, programming robot, evaluating robot performance

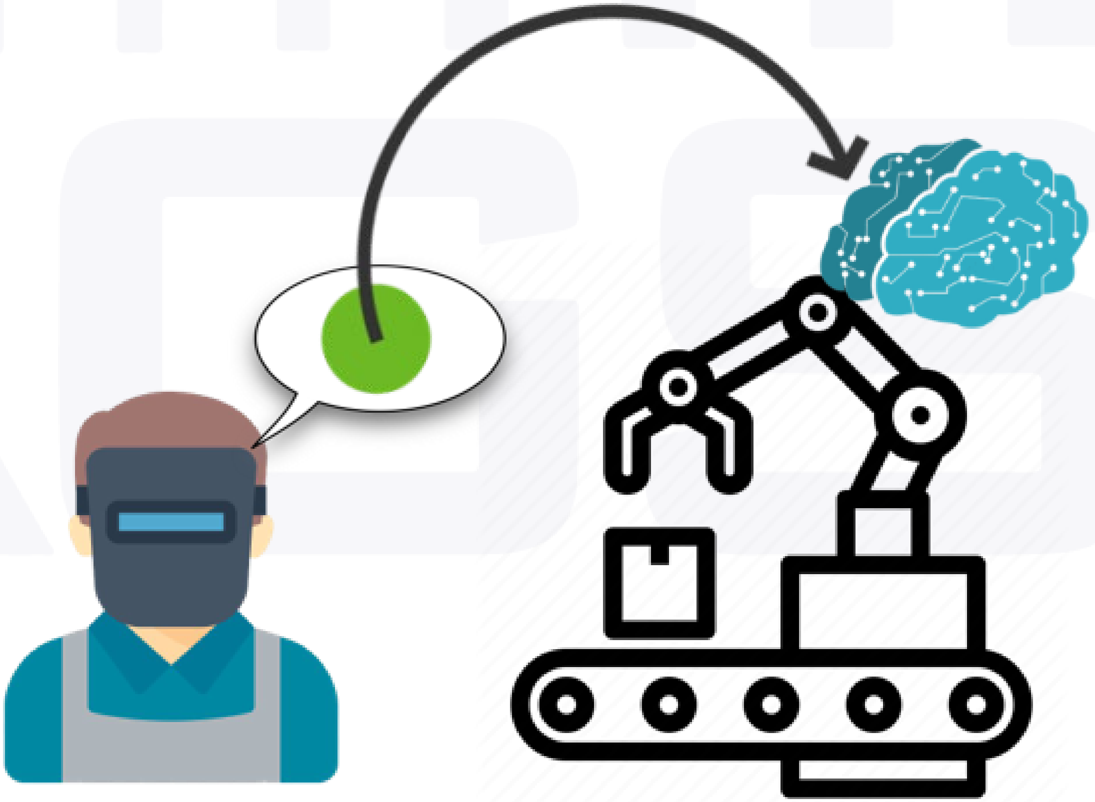
- Aim to **decrease coordination costs** by allowing skilled manufacturer to **directly instruct and program the robot**

Motivation: Apprenticeship learning in skilled manufacturing

- Skilled manufacturers are familiar with apprenticeship learning structure

- **Can we replicate apprentice learning and allow the robot to learn from demonstrations and instructions to complete a task?**

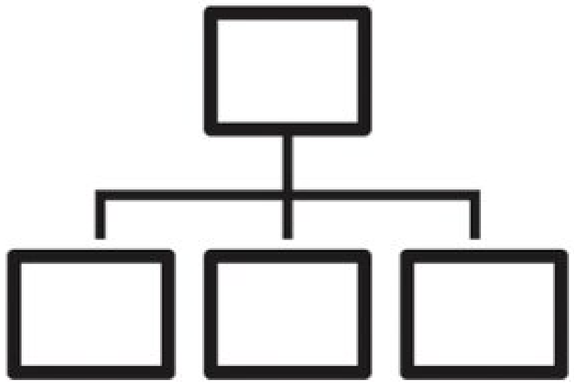
- Proposed benefits:
    - Reduced programming time
    - Reduced communication breakdowns and information loss
    - Increased adaptability of robot by re-using learned behaviors



Research objectives

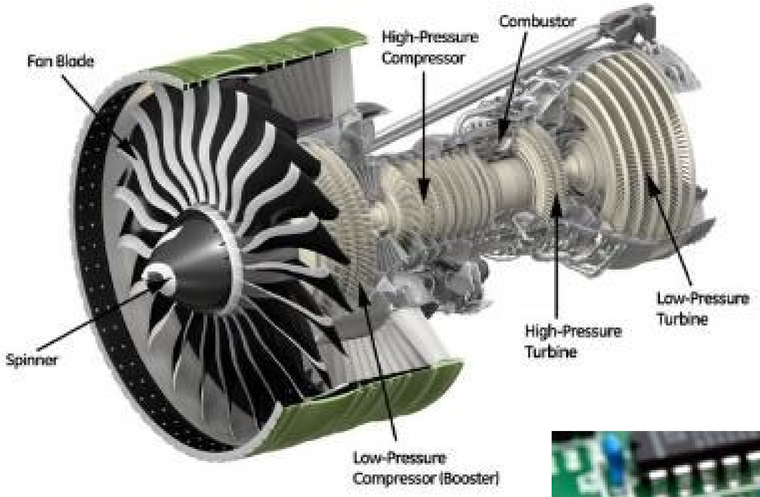
Enable robot programming through natural interaction

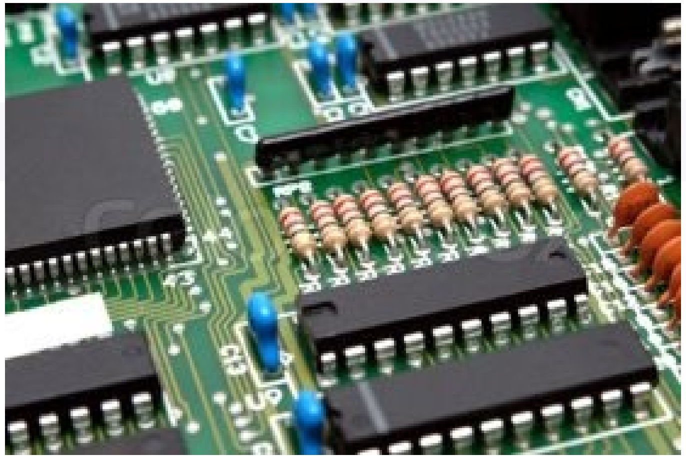
Learn how to perform assemblies given expert instruction



Re-use learned skills on new assemblies

Problem spaces: Large and small scale assemblies





- Assemblies are at different scales and complexity

- Assist with high-complexity assemblies at various scales
  - E.g., electronic subassemblies, assemblies of subassemblies, and final parts

- These problems are quite complex, so we start with a simplified problem

Proposed problem: Lego assembly

- Digital twin of the robot and legos will be used for initial testing
  - Currently uses oracle camera but will switch to simulated camera
- Robot will have a defined set of available actions
- Expert will demonstrate policy for a desired lego assembly
- Robot will execute the demonstrated policy using the defined primitives

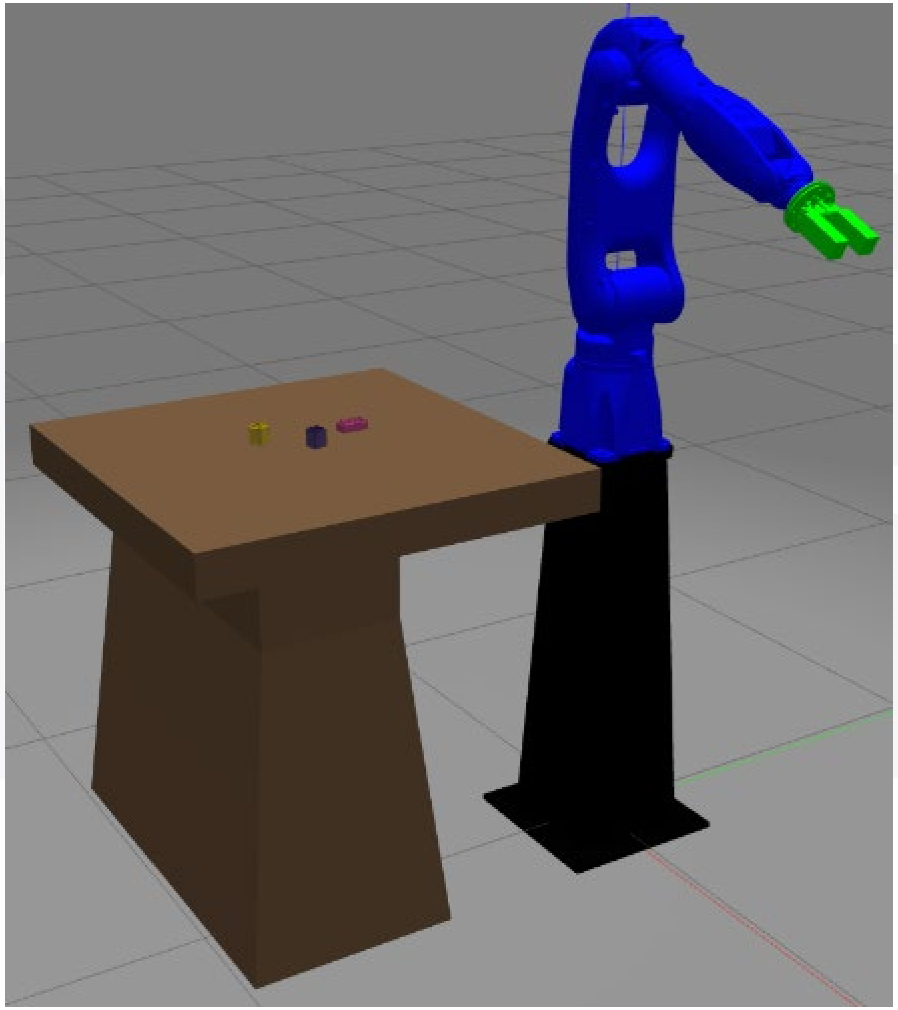


Figure 1: Digital twin of a Yaskawa robot in Gazebo. Legos are simulated on a table to the left of the robot.

Defining the actions

- The available actions are defined using a ROS compatible state machine
- Supported actions were identified from a dataset of natural language manipulation instructions

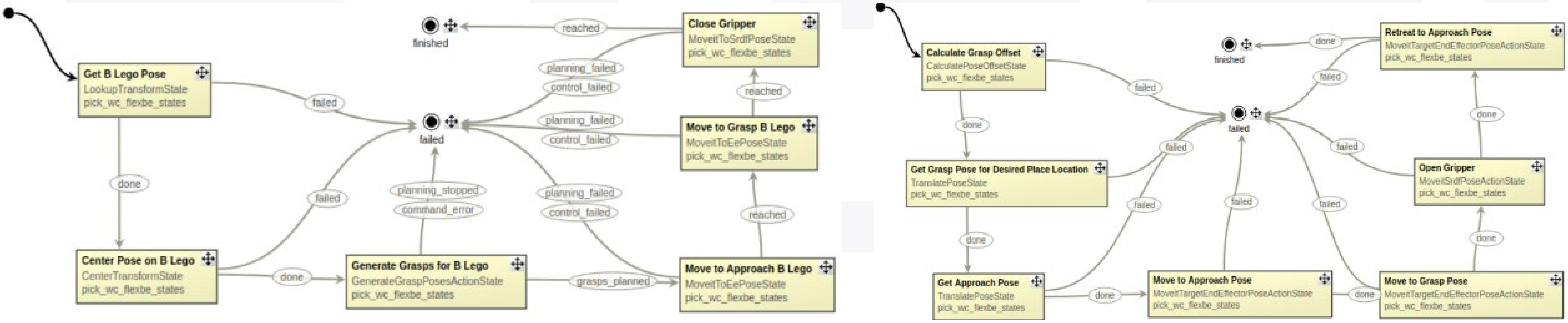
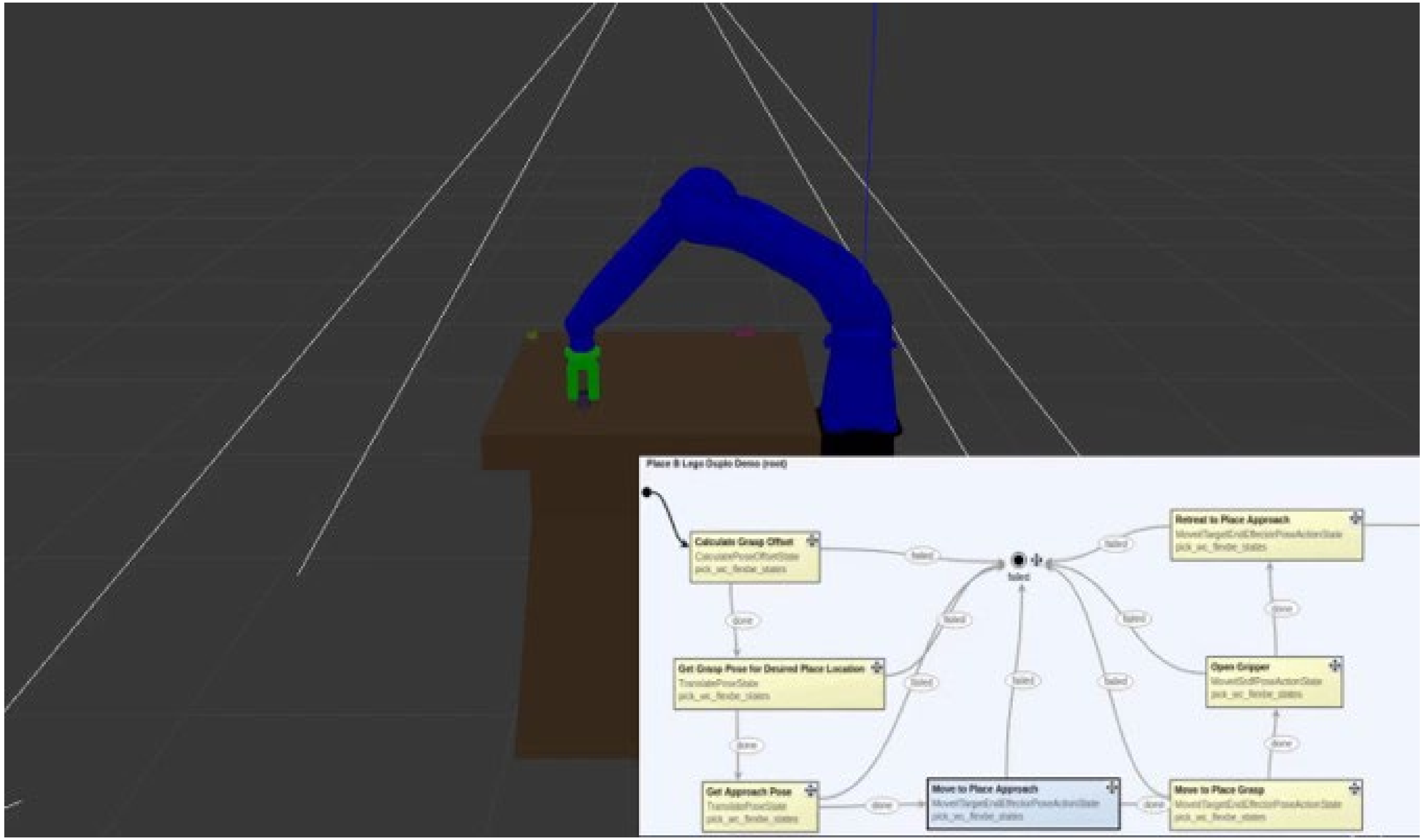


Figure 2: Pick (left) and place (right) behaviors defined using a FlexBe state machine. Each block is a state that calls a ROS service or action to perform a function

Executing actions in simulation



Linking language to actions

Place.01
+ isComplexSkill + hasArguments: **2** + hasPrimitveSkill: **MovementSkill** + hasPrimitiveSkill: **ManipulationSkill** + hasPrimitiveSkill: **VisualSkill**
+ hasProgram: placeObject(**Arg1, Arg2**)

placeObject()
Places object **Arg1** at the goal location **Arg2**
1) locateObject(**Arg1**) => **Arg3** 2) moveToGoal(**Arg3**) 3) pickObject(**Arg1**) 4) moveToGoal(**Arg2**) 5) releaseObject(**Arg1**)

Use database to match verbs to defined action program

Use the verb arguments to fill in action program variables

Ground the objects in the world using computer vision

Future work

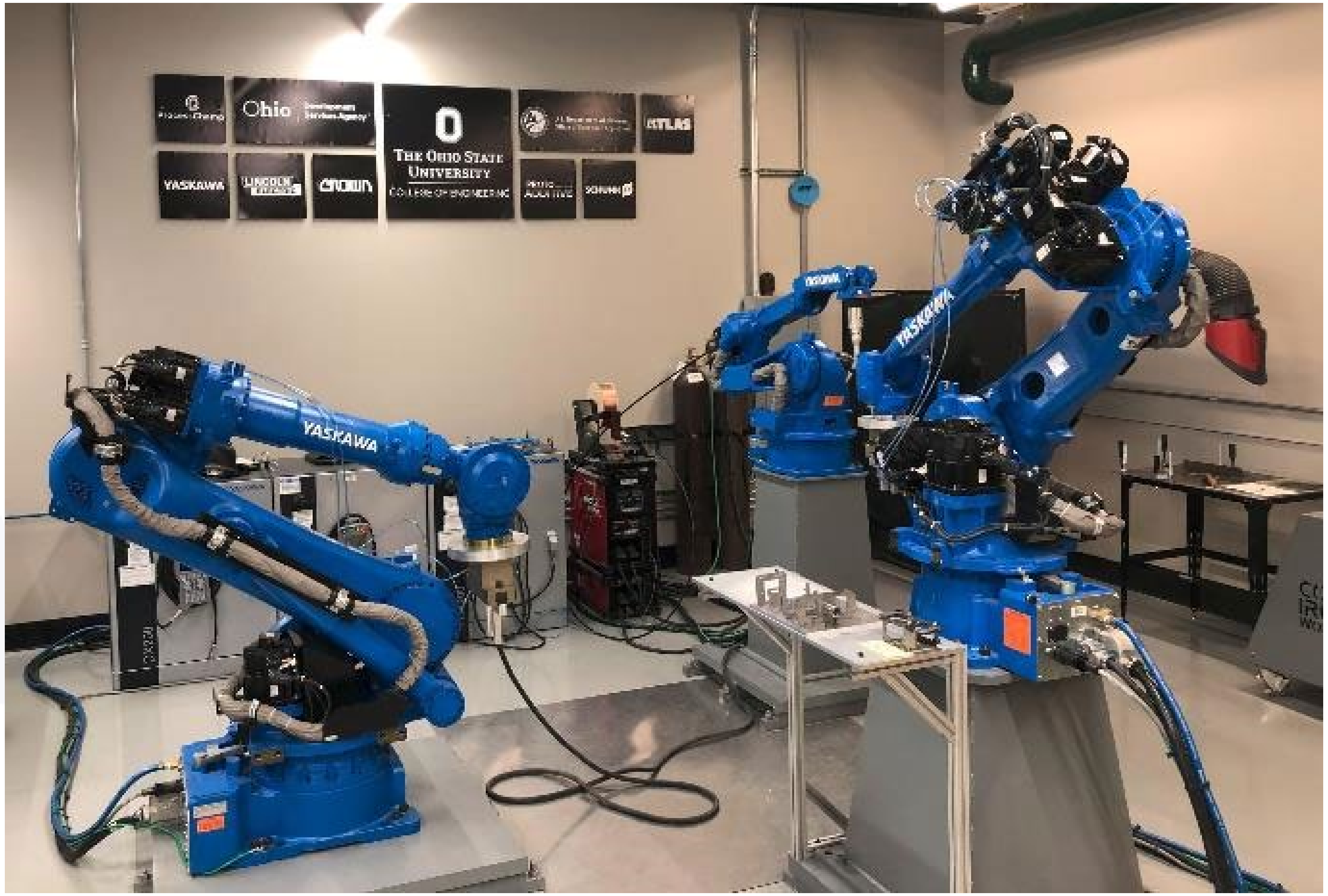
1. Script all possible actions for the assembly

2. Gather demonstrations of human building a structure out of legos

3. Label demonstrations actions and their arguments

4. Clone the behavior in the demonstrations via imitation learning

5. Compare performance of imitated demonstrations versus a state machine for a simulated and real world assembly



References

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