Final Project Proposal: Using Deep Reinforcement Learning to Teach a Robot Fine Motor Skills

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I. PROBLEM STATEMENT

With companies like Boston Dynamics and Engineered Arts gaining attention in the public eye, it's evident that robotics, mainly humanoid or real-world ready, has been on the rise. Despite the many breakthroughs these companies have had, one of the most common problems found in this type of field is how difficult it is to teach fine motor skills like balance, walking, and interaction within the real world. Even though it may appear like these things have been done before, in actuality, these problems are persistent and require further research before they can operate reliably [1]. In our project, we aim to emulate real-world interaction and develop a reinforcement learning algorithm that can teach a robotic arm a core fine motor skill by having it carefully move small objects. We will be using a prebuilt Jenga tower, made up of small individual blocks, and the robotic arm in the PyBullet and OpenAI Gym environments to have the arm carefully push out blocks from the stack, one by one, without knocking them over. Our main reinforcement learning (RL) approach will be two DRL algorithms which we will compare against one another, in order to find the optimal method to achieve our goal in a continuous 3D space.

II. APPROACHES

To teach our robot how to interact with blocks, we plan to use existing physics engines such as PyBullet, which is a powerful tool for simulating real-life physics in Python. By placing a robotic arm controlled by an agent in a physical environment, we can create a realistic and interactive Jenga stack that the robot can learn to play with. To achieve this, we will be using algorithms such as Deep Q Networks (DQNs) and Double Deep Q Networks (DDQNs), which are DRL algorithms that have been successful in various domains, including in similar past research [2]. DQNs and DDQNs operate by learning a value function that estimates the expected cumulative reward for each action in each state, and then use this value function to select actions that maximize the expected cumulative reward.

III. EXPECTED EXPERIMENTAL RESULTS

We expect to produce tables and graphics highlighting the rate of success of both the DQN and DDQN methods' attempts at moving blocks without knocking over the stack. Along with this, we will also produce other statistics highlighting run-times, resources used, as well as performances of each algorithm used. Another crucial component of our experimental results section will include a comparison of our results to previous papers that have also attempted to use RL as a way to teach the robot arm fine motor skills. It is important to note that our environments will be the same despite previous research attempting to emulate the game of Jenga.

IV. POTENTIAL CONTRIBUTIONS

We aim to recreate the work of a previous research paper, in which the robot arm was able to delicately move blocks within the stack. We will start by implementing RL algorithms to replicate those same actions in hopes to achieve a more optimal or efficient method. Subject to the availability of adequate resources and upon completion of our primary objective, we propose the possibility of extending our prior research by having the robotic arm grab the Jenga blocks and then carefully stack them on top of the tower [2]. We hope that this research will contribute to control systems innovations in the robotics space by teaching it how to emulate human touch. We believe that studying a continuous control system, such as interacting with Jenga blocks, through deep reinforcement learning (DRL) in a less complex environment can offer insights into solving other real-world problems. Research towards tactile learning systems, like pushing or tapping, can also contribute towards refining and improving robotic motor skills and can apply to other tasks that need similar careful interaction [3].

REFERENCES

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