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2DoF Robotic Arm using Reinforcement Learning

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ABSTRACT

The 2DoF Robo-Arm Reinforcement Learning aims to develop an intelligent system that can learn to control a robotic arm with two degrees of freedom using reinforcement learning techniques. The concept here involves the use of a simulated environment in which the robotic arm can interact with different objects and learn to perform tasks such as reaching, grasping, and moving objects. The idea here seeks to improve the efficiency and effectiveness of robotic arm control in industrial and manufacturing applications, enabling them to perform complex tasks with good accuracy and speed. The overview of the proposed system's objectives, methodology, and results, demonstrating the potential of this technology to control Robotic Arm and also its use in Automation are discussed here.

Key words: Arduino, Servo Motor, Sensor Sheild.

1. INTRODUCTION

In today's rapidly advancing world, robotics has emerged as a key technology with immense potential to transform various industries. Robotic arms, in particular, play a vital role in tasks ranging from manufacturing and assembly to healthcare and exploration. However, programming these arms to perform complex tasks in dynamic environments has been a persistent challenge. That's where reinforcement learning (RL) comes in, offering a groundbreaking solution to overcome these limitations.

Traditional methods of controlling robotic arms often rely on explicit programming, which requires intricate mathematical models and predefined algorithms. While effective for simple and well-defined tasks, these approaches struggle when faced with uncertain environments or complex objectives. Furthermore, the need for manual programming limits the adaptability and scalability of such systems.

Reinforcement learning, on the other hand, provides a paradigm shift by enabling robotic arms to learn and improve their performance through interaction with the environment[1]. It draws inspiration from how humans and animals learn from experience, using a trial-and-error process. By employing RL techniques, one can empower robotic arms to acquire skills, optimize their control policies, and tackle complex tasks more effectively.

Here, the primary focus lies on a 2DOF robotic arm, which offers a versatile and practical platform for various applications. The two degrees of freedom allow the arm to move in two independent directions, providing flexibility and manoeuvrability[2]. However, training such a robotic arm to perform intricate tasks with precision and adaptability is a daunting task for conventional control methods.

By harnessing the power of reinforcement learning, the proposed system aim to bridge this gap and empower the 2DOF robotic arm with intelligent decision-making capabilities. Through a trial and-error process, the robotic arm can explore its environment, learn from successes and failures, and gradually improve its control policy. This iterative learning process enables the arm to adapt to different situations, handle uncertainties, and optimize its actions for a wide range of tasks.

The benefits of employing reinforcement learning for controlling robotic arms extend beyond conventional programming limitations. RL allows robotic arms to autonomously acquire skills, adapt to changing environments, and learn from diverse scenarios without the need for explicit programming for each specific task[3]. This flexibility and adaptability make RL-powered robotic arms ideal for industries that demand efficiency, versatility, and cost-effectiveness. Furthermore, the learning capacities of robotic systems have been significantly improved by developments in reinforcement learning techniques, such as deep Q-networks (DQN), proximal policy optimization (PPO), and actor-critic approaches. Robust neural networks are utilized by these algorithms to approximate intricate control policies, hence facilitating more efficient mastery of difficult tasks by robotic arms.

By developing a 2DOF robotic arm control system using reinforcement learning techniques, an attempt is made to contribute to the advancement of robotics and automation in the contemporary world. The proposed method aims to showcase the potential of RL in enabling robotic arms to tackle complex tasks, adapt to diverse environments, and provide intelligent and autonomous solutions[4]. The outcomes of this method have implications for industries ranging from manufacturing and logistics to healthcare and space exploration, where robotic arms can revolutionize efficiency, safety, and productivity

2. BLOCK DIAGRAM

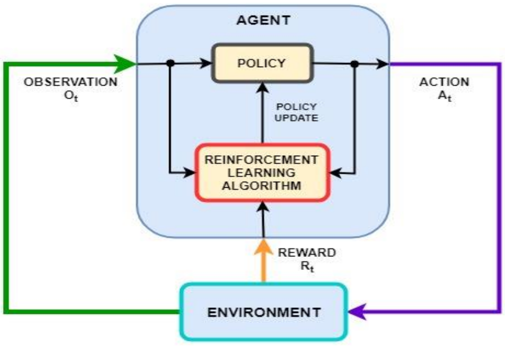

Figure 1: Block Diagram of a 2DoF Robotic Arm

To provide additional context, consider the 2D robot arm seen in Figure 1 above shows:

- The two arm joints make up the environment.
- The actions involve real valued up or down movements on each of the two joints.
- The reward is the negative of the distance between the finger and the target.

3.COMPONENTS

Arduino UNO:

An ideal board for beginning electronics and coding projects is the Arduino UNO. To begin experimenting with the platform for the first time, the UNO is the most sturdy board available. Of all the Arduino boards, the UNO is the most utilized and well-documented.

The ATmega328P as shown in figure 2, serves as the foundation for the Arduino UNO microcontroller board.In addition to a 16 MHz ceramic resonator, six analog inputs, a USB port, a power jack, an ICSP header, a reset button, and fourteen digital input/output pins—six of which can be used as PWM outputs—it also features three reset buttons[5]. It has all the components required to support the microcontroller; all you have to do is use an AC-to-DC adapter or a USB cable to connect it to a PC.

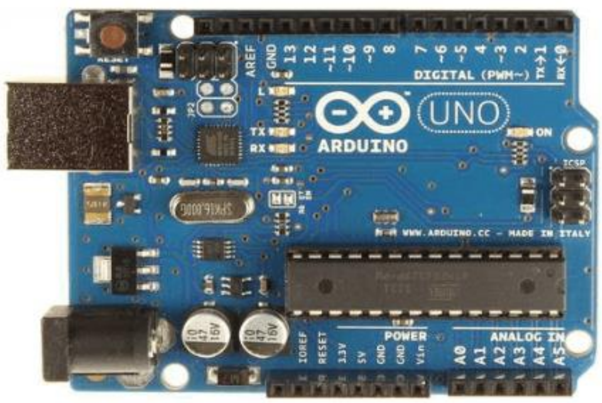

Figure 2: Arduino UNO

Battery Connector:

Figure 3 represents a normal 9V battery ,it is a wonderful way to power the Arduino UNO's barrel plug connector.

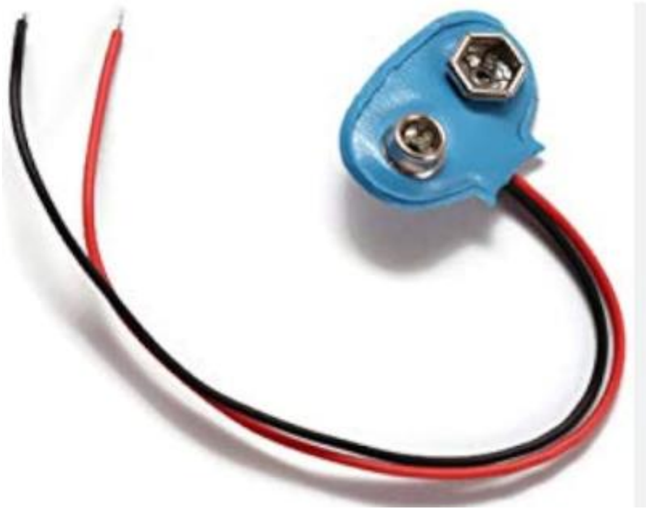

Figure 3: Battery Connector

Sensor Sheild:

The latest Sensor Shield V5 Expansion Board For Arduino as shown in figure 4 is produced by ALSRobot. This Sensor Shield expansion board as shown in figure represents how to retains the advantages of version V4.0 on the basis of stack design, PCB Immersion Gold processing technology. Newly added many kinds of interface, for example, IIC interface, 32 channels servo motor interface,Bluetooth communication module interface,SD Card communication module interface and so on, more convenient.Sensor shield allows you to connect to various modules like sensors, servos, relays, buttons , potentiometer and many more directly to your Arduino through this Sensor Shield.

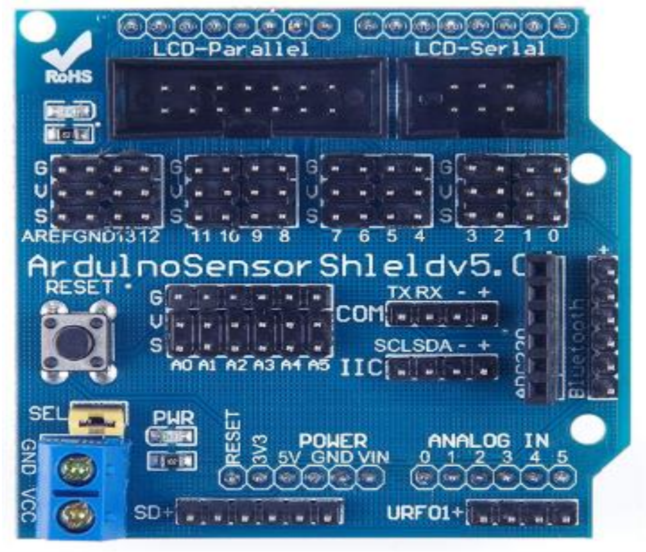

Figure 4: Sensor Sheild

Servo Motor:

Utilizing position feedback to regulate its motion and ultimate position, a servomotor is a closed-loop servomechanism as shown in figure 5. A signal, digital or analog, that indicates the output shaft's commanded position is the input to its control.

For the purpose of providing position and speed feedback, the motor is coupled with a position encoder. In simplest scenario, measurement is limited to position only. The controller's external input, the command position, is compared to the output's measured position. An error signal is generated if the output position is different from the necessary position. This signals the motor to rotate in either direction until the output shaft is in the correct position. The error signal gets smaller until it is zero as the positions get closer.

Figure 5: Servo Motor

Actuator:

One tool that converts energy and signals into the system to create motion is called an actuator shown in figure 6. Both linear and rotary motion can be produced using it. Linear motion is produced by electric linear actuators, as the term suggests. Therefore, linear actuators have a defined linear plane on which they can move forward or backward and a predetermined amount of distance before stopping[6]. When an actuator turns on a circular plane, it generates rotational motion, in contrast. Since it is not constrained by a predetermined path, the rotary actuator can continue rotating in the same direction indefinitely, unlike the linear actuator.

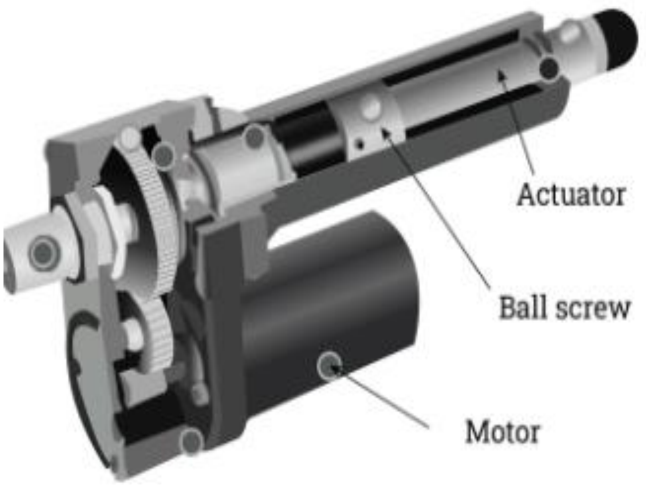

Figure 6 : Actuator

4.WORKING

Building an environment that simulates the physics and motion of the robotic arm is necessary for it to function. This environment enables the setting of joint angles, the location of the end-effector, and the simulation of the consequences of torque or force applied to joints[7]. Deep Deterministic Policy Gradients are used in the suggested method (DDPG). To accomplish a particular objective, the algorithm also looks for the best course of action[8]. The method is free of models. Low level observations, such as joint position, are all that is required.

The suggested approach calls for programming a two-dimensional robot arm consisting of joints and linkages. Pyglet is a potent library for environment development. The software trains itself based on the rewards and penalties it receives whenever ON_TRAIN is set to True.An award is given when the arm is close to the object; a punishment is applied when the arm is too far away[9]. The primary goal is to receive more rewards than penalties. It trains itself in this way.

5. RESULTS

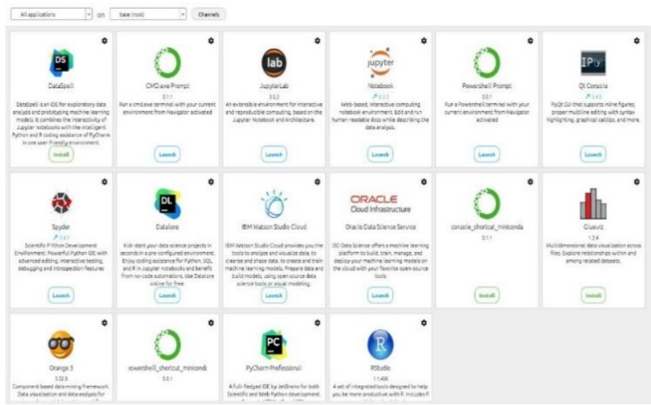

Figure 7: Launching of a Spyder

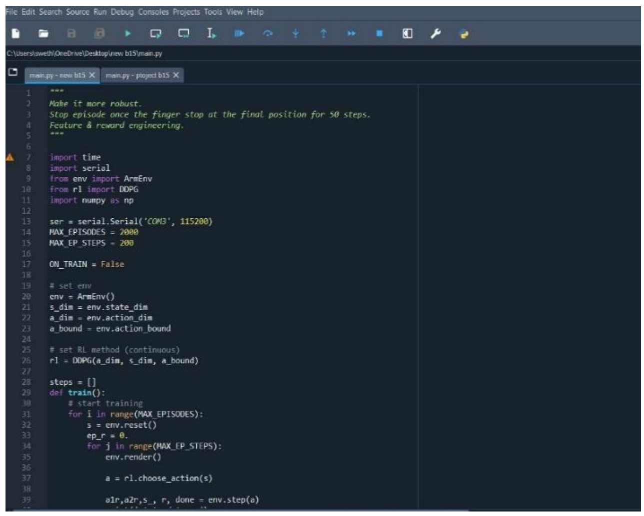

Figure 8: Run the initiated program

In Figure 8,after writing the code, click on the Run option which is present in the green colour in order to setup the Environment.

Figure 7 shows Environment setup.

a)illustration of 2dof robotic arm with two joints

b)Representation of robotic arms environment, including target.

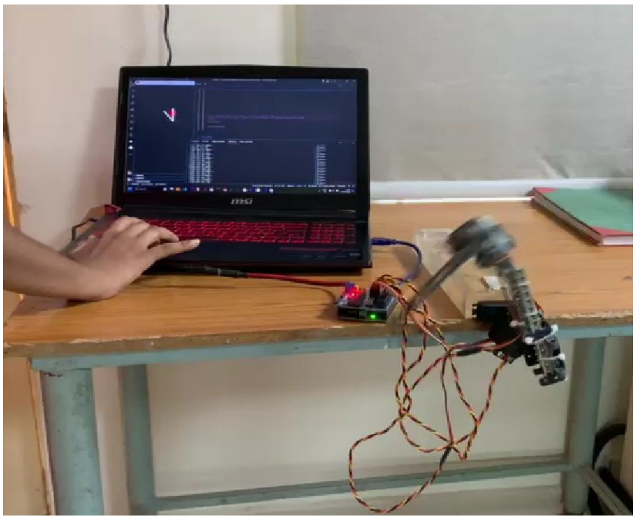

Figure 9: Represents moving a robotic arm.

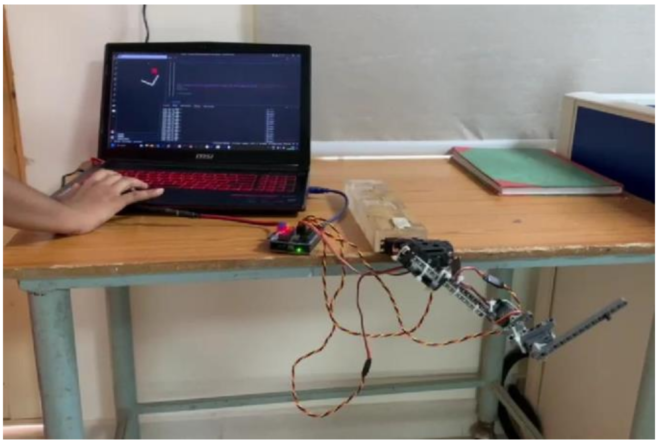

Figure 10: Goal achievement-the 2dof robotic arm successfully reaching the goal position, demonstrating the effectiveness of the trained reinforcement learning policy

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6.CONCLUSION

In conclusion, employing reinforcement learning for a 2DOF robotic arm can lead to a versatile and adaptive robotic system capable of learning and improving its performance over time. While facing challenges, this approach opens up exciting possibilities for the development of intelligent and autonomous robotic arms that can excel in various real-world applications.

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[5]. S. P. Das(2022), A Reinforcement Learning Approach for 2-DOF Robotic Arm Path Planning. This research suggests a reinforcement learning method for 2DOF robotic arm path planning. The strategy learns the arm's dynamics and control policy using a deep reinforcement learning algorithm, enabling the arm to arrive at the intended goal position as quickly as feasible.

[6]. In Lillicrap, Continuous control with deep reinforcement learning the authors initially introduced deep deterministic policy gradients. This groundbreaking article laid the groundwork for subsequent developments in continuous control tasks.

[7]. Schulman, Proximal Policy Optimization Algorithms work provides a helpful technique for optimizing policies in reinforcement learning-related scenarios.

[8]. Testing and using these techniques is made simpler by Patrick Emami's Deep Deterministic Policy Gradients in TensorFlow and the DLR-RM stable baselines. A complete understanding may be obtained by consulting surveys such as A Survey of Robotic Learning from Demonstration and Reinforcement Learning in Robotics.

[9] .Lee et al.'s study ,Sim-to-Real Transfer of Robotic Control with Dynamics Randomization looks at effective knowledge transfer strategies.