Abstract

The world of robotics has seen significant advancements in recent years, and this is largely due to the integration of machine learning techniques. Robots are now able to learn from their surroundings, make decisions, and carry out tasks with minimal human intervention. Machine learning has enabled robots to interact with humans and perform tasks that were previously considered impossible. In particular, reinforcement learning (RL) is a type of machine learning that models how humans learn from sensory input and motor responses in response to rewards. RL is based on the idea that an agent interacts with an environment by taking actions and receiving feedback in the form of rewards or punishments. Q-learning is a popular algorithm used in RL to learn the optimal policy, i.e., the best sequence of actions to maximize reward, for an agent. This thesis focuses on the application of reinforcement learning (RL) and Q-learning algorithms in controlling the motion of three joints of a six-degree-of-freedom (6-DOF) robotic arm in a simulated environment. To apply the Q-learning algorithms, the problem needs to be modeled as a Markov Decision Process, and during the learning process, the exploration and exploitation rate need to be balanced. The robotic arm is modeled in Gazebo, and the control commands are sent using the Robot Operating System (ROS 2). The objective of the robotic arm is to touch the target. The RL algorithm learns to maximize the reward function, which is based on the current and previous distance between the target and one end of the robotic arm and the angles of the three joints being controlled. The experimental results demonstrate that RL and Q-learning algorithms can effectively control the motion of a robotic arm in a simulated environment. The robotic arm successfully learns to approach and touch the target.

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1 Introduction

Designing, building, operating, and programming robots is the primary objective of the engineering and scientific discipline of robotics. A robot is a device created to carry out operations mechanically or somewhat autonomously, frequently imitating human actions or behavior [5]. Numerous industries and applications, including agriculture, manufacturing, healthcare, transportation, entertainment, and the military, use robots. Robots are frequently utilized in industry to complete tasks like welding, creating art, integration, and packing that could be repetitious or dangerous for human workers. Robots are employed in agriculture to do duties including planting, harvesting, and crop monitoring [6]. Robots are utilized in the transportation industry for logistics, warehouse management, and autonomous driving. Robots are employed in the entertainment industry for activities including animatronics as well as special effects. Robots are employed in the military for operations including bomb disposal, surveillance, and reconnaissance. Robots are evolving rapidly in terms of versatility, intelligence, and adaptability, as well as in terms of possible applications. Robotics is an emerging discipline that has the potential to significantly alter numerous aspects of our everyday lives and will probably become more crucial in determining our future [7].

Numerous companies have embraced the use of robotics to aid humans in tasks that are monotonous, physically demanding, or hazardous. Yet, acquiring a robot and hiring a robotic engineer to create a tailored solution for a particular task requires a significant investment of resources. The duties of a robot engineer include setting up communication, designing control scripts, computing coordinate transformations, and creating error-handling programs. Typically, a technician takes on the task of operating the robot on a daily basis, or the robot operates on its own. However, if the task requirements or processes change, it is difficult to modify the existing robotic solution to suit a new configuration or application without the assistance of a robot engineer, despite the significant resources invested in acquiring and developing it. Instead of relying on a robotic engineer to manually program a robot's operations for a new application, companies could employ deep reinforcement learning to train an intelligent agent to control the robot specifically for that application. This approach would enable the resources invested in robotics to be more adaptable and versatile, suitable for a broader range of applications and purposes.

This thesis is about reinforcement learning which is a type of machine learning that involves an agent learning from its interactions with an environment in order to maximize a reward signal over time [8]. It is a method of learning that involves trial and error, with the agent receiving feedback in the form of rewards or punishments for its actions. According to Kaelbling, Littman, and Moore [9], reinforcement learning can be defined as "a problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment". Many different concepts and methodologies can be used to break down reinforcement learning. This work focuses on Deep Q learning, and to study it, a simulated robotic arm is trained to touch a can.

1.1 Context

1.1.1 Simulated Robotics

Simulated robotics is a rapidly developing field of study that strives to create intelligent systems that can communicate with virtual worlds in a manner that is comparable to how actual robots communicate with the real world [10]. Compared to traditional robots, simulated robotics has many benefits, such as lower costs, more flexibility, and the ability to test and improve algorithms in a secure setting. Simulated robotic systems can be applied to a variety of tasks, from straightforward ones like object detection and manipulation to more difficult ones including autonomous navigation, group decision-making, and experience-based learning.

Figure 1: Simulated urban scenario created in Gazebo [1].

The application of virtual environments for autonomous vehicle training and testing is an illustration of simulated robotics [11]. To train and test the computer programs that operate autonomous vehicles, researchers can develop realistic simulations of numerous driving circumstances and scenarios, like traffic patterns, atmospheric conditions, and unforeseen incidents. With this strategy, researchers may evaluate the dependability and safety of autonomous vehicles in a safe setting before placing them on public roads. The application of virtual environments to train and test robots for search and rescue missions is another illustration of simulated robotics [12]. In order to train and test robotics that can aid in rescue operations, researchers can develop simulations of emergencies such as earthquakes or floods. With this method, researchers may test the efficacy and security of various robotic systems and algorithms in a range of circumstances without endangering human responders. Systems for industrial automation can also be developed using simulated robotics. For instance, manufacturers can build

and test robotic assembly lines, improve production workflows, and spot possible bottlenecks or safety risks using simulations. Before installing physical systems in the real world, this method enables manufacturers to optimize their procedures and increase productivity.

1.1.2 Industrial Automation

Automation of industrial processes, such as manufacturing and construction, via the use of technological devices and control systems, is known as industrial automation [13]. Industrial automation can be accomplished by utilizing simulated robotic arms to carry out operations that would typically be carried out by human workers or actual robots. This entails creating the algorithms and control frameworks necessary for the virtual robotic arm to move and handle items precisely and effectively, as well as incorporating the virtual arm into a larger system that is capable of carrying out difficult tasks on its own. Applications for simulated robotic arms in industrial automation include material handling, manufacturing work, quality control examinations, and machine maintaining. Companies can decrease the expenses of real robots and human labor while boosting production and efficiency by deploying virtual robotic arms [14]. Additionally, for increased flexibility and scalability, simulated robotic arms can be flexibly customized and adapted to various industrial environments. All things considered, the employment of simulated automated arms for automation in industry is a promising area of study and development, with tremendous potential for enhancing industrial procedures and developing the field of robotics.

Figure 2: Small Warehouse Gazebo simulation [2].

1.1.3 Robotic Arms

Traditionally developed industrial robots have been confined to closed cells or limited-access warehouse areas [15]. They typically perform repetitive operations on standardized objects without human interaction. Programming these robots is usually a time-consuming process that requires specialized knowledge of the machine's software. However, current trends in robotics aim to make robots capable of operating in dynamic and open environments where they can work alongside humans. This presents new challenges that require equipping the robot with sensors to perceive its surroundings and interact with objects. However, integrating and utilizing sensor data for planning the robot's actions is not an easy task. A robotic arm functions like a human arm and is a mechanical system that typically includes an end effector for manipulating and interacting with the environment [16]. Robotic arms have various applications in industrial and service fields, such as pick and place, exploration, manufacturing, laboratory research, and space exploration. An arm with 6 degrees of freedom can pivot in six different directions, similar to a human arm. In industrial robotic arms, the mechanical structure and control mechanism are major factors of concern.

Figure 3: A robot arm helps make engine components at a Volkswagen factory in Germany [3]

These arms are commonly used in a variety of applications, such as manufacturing, assembly, material handling, and surgery. Robotic arms can be controlled by various means, including joystick or slider controls, keyboard-based interfaces, and programmed motions. They can be programmed to perform repetitive tasks with high precision and speed, which makes them ideal for use in industrial settings where consis-

tency and efficiency are crucial. These arms can be equipped with various end effectors, such as grippers, cameras, or welding tools, depending on the specific task that needs to be performed. They can also be designed to have multiple joints or degrees of freedom, which enables them to move in a wide range of directions and perform complex tasks. Advancements in robotics technology have led to the development of lightweight and portable robotic arms that can be easily integrated into various systems [17]. These arms are becoming increasingly popular in areas such as healthcare and rehabilitation, where they can assist with tasks such as lifting and moving patients.

The primary focus of current research efforts is on training the robot's arm to carry out various tasks autonomously using deep learning technologies. However, due to the massive amount of data required to teach a robot effectively, a data-driven approach is necessary. This can be challenging to achieve using a physical robotic arm. Therefore, developers have turned to robot simulation software [18], [19] to overcome the limitations of data-intensive AI approaches and to provide a stable environment [20]. In a simulated environment, it is possible to control every aspect of the world, including impractical factors in reality. Moreover, there is no risk of damaging robots or human operators in simulations, and time control allows for faster data collection.

1.1.4 Robot Operating System (ROS) and Gazebo

The Robot Operating System (ROS) is a set of software libraries and tools that enables developers to build robotic applications [21]. It provides a framework for writing and running code across multiple computers and devices, making it easier to create complex robotic systems. ROS was first developed in 2007 by Willow Garage, at robotics research lab [22]. Since then, it has become widely adopted by the robotics community and is now supported by the Open Robotics organization. It offers a comprehensive platform for managing robotic systems. Originally designed to facilitate research in robotics, ROS is a unique framework. To grasp the fundamentals of the ROS framework, it is essential to comprehend the concept of message communication between nodes using topics. One of the key features of ROS is its ability to handle communication between different components of a robotic system, such as sensors, actuators, and controllers [23]. This communication is done using a publish-subscribe messaging system, which allows components to share data and commands in real time. ROS also provides a wide range of tools and libraries for tasks such as perception, navigation, and manipulation, which can be used to build complex robotic applications. These tools include algorithms for object recognition, path planning, and motion control, among others. Another advantage of ROS is its open-source nature, which means that developers can contribute to the development of the software and share their own code with the community. This has led to a large and active community of developers working on ROS, which has helped to drive its development and adoption.

Gazebo, on the other hand, is like a virtual playground for robots. It is a special computer program that lets you create a digital world where robots can move around and interact. It is like a video game, but instead of playing as a character, we get to

control and test robots. In Gazebo, we can build different environments like houses, parks, or even other planets. We can also design and customize our own robots with different shapes, sizes, and abilities. Once we have our world set up and our robots ready, we can make them move, perform tasks, and see how they interact with the surroundings.

Gazebo is useful because it allows us to experiment and learn about robotics without having to build and test everything in the real world. We can try out different robot designs, program them to do specific tasks, and see how they behave in different situations. It helps engineers and researchers save time and resources by simulating and testing their ideas virtually.

So, Gazebo is a computer program that lets us create worlds for robots to explore and learn in. It can be seen as a virtual playground where we can build robots and see how they work before bringing them to life in the real world.

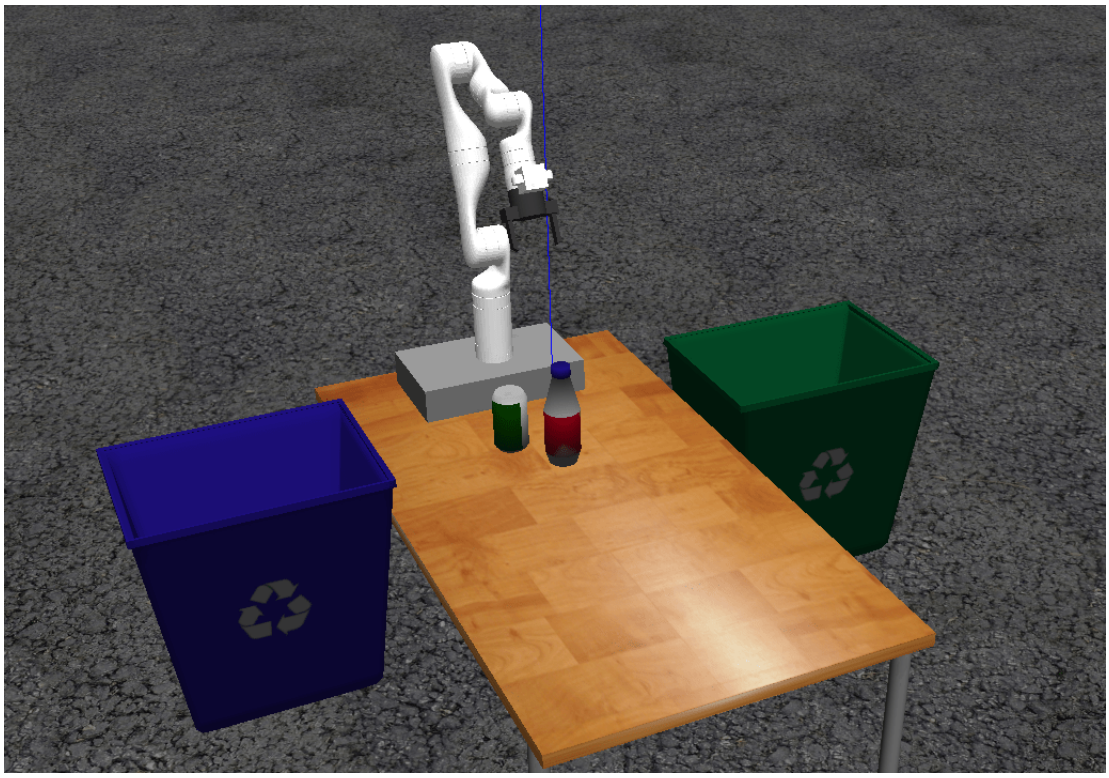


Figure 4: Gazebo simulation of a Robotic Arm in a Pick and Place setup. [4].

1.1.5 Simulations

Simulations serve as an entry point for Digital Twins, which are highly accurate depictions of the physical world [24]. These Twins can aid in boosting manufacturing output and improving the flexibility of supply chains. To streamline the implementation of manufacturing processes during production line changes, digital twinning involves

linking simulation software to an actual self-governing robotic system. A robotic arm digital twin solution is showcased in a recent study [25], where the authors employed ROS [26] to achieve smooth functioning between the virtual and real worlds. Simulating software has its limitations as it cannot accurately represent the real world due to the imperfections in their physics engines.

Additionally, simulations have the advantage of providing perfect data with no interference, which has supported the exploration of deep learning approaches in robotics research. Simulations are a powerful tool for designing and testing robotic arms. They allow engineers to create virtual models of robotic arms and simulate their behavior in different scenarios, without the need for a physical prototype. In a robotic arm simulation, the arm's mechanical structure, control system, and sensors are modeled in a virtual environment. The simulation can then be used to test the arm's performance in various tasks, such as picking and placing objects, assembling parts, or performing complex movements. One of the key benefits of using simulations for robotic arm design is that they can help identify potential issues or inefficiencies before a physical prototype is built [27]. This can save time and resources, as well as improve the overall design of the arm. Simulations can also be used to optimize the control system of a robotic arm. By simulating the arm's behavior in different scenarios, engineers can identify the optimal control strategy for achieving a specific task or movement.

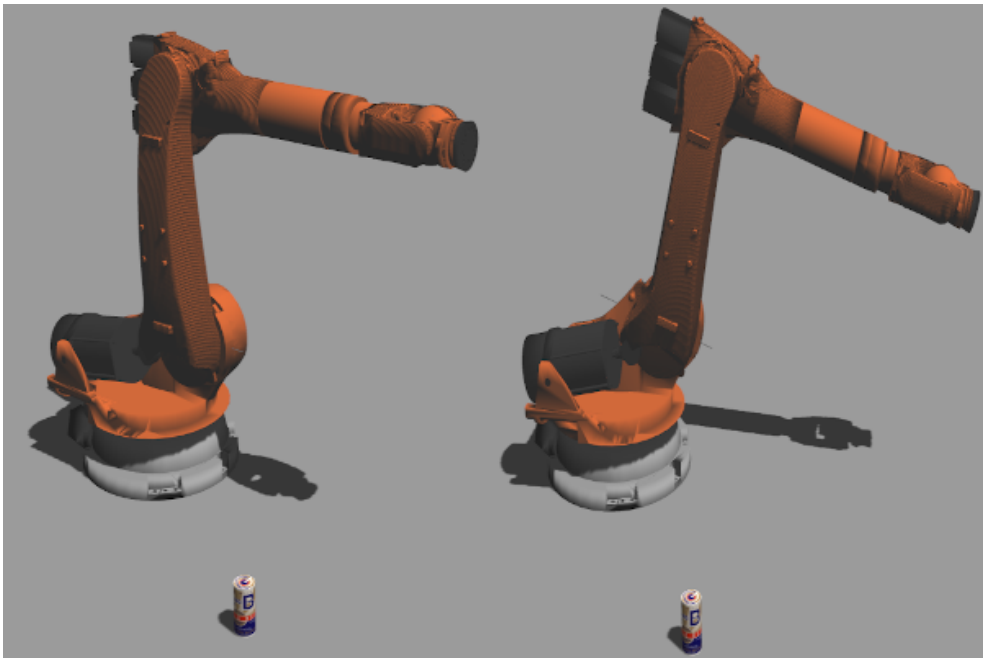
The ROS framework includes a useful tool called RViz, which enables us to observe the robot's pose or estimation in a 3D environment [28]. With the correct configuration of the URDF file, the robot model can be visualized in RViz. Furthermore, simulations can help train and test algorithms for robotic arm control, such as RL methods or deep learning approaches. This can be done by running simulations with different environments and scenarios and using the resulting data to train and refine the algorithms.

1.1.6 Reinforcement Learning

Reinforcement learning is like teaching a computer to make decisions and get better at them over time, similar to how we learn from our mistakes and improve. Consider the robotic arm in this thesis, we want to train it to perform a simple task which is touching an object. We do not give the robotic arm a list of instructions for every situation; instead, we want the robotic arm to learn on its own.

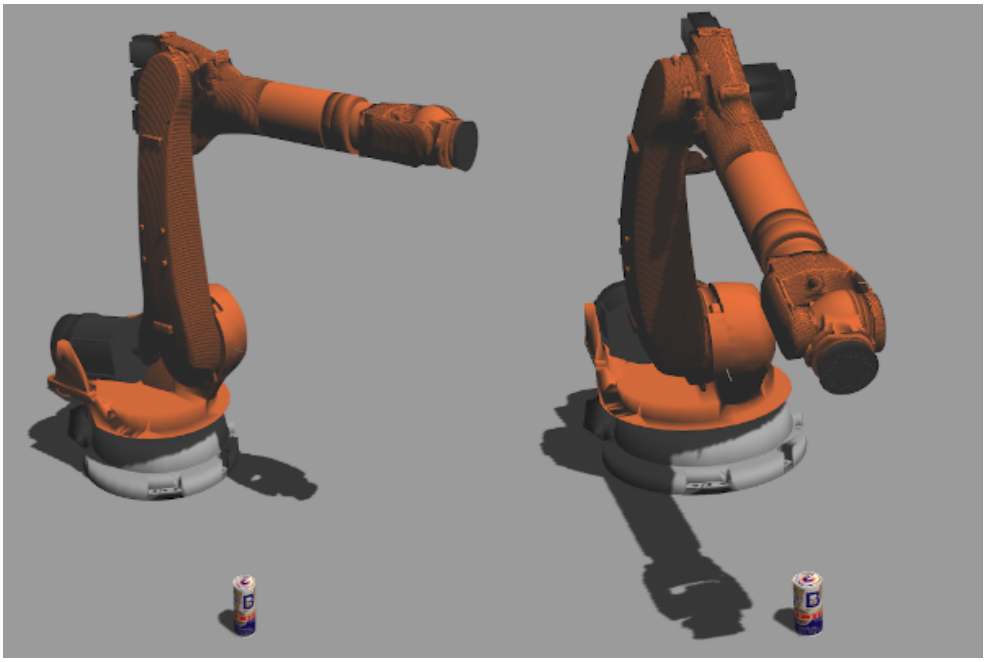
In reinforcement learning, the robot interacts with its environment. It takes actions, and based on those actions, it receives feedback in the form of rewards or punishments. Just like when humans do something good, they get a reward, and when they do something bad, they might get scolded.

The robot's goal is to figure out the best actions to take in different situations to maximize its rewards. It starts by trying random actions and seeing what happens. Over time, it learns from the feedback and adjusts its actions to get more rewards and fewer punishments.



(a) Simulated robotic arm starting position.

(b) Simulated robotic arm moving away from the target object.



(c) Simulated robotic arm starting position.

(d) Simulated robotic arm moving closer to the target object.

Figure 5: Robotic arm Kuka KR210 moving closer and away from the target.

For example, in the process of trying random actions; in Figure 5, when the robotic

arm moves from Figure 5a to Figure 5b it gets away from the target object so in this case the robotic arm is punished with a negative reward. On the other hand, when it moves from Figure 5c to Figure 5d it gets closer to the target object, and therefore it receives a positive reward. It can be seen as a game where the robotic arm is the player, the environment is the game world, and the rewards are the points it earns. The more points it earns, the better it gets at playing the game. In our example, consider Figure 6 when the robotic arm finally touches the target object it gets the highest possible reward and ends the game victoriously. To help the robot learn, we use special algorithms that guide its decision-making instead of just random actions. These algorithms learn from the experiences and feedback, just like humans learn from our mistakes and successes.

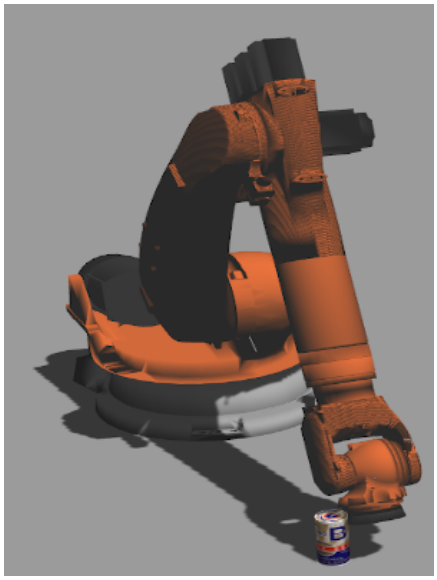


Figure 6: Simulated robotic arm touching the target object.

Reinforcement learning is exciting because it allows machines to learn and adapt without us telling them exactly what to do. They explore, learn from their actions, and become better at solving problems. It is like watching our pet robot grow smarter and more capable over time.

1.2 Problem Statement

Many studies have demonstrated that utilizing reinforcement learning (RL) presented a viable solution for addressing the limitations of conventional methods in tackling intricate robotics tasks. Numerous AI experts have created various frameworks and toolkits to examine and assess their algorithms' effectiveness in solving challenging problems [29]. Although the outcomes were remarkable, these applications were generally limited to simulated environments and seldom deployed in real-world scenarios. Numerous researchers are presently focused on a highly promising mission of bridging the

gap between simulation and reality. However, proficiency in various domains is crucial in the intricate field of RL, which might be an obstacle to entry for roboticists. For problems involving an agent interacting with the environment to maximize a reward signal, RL, a potent branch of machine learning (ML), is used. Gaming, robotics, and finance are just a few of the industries where RL has been successfully used. RL has been applied to robotics to tackle a variety of problems, including grasping, manipulating, and navigating. One of these tasks involves teaching a virtual robotic arm to touch an object using reinforcement learning. The objective of this proposed study is to create a simulated environment in which a simulated robotic arm learns to touch an object by using the Double Q Learning method for RL. Implementing this brings the following challenges:

- Designing the incentive function: It is difficult to create a reward mechanism that encourages the robotic arm to interact with the object without damaging it or knocking it over.
- Tackling high-dimensional events and action spaces: It is difficult to apply RL methods to the robotic arm's highly dimensional state space and continuous action space.
- Safeguarding the surroundings and the robotic arm is essential while instructing the agent.

We will utilize the Double Q Learning technique to address this issue since it uses two Q-value functions to address the overestimation problem with Q Learning. The best course of action is chosen using one Q-value function, and the chosen course of action is assessed using the other Q-value function. The environment and robotic arm will be simulated using a physical simulator. The robotic arm will use the Double Q Learning method to choose an action after receiving state information from the simulator. In order to give the agent knowledge about the next state and a reward signal, a simulator will model the dynamics of the robotic arm and the object.

1.3 Goals

The goal of this thesis is to develop a robotic arm that can learn to touch an object using the double Q-learning algorithm. The focus will be on creating the simulated environment as well as implementing and evaluating the algorithm's performance in the simulated environment, with the aim of demonstrating the effectiveness of the approach and the potential for real-world applications. The thesis will also explore the impact of different hyperparameters on the performance of the algorithm, and investigate ways to enhance the system's robustness and generalization capabilities. Ultimately, the goal is to provide insights into the use of reinforcement learning algorithms for robotic manipulation tasks and pave the way for further research in this area. Specifically the goals are:

- Creating a robotic arm simulation in Gazebo and ROS 2 that can be treated as a Markov Decision Process, which will enable future integration of various reinforcement learning algorithms.
- Training a robotic arm, using the Double Q-learning algorithm to learn to touch an object.
- Defining an appropriate reward mechanism to motivate the robotic arm to effectively touch the target.
- Tackling the exploration vs exploration problem in the case of a simulated robotic arm learning to touch an object.

1.4 Related Work

Reinforcement learning has been widely used for controlling robotic arms, and the deep Q-network (DQN) algorithm has shown great potential in this regard. Some related work regarding the field of Reinforcement Learning is described in this section.

In [30], the author uses deep Q-networks to train a 7-DOF robotic arm in a control task without any prior knowledge. The only input for the arm controller is images from the environment and the output is actions in order to achieve the task of locating, and grasping a cube. An interesting thing to mention regarding this work is how they define the reward function for intermediate steps. Similarly to the presented work, in this scenario, the robotic arm also has to learn to approach an object. In [31], the authors examine the impact of reward functions and hyper-parameters on the effectiveness of policy learning using four deep reinforcement learning (DRL) algorithms for continuous torque control policies in model-free manipulation tasks. They simulate a manipulator robot and define two tasks, random target reaching and pick&place, each with two distinct reward functions. The authors compare the performance of the algorithms using multiple hyper-parameters and analyze their results across the two tasks. The study includes both simulated and real-world executions of their best policies, which demonstrate the effectiveness of their approach. The authors suggest that their approach can be used to select the best-performing algorithm for different tasks and manipulator robots, with policies that can be easily transferred to physical setups, ensuring a match between simulated and real-world behaviors. Similarly, in [32], the authors use the DQN algorithm for solving the Inverse Kinematics problem of a 7-Degree of Freedom (DOF) robotic manipulator. It is shown that DQNs can also be applied to create joint space trajectories in the continuous joint angles space instead of in just discrete solution space scenarios. Finally in [33] the authors combine computer vision, Q-learning, and neural networks to generate paths for a robotic arm to move. The proposed method uses two images to obtain accurate spatial coordinates of objects in real time, Q-learning to determine a sequence of simple actions, and a trained neural network to determine a sequence of joint angles. The results of simulation and experimental tests prove that the robotic arm is able to follow the path avoiding obstacles and reaching the target.

1.5 Contribution

The main contributions of this work can be listed as follows:

- Implementation of a simulated robotic arm environment that in Gazebo compatible with ROS 2 that publishes images, and other sensor reading from the simulated environment to topics accessible from outside the simulation.
- Implementation of the Double Q learning algorithm in the ROS 2 framework.
- Implementation of a communication pipeline between the robotic arm simulation in Gazebo and the reinforcement learning algorithm in ROS 2 so that these two can interact with each other.

2 Foundations

2.1 Python

Python is a popular language for implementing deep learning algorithms because of its simplicity, adaptability, and abundance of tools and frameworks. It has grown in popularity as a programming language for machine learning, deep learning, and robotics due to its simplicity of use, wide library support, and adaptability. TensorFlow, PyTorch, Keras, OpenCV, NumPy, SciPy, ROS, and Gazebo are just a few of the libraries and frameworks available in Python for machine learning, deep learning, and robotics. These libraries and frameworks provide developers with a variety of tools and methods for developing and deploying machine learning, deep learning, and robotic applications. Python's readability and ease of use make it an appealing choice for machine learning and robotics developers. Its syntax is straightforward and clear, making it easier to develop and comprehend code. Furthermore, the dynamic nature of Python allows for quick prototyping and experimentation, which is vital for building and testing machine learning and robotics algorithms. Python's extensive library and frameworks, paired with its simplicity of use and adaptability, makes it an excellent choice for machine learning, deep learning, and robotics applications. Here are some of the most important Python modules and frameworks for these fields:

1. TensorFlow: Google's popular deep learning package that supports both static and dynamic computation graphs. TensorFlow is utilized in a variety of applications such as computer vision, natural language processing, and robotics.
2. PyTorch: A famous deep learning library created by Facebook that is noted for its simplicity and adaptability. PyTorch is utilized in a variety of applications such as computer vision, natural language processing, and robotics.
3. Keras: Keras is a high-level deep learning API that may be used in conjunction with TensorFlow, Theano, or CNTK. Keras is well-known for its simplicity and is frequently used for quick prototyping and experimentation.

4. OpenCV: OpenCV is a free and open-source computer vision toolkit that includes a variety of image processing and computer vision methods. OpenCV is frequently used in robotics applications like object identification and tracking.

5. NumPy: A Python library for numerical computing that supports massive, multi-dimensional arrays and matrices. NumPy is commonly used as a basis for many other scientific computing libraries, as well as in machine learning and robotics applications.

6. SciPy: A Python library for scientific computing that supports optimization, signal processing, and other scientific computing activities. For tasks such as optimization and control, SciPy is frequently utilized in machine learning and robotics applications.

7. Python: Python has a variety of robotics libraries, including ROS (Robot Operating System) and Gazebo, which are frequently used for designing and modeling robotic applications.

Python's popularity in robotics is growing due to its simplicity of use, adaptability, and wide library support. Here are some of the reasons why Python is useful in robotics:

1. Python features a basic and easy-to-learn syntax, making it accessible to both beginners and professionals. Python's readability and compact syntax make it simple to create and comprehend code, which is required while designing and testing robotics algorithms.

2. Python is a versatile programming language that may be used for a variety of purposes, including robots. Python is a versatile choice for robotics developers since it can be used for both high-level and low-level programming.

3. Extensive library support: Python has a number of libraries and frameworks intended expressly for robotics, such as ROS, Gazebo, and PyBullet. These libraries and frameworks provide developers a variety of tools and algorithms for developing and delivering robotics applications.

4. Python's dynamic nature enables quick prototyping and experimentation, which is vital for designing and testing robotics algorithms. Python's interactive shell also makes it simple to test code and try out new ideas.

5. Integration with other languages: Python can readily integrate with other programming languages used in robotics, such as C++ and MATLAB. This enables robotics engineers, regardless of programming language, to employ the finest tools for the job.

2.1.1 The Python Deque Data Structure

A `deque` in Python is a double-ended queue data structure that allows efficient adding and removing of elements from both ends. It is provided as a built-in class in the `collections` module [34].

The following are the main methods available for a `deque`:

- `append(x)`: Adds an element `x` to the right end of the deque.
- `appendleft(x)`: Adds an element `x` to the left end of the deque.
- `pop()`: Removes and returns the rightmost element from the deque.
- `popleft()`: Removes and returns the leftmost element from the deque.
- `rotate(n)`: Rotates the deque `n` steps to the right (if `n` is positive) or to the left (if `n` is negative).
- `count(x)`: Counts the number of occurrences of an element `x` in the deque.
- `extend(iterable)`: Extends the deque by appending all elements from the iterable to the right end.
- `extendleft(iterable)`: Extends the deque by appending all elements from the iterable to the left end (in reverse order).

One of the main advantages of using a `deque` over a list for implementing a queue or a stack is that both append and pop operations have O(1) time complexity. This means that adding or removing elements from either end of the deque is very efficient, even for very large data sets [34].

2.2 Pytorch

PyTorch is a Python-based open-source machine learning library based on the Torch library, which was created by Facebook's AI Research (FAIR) team [35]. It is generally employed for creating deep learning models for applications like speech recognition, computer vision, and natural language processing. PyTorch uses a dynamic computational network to construct and adapt models, which gives it a competitive advantage over competing deep learning frameworks. It also provides a variety of tools and utilities for developing, training, and assessing deep learning models, including as data loaders, optimizers, and loss functions. One of PyTorch's primary advantages is its ability to easily integrate with Python, making it simple to use for developers and researchers who are already familiar with Python. Furthermore, PyTorch provides a user-friendly interface for developing and training deep learning models, reducing the time and effort necessary to design and deploy models. PyTorch provides a versatile and

fast framework for creating and training deep neural networks, making it an excellent candidate for DDQN implementation. Typically, the procedure entails establishing the neural network architecture, configuring the environment, and performing training loops to update the network weights depending on the agent's actions and rewards. PyTorch also has several important DDQN capabilities, such as the ability to build various optimization algorithms and loss functions, which can assist to increase the efficiency and efficacy of the learning process. Furthermore, PyTorch's automated differentiation capability can make it easier to construct and debug complicated DDQN algorithms by automatically calculating gradients during the training phase.

2.3 Gazebo

Gazebo is a free and open-source 3D simulation platform for robotics and automation [36]. It enables users to design and simulate complex systems like robots, sensors, and surroundings, and it is used for a variety of applications such as robot development, testing, and validation. Gazebo has a realistic physics engine that properly replicates object behavior and interactions with the environment, allowing developers to test and debug their algorithms in a safe and controlled setting. It also includes a variety of sensors and actuators for simulating various sorts of robotics and automation systems. Gazebo is built on top of the ODE (Open Dynamics Engine) physics engine and generates realistic images with the Ogre 3D rendering engine. It is developed in C++ and works with a variety of programming languages such as Python, Java, and MATLAB. Gazebo is frequently used in combination with other robotics libraries and frameworks, such as ROS (Robot Operating System), which offers a comprehensive collection of tools and utilities for developing and testing robotic systems. ROS contains a Gazebo integration package that enables smooth integration of the two platforms, making it simple to model and test robotic systems with Gazebo. Gazebo is largely used in robotics and automation applications for simulation. It offers a realistic simulation environment for testing and evaluating algorithms and systems before deploying them in the real world. Users may use Gazebo to design and simulate complex systems such as robots, sensors, and surroundings, as well as test their algorithms in a safe and controlled environment. The simulation environment contains a physics engine that realistically models object behavior and interactions with the environment, allowing developers to test and debug their algorithms and systems under a variety of scenarios. Gazebo offers a wide range of sensors and actuators, such as cameras, lidar, and GPS, that may be used to mimic many sorts of robots and automation systems [37]. It also allows plugins, which let users customize and enhance the simulation environment's capabilities to match their individual needs. Gazebo is often used in robotics research and development, as well as in robotics and automation system teaching and training. It may be used in conjunction with other robotics libraries and frameworks, such as ROS (Robot Operating System), to offer a full simulation and development environment for robotic systems. Gazebo is commonly used for simulating robotic arms in robotics research and devel-

opment. Gazebo offers a diverse set of sensors and actuators for simulating many sorts of robotic arms. Joint controllers, for example, can be used to regulate the position and velocity of the joints in the arm, and force/torque sensors can be used to mimic contact with objects and surfaces. Furthermore, Gazebo has a plugin system that allows developers to customize and enhance the simulation environment to match their individual requirements. Developers can write plugins, for example, to imitate certain sensors or actuators or to provide new control techniques for the robotic arm.

2.4 ROS 2

A collection of ROS software packages available for download is referred to as a ROS distribution, backed by the non-profit organization, Open-Source Robotics Foundations (OSRF). The ROS organization periodically updates these packages and assigns distinct titles to each distribution. ROS 2 (Robot Operating System 2) [38] is the second edition of the popular open-source robotics middleware framework, ROS, launched in 2017 to address some of the limits and issues of the original ROS framework. ROS 2's primary features and benefits include the following:

1. Enhanced real-time performance: In comparison to the original ROS middleware, ROS 2 incorporates a new middleware layer called the Data Distribution Service (DDS), which delivers enhanced real-time speed and stability.

2. Improved support for multi-robot systems: ROS 2 introduces the ROS 2 Multi-Robot System (MRS) architecture, which improves communication and coordination between numerous robots.

3. ROS 2 features support for Transport Layer Security (TLS) and X.509 certificates, which enables increased security and authentication for node-to-node connections.

4. Better non-Unix platform compatibility: ROS 2 has enhanced support for non-Unix systems such as Windows and macOS.

5. ROS 2 features better development tools and documentation, making it easier for developers to get started with the framework.

Conclusively, ROS 2 is intended to provide a more robust, dependable, and adaptable platform for developing and deploying robotic systems. It is interoperable with a broad range of robotic hardware and software platforms, and it has a big and active development and user community. In robotics research and development, ROS 2 is often used to operate robotic arms. Developers may use ROS 2 to design a software stack that contains the control algorithms, sensors, and communication interfaces needed to control the robotic arm. ROS 2 is a flexible and modular design that enables developers to construct software modules known as nodes that connect with one another via a

publish-subscribe messaging model. For example, one node may be in charge of reading sensor data from the robotic arm, while another node may be in charge of operating the motors of the arm depending on the sensor data. A large selection of software libraries and tools referred to as packages, are also offered by ROS 2 and may be used to create and test robotic arm control software. For instance, the *ros_control* package offers a variety of hardware interfaces and controllers for interacting with robotic arm hardware, while the *MoveIt* package offers a set of motion planning and control algorithms for robotic arms. Developers often begin by specifying the hardware interface for the arm, which comprises the joints, motors, and sensors, in order to control a robotic arm using ROS 2. Then, using ROS 2 nodes and packages, they create the control algorithms and sensor interfaces needed to control the arm. Finally, before implementing their robotic arm control software on the MoveItactual robot, engineers may test and evaluate it using simulation tools like Gazebo. This enables the software to be developed and iterated upon quickly without endangering the physical robot or its surroundings.

2.4.1 ROS 2 Nodes

ROS 2 nodes are the fundamental building blocks of a ROS 2 system. A node is a process that performs computation and communicates with other nodes in the ROS 2 system. In ROS 2, nodes are implemented using the rclpy.node.Node class in Python. This class provides a way to create a node and interact with the ROS 2 middleware. It provides methods to create publishers, subscribers, services, clients, timers, and parameters. By inheriting from this class, a Python class can become a ROS 2 node and use these methods to interact with the ROS 2 system. To create a ROS 2 node, one needs to create a ROS 2 package and a Python file inside it. The Python file should inherit from the $rclpy.node.Node$ class and override its $\_\_init\_\_()$ method to create publishers, subscribers, services, clients, timers, and parameters. The $main()$ function initializes the ROS 2 system, creates an instance of the Python class, and spins the node to process callbacks. Finally, the $rclpy.shutdown()$ function is called to shut down the ROS 2 system.[39] ROS 2 nodes can be created using object-oriented programming (OOP) techniques. OOP is the recommended way to write a node in ROS 2, and it works pretty well. OOP allows for better code organization, encapsulation, and reusability. It also makes it easier to write testable code. In conclusion, ROS 2 nodes are the fundamental building blocks of a ROS 2 system. They are implemented using the rclpy.node.Node class in Python. By inheriting from this class, a Python class can become a ROS 2 node and use its methods to interact with the ROS 2 system. OOP is the recommended way to write a node in ROS 2, and it allows for better code organization, encapsulation, and reusability.

2.4.2 ROS 2 Services

ROS 2 services provide a way for nodes to communicate with each other by requesting and providing specific functionalities or operations. This is done through a client-server

communication model where the node requesting the service acts as the client and the node providing the service acts as the server.

One advantage of ROS 2 services is their ability to handle both synchronous and asynchronous communication. Synchronous communication blocks the client node until a response is received from the server node. Asynchronous communication allows the client node to continue with other operations while waiting for a response from the server node.

ROS 2 services also provide a way to handle errors that may occur during service communication. In the case of a failure, the server node can send an error message to the client node, indicating the reason for the failure. This makes it easier for developers to debug their code and troubleshoot issues that may arise.

ROS 2 services can easily scale. Multiple nodes can request the same service from a single server node, which can handle all requests concurrently. This can improve the overall performance of the system and reduce latency.

However, ROS 2 services also have some limitations. For example, they do not support streaming data or continuous communication. They are intended for point-to-point communication, where a client node requests a specific operation from a server node and receives a single response.

In summary, ROS 2 services provide a flexible and reliable way for nodes to communicate with each other by requesting and providing specific functionalities or operations. They are suitable for point-to-point communication and can handle both synchronous and asynchronous communication, making them a valuable tool for ROS 2 developers.

2.4.3 ROS 2 Topics

ROS 2 topics provide a way for nodes to communicate with each other by exchanging messages on a specific topic. This is done through a publish-subscribe communication model where the node publishing the message acts as the publisher and the node receiving the message acts as the subscriber.

ROS 2 topics can handle asynchronous communication. This means that the publisher node does not have to wait for the subscriber node to receive the message before continuing with other operations. This can improve the overall performance of the system and reduce latency.

ROS 2 topics also provide a way to handle errors that may occur during message communication. In the case of a failure, the subscriber node can request that the publisher node resend the message or ignore the message and continue receiving subsequent messages. This makes it easier for developers to debug their code and troubleshoot issues that may arise.

Another advantage of ROS 2 topics is their flexibility. Multiple nodes can subscribe to the same topic, and publishers can send messages to multiple subscribers simultaneously. This can improve the overall efficiency of the system and reduce the amount of code required to implement certain functionalities.

One limitation of ROS 2 topics is that they do not provide any mechanism for ensuring that messages are received in a particular order, and they do not guarantee message delivery. Additionally, topics are not suitable for point-to-point communication, as any node subscribed to a topic will receive all messages published on that topic.

Finally, ROS 2 topics provide a flexible and reliable way for nodes to communicate with each other by exchanging messages on a specific topic. They are suitable for asynchronous communication, and can handle multiple subscribers and publishers, making them a valuable tool for ROS 2 developers. However, they have some limitations and may not be suitable for all communication scenarios.

2.4.4 ROS 2 Actions

ROS 2 actions provide a way for nodes to communicate with each other by executing a specific goal and receiving a result. This is done through an action client-server communication model where the node requesting the action acts as the client and the node executing the action acts as the server.

One advantage of ROS 2 actions is their ability to handle long-running operations. Unlike ROS 2 services, which are intended for point-to-point communication, ROS 2 actions can handle operations that may take a significant amount of time to complete. This makes them ideal for tasks such as robot arm motion planning, where the task may take several seconds or even minutes to complete.

ROS 2 actions also provide a way to handle feedback during the execution of an action. The server node can send periodic updates to the client node, indicating the progress of the operation. This makes it easier for developers to monitor the execution of an action and respond to any issues that may arise.

Another advantage of ROS 2 actions is their ability to handle cancel requests. If the client node needs to abort the execution of an action, it can send a cancel request to the server node. The server node can then gracefully stop the execution of the action and return a result indicating that the action was canceled.

However, ROS 2 actions also have some limitations. For example, they are more complex than ROS 2 topics and services and require more code to implement. Additionally, they are not suitable for operations that do not have a clear goal and result, such as continuous data streams.

In the end, ROS 2 actions provide a powerful and flexible way for nodes to communicate with each other by executing long-running operations and providing feedback and cancellation capabilities. They are suitable for tasks that require a clear goal and result, such as robot arm motion planning, and can handle operations that may take several seconds or minutes to complete. However, they are more complex to implement than ROS 2 topics and services and may not be suitable for all communication scenarios.

2.4.5 The gazebo_ros package

Gazebo_ros is an essential package for robotics researchers and developers as it enables the testing and verification of algorithms and systems on simulated robots.

The gazebo_ros package provides a bridge between the Gazebo simulator and ROS. It includes plugins for various types of sensors and actuators commonly used in robotics, such as cameras, lidars, and motors. These plugins allow the user to publish and subscribe to ROS topics, enabling communication between the simulated robot and other ROS nodes. The package also includes a set of launch files that provide an easy way to set up the simulator with various sensors and actuators.

One of the main advantages of the gazebo_ros package is its ability to simulate complex environments that are difficult or impossible to replicate in the real world. For example, testing a drone in a windy environment or a ground vehicle on a slippery surface can be challenging and risky in the real world. With Gazebo, developers can create realistic virtual environments that simulate these conditions and test their algorithms and controllers without any risk. Additionally, the package allows for easy customization of the robot model, sensor configuration, and other parameters, providing flexibility and control over the simulation environment.

At a high level, the communication between ROS 2 and Gazebo using the gazebo_ros package follows these steps:

- The Gazebo server is started with a specific world file that defines the simulation environment.
- The gazebo_ros node is launched, which connects to the Gazebo server and initializes the ROS 2 interface.
- ROS 2 nodes can then be launched to control the simulated robots and sensors, and to receive data from them.
- ROS 2 messages are translated into Gazebo messages and sent to the Gazebo server, which updates the simulation environment accordingly.
- Gazebo messages are translated into ROS 2 messages and published on the ROS 2 network for other nodes to consume.

As an example, let's consider a simple simulation scenario involving a two-wheeled robot. The robot's motion is controlled by a ROS 2 node that publishes velocity commands on a topic. A gazebo_ros node subscribes to this topic and sends the commands to the Gazebo server, which updates the robot's position and orientation accordingly. Another ROS 2 node subscribes to a topic that publishes sensor data from the robot, such as sonar or lidar measurements. The gazebo_ros node reads the sensor data from Gazebo and publishes it on the corresponding ROS 2 topic.

2.4.6 The /joint_states topic

The *joint_states* topic is a standard ROS 2 topic that provides the current joint positions, velocities, and effort (torque or force) values for all joints in a robot. This topic is typically published by a robot's joint state publisher node, which reads the joint positions, velocities, and effort values from the robot's joint sensors and publishes them on the *joint_states* topic.

Here's an example Python script that subscribes to the /joint_states topic and prints the current joint positions for a robot arm:

```
import rclpy
from rclpy.node import Node
from sensor_msgs.msg import JointState

class JointStateSubscriber(Node):
    def __init__(self):
        super().__init__('joint_state_subscriber')
        self.subscription = self.create_subscription(JointState, '/joint_states',
        ↪  self.joint_state_callback, 10)

    def joint_state_callback(self, msg):
        # Print the current joint positions
        for i, name in enumerate(msg.name):
            position = msg.position[i]
            self.get_logger().info(f"Joint {name} position: {position}")

def main(args=None):
    rclpy.init(args=args)
    node = JointStateSubscriber()
    rclpy.spin(node)
    node.destroy_node()
    rclpy.shutdown()

if __name__ == '__main__':
    main()
```

This script creates a *JointStateSubscriber* node that subscribes to the */joint_states* topic and defines a *joint_state_callback* function that prints the current joint positions for each joint in the robot arm. The *create_subscription* method of the Node class is used to create a subscription to the */joint_states* topic, and the spin method is called to start the ROS event loop and receive messages from the subscription.

Assuming that the joint state publisher node is running and publishing joint state messages on the */joint_states* topic, running this script will cause the current joint positions for each joint in the robot arm to be printed to the console whenever a new joint state message is received on the */joint_states* topic.

2.4.7 The /robot_state_publisher node

The *robot_state_publisher* node in ROS 2 is a tool used to publish the robot's state in the form of a tree of coordinate frames. It calculates the forward kinematics of a robot by combining joint angle values with the robot's URDF (Unified Robot Description Format), which is an XML file that describes the robot's kinematic and dynamic properties.

For example, consider a robot arm that has three revolute joints (joints that rotate around a fixed axis) and an end effector attached to the third joint. The *URDF* file for this robot would describe the length of each link, the orientation of each joint, and the location of the end effector relative to the third joint. The $robot\_state\_publisher$ node would then use this information to calculate the transformation matrices between each link and joint, and ultimately the transformation matrix between the base link and end effector.

Once the transformation matrix is calculated, the $robot\_state\_publisher$ node publishes it to the $/tf$ topic. This transformation can be used by other nodes in the ROS 2 system to determine the position and orientation of the end effector relative to the base link, which can be useful for tasks such as robot control, path planning, and visualization.

Overall, the $robot\_state\_publisher$ node plays a crucial role in enabling the integration of various components of a robotic system in ROS 2 by providing a common coordinate frame for all components to work with.

2.4.8 The /joint_trajectory_controller/follow_joint_trajectory server

The $/joint\_trajectory\_controller/follow\_joint\_trajectory$ is an action server in ROS (Robot Operating System) that allows a client to send a joint trajectory command to a joint trajectory controller. This action server is part of the ros_controllers package and is typically used to control the motion of a robot arm or any other mechanism with multiple joints.

The joint trajectory command is specified in a $FollowJointTrajectory.Goal$ message, which contains a $JointTrajectory$ message that specifies the desired joint positions, velocities, accelerations, and time stamps. The joint trajectory controller then uses this command to interpolate a trajectory and generate the corresponding joint motion for the robot.

The $/joint\_trajectory\_controller/follow\_joint\_trajectory$ action server follows the standard ROS action interface, which consists of a goal, feedback, and result. When a client sends a joint trajectory goal to the action server, it sends a FollowJointTrajectory.Goal message as the action goal. The action server then sends a FollowJointTrajectory.Feedback message to the client periodically during the trajectory execution, which can be used to provide real-time feedback on the robot's progress. Finally, when the trajectory execution is complete, the action server sends a FollowJointTrajectory.Result message to the client.

For example, assuming that we have a robotic arm with a joint trajectory controller set up in a ROS 2 system, the following steps demonstrate how to send a trajectory command to the controller using the $/joint\_trajectory\_controller/follow\_joint\_trajectory$ action server:

1. Create a rclpy node that acts as the client for the $/joint\_trajectory\_controller/follow\_joint\_trajectory$ action server. This node should

import the necessary ROS libraries and create an instance of the $rclpy.action.ActionClient$ class to communicate with the server.

```
import rclpy
from rclpy.action import ActionClient
from control_msgs.action import FollowJointTrajectory

rclpy.init(args=None)
node = rclpy.create_node('joint_trajectory_controller_client')
client = ActionClient(node, FollowJointTrajectory,
↪  '/joint_trajectory_controller/follow_joint_trajectory')
```

2. Construct a $FollowJointTrajectory.Goal$ object that contains the desired trajectory for the robot arm. This object should contain a $JointTrajectory$ message, which specifies the joint positions, velocities, accelerations, and time stamps for the trajectory. Here's an example $FollowJointTrajectory.Goal$ object for a simple two-joint robot arm:

```
from trajectory_msgs.msg import JointTrajectory, JointTrajectoryPoint

goal_msg = FollowJointTrajectory.Goal()
goal_msg.trajectory.joint_names = ['joint1', 'joint2']
point1 = JointTrajectoryPoint()
point1.positions = [0.0, 0.0]
point1.time_from_start = rclpy.time.Duration(seconds=1.0).to_msg()
point2 = JointTrajectoryPoint()
point2.positions = [1.0, 1.0]
point2.time_from_start = rclpy.time.Duration(seconds=2.0).to_msg()
goal_msg.trajectory.points = [point1, point2]
```

This $FollowJointTrajectory.Goal$ object specifies a trajectory with two points, where the first point has joint positions of $[0.0, 0.0]$ and occurs 1 second after the start of the trajectory, and the second point has joint positions of $[1.0, 1.0]$ and occurs 2 seconds after the start of the trajectory.

3. Send the $FollowJointTrajectory.Goal$ object to the $/joint\_trajectory\_controller/follow\_joint\_trajectory$ action server using the $send\_goal$ method of the $ActionClient$ object.

```
future = client.send_goal_async(goal_msg)
```

4. Wait for the server to complete the trajectory by calling the result method of the Future object returned by the $send\_goal\_async$ method. This method will block until the server reports that the trajectory has been completed or an error occurs

```
rclpy.spin_until_future_complete(node, future)
result = future.result()
```

```python
import rclpy
import tf2_ros

def main(args=None):
    rclpy.init(args=args)

    # Initialize the buffer and listener
    buffer = tf2_ros.Buffer()
    listener = tf2_ros.TransformListener(buffer)

    # Wait for the transform to become available
    try:
        buffer.lookup_transform('map', 'robot', rclpy.time.Time())
    except tf2_ros.TransformException as ex:
        print(ex)

    # Get the transform between map and robot
    transform = buffer.lookup_transform('map', 'robot', rclpy.time.Time())

    # Print the transform
    print(transform)

    rclpy.shutdown()

if __name__ == '__main__':
    main()
```

Listing 1: Example of how to use $TransformListener$ to obtain the transform between two frames.

2.4.9 The tf_ros.TransformListener

The $tf2\_ros.TransformListener$ is a ROS 2 utility class that allows a node to receive the transform between two frames from the tf2 system. This class provides a simple way to listen for and access transforms between frames in a ROS 2 system.

To use the $tf2\_ros.TransformListener$, a node must first initialize a $tf2\_ros.Buffer$ object. This buffer object is used to store and manage the transforms that the node receives from the tf2 system. Once the buffer is initialized, the node can then create an instance of the $tf2\_ros.TransformListener$ class, passing in a reference to the buffer object.

Here is an example of how to use the $tf2\_ros.TransformListener$ to get the transform between two frames:

In this example, the node initializes a $tf2\_ros.Buffer$ object and a $tf2\_ros.TransformListener$ object. The node then waits for the transform between the map and robot frames to become available. Once the transform is available, the node retrieves it from the buffer and prints it to the console.

The $tf2\_ros.TransformListener$ class is a useful tool for nodes that need to access transforms between frames in a ROS 2 system. It provides a simple interface for listening for and accessing transforms, allowing nodes to easily interact with the tf2 system.

2.5 Unified Robot Description Format (URDF)

Unified Robot Description Format is an XML-based file format used to describe the kinematics and dynamics of a robot for simulation or visualization purposes. The main purpose of URDF is to provide a standardized way to represent robots that can be easily shared and used across different robotics platforms and simulation tools.

Here are some of the main tags used in a URDF file and their brief explanations:

- **<robot>:** The root tag of the URDF file that defines the robot and its properties.
- **<link>:** Defines the properties of a rigid body link of the robot, such as its name, its visual and collision geometries, and its inertial properties.
- **<joint>:** Defines a joint that connects two links together and specifies the type of joint, its name, and its parent and child links.
- **<gazebo>:** Defines the properties of the robot for Gazebo, a popular open-source physics engine used for robot simulation. This tag includes sub-tags such as <*plugin*> to specify Gazebo plugins, <*material*> to define material properties, and <*sensor*> to define sensors attached to the robot.
- **<transmission>:** Defines the transmission properties of the robot, which specify how the input and output shafts of a joint are connected and how torque, force, or velocity is transmitted between them.

2.6 Simulation Description Format (SDF)

Simulation Description Format is a file format used to describe the physical properties and dynamics of objects in a simulation environment. It is often used in robotics and autonomous systems, and is supported by popular simulators such as Gazebo, Ignition, and Webots. Here are the main tags used in SDF:

1. **<sdf>:** This is the root tag of the SDF file, and it specifies the version of the SDF format being used.
2. **<model>:** This tag is used to define a model in the simulation environment. It contains sub-tags such as <*link*>, <*joint*>, and <*plugin*> that define the properties of the model.
3. **<link>:** This tag is used to define a link in a model. It contains sub-tags such as <*inertial*>, <*collision*>, and <*visual*> that define the physical properties of the link.
4. **<joint>:** This tag is used to define a joint that connects two links in a model. It contains sub-tags such as <*axis*>, <*dynamics*>, and <*limit*> that define the properties of the joint.

5. **<plugin>:** This tag is used to define a plugin that provides additional functionality to the simulation. It contains attributes such as name and filename that specify the name and location of the plugin.

6. **<sensor>:** This tag is used to define a sensor that can be attached to a link in a model. It contains sub-tags such as <*camera*>, <*imu*>, and <*ray*> that define the properties of the sensor.

7. **<collision>:** This tag is used to define the collision properties of a link. It contains sub-tags such as <*geometry*> and <*surface*> that define the shape and surface properties of the link.

8. **<visual>:** This tag is used to define the visual properties of a link. It contains sub-tags such as <*geometry*> and <*material*> that define the shape and appearance of the link.

9. **<inertial>:** This tag is used to define the inertial properties of a link. It contains sub-tags such as <*mass*> and <*inertia*> that define the mass and moment of inertia of the link.

10. **<geometry>:** This tag is used to define the shape of a link or collision object. It contains sub-tags such as <*box*>, <*cylinder*>, and <*mesh*> that define the shape of the object.

11. **<material>:** This tag is used to define the appearance of a link or collision object. It contains sub-tags such as <*ambient*>, <*diffuse*>, and <*specular*> that define the color and reflectivity of the object.

12. **<include>:** This tag is used to include another SDF file into the current SDF file. It contains attributes such as uri that specify the location of the included file.

Overall, SDF is a powerful format that allows developers to describe complex robotic systems with multiple links, joints, sensors, and plugins. It provides a standardized way to simulate and test robots in a variety of environments and scenarios, which can greatly improve the performance and safety of the final product.

2.7 DAE and STL file formats

DAE stands for Digital Asset Exchange, and it is a file format used for exchanging 3D digital assets between different software applications. DAE files can contain information about the geometry, materials, textures, animations, and other properties of 3D models. DAE files are supported by many 3D modeling software applications such as Blender [40], Autodesk Maya [41], and SketchUp [42].

STL stands for Standard Triangle Language, and it is a file format used for storing 3D models as a series of connected triangles. STL files only represent the surface geometry of a 3D model and do not include information about materials, textures, or other

properties. STL files are commonly used for 3D printing and rapid prototyping, as they can be easily sliced into layers and printed using a 3D printer.

Both DAE and STL files are commonly used in 3D modeling and engineering applications. While DAE files are more versatile and can contain a wider range of information about a 3D model, STL files are simpler and more commonly used in the 3D printing industry.

2.8 RViz, RQt, and RQt Graph

RViz, RQt, and RQt Graph are three useful tools in the ROS ecosystem that allow developers to visualize, interact with, and analyze data from ROS nodes and topics. Here's a brief explanation of each tool:

1. **RViz:** RViz is a 3D visualization tool for ROS that allows developers to visualize robot models, sensor data, and other information in a simulated environment. With RViz, developers can view and manipulate 3D models of robots and their surroundings, as well as plot sensor data in real-time. RViz is useful for debugging and testing robot algorithms and behaviors, as well as for creating realistic simulations of robot environments.

2. **RQt:** RQt is a graphical user interface (GUI) tool for ROS that provides a suite of plugins for analyzing and debugging ROS nodes and topics. RQt plugins allow developers to monitor and visualize ROS topics, plot data, and inspect the internal state of nodes. With RQt, developers can easily interact with the ROS network and analyze the data flowing between nodes.

3. **RQt Graph:** RQt Graph is a visualization tool for ROS that allows developers to see the ROS network graph and visualize the data flow between nodes. With RQt Graph, developers can see the connections between nodes and topics, as well as the current state of each node (e.g., whether it is running, paused, or stopped). RQt Graph is useful for understanding the overall architecture of a ROS system and for debugging issues with data flow between nodes.

In summary, RViz, RQt, and RQt Graph are three powerful tools in the ROS ecosystem that allow developers to visualize, interact with, and analyze data from ROS nodes and topics. RViz provides 3D visualization capabilities, while RQt provides a suite of plugins for analyzing and debugging ROS nodes and topics. RQt Graph provides a visualization of the ROS network graph and data flow between nodes.

2.9 Neural Networks

Neural networks are machine learning models inspired by the structure and function of the human brain. They are effective tools for addressing a wide range of complicated issues, including as image and audio recognition, natural language processing,

and gameplay. This section will offer an overview of neural networks, covering their construction, training method, and applications.

2.9.1 Structure of Neural Networks

Layers of linked nodes or neurons form neural networks, which are organized into an input layer, one or more hidden layers, and an output layer. Each neuron takes input from neurons in the previous layer, processes it using an activation function, and generates an output signal that is transferred to neurons in the next layer [43]. A neural network's input layer accepts raw input data, such as an image or a written document, and routes it to the first hidden layer. Depending on the network's topology, each neuron in the hidden layer analyses this input and creates an output signal, which is then passed on to the next hidden layer or the output layer. The output layer generates the network's final output, which might be a classification label, a numerical value, or a collection of probabilities.

2.9.2 Training of Neural Networks

The process of training a neural network entail modifying the weights and biases of the neurons in order to minimize the discrepancy between the network's expected and actual output. This is accomplished using a technique known as backpropagation, which analyses the difference between the expected and actual output and propagates this mistake backward through the network layers to alter the weights and biases of the neurons. The backpropagation method adjusts the weights and biases of the neurons using an optimization approach such as gradient descent to minimize the error between the expected and actual output. The optimization procedure entails interactively changing the weights and biases of the neurons depending on the computed error until the error is reduced to an acceptable level.

2.9.3 Types of Neural Networks

There are several varieties of neural networks, each built for a unique issue or data format. Among the most frequent forms of neural networks are:

- **Feedforward neural networks** are the most basic sort of neural network, with information flowing from the input layer to the output layer in just one way.
- **Convolutional neural networks (CNNs)** are specialized neural networks developed for image and video processing, with a two-dimensional array of pixels as the input.
- R**ecurrent neural networks (RNNs)** are neural networks that are designed to process data sequences such as text or time series data.

- **Long short-term memory (LSTM) networks** are particularly developed for processing data sequences with long-term dependencies.

2.9.4 Applications of Neural Networks

Neural networks have several applications in domains such as computer vision, natural language processing, robotics, and finance. Among the most frequent neural network applications are:

- **Image and audio recognition:** Neural networks may be taught to accurately recognize and categorize pictures and sounds.
- **Natural Language Processing:** Neural networks may be used to analyze and create natural languages, such as machine translation and text production. Neural networks may be used to regulate and optimize robot motions such as grasping and manipulation.
- **Finance:** Neural networks may be used to forecast stock prices, assess credit risk, and detect fraud.

2.9.5 Neural networks in robotics

Because of their capacity to learn from data and make predictions or judgments based on that data, neural networks are commonly utilized in robotics. They are useful for a wide range of applications including object detection, path planning, motion control, and manipulation. Object recognition is one of the most popular applications of neural networks in robotics. Neural networks may be trained on vast datasets of images to recognize distinct objects and categories them. This can be applied to jobs like picking and arranging things, in which a robot must detect and grip an object in a chaotic environment. Neural networks can additionally be employed for route planning, which is the process of identifying a safe and efficient way for a robot to go from one site to another. By training a neural network on a dataset of maps and obstacle configurations, the network can learn to anticipate the optimum path for the robot to take. Neural networks can be used in motion control to regulate the movement of robotic joints and end effectors. By training a neural network on a dataset of joint angles and related end effector locations, the network may learn to anticipate the joint angles necessary to move the end effector to a desired position [44]. Manipulation tasks, such as grasping and assembling, are another use of neural networks in robotics. A neural network may learn to anticipate the optimum gripping stance for a particular item by training it on a dataset of grasping poses and matching object attributes.

2.9.6 Neural Network for the robotic arm

In robotics, neural networks may be used to control the movement of robotic arms, among other things. One typical way is to employ a neural network as an arm controller,

in which the network receives sensor readings and generates control signals to move the arm to a desired position. A neural network must be trained on a dataset of sensor readings and matching arm positions before it can be used for arms control. The network's inputs might comprise joint angles, velocities, and end effector locations, with the output being the joint torques necessary to move the arm to the desired position. The training method generally consists of iteratively modifying the network's weights to minimize the gap between the network's expected and true outputs. This may be accomplished through the use of various optimization techniques, such as stochastic gradient descent. Once trained, the network may be utilized to operate the arm in real time. The network receives sensor values from the arm and predicts the control signals required to move the arm to the desired position. The control signals may then be delivered to the arm's actuators, causing the arm to move. Other tasks connected to robotic arms, such as object identification and grasping, can also be performed using neural networks. A neural network, for example, may be trained on a collection of photographs of items and their related grasping stances and then used to predict the optimal gripping pose for a specific object.

2.10 Reinforcement Learning

Artificial neural networks (ANNs) are gaining importance in the field of robotics. In 2016, Levine et al.'s study [45] provided encouraging outcomes, indicating a direction toward a more straightforward approach to constructing robot behaviors. The end-to-end approach described in the study is more scalable than traditional programming methods. To meet the demand for autonomous systems that cater to societal needs, it is necessary to replace conventional, unsophisticated autonomous systems with intelligent ones. Intelligent systems can take on various forms of intervention, such as aiding humans with image and video analysis, language translation, simplifying sentences, solving math problems, managing portfolios, undertaking monotonous tasks in the manufacturing industry, driving cars, flying helicopters, and more. The complexity of certain tasks makes it impractical to solve them by specifying a set of rules due to the vast number of rules required, and programming an agent's behavior in advance is also difficult. However, machine learning techniques can be used to develop learned agents capable of addressing these challenges. Supervised learning techniques require large amounts of labeled data for training, making them less practical for certain scenarios. Unsupervised learning, on the other hand, is not well-suited to situations that involve interaction with the environment. Reinforcement learning (RL) [45] presents new opportunities for addressing various challenges. In the past, RL techniques were only effective in domains where handcrafted features or low-dimensional input were utilized, and could only handle discrete state and action spaces. However, recent advancements in Deep Learning (DL) have yielded promising results in several fields such as speech, vision, wireless communication, natural language translation, and assistive devices. These advancements in DL-based techniques have made it possible to over-

come the challenges faced by RL, and to process raw data for better performance. The progress in deep learning techniques has paved the way for resolving the difficulties encountered in RL and processing raw data. The latest developments that merge RL with deep learning, such as those highlighted in [46] increase their suitability to domains where handcrafted features are not present, and the state or action space is either vast or continuous. Such advanced methods can address both perception and planning issues, whereas RL can only handle the planning problem and deep learning only the perception problem. Rewarding or punishing agents for their actions, reinforcement learning (RL) is a kind of machine learning that enables agents to learn through interactions with an environment. RL deals with the development of decision-making algorithms. Its main focus is on creating a set of actions that an agent can perform in a specific environment. At each time step, the agent takes an action and receives feedback in the form of an observation and a reward. The ultimate goal of RL is to maximize the agent's total reward through a learning process that involves experimentation and feedback. In the learning process, an agent creates a policy. The agent begins in a particular state S_t of the environment, performs an action A_t, and transitions to another state S_{t+1}. The agent receives scalar feedback in the form of a reward R_{t+1} after taking the action A_t. This cycle is repeated many times during the learning process, as illustrated in Figure 7.

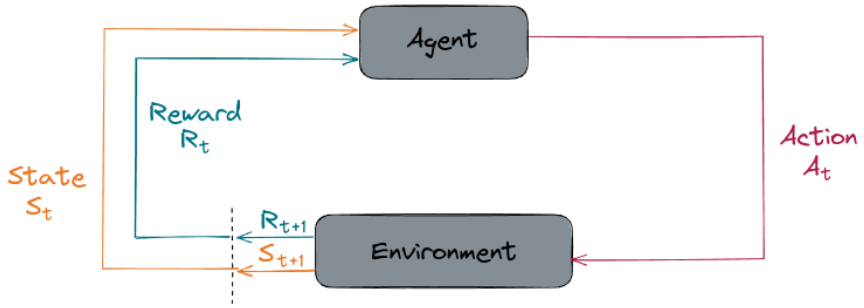


Figure 7: Agent Environment interaction in the Reinforcement Learning Model.

The action space represents the possible actions that the agent can take in a given state. In the past, the tabular approach was used to store state and action values. However, in environments with a large number of states or actions, the approximation approach has replaced the tabular method. Neural networks are commonly used as approximation methods. There are two types of action spaces:

- **Discrete action space:** A discrete action space is one in which the set of possible actions is finite and well-defined. The agent can choose only one of the available actions at a time. For example, in a game of tic-tac-toe, the action space consists of the nine possible positions on the board where a player can place their mark (X or O). This is a discrete action space because there are a finite number of possible actions (9) and the actions are well-defined (placing a mark in a specific location on the board).

- **Continuous action space:** A continuous action space is one in which the set of possible actions is infinite and not well-defined. The agent can choose any action within a continuous range of values. For example, in a self-driving car scenario, the action space might consist of the possible steering angles and accelerations that the car can take at any given moment. This is a continuous action space because the possible actions are not well-defined, as the car can take any steering angle or acceleration within a continuous range of values.

Deep Reinforcement Learning (DRL) is a field of study in which neural networks are utilized as function approximators to improve the performance of RL. Recently, several DRL techniques have achieved remarkable success in learning complex behavior skills and solving challenging control tasks in high-dimensional state-space [47] environments. However, many benchmarked environments such as Atari [48] and Mujoco [49] lack complexity or realism, which is often present in robotics. Additionally, these benchmarked environments [50] do not use commonly used tools in the field such as ROS. The research conducted in the previous work requires a considerable amount of effort for each specific robot, and therefore, the scalability of previous methods for modular robots is questionable. Consequently, trial and error learning process is often needed to apply the previous research to real-world robots. Training robotic arms to carry out certain actions, including touching an object in a virtual environment, is an intriguing use of RL. The robotic arm in this scenario must navigate a complicated state space while selecting actions that would maximize its reward while avoiding collisions with the environment.

2.10.1 Deep Reinforcement Learning

Deep Reinforcement Learning (DRL) leverages deep learning architectures as function approximators to tackle high-dimensional data and address the challenge of approximating in the presence of large state and action spaces [51]. Unlike traditional methods such as decision trees or SVMs, DRL employs neural networks to map states to actions, enabling it to handle high-dimensional data types such as images, videos, and time-series data. The approach also utilizes deep learning techniques such as convolutional or recurrent neural networks to address the limitations of traditional artificial neural networks which are unable to handle such data and often ignore input data topology. Prior research has focused on addressing various challenges in applying DRL to different fields, particularly control problems and games like Atari. Some of the key tasks involved in DRL include:

- **Exploration Exploitation:** The exploration refers to trying a new action, whereas exploitation makes use of learned knowledge to decide the action.
- **Generalization:** Generalization, on the other hand, refers to the capability of the agent to adapt to new environments, which can range from one task to another or from simulation to a real-life situation.

- **Finding Policy:** Finding a valuable policy involves identifying important states and actions that can help in learning an optimal policy for decision-making.
- **Finding a catastrophe:** Discovering a catastrophic event is crucial, as such events may cause significant harm. These events may include physical harm, offensive tweets, false stories, and so on. Avoiding such occurrences can help to improve the policy.
- **Handling Overestimation:** Overestimation occurs when inaccurate computation of action value takes place, often due to the use of the max operation in Q learning. It is important to handle overestimation to ensure that accurate values are computed.
- **Reducing Sample Size:** Deep reinforcement learning (DRL) requires a large number of samples for effective training, which may not always be feasible in real-world scenarios. This poses a challenge for DRL applications that deal with limited data availability.
- **Detection and prevention of overfitting:** overfitting is a common issue in DRL, especially when using high-capacity deep learning models. Overfitting occurs when the agent is too sensitive to small perturbations in the environment.
- **Robust Learning:** In recent years, there has been a growing interest in incorporating robustness into the DRL system using techniques such as deep learning. Researchers have proposed various adversarial attacks and defense mechanisms to address this challenge. Therefore, enhancing the robustness of DRL systems has become an active research topic in the community.

The field of Reinforcement Learning (RL) has seen significant contributions from various researchers who have proposed different network architectures and action selection criteria. Some methods include trial and error without human intervention, learning via demonstrations, learning via criticism, and learning with adversaries to tackle complex problems. Despite these advancements, the challenge of discovering an optimal policy that is both robust and able to meet multiple goals remains a topic of active research and an open area of investigation.

2.11 Reinforcement Learning Algorithms and The Markov Decision Process (MDP)

Reinforcement learning (RL) methods are particularly well-suited for robotics applications, such as robotic arm control. RL algorithms learn to control the arm by picking actions that maximize a reward signal, which may be a measure of how successfully the arm performs a task or how far it progresses toward a goal. Here are some popular RL algorithms used in robotics and for operating robotic arms:

- **Deep Deterministic Policy Gradient (DDPG):** The Deep Deterministic Policy Gradient (DDPG) is an actor-critic method that is meant to handle continuous action spaces, which is vital for directing the movement of a robotic arm [44]. It estimates the action-value function using a deterministic policy function and a critic network and has been effectively applied to tasks such as reaching and grasping.
- **Trust Region Policy Optimization (TRPO):** TRPO is a policy optimization algorithm that is well-suited for jobs requiring precise and accurate control, such as managing the position of a robotic arm [52], [53]. It employs a trust region strategy to guarantee that policy adjustments are not too significant, which aids in maintaining stability.
- **Asynchronous Advantage Actor-Critic (A3C):** A3C is a scalable and efficient RL technique designed to teach robotic arms to do complicated tasks such as item manipulation in crowded surroundings [54]. It explores the state space and updates the policy using numerous simultaneous agents, which can dramatically accelerate the learning process.
- **Deep Neural Networks for Q-Learning:** Q-Learning is a value-based RL algorithm that learns to assess the worth of actions in a given state. When Deep Q-Networks (DQN) are merged with deep neural networks, they form Deep Q-Networks (DQN), which are particularly helpful for applications involving high-dimensional sensory input, such as vision-based control of a robotic arm [55].
- **Proximal Policy Optimization (PPO):** PPO is a policy optimization algorithm that updates the policy using a clipped surrogate objective function [56]. It has been used effectively in a variety of robotics activities, including regulating the movement of a robotic arm to conduct pick-and-place operations.

2.11.1 The Markov Decision Process (MDP)

MDP is a framework for modeling decision-making issues when the consequence of an action is unknown [57]. It is commonly used in the field of reinforcement learning to simulate issues like robotic arm control, autonomous vehicle navigation, and gameplay. The decision-making agent in a MDP interacts with the environment in discrete time steps. At each time step, the agent performs an action depending on the current state of the environment and is rewarded with a new state. The agent's purpose is to discover a policy that maximizes the cumulative reward over time. To convert a situation to an MDP framework, we must first identify the MDP components: state space, action space, transition probabilities, and reward function. Here's a quick rundown of each component:

1. **The state space** is the collection of all conceivable states in which the environment can exist. The state space of a robotic arm might comprise variables such as the

arm's position and orientation, the placement of items in the environment, and the status of any sensors or actuators.

2. **The action space** is the collection of all conceivable actions that the agent can do in a given condition. The action space for a robotic arm might comprise orders to move the arm in different directions, alter its hold on an item, or activate sensors.

3. **Transition Probabilities** indicate the possibility of a state changing when a certain action is done. The transition probabilities of a robotic arm can be affected by the physical qualities of the arm and the objects in the surroundings, as well as any noise or uncertainty in the sensors or actuators.

4. **The reward function** assigns a monetary incentive to each state-action pair that represents the agent's aim. The reward function for a robotic arm can offer a positive reward for successfully gripping an object, a negative reward for colliding with an impediment, and zero otherwise.

Reinforcement learning algorithms use MDPs to learn how to make decisions in a sequential decision-making problem. These are only a few examples of RL algorithms that have been employed in robotics and robotic arm control. The algorithm used will be determined by the specific job and surroundings, as well as the features of the robot and sensors. RL algorithms offer the potential to make robotic arms more independent and adaptable, allowing them to adapt to changing surroundings and tasks in real-time.

2.11.2 The exploration and exploitation trade-off in RL

The exploration-exploitation trade-off in Reinforcement Learning (RL) refers to the issue encountered by an agent when deciding whether to continue exploring the environment to obtain additional knowledge or exploit the information it has already received to maximize its rewards. Exploration is the process of attempting new behaviors and evaluating their effects in order to understand more about the environment. It entails attempting actions that have never been attempted before or attempting previously attempted actions with a new parameter configuration. Exploitation, on the other hand, refers to the practice of maximizing the cumulative benefit by utilizing knowledge learned from prior acts. It entails doing behaviors that have provided high benefits in the past or are expected to bring high returns in the future. In RL, the trade-off between exploration and exploitation is crucial because if the agent concentrates just on exploration, it may not get enough incentives to develop an effective strategy. On the other side, if the agent is overly focused on exploitation, it may miss out on learning about other feasible, but lesser-known, positive acts that could contribute to higher long-term benefits. To balance the exploration-exploitation trade-off, several ways can be applied, including:

1. **Epsilon-greedy:** The agent chooses the action with the largest expected payoff with a probability of one minus epsilon ($1 - \epsilon$) and a random action with a probability of epsilon (ϵ). This enables the agent to explore the environment while still taking advantage of actions with high expected returns.

2. **Upper Confidence Bound (UCB):** The action with the highest upper confidence bound is chosen, which is determined by the mean reward and the variance of the reward distribution [58]. This method encourages the agent to investigate less-explored behaviors while continuing to exploit acts with greater predicted rewards.

3. **Thompson Sampling:** In this method, the agent keeps a probability distribution over the reward of each action and chooses an action based on a sample from that distribution. This technique strikes a balance between exploration and exploitation by choosing activities with a high likelihood of high rewards while also investigating actions with a low probability of high rewards.

2.12 Double Deep Q Learning (DDQN)

Double Deep Q Learning (DDQN) is a Q-Learning algorithm extension that overcomes Q-value overestimation in standard Q-Learning. DDQN is a DRL method that combines a deep neural network with the Q-Learning technique to develop an optimum policy for an agent to make decisions in an environment. The Double Deep Q-Learning (DDQN) method is an extension of the classic Q-Learning algorithm, which is widely used in Reinforcement Learning (RL) for robotics and robotic arm control. Deep RL method DDQN combines two deep neural networks to estimate the Q-values of state-action pairings in an environment. Q-Learning is a well-known RL method that may be used to identify the best policy for an agent in a given environment. The agent in Q-Learning attempts to learn a function $Q(s, a)$ that calculates the anticipated reward for doing an action in state s. The best policy is then found by choosing the action that maximizes the Q-value for a particular state. Q-Learning, on the other hand, can only be employed in tiny settings with a limited number of states and actions. It is unsuitable for big and complicated situations. Deep Q-Learning (DQL) is a Q-Learning variant that uses a deep neural network to estimate Q-values for state-action pairings in vast and complicated contexts. DQL has been demonstrated to be successful in a variety of difficult contexts, including video games and robotic control. However, it has been discovered that DQL can occasionally overstate Q-values, resulting in poor strategies. To overcome this issue, Double Deep Q-Learning (DDQN) was created, which estimates Q-values using two deep neural networks. One network, known as the target network, is used to produce Q-value targets, while the other, known as the policy network, is used to generate Q-value estimates. To promote training stability, the Q-value objectives are updated less frequently than the Q-value estimations. This method decreases overestimation and enhances algorithm convergence. To further improve learning, DDQN also

uses a technique called "replay memory". This involves storing the agent's experiences in a buffer and randomly sampling from the buffer to train the neural network. By doing so, the agent can learn from a more diverse set of experiences, rather than just learning from the most recent experience. The DDQN algorithm is summarized below:

1. Initialize the replay memory buffer D with capacity N.
2. Initialize the policy Q-network with random weights θ.
3. Clone the policy Q-network and let that be the target Q-network with weights $\theta^- = \theta$.
4. For each episode $e = 1, 2, ..., E$ do the following:
   (a) Initialize the environment with initial state s_0.
   (b) For each step $t = 1, 2, ..., T$ do the following:
      i. With probability ϵ select a random action a_t, otherwise select $a_t = \arg\max_a Q(s_t, a; \theta)$.
      ii. Execute action a_t and observe reward r_t and next state s_{t+1}.
      iii. Store the experience (s_t, a_t, r_t, s_{t+1}) in the replay memory buffer D.
      iv. Sample a mini-batch of experiences (s_j, a_j, r_j, s_{j+1}) from the replay memory buffer D.
      v. Compute the Q-learning target value for each experience (s_j, a_j, r_j, s_{j+1}):
      $$y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} Q(s_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}.$$
      vi. Compute the loss between the predicted Q-value and the target Q-value: $L(\theta) = \frac{1}{B} \sum_{j=1}^{B} (y_j - Q(s_j, a_j; \theta))^2$.
      vii. Update the policy Q-network weights using gradient descent: $\theta \leftarrow \theta - \alpha \nabla_\theta L(\theta)$.
      viii. Every C steps update the target Q-network weights: $\theta^- \leftarrow \theta$.
      ix. Update the current state, set $s_t = s_{t+1}$.

There are various advantages of using DDQN over standard Q-Learning and DQL. It decreases overestimation, enhances stability, and speeds up convergence. DDQN is also capable of dealing with vast and complicated settings with multidimensional state and action spaces. These characteristics make DDQN an appealing candidate for robotic control applications. DDQN may be used in robotics and robotic arm control to determine an optimum policy for the agent to complete certain tasks such as item grabbing or assembly. Without any prior understanding of the environment or the work, DDQN may be used to learn the policy from the ground up. The agent may investigate its surroundings and learn from its experiences in order to better its performance.

In this work, the simulated robotic arm would operate as the agent in a Double Q-learning framework, interacting with its surroundings and receiving rewards or punishments as a result of its actions. The orientation and position of the robotic arm, along

with the location and characteristics of the object it is attempting to touch, would all be included in the state space. The robotic arm's range of potential motions for approaching the object would make up the action space. The goal of the reward function is to persuade the robotic arm to touch the target without causing a collision or any other unfavorable outcomes. The Double Q-learning method is used by the robotic arm to investigate its environment during training and modify its Q-functions in response to incentives. By estimating the expected reward for every action using the two Q-functions, the algorithm would select the action featuring the largest expected reward. The robotic arm would develop a policy that enables it to consistently touch the target by continuing this process over a large number of attempts. In next chapters, we explore and present results for the use of Double Q-Learning in a simulated robotic arm to learn effective control policies for the arm.

3 Implementation

3.1 Environment Preparation

The SDF file 2.6 containing the object the robotic arm has to learn to touch was created and when launched in Gazebo, it looks like Figure 8a.

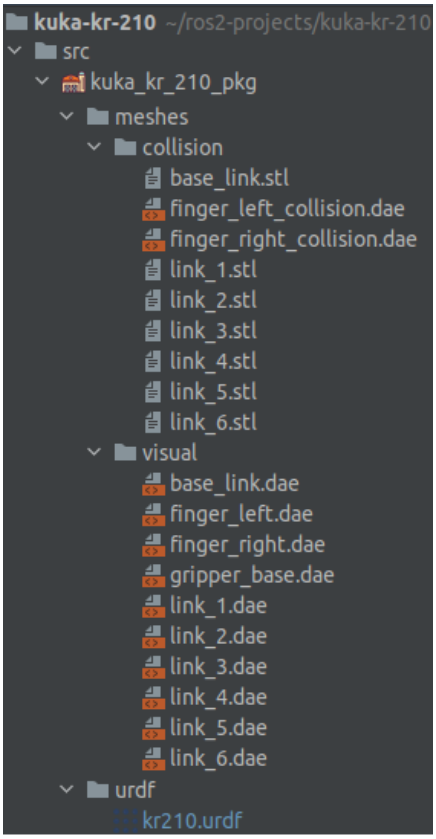
The robotic arm used in the simulation is the Kuka KR210. The necessary files to simulate such a robotic arm were taken from [59]. From this repository, we need the *DAE*, *STL*, and *URDF* files to make the robotic arm work.

To use the robotic arm in our simulation, the first step is to create a ROS 2 workspace and package to later place the simulation files in it; the simulation files and folders were placed in the directory structure in Figure 8b.

Once we have the simulation files in place, we can test if we can see and interact with the robotic arm; for this, we use the *ROS robot_state_publisher* node 2.4.7 and Rviz 2.8. The *ROS robot_state_publisher* receives the *URDF* file content as a parameter and publishes it to a topic called */robot_description*. Then to visualize the robot we use RViZ which would subscribe to */robot_description* topic and render the robotic arm. The result can be seen in Figure 9.

The communication between the *robot_state_publisher* node, the */robot_description* topic and *RViz* can be seen in Figure 10.

(a) Can described in the SDF file in Gazebo which is the object to be touched by the robotic arm.



(b) Project structure after copying the *DAE*, *STL*, and *URDF* files into our package.

Figure 8: World created in Gazebo and starting directory structure after copying the robotic arm simulation files.

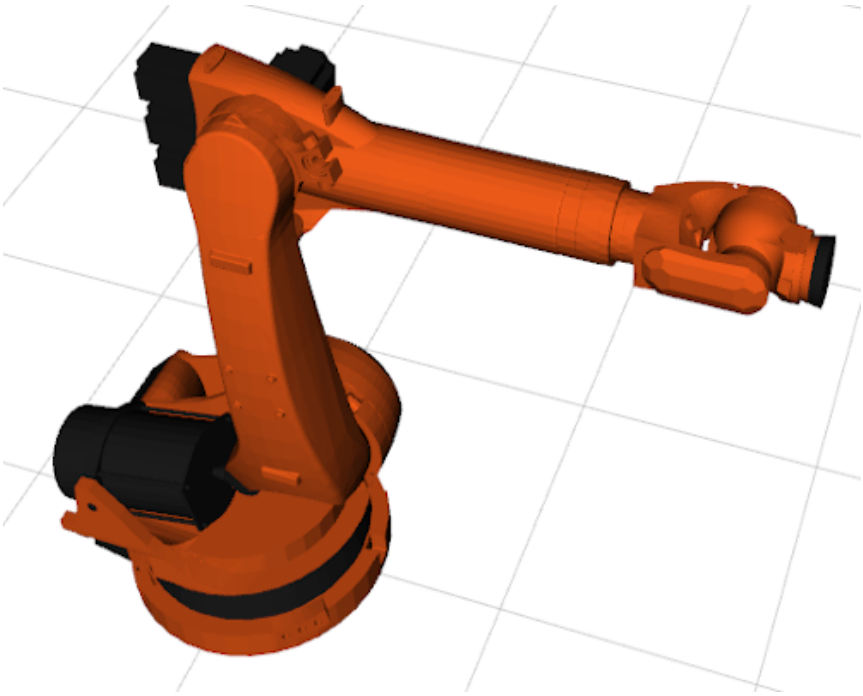


Figure 9: Kuka KR210 in RViz2.

Figure 10: The ROS **robot_state_publisher** node takes the URDF file content and publishes it to the **/robot_description** topic to which Rviz subscribes and gets the robotic arm information to finally show it.

The robotic arm Kuka KR210 consists of seven and links six joints that connect them.
The six joints of the KR210 are numbered J1 to J6 as can be seen in Figure 11, and they allow the robot to move in various directions and orientations.

- **J1:** The first joint is the base joint, which allows the robot to rotate horizontally around its vertical axis.
- **J2:** The second joint is the shoulder joint, which allows the robot to lift and lower its arm vertically.
- **J3:** The third joint is the elbow joint, which allows the robot to bend its arm vertically.

- **J4:** The fourth joint is the wrist roll joint, which allows the robot to rotate its wrist around its vertical axis.
- **J5:** The fifth joint is the wrist pitch joint, which allows the robot to tilt its wrist up and down.
- **J6:** The sixth joint is the wrist yaw joint, which allows the robot to rotate its wrist horizontally.

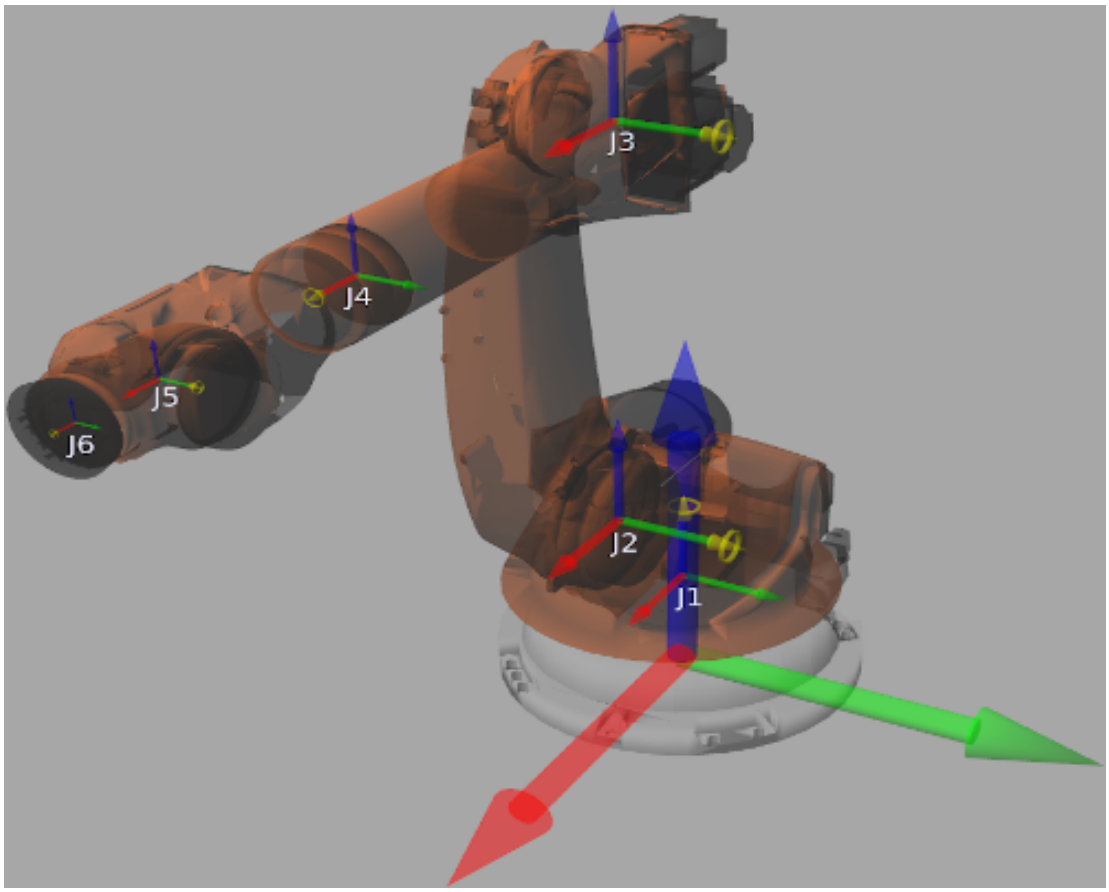
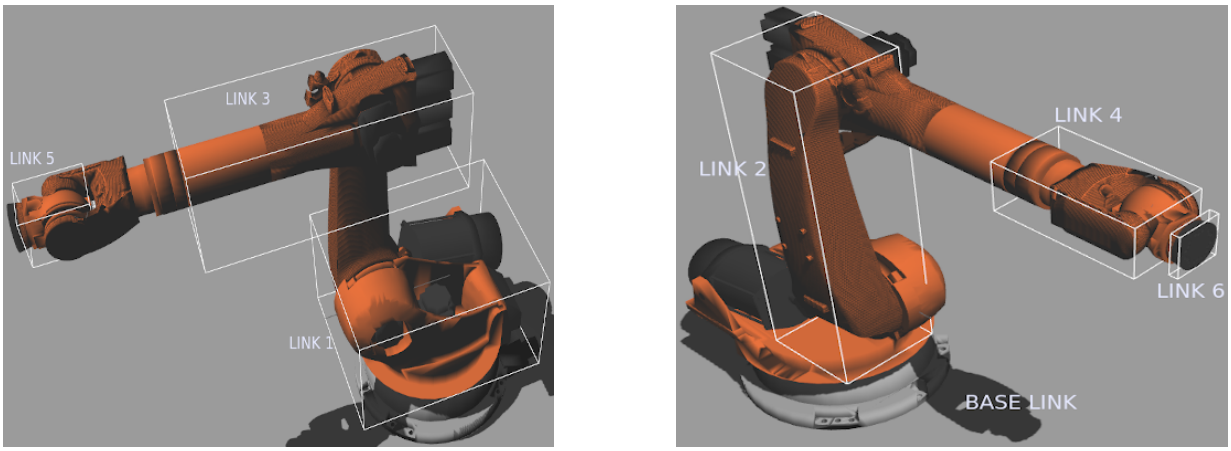


Figure 11: Joints and axis around which they allow movement in the Kuka KR210 arm.

The arm also has links that are connected by the joints; the links of the kuka KR210 are: the base, the lower arm, the upper arm, the wrist, and the end effector. These links are designed to provide strength and rigidity to the robot arm while allowing for smooth and precise movement. These links can be seen in Figure 12b and are:

- **Base Link:** The base link connects the robotic arm to the fixed base or mounting structure. It provides stability and support. In our simulation, it is attached to the ground.

- **Link 1:** Also known as the shoulder link, it connects the base link to the upper arm. It is responsible for the vertical movement of the upper arm and enables the arm to raise and lower. This is the first link that connects the base link via joint 1 (J1 in 3.1) in one end and joint 2 (J2 in 3.1) in the other end.
- **Link 2:** Also known as the upper arm link, it extends from the shoulder link to the elbow joint (J3 in 3.1). It is a rigid segment that allows for vertical and horizontal movements, providing reach and positioning capability. This link is between the joint 2 (J2 in 3.1) and the joint 3 (J3 in 3.1).
- **Link 3:** Also known as the forearm link, it extends from the elbow joint (J3 in 3.1) to the wrist roll joint (J4 in 3.1). It is a rigid segment that helps transmit motion and provides structural support.
- **Link 4:** This link extends from joint 3 (J3 in 3.1) to joint 4 (J4 in 3.1).
- **Link 5:** This link extends from joint 4 (J4 in 3.1) to joint 5 (J5 in 3.1).
- **End Effector (Link 6):** This is the tool or gripper attached to the last joint. It is the component that directly interacts with objects or the environment, enabling the arm to perform specific tasks.



(a) Links 1, 3 and 5 in the Kuka KR210.

(b) Base Link, Link 2, 4 and 6 in the Kuka KR210.

Figure 12: Links in the Kuka KR210.

After setting up the robotic arm, the next step is to add sensors to it and to configure them to work with ROS 2 and Gazebo.

- To detect collisions between the robotic arm and the object it should learn to touch, a bumper sensor is added to links 4, 5, and 6. This is done by adding the code in Listing 7 to the *URDF* file.

- A camera is added to the *URDF* file as well, this is done by adding the code in Listing 8 to the *URDF* file.
- In the *SDF* file, the Gazebo ROS state plugin was added. This is done by adding the code in Listing 9 in the *SDF* file. This plugin not only allows us to monitor our models' positions and velocities but also modify them programmatically.

Once the robotic arm and the sensors are in place, the next step is to launch our *SDF* file in Gazebo and spawn the robotic arm into the world to finally have our setup as in Figure 13

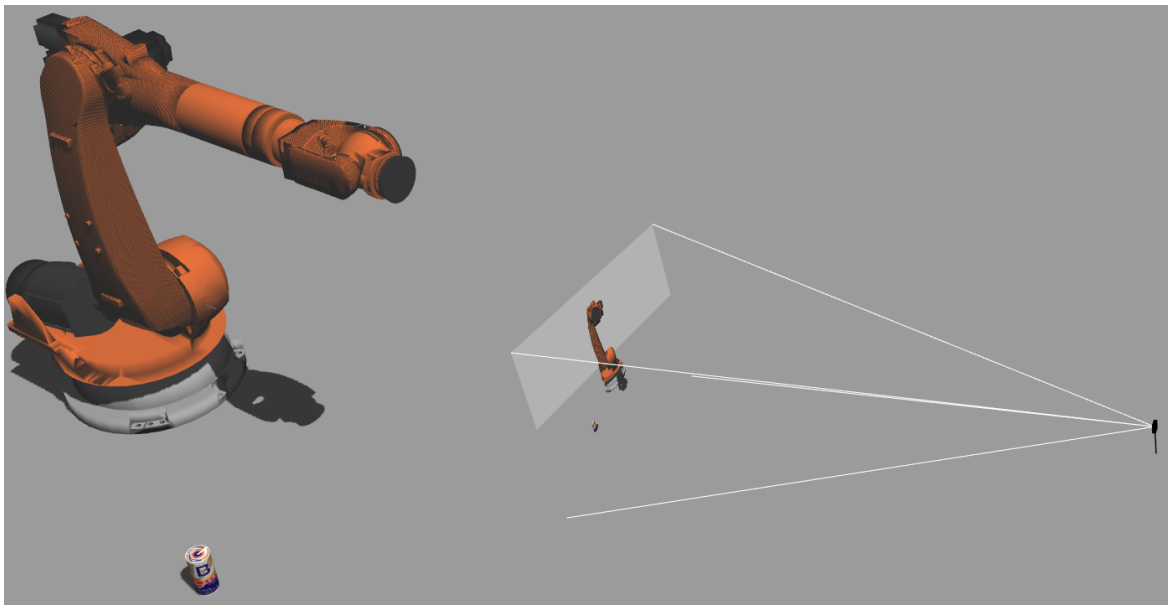


Figure 13: Gazebo world containing the robotic arm, the object to be touched, plus the sensors and plugins added.

A launch file was created to spawn the robotic arm in the gazebo world with the can as in Figure 13. Furthermore, the ROS nodes and topics in Figures 14, 15, 16, 17, 18 are initialized to be used later.

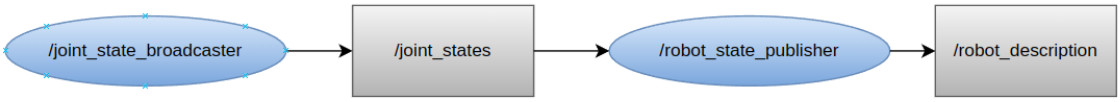


Figure 14: The joint state broadcaster node publishes the current state of each joint in the robot's body to the ROS (Robot Operating System) network. This state includes the joint's position, velocity, and effort (torque) values.

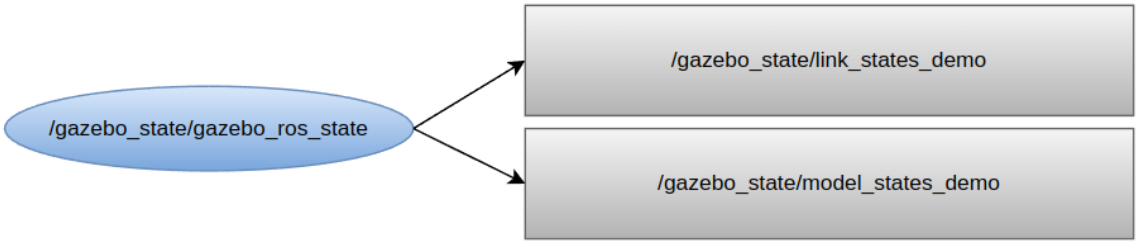


Figure 15: The node */gazebo_state/gazebo_ros_state* publishes the state of the models in the gazebo world to the topics */gazebo_state/link_states_demo* and */gazebo_state/model_states_demo* as specified in Listing 9

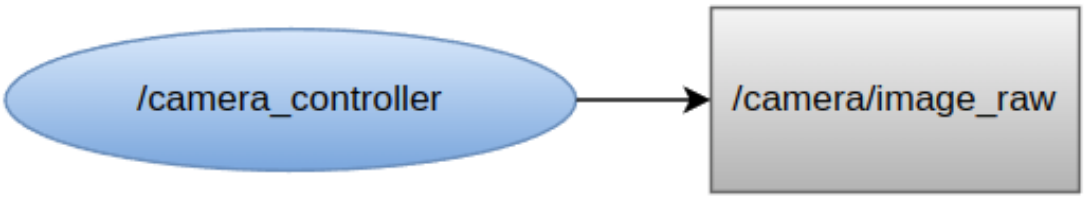


Figure 16: As a result of adding Listing 8 a node *camera_controller* is created and it publishes to the topics */camera/image_raw*.

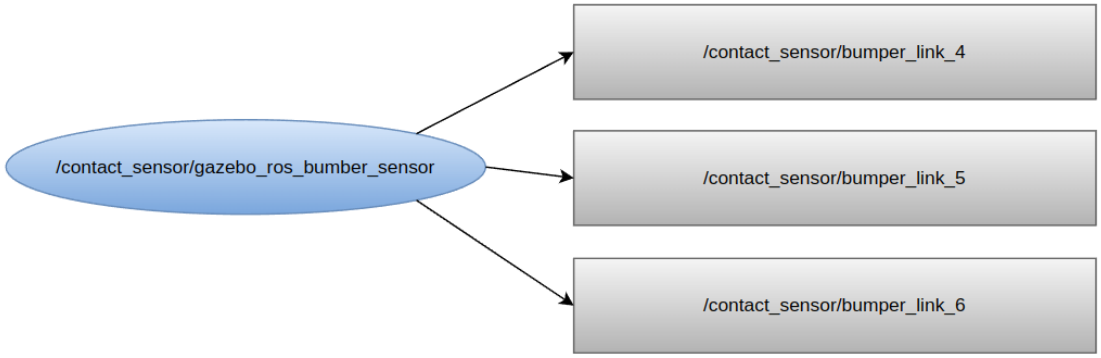


Figure 17: As a result of adding Listing 7 there are */contact_sensor/gazebo_ros_bumper_sensor* nodes publishing the collision details to the topics */contact_sensor/bumper_link_4*, */contact_sensor/bumper_link_5*, and */contact_sensor/bumper_link_6*.

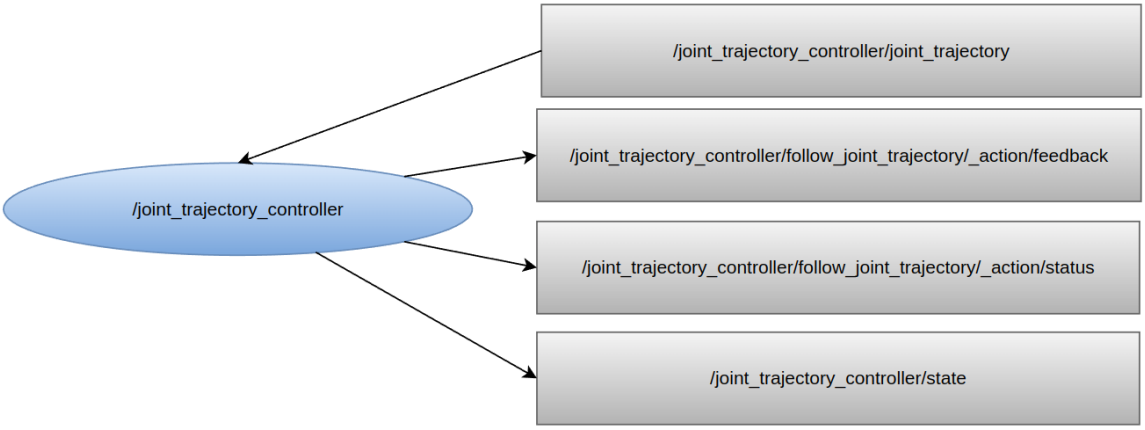


Figure 18: The joint trajectory controller node is responsible for generating and executing a trajectory plan for the robot's joints. This is the node used to send the desired positions when controlling the robotic arm.

With the robotic arm spawn and the nodes and topics running to interact with it, the next step is to create the classes that define the reinforcement learning environment.

Figure 19 is a description of the classes and relationships used to conduct the experiments.

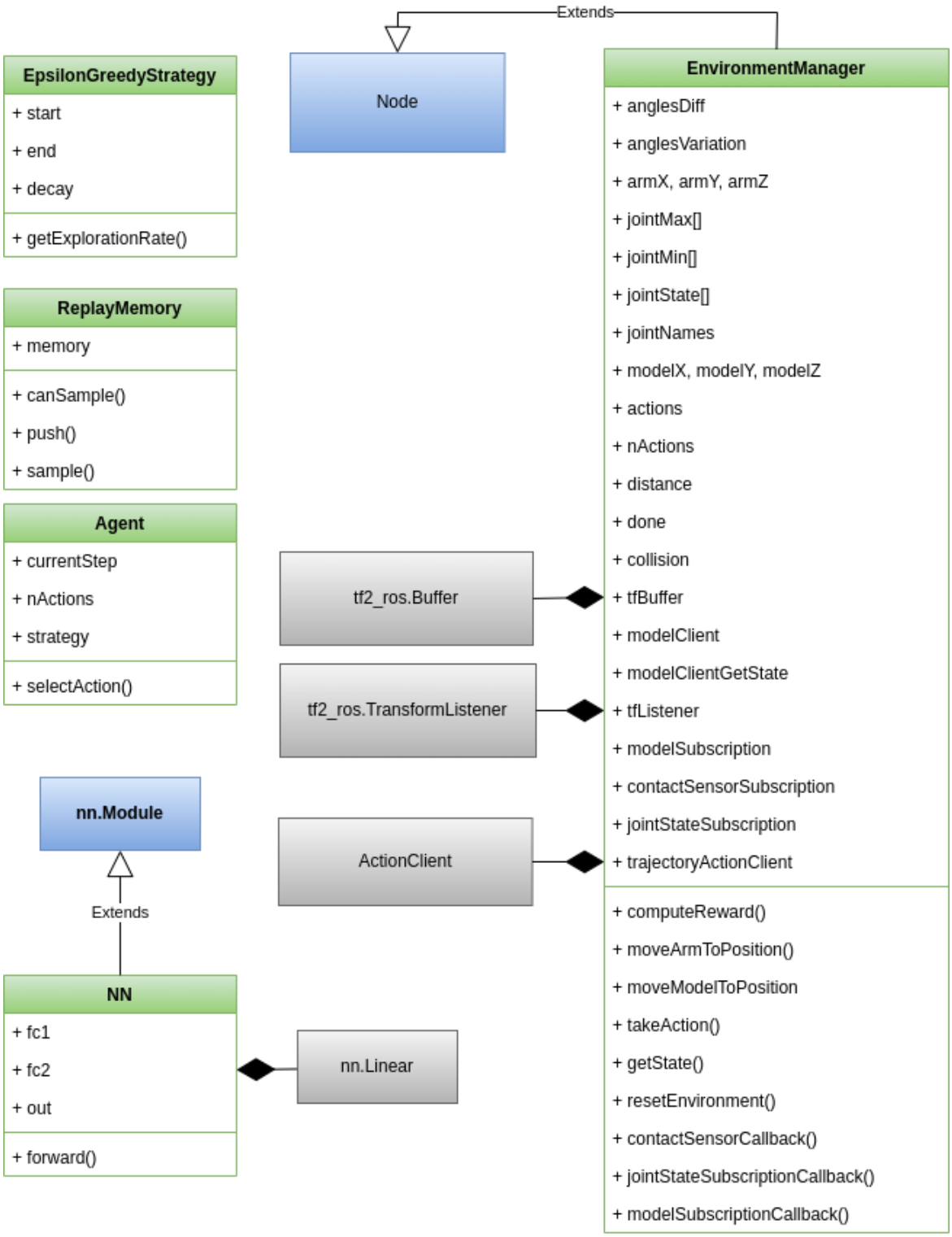


Figure 19: Classes defining the reinforcement learning framework that will run the environment experiments for the arm to learn to touch the object.

3.2 The NN class

The NN class in Figure 19 implements the neural network used in this framework, i.e. our DQN. PyTorch [60] is used for the neural network, specifically the *nn.Module*. The nn package contains a Module class which serves as the foundation for all neural network modules. This means that the used network and its layers will inherit from the Module class. To implement the neural network, the NN class that extends the nn.Module class is created. The neural network will be fed the current state (s) as follows:

$$s = input = (\theta_1, \theta_2, \theta_3, d) \tag{1}$$

where, $\theta_1, \theta_2, and \theta_3$ represent the joint angles of the robotic arm (J1, J2, and J3 in Figure 11), and d represents the distance between the end effector of the arm and the object.

A simple neural network with two fully connected layers and an output layer is used.

```
class NN(nn.Module):
    def __init__(self, nInputs=4, nOutputs=27):
        super().__init__()
        # input current angles and distance
        self.fc1 = nn.Linear(nInputs, out_features=32)
        self.fc2 = nn.Linear(in_features=32, out_features=64)
        self.out = nn.Linear(in_features=64, out_features=nOutputs)
```

Listing 2: Implementation of the Deep Neural Network.

In listing 2, the fully connected layers are referred to as $Linear$ layers in PyTorch.

The first Linear layer will accept input with a dimension of four. This first layer will generate 32 outputs, which will serve as the input for the second Linear layer. The second Linear layer will have 64 outputs, and the output layer will have 27 outputs, taking 64 inputs from the previous layer.

The network outputs *Q-values* that correspond to each possible action that the agent can take from a given state. Note that the network used does not have convolutional layers because no image processing takes place. The final step in defining the NN class is to create a function called $forward()$. This function will carry out a forward pass through the network. It's important to keep in mind that $forward()$ is a necessary function for all PyTorch neural networks.

When the network receives a state s; it passes it to the first fully connected layer and applies $relu$ to the output before sending it to the second fully connected layer. After that, $relu$ is applied before passing the result to the output layer. The $forward()$ function then returns the result obtained from the output layer.

```
def forward(self, s):
    s = F.relu(self.fc1(s))
    s = F.relu(self.fc2(s))
    s = self.out(s)
    return s
```

Listing 3: Implementation of the $forward()$ function needed for the DQN.

3.3 The Replay Memory class

To define the $ReplayMemory$ class, the Experience class which defines $Experience = (s_j, a_j, r_j, s_{j+1})$ is used. An experience contains the current state(s_j), the action taken in that state (a_j), the reward for the action taken (r_j), and the next state of the environment (s_{j+1}). To create an instance of the $ReplayMemory$ class, $capacity$ is the only parameter needed.

```
class ReplayMemory:
    def __init__(self, capacity):
        self.memory = deque(maxlen=capacity)
    def push(self, experience):
        self.memory.append(experience)
    def sample(self, batchSize):
        return random.sample(self.memory, batchSize)
    def canSample(self, batchSize):
        return len(self.memory) >= batchSize
```

Listing 4: Implementation of the Replay Memory class.

The code in Listing 4 implements the $ReplayMemory$ class. When $ReplayMemory$ is instantiated, its capacity is initialized to $capacity$, and the $memory$ attribute is defined as a **deque** data type 2.1.1. To add and store $experiences$ the $push$ function is defined, which is just a wrapper for the append built-in function. When the number of experiences in $memory$ reaches $capacity$, new experiences are kept and old ones are removed. The $sample()$ function provides a batch of random experiences which is used to train the neural network. Finally, the function $canSample()$ tells us whether we can sample from memory or not.

3.4 The Epsilon Greedy Strategy class

To balance exploration and exploitation the epsilon greedy strategy is used. An exploration rate called $epsilon$ is defined. Epsilon is the probability that the agent will choose a random action (exploration). An $epsilon$ value of one means that the agent will only explore the environment. As the agent learns, $epsilon$ decays by a defined decay rate; meaning that the agent will no longer just explore, but also use what is has learned about the environment or exploit.

```
class EpsilonGreedyStrategy:
    def __init__(self, start, end, decay):
        self.start = start
        self.end = end
        self.decay = decay
    def getExplorationRate(self, currentStep):
        return self.end + (self.start - self.end) * math.exp(-1. * currentStep * self.decay)
```

Listing 5: Implementation of the *EpsilonGreedyStrategy* class.

In Listing 5, *start*, *end*, and *decay* correspond to the starting, ending, and decay rate for *epsilon*. The function $get_exploration_rate()$ has the *currentStep* of the agent as parameter and returns the calculated exploration rate.

3.5 The Agent class

The implemented *Agent* class in Listing 6 has *strategy* and *nActions* parameters as inputs in its constructor. An instance of the *EpsilonGreedyStrategy* class is used for the *strategy* variable in order to create the agent object. The *nActions* parameter refers to the number of possible actions that the agent can take in a given state. In our case, this number is twenty seven; all possible actions for the agent in a given state are written in Equation 2.

```
class Agent:
    def __init__(self, strategy, nActions):
        self.strategy = strategy
        self.nActions = nActions
        self.currentStep = 0
    def selectAction(self, state, policyNetwork):
        rate = self.strategy.getExplorationRate(self.currentStep)
        self.currentStep += 1
        if rate > random.random():  # explore
            action = torch.tensor([random.randrange(self.nActions)])
        else:  # exploit
                with torch.no_grad():
                    action = policyNetwork(state).argmax(dim=1)
        return action
```

Listing 6: Implementation of the Agent class.

The parameter *currentStep* is set to zero at the beginning and indicates the current iteration of the agent in the environment.

The policy network refers to a deep Q-network that is trained to learn the optimal policy.

Inside the *selectAction()* function, the *rate* variable is set to the exploration rate returned from the *EpsilonGreedyStrategy* object that was passed in when creating the agent object; and the *currentStep* attribute of the agent is incremented by 1. Then, we

check whether the $rate$ variable is greater than a random number generated between 0 and 1. If it is, we explore the environment by randomly selecting an action from our action space A. If not, we exploit the environment by selecting the action that corresponds to the highest Q-value output from our policy network for the given state. To perform inference, the $torch.no\_grad()$ method is used to turn off gradient tracking since the model is only used for prediction, not training. During training, PyTorch tracks all the forward pass calculations that occur within the network. By turning off gradient tracking, PyTorch does not to keep track of any forward pass calculations.

3.6 The Environment Manager class

Finally, the class that manages the environment is the $EnvironmentManager$ class. This class implements the $rclpy.node.Node$ class in Python in order to create a node in our ROS 2 framework and interact with the other nodes in the environment. The following properties are initialized when the $EnvironmentManager$ class is instantiated:

1. The $done$ property indicates whether the episode has finished or not. An episode ends when there is a collision between the end effector or Link 6, Link 5, or Link 4 of the arm and the target object or when the episode has reached its maximum defined number of steps.

2. The $distance$ property stores the latest distance between the end effector of the arm and the object.

3. The $armX$, $armY$, and $armZ$ properties store the latest (x, y, z) coordinates of the end effector of the arm.

4. The $joint1State$, $joint2State$, $joint3State$, $joint4State$, $joint5State$, and $joint6State$ properties store the latest angles of the arm joints of the same name.

5. The $joint1Max$, $joint1Min$, $joint2Max$, $joint2Min$, $joint3Max$, and $joint3Min$ properties define the maximum each joint can move without causing collisions within the arm or with the floor. These values were found using Rviz 2.8.

6. The $tfBuffer = tf2\_ros.Buffer()$ and

   $tfListener = tf2\_ros.TransformListener(self.tfBuffer, self)$ properties are defined in order to calculate the $armX$, $armY$, and $armZ$ properties in 3.

7. The $angleDiff$ property defines how much each joint's angle can vary per step per episode in radians.

8. The $anglesVariation$ property defines the possible movements for each joints. Each joint can move $-angleDiff$, 0, or $+angleDiff$ rads.

9. The $actions$ property stores all the possible actions in the action space A

10. The $nActions$ property stores the number of actions in the action space A. The action space is defined as:

$$\begin{aligned} A = \{&(-\theta,-\theta,-\theta),(-\theta,-\theta,0),(-\theta,-\theta,\theta),(-\theta,0,-\theta),(-\theta,0,0),(-\theta,0,\theta),\\ &(-\theta,\theta,-\theta),(-\theta,\theta,0),(-\theta,\theta,\theta),(0,-\theta,-\theta),(0,-\theta,0),(0,-\theta,\theta),(\theta,\theta,-\theta),\\ &(\theta,-\theta,-\theta),(\theta,-\theta,0),(\theta,-\theta,\theta),(\theta,0,-\theta),(\theta,0,0),(\theta,0,\theta),(\theta,\theta,0),\\ &(0,0,-\theta),(0,0,0),(0,0,\theta),(0,\theta,-\theta),(0,\theta,0),(0,\theta,\theta),(\theta,\theta,\theta)\} \end{aligned} \tag{2}$$

    where θ is the $angleDiff$ defined in 7.

11. The $modelClient$ property is a service client for the *gazebo_state/set_entity_state* service, it is used to set the object's position in the simulated world.

12. The $modelClientGetState$ is a service client for the *gazebo_state/get_entity_state* service, it is used to obtain the object's position programmatically.

13. The properties $modelX$, $modelY$, and $modelZ$ store the (x, y, z) coordinates of the object. When the environment manager class is instantiated the $modelClientGetState$ in 12 property is used to obtain these values.

14. The property $trajectoryActionClient$ is an action client. It is used to send messages to the $/joint\_trajectory\_controller/follow\_joint\_trajectory$ server in order to move the arm. The messages are of type $FollowJointTrajectory$ as in 2.4.8.

15. The property $modelSubscription$ defines a subscription to the $/gazebo\_state/model\_states\_demo$ topic and is used to check the position of the object programmatically.

16. The property $jointStateSubscription$ is a subscription to the $/joint\_states$ topic. It is created and used later as in 2.4.6

17. The property $contactSensorSubscription$ is a subscription to the collision sensor topic.

18. The property $collision$ indicates if there is a collision in the simulated environment.

The $EnvironmentManager$ class implements the following methods :

1. The $jointStateSubscriptionCallback()$ method is a callback function defined when creating the property $jointStateSubscription$ 16. This method calculates the $distance$ property in 2. This method is executed every time a new message is received in the $/joint\_states$ topic. That is, every time the arm moves.

2. The $modelSubscriptionCallback()$ method is a callback function defined when creating the property $modelSubscription$ 15. This method is executed every time a new message is received in the $/gazebo\_state/model\_states\_demo$ topic. It is used to obtain the position of the object in the world.

3. The $moveArmToPosition(self, positions)$ function is used to move the arm to a certain position. The argument $positions$ is the desired end position of the joints. It works by using the $trajectoryActionClient$ property in 14.

4. The $moveModelToPosition(self, model, x, y, z)$ method is used to move the object to a certain position (x, y, z). It works by using the $modelClient$ property in 11.

5. The $resetEnvironment()$ method moves the arm to the starting position $positions = [0.0, 0.0, 0.0, 0.0, 0.0, 0.0]$ using 3, moves the object to the starting position by using 4, and sets the $done$ and $collision$ property to false.

6. The $contactSensorCallback4()$, $contactSensorCallback5()$, and $contactSensorCallback6()$ methods are executed when a collision between the Links 4, 5 o 6 and the object happens respectively.

7. The $getState()$ method returns the current state of the environment. The state is composed of the first three joints angles and the distance between the end effector or Link 6 and the object.

8. The $takeAction(actionIndex)$ method takes the $actionIndex$ parameter which identifies the action to be taken. Its responsibility is to move the arm accordingly to the action given, and returns the $reward$ which is consequence of the given action.

9. The $computeReward(previousDistance)$ computes the reward in the current state given the $previousDistance$. The $previousDistance$ is compared with the current distance between the end effector or Link 6 and the target to know if the arm is getting closer to the target or not. The reward is computed as follows:

$$reward = \begin{cases} 100 & \text{if the arm touches the object.} \\ 1 & \text{if the arm moves closer to the object.} \\ -1 & \text{if the arm moves away from the object.} \end{cases}$$

3.7 The Main Program

The main program implements the DDQN algorithm in 2.12. The steps done in the Main Program are the following:

1. Run $rclpy.init$ which must be called before any other $rclpy$ function as it takes care of several important initialization steps. Once the initialization is complete, the $rclpy$ library is ready to be used by all the created nodes, and they can communicate with other nodes and services in the ROS 2 system.

2. Initialize the hyperparameters:

   - *batchSize:* is the size for the batch used by the $ReplayMemory$.

- *gamma:* is the discount factor.
- *epsStart:* is the starting value for the exploration rate.
- *epsEnd:* is the ending value for the exploration rate.
- *epsDecay:* is the decay rate over time for the exploration rate.
- *targetUpdate:* is the number of episodes between updates for the target network weights with the policy network weights.
- *memorySize:* is the capacity of the Replay Memory.
- *lr:* is the learning rate used when training the DQN.
- *numEpisodes:* The number of episodes we want to use for the experiment.
- *maxStepsPerEpisode:* Number of episodes before the environment is reset.

3. Create the $strategy$, $replayMemory$, and $environment$ objects corresponding to the $EpsilonGreedyStrategy$, $ReplayMemory$, and $EnvironmentManager$ classes.

4. Run the non-blocking $rclpy.spin\_once$ with the Environment object as parameter. This allows us to perform actions on the $EnvironmentManager$ node, such as reading messages from topics or sending messages to other nodes.

5. Create an $Agent$ object, and two *NN* objects, one will be the *policyNetwork*, and the other the *targetNetwork*.

6. Set the weights in the *targetNetwork* equal to the weights in the *policyNetwork*.

7. Do the following for every episode:

   - Reset the environment and obtain the current state:

     ```
     environment.resetEnvironment()
     state = environment.getState()
     ```

   - Do the following for every step in the current episode:
     - Select an action, perform the action and save the new state in the $nextState$ variable.

       ```
       action = agent.selectAction(state, policyNetwork)
       reward = environment.takeAction(action)
       nextState = environment.getState()
       ```

     - Save the experience $(state, action, nextState, reward)$ into the $replayMemory$.

       ```
       replayMemory.push(experience=Experience(state, action, nextState, reward))
       ```

- Update $state$ with $nextState$ which now becomes the current state.

```
state = nextState
```

- Sample experiences from $ReplayMemory$, compute the $currentQValues$ using the $policyNetwork$, and the $targetQValues$ using the $nextQValues$ given by the $targenNetwork$, the discount factor $gamma$, and the $rewards$ taken from the $replayMemory$

```
experiences = replayMemory.sample(batchSize)
states, actions, rewards, nextStates = extractTensors(experiences)

currentQValues = policyNetwork(states).gather(dim=1,
↪  index=actions.unsqueeze(-1))
nextQValues = targetNetwork(nextStates).max(dim=1)[0].detach()
targetQValues = nextQValues * gamma + rewards
```

- Compute the loss using mean square error between $currentQValues$ and $targetQValues$ and apply gradient descent to update the weights in the $policyNetwork$.

```
loss = F.mse_loss(currentQValues, targetQValues.unsqueeze(1))
optimizer.zero_grad()
loss.backward()
optimizer.step()
```

- Stop if the $environment.done$ variable is true or if the maximum number of episodes has been reached.

- Update the $targetNetwork$ weights if $targetUpdate$ episodes have passed

Figure 20 shows all the ROS nodes and topics present when running the main program.

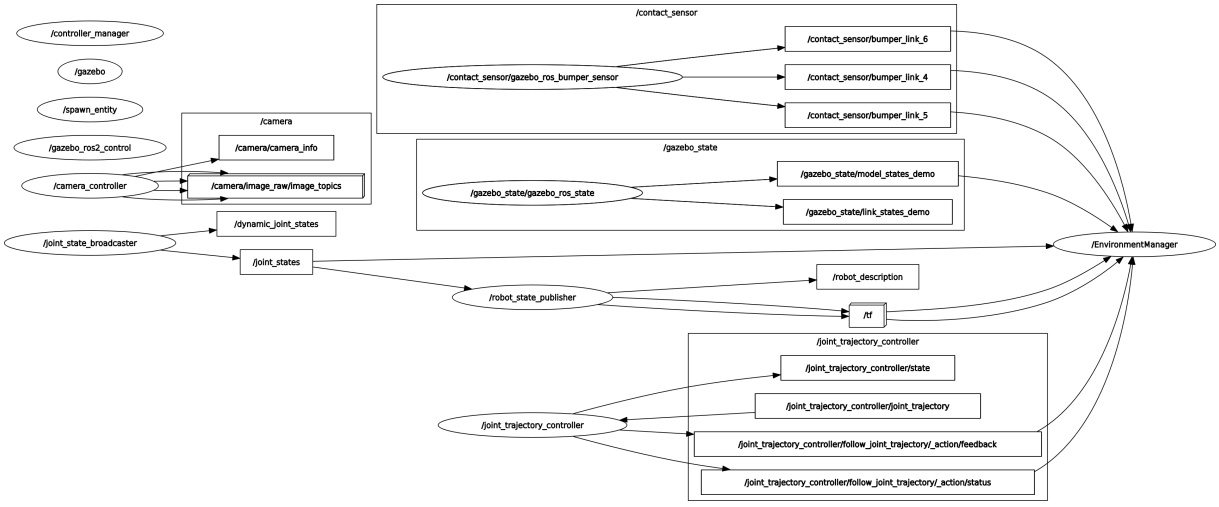


Figure 20: ROS nodes and topics active when running the main program.

3.8 Hardware and Development Environment

Environment Setup	
Main Component	**Metric**
Operating System	Ubuntu 20.04.3 LTS
Processor	Intel(R) Core(TM) i7-4790 CPU @ 3.60GHz
Memory / Disk Capacity	16GB / 500GB
Graphics Card (GPU)	NVIDIA GeForce GTX 1660 Ti
GPU Memory (VRAM)	6GB
Robot Operating System (ROS) Version	ROS 2 Foxy
Gazebo Version	Gazebo multi-robot simulator, version 11.11.0
Python Version	3.8.10

Table 1: Development environment setup.

4 Experiments

4.1 Testing the Environment

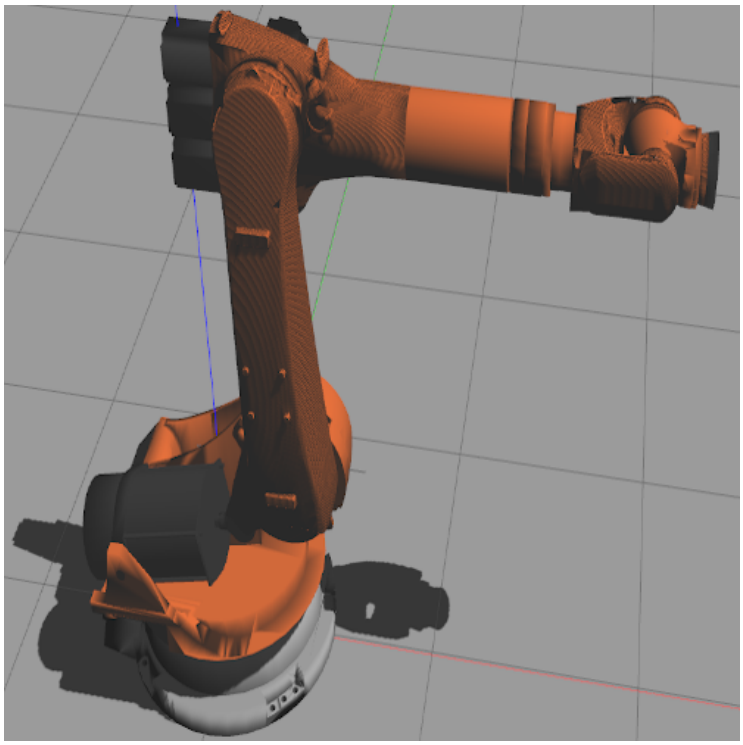
4.1.1 Moving the Arm

The script $anglesPublisher.py$ defining the class $AnglesPublisher$ allows us to move the arm by making use of the $/joint\_trajectory\_controller/joint\_trajectory$ and specifying the joint angles in radians via command line. To collect the data in Table 2 the following was run 5 times:

```
ros2 run kuka_kr_210_pkg anglesPublisher 0.5 0.5 0.5 0.5 0.5 0.5
```

After running the script specifying a target angle of 0.5 rads for all the joints, the results in Table 2 are obtained.

Making use of the values in Table 2, a measurement of $0.49999900427046 \pm 3.86729542790782 * 10^{-06} rad$ is obtained when the controller gets $0.5 rad$ as target value.



(a) Kuka Kr210 in starting position.

(b) Kuka Kr210 after moving every joint to 0.5 rads

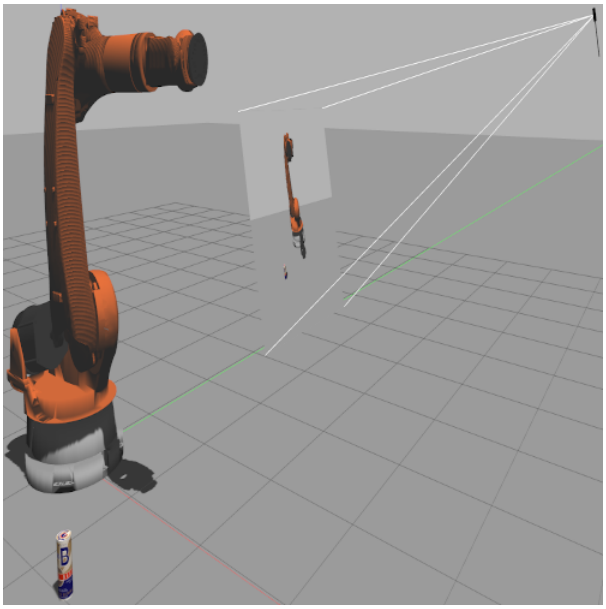
Figure 21: Robotic arm before and after publishing the target angles.

Real Value (Radians)	Target Value (Radians)	Difference (Radians)
0.499999687205044	0.5	0.00000312794956103257
0.499999668258356	0.5	0.00000331741643877503
0.499997756395531	0.5	0.0000224360446932081
0.499999687185443	0.5	0.00000312814556535645
0.499999687205041	0.5	0.00000312794958823304
0.50000422755606	0.5	-0.00000422755605988812
0.500004208609269	0.5	-0.00000420860926908517
0.500002296736044	0.5	-0.00002296736044401626
0.50000422753646	0.5	-0.00000422753645956675
0.500004227556057	0.5	-0.00000422755605722358
0.500000658598723	0.5	-0.000006585987231133357
0.500000639652042	0.5	-0.000006396520424445538
0.499998727789975	0.5	0.00001272210025327 07
0.500000658579123	0.5	-0.000006585791227919 91
0.50000065859872	0.5	-0.00000065859872033 78
0.499992295778437	0.5	0.00000770422156293193
0.499992276831646	0.5	0.00000772316835362386
0.499990364958472	0.5	0.00000963504152823314
0.499992295758838	0.5	0.00000770424116236512
0.499992295778435	0.5	0.00000770422156470829
0.50000168446693	0.5	-0.00000168446693038504
0.500001665520483	0.5	-0.00000166552048330715
0.499999753682106	0.5	0.000002463178941369 83
0.50000168444733	0.5	-0.00000168444733006368
0.500001684466927	0.5	-0.00000168446692683233
0.499997811745677	0.5	0.00000218825432352077
0.499997792799086	0.5	0.00000220720091448356
0.49999588094579	0.5	0.00000411905420971692
0.499997811726076	0.5	0.00000218827392378662
0.499997811745674	0.5	0.0000021882543261853

Table 2: Final values for the joints' angles after setting a target of 0.5 radians.

4.1.2 Reading Images from the Camera Sensor

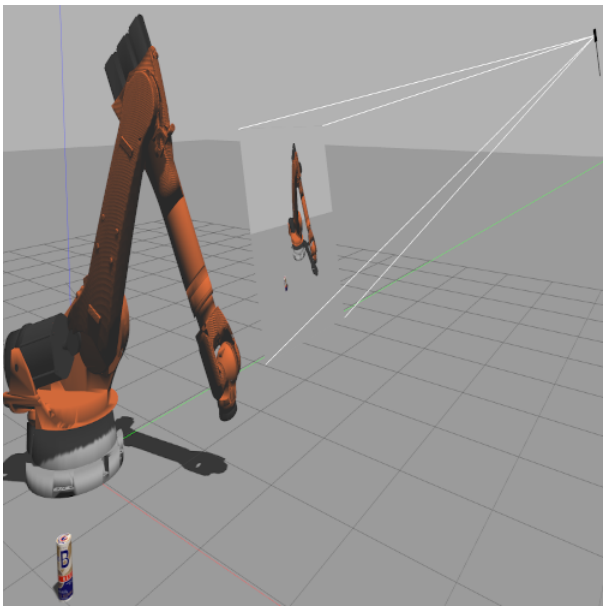
To test if it is really possible to get images from the camera sensor, the script $cameraSubscriber.py$ was created.



(a) Gazebo world and robotic arm at the beginning of the experiment.

(b) Image captured by the cameraSubscriber.py script before moving the arm.

Figure 22: Image of the gazebo world and from the camera sensor at starting position.



(a) Gazebo world and robotic arm position after executing a moving command.

(b) Image captured by the cameraSubscriber.py script after moving the arm.

Figure 23: Image of the gazebo world and from the camera sensor after moving the arm.

The *cameraSubscriber.py* subscribes to the */camera/image_raw* and as Figures 22b and 23b show, the script can obtain the images and in this case just shows them in a new window.

4.1.3 Detecting Collisions

In this experiment the script *anglesPublisher.py* is used to move the arm to touch the object (a can). While doing this the topics */contact_sensor/bumper_link_4*, */contact_sensor/bumper_link_5*, and */contact_sensor/bumper_link_6* are monitored using Rqt 2.8 so collisions between the beer can and Links 4, 5, or 6 can be detected. After moving the arm to make the collision happen between the can and Link 6 of the arm as in Figure 25, it can be seen in Figure 25 that for the topic */contact_sensor/bumper_link_6* there is a message of type *ContactState* in *states* which indicates that the collisions sensor is working properly and we can rely on them in future experiments.

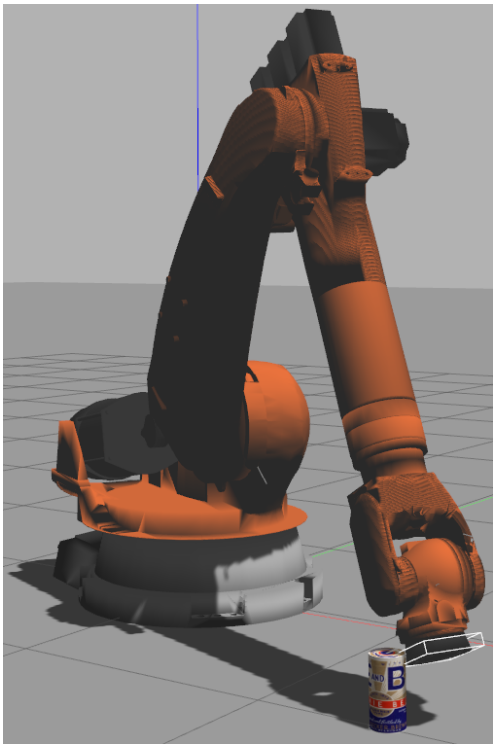


Figure 24: Collision between the can and Link 6 or end effector of the arm.

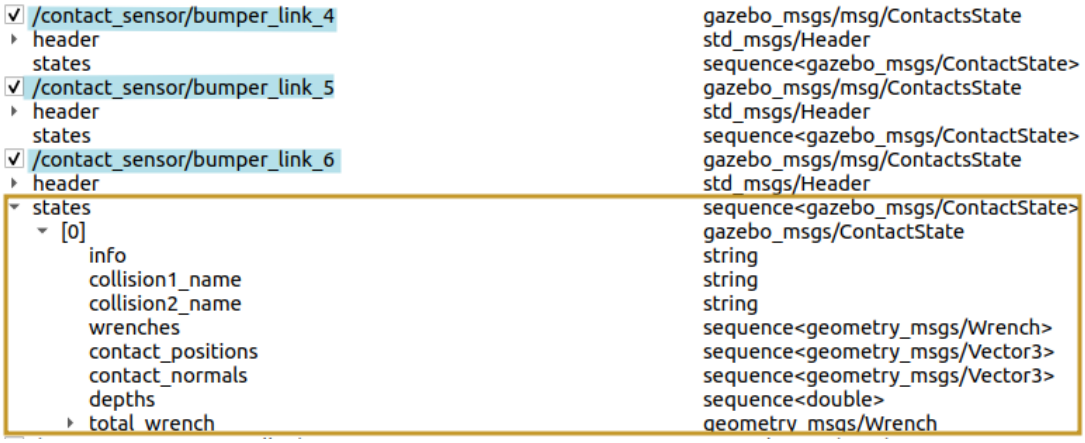


Figure 25: Monitoring the topics */contact_sensor/bumper_link_4*, */contact_sensor/bumper_link_5*, and */contact_sensor/bumper_link_6* in Rqt 2.8. The first column is the name of the topics, and the second is the type of message they handle.

4.2 Learning to touch the object

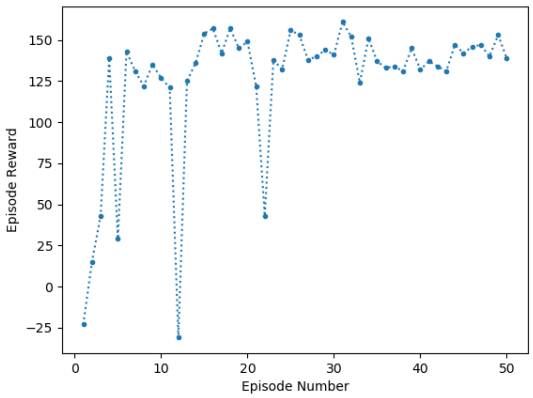
4.2.1 Experiment 1

In this experiment the Main Program 3.7 was run with the parameters in Table 3. The experiment consists in finding out if the arm can learn to touch the can.

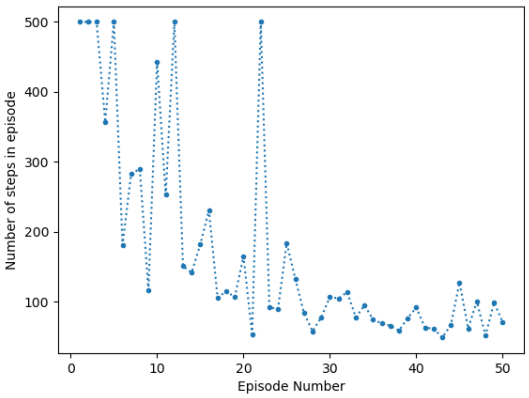
Parameter	Value
Discount Factor (γ)	0.99
Batch Size	512
Epsilon Start Value	1
Epsilon Final	0.01
Epsilon Decay Rate	0.0001
Episodes before updating the Target Network	10
Replay Memory size	10240
Learning Rate	0.001
Number of Episodes	50
Maximum Steps per episode	500

Table 3: Hyperparameters values for the reinforcement learning algorithm in Experiment 1.

As the results in Figure 26a show, the arm learns to get a reward of over 125 consistently from episode 25. Also in Figure 26b can be seen that the number of steps per episode stay around or below 100. This means that the arm learns to touch the object.



(a) Sum of rewards in an episode or episode reward per episode



(b) Number of steps per episode.

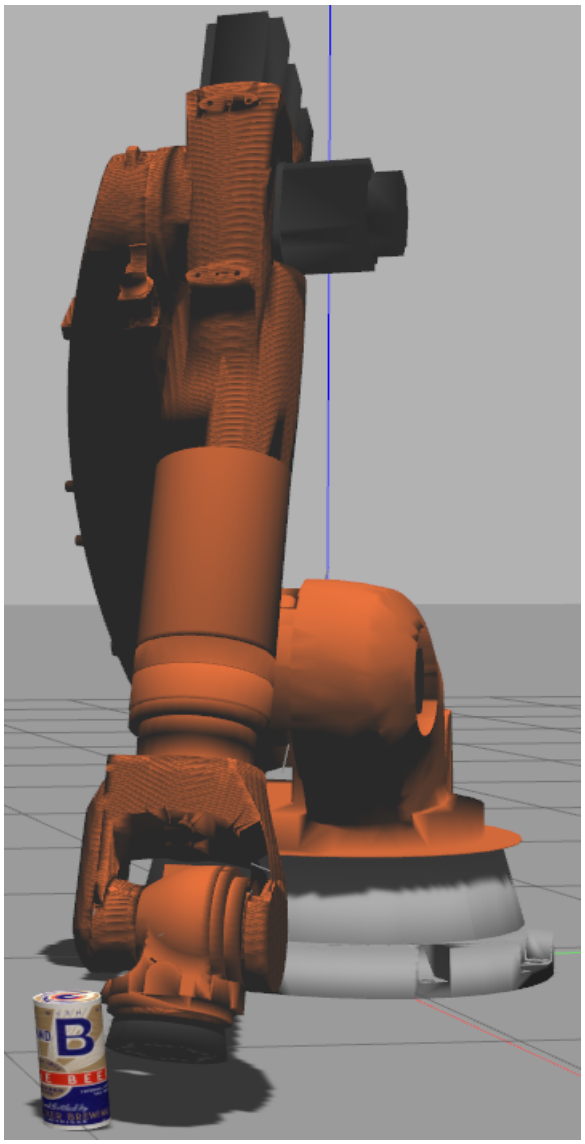
Figure 26: Reward per episode and number of steps per episode for experiment 1 with parameters in Table 3.

4.2.2 Experiment 2

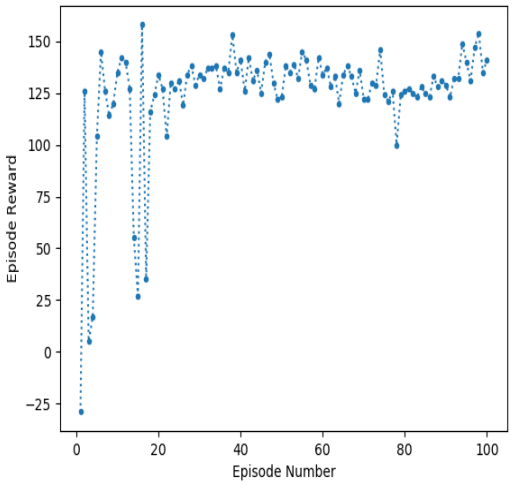
This experiment is similar to Experiment 1, just the number of episodes changes to 100 to see if the learning of the arm can be improved.

Parameter	Value
Discount Factor (γ)	0.99
Batch Size	512
Epsilon Start Value	1
Epsilon Final	0.01
Epsilon Decay Rate	0.0001
Episodes before updating the Target Network	10
Replay Memory size	10240
Learning Rate	0.001
Number of Episodes	100
Maximum Steps per episode	500

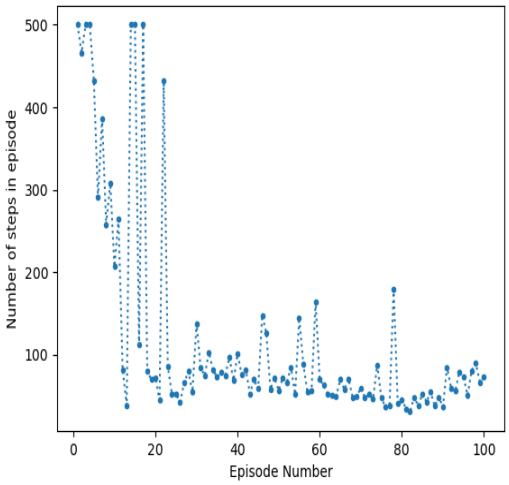
Table 4: Hyperparameters values for the reinforcement learning algorithm in Experiment 2.



(a) Collision between Link 6 of the robotic arm and can at the end of Experiment 2.



(b) Sum of rewards in an episode or episode reward per Episode



(c) Number of steps per episode.

Figure 27: Collision of the robotic arm and the can and Experiment 2 results.

4.2.3 Experiment 3

This experiment was run using the parameters in Table 5

Parameter	Value
Discount Factor (γ)	0.5
Batch Size	512
Epsilon Start Value	1
Epsilon Final	0.01
Epsilon Decay Rate	0.0001
Episodes before updating the Target Network	10
Replay Memory size	10240
Learning Rate	0.001
Number of Episodes	100
Maximum Steps per episode	500

Table 5: Hyperparameters values for the reinforcement learning algorithm in Experiment 3.

In addition to the total reward per episode and number of steps per episode, the exploration rate (ϵ) was also monitored in this experiment as can be seen in Figure 28.

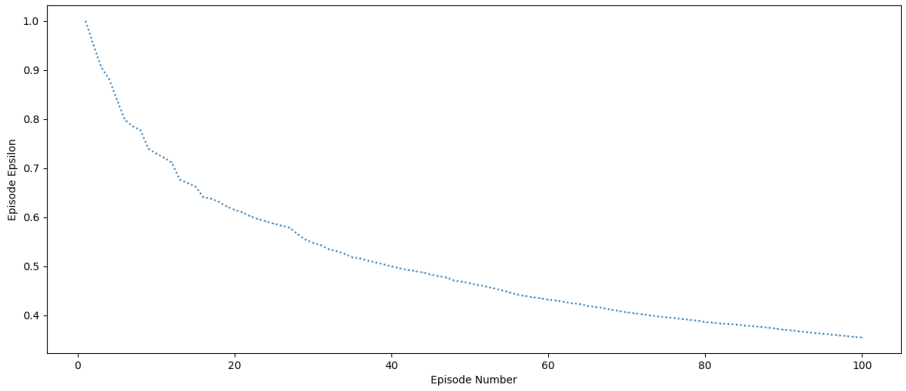
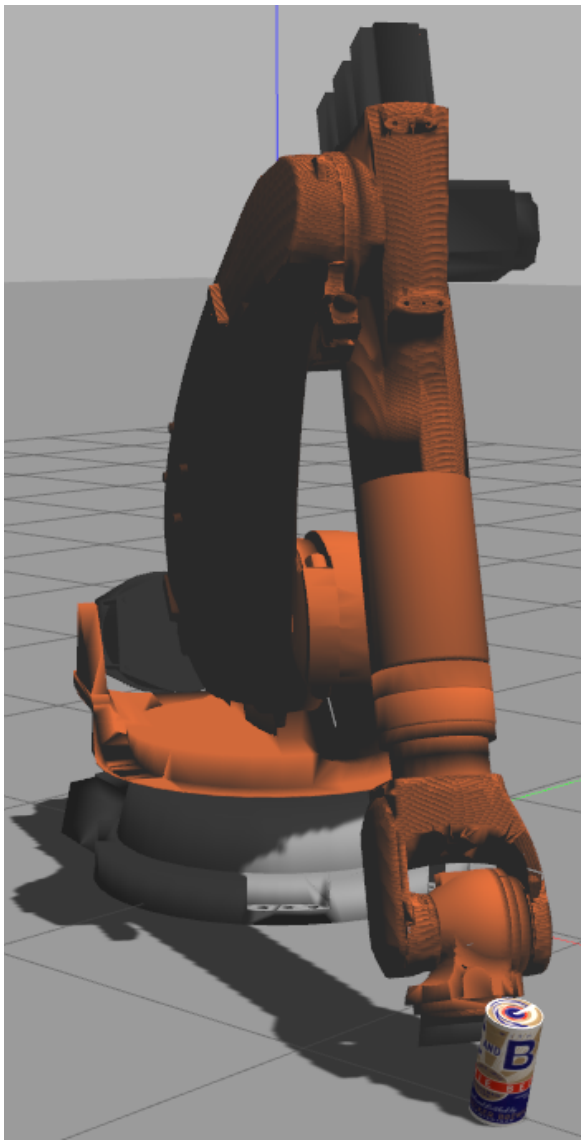
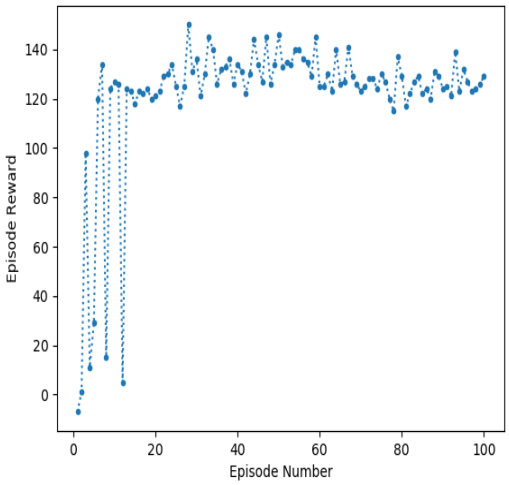


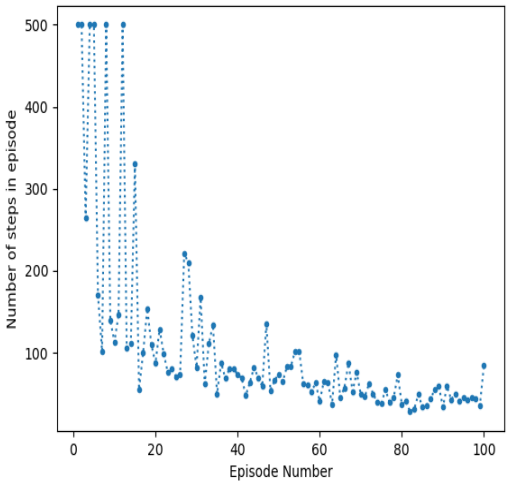
Figure 28: Exploration rate (ϵ) value at the beginning of each episode.



(a) Collision between Link 6 of the robotic arm and can at the end of Experiment 3.



(b) Sum of rewards in an episode or episode reward per episode



(c) Number of steps per episode.

Figure 29: Collision of the robotic arm and the can and Experiment 3 results.

4.2.4 Experiment 4

The experiment was run with parameters in Table 6.

Parameter	Value
Discount Factor (γ)	0.5
Batch Size	2048
Epsilon Start Value	1
Epsilon Final	0.01
Epsilon Decay Rate	0.00001
Episodes before updating the Target Network	5
Replay Memory size	10240
Learning Rate	0.001
Number of Episodes	300
Maximum Steps per episode	500

Table 6: Hyperparameters values for the reinforcement learning algorithm in Experiment 4.

The exploration rate at the beginning of each episode is shown in Figure 30

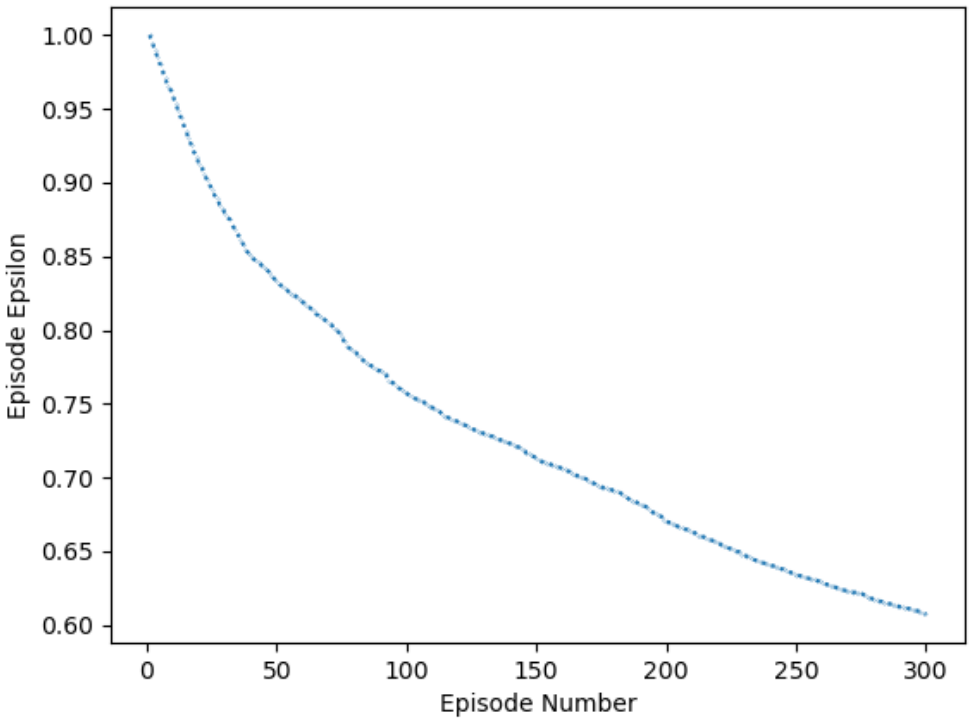
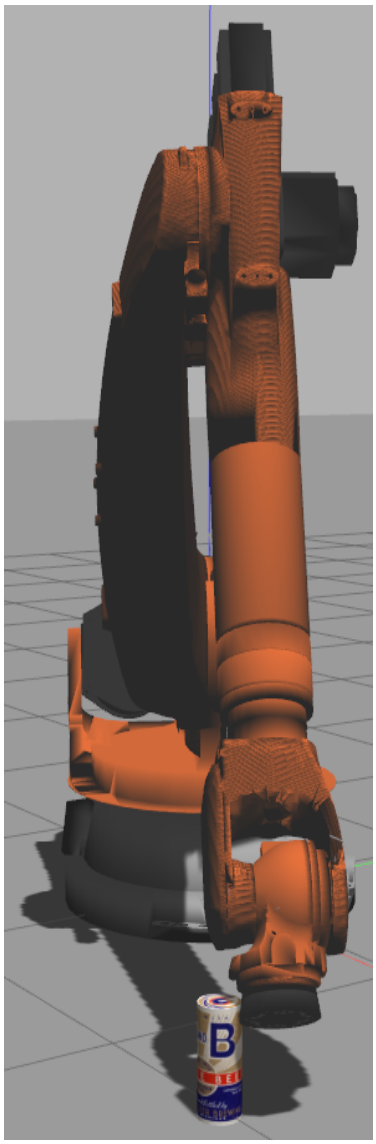
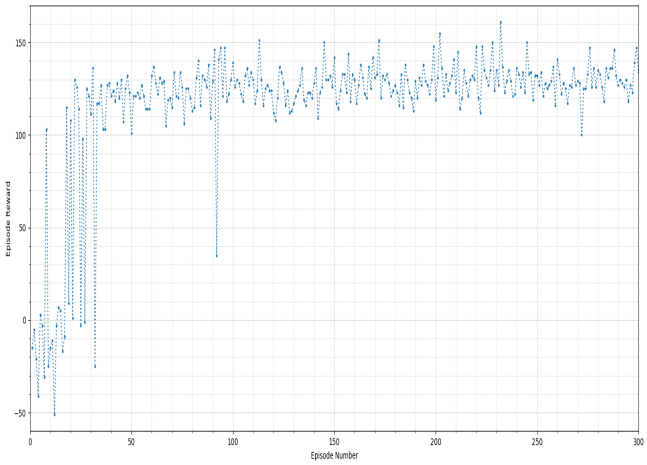


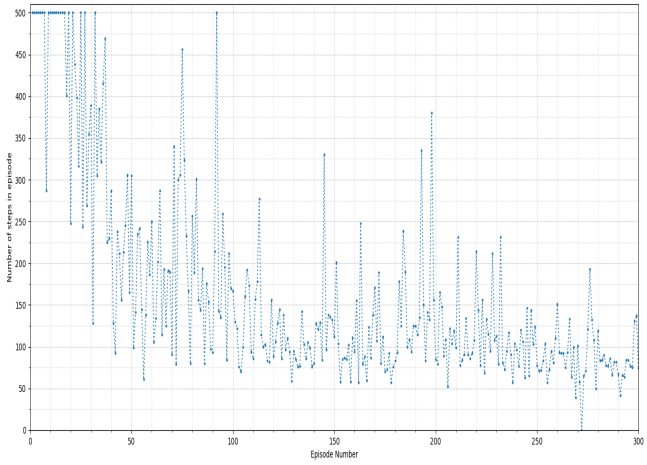
Figure 30: Exploration rate (ϵ) value at the beginning of each episode.



(a) Collision between Link 6 of the robotic arm and can at the end of Experiment 4.



(b) Sum of rewards in an episode or episode reward per episode



(c) Number of steps per episode.

Figure 31: Collision of the robotic arm and the can and Experiment 4 results.

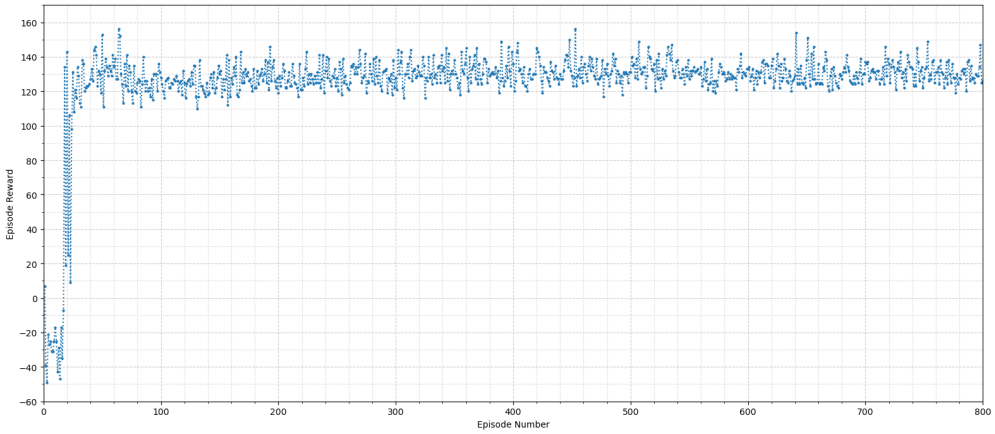
4.2.5 Experiment 5

The experiment was run with parameters in Table 7.

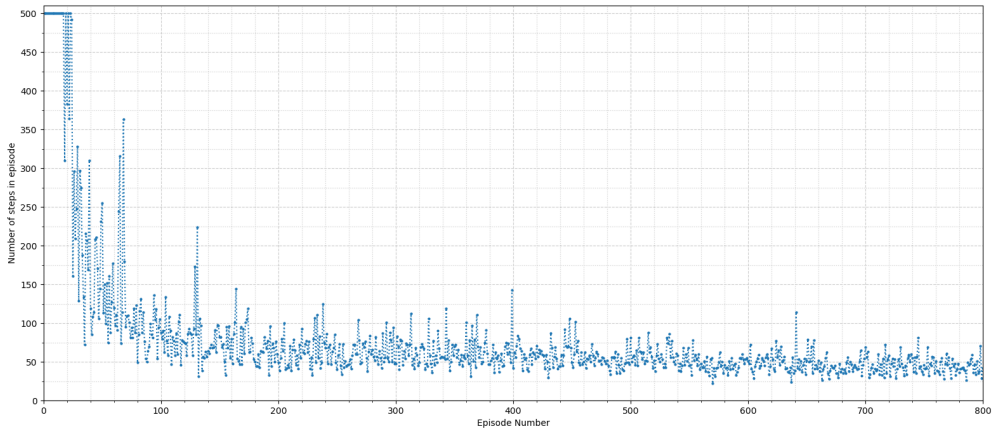
Parameter	Value
Discount Factor (γ)	0.5
Batch Size	8184
Epsilon Start Value	1
Epsilon Final	0.01
Epsilon Decay Rate	0.00002
Episodes before updating the Target Network	5
Replay Memory size	102400
Learning Rate	0.001
Number of Episodes	800
Maximum Steps per episode	500

Table 7: Hyperparameters values for the reinforcement learning algorithm in Experiment 5.

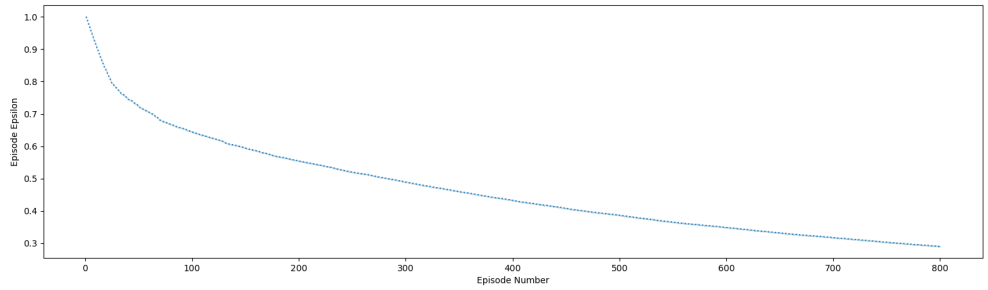
The experiment results can be seen in Figure 32.



(a) Sum of rewards in an episode or episode reward per episode.



(b) Number of steps per episode.



(c) Exploration rate (ϵ) value at the beginning of each episode.

Figure 32: Results for Experiment 5.

5 Discussion

In this thesis, we explored the use of a DQN to train a robotic arm to learn to touch an object. Our experiments were performed on a simulated robotic arm in a virtual environment as in 3.1. The results from experiments 4.1.1, 4.1.2, and 4.1.3 show that the robotic arm simulation was successfully implemented. Furthermore, it is possible to interact with the simulation programmatically, treating it as a Markov Decision Process. experiment 4.1.1 shows that we can rely on the used ROS 2 packages to control the position of the arm with an accuracy in the order of $10^{-06}rad$. Also, experiment 4.1.2 creates new possibilities for future studies as the images from the camera sensor could be used instead of the built-in Gazebo and ROS plugins to know the position of the objects in the simulated world, making easier the transition from the simulation to the real world because it is easier to work with a camera instead of location sensors in the end effector of the arm and in the can; in fact, the idea of adding a sensor to the can in the real world is a little troublesome because ideally, we should be able to just place any object in our world without having to alter it in any way. In addition, experiment 4.1.3 proves that it is possible to use contact sensors in the simulation and perform actions based on the readings from these sensors. Thus, it is safe to claim that experiments in 4.1 really represent a fully working simulation of a robotic arm in which not only Markov Decision Processes can be implemented, but also Reinforcement Learning algorithms can be run. In fact, experiments in 4.2 show that it is possible. For example, in experiment 1, in 4.2.1 in Figure 26 it can be seen that the arm consistently achieves higher rewards and finishes the episodes in fewer iterations as the simulation goes on, this proves that the arm learns about the environment and in time finds the can and learns to touch it. However, to know if the arm can learn a better way to touch the arm, experiment 2 in 4.2.2 is run. Here, we just let the experiment run 50 more steps compared to Experiment 1 in 4.2.1. As can be seen in Figure 27b in the last steps of the process, the total rewards do not significantly improve compared to Figure 26a, neither does the number of steps the arm needs to touch the can when we compare Figures 26b and 27c. The goals in 1.3 have been so far achieved as we have a working simulation of a robotic arm working, the simulated robotic arm learns to touch the can in the simulated world (Figure 27a). Next, let us examine if this can be improved and how the exploration-exploitation trade-off is being dealt with.

Experiment 3 in 4.2.3 examines the learning process with a discount factor of $\gamma = 0.5$ instead of a $\gamma = 0.99$ as in the previous experiments. The idea is to see if the learning process improves or gets worse. When comparing Figure 27a and Figure 29a we can see that even though the arm touches the can from different positions, it does learn to touch it. Moreover, by comparing Figures 29b, 29c to Figures 27b, 27c we can see that the learning process is neither better nor worse. On the other hand, Figure 28 shows that during the whole performance, there was some randomness due to the explore-exploit trade-off therefore there were always random actions in every episode.

Experiment 4 in 4.2.4 is an attempt to improve results i.e. obtaining higher rewards and finishing the episode in fewer steps. To try this, the Batch size is increased to 2048,

the Decay rate for epsilon ϵ is reduced to 0.00001, and the number of episodes is increased to 300. With these parameters as can be seen in Figure 31, the total rewards per episode in Figure 31b are not significantly better than the ones in Figure 29b since in both cases, they hover around a total reward value of 150. But as can be seen in Figure 28 the exploration rate in Experiment 4 was always above 0.6 compared to the exploration rate in Figure 28 in Experiment 3 which gets to values lower than 0.4. It is important to note that with higher exploration rates, more random actions take place and these random actions make the episode longer as the action does not necessarily aim to get the arm closer to the can.

Experiment 5 in 4.2.5 is designed to compare the total rewards and iterations per episodes with parameters that would let the simulation run for more time steps and consider more experiences when training the neural network. With the number of steps per episode set to 800, a higher batch size of 8184, and a decay rate for epsilon of 0.00002 it is possible to see the total rewards of the robotic arm at exploration rates (Figure 32c) that have similar values as those in Figure 28. Comparing the total rewards in Figures 31b and 32a it can be seen that the performance is not significantly different as the total reward still hovers between 120 and 140, and the number of steps per episode in Figure 31c is around 75 whereas in Figure 32b it consistently stays below 50 from episode 500. Therefore, even though the total rewards per episode are similar, the steps the agent takes to complete the episodes are less which means the arm learns a more efficient set of movements to touch the can in Experiment 5 4.2.5 than in previous experiments.

Our results show that the DQN approach was successful in training the robotic arm to complete the task of touching an object. The agent was able to learn a functional policy over time and consistently achieve the desired objective. The performance of the trained agent was evaluated using two metrics: the total reward per episode and the number of episodes it took to reach the goal. The total reward per episode of the agent increased steadily during training and stabilized after approximately 200 steps in experiments 4.2.4 and 4.2.5. The number of steps to complete an episode also decreased during training, indicating that the agent was learning to perform the task more efficiently.

Several experiments were also conducted to analyze the impact of different hyperparameters on the performance of the DQN agent. Our findings suggest that the choice of hyperparameters, such as the discount factor, can affect the training. Additionally, increasing the size of the replay memory improved the performance of the agent.

One of the limitations of our study is that it was performed on a simulated robotic arm. The transferability of the learned policy to a physical robotic arm in the real world is an important aspect to consider in future work. Another limitation is the relatively simple task of just touching an object. Future work can investigate the use of DQN for more complex tasks, such as manipulation of objects in cluttered environments.

In conclusion, the application of DQN to train a robotic arm to perform a specific task shows promising results. Our experiments demonstrate the effectiveness of this approach and provide insights into the impact of different hyperparameters on the training process. The results of this study can contribute to the development of more

advanced reinforcement learning algorithms for robotics.

6 Conclusion

This thesis explored the application of the Double Q-Learning algorithm to a simulated robotic arm in a reinforcement learning setting. The theoretical foundation of the algorithm was introduced, implemented, and applied to a simple task using the Gazebo simulator and ROS 2 libraries. The experimental results show that the Double Q-Learning algorithm works as the simulated arm learns to touch the can. This work contributes to the development of reinforcement learning algorithms for training robotic arms and provides not only a robust and efficient approach but also an alternative to solving complex tasks in the robotics area.

In the experiments, a simple task for the robotic arm to perform was designed, this task consists in moving the robotic arm to a given target location so it touches an object (a can). The robotic arm had six degrees of freedom; out of which only three were manipulated in the experiments. The task required a combination of forward and backward movements of these joints. The state space was given by the three joint angles and the distance between the robotic arm and the can; whereas the action space was discrete and given by the combination of possible variations for the angles. The robotic arm was trained using the Double Q-Learning algorithm.

Future work can explore the application of the algorithm to more complex tasks and environments as there are several possible avenues for future research in the field of reinforcement learning, DQN, and robotic arms. One possible direction is to explore the use of the prioritized experience replay method, to improve the performance and stability of the robotic arm. Additionally, incorporating more complex reward functions, such as those that incorporate task completion time or energy efficiency, could be explored.

Another direction for future research is to investigate the use of deep reinforcement learning in more complex robotic tasks, such as manipulation and grasping. These tasks require more fine-grained control over the robotic arm's movements and may involve multiple objects or obstacles in the environment. Therefore, new approaches to reinforcement learning that can handle such complexity could be explored.

The use of transfer learning in reinforcement learning for robotic arms is another potential topic to investigate. Transfer learning involves leveraging knowledge gained from one task to aid in learning a new task. This approach has shown promise in the field of deep learning, and its application to reinforcement learning in robotics could lead to more efficient learning and faster convergence.

Also, the deployment of reinforcement learning in real-world robotic applications could also be explored. This involves overcoming several challenges, such as ensuring the safety and reliability of the robotic arm and dealing with noisy and uncertain sensory data. However, successful implementation of reinforcement learning in real-world robotic applications could have significant practical applications in areas such as manufacturing, healthcare, and logistics.

Finally, trying different hyperparameters combinations and comparing their different results seem the next logical step. However, also other reward function definitions could be used to see if better results can be achieved in the experiments. The use of camera images and object detection algorithms instead of the sensors plugins in the experiments is also something that could be implemented.

Regarding the simulated environment setup, a docker implementation of the whole reinforcement learning framework created in this thesis could be done since installing ROS 2, Gazebo, and making them work together is not a straightforward process.

In conclusion, the application of reinforcement learning and DQN to a simulated robotic arm has shown promising results in one single simple task and future work could also adapt this to complex behaviors and scenarios. However, there are still several directions for future research in this field, including exploring different variants of the DQN algorithm, investigating more complex robotic tasks, incorporating transfer learning, and deploying reinforcement learning in real-world robotic applications. In addition to that, the implementation of object detection techniques and the use of images from the camera sensor as inputs to our DQN can be done as well as performing benchmarking using different hyperparameters.

References

[1] Leticia Oyuki Rojas Pérez, Roberto Munguia-Silva, and Jose Martinez-Carranza. Real-time landing zone detection for uavs using single aerial images. 11 2018.

[2] Amazon Web Services. AWS RoboMaker Small Warehouse World. `https://github.com/aws-robotics/aws-robomaker-small-warehouse-world`, 2019. Accessed: May 5, 2023.

[3] Jenny Hsu. Car factories turn robots and humans into co-workers. *WAMU 88.5 American University Radio*, September 2013. Accessed on May 7, 2023.

[4] MathWorks. Pick and place workflow in gazebo using ros. `https://de.mathworks.com/help/robotics/ug/pick-and-place-workflow-in-gazebo-using-ros.html`, 2021. Accessed on May 7, 2023.

[5] N. Nevejans, C. Allen, A. Blyth, S. Leonard, U. Pagallo, K. Holzinger, A. Holzinger, M. I. Sajid, and H. Ashrafian. Legal, regulatory, and ethical frameworks for development of standards in artificial intelligence (ai) and autonomous robotic surgery. *The international journal of medical robotics and computer assisted surgery*, 15(1):e1968, 2019.

[6] Juan Jesús Roldán, Jaime del Cerro, David Garzón-Ramos, Pablo Garcia-Aunon, Mario Garzón, Jorge de León, and Antonio Barrientos. Robots in agriculture: State of art and practical experiences. In Antonio J. R. Neves, editor, *Service Robots*, chapter 4. IntechOpen, Rijeka, 2017.

[7] Nick Bostrom and Eliezer Yudkowsky. The ethics of artificial intelligence. In *Artificial Intelligence Safety and Security*, pages 57–69. Chapman and Hall/CRC, 2018.

[8] Richard S Sutton and Andrew G Barto. *Reinforcement Learning: An Introduction*. MIT Press, 2018.

[9] Leslie Pack Kaelbling, Michael L. Littman, and Andrew W. Moore. Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, 4:237–285, 1996.

[10] HeeSun Choi, Cindy Crump, Christian Duriez, Asher Elmquist, Gregory Hager, David Han, Frank Hearl, Jessica Hodgins, Abhinandan Jain, Frederick Leve, Chen Li, Franziska Meier, Dan Negrut, Ludovic Righetti, Alberto Rodriguez, Jie Tan, and Jeff Trinkle. On the use of simulation in robotics: Opportunities, challenges, and suggestions for moving forward. *Proceedings of the National Academy of Sciences*, 118(1):e1907856118, 2021.

[11] Asher Elmquist, Radu Serban, and Dan Negrut. A sensor simulation framework for training and testing robots and autonomous vehicles. *Journal of Autonomous Vehicles and Systems*, 1(2), 2021.

[12] Carlos Sampedro, Alejandro Rodriguez-Ramos, Hriday Bavle, Adrian Carrio, Paloma de la Puente, and Pascual Campoy. A fully-autonomous aerial robot for search and rescue applications in indoor environments using learning-based techniques. *Journal of Intelligent & Robotic Systems*, 95:601–627, 2019.

[13] Paulo Leitão, Armando Walter Colombo, and Stamatis Karnouskos. Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Computers in Industry*, 81:11–25, 2016.

[14] Mohd Javaid, Abid Haleem, Ravi Pratap Singh, and Rajiv Suman. Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cognitive Robotics*, 1:58–75, 2021.

[15] Matteo Lucchi, Friedemann Zindler, Stephan Mühlbacher-Karrer, and Horst Pichler. robo-gym - an open source toolkit for distributed deep reinforcement learning on real and simulated robots. *CoRR*, abs/2007.02753, 2020.

[16] Preston Ohta, Luis Valle, Jonathan King, Kevin Low, Jaehyun Yi, Christopher G. Atkeson, and Yong-Lae Park. Design of a lightweight soft robotic arm using pneumatic artificial muscles and inflatable sleeves. *Soft Robotics*, 5(2):204–215, 2018.

[17] Balkeshwar Singh, N. Sellappan, and Poomani Kumaradhas. Evolution of industrial robots and their applications. 2013.

[18] Open Robotics. Ignition robotics. `https://ignitionrobotics.org/home`, Accessed: 2023-04-24.

[19] Erwin Coumans and Yunfei Bai. Pybullet, a python module for physics simulation for games, robotics and machine learning, 2016.

[20] Jerry Banks. *Introduction to simulation*. 1999.

[21] Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, and Andrew Ng. Ros: an open-source robot operating system. volume 3, 01 2009.

[22] Steve Cousins. Willow garage retrospective [ros topics]. *IEEE Robotics & Automation Magazine*, 21(1):16–20, 2014.

[23] Luis Emmi, Mariano Gonzalez de Soto, Gonzalo Pajares, and Pablo Gonzalez de Santos. New trends in robotics for agriculture: integration and assessment of a real fleet of robots. *The Scientific World Journal*, 2014, 2014.

[24] Yuqian Lu, Chao Liu, Kevin I-Kai Wang, Huiyue Huang, and Xun Xu. Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing*, 61:101837, 2020.

[25] Pedro Tavares, Joao André Silva, Pedro Costa, Germano Veiga, and António Paulo Moreira. Flexible work cell simulator using digital twin methodology for highly complex systems in industry 4.0. 2018.

[26] Stanford Artificial Intelligence Laboratory et al. Robotic operating system. `https://www.ros.org`. [Online; accessed 24-April-2023].

[27] T. R. Browning. Applying the design structure matrix to system decomposition and integration problems: a review and new directions. *IEEE Transactions on Engineering Management*, 48(3):292–306, 2001.

[28] Mihir Kulkarni, Pranay Junare, Mihir Deshmukh, and Priti P. Rege. Visual slam combined with object detection for autonomous indoor navigation using kinect v2 and ros. In *2021 IEEE 6th International Conference on Computing, Communication and Automation (ICCCA)*, pages 478–482. IEEE, 2021.

[29] Wei Wu, Tingting Huang, and Ke Gong. Ethical principles and governance technology development of ai in china. *Engineering*, 6(3):302–309, 2020.

[30] Stephen James and Edward Johns. 3d simulation for robot arm control with deep q-learning. *CoRR*, abs/1609.03759, 2016.

[31] Andrea Franceschetti, Elisa Tosello, Nicola Castaman, and Stefano Ghidoni. Robotic arm control and task training through deep reinforcement learning. In *Intelligent Autonomous Systems 16: Proceedings of the 16th International Conference IAS-16*, pages 532–550. Springer, 2022.

[32] Aryslan Malik, Yevgeniy Lischuk, Troy Henderson, and Richard Prazenica. A deep reinforcement-learning approach for inverse kinematics solution of a high degree of freedom robotic manipulator. *Robotics*, 11(2):44, 2022.

[33] Ali Abdi, Mohammad Hassan Ranjbar, and Ju Hong Park. Computer vision-based path planning for robot arms in three-dimensional workspaces using q-learning and neural networks. *Sensors*, 22(5):1697, 2022.

[34] Python Software Foundation. Python documentation. `https://docs.python.org/`, 2021. Accessed: May 2, 2023.

[35] Zhaobin Wang, Ke Liu, Jian Li, Ying Zhu, and Yaonan Zhang. Various frameworks and libraries of machine learning and deep learning: a survey. *Archives of computational methods in engineering*, pages 1–24, 2019.

[36] Bulat Abbyasov, Roman Lavrenov, Aufar Zakiev, Konstantin Yakovlev, Mikhail Svinin, and Evgeni Magid. Automatic tool for gazebo world construction: from a grayscale image to a 3d solid model. 06 2020.

[37] Gilberto Echeverria, Nicolas Lassabe, Arnaud Degroote, and Séverin Lemaignan. Modular open robots simulation engine: Morse. In *2011 IEEE International Conference on Robotics and Automation*, pages 46–51, 2011.

[38] Phuwanat Phueakthong and Jittima Varagul. A development of mobile robot based on ros2 for navigation application. In *2021 International Electronics Symposium (IES)*, pages 517–520, 2021.

[39] Steven Macenski, Tully Foote, Brian Gerkey, Chris Lalancette, and William Woodall. Robot operating system 2: Design, architecture, and uses in the wild, may 2022.

[40] Roland. Hess. Blender foundations: The essential guide to learning blender 2.6, 2010.

[41] Kelly. Murdock. Autodesk maya 2023 basics guide, 2022.

[42] Bill Fane, Mark Harrison, and Josh Reilly. Sketchup for dummies, 2020.

[43] Khader Hamdia, Xiaoying Zhuang, and Timon Rabczuk. An efficient optimization approach for designing machine learning models based on genetic algorithm. *Neural Computing and Applications*, 33, 03 2021.

[44] Ruben Villegas, Jimei Yang, Duygu Ceylan, and Honglak Lee. Neural kinematic networks for unsupervised motion retargetting. volume abs/1804.05653, 2018.

[45] John E. Ball, Derek T. Anderson, and Chee Seng Chan. Comprehensive survey of deep learning in remote sensing: theories, tools, and challenges for the community. *Journal of Applied Remote Sensing*, 11(04):1, sep 2017.

[46] Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. 2016.

[47] Yuhuai Wu, Elman Mansimov, Shun Liao, Roger Grosse, and Jimmy Ba. Scalable trust-region method for deep reinforcement learning using kronecker-factored approximation. 2017.

[48] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. 2013.

[49] Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5026–5033, 2012.

[50] Tiago Nogueira, Simone Fratini, and Klaus Schilling. Autonomously controlling flexible timelines: From domain-independent planning to robust execution. In *2017 IEEE Aerospace Conference*, pages 1–15, 2017.

[51] Robert N. Boute, Joren Gijsbrechts, Willem van Jaarsveld, and Nathalie Vanvuchelen. Deep reinforcement learning for inventory control: A roadmap. *European Journal of Operational Research*, 298(2):401–412, 2022.

[52] Hyun-Kyo Lim, Ju-Bong Kim, Joo-Seong Heo, and Youn-Hee Han. Federated reinforcement learning for training control policies on multiple iot devices. *Sensors*, 20(5), 2020.

[53] MyeongSeop Kim, Dong-Ki Han, Jae-Han Park, and Jung-Su Kim. Motion planning of robot manipulators for a smoother path using a twin delayed deep deterministic policy gradient with hindsight experience replay. *Applied Sciences*, 10(2), 2020.

[54] Dong Han, Beni Mulyana, Vladimir Stankovic, and Samuel Cheng. A survey on deep reinforcement learning algorithms for robotic manipulation. *Sensors*, 23(7), 2023.

[55] Surbhi Gupta, Gaurav Singal, and Deepak Garg. Deep reinforcement learning techniques in diversified domains: a survey. *Archives of Computational Methods in Engineering*, 28(7):4715–4754, 2021.

[56] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. 2017.

[57] Erick Delage and Shie Mannor. Percentile optimization for markov decision processes with parameter uncertainty. *Operations Research*, 58(1):203–213, 2010.

[58] Emilie Kaufmann, Olivier Cappe, and Aurelien Garivier. On bayesian upper confidence bounds for bandit problems. In Neil D. Lawrence and Mark Girolami, editors, *Proceedings of the Fifteenth International Conference on Artificial Intelligence and Statistics*, volume 22 of *Proceedings of Machine Learning Research*, pages 592–600, La Palma, Canary Islands, 21–23 Apr 2012. PMLR.

[59] Udacity. Robond-kinematics-project. `https://github.com/udacity/RoboND-Kinematics-Project`, 2019. Accessed: April 25, 2023.

[60] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. `https://pytorch.org/`, 2019.

A Code Snippets

```
<gazebo reference="link_4">
  <!-- contact sensor -->
  <sensor name="end_effector_sensor" type="contact">
    <selfCollide>true</selfCollide>
    <alwaysOn>true</alwaysOn>
    <update_rate>500</update_rate>
    <contact>
      <collision>link_4_collision</collision>
    </contact>
    <!-- gazebo plugin -->
    <plugin name="gazebo_ros_bumper_sensor" filename="libgazebo_ros_bumper.so">
      <ros>
        <namespace>contact_sensor</namespace>
        <remapping>bumper_states:=bumper_link_4</remapping>
      </ros>
      <frame_name>link_4</frame_name>
    </plugin>
  </sensor>
</gazebo>
```

Listing 7: Bumper Sensor

```
<gazebo reference="camera_link">
  <material>Gazebo/Black</material>
  <sensor name="camera" type="camera">
    <pose>0 0 0 0 0 0</pose>
    <visualize>true</visualize>
    <update_rate>10</update_rate>
    <camera>
      <horizontal_fov>1.089</horizontal_fov>
      <image>
        <format>R8G8B8</format>
        <width>640</width>
        <height>480</height>
      </image>
      <clip>
        <near>0.05</near>
        <far>8.0</far>
      </clip>
    </camera>
    <plugin name="camera_controller" filename="libgazebo_ros_camera.so">
      <frame_name>camera_link_optical</frame_name>
    </plugin>
  </sensor>
</gazebo>
```

Listing 8: Camera Sensor

```
<plugin name='gazebo_ros_state' filename='libgazebo_ros_state.so'>
  <ros>
    <namespace>/gazebo_state</namespace>
    <argument>model_states:=model_states_demo</argument>
    <argument>link_states:=link_states_demo</argument>
  </ros>
  <update_rate>1.0</update_rate>
</plugin>
```

Listing 9: Gazebo ROS state plugin